Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Behind the Curve: Econometric Estimation and Sectoral Decomposition of the Japanese Beveridge Curve's Evolution Around the COVID-19 Pandemic

CAMA Working Paper 20/2024
March 2024

Corrado Di Guilmi
University of Florence
University of Technology Sydney
Kobe University
Centre for Applied Macroeconomic Analysis, ANU

Georgia K. Rylah
University of Technology Sydney

Abstract

This paper examines the Japanese Beveridge curve in order to identify a possible structural break prior to the COVID-19 pandemic. We utilize two levels of analysis to detect a break in the relationship between unemployment and vacancies and determine its timing and potential causes. First, the relationship for the period January 2000 - June 2023 is estimated by means of a Vector Error Correction Model. We detect a structural break in November 2019 and find evidence of change in the relationship between unemployment and vacancies as early as 2018. Second, we use disaggregated vacancy and unemployment data to analyze the Beverdige curves for sub-groups at the occupational, industrial, and contractual levels and carry on an extensive mismatch analysis. We find that services-related industries and occupations contributed to a relatively larger extent to the break in the curve. Counterfactual experiments suggest that the decline in vacancies and the increase in unemployment recorded during the pandemic period were amplified by the break.

Keywords

Beveridge curve, Vector Error Correction Model, labor market mismatch

JEL Classification

C32, E24, J01

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

Behind the curve: econometric estimation and sectoral decomposition of the Japanese Beveridge curve's evolution around the COVID-19 pandemic

Corrado Di Guilmi[1,2,3,4] and Georgia K. Rylah[2]

[1]University of Florence, Italy
[2]University of Technology Sydney, Australia
[3]Center for Computational Social Science, Kobe University, Japan
[4]Centre for Applied Macroeconomic Analysis, Australian National University, Canberra, Australia

March 4, 2024

Abstract

This paper examines the Japanese Beveridge curve in order to identify a possible structural break prior to the COVID-19 pandemic. We utilize two levels of analysis to detect a break in the relationship between unemployment and vacancies and determine its timing and potential causes. First, the relationship for the period January 2000 - June 2023 is estimated by means of a Vector Error Correction Model. We detect a structural break in November 2019 and find evidence of change in the relationship between unemployment and vacancies as early as 2018. Second, we use disaggregated vacancy and unemployment data to analyze the Beverdige curves for sub-groups at the occupational, industrial, and contractual levels and carry on an extensive mismatch analysis. We find that services-related industries and occupations contributed to a relatively larger extent to the break in the curve. Counterfactual experiments suggest that the decline in vacancies and the increase in unemployment recorded during the pandemic period were amplified by the break.

Keywords: Beveridge curve; Vector Error Correction Model; labor market mismatch.
JEL codes: C32, E24, J01.

1 Introduction

The Beveridge curve has proven to be a valuable tool to gain insights about the effects on the labor market of the major shocks generated by the great recession and the Covid-19 pandemic. Considering the results of the recent literature that has focused on the evolution of the Beveridge curves in different countries, the Japanese one, illustrated in Figure 1, appears peculiar. With respect to the US, for example, Figure 2 shows that the Japanese curve was relatively stable during the Great Recession and appears to have shifted inwards around the start of the COVID-19 pandemic, whereas the US curve experienced two clear outward shifts around both events.

This paper focuses on the most recent movement of the Japanese curve. By studying the dynamics of the relationship between the unemployment rate and the vacancy rate, we aim to test the hypothesis of a structural break in the Beveridge curve and posit that this break occurred prior to the onset of the COVID-19 pandemic.

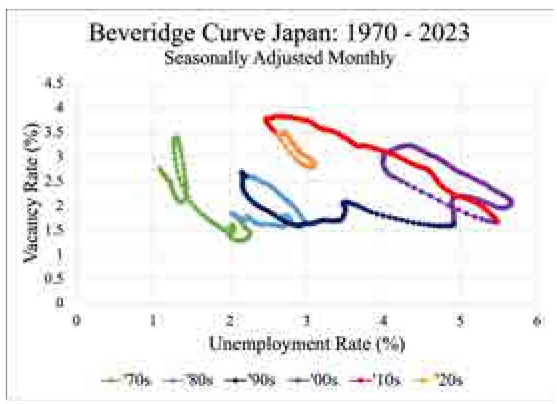


Figure 1: Japanese Beveridge curve: seasonally adjusted monthly from 1970 to 2023.

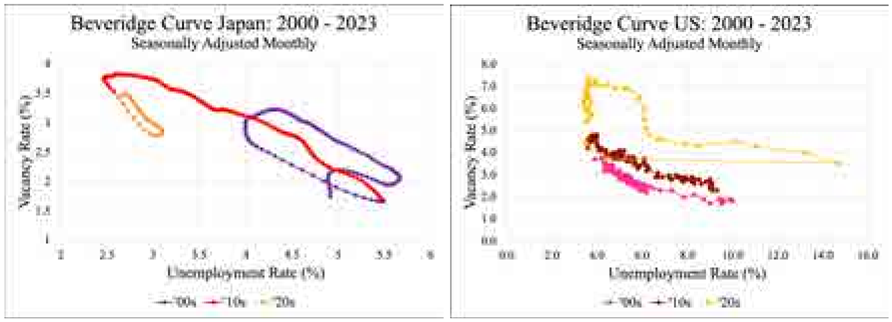


Figure 2: Japanese Beveridge curve and US Beveridge curve: seasonally adjusted monthly from 2000 to 2023.

The Japanese labor market has attracted interest in the last decades for its rapid transformations, in particular the flexibilization and precarization of the workforce, and the relative rigidity of wages to the unemployment rate. The share of non-regular employment[1] has increased on average since the 1990s, representing 36 per cent of the labor force in 2023. This increase in non-regular employment in Japan is intertwined with demographic changes, notably the aging population and increased participation of women and older people in the workforce. The speed of the decline in the working-age population (over 12 million from 2000 to 2020) was the fastest among OECD countries (Kawaguchi and Mori, 2019). Over the same period, the size of the labor force was expanding, driven by a surge in the female and senior citizens workforce participation.

The aging of population has implications not only for the supply of labor, but it directly affects the composition of the demand for goods and services in the economy (Esteban-Pretel and Fujimoto, 2020) and, consequently, on the industrial composition of the workforce. Employment growth has been concentrated in the services industries, most strikingly in the medical, healthcare and welfare services (Kawaguchi and Mori, 2019), required to support the ageing population. Service industries demand more non-regular workers than the manufacturing sector (Asano et al., 2013). As such, the increase in service employment from 1986 to 2008 has contributed to the increased the number of non-regular workers.

In 2019, Japan's unemployment rate hit a 27-year low of 2.2 per cent, and the effective job-opening ratio - how many jobs are available relative to the number of job seekers - hit a 46-year high (MHLW, 2019). The number of regular employees increased for the fifth consecutive year, reaching 35.14 million by the end of 2019.

In light of these developments, we analyze the Japanese Beveridge curve through three main steps. First, we estimate the relationship between unemployment rate and vacancy rate with a Vector Error Correction Model (VECM) using monthly data from 2000 to 2023. Second, we extend the VECM by including an indicator dummy variable to detect a structural break in the relationship. The estimation of two (par-

[1] Following Di Guilmi and Fujiwara (2022), non-regular employment includes temporary, part-time, or agency workers, and regular refers to permanent workers.

tially) different models allows us to carry on some counterfactual experiments. Third, in order to provide a possible explanation for the evidence detected by the VECM analysis, we employ industry, profession, and type of employment data to create disaggregated group-level Beveridge curves and compute different mismatch indexes.

The main finding of this paper is the detection of a structural break in the relationship between unemployment and vacancies that occurred before the COVID-19 pandemic. More specifically, a rapid decrease in vacancies coexisted with a mild raise in unemployment, determining a steeper Beveridge curve. This break has potentially magnified the decline in the vacancy rate that the Japanese labor market experienced during the pandemic and slowed down the recovery of employment. The analysis of disaggregated data reveals that the service sector experienced the largest reduction in vacancies, which was only partially offset by a reallocation of workers across professions, and therefore led to aggregate larger mismatch and mildly raising unemployment. As expected, the role of mismatch in unemployment was less important during the restrictions implemented to curb the contagion, but still relevant at least until the end of 2021.

This paper intends to provide three main contributions. The first is identifying a structural break in the Japanese Beveridge curve before the COVID-19 pandemic as a consequence of changes in the labor market. This finding fills a gap in recent literature (not only for Japan), which has, to the best of our knowledge, primarily focused on the COVID-19 pandemic as a catalyst for modifications in the Beveridge-curve relationship, potentially overlooking relevant changes in the pre-pandemic period. Secondly, we propose a novel approach since, to the best of our knowledge, this is the first application of VECM analysis to the Japanese Beveridge curve. Finally, in order to shed light on the factors determining the aggregate change, the econometric analysis is integrated by the study of group-level Beveridge curves at industrial, professional, and contractual levels, and by an extensive analysis of mismatch indexes. Given its scope, the computation and analysis of the different levels of mismatch also expand this specific literature.

The paper is organized as follows. Section 2 reviews the relevant literature on the Beveridge curve, the Japanese labor market, and the effect of the COVID-19 pandemic; section 3 introduces the data and econometric methodology used in this study; section 4 presents the econometric results, and section 5 extends the econometric analysis by using disaggregated group-level Beveridge curves and mismatch indexes. The results are discussed in section 6 while section 7 concludes the paper and suggests directions for further research.

2 Relevant Literature

This section provides a succinct overview of the relevant literature on the Beveridge curve with a focus on determinants of its shifts, relevant studies on mismatch in the Japanese context, and the impact of the COVID-19 pandemic on the labor market.

2.1 Beveridge curve and Labor Market and Mismatch

As documented by Consolo and Da Silva (2019), outward shifts of the Beveridge curve generally occur after periods of recession, as firms post vacancies faster than unemployed individuals are matched to jobs. Recent literature has been particularly focused on the Great Recession and its aftermath. A cross-country comparison by Bova et al. (2018) provides evidence of an outward shift of the Beveridge curves of several OECD countries after the Great Recession. Outward shifts in the US have been widely documented (Barnichon et al., 2011; Hobijn and Sahin, 2013; Lubik and Rhodes, 2014; Diamond and Şahin, 2015), as well as in the EU (Bonthuis et al., 2016; Bova et al., 2018).

Long-term unemployment is cited as a crucial determinant of an outward shift (Bova et al., 2018), as it implies poor matching between unemployed workers and available jobs. An increase in the share of long-term employment lowers search efforts and the propensity of employers to fill vacant positions (Consolo and Da Silva, 2019). The composition and size of the labor force may also influence shifts in the curve. An extensive study on the Beveridge curves of European countries by Bonthuis et al. (2016) find that the proportion of low-skilled workers, young workers, and female labor force participation are pivotal factors in the curve's position. Notably, a smaller proportion of low-skilled workers and higher female labor force participation are associated with a reduced likelihood of an outward shift.

Barnichon et al. (2011) investigates the role of specific industries in driving shifts of the US Beveridge curve during the Great Recession. Using disaggregated vacancy rates, layoff rates, and quit rates at the industry level, they find that the decline in the vacancy rate is most pronounced in the construction, manufacturing, trade and transportation, leisure and hospitality industries. The housing-driven recession in the US significantly diminished the demand for labor in the construction industry whilst increasing the demand for low-turnover industries. Consequently, there was a disproportionate decline in activity across sectors. There is also evidence of industry-level mismatches in Europe during the Great Recession, as highlighted by Pater (2017). These mismatches may stem from sectoral shifts, changing skill requirements, and geographical dispersion, as outlined by Lubik (2021).

Evidence of inwards shifts of the Beveridge curve is limited. Bleakley and Fuhrer (1997) presents a comprehensive analysis of the inward shift of the US Beveridge curve in the early 1990s, providing three possible reasons. The first is the improvement in the matching efficiency between unemployed persons and vacant positions. Second, they argue that a significant drop in the flows of new entrants to the workforce, instigated by a baby bust in the US and the levelling off of female labor force participation, implied a lower unemployment rate, shifting the curve inwards. Third, they document a drop in the degree of churning in the labor market

Different methods have been employed to identify structural breaks in the Beveridge curve. Valletta (2005) and Bova et al. (2018), among others, first detect shifts through visual inspection and then subject these shifts to statistical tests. A substantial body of literature has estimated the Beveridge curve through autoregressive (AR) models. For example, Benati and Lubik (2014) identify time-variation in the Beveridge curve relationship by employing a time-varying parameter vector autoregressive (VAR) model. Pater (2017) utilizes a Bayesian vector autoregressive (BVAR) model, while Bonthuis et al. (2016) employ an autoregressive distributed lag (ARDL) specification.

The position and the shifts of the the Beveridge curve are usually linked to changes in matching efficiency, which can occur in different segments of the labor market and can be investigated by using mismatch indexes. Measures of mismatch have been employed (see for example Sahin et al., 2014; Shibata, 2020, for the US and Japan, respectively) to describe changes in matching efficiency. Our analysis presented in section 5.2 builds on Canon et al. (2013), who surveys five studies that have contributed to the development of mismatch indexes and computes the corresponding indexes using US data. Industry and occupation data are used to calculate disaggregated mismatch measures, which vary significantly among indexes and across types of disaggregation. Namely, Canon et al. (2013) reviews and applies the indexes proposed by Lilien (1982), Jackman and Roper (1987), Jackman et al. (1990), and Evans (1993). We introduce and discuss these indexes in section 5.2, where we present their application to the Japanese data.

Canon et al. (2013) identifies the index by Jackman and Roper (equivalent to the index by Sahin et al.) as the most suitable indexes for describing mismatch in the US due to their intuitive interpretations and measurement of the contribution of mismatch to unemployment.

2.2 Relevant Studies of Japan's Labor Market

The Japanese labor market has undergone profound structural changes in recent decades, such as the decline in lifetime employment, the expansion of non-regular work arrangements, the aging of the population, and shifts in labor force participation (Fukao and Perugini, 2021). In particular, the transition away from lifetime employment to less structured forms of employed has been analyzed, for example, for its implications for the functional distribution of income (Fukao and Perugini, 2021), inflation (Di Guilmi and Fujiwara, 2022), productivity dynamics (Fukao and Ug Kwon, 2006), and the flattening of the Phillips curve (Aoyama et al., 2022). Of particular relevance for the present paper are recent studies on mismatch in the labor market.

Ito et al. (2009) examines labor market mismatch within the framework of the Beveridge curve, citing the relationship as a valuable tool to analyze labor mismatches. Despite the absence of an official job vacancy rate in Japan, Ito et al. (2009) employed the number of effective job offers less new employment as a proxy for total job vacancies to construct the Japanese Beveridge curve. This measure captures the general movements of the curve and shifts, even in the absence of official vacancy data. Higuchi et al. (2012) explores labor market mismatch in the areas affected by the 2011 Great Eastern Earthquake, using the mismatch index developed by Jackman and Roper (1987). The analysis reveals that labor market mismatch peaked in the month following the earthquake, primarily driven by persistent labor shortages induced by heightened demand in the construction sector. Among different job categories, professional and technical roles, and manufacturing process jobs played significant roles in contributing to the mismatch. At the same time, clerical positions negatively impacted the growth of mismatch.

More recently, Shibata (2020) examines the effect of labor market mismatch on the dynamics of unemployment from 2000 to 2019. He decomposes mismatch into three categories: contract-type (regular vs. non-regular), employment-type (full-time vs. part-time), and occupation-type mismatch. The approach of the study involves the construction of a mismatch index for these different dimensions, by employing the framework developed by Sahin et al. (2014). Shibata (2020) quantifies the contribution of mismatch to changes in the unemployment rate by calculating counterfactual unemployment rates in the absence of mismatch. He finds that mismatch surges during the Great Recession, and an increase in the contribution of mismatch to the rising unemployment rate. Specifically, occupation-type and contract-type mismatch account for a substantial proportion of the surge in unemployment during the crisis, while employment-type mismatch appears to have a negligible impact. Labor market mismatch was already present before the onset of the COVID-19 pandemic, as documented by Higashi and Sasaki (2023) across broad occupational classifications.

2.3 COVID-19 and the labor Market

The COVID-19 crisis has generated a renewed interest in the Beveridge curve, particularly in response to the outward shift observed in the US (Lubik, 2021; Rodgers and Kassens, 2022). Like previous major crises, the COVID-19 pandemic triggered substantial transformations in the labor market. The economic disruptions generated by the pandemic, stemming from widespread lockdowns, surging infection rates, and uncertainty, has had significant consequences for unemployment and job vacancies. Notably, the shifts and alterations observed in the US Beveridge curve during the COVID-19 crisis have proven to be more profound than those experienced during the Great Recession, as emphasized by Lubik (2021). Emerging evidence suggests that the pandemic has instigated changes in job search behavior, where job-seekers increasingly looked for low-risk-of-infection job opportunities (Higashi and Sasaki, 2023). Simultaneously, firms, notably those in infection-prone industries, scaled back hiring activities, reducing the number of job vacancies.

Barlevy et al. (2023) examine the outward shift of the US Beveridge curve after the onset of the COVID-19 pandemic. In 2020, two major events occurred in the labor market. First, there was a mass layoff of workers in March 2020 when COVID-19 broke out. Second, in the latter part of the year, there was a phenomenon of "rematching" unemployed workers with their prior employers as the US economy began to reopen. This short-lived effect was also discernible in measures of mismatch for both the US and the UK, with a sharp surge in mismatch observed at the pandemic's outset, followed by a return to prior levels within a few quarters, as found by Pizzinelli and Shibata (2023). They also present empirical evidence on heterogeneous impacts across industries, where government-imposed lockdowns significantly impeded activity in specific sectors, especially in service-based industries.

In Japan, the impact of the COVID-19 pandemic exhibited substantial heterogeneity across industries (Kotera and Schmittmann, 2022). Industries heavily reliant on close physical contact and manufacturing were disproportionately affected, whilst medical, financial, and IT services were relatively resilient. By clustering occupations into "vulnerable" and "not vulnerable", Higashi and Sasaki (2023) noted that contact-intensive service industries were the most affected. Notably, non-regular workers were more impacted by the shock than regular workers, a pattern in line with firms' ability to adjust to economic conditions by reducing their non-regular workforce. Higashi and Sasaki (2023) also find that the pandemic escalated the overall labor market mismatch, possibly due to government employment subsidies that acted as disincentives for mobility and layoffs.

3 Data

This paper uses aggregate and group-level data for employed persons (E), unemployed persons (U), job vacancies (V), the unemployment rate (u) and the vacancy rate (v). We first introduce the aggregate data used in the econometric model and then discuss the group-level data used for the mismatch analysis. Figure 3 shows the seasonally adjusted series, using a state-space model approach.

Figure 3: Aggregate unemployment rate and vacancy rate: seasonally adjusted and non-adjusted series.

3.1 Aggregate Data

The aggregate monthly figures for unemployed persons and the official unemployment rate are obtained from the Labour Force Survey (LFS) The LFS is a monthly household survey, conducted by the Ministry of Health, Labour and Welfare (MHLW), that collects data on the state of employment and unemployment every month.[2] The LFS is divided into a Basic Tabulation, released monthly, and a Detailed Tabulation, released quarterly. The unemployment series used in this paper comes from the Basic Tabulation.

With respect to the vacancy rate, no official estimate is available in Japan. However, the Employment Referral for General Workers, released by the MHLW, contains

[2] The data are available at `https://www.mhlw.go.jp/stf/english/index.html`.

monthly data on job openings, applications and persons who found employment.[3] We use these data to construct a proxy measure of vacancies, and hence the vacancy rate.[4] Following Ito et al. (2009), we use the number of job openings less workers who found employment as a proxy for total job vacancies in a given month. The vacancy rate is calculated as follows:

$$v = 100 \times \frac{V}{V+E} \tag{1}$$

The summary statistics for the unemployment rate and vacancy rate are summarised in Table 3.1.

Series	Min	Max	Mean	Std
u	2.462	5.660	4.088	1.007
v	1.662	3.824	2.860	0.621

Table 1: Summary statistics: unemployment and vacancies 2000-2023.

Additional aggregate data, used as controls in the main model, are obtained from the LFS, Federal Reserve Economic Data (FRED), and from monthly macroeconomic series data base for Japan constructed by Maehashi and Shintani (2020). Specifically, the activity rate measures the proportion of those active in the labor market over the working-age population. The index of regular workers is the log-difference of the seasonally adjusted series of regular employees. The index of industrial production measures the output of the industrial sector of the economy and indicates the level of economic activity. The number of employees in the service occupation is based on the Japan Standard Occupational Classification (rev. 2009). Importantly, the classification revision in 2009 did not affect the service classification. The index is the log-difference of the number of service workers.

3.2 Group Level Data

Group-level data on employment, vacancies and unemployment are required for the mismatch analysis in section 5. We decompose the data at occupation, industry and contract-type levels. Occupation and industry reclassifications occurred in 2003 and 2009, respectively. Industry disaggregations are based on the 12th revision of the Japan Standard Industrial Classification and occupation disaggregations are based on the Japan Standard Occupational Classification (rev. 2009). Contract-type

[3] The data from MHLW are collected only for those who went through the Public Employment Securities Offices and do not cover vacancy posts and hire through private agencies. Shibata (2020) finds the general trend observed in public data tracks the one of private vacancies and hires.

[4] Data are available at `https://www.mhlw.go.jp/english/database/db-l.html`.

is disaggregated into two broad classifications: regular and non-regular.[5]

Group-level data for all three categories are available consistently from 2013 to 2023.[6] and accordingly, we focus on this period for the mismatch analysis. In order to be able to consistently interpret both the econometric and the mismatch analysis, we check that the VECM model results for the period 2000-2023 are robust to this reduced sample.

Disaggregated data for employment and vacancies for occupation, industry and contract-type disaggregations are available in the LFS. However, there are no official unemployment figures for any group. Following a standard approach in the specialized literature, for occupation and industry level unemployment, we use data on the number of workers who left a job in a given occupation or industry in the previous year, respectively. Quarterly data are available in the Detailed Tabulation of the LFS. This measure may not fully describe the level of unemployment, as it does not capture workers who left the workforce entirely or moved to employment in another industry. For the purpose of this study, the measure is satisfactory as it still captures the heterogeneity and changes in unemployment across group-level disaggregations. There are no similar data for contract-type unemployment. Based on the LFS, which defines unemployed persons as individuals who participate in job-seeking activity, we use the number of job applicants in each contract-type as a proxy for unemployed persons.[7]

4 Econometric Analysis

The econometric methodology used in this paper includes four main steps. First, we preliminarily test for stationarity and cointegration in the series. Second, we estimate the Beveridge curve using a VECM, which is selected on the basis of the presence of a cointegrating relationship between unemployment and vacancy rates. Third, we introduce a dummy indicator variable into the model in order to test for a structural break in the relationship. We begin by presenting the stationarity and cointegration analysis results in section 4.1. Subsequently, the results of the main econometric model are presented in Section 4.2. In section 4.3, we extend the model to test for a structural break in the Beveridge curve relationship. The results of the extended model are then subject to robustness checks. Finally, 4.4 presents some counterfactual scenarios generated using the main model.

4.1 Stationarity and Cointegration Results

Stationarity is tested using the Augmented Dickey-Fuller (ADF) unit root test, whose results are shown in Table 3. While nonstationarity in levels cannot be rejected for

[5] Regular employment is described as open-ended, full-time, direct employment. Therefore, non-regular employment is anything that contradicts this definition, which includes part-time workers, temporary workers, dispatched workers, contract employees, entrusted employees.

[6] Contract-type data were introduced to the Labour Force Survey Basic Tabulation in 2013.

[7] The choice is supported by the fact that aggregate series of unemployed persons and job applicants display a positive correlation of 0.94 since 2000.

both the unemployment rate and vacancy rate, taking the first difference we are able to reject nonstationarity at the 1% confidence level for both series.

Accordingly, we test for the presence of a cointegrating relationship by means of the Johansen maximum eigenvalue test statistic (Johansen, 1988), which examines the null hypothesis of r cointegrating vectors against the alternative hypothesis of $r+1$ cointegrating vectors. For the selection of the lag order for the test, we apply the Hannan-Quinn Criterion (HQ), using the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC) as further tests, on the following vector autoregressive (VAR) model:

$$y_t = c + \Gamma_1 y_{t-1} + ... + \Gamma_{p-1} y_{t-p+1} + \epsilon_t \tag{2}$$

where $y_t = (u_t, v_t)'$ is a (2×1) vector of observations at time t, c is a 2×1 vector of constant terms, Γ_p is a 2×2 matrix capturing the relationship at lag p, and ϵ_t is the vector of error terms $(\epsilon_{u,t}, \epsilon_{v,t})$. The HQ criteria identifies a lag order of 7 for the Johansen test. This corresponds to a VECM lag order of 6. The result of the Johansen maximum eigenvalue test is in Table 2. We can reject the null hypothesis of no cointegration at 6 lags, but also for the 5 and 8 lags indicated by the AIC and SQ criteria, respectively, as shown by tables A.1 and A.2 in the Appendix. As the unemployment and vacancy rate series are $I(1)$, we adopt a VECM.

Series	Lag	ADF test statistic	P-value
u	6	-0.63661	0.9756
v	6	$-$ 3.5138	0.04098
Δu	6	-6.0689	< 0.01
Δv	6	-5.5735	< 0.01

Table 2: Johansen cointegration test statistics and critical values.

Cointegration relationship	Test statistic	10 pct	5 pct	1 pct
$r \leq 1$	0.79	6.50	8.18	11.65
$r = 0$	20.31	12.91	14.90	19.19

Table 3: Augmented Dickey-Fuller test for unemployment and vacancy series.

4.2 Main Model Results

Given the nature of the two series, we estimate a VECM according to the following model (Lütkepohl, 2005):

$$\Delta y_t = c + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + ... + \Gamma_{p-1} \Delta y_{t-p+1} + \epsilon_t \tag{3}$$

where $y_t = (u_t, v_t)'$ is a 2×1 vector of observations at time t, c is a 2×1 vector of constant terms, Γ_p is a 2×2 matrix capturing the short-run dynamic at lag p, Π is a 2×2 matrix capturing the long-run effect, and ϵ_t is the vector of error terms $(\epsilon_{u,t}, \epsilon_{v,t})$. The Error Correction Term (ECT) relationship is indicated by Π.

According to the results of the stationarity tests, cointegration tests and the lag selection criteria discussed in Section 4.1, the chosen number of lags is 6 (VECM-6). The result of the VECM-6 model (henceforth referred to as the main model), shown in Table A.3, identifies a significant, negative relationship between the unemployment rate and the vacancy rate. Notably, the ECT coefficient is negative and statistically significant for both equations, indicating that the relationship converges to the cointegrating relationship in the long run. The intercept coefficient is also statistically significant, however small. The sign of the coefficients of the first lag of unemployment and vacancies are consistent the Beveridge curve relationship.

Before proceeding to the identification of possible breaks, we run a battery of tests on the robustness of the VECM-6. First, we check for autocorrelation in the residuals through the Box-Ljung test (results are in Table A.4 in the Appendix), which shows no autocorrelation at six lags for the unemployment and vacancy equation residuals. The autocorrelation functions of the residuals are visualised in Figure A.1 in the Appendix, and show no persistent autocorrelation for either series.

Second, a VECM-6 model is estimated over a reduced sample, beginning in January 2013 and ending in June 2023. The motivation for choosing this period is twofold: firstly, at least up to the possible break, the Beveridge curve exhibits a relatively more regular behavior in this subperiod, and secondly, it corresponds to the time frame used for the mismatch analysis. The significance and sign of the coefficients of the reduced sample model are consistent with the corresponding coefficients in the main model, although the coefficients differ significantly in size (full results in Table A.5.). In particular, the ECT coefficient is roughly double that of the main model. On the other hand, the lagged variable coefficients are smaller in the reduced sample model. This suggests that in the reduced sample, the long-run cointegrating relationship better captures the Beveridge curve, and the effect of short-run deviations is less important, which is consistent with the relatively more regular pattern exhibited by the curve within this period (see Figure 2).

Third, we test multiple lag orders by estimating a VECM-4 model and a VECM-8 model (full results in tables A.6 and A.7 in the Appendix). The coefficients of the VECM-4 and VECM-8 models lie within the confidence bounds of the main model.

The fourth and final robustness check of the main model is the inclusion of the four control variables related to the macroeconomy and the labor market, introduced in section 3: the first difference in the activity rate (indicated by a), the share of regular employment (r), the logarithmic difference in industrial production (i), and the share of employment in the service sector (s). The activity rate accounts for the changes in aggregate labor supply. The changes in regular employment are captured by the index of regular worker employment. The trend in regular employment has changed since 2000 as the long-term decline in the share of regular employees appears to have plateaued around 2014. We use industrial production as a proxy for the aggregate level of economic activity, given its monthly frequency. The fourth control, the share of employment of the service sector, accounts for the substantial changes in the industrial composition of the workforce. Service industries and occupations have increased in size, also driven by the ageing population (OECD, 2021), and were most affected by the COVID-19 pandemic due to their face-to-face nature (Higashi and Sasaki, 2023). At the same time, manufacturing and construction industries and occupations have decreased in relative importance.

After adding controls, the model becomes:

$$\Delta y_t = c + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + ... + \Gamma_{p-1} \Delta y_{t-p+1} + \Theta_1 x_{t-1} + ... + \Theta_{p-1} x_{t-p+1} + \epsilon_t \quad (4)$$

where $x_t = (a_t, r_t, i_t, s_t)$ is a 4×1 vector of control variables at time t. Θ_p is a 4×1 vector that captures the effect of the control variables at lag p. Occasionally, the coefficients for activity rate and index of industrial production are significant but no clear effect on the model is detectable since the size and sign of the coefficients for the ECT, intercept, and lagged values of unemployment and vacancies of the control model are consistent with those of the main model. To conclude, including the control variables does not significantly alter the main model (full results in Table A.8.).

4.3 Structural Break Testing Results

The structural-break model is an extension of the main VECM model, integrated by a new set of variables, called indicators, which are multiplied by a dummy variable equal to 0 (1) before (after) the breakdate. This approach allows us to capture a change in the relationship around the hypothesized breakdate period in very intuitive way.

The structural-break model is estimated as:

$$\begin{aligned} \Delta y_t = c + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + ... + \Gamma_{p-1} \Delta y_{t-p+1} \\ + \left(\hat{\Gamma}_1 \Delta y_{t-1} + ... + \hat{\Gamma}_{p-1} \Delta y_{t-p+1}\right) \mathbb{1}_{(t>\tau)} + \epsilon_t \end{aligned} \quad (5)$$

where τ is a specified breakdate and $\mathbb{1}_{(t>\tau)}$ is a dummy variable that is 0 when $t \leq \tau$ and is 1 when $t > \tau$. $\hat{\Gamma}$ is the coefficient of the indicator variable $\Delta y_{t-p+1} \mathbb{1}_{(t>\tau)}$. We can simplify Equation (5) into the following model for a more intuitive representation:

$$\Delta y_t = c + \Pi y_{t-1} + (\Gamma_1 + \hat{\Gamma}_1 \mathbb{1}_{(t>\tau)}) \Delta y_{t-1} + ... + (\Gamma_{p-1} + \hat{\Gamma}_{p-1} \mathbb{1}_{(t>\tau)}) \Delta y_{t-p+1} + \epsilon_t \quad (6)$$

The dummy variable method to detect structural breaks with a VECM, as suggested by Bai and Perron (1998) and Güler and Bakýr (2019), allows for the detection of a structural break and can determine the timing of the break.[8]. We firstly identify the presence of a structural break and, secondly determine the timing of the break. To do so, we estimate the model with different τ, namely for each month from July 2017 to June 2020. We test if $\hat{\Gamma}_{p-1}$ is significantly different from zero for $t > \tau$. If this is the case, we find evidence that the coefficients change after τ, suggesting a

[8] As the possible breakdate is close to the sample end, a Chow test may return unreliable results, as the estimators may not be available due to the lack of degrees of freedom. This makes the dummy variable approach preferable to the Chow test, which is commonly used to detect the existence of a break.

structural break. Secondly, to determine the timing of the structural break, we compare the sum of squared residuals (SSR) of the models from the sequential testing procedure in order to identify the τ that minimizes the SSR (Bai and Perron, 1998). This sequential breakdate testing is also useful to determine when the change in the relationship begins.

As we are primarily interested in the significance of the indicator dummy variables, we provide a summary of the sign and significance in Table 4 and Table 5. For the reader's convenience, we do not include the value of the coefficient to not overcrowd the results.[9] The sign, significance, and size of the ECT, intercept, and lagged variables are not significantly different to the values of the main model.

The coefficients of the indicator variables first become significant in January 2018 and consistent in terms of their sign and significance from August 2018. The significance of the indicator coefficients continues consistently in 2019 and the start of 2020. The coefficients of the ECT, intercept and lags of unemployment and vacancies do not significantly change from those in the main model. Notably, the indicator variables significantly affect only the vacancy equation. In particular, the first unemployment lag has a relatively large significant negative effect on the vacancy equation. This result aligns with the behaviour of the Beveridge curve around these dates, shown in Figure 1, when unemployment becomes inelastic to the fall in vacancies, and the slope of the Beveridge curve appears to steepen. The fact that the intercept does not significantly change in the model with indicators suggests that the movement of the Beveridge curve was a tilt, due to a change in the slope, and there was no detectable shift. The sum of squared residuals of each model in the testing window are shown in Figure 4. The SSR decreases as the potential breakdate approaches November 2019 and immediately increases afterwards. We identify the structural break in November 2019, when the SSR is minimized. The full result of the structural break model for November 2019 is shown in Table A.9.

The robustness of the results of the structural break testing is first checked by testing the autocorrelation of the residuals for the November 2019 model. The Box-Ljung test detects no autocorrelation at six lags. The results of the test are shown in Table A.10 and the ACF of residuals for both equations are visualised in Figure A.2 (which show no persistent autocorrelation) in the Appendix.

Secondly, we test the robustness of the structural break results by adding control variables to the model. We repeat the sequential break testing and SSR analysis for the structural break model with controls. The sequential breakdate testing is extended to April 2020 to identify any changes in the significance of the indicator or control variables in response to the COVID-19 pandemic. There is no significant change in the indicator variable coefficients. The first lag of the services occupation control for the vacancy equation becomes significant in the first month of 2020, possibly due to the fact that the recruitment for workers by a sector that typically use non-permanent contracts was hindered by the reluctance of workers to take on jobs that could involve physical contacts (full results for sign and significance of the relevant coefficients can be found in Table A.11).

[9] The size of the indicator coefficients does not change significantly over the testing window. Full results are available on request.

The sequential breakdate testing of the model with controls identifies the same breakdate as the main model, November 2019, as shown in Figure A.3. The results of the structural break model with controls for November 2019 are presented in Table A.12, confirming that the significance and signs of the indicator coefficients do not change when controls are added to the model. Comparing the structural break model with controls and the main model with controls, it is worth noting the smaller negative coefficients of the industrial production in the former. This discrepancy suggests the negative sign of the industrial production coefficients are at least partly due to the sharp decline in vacancies that happened around the break.

	7/17		8/17		9/17		10/17		11/17		12/17	
	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv
Δu -1 $\mathbb{1}_{(t>\tau)}$												
Δv -1 $\mathbb{1}_{(t>\tau)}$												
Δu -2$\mathbb{1}_{(t>\tau)}$												
Δv -2 $\mathbb{1}_{(t>\tau)}$												
Δu -3 $\mathbb{1}_{(t>\tau)}$												
Δv -3 $\mathbb{1}_{(t>\tau)}$												
Δu -4 $\mathbb{1}_{(t>\tau)}$												
Δv -4 $\mathbb{1}_{(t>\tau)}$												
Δu -5 $\mathbb{1}_{(t>\tau)}$												
Δv -5 $\mathbb{1}_{(t>\tau)}$												
Δu -6 $\mathbb{1}_{(t>\tau)}$												
Δv -6 $\mathbb{1}_{(t>\tau)}$												

	1/18		2/18		3/18		4/18		5/18		6/18	
	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv
Δu -1 $\mathbb{1}_{(t>\tau)}$									$-^{**}$			$-^{**}$
Δv -1 $\mathbb{1}_{(t>\tau)}$											$+^{*}$	
Δu -2 $\mathbb{1}_{(t>\tau)}$							$-^{*}$		$+^{**}$			
Δv-2 $\mathbb{1}_{(t>\tau)}$												
Δu -3 $\mathbb{1}_{(t>\tau)}$							$+^{**}$					
Δv -3 $\mathbb{1}_{(t>\tau)}$												
Δu -4 $\mathbb{1}_{(t>\tau)}$					$+^{**}$							
Δv -4 $\mathbb{1}_{(t>\tau)}$												
Δu -5 $\mathbb{1}_{(t>\tau)}$	$-^{*}$		$+^{*}$									
Δv -5 $\mathbb{1}_{(t>\tau)}$												
Δu -6 $\mathbb{1}_{(t>\tau)}$	$+^{*}$											
Δv -6 $\mathbb{1}_{(t>\tau)}$												

	7/18		8/18		9/18		10/18		11/18		12/18	
	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv
Δu -1 $\mathbb{1}_{(t>\tau)}$		$-^{***}$		$-^{**}$		$-^{***}$		$-^{**}$		$-^{*}$		$-^{**}$
Δv -1 $\mathbb{1}_{(t>\tau)}$	$+^{*}$											
Δu -2 $\mathbb{1}_{(t>\tau)}$		$+^{**}$		$+^{*}$		$+^{**}$		$+^{**}$		$+^{*}$		$+^{*}$
Δv -2 $\mathbb{1}_{(t>\tau)}$												
Δu -3 $\mathbb{1}_{(t>\tau)}$												
Δv -3 $\mathbb{1}_{(t>\tau)}$												
Δu -4 $\mathbb{1}_{(t>\tau)}$												
Δv -4 $\mathbb{1}_{(t>\tau)}$												
Δu -5 $\mathbb{1}_{(t>\tau)}$								$+^{*}$		$+^{*}$		$+^{*}$
Δv -5 $\mathbb{1}_{(t>\tau)}$												
Δu -6 $\mathbb{1}_{(t>\tau)}$		$-^{**}$				$-^{*}$		$-^{*}$		$-^{*}$		$-^{*}$
Δv -6 $\mathbb{1}_{(t>\tau)}$												

Table 4: Summary of indicator coefficient significance and sign: 7/17 to 12/18.

	1/19		2/19		3/19		4/19		5/19		6/19	
	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv
Δu -1 $\mathbb{1}_{(t>\tau)}$		$-^{*}$				$-^{**}$		$-^{*}$		$-^{**}$		$-^{***}$
Δv -1 $\mathbb{1}_{(t>\tau)}$									$+^{*}$			
Δu -2 $\mathbb{1}_{(t>\tau)}$		$+^{*}$				$+^{**}$		$+^{*}$		$+^{**}$		$+^{**}$
Δv -2 $\mathbb{1}_{(t>\tau)}$									$-^{*}$		$-^{*}$	
Δu -3 $\mathbb{1}_{(t>\tau)}$												
Δv -3 $\mathbb{1}_{(t>\tau)}$												
Δu -4 $\mathbb{1}_{(t>\tau)}$												
Δv -4 $\mathbb{1}_{(t>\tau)}$												
Δu -5 $\mathbb{1}_{(t>\tau)}$										$+^{*}$		$+^{*}$
Δv -5 $\mathbb{1}_{(t>\tau)}$												
Δu -6 $\mathbb{1}_{(t>\tau)}$										$-^{*}$	$-^{**}$	
Δv -6 $\mathbb{1}_{(t>\tau)}$												

	7/19		8/19		9/19		10/19		11/19		12/19	
	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv
Δu -1 $\mathbb{1}_{(t>\tau)}$		$-^{***}$		$-^{***}$		$-^{***}$		$-^{***}$		$-^{***}$		$-^{**}$
Δv -1 $\mathbb{1}_{(t>\tau)}$						$-^{*}$		$-^{**}$			$-^{*}$	
Δu -2 $\mathbb{1}_{(t>\tau)}$		$+^{**}$		$+^{*}$				$+^{*}$		$+^{**}$		$+^{*}$
Δv -2 $\mathbb{1}_{(t>\tau)}$		$-^{*}$						$+^{**}$				
Δu -3 $\mathbb{1}_{(t>\tau)}$												
Δv -3 $\mathbb{1}_{(t>\tau)}$												
Δu -4 $\mathbb{1}_{(t>\tau)}$												
Δv -4 $\mathbb{1}_{(t>\tau)}$												
Δu -5 $\mathbb{1}_{(t>\tau)}$				$+^{*}$								
Δv -5 $\mathbb{1}_{(t>\tau)}$				$-^{*}$								
Δu -6 $\mathbb{1}_{(t>\tau)}$		$-^{***}$		$-^{**}$		$-^{**}$		$-^{*}$				
Δv -6 $\mathbb{1}_{(t>\tau)}$												

	1/20		2/20		3/20		4/20		5/20		6/20	
	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv
Δu -1 $\mathbb{1}_{(t>\tau)}$		$-^{**}$		$-^{**}$		$-^{*}$		$-^{*}$		$-^{*}$		$-^{**}$
Δv -1 $\mathbb{1}_{(t>\tau)}$		$-^{**}$		$-^{*}$		$-^{**}$		$-^{**}$		$-^{**}$		$-^{**}$
Δu -2 $\mathbb{1}_{(t>\tau)}$		$+^{*}$		$+^{*}$		$+^{*}$		$+^{*}$		$+^{*}$		$+^{**}$
Δv -2 $\mathbb{1}_{(t>\tau)}$		$+^{**}$		$+^{*}$		$+^{*}$		$+^{*}$		$+^{*}$		$+^{*}$
Δu -3 $\mathbb{1}_{(t>\tau)}$												
Δv -3 $\mathbb{1}_{(t>\tau)}$												
Δu -4 $\mathbb{1}_{(t>\tau)}$												
Δv -4 $\mathbb{1}_{(t>\tau)}$												
Δu -5 $\mathbb{1}_{(t>\tau)}$												
Δv -5 $\mathbb{1}_{(t>\tau)}$												
Δu -6 $\mathbb{1}_{(t>\tau)}$												
Δv -6 $\mathbb{1}_{(t>\tau)}$												

Table 5: Summary of indicator coefficient significance and sign: 1/19 to 6/20.

Figure 4: SSR over the testing window.

4.4 Counterfactual experiments

The detected modification in the relationship between unemployment rate and vacancy rate provides the opportunity of testing some conterfactual scenarios, generated by projecting the model without break on the post-November 2019 data. Figure 5 compares the actual Beveridge curve and the one generated by the extrapolation of the forecast of the main model using the data up to October 2019. The counterfactual curve is flatter and higher than the actual one, mimicking the pattern displayed by the pre-break curve. Notably, during the central period of the pandemic, the vacancy rate is higher and unemployment lower in the counterfactual scenario, while in the recovery period the actual curve lies above the counterfactual one.

While Figure 5 shows counterfactual series for both variables, Figures 6 and 7 display the counterfactual only for the vacancy rate and the unemployment rate, respectively, obtained by the forecast of the main model conditional on the actual data of the other series.

Figure 6 shows that the the vacancy rate in the counterfactual scenario declines slowly and is always above the actual one, reaching a minimum of 3.05 instead of 2.78. Figure 7 shows a lower unemployment rate in the counterfactual scenario. Interestingly, both the series of actual and the one of counterfactual unemployment rate follow the same evolution up to July 2020 when the growth of the counterfactual series slows down. It peaks in September 2020 while the actual series peaks in December, declining at a seemingly faster pace afterwards.

The counterfactual analysis allows us to appreciate how the already existing declining trend of the vacancy rate might have exacerbated the slump due to the pandemic and the following restrictions to businesses. It is plausible that the negative effect of the pandemic on the vacancy rate added to its ongoing decline. This initial negative trend may have amplified the effects on unemployment of the exogenous shock due to the pandemic and the consequent restrictions on economic activity. In order to shed further light on this mechanism, we perform Granger-causality tests at different lags but without obtaining conclusive results as each series appears to Granger-cause the other.

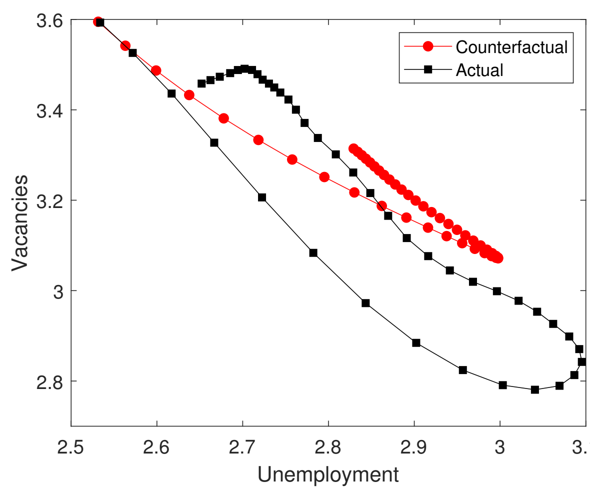


Figure 5: Actual Beveridge curve for the period 11/2019-06/2023 (black squares) and forecast generated by the model in table **??** (red circles).

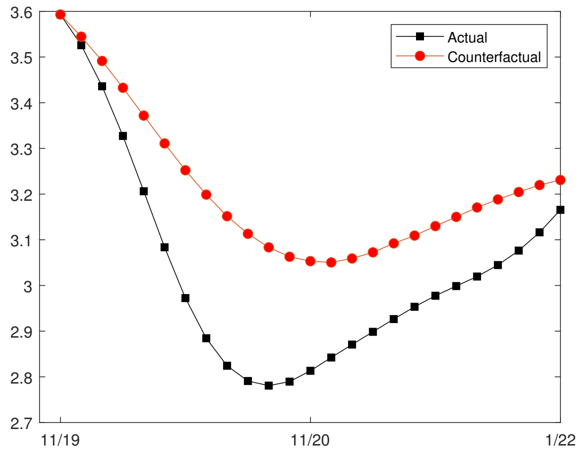


Figure 6: Time series of the vacancy rate for the period 11/2019-01/2022 (black squares) and forecast generated by the model in table **??** conditional on the actual unemployment rate (red circles).

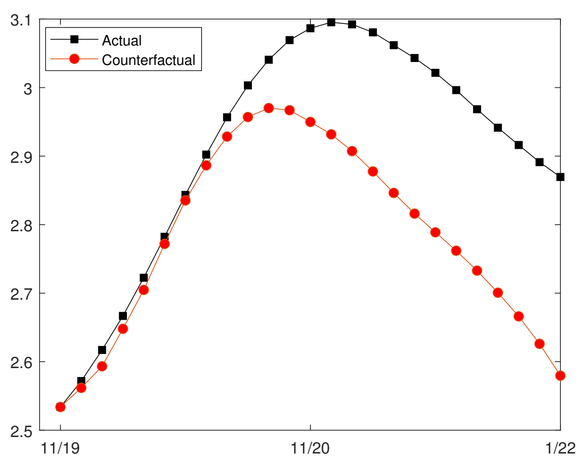


Figure 7: Time series of the unemployment rate for the period 11/2019-01/2022 (black squares) and forecast generated by the model in table **??** conditional on the actual vacancy rate (red circles).

5 Group-level Analysis

According to Blanchard and Diamond (1989), business fluctuations determine a counter-clockwise loop along a downward sloping locus in the U-V plane, while reallocation shocks lead to a parallel movement of unemployment and vacancy rates, which shifts the locus. In order to test whether the changes in the relationship between the two variables detected through the VECM are related to modifications in the reallocation of employed and unemployed workers across sectors or group and to check whether the break originated in specific segments of the labor market, in this section we extend the analysis to a deeper level of granularity. Namely, in section 5.1, we analyze group-level Beveridge curves and, in section 5.2 we provide an extensive overview of a series of mismatch measures. Using the data described in section 3.2, the analysis is developed across three different levels of disaggregation: occupation, industry, and contract-type.

5.1 Group Beveridge curves

In this section we investigate whether the inward movement of the Beveridge curve is reproduced also at the group level in order to identify which individual occupations, industries or contract-types drive the change, if any.

5.1.1 Occupation Beveridge curves

We compute Beveridge curves for the five largest occupations by number of employees: service, sales, clerical, manufacturing process, and professional and engineering. The occupation-specific curves are shown in Figure 8.

While an inwards shift is apparent across all occupation-specific curves, the curves differ in their shape. In particular, the movement in manufacturing occupation curve is relatively small, also considering its scale. Since, at November 2019, this profession accounted for about 15% of total employment, we can conclude that its contribution to the position of the aggregate curve was relatively marginal, compared for example to service and sales (which together account for almost 50% of the employment).

5.1.2 Industry Beveridge curves

We construct industry-specific Beveridge curves for the six largest industries by number of employees: wholesale and retail trade industry, manufacturing industry, medical, healthcare and welfare industry, construction industry, services not elsewhere classified (NEC) industry, and accommodation, eating and drinking services industry. The curves are shown in Figure 9.

The figure reveals a significant level of heterogeneity across industries. Specifically, the curves for the medical, healthcare and welfare, manufacturing and construction industries remained relatively stable. In contrast, the service NEC and wholesale and retail trade curves closely mimic the pattern of the aggregate curve, with a sharp fall in vacancies, accompanied by relatively stable unemployment, suggesting a possible major role played by these sectors in the change observed in the aggregate.

Because of the impossibility of a reliable econometric analysis on such a short time horizon with low frequency data, in order to gain further insights about a possible change in the relationship at the industrial level, we estimate a linear regression model on the period 01/2013-06/2019 and test its fit for the out-of-sample observations. Figure 10 compares the residuals from the regressions (with vacancies as dependent variable) for three relatively large sectors for employment: services NEC, wholesale and retail (for which both Beveridge curves show changes compatible with the aggregate curve), and manufacture. The plot shows that for all three sectors, the decline in vacancies observed from the end of 2019 leads to a constant overestimation. However, the difference is clearly larger for services NEC and wholesale and hospitality, although to a lesser extent for the latter.

The above analysis reveals the different contributions of industries to the observed change in the aggregate Beverdidge curve. More specifically, while vacancies appear to decline across the board for professions, significant differences emerge across industries. This piece of evidence has obvious implications in terms of the relationship between unemployment and vancancies and for employment itself, as further analyzed in section 5.2.

5.1.3 Contract-type Beveridge curves

We disaggregate contract-types into two broad classifications: regular and non-regular employment. The disaggregated Beveridge curves, shown in Figure 11, illustrate the differences between regular and non-regular contract-types.

The contract-type curves both follow a similar trajectory: unemployment becomes relatively less sensitive to vacancies. The pattern of the regular-contract curve mimics the aggregate one, showing a tilt inwards. The non-regular curve differs because the unemployment rate falls over the entire period, and the vacancy rate rises near the sample's end. Notably, the difference in scale between the two curves is significant. The unemployment and vacancy rate for regular contracts exceeds that of both the non-regular and aggregate series. This is possibly a result of the proxy measure used for contract-type unemployment, since the measure of applications by contract-type may also capture non-regular workers who wish to transition to regular work.

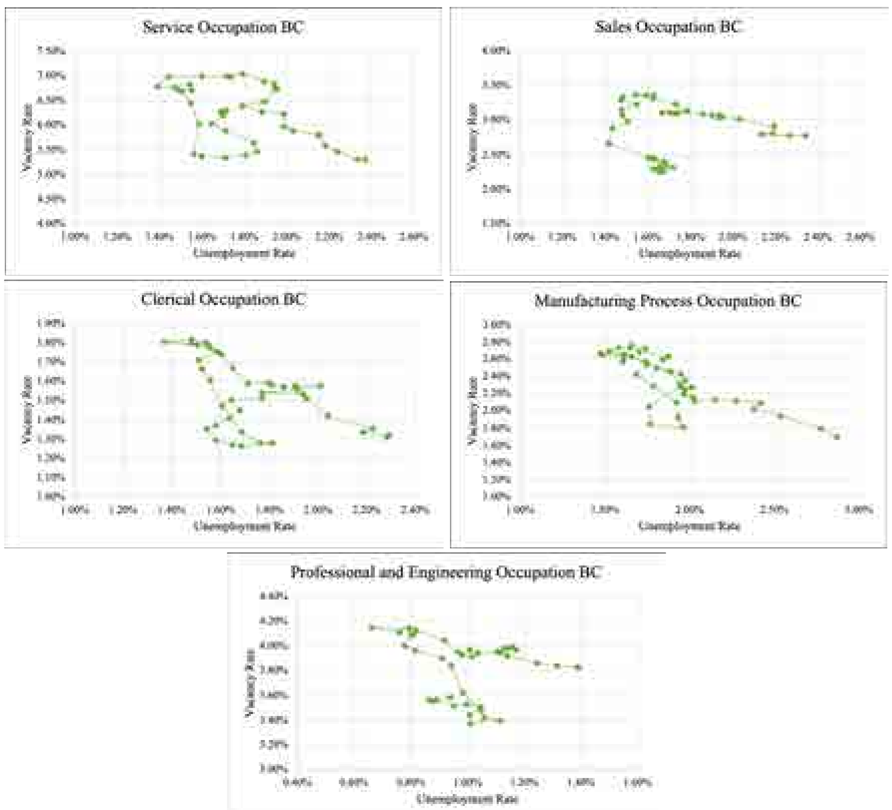


Figure 8: Occupation-specific Beveridge curves.

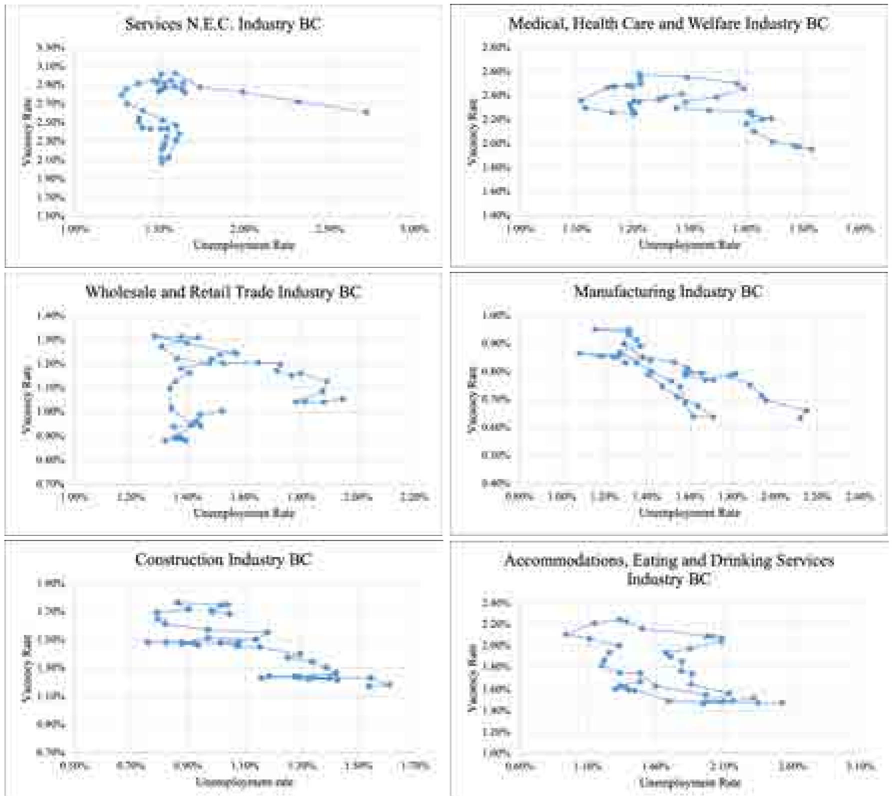


Figure 9: Industry-specific Beveridge curves.

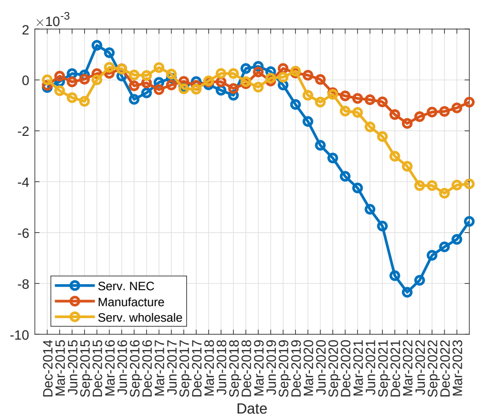
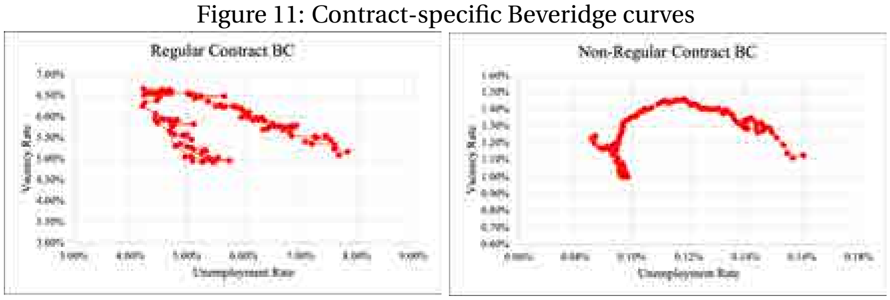


Figure 10: Residual for each observation on linear regression estimated on the period 01/2013-06/2019.

Figure 11: Contract-specific Beveridge curves



5.2 Mismatch Indexes

In order to investigate the factors at the root of the different patterns exhibited by the group-level Beveridge curves, we compute and analyze a series of mismatch indexes. The calculation of these indexes involves disaggregated unemployment and vacancies data to quantify employment and unemployment dispersion and the efficiency of reallocation of workers across professions, industries, and types of contract. Their evolution during the period of the tilt of the Beveridge curve can therefore provide additional valuable insights on the factors impacting the joint dynamics of the two variables.

We use quarterly group-level data, introduced in section 3.2, from 2013 to 2023. Occupational mismatch is computed over the five main occupations used for the occupation Beveridge curves. To examine industrial mismatch, we use fifteen non-agricultural industries. For the contract-type mismatch, we distinguish regular and non-regular employment. For the reader's convenience the main results for each indexes are summarized in table 6.[10]

5.2.1 Lilien Index

Lilien (1982) develops an index that estimates the dispersion of employment demand conditions across the labor market, emphasizing the role of workers' attachment to specific sectors in explaining unemployment. Such attachment reduces workers' willingness to seek opportunities in other sectors, resulting in slower labor market adjustments during sectoral demand shifts. The index is interpreted as a measure of the dispersion of employment growth across sectors, where a higher index level corresponds to a greater dispersion of employment conditions.[11] Lilien's index measures sectoral employment share-weighted percentage log deviations of sectoral employment from total employment. The index is calculated as:

$$I_{Lilien} = \sigma^2 = \left[\sum_{i=1}^{n} \frac{x_{it}}{X_t} \left(\Delta \log x_{it} - \Delta \log X_t \right)^2 \right]^{\frac{1}{2}} \tag{7}$$

where x_{it} is the number of employees in sector i at time t and X_t is the total employment for all sectors.

The results, shown in Figure 12, indicate that the level of dispersion is the greatest at industry level. In comparison, employment conditions were almost always the least dispersed across contract-types. Employment conditions were most volatile across occupations. The occupation index spikes in 2018, then falls to its previous level before another increase around November 2019. The industry index also increases in the last quarter of 2019.

The Lilien index integrates the visual inspection of the disaggregated curves by revealing that the dispersion of employment conditions across occupations height-

[10] The scale of the indexes we calculate appears small but it is consistent with the scale of the indexes calculated, for example, by Canon et al. (2013) on US data.

[11] A critique of Lilien's index is its correlation with sectoral shifts and aggregate demand fluctuations (Entorf, 2003; Canon et al., 2013).

Figure 12: Lilien mismatch index: dispersion of employment conditions.

ens in 2018, coinciding with the beginning of the change in the Beveridge curve relationship. This dispersion may be attributed to the different variations in the slopes of occupation-specific curves (see Figure 8), in particular considering the inwards shift of services and wholesale and retail trade curves and the relative stability of the other industry curves.

5.2.2 Jackman and Roper Indexes

Jackman and Roper (1987) propose a measure of structural unemployment and three mismatch indexes to quantify labor market mismatches. The three indexes, JR1, JR2, and JR3, measure the proportion of unemployed in the wrong sector, the proportion of the labor force in the wrong sector, and the proportion of observed unemployment attributable to structural imbalance or mismatch, respectively.

Jackman and Roper (1987) preliminarily define structural imbalance as a situation in which the characteristics of unemployed workers (e.g. skill, experience, location) differ from those required for vacant jobs. They specify structural unemployment as a situation where it would be possible to reduce unemployment by moving an unemployed worker from one sector to another, for a given number of vacancies, and calculate their measure of structural unemployment as:

$$SU = \frac{1}{2} U \sum_i |\hat{u}_i - \hat{v}_i| \tag{8}$$

where $U = \sum_{i=1}^{n} U_i$ is the total stock of unemployed workers and $\hat{u}_i$ and $\hat{v}_i$ are sector i's share of the total stock of unemployed workers and vacanct positions, respectively. Its results for Japan are shown in Figure 13.

The SU measure of structural unemployment is normalized in the first two indexes. The first index (JR1) measures the proportion of unemployed workers in the wrong sector and is computed as:

$$I_{JR1} = \frac{SU}{U} = \frac{1}{2} \sum_i |\hat{u}_i - \hat{v}_i| \tag{9}$$

From the results displayed in Figure 14, it is evident that the proportion of unemployed persons in the wrong occupation is greater than in the wrong industry or contract-type. The proportion of unemployed persons in the wrong occupation remains relatively stable, around 0.27, from the second quarter of 2015 to the first quarter of 2020. Also, the proportion of unemployed persons in the wrong industry increases from around 15 per cent in 2017 to 25 per cent in 2020. The proportion of unemployed persons in the wrong contract-type remains stable over the 10 years, around 10 per cent.

The second index (JR2) measures the proportion of the labor force in the wrong sector. It is computed as:

$$I_{JR2} = \frac{SU}{L} = \frac{1}{2}\frac{U}{L}\sum_i |\hat{u}_i - \hat{v}_i| \tag{10}$$

where L is the size of the labor force. Figure 15 show a declining trend up the end of 2019 followed by a contemporaneous increase across all three dimensions, clearly indicating a negative shock in matching efficiency.

The limitation of JR1 and JR2 is that they do not indicate how much current unemployment is due to mismatch. To address this limitation, a third index (JR3) is constructed, which measures the proportion of the observed unemployment attributable to structural imbalance or mismatch, and is computed as:

$$I_{JR3} = 1 - \sum_i (\hat{u}_i \hat{v}_i)^{\alpha} \tag{11}$$

assuming a Cobb-Douglas hiring function and an elasticity of substitution of $\alpha = 0.5$.[12]

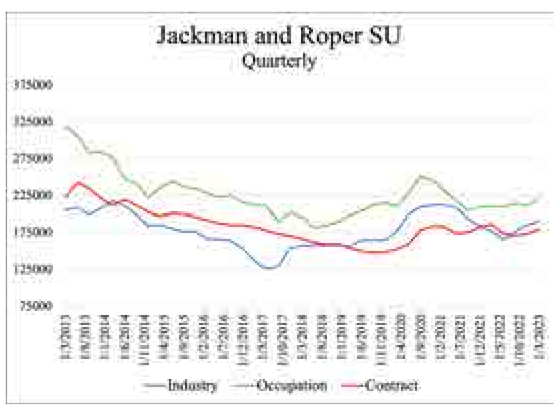


Figure 13: SU measure of equation (8) for Japan.

[12] An advantage of the three JR indexes is their invariance to aggregate demand. However, the indexes require job vacancy data at a disaggregated level, which may not always be available (Entorf, 2003). For instance, the US does not have aggregate nor disaggregate vacancy data; therefore, the "help-wanted" index is used instead.

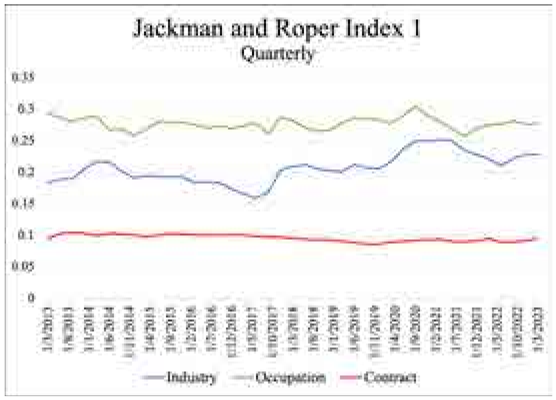


Figure 14: Jackman and Roper index 1: proportion of unemployed persons in the wrong sector.

The results in Figure 16 show that occupational mismatch contributes the most to the level of unemployment relative to the other types of mismatch. The occupation index declines in 2017 and then slowly increases, reaching a peak above 0.05 in the third quarter of 2020. The industry index rises steadily from 0.02 in the second quarter of 2017 to 0.04 in the third quarter of 2020. The contract-type index remains relatively stable over the period.

JR3 reveals that whilst occupational mismatch plays an important role, industrial and contract-type mismatches are relatively less important for unemployment. Notably, the proportion of unemployment attributed to occupational mismatch exhibits volatility in early 2018, coinciding with the changes in the Beveridge curve relationship.

5.2.3 Jackman, Layard and Savouri Index

Jackman et al. (1990) construct a mismatch index (JLS) defining mismatch unemployment as the distance between the observed unemployment rate and the equilibrium rate. The equilibrium rate is determined when unemployment rates are equalised across sectors. The index measures the proportional excess of actual employment over equilibrium unemployment. The calculation of the index relies on the critical assumption of Cobb-Douglas production functions and double logarithmic wage function of the form $\log w_i = \beta_i - \gamma \log u_i$. The index is defined as:

$$I_{JLS} = \frac{1}{2} var\left(\frac{u_i}{u}\right) = \log u - \log u_{min} \tag{12}$$

where u_i is the unemployment rate in sector i and u is the mean of the sector-specific unemployment rates. The index is interpreted as a measure of the dispersion of unemployment conditions across sectors. Jackman et al. (1990) find that average unemployment increases with the variance of relative unemployment rates across groups. Due to the large difference in the level of unemployment for regular

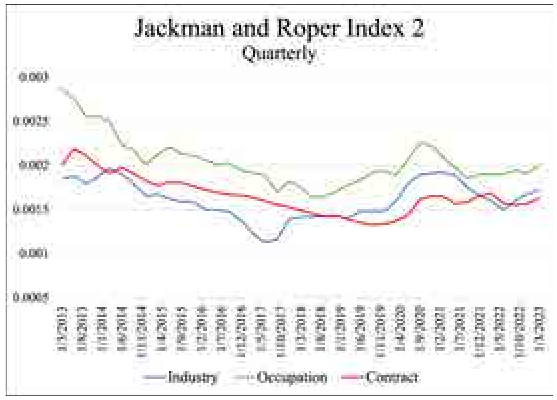


Figure 15: Jackman and Roper index 2: proportion of the labor force in the wrong sector

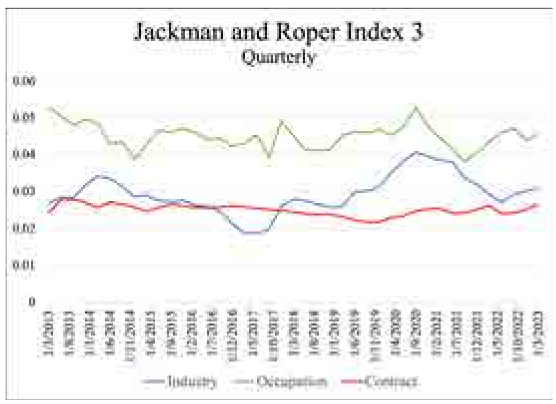


Figure 16: Jackman and Roper index 3: contribution of mismatch to unemployment.

and non-regular contracts, the contract-type index is not informative. Therefore, for the JLS index, we present only the results of the occupational and industrial indexes.

The results in Figure 17 show the dispersion of unemployment across industries and occupations are relatively similar from 2013 until the last quarter of 2019 when they diverge. The dispersion of unemployment across industries increases sharply, whereas that across occupations decreases sharply in November 2019.

The divergence of the occupation and industry indexes aligns with the timing of the structural break, pointing to differences between occupation and industry level mismatch. The increase in the industry index at the end of 2019 is also consistent with the heterogeneity of Beveridge curves across industries. The higher index suggests that there are more displaced workers on the industry level, whilst the converse is evident for the occupation level.

Figure 17: JLS index: dispersion of unemployment conditions.

5.2.4 Evans Index

Evans (1993) examines the extent to which sectoral imbalance (mismatch) contributes to increased unemployment rates in the UK. Evans defines sectoral balance as the equalising of absolute differences between sectoral and aggregate unemployment rate deviations from the sectoral and aggregate vacancy rates. Evans constructs a measure of structural imbalance that calculates the average deviation of the percentage difference between the supply and demand for labor across sectors. The measure is calculated as:

$$I_{Evans} = \frac{1}{2}\sum_{i=1} l_i \left|(u_i - v_i) - (u - v)\right| \tag{13}$$

where l_i is the sector i's share of labor force; u_i and v_i are the unemployment and vacancy rates in sector i, respectively; and u and v are the aggregate rates.[13]

The results in Figure 18 show industrial and contract-type mismatch follow a similar downward trend from 2013. The dispersion across industries falls from 0.01 in the first quarter of 2013 to a low of 0.006 in the first quarter of 2019. The industry index rises quickly over 2019, and peaks in the last quarter 2019. The dispersion across contract-types falls from around 0.008 to near zero from the first quarter of 2013 to the first quarter of 2017. The contract-type index remains relatively low for the rest of the sample, increasing in the second quarter of 2020 and then tapering off. Dispersion across occupations, in contrast, remains stable around 0.008 from 2013 to the last quarter of 2017, where it starts to trend downward.

[13] An advantage of this index is its invariance to a neutral change in aggregate demand and its ability to measure the overall state of labor market imbalance (Canon et al., 2013).

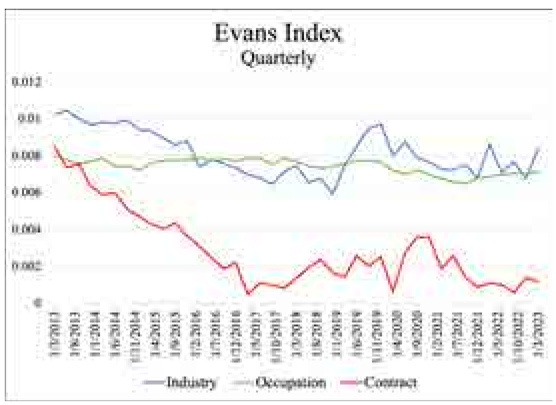


Figure 18: Evans index: dispersion of labor market tightness.

Index (and interpretation)	Dynamics
Lilien (dispersion of employment)	Occupation and industry increase in 11/2019 and remain relatively hight until 12/2021.
JRSU (measure of structural unemployment)	Relatively high levels from 11/2019 to 12/2021 across all groups.
JR1 (proportion of unemployed workers in the wrong sector)	Relatively high levels from 11/2019 to 12/2021 for occupation and industry.
JR2 (proportion of the labor force in the wrong sector)	Industry grows from 8/2019; industry and occupation start declining from 11/2019.
JR3 (proportion of unemployment due to mismatch)	Industry and occupation grow from 6/2019 and start declining from 9/2020.
JLS (dispersion of unemployment conditions across sectors)	Industry and occupation diverge from 11/2019: industry increases and starts declining from 2/2021, occupation declines until 4/2020
Evans (disequilibrium in labor market across sectors)	Industry increases from 1/2019 to 11/2019; occupation too declines from 11/2019.

Table 6: Summary of the results (for the period 2018-2023) of the mismatch indexes.

6 Discussion

The change in slope of the Beveridge curve at the end of 2019 implies that unemployment became more rigid to vacancies, likely exacerbating the unemployment effects of the Covid-19 shock from a two-fold perspective: first, the process of reducing vacancies from the end of 2019 was compounded by the uncertainty and the restrictions related to the pandemic; second, due to the lower sensitivity of unemployment to vacancies, the recovery in terms of employment was slower once firms started re-opening positions in early 2021.

A counter-clockwise movement towards South-East in the U-V plane is compatible with a typical cyclical downswing. From this perspective, the raising unemployment and declining vacancies recorded at the end of the 2010s could simply signal the end of the period of the post-Great Recession growth. However, this inversion occurred along a different downward locus. The fact that a break in the econometric model is detectable only for the short-run component implies a quantitatively different response of variables to a divergence from the long-run equilibrium relationship. In particular, the vacancy rate appears to react to a larger extent to deviations signifying a faster adjustment to the equilibrium relationship quantified by the ECT. Admittedly, given the relative short time elapsed from the break, also a modification in the equilibrium relationship could be underway but not yet be detectable. In any case, the asymmetric dynamics of sectoral employment reallocation discussed in section 5 suggests that the curve could indeed be undergoing a permanent alteration, also considering that the post-pandemic recovery has so far aligned with a North-West movement along the new steeper locus.

According to the established theoretical literature on labor search and matching, in the tight market conditions prevailing in the last quarter of 2019, the expected payoff of vacancies declined, given the low probability of filling a position, with the consequent reduction of openings by firms. Further, the expected low probability of a successful recruiting could have induced employers to retain existing non-regular workers by transforming their jobs into regular ones, as testified by the fact that the average share of regular workers for the period January 2013 - November 2019 was 73.6% (with an average quarterly variation of 0.01%), while in the period December 2019 - April 2023 was 77.4% (with an average variation of 0.09%).[14]

This evolution was uneven across sectors, as illustrated in section 5.1. More specifically, the manufacturing and construction sectors (and the related professions) did not experience the same steep decline in vacancies recorded in service and retail, even in the pre-pandemic period. The dispersion of labor market tightness across industries increased throughout 2019, suggesting deteriorating reallocation efficiency across industries. The services NEC and wholesale and retail trade industries become increasingly tight with respect to the other industries from 2019 to 2023.

As a consequence, dispersion in unemployment across both industries and pro-

[14]Provided that the changes in contract for the same types of job have little impact on aggregate wage inflation, this change on the intensive margin could also be a factor in the lower sensitivity of wages to unemployment and the consequent flattening of the Phillips curve. However, an investigation on this possibility is beyond the scope of the present paper.

fessions increased in November 2019 (as visible in figures 12 and 14). However, figures 17 and 18 reveals that the redistribution across occupations was relatively more efficient. The increase in the JR2 and JR3 indexes (figures 15 and 16, respectively) confirms the presence of inefficiencies in the adjustment of the labor market to the decline in vacancies. Interestingly, both these indexes decline when the restrictions to economic activities due to the pandemic took place, implying a lesser role of employment mismatch in the increase in unemployment in the middle of 2020.

The increase in the measure of structural unemployment (8) due to the worsening of mismatch for profession and industry at the end of 2019 (Figure 13), temporarily aligns with the detected change in the Beveridge curve. The same measures for contracts start increasing in April 2020, when the first restrictions were implemented, signaling that an increasing number of workers could not find the desired type of employment, whether regular or irregular.

It is reasonable to conclude that the reduction in vacancies increased the mismatch at industry level but the consequences on employment were lessened by the redistribution across professions and the transformation of irregular jobs into regular ones. The resulting mild increase in unemployment, combined with the sharply decreasing number of vacancies, is consistent with the change in shape of the Beveridge curve at the end of 2019. Accordingly, the loss in matching efficiency across industries made unemployment less sensitive to openings with three main consequences: first, a mild decline in employment despite a sizable decrease in the vacancy rate; second, a consequent further lowering of the payoff of opening positions, due to the small growth in the availability of potential job candidates, which further strengthened the declining trend in the vacancy rate; and third, a slow recovery of employment in spite of the increase in vacancies from mid-2020.

Coming to the specific effect of the Covid-19 shock, when the pandemic started, unemployment was already mildly rising. The most evident effect of the pandemic appears to be an increase in the dispersion of unemployment, as testified by the increase in the Lilien's, JR1, and the Evans' index, which all peaked around the highest points of the actual and counterfactual unemployment rate (December and September 2020, respectively). The dispersion is mostly caused by the asymmetric impact of the pandemic across industries, with the service sector disproportionally affected. The JLS index for occupation has a through in April 2020, revealing that, when the restrictions came into effect, unemployment increased unevenly across professions. Given the relative efficiency of reallocation across professions displayed up to that point, the change in the trend of dispersion is a possible factor in unemployment dynamics during the pandemic.

Our findings can provide valuable indications for policy makers. In the current demographic context, it is reasonable to foresee further increases in service demand, which can have an impact in matching efficiency between employers and employees across industries and professions, as occurred before the pandemic. A further push towards flexibilization of the workforce to ease the transition of workers across different jobs is a solution with a potential drawback for the matching at the contractual level.[15] The measure of structural unemployment (8) for type of employ-

[15] Industries with the highest shares of non-regular employment include the accommodations, eating

ment inverted its trend in 2020 and, to the extent that this inversion is not merely a consequence of the Covid-19 restrictions, can become a factor in labor mismatch, in particular given the little room of further expansion in workforce participation of the main suppliers of irregular workers (especially female workers).

7 Concluding Remarks

In this paper, we find evidence of a structural break in the Japanese Beveridge curve prior to the COVID-19 pandemic. Through the application of a VECM, a structural break is detected in November 2019, thus before the onset of the pandemic and the consequent restrictions. Furthermore, the econometric analysis reveals that the relationship between unemployment and vacancies began to change as early as 2018.

More specifically, in the period under exam, vacancies rapidly declined while unemployment rose only slightly, determining a steeper Beveridge curve. Variations in the two variables were different across industries and professions. The reduction in vacancies was larger in services, and was partly absorbed with a reallocation of workers across professions, but nevertheless leading to an overall larger mismatch and raising unemployment. It is also worth noting that the service sector typically has the highest rate of turnover, so a lower number of vacancies implies that some of the irregular workers could not find a new employment once their contracts expired. This evolution has potential implications for the matching at contractual level, which has been relatively low but has given signs of deterioration during 2020.

Looking at the individual sectors, service-based industries and professions, and specifically the services NEC and wholesale and retail trade industry, as well as the sales occupations, appear to have played a relatively larger role in the break in the curve.

The mismatch analysis expands upon the related work of Shibata (2020), namely by using a broader set of data, looking at more types of mismatch and using additional measures of mismatch. Our findings align with those of Higashi and Sasaki (2023), indicating that occupational mismatch was already present in the Japanese labor market before the reallocation shocks at the end of the 2010s. In contrast, we do not find strong evidence for the contract-type mismatch detected by Shibata (2020). A possible reason for this discrepancy is the potential overlap among dimensions of mismatch. Non-regular employment is concentrated in specific occupations and industries, possibly blurring the lines between contract-type, occupational, and industrial mismatches. Attempts to disentangle the mismatch effects across dimensions would require a econometric analysis at a more granular level.

These results provide a novel perspective for the post-pandemic literature and policy discussion, which has so far tended to depict COVID-19 as the catalyst of structural change. Our contribution suggests that, as the transitory effects of the pandemic fade, policymakers should refocus on the already ongoing structural changes, due to the continuous increase in the share of service employment and the consequent reallocation across not only industries and professions, but also contracts,

and drinking services, retail, services NEC, and medical, healthcare and welfare. Occupations with a large share of non-regular employment include services, production process, clerical and sales occupations.

given the specificities of the service-sector employment. Overlooking these pre-crisis dynamics may lead to incomplete or misguided policy responses.

Our contribution can be expanded from both an empirical and theoretical perspective. Further econometric analysis on micro-level data on unemployed workers could shed more light on the frictions and the evolution of mismatch across industries. The data currently available on the characteristics and preferences of unemployed workers do not have the necessary frequency and temporal depth. Our research could also be integrated by a search and matching model to investigate the firm's strategies and expected payoff for the opening of vacancies in different labor market conditions.

Acknowledgments

This research was inspired by conversations with Hiroshi Yoshikawa in Tokyo, to which also Hideaki Aoyama and Yoshi Fujiwara participated. Mengheng Li provided a very reliable guidance for the econometric part. Peter Docherty and Masahiko Shibamoto helped us with invaluable suggestions and comments. The paper also benefited from helpful feedback during a presentation at the Economics Discipline Group at the University of Technology Sydney. Qiaoxi Li provided excellent research assistance. All remaining errors are ours.

References

AOYAMA, H., DI GUILMI, C., FUJIWARA, Y. and YOSHIKAWA, H. (2022): Dual labor market and the "Phillips curve puzzle": the Japanese experience, *Journal of Evolutionary Economics*, **32**: p. 1419–1435, doi:10.1007/s00191-022-00781-8.

ASANO, H., ITO, T. and KAWAGUCHI, D. (2013): Why Has the Fraction of Non-standard Workers Increased? A Case Study of Japan, *Scottish Journal of Political Economy*, **60**(4): pp. 360–389, URL `https://ideas.repec.org/a/bla/scotjp/v60y2013i4p360-389.html`.

BAI, J. and PERRON, P. (1998): Estimating and Testing Linear Models with Multiple Structural Changes, *Econometrica*, **66**(1): pp. 47–78, URL `https://ideas.repec.org/a/ecm/emetrp/v66y1998i1p47-78.html`.

BARLEVY, G., FABERMAN, R. J., HOBIJN, B. and ŞAHIN, A. (2023): The Shifting Reasons for Beveridge-Curve Shifts, Working Paper 31783, National Bureau of Economic Research, doi:10.3386/w31783, URL `http://www.nber.org/papers/w31783`.

BARNICHON, R., ELSBY, M., HOBIJN, B. and SAHIN, A. (2011): Which Industries are Shifting the Beveridge Curve?, Tinbergen Institute Discussion Papers 11-157/3, Tinbergen Institute, URL `https://ideas.repec.org/p/tin/wpaper/20110157.html`.

BENATI, L. and LUBIK, T. A. (2014): The Time-varying Beveridge Curve, in: *Advances in Non-linear Economic Modeling: Theory and Applications*, pp. 167–204, Springer.

BLANCHARD, O. J. and DIAMOND, P. (1989): The Beveridge Curve, *Brookings Papers on Economic Activity*, **1989**(1): pp. 1–76, URL `http://www.jstor.org/stable/2534495`.

BLEAKLEY, H. and FUHRER, J. C. (1997): Shifts in the Beveridge Curve, Job Matching, and Labor Market Dynamics, *New England Economic Review*, (Sep): pp. 3–19, URL `https://ideas.repec.org/a/fip/fedbne/y1997isepp3-19.html`.

BONTHUIS, B., JARVIS, V. and VANHALA, J. (2016): Shifts in Euro Area Beveridge Curves and Their Determinants, *IZA Journal of Labor Policy*, **5**(1): pp. 1–17, doi: 10.1186/s40173-016-0076-7, URL `https://ideas.repec.org/a/spr/izalpo/v5y2016i1d10.1186_s40173-016-0076-7.html`.

BOVA, E., JALLES, J. T. and KOLERUS, C. (2018): Shifting the Beveridge Curve: What Affects Labour Market Matching?, *International Labour Review*, **157**(2): pp. 267–306, doi:10.1111/ilr.12046, URL `https://ideas.repec.org/a/bla/intlab/v157y2018i2p267-306.html`.

CANON, M. E., CHEN, M. and MARIFIAN, E. A. (2013): Labor Mismatch in the Great Recession: A Review of Indexes Using Recent US Data, *Federal Reserve Bank of St Louis Review*, **95**(May/June 2013).

CONSOLO, A. and DA SILVA, A. D. (2019): The Euro Area Labour Market Through the Lens of the Beveridge Curve, *Economic Bulletin Articles*, **4**, URL `https://ideas.repec.org/a/ecb/ecbart/201900041.html`.

DI GUILMI, C. and FUJIWARA, Y. (2022): Dual labor market, financial fragility, and deflation in an agent-based model of the Japanese macroeconomy, *Journal of Economic Behavior and Organization*, **196**: pp. 346–371, doi:https://doi.org/10.1016/j.jebo.2022.02.003, URL `https://www.sciencedirect.com/science/article/pii/S016726812200049X`.

DIAMOND, P. A. and ŞAHIN, A. (2015): Shifts in the Beveridge Curve, *Research in Economics*, **69**(1): pp. 18–25, doi:https://doi.org/10.1016/j.rie.2014.10.004, URL `https://www.sciencedirect.com/science/article/pii/S1090944314000465`.

ENTORF, H. (2003): Do Aggregate Measures Of Mismatch Measure Mismatch? A Time Series Analysis Of Existing Concepts, Labor and Demography 0312006, University Library of Munich, Germany, URL `https://ideas.repec.org/p/wpa/wuwpla/0312006.html`.

ESTEBAN-PRETEL, J. and FUJIMOTO, J. (2020): Non-regular Employment Over the Life-cycle: Worker Flow Analysis for Japan, *Journal of the Japanese and International Economies*, **57**: p. 101088, doi:https://doi.org/10.1016/j.

jjie.2020.101088, URL https://www.sciencedirect.com/science/article/pii/S0889158320300253.

EVANS, G. W. (1993): Sectoral Imbalance and Unemployment in the United Kingdom: 1963-84, *Oxford Economic Papers*, **45**(3): pp. 440–456, URL https://ideas.repec.org/a/oup/oxecpp/v45y1993i3p440-56.html.

FUKAO, K. and PERUGINI, C. (2021): The Long-Run Dynamics of the Labor Share in Japan, *Review of Income and Wealth*, **67**(2): pp. 445–480, doi:10.1111/roiw.12465, URL https://ideas.repec.org/a/bla/revinw/v67y2021i2p445-480.html.

FUKAO, K. and UG KWON, H. (2006): Why Did Japan's TFP Growth Slow Down in the Lost Decade? An Empirical Analysis Based on Firm-Level Data of Manufacturing Firms, *The Japanese Economic Review*, **57**(2): pp. 195–228, doi:10.1111/j.1468-5876.2006.00359.x, URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-5876.2006.00359.x.

GÜLER, Z. and BAKÝR, M. A. (2019): Performance of Methods Determining Structural Break in Linear Regression Models, *International Econometric Review (IER)*, **11**(2): pp. 70–83, URL https://ideas.repec.org/a/erh/journl/v11y2019i2p70-83.html.

HIGASHI, Y. and SASAKI, M. (2023): Did COVID-19 Deteriorate Mismatch in the Japanese Labor Market?, IZA Discussion Papers 15917, Institute of Labor Economics (IZA), URL https://ideas.repec.org/p/iza/izadps/dp15917.html.

HIGUCHI, Y., INUI, T., HOSOI, T., TAKABE, I. and KAWAKAMI, A. (2012): The Effects of the Great East Japan Earthquake on the Labor Market: Increased Mismatches in Employment in the Disaster Areas, *The Japanese Journal of Labor Studies*, **622**: pp. 4–16.

HOBIJN, B. and SAHIN, A. (2013): Beveridge Curve Shifts across Countries since the Great Recession, *IMF Economic Review*, **61**(4): pp. 566–600, URL https://ideas.repec.org/a/pal/imfecr/v61y2013i4p566-600.html.

ITO, Y., TAKEI, H., FELLMAN, P. V. and WRIGHT, R. (2009): Labour Mismatch in Japan: An Empirical Analysis, *Research in Applied Economics*, **1**(1): p. E2.

JACKMAN, R., LAYARD, R. and SAVOURI, S. (1990): Mismatch: A Framework for Thought, CEP Discussion Papers dp0001, Centre for Economic Performance, LSE, URL https://ideas.repec.org/p/cep/cepdps/dp0001.html.

JACKMAN, R. and ROPER, S. (1987): Structural Unemployment, *Oxford Bulletin of Economics and Statistics*, **49**(1): pp. 9–36, URL https://ideas.repec.org/a/bla/obuest/v49y1987i1p9-36.html.

JOHANSEN, S. (1988): Statistical Analysis of Cointegration Vectors, *Journal of Economic Dynamics and Control*, **12**(2): pp. 231–254, doi:https://doi.org/10.1016/0165-1889(88)90041-3, URL https://www.sciencedirect.com/science/article/pii/0165188988900413.

KAWAGUCHI, D. and MORI, H. (2019): The Labor Market in Japan, 2000–2018, *IZA World of Labor*, pp. 385–385, URL https://ideas.repec.org/a/iza/izawol/journl2019n385.html.

KOTERA, S. and SCHMITTMANN, J. M. (2022): The Japanese Labor Market During the COVID- 19 Pandemic, IMF Working Papers 2022/089, International Monetary Fund, URL https://ideas.repec.org/p/imf/imfwpa/2022-089.html.

LILIEN, D. M. (1982): Sectoral Shifts and Cyclical Unemployment, *Journal of Political Economy*, **90**(4): pp. 777–793, doi:10.1086/261088, URL https://ideas.repec.org/a/ucp/jpolec/v90y1982i4p777-93.html.

LUBIK, T. (2021): Revisiting the Beveridge Curve: Why Has It Shifted so Dramatically?, *Richmond Fed Economic Brief*, **21**(36), URL https://EconPapers.repec.org/RePEc:fip:fedreb:93370.

LUBIK, T. A. and RHODES, K. (2014): Putting the Beveridge Curve Back to Work, *Richmond Fed Economic Brief*, (Sept), URL https://ideas.repec.org/a/fip/fedreb/00019.html.

LÜTKEPOHL, H. (2005): *New Introduction to Multiple Time Series Analysis*, no. 978-3-540-27752-1 in Springer Books, Springer, doi:10.1007/978-3-540-27752-1, URL https://ideas.repec.org/b/spr/sprbok/978-3-540-27752-1.html.

MAEHASHI, K. and SHINTANI, M. (2020): Macroeconomic Forecasting Using Factor Models and Machine Learning: An Application to Japan, *Journal of the Japanese and International Economies*, **58**(C), doi:10.1016/j.jjie.2020.10110, URL https://ideas.repec.org/a/eee/jjieco/v58y2020ics0889158320300411.html.

MHLW (2019): Analysis of the Labour Economy, White paper, Ministry of Health, Labour and Welfare, URL https://www.mhlw.go.jp/english/wp/l-economy/2019/summary.pdf.

OECD (2021): *Creating Responsive Adult Learning Opportunities in Japan*, doi:https://doi.org/https://doi.org/10.1787/cfe1ccd2-en, URL https://www.oecd-ilibrary.org/content/publication/cfe1ccd2-en.

PATER, R. (2017): Is There a Beveridge Curve in the Short and the Long Run?, *Journal of Applied Economics*, **20**(2): pp. 283–303, doi:https://doi.org/10.1016/S1514-0326(17)30013-2, URL https://www.sciencedirect.com/science/article/pii/S1514032617300132.

PIZZINELLI, C. and SHIBATA, I. (2023): Has COVID-19 Induced Labor Market Mismatch? Evidence from the US and the UK, *Labour Economics*, **81**(C).

RODGERS, W. M. and KASSENS, A. L. (2022): What Does the Beveridge Curve Tell Us about the Labor Market Recovery?, URL https://www.stlouisfed.org/on-the-economy/2022/jul/beveridge-curve-labor-market-recovery.

SAHIN, A., SONG, J., TOPA, G. and VIOLANTE, G. L. (2014): Mismatch Unemployment, *American Economic Review*, **104**(11): pp. 3529–3564, URL https://ideas.repec.org/a/aea/aecrev/v104y2014i11p3529-64.html.

SHIBATA, I. (2020): Is Labor Market Mismatch a Big Deal in Japan?, *The BE Journal of Macroeconomics*, **20**(2): p. 20160179, doi:doi:10.1515/bejm-2016-0179.

VALLETTA, R. G. (2005): Why has the U.S. Beveridge Curve Shifted Back? New Evidence Using Regional Data, Tech. rep.

A Appendix

Cointegration relationship	Test	10pct	5pct	1pct
$r <= 1$	1.61	6.50	8.18	11.65
$r = 0$	18.11	12.91	14.90	19.19

Table A.1: Johansen Cointegration Tests Statistics and Critical Values: 5 Lags

Cointegration relationship	Test	10pct	5pct	1pct
$r <= 1$	0.39	6.50	8.18	11.65
$r = 0$	19.23	12.91	14.90	19.19

Table A.2: Johansen Cointegration Tests Statistics and Critical Values: 8 Lags

Equation	Δu	Δv
ECT	-0.0008(0.0003)**	-0.0007(0.0002)**
Intercept	0.0093(0.0034)**	0.0074(0.0023)**
$\Delta u-1$	1.6839(0.0612)***	-0.2078(0.0410)***
$\Delta v-1$	-0.1319(0.0913)	2.5142(0.0611)***
$\Delta u-2$	-0.9760(0.1209)***	0.1672(0.0809)*
$\Delta v-2$	0.0738(0.2439)	-2.5872(0.1633)***
$\Delta u-3$	0.5937(0.1338)***	0.0132(0.0896)
$\Delta v-3$	0.1382(0.3291)	1.6080(0.2204)***
$\Delta u-4$	-0.3561(0.1342)**	0.0524(0.0899)
$\Delta v-4$	-0.3139(0.3291)	-0.9956(0.2204)***
$\Delta u-5$	0.0443(0.1213)	0.0037(0.0812)
$\Delta v-5$	0.4272(0.2447)	0.5906(0.1639)***
$\Delta u-6$	-0.0457(0.0604)	-0.0529(0.0405)
$\Delta v-6$	-0.2224(0.0916)*	-0.1579(0.0613)*

Table A.3: VECM-6 results. The stars denote the usual levels of significance.

	X- squared	P-value
Δu residuals	1.5791	0.9541
Δv residuals	7.0184	0.3192

Table A.4: Box-Ljung test for autocorrelation at 6 lags

Equation	Δu	Δv
ECT	-0.0022(0.0009)*	-0.0015(0.0007)*
Intercept	0.0186(0.0076)*	0.0136(0.0059)*
$\Delta u-1$	1.4460(0.0970)***	-0.3309(0.0755)***
$\Delta v-1$	-0.1417(0.1235)	2.5700(0.0961)***
$\Delta u-2$	-0.7251(0.1684)***	0.3495(0.1311)**
$\Delta v-2$	0.0483(0.3328)	-2.7717(0.2591)***
$\Delta u-3$	0.4526(0.1852)*	-0.1193(0.1442)
$\Delta v-3$	0.2603(0.4561)	1.8139(0.3550)***
$\Delta u-4$	-0.1547(0.1859)	0.0181(0.1447)
$\Delta v-4$	-0.5429(0.4570)	-1.1285(0.3558)**
$\Delta u-5$	-0.0791(0.1715)	0.1609(0.1335)
$\Delta v-5$	0.5664(0.3381)	0.6403(0.2632)*
$\Delta u-6$	-0.0585(0.0920)	-0.1470(0.0717)*
$\Delta v-6$	-0.2388(0.1283)	-0.1755(0.0998)

Table A.5: VECM-6 results over a reduced sample: 2013 to 2023.

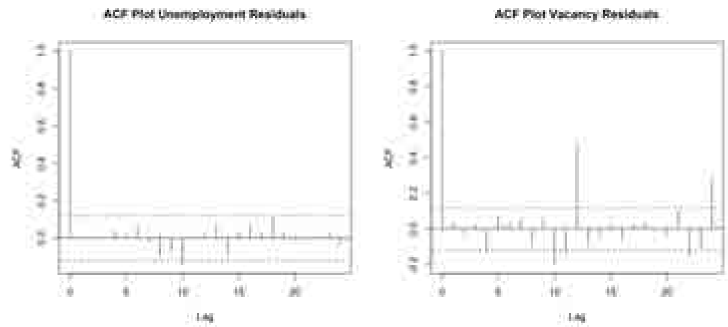


Figure A.1: Autocorrelation function for the residuals of the VECM-6.

	Δu	Δv
ECT	-0.0010(0.0003)**	-0.0006(0.0002)**
Intercept	0.0104(0.0034)**	0.0062(0.0023)**
Δu - 1	1.6982(0.0579)***	-0.1883(0.0397)***
Δv - 1	-0.1513(0.0885)	2.4799(0.0606)***
Δu - 2	-0.9856(0.1143)***	0.1499(0.0783)
Δv - 2	0.0754(0.2226)	-2.3403(0.1525)***
Δu - 3	0.5550(0.1143)***	0.0769(0.0783)
Δv - 3	0.1249(0.2237)	0.9455(0.1532)***
Δu - 4	-0.3170(0.0569)***	-0.0578(0.0390)
Δv - 4	-0.0705(0.0892)	-0.1134(0.0611)

Table A.6: VECM-4

	Δu	Δv
ECT	-0.0007(0.0003)*	-0.0006(0.0002)**
Intercept	0.0074(0.0038)	0.0071(0.0025)**
Δu - 1	1.6792(0.0625)***	-0.1845(0.0413)***
Δv - 1	-0.1143(0.0949)	2.5481(0.0627)***
Δu - 2	-0.9697(0.1219)***	0.1490(0.0806)
Δv - 2	0.0286(0.2586)	-2.7066(0.1709)***
Δu - 3	0.5914(0.1360)***	-0.0009(0.0899)
Δv - 3	0.1952(0.3589)	1.8113(0.2372)***
Δu - 4	-0.3151(0.1408)*	0.0750(0.0930)
Δv - 4	-0.3810(0.3845)	-1.3261(0.2541)***
Δu - 5	-0.0255(0.1406)	-0.0758(0.0929)
Δv - 5	0.5260(0.3861)	1.1208(0.2552)***
Δu - 6	0.0601(0.1361)	0.0717(0.0899)
Δv - 6	-0.3466(0.3640)	-0.6722(0.2406)**
Δu - 7	-0.1752(0.1214)	-0.0958(0.0802)
Δv - 7	0.0796(0.2645)	0.1915(0.1748)
Δu - 8	0.1029(0.0608)	0.0433(0.0402)
Δv - 8	-0.0181(0.0969)	0.0106(0.0640)

Table A.7: VECM-8

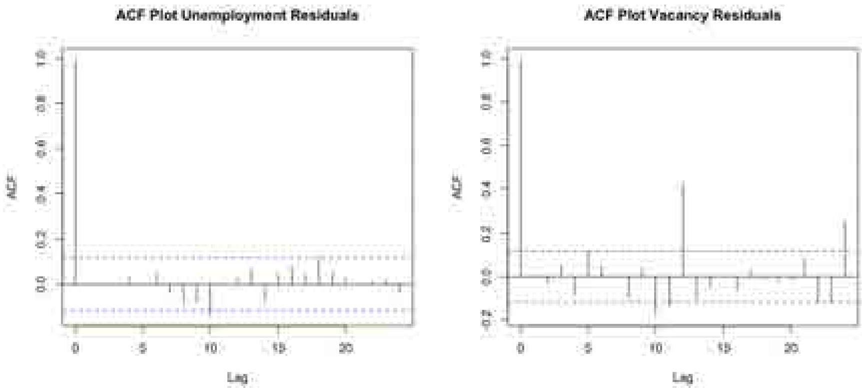


Figure A.2: ACF for residuals of structural break VECM-6 November 2019.

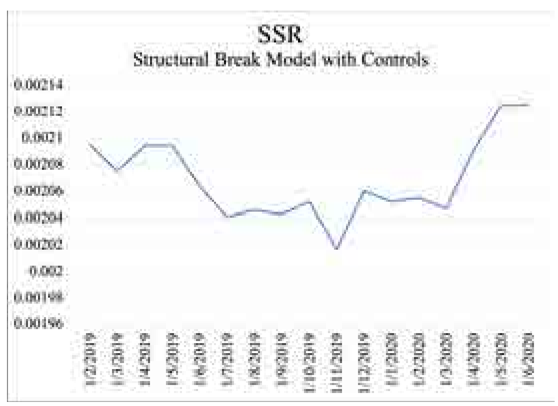


Figure A.3: SSR over the testing window with controls.

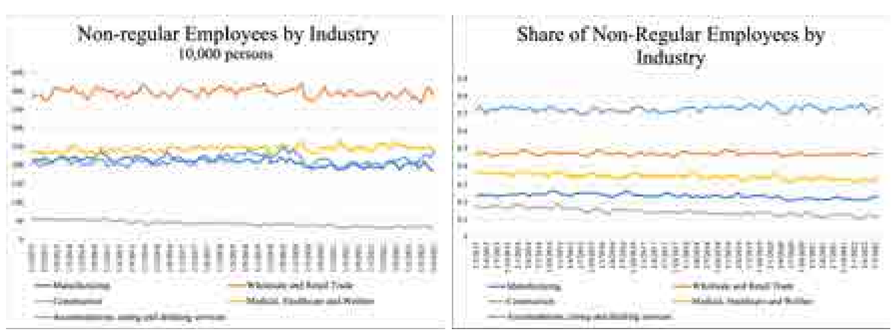


Figure A.4: Non-regular workers by major industries.

Equation	Δu	Δv
ECT	-0.0009(0.0003)**	-0.0005(0.0002)*
Intercept	0.0097(0.0036)**	0.0058(0.0023)*
Δu -1	1.6868(0.0644)***	-0.2400(0.0409)***
Δv -1	-0.1612(0.0995)	2.4660(0.0632)***
Δu -2	-1.0150(0.1274)***	0.2118(0.0809)**
Δv -2	0.1639(0.2617)	-2.5040(0.1661)***
Δu -3	0.6581(0.1420)***	-0.0560(0.0902)
Δv -3	0.0215(0.3497)	1.5757(0.2220)***
Δu -4	-0.4064(0.1435)**	0.1155(0.0911)
Δv -4	-0.2189(0.3491)	-1.0305(0.2216)***
Δu -5	0.0988(0.1295)	-0.0311(0.0822)
Δv -5	0.3460(0.2606)	0.6712(0.1654)***
Δu -6	-0.0782(0.0647)	-0.0344(0.0410)
Δv -6	-0.1807(0.0991)	-0.2059(0.0629)**
a-1	-0.2752(0.1204)*	-0.0157(0.0764)
a-2	0.0795(0.1226)	-0.2141(0.0779)**
a-3	-0.0277(0.1242)	-0.0386(0.0788)
a-4	0.1879(0.1247)	-0.0892(0.0792)
a-5	0.0390(0.1229)	0.0013(0.0780)
a-6	0.2041(0.1223)	-0.0410(0.0776)
r-1	0.0571(0.0944)	-0.1000(0.0599)
r-2	-0.0234(0.0954)	0.0177(0.0606)
r-3	-0.0938(0.0953)	-0.0069(0.0605)
r-4	-0.0705(0.0938)	-0.0936(0.0595)
r-5	-0.0853(0.0931)	-0.0514(0.0591)
r-6	0.0421(0.0938)	-0.1100(0.0596)
i-1	-0.0186(0.0673)	-0.1122(0.0427)**
i-2	0.0165(0.0687)	-0.0628(0.0436)
i-3	0.0458(0.0682)	-0.1006(0.0433)*
i-4	0.0491(0.0694)	-0.0009(0.0441)
i-5	0.0636(0.0695)	-0.0581(0.0441)
i-6	0.0706(0.0683)	-0.1080(0.0433)*
s-1	0.0771(0.0459)	0.0555(0.0292)
s-2	-0.0197(0.0531)	-0.0238(0.0337)
s-3	0.0564(0.0562)	-0.0159(0.0357)
s-4	-0.0490(0.0565)	-0.0209(0.0359)
s-5	-0.0090(0.0534)	-0.0323(0.0339)
s-6	-0.0430(0.0462)	-0.0076(0.0293)

Table A.8: VECM-6 with controls.

Equation	Δu	Δv
ECT	-0.0010(0.0003)**	-0.0006(0.0002)**
Intercept	0.0106(0.0036)**	0.0063(0.0022)**
Δu -1	1.6708(0.0654)***	-0.1572(0.0403)***
Δv-1	-0.1550(0.1027)	2.4661(0.0632)***
Δu -2	-0.9947(0.1292)***	0.0818(0.0796)
Δv -2	0.0580(0.2641)	-2.4780(0.1627)***
Δu -3	0.6421(0.1441)***	0.0591(0.0888)
Δv -3	0.2052(0.3502)	1.4833(0.2157)***
Δu -4	-0.4011(0.1447)**	0.0600(0.0891)
Δv -4	-0.3909(0.3511)	-0.8643(0.2163)***
Δu -5	0.1035(0.1297)	-0.0336(0.0799)
Δv -5	0.5150(0.2688)	0.5082(0.1656)**
Δu -6	-0.0815(0.0649)	-0.0265(0.0400)
Δv -6	-0.2720(0.1051)*	-0.1369(0.0647)*
$\Delta u - 1\mathbb{1}_{(t>\tau)}$	-0.0524(0.1746)	-0.4708(0.1076)***
$\Delta u - 2\mathbb{1}_{(t>\tau)}$	0.1838(0.3172)	0.5972(0.1954)**
$\Delta u - 3\mathbb{1}_{(t>\tau)}$	-0.3706(0.3562)	-0.1663(0.2195)
$\Delta u - 4\mathbb{1}_{(t>\tau)}$	0.2904(0.3566)	-0.1506(0.2197)
$\Delta u - 5\mathbb{1}_{(t>\tau)}$	-0.2601(0.3163)	0.2838(0.1948)
$\Delta u - 6\mathbb{1}_{(t>\tau)}$	0.1149(0.1576)	-0.1864(0.0971)
$\Delta v - 1\mathbb{1}_{(t>\tau)}$	-0.0310(0.1007)	-0.0880(0.0620)
$\Delta v - 2\mathbb{1}_{(t>\tau)}$	0.1406(0.1852)	0.1624(0.1141)
$\Delta v - 3\mathbb{1}_{(t>\tau)}$	-0.1589(0.2013)	-0.1463(0.1240)
$\Delta v - 4\mathbb{1}_{(t>\tau)}$	0.0348(0.2006)	-0.0034(0.1236)
$\Delta v - 5\mathbb{1}_{(t>\tau)}$	-0.0456(0.1797)	0.0329(0.1107)
$\Delta v - 6\mathbb{1}_{(t>\tau)}$	0.0203(0.0967)	-0.0149(0.0596)

Table A.9: Structural break model for November 2019.

	X- squared	P-value
Δu residuals	0.99222	0.9859
Δv residuals	7.5521	0.2728

Table A.10: Box-Ljung test for autocorrelation of residuals for structural break model at 6 lags.

	1/20		2/20		3/20		4/20	
	Δu	Δv	Δu	Δv	Δu	Δv	Δu	Δv
Δu -1 $\mathbb{1}_{(t>\tau)}$		$-^{***}$		$-^{**}$		$-^{**}$		$-^{**}$
Δv -1 $\mathbb{1}_{(t>\tau)}$		$-^{***}$		$-^{**}$		$-^{***}$		$-^{**}$
Δu -2$\mathbb{1}_{(t>\tau)}$		$+^{*}$		$+^{**}$		$+^{*}$		$+^{*}$
Δv -2 $\mathbb{1}_{(t>\tau)}$		$+^{**}$		$+^{*}$		$+^{*}$		$+^{*}$
Δu -3 $\mathbb{1}_{(t>\tau)}$								
Δv -3 $\mathbb{1}_{(t>\tau)}$								
Δu -4 $\mathbb{1}_{(t>\tau)}$								
Δv -4 $\mathbb{1}_{(t>\tau)}$								
Δu -5 $\mathbb{1}_{(t>\tau)}$								
Δv -5 $\mathbb{1}_{(t>\tau)}$								
Δu -6 $\mathbb{1}_{(t>\tau)}$								
Δv -6 $\mathbb{1}_{(t>\tau)}$								
s-1		$+^{*}$		$+^{*}$		$+^{*}$		$+^{*}$
s-2								
s-3								
s-4								
s-5								
s-6								

Table A.11: Selected results of indicator and services coefficient significance and sign.

Equation	Δu	Δv
ECT	-0.0009(0.0003)**	-0.0004(0.0002)*
Intercept	0.0101(0.0035)**	0.0052(0.0021)*
Δu -1	1.6766(0.0679)***	-0.1862(0.0396)***
Δv -1	-0.1764(0.1114)	2.4413(0.0649)***
Δu -2	-1.0321(0.1343)***	0.1271(0.0782)
Δv -2	0.1584(0.2834)	-2.4151(0.1651)***
Δu -3	0.7101(0.1503)***	-0.0168(0.0876)
Δv -3	0.0396(0.3708)	1.4583(0.2160)***
Δu -4	-0.4429(0.1518)**	0.1306(0.0884)
Δv -4	-0.2774(0.3690)	-0.9071(0.2149)***
Δu -5	0.1501(0.1363)	-0.0771(0.0794)
Δv -5	0.4661(0.2832)	0.5714(0.1649)***
Δu -6	-0.1159(0.0687)	-0.0052(0.0400)
Δv -6	-0.2469(0.1120)*	-0.1706(0.0653)**
$\Delta u - 1\mathbb{1}_{(t>\tau)}$	-0.1016(0.1839)	-0.4996(0.1071)***
$\Delta u - 2\mathbb{1}_{(t>\tau)}$	0.2198(0.3352)	0.6082(0.1953)**
$\Delta u - 3\mathbb{1}_{(t>\tau)}$	-0.3257(0.3801)	-0.0877(0.2214)
$\Delta u - 4\mathbb{1}_{(t>\tau)}$	0.2446(0.3790)	-0.2072(0.2208)
$\Delta u - 5\mathbb{1}_{(t>\tau)}$	-0.3464(0.3396)	0.3809(0.1978)
$\Delta u - 6\mathbb{1}_{(t>\tau)}$	0.1597(0.1720)	-0.2569(0.1002)*
$\Delta v - 1\mathbb{1}_{(t>\tau)}$	-0.0554(0.1080)	-0.1238(0.0629)
$\Delta v - 2\mathbb{1}_{(t>\tau)}$	0.1526(0.1988)	0.1940(0.1158)
$\Delta v - 3\mathbb{1}_{(t>\tau)}$	-0.1330(0.2165)	-0.1209(0.1261)
$\Delta v - 4\mathbb{1}_{(t>\tau)}$	0.0176(0.2151)	-0.0245(0.1253)
$\Delta v - 5\mathbb{1}_{(t>\tau)}$	-0.0716(0.1943)	0.0702(0.1132)
$\Delta v - 6\mathbb{1}_{(t>\tau)}$	0.0103(0.1048)	-0.0275(0.0611)
a-1	-0.2627(0.1239)*	-0.0069(0.0722)
a-2	0.1072(0.1275)	-0.1679(0.0743)*
a-3	0.0124(0.1304)	-0.0033(0.0759)
a-4	0.2489(0.1309)	-0.0937(0.0763)
a-5	0.0912(0.1298)	0.0576(0.0756)
a-6	0.2438(0.1279)	0.0158(0.0745)
r-1	0.0006(0.0010)	-0.0011(0.0006)
r-2	-9.5e-05(0.0010)	9.3e-05(0.0006)
r-3	-0.0012(0.0010)	0.0002(0.0006)
r-4	-0.0006(0.0010)	-0.0011(0.0006)*
r-5	-0.0008(0.0010)	-0.0004(0.0006)
r-6	0.0005(0.0010)	-0.0009(0.0006)
i-1	3.6e-05(0.0007)	-0.0010(0.0004)*
i-2	0.0003(0.0007)	-0.0009(0.0004)*
i-3	0.0009(0.0007)	-0.0011(0.0004)**
i-4	0.0008(0.0007)	4.2e-05(0.0004)
i-5	0.0010(0.0007)	-0.0008(0.0004)
i-6	0.0008(0.0007)	-0.0009(0.0004)*
s-1	0.0512(0.0483)	0.0547(0.0281)
s-2	-0.0142(0.0548)	-0.0422(0.0319)
s-3	0.0354(0.0582)	0.0031(0.0339)
s-4	-0.0396(0.0582)	-0.0250(0.0339)
s-5	-0.0163(0.0548)	-0.0280(0.0319)
s-6	-0.0444(0.0475)	-0.0265(0.0277)

Table A.12: Structural break model with controls for November 2019.

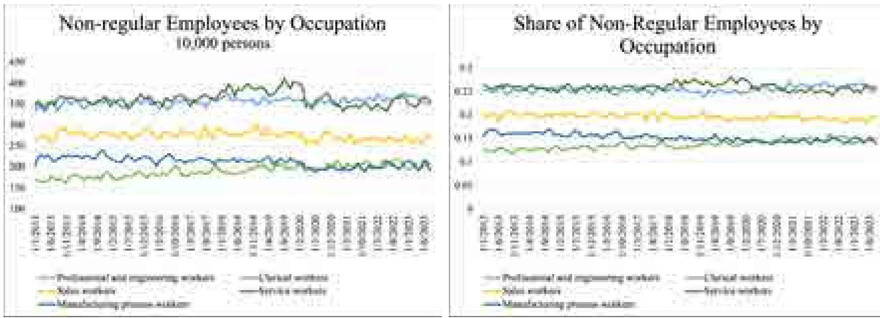


Figure A.5: Non-regular workers by occupation.