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Structural unemployment after the crisis in Austria

Michael Christl*†, Monika Köppl–Turyna† and Dénes Kucsera†

*Correspondence:
michael.christl@agenda-austria.at
†Equal Contributors
Agenda Austria, Schottengasse 1/3,
1010 Vienna, Austria

Abstract
This paper analyzes the Austrian Beveridge curve as well as the Beveridge curves for different economic sectors in Austria over the period from 2008 onwards. We find significant outward shifts of the Beveridge curves in eight of the 21 sectors of the economy. We further analyze what factors have contributed to this change. Our results suggest that a significant part of the currently rising unemployment in Austria may be attributed to structural changes. Those structural changes mainly affect the four large sectors: construction, wholesale, transportation, and accommodation and food service activities.

JEL Classification: J62, J63, E24, E32

Keywords: Beveridge curve, Crisis, Mismatch, Structural unemployment

1 Introduction

The Beveridge curve describes the negative relation between the unemployment rate and the vacancy rate over the business cycle. This negative relationship is one of the most established stylized facts in macroeconomics (Beveridge 1944). During booms, vacancy rates are high and unemployment rates are low, while during recessions, vacancy rates go down and unemployment rises. The evolution of the Beveridge curve is traditionally used to distinguish between cyclical and structural shifts in the labor market, allowing an analysis of structural changes within a country and within sectors of the economy. According to Diamond (2013) "an outward shift [of the Beveridge curve] is representing a decline in ability of the labor market to form mutually beneficial matches between workers and firms." Outward shifts in the Beveridge curve can be a sign that the labor market is undergoing a structural change.

According to Dow and Dicks-Mireaux (1958), this interpretation supports the following policy implication: however useful aggregate stabilization policies may be while unemployment is very high, they are likely to fail to lower the unemployment rate all the way to the levels that prevailed before the recession, since the labor market is presumed to be structurally less efficient than before in creating successful matches (Diamond and Şahin 2015).

In many European countries, vacancy rates fell sharply from the beginning of the crisis in 2007. However, while vacancy rates recovered at the start of 2009, the unemployment rates remained high or they kept rising. These facts suggest a shift in the Beveridge curves and are therefore evidence of structural changes in the labor market (see, e.g., Bonthuis et al. (2013)).

In Austria, the Beveridge curve did not seem to change after 2009, contrary to economies struck harder by the financial crisis such as Greece, Italy, Spain, France, and the Eurozone as a whole (see Bonthuis et al. (2015)). However, since 2013, a new development can be observed in Austria: rising unemployment rates unaccompanied by changes in vacancy rates. Previous studies concerning the Austrian Beveridge curve were carried out by Christl (1988) and Bonthuis et al. (2013). The latter looked at the development of the Austrian Beveridge curve after the crisis until 2012, finding no significant shift in this curve.

The goal of this paper is to examine this hypothesized shift in the long-run Beveridge curve in Austria by using an autoregressive distributive lag (ARDL) dynamic-panel specification. In the second step, we examine the Beveridge curves for all economic sectors in Austria. If there is a shift in the overall Beveridge curve, this allows us to determine which economic sectors are responsible for the structural problems. We estimate the shifts within the sectors by using an error-correction model (ECM) to identify the long-run and short-run relations. While the studies by Bonthuis et al. (2013) and Bonthuis et al. (2015) suggest that there was no shift of the Beveridge curve in Austria after the crisis, we show that a statistically significant shift simply took place later than in other European countries (such as Spain, France, and Portugal).

The paper is structured as follows: The next section describes briefly the theoretical foundations of the Beveridge curve. Sections 3 and 4 describe the data and empirical model used. Section 5 examines the significance of the shifts of the Beveridge curves for Austria as a whole and for all economic sectors. Section 6 analyzes the structural factors that contributed to the changes in the Beveridge curves. Section 7 summarizes.

2 Theory

The basic theoretical foundation of the Beveridge curve is given by a canonical search model. Given a matching function $m(v, u)$, we define $\theta \equiv (v/u)$ as the job market tightness, given by the vacancy–unemployment ratio and $p(\theta) \equiv (m/u)$ as the job-finding rate. The idiosyncratic shocks to matching arrive at Poisson rate λ. Therefore, the unemployment dynamics are given by

$$\dot{u} = \lambda(1 - u) - p(\theta)u, \tag{1}$$

which is the difference between the separation flow and the matching flow. In the steady state, the rate of unemployment is given by

$$u = \frac{\lambda}{\lambda + p(\theta)}, \tag{2}$$

which defines the Beveridge curve. A movement along the Beveridge curve occurs if the value of taking on an additional worker relative to the cost of posting vacancy changes. Various events can shift this value, including a change in worker productivity, a change in the bargaining power of workers, a change in aggregate demand, and a change in the employer's operating costs, such as a change to the cost of borrowing (Barlevy 2011). On the other hand, a shift in the Beveridge curve can also occur as a result of a change in matching efficiency or due to an exogenous shock to the separation rate.

In this paper, to analyze the development of the Beveridge curves, we use two approaches that are complementary and thus serve us mutual robustness checks. In the first part (Section 5), we explore the dataset without making specific assumptions about the underlying matching process. That is, by using econometric techniques, we simply want to establish whether the observed relationship between the unemployment rates and vacancy rates has changed since 2013. In the second part (Section 6), we assume that the matching process in each sector is given by a Cobb–Douglas function, and given this assumption, we are able to establish whether a shift in a Beveridge curve is caused by a change in separation rates or matching efficiency. The second approach is, however, more restrictive: owing to the strict assumption of Cobb–Douglas matching, the results systematically *overestimate* the shift of the curves compared with the observables-driven approach.

3 Data

Figure 1 depicts the long-run Beveridge curve for Austria. While the inverse relation between the unemployment rate and the vacancy rate remained stable from 1995 until 2013, there seemed to be a shift after 2013.[1] While the vacancy rate stayed stable, the unemployment rate increased, which could be a sign of increasing structural unemployment.

Unlike (Bonthuis et al. 2015), who focus on Beveridge curves in European countries based on Labor Force Survey (LFS) data,[2] our study focuses solely on the Austrian labor market. Hence, the national definition based on the number of unemployed registered at the Austrian Public Employment Service (AMS) might better reflect all the changes in the Austrian labor market.[3] An additional argument for the choice of this dataset is that the

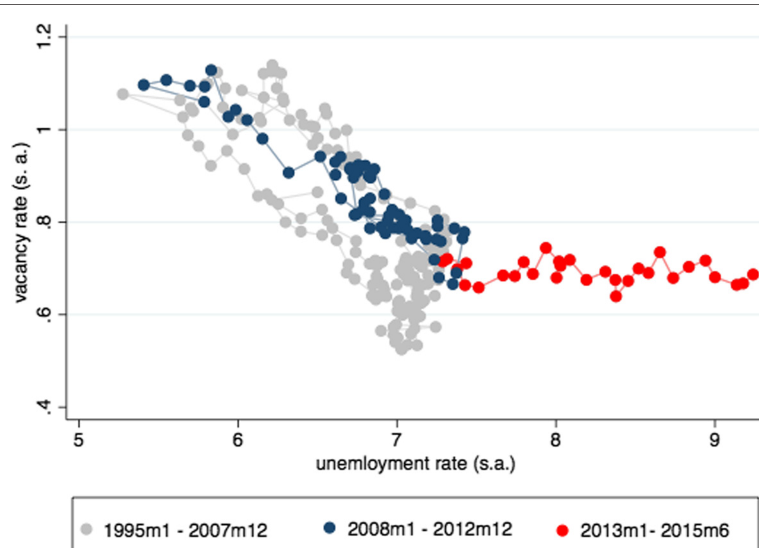

Fig. 1 The Beveridge curve in Austria

data based on national definition are collected on a monthly basis (contrary to quarterly LFS data) and that the number of vacancies is collected by the same authority (AMS), hence based on the same methodology.[4] There are some differences in the unemployment rates stemming from the two definitions. Unemployment according to the national definition is approximately 3 percentage points above the international definition. The main differences in details are as follows:

- Self-employed people and family workers are not included in the AMS definition, while they are included in the LFS statistics. The development of this group of people stayed constant over the investigated period (540,900 in 2008 and 546,500 in 2014 (latest available data)).
- Contrary to the LFS measure, a person is counted as unemployed in the AMS definition (national) although he or she could be marginally employed (earnings below 416 EUR per month). As the number of marginally employed people has increased significantly in the examined period from 317,018 in 2008 to 371,320 in 2015; this increase can partially explain the difference in the two unemployment rates indicated by the two definitions.

We use monthly data on vacancy rates, unemployment rates, and labor force sizes (expressed as a percentage of the total labor force) from the AMS between January 2008 and June 2015 for NACE08-classified sectors of the economy. Sectoral data are available for the sectors listed in Table 1. The industry disaggregation of the unemployed is chosen according to the previous employment of the unemployed person.

As indicated in Table 1, the most important sectors in the Austrian economy are manufacturing (C), wholesale and retail trade (G), and the public administration sector (O), each covering around 15 % of the total labor force. The construction sector (F), the

Table 1 NACE sectors

Code	Element	Sectoral share (%)
A	AGRICULTURE, FORESTRY AND FISHING	0.80
B	MINING AND QUARRYING	0.15
C	MANUFACTURING	15.70
D	ELECTRICITY, GAS, STEAM, AND AIR CONDITIONING SUPPLY	0.70
E	WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT, AND REMEDIATION ACTIVITIES	0.43
F	CONSTRUCTION	7.30
G	WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES	15.03
H	TRANSPORTATION AND STORAGE	5.21
I	ACCOMMODATION AND FOOD SERVICE ACTIVITIES	6.34
J	INFORMATION AND COMMUNICATION	2.35
K	FINANCIAL AND INSURANCE ACTIVITIES	3.06
L	REAL ESTATE ACTIVITIES	1.13
M	PROFESSIONAL, SCIENTIFIC, AND TECHNICAL ACTIVITIES	4.53
N	ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES	6.55
O	PUBLIC ADMINISTRATION AND DEFENSE; COMPULSORY SOCIAL SECURITY	14.50
P	EDUCATION	2.85
Q	HUMAN HEALTH AND SOCIAL WORK ACTIVITIES	7.03
R	ARTS, ENTERTAINMENT, AND RECREATION	1.09
S	OTHER SERVICE ACTIVITIES	2.52
T	ACTIVITIES OF HOUSEHOLDS AS EMPLOYERS	0.10

transportation sector (H), accommodation and food service activities (I), administrative and support service activities (N), and human health and social work activities (Q) are smaller but still cover more than 5 % of the total labor force each.

Since our unemployment definition is based on the sector of previous employment, we need to make sure that workers changing sectors do not influence the unemployment–vacancy relationship; therefore, the relative size of the labor force in a sector is an important variable to analyze. Figures 9 and 10 in the Appendix show a decrease in the relative labor force size for sectors B, C, D, F, H, and O between 2008 and 2015, while for sectors E, I, J, K, M, N, P, Q, and R it is increasing. Sectors L, S, and T show quite stable development.

Workers that change jobs between sectors might indeed lead to problems in our estimation, even though we control for the relative labor force size. Therefore, we take a closer look at those workers that change the sectors of employment. We use yearly data from the AMS on the movements of the workforce between economic sectors.[5] Table 2 shows that most workers that became unemployed found employment in the same sector. About two-thirds of workers that changed jobs in the sample period were unemployed beforehand, while only one-third has changed form employment to employment in another sector.

In the construction sector, more than 90 % of the unemployed found employment in the same sector. In the retail sector, the proportion is about 75 % and it is close to 80 % in the transportation sector, while almost 90 % stayed in the accommodation and food service sector after becoming unemployed. Importantly, these figures remain stable over the sample period. Only in 2008 and 2009 are the figures slightly lower for those sectors perhaps because the financial crisis hit the Austrian labor market between 2008 and 2009 and led to an increase in the unemployment rate.

Table 2 Percentage of unemployed that became employed in the same sector

	2008	2009	2010	2011	2012	2013	2014
A	63.8 %	68.4 %	82.4 %	80.6 %	82.9 %	81.5 %	81.4 %
B	71.6 %	79.9 %	89.5 %	90.7 %	90.7 %	89.0 %	87.9 %
C	47.8 %	75.0 %	79.4 %	74.0 %	76.3 %	76.4 %	74.8 %
D	25.2 %	35.2 %	54.7 %	52.3 %	45.1 %	52.1 %	48.6 %
E	22.2 %	46.3 %	66.5 %	66.0 %	66.2 %	65.9 %	63.4 %
F	79.9 %	84.4 %	92.4 %	91.5 %	92.0 %	92.5 %	92.5 %
G	48.6 %	62.5 %	75.0 %	73.2 %	74.9 %	74.1 %	73.6 %
H	52.3 %	71.6 %	79.6 %	78.1 %	79.8 %	79.3 %	78.8 %
I	77.1 %	82.9 %	88.2 %	87.6 %	88.2 %	88.3 %	88.3 %
J	44.9 %	57.2 %	68.9 %	66.4 %	67.1 %	67.9 %	66.1 %
K	27.4 %	39.8 %	51.3 %	48.7 %	50.1 %	50.9 %	48.6 %
L	24.7 %	41.8 %	58.7 %	55.6 %	59.1 %	60.6 %	56.9 %
M	28.2 %	48.3 %	65.5 %	63.1 %	63.9 %	64.1 %	61.7 %
N	52.0 %	70.6 %	81.1 %	80.0 %	81.6 %	80.3 %	79.9 %
O	50.5 %	57.9 %	69.3 %	68.8 %	68.5 %	65.8 %	64.7 %
P	39.0 %	61.8 %	72.7 %	73.3 %	71.2 %	70.3 %	69.7 %
Q	36.9 %	50.8 %	66.2 %	65.3 %	68.0 %	67.3 %	65.9 %
R	40.5 %	54.7 %	70.4 %	68.4 %	70.5 %	68.5 %	66.8 %
S	38.8 %	53.0 %	68.7 %	67.2 %	67.9 %	67.4 %	66.2 %
T	25.5 %	34.4 %	52.4 %	54.2 %	52.9 %	51.5 %	53.6 %

Whereas, theoretically, workers changing sectors could lead to problems in our estimations of the Beveridge curves in each sector, we can see that especially in those sectors, where we found shifts in the Beveridge curves, sector changes are rare and the proportion of workers that find employment in another sector is stable over time. Therefore, we do not expect any influence on the shifts of the Beveridge curve due to sectoral changes. Still, those changes could indeed explain why we do not find traditional Beveridge curves in some sectors, especially in those that are small and thus sectoral changes more common.

Figures 2 and 3 show Beveridge curves for all sectors in Austria. The red dots are observations starting in January 2013. These figures suggest changes in the Beveridge curves of some of the sectors. For example, in sector G (wholesale and retail trade), H (transportation and storage), K (financial and insurance activities), L (real estate activities), and M (professional, scientific, and technical activities), the figures indicate a shift of the Beveridge curve.

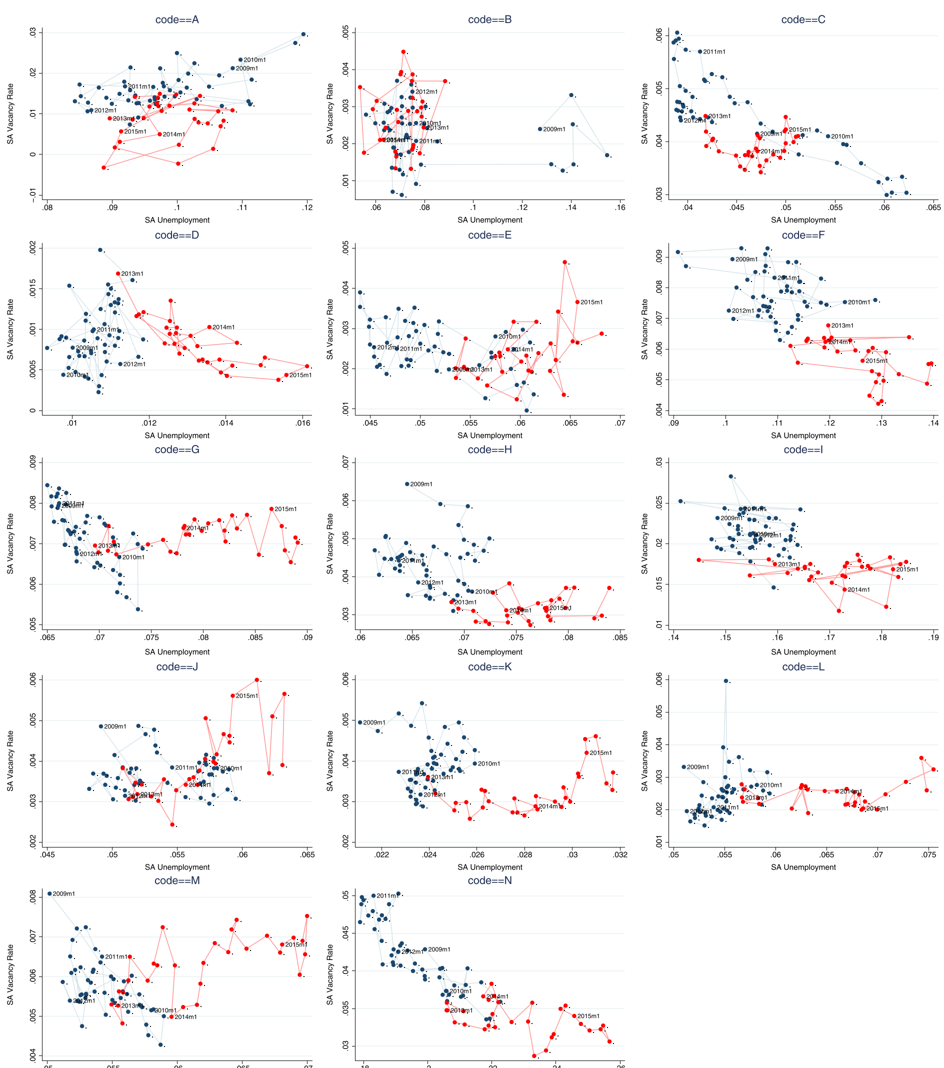

Fig. 2 Seasonally adjusted unemployment rates and vacancy rates by sector, part 1

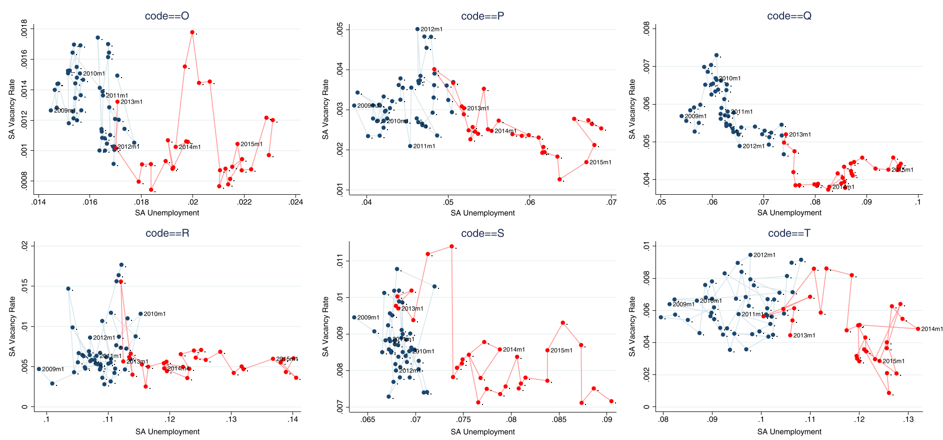

Fig. 3 Seasonally adjusted unemployment rates and vacancy rates by sector, part 2

4 The empirical model

The basic model is the following ARDL dynamic-panel specification:

$$u_{it} = \sum_{j=1}^{p} \lambda_{ij} u_{i,t-j} + \sum_{j=0}^{q} \delta_{ij} v_{i,t-j} + \sum_{j=0}^{r} \gamma_{ij} LF_{i,t-j} + \mu_i + \varepsilon_{it}, \tag{3}$$

where u_{it} is the seasonally adjusted unemployment rate in sector i at time t, v_{it} are the seasonally adjusted vacancy rates, LF_{it} are the seasonally adjusted relative labor force sizes at time t in sector i, and μ_i are the sector-specific effects. This specification as proposed by Pesaran et al. (2001) is appropriate when the time series in question are not necessarily of the same order of integration. To analyze the effects of the crisis, we introduce dummy variables for the years after the crisis and in particular since 2013, as starting from this year, a significant change in the relationship between the unemployment rate and vacancy rates was suggested by Fig. 1.

As explained in the previous section, it is possible that workers are searching for a job in another sector. This possibility could lead to problems in the estimation of the Beveridge curve for specific sectors. We show in Section 3 that this is a minor issue as most of the unemployed stay in the same sector; nevertheless, we want to further control for the changes in the relative labor force that could be driving our results. Therefore, we include changes in the relative size of specific industries in the estimation. This control variable will help overcome the problem that might occur due to an increase or decrease of a sector.[6]

We can rewrite the above equation as an unrestricted ECM to clearly identify the long-run and short-run relationships within the data. The unrestricted ECM has the form:

$$\Delta u_{it} = \beta_0 + \sum_{j=1}^{p} \lambda_j^* \Delta u_{i,t-j} + \sum_{j=0}^{q} \delta_j^* \Delta v_{i,t-j} + \sum_{j=0}^{r} \gamma_j^* \Delta LF_{i,t-j} + \\ + \theta_0 u_{i,t-1} + \theta_1 v_{i,t-1} + \theta_2 LF_{i,t-1} + \mu_t + \epsilon_{it} \tag{4}$$

Additionally, we estimate the relationships for each sector separately by using the following specification:

$$\Delta u_t = \beta_0 + \sum_{j=1}^{p} \lambda_j^* \Delta u_{t-j} + \sum_{j=0}^{q} \delta_j^* \Delta v_{t-j} + \sum_{j=0}^{r} \gamma_j^* \Delta LF_{t-j} + \\ + \theta_0 u_{t-1} + \theta_1 v_{t-1} + \theta_2 LF_{t-1} + \epsilon_t, \tag{5}$$

and having established a cointegrating relationship, we report the results of the unconditional ECM, in which we analyze the effect of the crisis on the position of the Beveridge curve by using a dummy variable:

$$\Delta u_t = \beta_0 + \sum_{j=1}^{p} \lambda_j^* \Delta u_{t-j} + \sum_{j=0}^{q} \delta_j^* \Delta v_{t-j} + \sum_{j=0}^{r} \gamma_j^* \Delta LF_{t-j} + \\ - \theta (u_{t-1} + \theta_1^* v_{t-1} + \theta_2^* LF_{t-1} + \theta_3^* \text{Crisis}) + \epsilon_t. \tag{6}$$

For the sectors for which no cointegration relationship is found, we report the results of the regressions of the first differences of the variables of interest.

5 Beveridge curves

This section shows the results for the Beveridge curve in Austria using a panel ARDL model as well as estimations by economic sector to analyze the shifts in different sectors separately.

5.1 Beveridge curve for the whole economy

Before estimating an ARDL model, the stationarity of the time series under investigation has to be tested. Table 3 presents the results of the unit root tests for the whole panel.[7]

We observe that both the unemployment rates and the labor force size variables contain a unit root, whereas the V variable is stationary. Firstly, we perform the Bounds test on the results of the fixed-effects regression with White-corrected clustered standard errors, and test the hypothesis of $\theta_0 = \theta_1 = \theta_2 = 0$ with the F-statistic equal to 3.95, thus suggesting the existence of a long-run relationship. Given this result, we fit the ARDL models and analyze the relationship between unemployment rates and vacancy rates for all sectors of the Austrian economy. We report the results of the dynamic fixed-effects estimations with clustered standard errors, for which both the short-run and the long-run effects, except for the intercept, are assumed to be equal across panels, and with the pooled mean-group estimator of Pesaran et al. (1999), for which the short-run effects are unconstrained across

Table 3 Unit roots for the panel (p values)

Test	U	V	LF
LLC	1.00	0.00	0.09
IPS	1.00	0.00	0.78
HT	0.44	0.00	0.98

panels. The lag structure has been chosen on the basis of information criteria. The results are presented in Table 4.

We can see the typical Beveridge curve in the long-run relationship, where the lagged vacancy rate ($L.v$) is highly significant in both specifications of the model. The coefficient varies between −1.51 and −1.35, thus indicating an inverse relation between unemployment rates and vacancy rates. The lagged labor force size ($L.LF$) is only significant in the PMG model. The positive relation indicates that a higher relative labor force size increases the unemployment rate.

The focus is on the change in the long-run relationship. The highly significant and positive coefficient of the dummy variable (Crisis) in both specifications indicates a shift in the long-run relationship after 2013.

5.2 Beveridge curves for economic sectors

Since the available data comprise a long period (90 observations per panel), the first step of the analysis requires the identification of potential non-stationarity in the data. The

Table 4 Panel ADRL model for all sectors

	PMG		FE	
	LR	SR	LR	SR
L.LF	2.11***		0.65	
	(3.66)		(0.37)	
L.v	−1.51***		−1.35**	
	(−3.44)		(−2.24)	
Crisis	0.02***		0.02**	
	(8.90)		(2.45)	
θ		−0.05***		−0.05**
		(−4.25)		(−2.32)
L.dU		0.02		−0.05
		(0.54)		(−0.63)
L2.dU		−0.03		−0.01
		(−0.98)		(−0.16)
L3.dU		0.04		−0.03
		(1.29)		(−1.20)
dv		−0.32***		−0.12
		(−3.25)		(−0.77)
L.dv		−0.11		−0.05
		(−0.79)		(−0.49)
dLF		72.56		−2.63**
		(1.08)		(−2.14)
L.dLF		−0.38		0.72
		(−0.05)		(0.94)
L2.dLF		7.39		−0.09
		(1.02)		(−0.49)
L3.dLF		−17.31		0.37
		(−0.74)		(1.40)
Constant		0.00		0.00
		(0.76)		(0.85)
Observations	1892		1892	
$P(L.v) \leq 0$	0.9099		0.8661	

Standard errors clustered at sector level; t-Stats in parentheses
Significance: *0.1, **0.05, ***0.01

results of the tests for unit roots for the variables of interest for each panel are presented in Table 5. For all panels, at least two of the variables are I(1), and in some cases all three are I(1). Since for some panels we need to consider a mixture of I(1) and I(0) series, the correct approach in this case is the ARDL/Bounds testing model of Pesaran et al. (2001).

In the second stage of the analysis, we choose the appropriate number of lags by using the information criteria for each differenced variable Δu_t, Δv_t, and ΔLF_t. The chosen numbers of lags are given in Table 9 in the Appendix.

After finding the appropriate number of lags, we estimate an unrestricted ECM for each panel and use the ARDL/Bounds test, therefore again testing whether $\theta_0 = \theta_1 = \theta_2 = 0$ to establish whether a level relationship between the variables can be found. Finally, we report the ECMs for the panels in which a long-run relationship has been found and analyze the effect of the crisis dummy on the position of the Beveridge curve. Table 10 in the Appendix presents the results of the Bounds tests for each panel.

Detailed results of the ECM estimations can be found in Tables 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, and 22 in the Appendix. In Table 6, we summarize the long-run relationships, crisis variables, and the ECM θ parameters. Furthermore, Tables 6 and 7 contain the elasticities of the unemployment rate with respect to the vacancy rates in each sector where the negative relationship has been found to be significant, evaluated at the means (denoted ξ).

A significant, negative long-run relationship (θ) can be found in sectors C (manufacturing), D (electricity), E (water supply sector), F (construction), G (wholesale and retail trade), and R (arts, entertainment, and recreation).

Typical Beveridge curve relations (significant coefficients of the lagged vacancy rates $L.v$) can be seen in sectors C (manufacturing), E (water supply sector), F (construction), G

Table 5 Unit root tests of the data (*p* values)

	U		V		LF	
Sector	ADF	PP	ADF	PP	ADF	PP
A	0.00	0.00	0.04	0.04	0.86	0.55
B	0.39	0.37	0.00	0.00	0.60	0.64
C	0.04	0.42	0.10	0.10	0.44	0.51
D	0.59	0.59	0.00	0.00	0.62	0.63
E	0.83	0.89	0.00	0.00	0.86	0.85
F	0.00	0.14	0.00	0.00	0.72	0.70
G	0.95	0.98	0.16	0.47	0.49	0.27
H	0.47	0.81	0.07	0.07	0.03	0.05
I	0.72	0.42	0.04	0.12	0.89	0.89
J	0.87	0.84	0.12	0.17	0.99	0.99
K	0.89	0.95	0.01	0.00	0.98	0.98
L	0.98	0.99	0.07	0.25	0.06	0.07
M	0.92	0.95	0.07	0.00	0.19	0.19
N	0.47	0.77	0.05	0.01	0.97	0.97
O	0.99	0.99	0.13	0.18	0.62	0.53
P	0.99	0.99	0.00	0.00	0.06	0.09
Q	0.99	0.99	0.05	0.00	0.53	0.58
R	0.94	0.98	0.60	0.66	0.25	0.40
S	0.99	0.99	0.00	0.00	0.32	0.36
T	0.87	0.86	0.05	0.00	0.43	0.43

Table 6 Summary of the results for the sectors with significant long-run relationship

	C	D	E	F	G	H	M	O	P	Q	R	S
L.LF	0.88*	−2.80***	11.33	2.99	0.07	3.60	−2.35	−0.39	3.27**	3.81	6.32	12.12
	(1.68)	(−2.87)	(0.26)	(1.57)	(0.01)	(1.34)	(−0.72)	(−0.25)	(2.21)	(0.51)	(0.59)	(0.92)
L.v	−3.94***	−0.83	−5.84*	−4.90**	−5.59**	−5.89*	8.44*	0.51	−5.05	−20.25	−1.53*	−3.06
	(−2.71)	(−1.34)	(−1.90)	(−2.59)	(−2.42)	(−1.81)	(1.86)	(0.07)	(−1.40)	(−0.40)	(−1.86)	(−0.86)
Crisis	0.00	0.00***	0.01	0.01**	0.02***	0.01**	0.02*	0.01	0.01	0.03	0.02	0.03*
	(1.39)	(6.01)	(1.53)	(1.99)	(3.18)	(2.02)	(1.70)	(1.32)	(1.44)	(0.39)	(1.50)	(1.69)
ξ	−0.34	–	−0.21	−0.21	−0.53	−0.25	–	–	–	–	−0.08	–
θ	−0.10***	−0.32***	−0.10**	−0.45***	−0.06**	−0.07	−0.03	−0.02	−0.04	−0.01	−0.08 *	−0.04
	(−2.78)	(−3.88)	(−2.36)	(−6.81)	(−4.36)	(−1.63)	(−1.58)	(−0.77)	(−1.08)	(−0.34)	(−1.76)	(−1.27)

t-Stats in parentheses
Significance: *0.1, **0.05, ***0.01

Table 7 Results for other sectors

	B	I	J	K	L	N	T
dLF	354.26***	−8.04***	−2.94***	0.17	−3.98**	−3.10***	−169.09***
	(6.25)	(−6.93)	(−2.65)	(0.34)	(−2.29)	(−2.91)	(−4.31)
dv	0.11	−0.83***	−0.41**	−0.02	−0.03	−0.49***	0.09
	(0.12)	(−3.26)	(−2.32)	(−0.14)	(−0.15)	(−3.60)	(0.29)
Crisis	−0.00	0.00*	0.00	0.00	0.00*	0.00	0.00
	(−0.52)	(1.80)	(1.66)	(1.27)	(1.91)	(1.54)	(1.39)
L.dU		−0.42***	0.03	0.19*		0.16	−0.31***
		(−4.39)	(0.32)	(1.71)		(1.37)	(−3.20)
L2.dU			0.28***			0.11	−0.13
			(2.82)			(0.94)	(−1.35)
L3.dU						−0.29***	
						(−2.66)	
L4.dU						0.17	
						(1.67)	
L.dv		−1.03***	−0.22	−0.07	−0.08	−0.42***	0.43
		(−4.25)	(−1.14)	(−0.55)	(−0.39)	(−2.76)	(1.22)
L2.dv		−0.88***	−0.24	−0.02		−0.12	0.62**
		(−3.77)	(−1.28)	(−0.18)		(−0.79)	(2.00)
L3.dv		−0.54**		−0.03		−0.27*	
		(−2.31)		(−0.22)		(−1.89)	
L.dLF		2.09	1.73			0.31	
		(1.49)	(1.48)			(0.28)	
L2.dLF		2.00				1.60	
		(1.60)				(1.51)	
L3.dLF						0.31	
						(0.30)	
Constant	0.00	−0.00	0.00	0.00	0.00	0.00	0.00
	(1.44)	(−0.05)	(0.39)	(1.31)	(0.51)	(0.52)	(0.47)
ξ	–	−0.20	−0.02	–	–	−0.07	–
Observations	89	86	87	86	88	85	87

t-Stats in parentheses
Significance: *0.1, **0.05, ***0.01

(wholesale and retail trade), H (transportation and storage), and R (arts, entertainment, and recreation). The Beveridge curve coefficients are especially high in C (manufacturing), F (construction), G (wholesale and retail trade), and H (transportation and storage). This finding implies that those sectors are highly sensitive to the business cycle. A less significant coefficient, but also high sensitivity to the business cycle, can be seen in sectors H (transportation and storage) and E (water supply sector).

Significant positive shifts of the Beveridge curves can be seen in sectors D (electricity), F (construction), G (wholesale and retail trade), H (transportation and storage), M (professional, scientific, and technical activities), and S (other service activities).

The most significant shifts are measured in the construction sector (F), wholesale and retail trade sector (G), and transportation sector (H). Structural problems, especially in the construction and transportation sectors, occur due to higher competition from firms from Eastern European countries that gain market share in the Austrian market. Still, there is no reduction in the vacancy rate, which would additionally suggest problems in matching.

On the other hand, the wholesale and retail trade sector (G) shows not only a higher rate of unemployment, but also a higher rate of vacancies. Even though this sector is strongly influenced by the fourth industrial revolution, the structural problems seem to originate from a matching problem in the labor market. Some of the reasons are institutional, such as the small difference between minimum wages and unemployment benefits. Minimum wages in the retail and trade sectors compared with other sectors are quite low; therefore, there is little incentive to accept jobs. It is also possible that the increase in structural unemployment occurs from a classical mismatch problem due to over- or underqualification.

For the other sectors of the economy (*B*, *I*, *J*, *K*, *L*, *N*, *T*, and *U*) for which no cointegrating vector was found, we report the results of the regression of the first differenced u_t and the first differences of v and LF, with appropriate lag structures. The results can be found in Table 7.

Typical Beveridge curve relations (significant coefficients of the differenced vacancy rates, dv) can be seen in sectors I (accommodation and food service activities), J (information and communication), and N (administrative and support service activities). An especially high sensitivity to the business cycle can be found in the accommodation and food service activities sector (I).

Significant positive shifts of the Beveridge curves can only be observed in sectors I (accommodation and food service activities) and L (real estate activities). In the accommodation sector, although many jobs are taken by foreigners, many vacancies remain open. The most likely explanation is a regional mismatch (especially in tourism) as well as the fact that minimum wages are low in this sector and jobs are not attractive for unemployed workers (working hours, working time).

6 Structural factors

In this section, we further analyze which factors have contributed to the changes in the Beveridge curves for the relevant sectors of the economy. As mentioned in the Introduction, structural changes can be a result of either decreasing matching efficiency or increasing separation rates. In this section, we establish which of these factors may have contributed to the sectoral changes. We follow the methodology of Elsby et al. (2013) (also used by Arpaia et al. (2014)) to analyze the development of matching efficiency and separation rates for those sectors of the economy for which the Beveridge curves have shifted. In the first step, we apply the procedure introduced by Shimer (2012) to find the outflow rates of unemployment for each sector. The job-finding rate is calculated based on the AMS data regarding the duration of unemployment by category: (a) less than 3 months; (b) between 3 and 6 months; (c) between 6 and 12 months; and (d) more than 12 months. Secondly, we evaluate the separation rates, based on the steady-state condition derived from Eq. (1) and assuming a Cobb–Douglas matching function.

Under the standard assumption of a Cobb–Douglas functional form for the matching function, that is:

$$m_t(v, u) = A u_t^{\alpha} v_t^{1-\alpha}, \tag{7}$$

the elasticities of the job-finding rate and of the separation rate with respect to labor market tightness can be estimated from the following equations:

$$\log(f_t) = \beta_0 + \beta_1 \log(\theta_t) + \varepsilon_t, \tag{8}$$

$$\log(s_t) = \beta_0 + \beta_1 \log(\theta_t) + \varepsilon_t, \tag{9}$$

where f_t are the job-finding rates, s_t are the separation rates, and θ_t denotes the job market tightness. Table 8 presents the results of the estimations of the elasticities from a panel regression across all sectors (with sectoral fixed effects) and for each sector separately. The predicted elasticity of the job-finding rate with respect to labor market tightness equals 0.26 for the whole economy and corresponds to the previous estimates of Arpaia et al. (2014). We observe large heterogeneity across sectors: the public sectors (O, P, and Q) and agriculture (A) almost do not react to the changes in labor market tightness. Real estate (L) and professional services (M) are the most elastic sectors, in terms of both the job-finding rate and the separation rate.

Table 8 reveals that the job-finding rates in some sectors react strongly to cyclical changes in the tightness of the job market. This is especially true for the case of construction (F), information and communication (J), and professional services (M). On the other hand, agriculture (A), mining (B), and public services (O, P, and Q) as well as energy and water services (D and E) do not react to changes in the business cycle.

Table 8 Elasticities of the job-finding rate and the separation rate with respect to labor market tightness

Sector	Job finding	Separation
Joint	0.26***	−0.23***
A	0.09	−0.03
B	0.06	−0.25***
C	0.12**	−0.43***
D	−0.02	−0.11***
E	−0.00	−0.21***
F	0.45***	−0.34***
G	−0.18	−0.50***
H	−0.8	−0.23***
I	0.35***	−0.27***
J	0.77***	−0.03
K	0.04	−0.27***
L	2.17***	−0.09*
M	1.36***	−0.22***
N	0.19***	−0.37***
O	−0.15*	−0.31***
P	−0.30**	−0.34***
Q	−0.01	−0.44***
R	0.51***	−0.06***
S	−1.36***	−0.38***
T	0.00	−0.17***

Significance: *0.1, **0.05, ***0.01

Following Shimer (2012), we calculate the α parameter of the Cobb–Douglas relationship by using Eq. (11) of Veracierto (2011), choosing as the calibration values the two months between January 2009 and January 2013 with the highest and lowest values of job market tightness for each sector. Given that, we can calculate the matching efficiency for each sector by using the relationship

$$A_t = \left[\frac{s_t}{u_t} - s_t\right]\left(\frac{1}{\theta_t}\right)^{1-\alpha}. \tag{10}$$

This allows us to look more closely at the reasons behind the rise in structural unemployment across specific sectors. The development of the separation rates and matching efficiency (for comparison purposes, both values are normalized so that January 2013 = 1)[8] for each sector are visualized in Figs. 4 and 5.

Fig. 4 Matching (*red*) and separation rates (*blue*) (normalized, January 2013 = 1), part 1

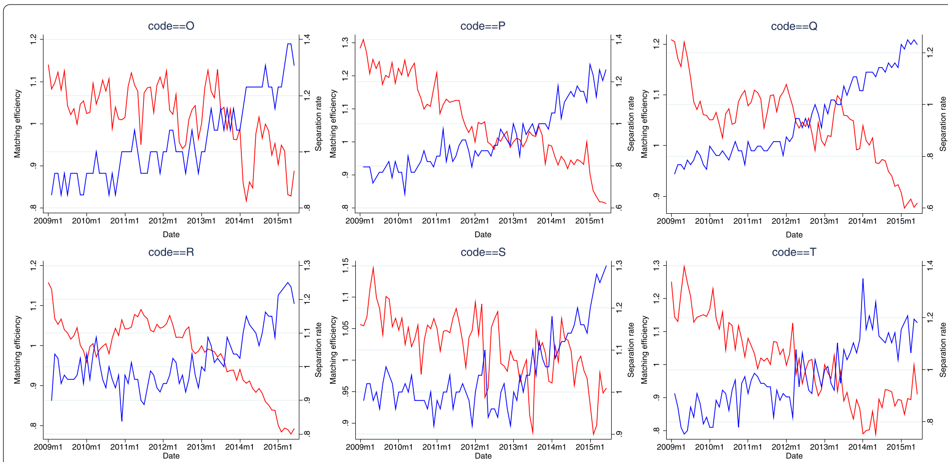

Fig. 5 Matching (*red*) and separation rates (*blue*) (normalized, January 2013 = 1), part 2

Recalling the results of the previous section, we find a significant shift of the Beveridge curve in sectors D, F, G, H, I, L, M, and S. At the same time, in exactly these sectors, we can observe that not only has the separation rate been increasing from 2013 onwards, but also matching efficiency has been decreasing. Therefore, there is evidence of both higher job separation and lower matching efficiency in the labor market. In sector S, we find an increase in the separation rate, whereas matching efficiency remains unchanged. For sector F, the previous results that suggested a shift in the Beveridge curve cannot be confirmed by a change in the separation rate and matching efficiency, as we only observe a slight increase in the separation rate, while matching efficiency remains stable.

In the other sectors for which we did not find significant shifts in the Beveridge curves after 2013 (C, E, J, K, N, O, P, Q, and R), we still find an upward trend in separation rates and a downward trend in matching efficiency. Taking a closer look at these sectors, we can identify that the separation rate and matching efficiency diverge. The labor market characteristics in these sectors show similar patterns to the abovementioned ones, but the divergence began only after 2014. This in fact could explain why we did not find any significant shifts in the Beveridge curve in these sectors in the previous section. Finally, in the other sectors, we find no clear trends in the separation rates or matching efficiency. This holds true for sector F, as mentioned before, as well as for sectors A, B, and T. In these sectors, we cannot observe any increase in structural unemployment.

By using a Cobb–Douglas matching function and assuming that the labor market converges to the steady state at a constant rate (compare Arpaia et al. (2014)), we can calculate the vacancy rates that would have been observed if the matching efficiency had not changed after 2013, using the formula

$$v_t = \left[\left(\frac{s_t}{u_t} - s_t\right)\frac{1}{A}\right]^{\frac{1}{1-\alpha}} u_t, \tag{11}$$

where A has been calibrated to be the average of all periods before January 2013. The resulting vacancy rates are visualized in Figs. 6 and 7. If the observations after 2012 remain close to the counterfactual Beveridge curves (green points)—the Beveridge curve that would occur if matching efficiency had not changed—this would suggest no shifts in

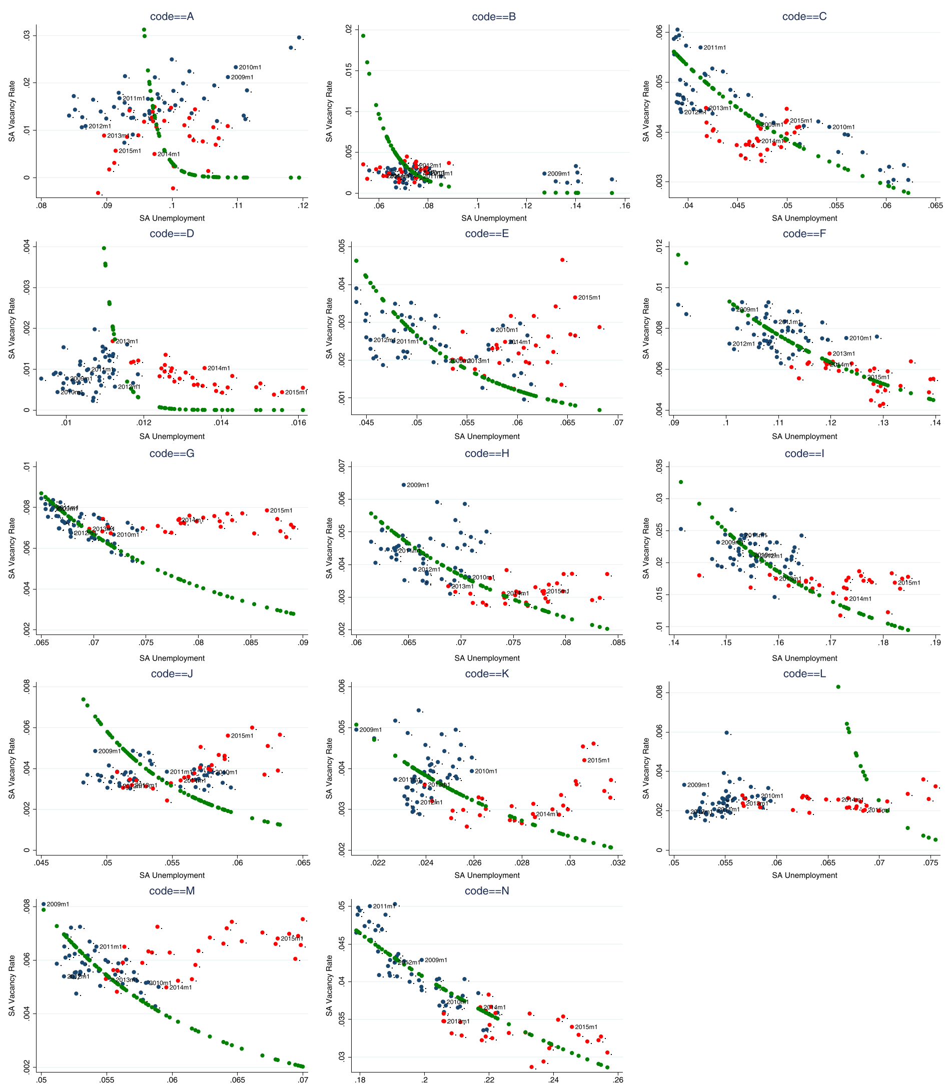

Fig. 6 Counterfactual Beveridge curves (*green*), part 1

the Beveridge curves. Observations that are far away from the counterfactual Beveridge curves indicate an increase (or decrease) in structural unemployment.

Divergence from the counterfactual Beveridge curve is clearly visible in those sectors that have been showing a shift in the Beveridge curve. The most convincing examples are sectors D, G, L, and M, for which the observations are far and to the right of the counterfactual Beveridge curves.

Finally, Fig. 8 depicts the time development of the sectoral mismatch indicator, calculated as

$$MI = \sum_{i=1}^{I} e_i |vq_i - uq_i|, \tag{12}$$

where i is the index of the NACE sector, e_i is the share of employment in sector i in total employment, vq_i is the share of vacancies in sector i in the total number of vacancies, and uq_i is the share of unemployment in sector i in total unemployment. The value of the

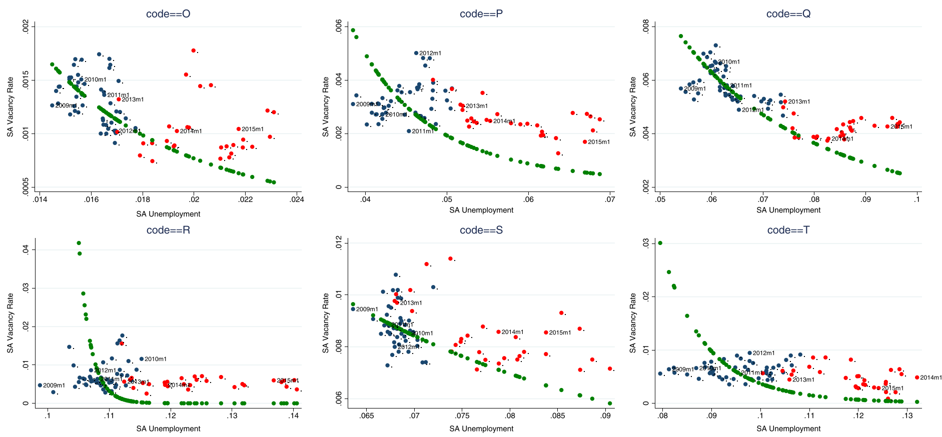

Fig. 7 Counterfactual Beveridge curves (*green*), part 2

indicator is low if sectors that shed many workers also post many vacancies. If instead the composition of unemployment and that of vacancies is very different (so that sectors with a high share of unemployment have a low share of vacancies and vice versa), the value of the indicator is high, indicating a high degree of mismatch. Additionally, average matching efficiency across sectors, weighted by the share of employment in each sector, is shown in Fig. 8.

Average matching efficiency was stable until 2013 but has been steadily decreasing since. On the contrary, the sectoral mismatch indicator decreased until 2013 and has been increasing since. Sectors with a high share of unemployment have a low share of open vacancies and vice versa. This finding indicates that sectoral mismatch has been increasing since 2013, which implies that changing sectors is becoming more difficult, or at least less common, for workers.

7 Conclusions

Labor market responses to the 2009 crisis have been quite diverse within the European Union. While in many countries the unemployment rate rose after 2009 (even earlier in those countries most strongly affected by the crisis), the Austrian unemployment rate remained stable for some years thereafter. However, since 2013, the unemployment

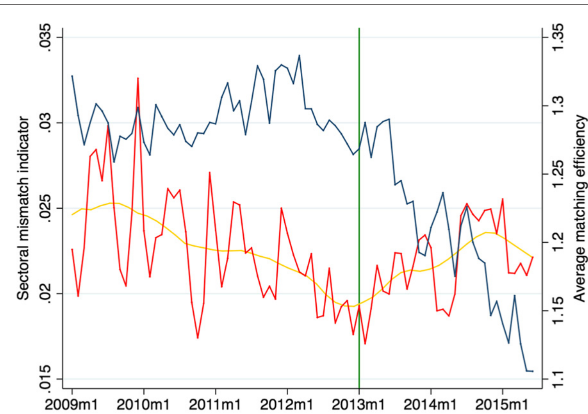

Fig. 8 Sectoral mismatch indicator (*red*) and average matching efficiency (*blue*) over time

rate in Austria has been steadily increasing. As many economists have argued, there are some signs that these changes in the labor market are not merely cyclical; there is a risk that structural unemployment has increased. Consequently, Austria is slowly losing its position as one of the European leaders of low unemployment.

The identified structural changes have important policy implications. Cyclical problems in an economy are usually caused by a lack of labor demand and are therefore transitory, but a rise in structural unemployment is typically caused by a mismatch in the labor market and/or job separation and is therefore often persistent.

This paper shows that there is a significant shift in the Beveridge curve of the Austrian labor market. While the studies by (Bonthuis et al. 2013) or (Bonthuis et al. 2015) suggested that there was no shift of the Beveridge curve in Austria after the crisis, we show that a statistically significant shift simply took place later than in other European countries (such as Spain, France, and Portugal).

If the unemployment is structural and not cyclical, there is a possibility that unemployment could stay permanently high even when economic recovery takes over. This paper identifies the roots of those shifts in the Beveridge curves. When we estimated the Beveridge curves for different sectors, we found significant outward shifts of the Beveridge curve in 2013 in eight of 21 sectors.

Our analysis shows that the structural problems in the Austrian labor market stem mainly from the four large sectors of the Austrian economy: construction, wholesale, transportation, and accommodation and food service activities. Those sectors not only face new competitors from Eastern European countries (construction and transportation) that gain market share in Austria, but also show a decrease in matching efficiency, which implies a mismatch problem in the labor market. This mismatch might arise not only from qualification problems but also from institutional factors.

Our finding suggests that, especially in these sectors, which cover a vast number of workers, there is a high risk of persistent high unemployment. Additionally, we show that in many other sectors, an increase in structural unemployment is still taking place but simply at a later time.

Our results suggest that in most sectors of the Austrian economy, structural problems are caused not only by higher job separation but also by a decline in matching efficiency. Even though the latter effect seems to be smaller, this finding is especially interesting for policymakers, since a decrease in matching efficiency is something policy changes can oppose more easily than job separation. Therefore, it is important to target labor policies to those sectors of the economy in which a significant structural change has taken place.

Many unemployed workers in Austria are less skilled; therefore, the efficiency of training has to be increased. Additionally, one has to think about alternative ways to overcome the sectoral mismatch, especially for those workers who have problems finding jobs in other sectors. Sectoral reallocation will be an important factor within the next year. For those workers who became unemployed due to the downsizing of their sectors, it is necessary to provide training and upskilling, so that they might change sectors more easily.

The drive-back of the low-pay sector might also be an issue that leads to less job creation, especially for low-skilled workers. Most of the sectors that show a strong and significant shift in the Beveridge curve are typical sectors where less-skilled workers are employed, such as construction or trade. If these sectors are downsized, the only policy tool available may be to improve the skills of the workforce.

Additionally, decreasing matching efficiency could result from high social benefits, especially during the crisis. If unemployment benefits can be kept for a long period, workers might not be willing to accept a new job, especially during a recession when wages are usually lower. If this is the case, structural unemployment might not be persistent. When the recovery starts and wages begin to increase, those workers might return to work; however, there is still a high risk that the long-term unemployed will face problems with the reintegration of labor markets, which might lead to further structural problems.

Endnotes

[1] Please note that our dataset only covers the period from 2008m1 until 2015m6 (blue and red lines).

[2] One of the main targets in the development of LFS data was to correct for the differences in the national definitions/computations of unemployment in European countries. The international definition (LFS) is based on interviews. Unemployed are defined as all people between 15 and 74 years, who have not worked at least 1 h (employed or self–employed) during the week before the interview and have actively searched for work last week as unemployed. On the other hand, the labor force is defined as unemployed people, people in paid employment, self-employed people and people, who are temporarily absent from work.

[3] The unemployment rate according to the national definition is defined as the number of unemployed people registered with the Public Employment Service (AMS) divided by the total labor force, which is defined as the number of employees recorded by the Main Association of Austrian Social Insurance Institutions plus the number of registered unemployed.

[4] In the investigated period, one methodological change, namely the change in the training-strategy of the AMS (introduced in 2015), might affect the results. Starting from 2015, the number of short-term courses has been reduced and more long-term training has been offered. This might negatively affect the number of training participants. Although people in training are not directly included in the unemployment rate, they might indirectly affect the statistics. Since fewer short-term courses were offered, the number of people in training reduced. This increases the number of registered unemployed. The number of people in training in 2015 reduced by 10 191 people to the level of 65 126 people. The maximal possible effect of this change on the unemployment rate (if all people register as unemployed; labor force in 2015 was 3 889 185) would therefore be about 0.26 pp. Hence, the effect of this methodological change can be safely neglected.

[5] Data are available upon request

[6] The results do not change if we do not include this control variable: we still find significant shifts in those sectors. When we control for absolute labor force growth instead of relative labor force size, the results become less significant, but the shifts are still visible. However, with the latter methodology, the regressions might suffer from endogeneity. The results of the alternative specifications are available from the authors upon request.

[7] Including a deterministic trend component does not significantly change the results.

[8] For the purpose of comparison with the previous sections, we index the series with the base year as 2013. For the actual values of the separation rates please consult Figs. 11 and 12 in the Appendix.

Appendix

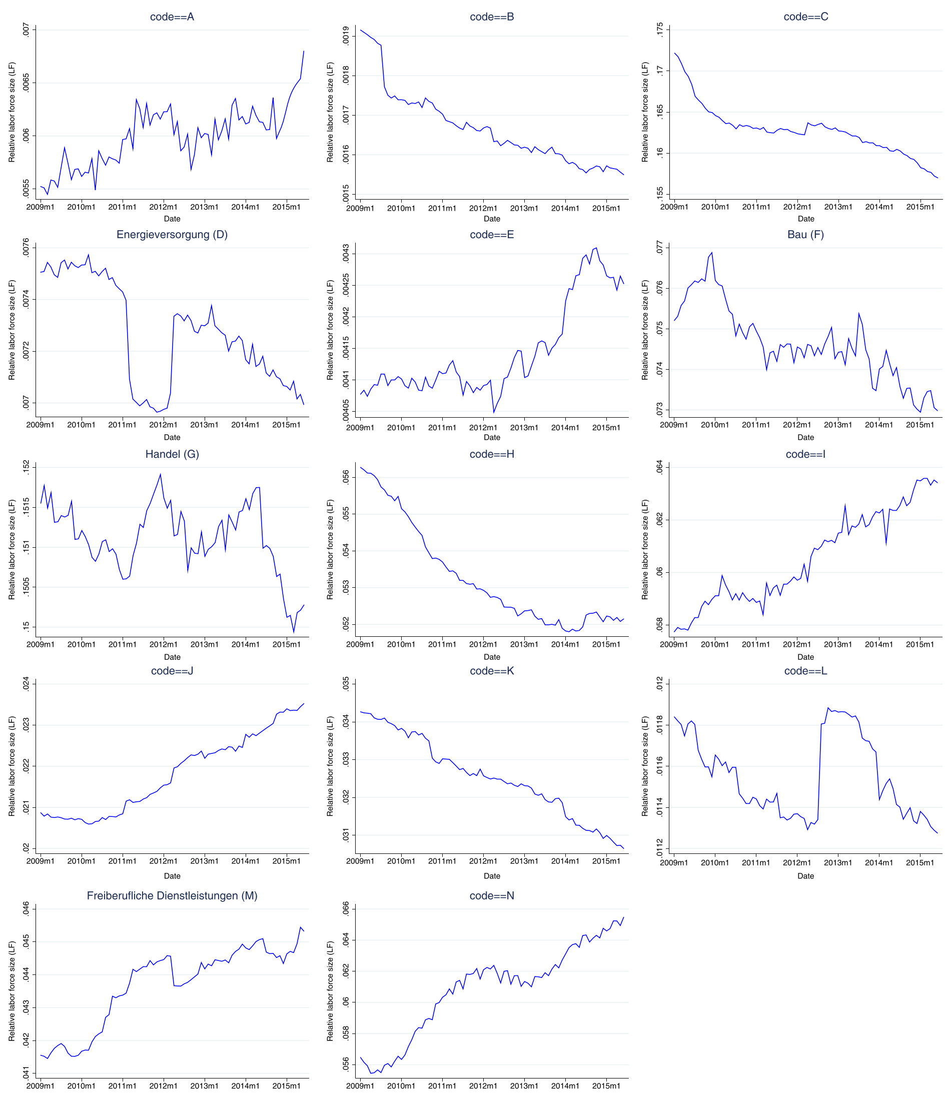

Fig. 9 Relative size of the labor force by sector, part 1

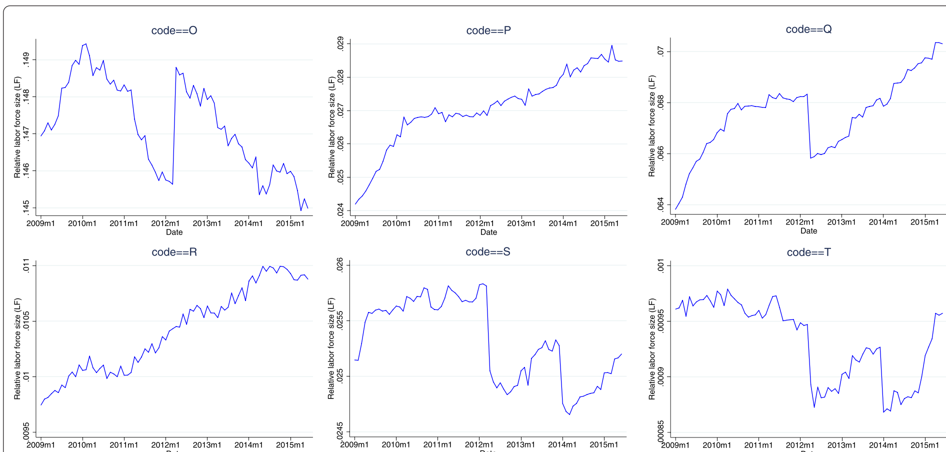

Fig. 10 Relative size of the labor force by sector, part 2

Fig. 11 Matching (*red*) and separation rates (*blue*), part 1

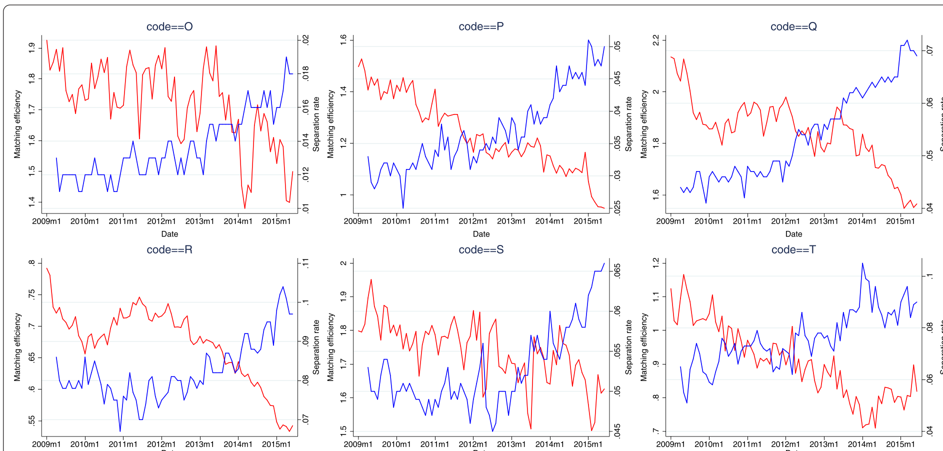

Fig. 12 Matching (*red*) and separation rates (*blue*), part 2

Table 9 Lag structure for each panel

	dU	dv	dLF
A	1	0	2
B	0	0	0
C	1	0	4
D	0	2	0
E	0	0	0
F	1	0	0
G	3	1	1
H	1	3	0
I	1	3	2
J	2	2	1
K	1	3	0
L	0	1	0
M	3	1	0
N	4	3	3
O	3	0	0
P	1	0	1
Q	0	2	0
R	0	1	3
S	0	0	0
T	2	2	0
U	0	3	1

Table 10 ADRL Test results (95 %-level, k=3)

	ADRL Test	Crit. value I(0)	Crit. value I(1)	Comment
A	3.40	2.45	3.63	Excluded, LF is I(2)
B	1.81	2.45	3.63	
C	**3.93**	2.45	3.63	
D	*2.99*	2.45	3.63	Included
E	*3.29*	2.45	3.63	Included
F	**14.27**	2.45	3.63	
G	*3.04*	2.45	3.63	Included, based on Johansen
H	*2.87*	2.45	3.63	Included, based on Johansen
I	1.70	2.45	3.63	
J	1.58	2.45	3.63	
K	2.76	2.45	3.63	
L	2.42	2.45	3.63	
M	**6.21**	2.45	3.63	
N	2.99	2.45	3.63	Excluded, based on Johansen
O	**5.53**	2.45	3.63	
P	**4.91**	2.45	3.63	
Q	**8.24**	2.45	3.63	
R	*2.82*	2.45	3.63	Included, based on Johansen
S	**4.68**	2.45	3.63	
T	1.95	2.45	3.63	
U	1.72	2.45	3.63	

Table 11 Error correction model: Sector C

	LR	SR
L.LF	0.88*	
	(1.68)	
L.v	−3.94***	
	(−2.71)	
Crisis	0.00	
	(1.39)	
θ		−0.10***
		(−2.78)
L.dU		0.55***
		(5.85)
dv		−0.59
		(−1.53)
dLF		−0.42
		(−1.35)
L.dLF		−0.19
		(−0.58)
L2.dLF		−0.11
		(−0.35)
L3.dLF		0.18
		(0.59)
L4.dLF		−0.53*
		(−1.70)
Constant		−0.01
		(−1.31)
Observations	86	

t-Stats in parentheses
Significance: *0.1, **0.05, ***0.01

Table 12 Error correction model: Sector D

	LR	SR
L.LF	−2.80***	
	(−2.87)	
L.v	−0.83	
	(−1.34)	
Crisis	0.00***	
	(6.01)	
θ		−0.32***
		(−3.88)
dv		−0.45**
		(−2.07)
L.dv		−0.04
		(−0.17)
L2.dv		0.02
		(0.09)
dLF		−2.62***
		(−2.71)
Constant		0.01***
		(2.69)
Observations	88	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 13 Error correction model: Sector E

	LR	SR
L.LF	11.33	
	(0.26)	
L.v	−5.84*	
	(−1.90)	
Crisis	0.01	
	(1.53)	
θ		−0.10**
		(−2.36)
dv		−0.25
		(−0.83)
dLF		−16.53
		(−1.34)
Constant		0.00
		(0.11)
Observations	89	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 14 Error correction model: Sector F

	LR	SR
L.LF	2.99	
	(1.57)	
L.v	−4.90**	
	(−2.59)	
Crisis	0.01**	
	(1.99)	
θ		−0.45***
		(−4.36)
d.U		0.16
		(1.44)
d.v		−2.75*
		(−2.04)
d.LF		−2.69
		(−1.43)
Constant		−0.03
		(−0.55)
Observations	89	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 15 Error correction model: Sector G

	LR	SR
L.LF	0.07	
	(0.01)	
L.v	−5.59**	
	(−2.42)	
Crisis	0.02***	
	(3.18)	
θ		−0.06**
		(−2.40)
L.dU		0.17
		(1.60)
L2.dU		0.13
		(1.24)
L3.dU		0.23**
		(1.98)
dv		−0.29
		(−1.34)
L.dv		−0.23
		(−1.17)
dLF		−0.06
		(−0.14)
L.dLF		−0.20
		(−0.46)
Constant		0.02
		(0.58)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 16 Error correction model: Sector H

	LR	SR
L.LF	3.60	
	(1.34)	
L.v	−5.89*	
	(−1.81)	
Crisis	0.01**	
	(2.02)	
θ		−0.07
		(−1.63)
L.dU		0.15
		(1.34)
dv		−0.37
		(−0.86)
L.dv		−0.05
		(−0.11)
L2.dv		0.16
		(0.35)
L3.dv		−0.57
		(−1.32)
dLF		0.21
		(0.13)
Constant		−0.00
		(−0.25)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 17 Error correction model: Sector M

	LR	SR
L.LF	−2.35	
	(−0.72)	
L.v	8.44*	
	(1.86)	
Crisis	0.02*	
	(1.70)	
θ		−0.03
		(−1.58)
L.dU		0.03
		(0.28)
L2.dU		0.02
		(0.18)
L3.dU		0.26***
		(2.85)
dv		−0.22
		(−1.64)
L.dv		−0.34**
		(−2.48)
dLF		−1.70***
		(−4.24)
Constant		0.00
		(0.93)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 18 Error correction model: Sector O

	LR	SR
L.LF	−0.39	
	(−0.25)	
L.v	0.51	
	(0.07)	
Crisis	0.01	
	(1.32)	
θ		−0.02
		(−0.77)
L.dU		−0.16
		(−1.39)
L2.dU		−0.22**
		(−2.03)
L3.dU		−0.15
		(−1.31)
dv		−0.08
		(−0.49)
dLF		−0.11
		(−1.52)
Constant		0.00
		(0.48)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 19 Error correction model: Sector P

	LR	SR
L.LF	3.27**	
	(2.21)	
L.v	−5.05	
	(−1.40)	
Crisis	0.01	
	(1.44)	
θ		−0.04
		(−1.08)
L.dU		−0.09
		(−0.87)
dv		−0.71***
		(−3.05)
dLF		−3.77***
		(−5.49)
L.dLF		0.93
		(1.10)
Constant		−0.00
		(−0.26)
Observations	89	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 20 Error correction model: Sector Q

	LR	SR
L.LF	3.81	
	(0.51)	
L.v	−20.25	
	(−0.40)	
Crisis	0.03	
	(0.39)	
θ		−0.01
		(−0.34)
dv		0.02
		(0.05)
L.dv		0.65*
		(1.87)
L2.dv		−0.09
		(−0.26)
dLF		−0.56*
		(−1.79)
Constant		−0.00
		(−0.06)
Observations	88	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 21 Error correction model: Sector R

	LR	SR
L.LF	6.32	
	(0.59)	
L.v	−1.53 *	
	(−1.86)	
Crisis	0.02	
	(1.50)	
θ		−0.08*
		(−1.76)
dv		−0.09
		(−1.34)
L.dv		0.06
		(0.93)
dLF		−9.81**
		(−2.55)
L.dLF		6.20
		(1.31)
L2.dLF		2.21
		(0.51)
L3.dLF		−0.10
		(−0.03)
Constant		0.00
		(0.57)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 22 Error correction model: Sector S

	LR	SR
L.LF	12.12	
	(0.92)	
L.v	−3.06	
	(−0.86)	
Crisis	0.03*	
	(1.69)	
θ		−0.04
		(−1.27)
dv		0.01
		(0.04)
dLF		−2.07**
		(−2.06)
Constant		−0.01
		(−0.78)
Observations	89	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 23 Error correction model: Sector C - robustness

	(1)	
	dU_sa	
	LR	SR
L.v	−6.26*	
	(−1.88)	
Crisis	0.00	
	(0.28)	
θ		−0.05**
		(−2.05)
L.dU		0.63***
		(7.20)
dv		−0.73
		(−1.48)
Constant		0.00*
		(1.69)
Observations	86	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 24 Error correction model: Sector D - robustness

	LR	SR
L.v	−0.55	
	(−0.62)	
Crisis	0.00***	
	(5.16)	
θ		−0.23***
		(−3.38)
dv		−0.48**
		(−2.05)
L.dv		−0.27
		(−1.11)
L2.dv		−0.03
		(−0.12)
Constant		0.00***
		(3.25)
Observations	88	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 25 Error correction model: Sector E - robustness

	LR	SR
L.v	−7.15	
	(−1.32)	
Crisis	0.02**	
	(2.35)	
θ		−0.07*
		(−1.90)
dv		0.02
		(0.07)
Constant		0.01**
		(2.19)
Observations	89	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 26 Error correction model: Sector F - robustness

	LR	SR
L.v	−4.14**	
	(−2.04)	
Crisis	0.01	
	(1.50)	
θ		−0.41***
		(−4.12)
L.dU		0.14
		(1.19)
dv		−1.76
		(−1.36)
Constant		0.06***
		(3.91)
Observations	89	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 27 Error correction model: Sector G - robustness

	LR	SR
L.v	−3.71	
	(−0.88)	
Crisis	0.02***	
	(2.96)	
θ		−0.04**
		(−2.03)
L.dU		0.11
		(1.01)
L2.dU		0.09
		(0.86)
L3.dU		0.17
		(1.51)
dv		−0.34
		(−1.50)
L.dv		−0.25
		(−1.26)
Constant		0.00*
		(1.90)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 28 Error correction model: Sector H - robustness

	LR	SR
L.v	−5.12	
	(−1.09)	
Crisis	0.02**	
	(2.32)	
θ		−0.08*
		(−1.78)
L.dU		0.09
		(0.78)
dv		−0.45
		(−1.06)
L.dv		−0.33
		(−0.70)
L2.dv		−0.22
		(−0.48)
L3.dv		−0.57
		(−1.37)
Constant		0.00
		(1.09)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 29 Error correction model: Sector M - robustness

	LR	SR
L.v	−5.19	
	(−1.45)	
Crisis	0.01***	
	(2.58)	
θ		−0.05**
		(−2.08)
L.dU		−0.01
		(−0.06)
L2.dU		0.12
		(1.16)
L3.dU		0.23**
		(2.18)
dv		−0.28*
		(−1.70)
L.dv		−0.37**
		(−2.16)
Constant		0.00
		(0.84)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 30 Error correction model: Sector O - robustness

	LR	SR
L.v	−2.08	
	(−1.33)	
Crisis	0.03	
	(1.49)	
θ		−0.07*
		(−1.82)
L.dU		0.19*
		(1.67)
L2.dU		0.22*
		(1.90)
L3.dU		−0.03
		(−0.28)
dv		−0.24
		(−1.25)
Constant		0.02
		(1.59)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 31 Error correction model: Sector P - robustness

	LR	SR
L.v	−1.56	
	(−0.38)	
Crisis	0.01**	
	(2.25)	
θ		−0.04
		(−1.44)
L.dU		−0.09
		(−0.79)
dv		−0.11
		(−0.65)
Constant		0.00
		(1.47)
Observations	89	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 32 Error correction model: Sector Q - robustness

	LR	SR
L.v.	10.56	
	(0.42)	
Crisis	0.03	
	(0.74)	
θ		−0.02
		(−0.48)
dv		−0.81***
		(−2.63)
L.dv		0.07
		(0.21)
L2.dv		−0.18
		(−0.59)
Constant		0.00
		(0.82)
Observations	88	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 33 Error correction model: Sector R - robustness

	LR	SR
L.v	18.68	
	(0.90)	
Crisis	0.01	
	(0.47)	
θ		−0.02
		(−0.88)
dv		−0.09
		(−0.25)
L.dv		0.81**
		(2.33)
Constant		0.00
		(1.62)
Observations	87	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Table 34 Error correction model: Sector S - robustness

	LR	SR
L.v	−0.74	
	(−0.44)	
Crisis	0.02**	
	(2.38)	
θ		−0.06
		(−1.55)
dv		−0.07
		(−0.84)
Constant		0.01*
		(1.68)
Observations	89	

t-Stats in parentheses; significance: 0.1*, 0.05**, 0.01***

Competing interests
The IZA Journal of European Labor Studies is committed to the IZA Guiding Principles of Research Integrity. The authors declare that they have observed these principles.

Authors' information
Michael Christl and Dénes Kucsera are economists at Agenda Austria. Monika Köppl–Turyna is a senior economist at Agenda Austria and a lecturer at the Vienna University of Economics and Business.

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