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How Phillips Curve Dynamics Enhance Business Cycle Synchronization Analysis in Central and Eastern Europe

Nico Petz, Thomas O. Zörner

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How Phillips Curve Dynamics Enhance Business Cycle Synchronization Analysis in Central and Eastern Europe*

NICO PETZ and THOMAS O. ZÖRNER

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Abstract

This paper analyzes business cycle synchronization and the Phillips curve (PC) relationship in Central, Eastern, and Southeastern European (CESEE) economies relative to the euro area. We find an overall increase in business cycle synchronicity, particularly among Euro adoption candidates, with notable heterogeneities during the early 2000s, the global financial crisis, and the euro crisis. Using a Kalman filter to extract business cycles and various measures of synchronicity, we show that CESEE EU countries align more closely with the euro area than non-EU countries. The unemployment-inflation relationship, analyzed with time-varying parameter (TVP) models, reveals a steepening of the Phillips curve post-COVID-19, with negative slope coefficients across all countries. We observe a growing convergence of the PC slope toward the euro area, especially in candidate countries. These results highlight the role of EU membership in fostering economic synchronization and emphasize the importance of considering time-varying dynamics in assessing economic convergence amid major shocks.

Keywords: Business cycle alignment, synchronization, EMU, euro area, CESEE, time-varying parameter model

JEL Codes: C22, E32, F15, F45, O47

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Non-technical summary

This study examines a key aspect of economic alignment, namely business cycle synchronization, across nine countries from Central, Eastern, and Southeastern Europe (CESEE). These countries, including both EU members and potential future euro area members, offer valuable insights into how closely their economic dynamics align with those of the euro area. Additionally, the research explores inflation and unemployment dynamics, represented through the Phillips curve, which provides a deeper measure of synchronization between these economies.

Our study contributes to the broader body of research on business cycle convergence and synchronization within the EMU, particularly in light of the global financial crisis and the euro sovereign debt crisis. While much of this research has focused on Western Europe, recent economic shocks and the potential enlargement of the euro area have rekindled interest in understanding how the economies of Central and Eastern Europe align with the euro area. Our findings suggest that while convergence has been progressing, it is still characterized by asymmetries in timing, intensity, and underlying drivers. Notably, some countries in the CESEE region continue to experience significant structural differences, which influence the extent to which they synchronize with the euro area.

To measure business cycle synchronization, we focus on the unemployment rate as a proxy for economic activity. By applying the Kalman filter, we isolate the cyclical component of unemployment, allowing us to consistently compare economic fluctuations across countries. This approach helps us assess how synchronized the business cycles of different countries are. Our analysis reveals that, over time, the business cycles of CESEE countries have increasingly aligned with those of the euro area, especially in recent years. However, during key events, such as the early 2000s, the global financial crisis, the euro crisis, and the Covid-19 pandemic, differences to the euro area cycle increase in most countries. These findings suggest that while synchronization is improving, certain countries continue to experience periods of economic dislocation that affect them more than others.

Another key finding of this paper is the growing synchronization of inflation-unemployment dynamics, as captured by the Phillips curve. Before the Covid-19 pandemic, the relationship between inflation and unemployment was weak or insignificant in both the euro area and most CESEE countries. However, since the pandemic, the curve has steepened significantly, with a stronger negative relationship emerging between inflation and unemployment across nearly all countries in our sample. This reduced-form evidence suggests that labor market dynamics in these countries are increasingly aligning with those of the euro area.

Overall, the results suggest that closer economic integration leads to greater synchronization of business cycles and labor market dynamics. This trend is particularly evident among EU member states in the CESEE region, which are increasingly aligning with the economic dynamics of the euro area. These findings offer valuable insights for policymakers and researchers focused on economic integration within the EU, as well as those considering the potential future enlargement of the euro area.

Looking ahead, future research could explore the long-term implications of these convergence trends, especially in light of ongoing changes in EU monetary and fiscal policies. Additionally, examining the structural drivers of Phillips curve dynamics, such as labor market reforms and wage-setting mechanisms could provide further insights into the broader process of economic synchronization.

1 Introduction

The European Economic and Monetary Union (EMU) has faced a series of challenges over the past two decades, including the global financial crisis, the euro area debt crisis, the COVID-19 pandemic, unprecedented energy price surges, and geopolitical tensions. These shocks have significantly affected member states and were addressed with substantial stabilization measures at both the national and supranational levels. Given the distinctive structure of the EMU and the complexities of the euro area in particular, effective monetary policy relies heavily on aligned economic performance among member states. As the euro area continues to expand, ensuring economic alignment among prospective members becomes increasingly vital to support the stability and efficiency of the common monetary policy framework.

In this paper, we examine an essential determinant of economic alignment: business cycle synchronization. To deepen this analysis, we complement it with a detailed exploration of inflation-unemployment dynamics, as represented by the Phillips curve (PC). Our focus is on nine countries in the Central, Eastern, and Southeastern European (CESEE) region, whose economic dynamics are compared with those of the euro area. We derive our business cycle measure by extracting the cyclical component of the unemployment rate using a Kalman filter, capturing deviations from the underlying trend. This allows for a consistent comparison of cyclical fluctuations across countries.

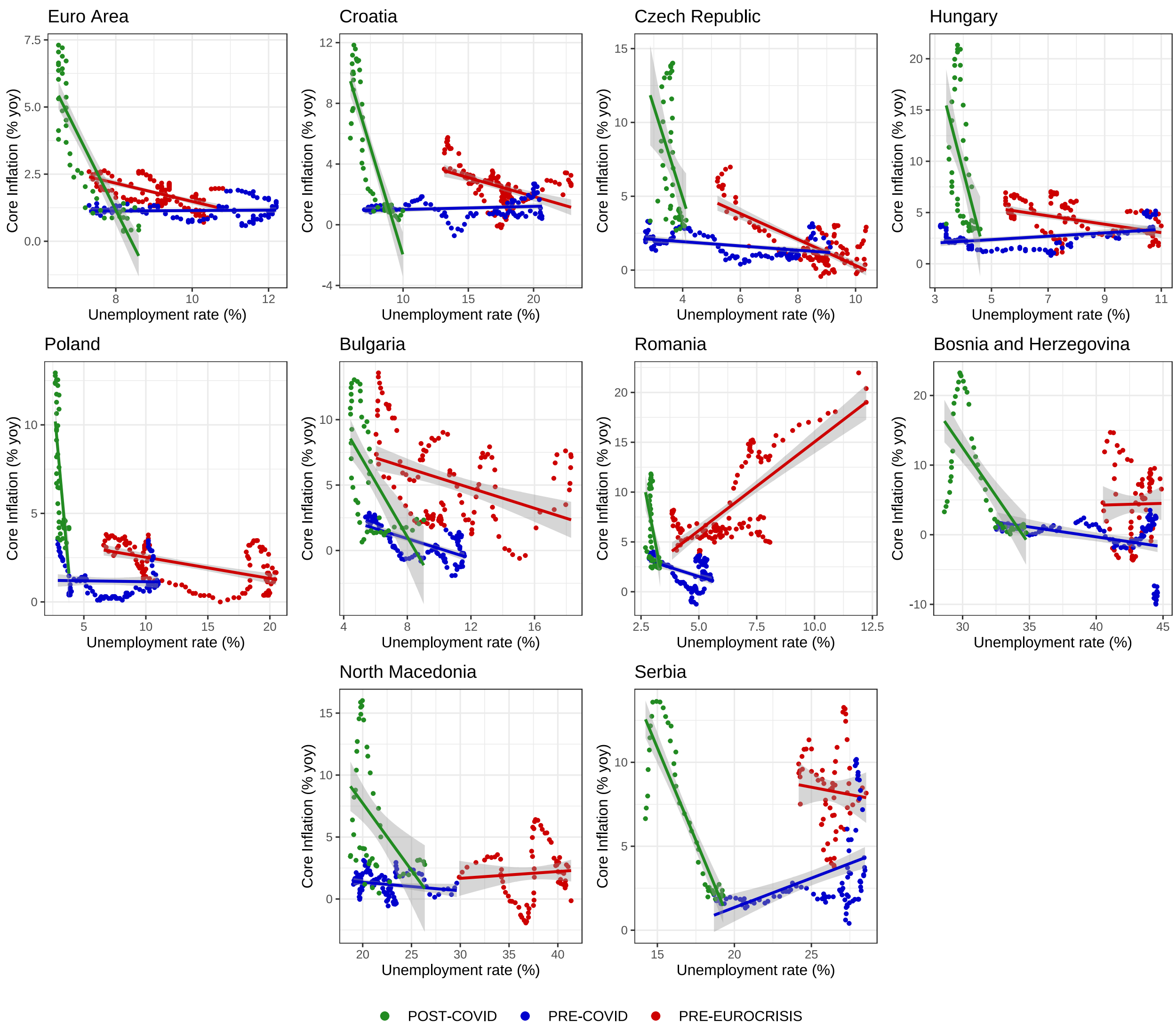
Our findings suggest that the business cycles of CESEE economies are largely well-aligned with those of the euro area, particularly in recent years. However, significant heterogeneities emerge during key periods, such as the early 2000s, the global financial crisis, and the euro crisis. Over time, the absolute differences between CESEE cycles and those of the euro area have moderately declined, with CESEE EU member states exhibiting a notably higher degree of synchronization than their non-EU counterparts.

This growing alignment is further reflected in the inflation-unemployment dynamics captured by the reduced-form Phillips curve. Time-varying estimates of the Phillips curve slope coefficients corroborate the observed business cycle convergence: prior to the COVID-19 pandemic, the inflation-unemployment trade-off was weak or insignificant in both the euro area and most CESEE countries, consistent with subdued cyclical pressures. However, a notable steepening of the curve is observed in the post-pandemic period, with many CESEE countries displaying Phillips curve dynamics that increasingly mirror those of the euro area.

To gain a preliminary insight into the Phillips curve relationship within our sample, we present in Figure 1 the core inflation and unemployment rate data for the countries analyzed. For illustrative purposes, though relaxed in later stages of the analysis with our time-varying framework, the data is divided into three subsamples: the period prior to the euro crisis (red), the period between the euro crisis and the onset of the COVID-19 pandemic (blue), and the period following the initial COVID-19 shock (green). For each subsample, we include a linear OLS regression line to illustrate the relationship.

Our observations reveal that, for most countries, the PC relationship was weak during the 2000s (red) and the PC slope close to zero between the euro crisis and the onset of the pandemic (blue), with notable exceptions such as Romania and Serbia. However, after the first quarter of 2020, the relationship turned strongly negative across all countries. These findings may suggest possible structural changes, e.g., evolving labor market institutions, demographic factors or the compositions of aggregate shocks hitting the economy, that have significantly influenced the PC relationship over time. Consequently, we argue that an analysis based on Phillips curves must account for time variation to accurately capture such potential structural changes.

Figure 1: Relationship between core inflation and the unemployment rate in three period subsamples



Notes: The figure shows monthly data on core inflation and the unemployment rate from 2002M1 to 2023M12 for each sample country. We split the data into three subsamples: 2002M1 to 2011M12 (PRE-EUROCRISIS, red), 2012M1 to 2020M2 (PRE-COVID, blue) and 2020M3 to 2023M12 (POST-COVID, green). Due to data limitations for Bosnia and Herzegovina, North Macedonia and Serbia, their samples start in 2006M1, 2005M12 and 2006M12, respectively. For each subsample we estimate a linear OLS regression, as denoted by the thick line. The shaded grey area corresponds to the respective 95% confidence interval.

A substantial body of literature examines business cycle convergence and synchronization within the EMU and the euro area. Much of this research emerged in response to the Global Financial Crisis (GFC) and the euro sovereign debt crisis, though recent economic shocks have renewed interest in the degree of economic alignment across Europe (see, e.g., Giannone and Reichlin, 2006; Mink et al., 2007; Crespo-Cuaresma and Fernández-Amador, 2013a;b; Franks et al., 2018).

However, business cycle alignment is not only relevant for assessing intra-union cohesion but also plays a crucial role in evaluating the readiness of prospective euro area members. While there is general agreement on increasing convergence among EU member states, particularly following major integration steps such as the 2004 enlargement, most studies focusing on CESEE economies remain limited in scope or yield mixed results depending on methodology, time period, or country coverage.

For instance, Gächter et al. (2013) document strong comovement between CESEE and euro area business cycles but observe a temporary decoupling during the global financial crisis. Stanišić (2013) and Kolasa (2013) find evidence of increasing convergence, particularly after the 2004 enlargement, though they emphasize structural differences and persistent heterogeneity across countries. Using synchronicity and similarity measures, Fidrmuc and Korhonen (2003) identify low levels of alignment for countries such as Romania, Hungary, and Croatia. Along similar lines, Beck (2020) highlights the existence of two distinct regional cycles in the euro area and CEE region, pointing to a persistent divergence in broader EU dynamics despite increasing internal convergence within Eastern and Western subgroups. Nonetheless, there are also contributions highlighting a stronger trend of synchronization, particularly in the aftermath of the global financial crisis (see, e.g., de Lucas Santos and Rodríguez, 2016).

Taken together, these studies reveal a complex picture: while convergence has progressed, it remains marked by asymmetries in timing, intensity, and underlying drivers. Understanding these dynamics requires closer attention to the mechanisms that foster or hinder synchronization. The economic transmission channels that underpin synchronization have been widely studied and can broadly be categorized according to how countries absorb and transmit shocks across borders.[1]

First, several studies emphasize the role of real economic linkages, including international and intra-industry trade as well as the similarity of production structures. Strong trade ties and similar sectoral specializations can lead to more synchronized cycles through shared demand and supply shocks (e.g., Baxter and Kouparitsas, 2005; Duval et al., 2016; di Giovanni and Levchenko, 2010; Ng, 2010; Kalemli-Ozcan et al., 2001; Imbs, 2004; Beck and Okhrimenko, 2025). Second, financial and investment integration also plays a significant role. Capital mobility, financial market integration, and cross-border investment flows can transmit shocks across countries, leading to closer alignment of business cycles (Kalemli-Ozcan et al., 2013; Beck, 2021a; Jansen and and, 2014). Third, the degree of macroeconomic coordination, particularly through fiscal and monetary policies, can help smooth asymmetric shocks (Chang et al., 2013; Ductor and Leiva-Leon, 2016; Beck, 2022).[2]

Rather than focusing on specific mechanisms, we adopt a macro-level perspective that captures the cumulative effects of these channels as they manifest in overall co-movement with the euro area business cycle. Still, this aggregate approach resonates with ongoing concerns raised in structural analyses regarding the depth and quality of observed alignment. For instance, de Haan et al. (2008) find that many accession countries continue to experience largely idiosyncratic supply and demand shocks, while Kolasa (2013) show that cyclical fluctuations in CEE economies are driven by structural wedges that diverge significantly from

[1] For comprehensive reviews of these channels and their empirical relevance, see de Haan et al. (2008), Beck (2021c), and Stoforos et al. (2021).

[2] From a broader institutional context, the criteria established by the Optimum Currency Area (OCA) theory are also important for understanding synchronization (Mundell, 1961; McKinnon, 1963; Kenen, 1969).

those in the euro area. These findings suggest that headline convergence may mask persistent asymmetries in underlying economic structures or policy transmission mechanisms, a point our study indirectly engages by assessing synchronization at the aggregate level.

In light of such mixed evidence, it becomes increasingly important to move beyond aggregate measures of co-movement and assess whether economies respond in a structurally similar manner to macroeconomic shocks. One way to analyse this deeper layer of alignment is through the Phillips curve, which links inflation to economic slack and serves as a proxy for underlying cyclical dynamics. When the slope and timing of the PC relationship in one country closely mirror those in others, particularly in terms of inflationary responses to labor market pressures, this signals a shared cyclical position and deeper economic synchronization. Given the challenges associated with identifying structural PCs, reduced-form estimates, especially in a time-varying framework, offer a more empirically tractable approach to comparing inflation-unemployment trade-offs across countries and over time. These dynamics are particularly revealing in cross-country comparisons, where shared external shocks may yield varying inflation sensitivities. While synchronization indices may highlight common phases of expansion or contraction, divergence in PC behavior can point to the presence of asymmetric shocks or structural heterogeneity. Moreover, the reduced-form PC offers initial insight into the extent to which labor market institutions, wage-setting mechanisms, and inflation expectations contribute to or inhibit cyclical alignment.

Beyond serving as a lower-bound estimate of the structural slope, the reduced-form Phillips curve remains foundational to many central banks' forecasting models (Eser et al., 2020). While reduced-form estimates do not imply causality, convergence in these parameters across countries, when interpreted alongside broader synchronization measures, can reveal shared macroeconomic structures and commonalities in policy transmission. In this way, the Phillips curve complements traditional synchronization metrics by offering a more granular diagnostic lens on economic alignment, without relying on strict structural identification assumptions.

The remainder of the paper is structured as follows. In Section 2 we extract the cyclical component and discuss the aggregate assessment of business cycle alignment between individual CESEE countries and the euro area. The second-stage analysis based on the underlying relationship of core inflation and economic slack is presented in Section 3, while Section 4 concludes the article.

2 Assessing business cycle alignment

We conduct our analysis using monthly data from January 2002 to December 2023, focusing on nine countries in the Central, Eastern, and Southeastern European (CESEE) region. Specifically, we examine six CESEE EU countries – Czech Republic, Croatia, Hungary, Poland, Bulgaria, and Romania – including the latter two actively progressing toward euro area accession. Although Croatia joined the euro area in January 2023, it remained outside the currency union for most of the sample period. Additionally, we analyze three CESEE non-EU countries: Bosnia and Herzegovina, North Macedonia, and Serbia. Due to data limitations, the samples for Bosnia and Herzegovina, North Macedonia, and Serbia begin in January 2006, December 2005, and December 2006, respectively.

Our business cycle assessment uses the unemployment rate as a proxy for economic activity, offering several advantages over output or wage measures for this region. From a technical perspective, unemployment data is available on a monthly basis, enabling an analysis of fluctuations within a year. In contrast, other monthly output measures, such as industrial production, may be less suitable as proxies for economic activity in these economies, which often rely heavily on agriculture and services rather than industry.[3] Moreover, data on alternative output measures is either scarce or unreliable for some countries in our sample. Frequent revisions further undermine their reliability, especially toward the end of the sample period. An overview of the data can be found in Appendix A.

2.1 Extracting the latent trend component

Our goal is to examine deviations from trend growth in economic activity over time to characterize periods of expansion and contraction. Since this trend is a latent quantity and not directly observable in raw economic data, analytical techniques are required to extract it. Much of the existing literature employs either the Hodrick-Prescott (HP) filter (see, e.g., Stanišić, 2013; Drehmann and Yetman, 2018; Phillips and Shi, 2021; Schularick et al., 2021) or the Hamilton filter (see, e.g., Balashova and Serletis, 2020; Quast and Wolters, 2022). However, given the significant drawbacks of these methods, we adopt a different approach.[4]

To address these challenges, we extract the trend component of the unemployment rate using the Kalman filter (see Kalman, 1960). This approach avoids the sample shortening and end-point biases inherent in the HP and Hamilton filters.[5] We set up the Kalman filter in a way such that it resembles a special case of an unobserved components model, namely a local level model:

$$y_t = \tau_t + \nu_t, \quad \nu_t \sim \mathcal{N}(0, r), \quad t = 1, \ldots, T, \tag{2.1}$$

where y_t is the observed unemployment rate of a specific country in our sample, τ_t is the latent trend and ν_t is a Gaussian error term with constant variance, r. The latent trend evolves according to the following law of motion, described by the state equation:

$$\tau_t = \tau_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, q), \tag{2.2}$$

[3] It is worth noting that labor force participation rates ideally should be controlled for, as structural labor market conditions can lead to individuals exiting the labor force entirely after job termination, e.g., through migration. Unfortunately, such data is unavailable at the required frequency for our sample. The same holds for hours worked. However, by extracting a latent trend component using Kalman filtering, we account for both temporary and persistent structural changes in labor markets. This approach aligns with applications of the Kalman filter, such as estimating the non-accelerating inflation rate of unemployment (NAIRU) (see, e.g., Logeay and Tober, 2006). On the other hand, Beck (2021b) shows that labor force mobility is relatively less important compared to other well-established determinants of business cycle synchronization in the EU.

[4] The HP filter has well-documented limitations, famously criticized by Hamilton (2018). Choosing the smoothing parameter can be arbitrary, and determining an optimal value for a given data frequency remains debated (see, e.g., Ravn and Uhlig, 2002; Maravall and Del Rio, 2007). Moreover, the HP filter is prone to distortion at the sample's start and end, which is particularly problematic for our analysis focusing on these periods (see Baxter and King, 1999). Similarly, the Hamilton filter has its own drawbacks, particularly related to data requirements. As outlined in Hamilton (2018), the method would exclude the first three years of our sample, representing approximately 15% of the data, including critical periods such as the global financial crisis. Additionally, simulations by Schüler (2021) demonstrate that the Hamilton filter can distort the variance of different frequencies in the cyclical component and extract fluctuations longer than the desired cycle length.

[5] Nevertheless, as shown in Appendix D, alternative results using the HP filter are qualitatively consistent with our main findings, providing further validation of our approach.

where η_t is a Gaussian error term with constant variance q. Then, for each country, we obtain the business cycle, c_t, as the difference between the observed unemployment rate and the trend estimate obtained from the Kalman filter,

$$c_t = y_t - \tau_t. \tag{2.3}$$

We emphasize the importance of the parameters r and q, which govern the trade-off between the responsiveness and smoothness of the Kalman filter estimates. Higher values of r and q produce a more responsive filter that quickly adapts to new observations, while lower values yield smoother estimates that evolve more gradually. This flexibility enables the Kalman filter to accommodate varying characteristics of the time series under analysis.

However, this approach may lead to arbitrary choices for r and q. To ensure transparency, we do not fix these parameters to specific values but instead impose prior assumptions on them. Following standard practice in the Bayesian literature, we assume that the inverses of the two variances follow a Gamma distribution:

$$r^{-1} \sim \mathcal{G}(a_r, b_r) \quad \text{and} \quad q^{-1} \sim \mathcal{G}(a_q, b_q), \tag{2.4}$$

where the hyperparameters are specified as follows:

$$a_r = \frac{T}{2}, \qquad b_r = 10^2 + \frac{1}{2}\sum_{t=1}^{T} \tilde{y_t}^2, \tag{2.5}$$

$$a_q = 10^2 + \frac{T}{2}, \qquad b_q = \frac{1}{2} + \frac{1}{2}\sum_{t=1}^{T} (\tau_t - \tau_{t-1})^2. \tag{2.6}$$

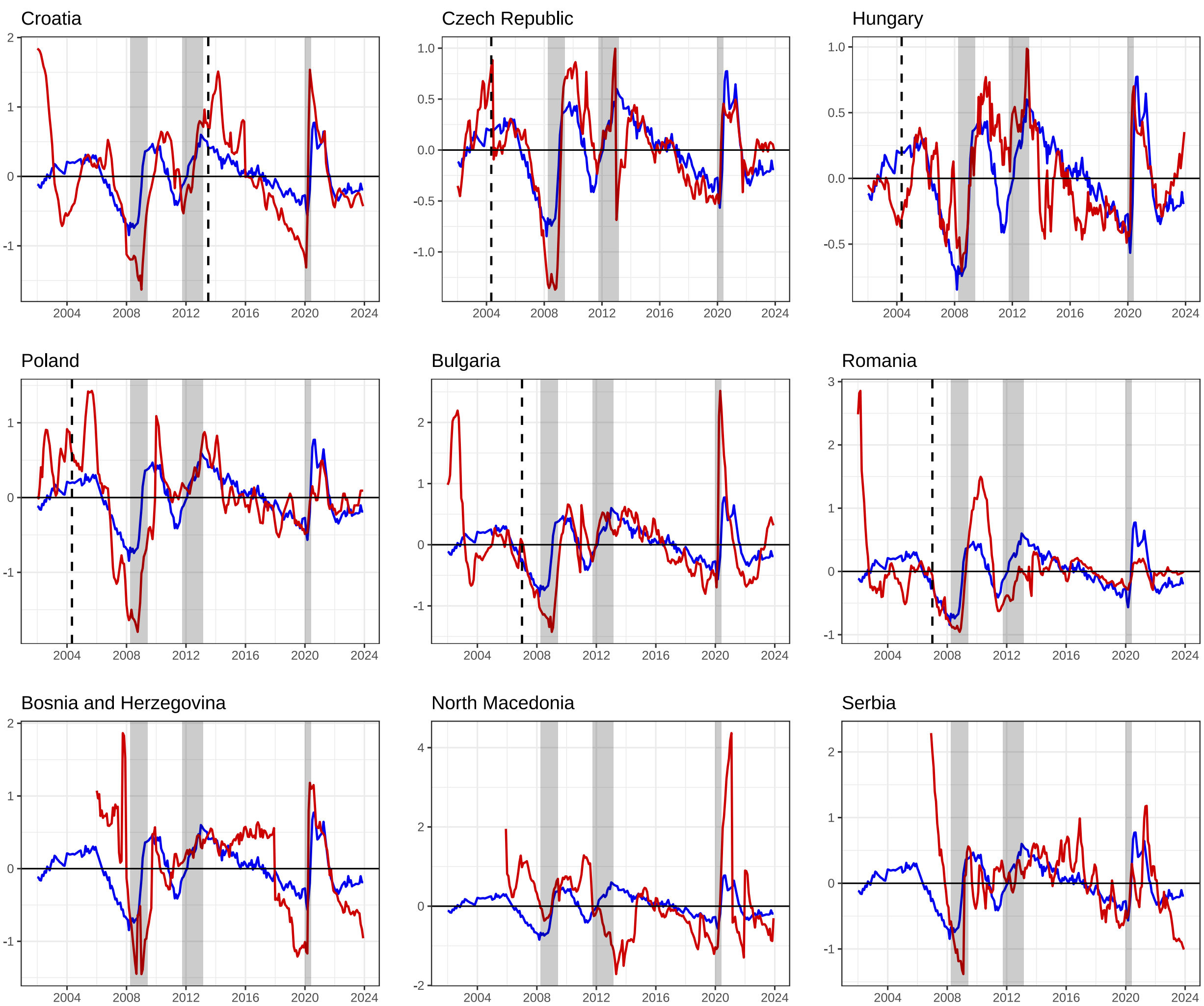
The hyperparameters a_i and b_i (for $i \in \{r, q\}$) allow us to specify a ratio between the measurement variance and the innovation variance. Based on the observed data, we selected hyperparameters such that the means implied by the inverse Gamma distributions reflect an approximate 15:1 ratio between these variances. A sufficiently small value for q allows the estimate to capture the long term trend without adjusting for short term fluctuations. This configuration results in trend estimates that explain between 70% and 90% of the total variance in the unemployment series. For further details, Table D.1 in the appendix provides a comprehensive comparison of variance explanations across different trend estimation methods, including the HP and Hamilton filters. Our findings indicate that the Kalman filter explains more variance than the Hamilton filter but less than the HP filter. This difference is primarily due to the significant data loss inherent in the Hamilton filter and the well known end point bias of the HP filter.

2.2 Characterizing the business cycles

The results of our business cycle estimation are shown in Figure 2. For each country, we compare the extracted respective business cycle (in red) with the euro area business cycle (in blue). For CESEE EU countries, the dashed black line indicates the date of joining the European Union. Shaded grey areas represent the euro area recessionary periods, as defined by the Euro Area Business Cycle Network (EABCN). Since we use the unemployment rate to measure the business cycle, deviations are expressed in percentage points.

Positive cycle values thus indicate an unemployment rate above trend, typically observed during business cycle downturns or recessions, while negative values indicate an unemployment rate below trend, which corresponds to expansionary periods or booms.[6]

Figure 2: CESEE business cycles (red) in comparison to the euro area (blue).



Notes: The figure shows the business cycle of the euro area (blue) and the respective country (red), which is the difference between the observed unemployment rate and its Kalman-filtered trend component. The dashed black line indicates the date of joining the European Union, and the shaded grey areas represent recessions as defined by the Euro Area Business Cycle Network (EABCN). The vertical axis shows the deviation from the trend in percentage points, and the horizontal axis represents time in months.

We begin our analysis with *Croatia*, which for most of the sample period was not part of the euro area until it joined the Eurosystem in 2023, ten years after its accession to the European Union. While Croatia's business cycle appears out of sync with the euro area, the pattern suggests lagged dynamics that are most

[6] While it can be argued that business cycle divergence within the euro area has increased, particularly in the post pandemic period (e.g., Beck, 2023), we maintain that the use of the euro area aggregate remains justified. This is because the euro area operates under a single monetary authority, which pursues a unified objective: maintaining euro area wide HICP inflation close to 2%. Therefore, analyzing synchronization with the euro area aggregate is appropriate from the perspective of common monetary policy implementation.

noticeable prior to joining the EU.[7] Additionally, we observe stronger amplitudes in Croatia's cyclical peaks and troughs. One possible explanation for these lagged dynamics is the strong economic ties of Croatia, as a small open economy, with the euro area. These ties expose Croatia to the euro area's business cycle but with a slight delay (see, e.g., Deskar-Škrbić et al., 2020). Moreover, Croatia's relatively slow recovery from the GFC, coupled with a rise in the unemployment rate that persisted until 2014, contributed to weak alignment during that period. In the subsequent moderation phase, the downward pressure on the cyclical component was stronger compared to the euro area, peaking just before the onset of the COVID-19 pandemic. High levels of emigration may also play a significant role in reducing short-term unemployment, as highlighted by Pryymachenko et al. (2013). The freedom for Croatian citizens to emigrate and access labor markets in other EU countries post-2014 triggered a significant wave of emigration. This, combined with economic expansion, likely contributed to the downward pressure on the unemployment rate. In recent years, Croatia's deeper economic integration with the euro area in 2023 has also resulted in further alignment of its business cycle.

The *Czech Republic*, *Hungary*, and *Poland* joined the European Union in 2004. Since the transition period of the 1990s, the Visegrád Group member countries have shared a common objective of integrating into Euro-Atlantic institutions. Nevertheless, divergences in economic fundamentals among these countries may have contributed to relatively low synchronization of their business cycles (Hanus and Vácha, 2020). In 2004 and the period immediately preceding it, the cyclical components of unemployment rates in these countries showed distinct trends. For the Czech Republic, unemployment was above trend during this time, aligning with that of euro area countries but with stronger magnitudes, peaking in 2004. Following this period, the business cycle dynamics of the Czech Republic closely resembled those of the euro area, albeit with more pronounced magnitudes. A notable divergence occurred in 2013, when the cyclical unemployment fell below trend, but the alignment with the euro area improved remarkably afterward. Hungary's cyclical component of the unemployment rate exhibited several periods of divergence from the euro area. However, during the COVID-19 pandemic, the dynamics aligned closely with the euro area. Poland's cyclical unemployment prior to the euro crisis roughly followed the euro area trend but exhibited greater volatility. Over time, this volatility decreased slightly, and from 2013 onward, Poland demonstrated strong alignment with the euro area.

Bulgaria and *Romania*, which joined the European Union in 2007, committed to the Lisbon Agenda objectives established in 2000, aimed at addressing low productivity and economic stagnation. During the early years of the sample period, high fluctuations in the cyclical component and its misalignment with the euro area suggest structural inefficiencies in their labor markets. However, business cycles in both countries became increasingly aligned with the euro area after 2007. Notably, Bulgaria exhibited a pronounced response to the initial COVID-19 shock, while unemployment in Romania showed greater persistence, with only minor deviations from the trend observed after 2013.

Finally, the non-EU countries in our sample exhibit distinct business cycles characterized by more pronounced fluctuations in the cyclical component, evident in both peaks and troughs. Time shifts in the cycles relative to the euro area are more apparent compared to CESEE EU countries. Just before the onset of

[7] As noted by de Haan et al. (2024), the synchronicity and similarity of accession countries' business cycles with that of the euro area, as measured by output gaps, may initially be low but tend to increase over time.

the 2008 financial crisis, the cyclical components for *Bosnia and Herzegovina* and *Serbia* experienced notable declines, occurring with a time lag relative to the less pronounced decrease in the euro area's component. This lag might reflect the greater adverse effects of the GFC on these economies compared to the EA countries. Consequently, the larger and more persistent increase in the cyclical component of unemployment rates in the post-crisis period is unsurprising. In Bosnia and Herzegovina, much stronger amplitudes are observed compared to the euro area, particularly during crises and their aftermath. Persistent challenges, such as high youth unemployment, significant workforce outflows, and a substantial informal sector, continue to weigh on the country's labor market dynamics (see, e.g., Krstić and Sanfey, 2007; International Labour Organization, 2024). Looking at the unemployment rate, labor markets in Serbia and *North Macedonia* exhibit dynamics similar to those of Bosnia and Herzegovina, with unemployment rates consistently exceeding those in the European Union (see, e.g., Reva, 2012). The above-average surge in the cyclical component of unemployment during the COVID-19 pandemic, particularly in North Macedonia, may be attributed to the severity of the pandemic's impact and the differing COVID-19 restriction strategies employed.

Nonetheless, a gradual increase in the alignment of the Western Balkan countries' cyclical components with the euro area is evident over time. This convergence is accompanied by overall stabilization, as reflected in decreased volatility, particularly in the post-COVID-19 period. However, towards the end of the sample, there are tendencies of divergence, suggesting potential shifts in labor market dynamics.

2.3 Dating the business cycles

Business cycle dating is generally conducted by research institutes using a wide range of inputs. For the US and the euro area, the National Bureau of Economic Research (NBER) and the Euro Area Business Cycle Network (EABCN) provide widely accepted business cycle datings, identifying peaks and troughs, and offering metrics such as cycle duration. However, to the best of our knowledge, these methodologies have not been systematically applied to the CESEE region, and similar alternatives are scarce.

To enhance our understanding of CESEE business cycles and inform our analysis in the subsequent section, we employ the algorithm proposed by Harding and Pagan (2002) to calculate business cycle durations for our sample.[8] This method produces results comparable to the NBER's dating for the US (see Harding and Pagan, 2003).

Table 1 presents the estimated durations, revealing shorter cycles for CESEE countries compared to conventional expectations. This may partially reflect our use of the unemployment rate as a measure of economic activity and the relatively small sample sizes. Nevertheless, we confirm a common finding in the literature that business cycles in developed economies tend to last longer (Rand and Tarp, 2002). Specifically, we estimate the euro area's average cycle duration at 53 months, compared to 39.21 months for CESEE countries. Figure C.4 in the appendix illustrates the business cycle periods for each country, from trough to peak. Notably, the estimated recessionary periods for the euro area closely align with the EABCN's datings.

[8] The algorithm is implemented via the R-package BCDating, available at `https://CRAN.R-project.org/package=BCDating`. We set the minimum cycle length to 15 months and the minimum phase length to 6 months, mirroring the quarterly settings in the original study.

Table 1: Business cycle duration across countries

Region/Country	Duration in months
Euro area	53.00
CESEE average	39.21
Croatia	46.60
Czech Republic	44.00
Hungary	35.81
Poland	31.11
Bulgaria	30.66
Romania	30.86
Bosnia and Herzegovina	39.50
North Macedonia	37.17
Serbia	57.17

Notes: The right column, `Duration`, represents the average business cycle duration in months, calculated as the sum of the average recession length and the average expansion length.

2.4 Business cycle synchronization: CESEE countries and the euro area

In this section, we propose a comprehensive methodology to assess the business cycle alignment between CESEE countries and the euro area. Traditional approaches often rely on single measures to capture the similarity of economic cycles, which can overlook important dimensions of synchronization. To address this limitation, we employ a set of four distinct measures, encompassing both time-domain and frequency-domain techniques. Hence, our approach ensures a more nuanced and robust assessment of business cycle synchronization, contributing to the broader discussion on economic convergence within the region.

We begin by defining a well-known synchronicity measure introduced by Mink et al. (2007). This measure evaluates the alignment of business cycles for country c_i and country c_j at time t as follows:

$$synch_{ij,t} = \frac{c_{i,t}\, c_{j,t}}{|c_{i,t}\, c_{j,t}|}. \tag{2.7}$$

The synchronicity measure takes a value of +1 if the two cycles share the same sign, indicating that the economies are moving in the same direction (both expansions or both contractions). Conversely, if the signs differ, the measure equals -1, reflecting opposite cyclical movements. To provide a more stable and interpretable measure over time, we smooth the series using a moving average. Specifically, the synchronicity value at time t is computed as the average synchronicity of the current period and the preceding $w-1$ months, where w represents the window size of the moving average. We set $w = 53$ months to align with the typical business cycle duration of the euro area, as shown in Table 1. This smoothing process captures the broader trends in synchronicity, minimizing the noise from short-term fluctuations.

An immediate drawback of this measure is its inability to account for differences in the *magnitudes* of expansions and contractions. This limitation becomes particularly relevant when analyzing responses to (global) shocks, where the signs of the cycles may align, but structural differences across economies result in varying amplitudes. Another scenario where this measure may overstate synchronization occurs during simultaneous slowdowns in two economies. Even if the measure indicates perfect alignment due to shared signs, the divergence in the speed of contraction could point to fundamental differences in their economic dynamics.

To address these shortcomings, we extend our analysis by incorporating measures that capture both the co-movement and the absolute differences of the cycles. Specifically, we calculate the rolling correlation, rc, and the Euclidean distance, $dist$. These measures are defined as follows:

$$rc_t = \frac{\sum_{t-w-1}^{t}(c_{i,t} - \bar{c}_i)(c_{j,t} - \bar{c}_j)}{\sqrt{\sum_{t-w-1}^{t}(c_{i,t} - \bar{c}_i)^2 \sum_{t-w-1}^{t}(c_{j,t} - \bar{c}_j)^2}} \tag{2.8}$$

and

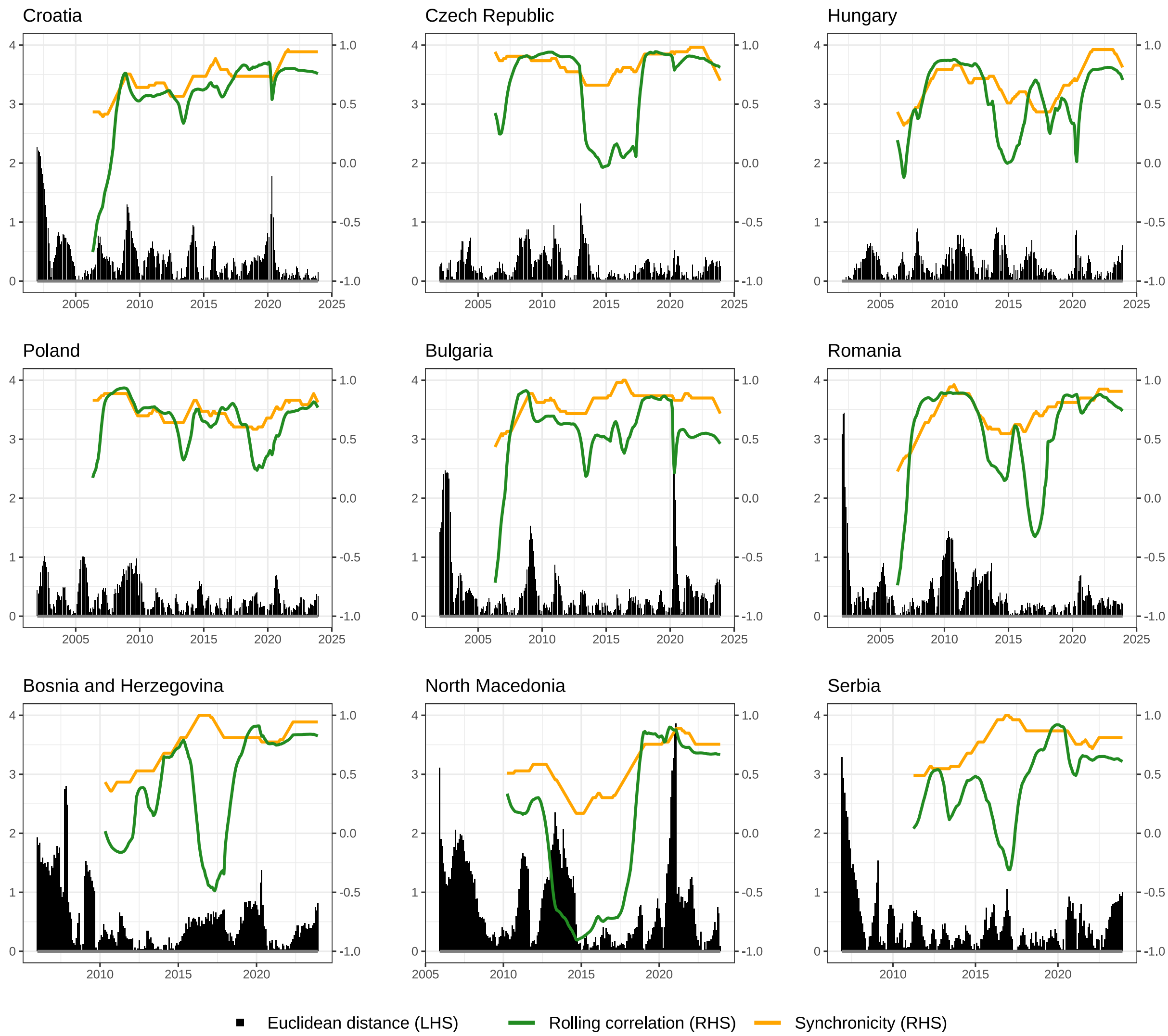
$$dist_t = \sqrt{(c_{i,t} - c_{j,t})^2}, \tag{2.9}$$

Where the business cycles of countries c_i and c_j are conditional on period t. Eq. (2.8) shows that at each point in time t, we calculate the average correlation over the current and preceding $w - 1$ months between the two cycles. This rolling correlation provides insights into both the strength and direction of the linear relationship between the cycles. Additionally, it complements our analysis by offering information about the absolute deviations between the cycles, helping to capture key dynamics that the synchronicity measure alone may overlook.

Figure 3 illustrates the synchronicity measure (yellow line, RHS axis), the rolling correlation (green line, RHS axis), and the Euclidean distance (black bars, LHS axis). Notably, both measures reveal periods of heterogeneity at the start of the sample and during the euro crisis. These variations are particularly pronounced for non-EU countries, where the synchronicity measures are, on average, lower.

Croatia experienced an increase in synchronicity and correlation with the euro area over time, with significant changes occurring after its EU accession, particularly in the post-COVID-19 period. During this time, Croatia's recovery closely mirrored that of the euro area. In contrast, the Visegrád Group displayed a less gradual development. For Czechia and Hungary, we observed decreases in synchronicity and correlation over the past decade, particularly during the euro crisis and the low-interest-rate period. Despite these declines, synchronicity remained relatively high, suggesting that the differences primarily arose within the same economic phase. Poland, on the other hand, experienced stagnation or slight decline in its synchronicity and correlation measures over the sample period. While the (Euclidean) differences in Hungary remained stable and low over time, the differences in Poland and Czechia significantly declined after 2010 and 2013, respectively. Among the countries in our sample, the Visegrád Group showed the smallest absolute differences relative to the euro area. Turning to Bulgaria and Romania, both countries experienced a similar upward trend in synchronicity, reaching their highest values in 2018/19. However, the rolling correlation for these countries exhibited greater volatility. Bulgaria saw larger business cycle differences in recent years, notably during the initial COVID-19 shock. In contrast, Romania experienced a sharp decline in business cycle differences post-2013, a trend that was particularly evident during the COVID-19 pandemic and the energy price shocks.

Figure 3: Business cycle synchronization of CESEE countries with the euro area



Notes: This figure illustrates the country-specific relationships with the euro area business cycle over time. The orange line (right-hand side axis) represents the rolling mean of the synchronicity measure, while the green line (right-hand side axis) shows the rolling correlation. The black bars (left-hand side axis) display the Euclidean distance between the two corresponding cycles. Both the rolling mean of the synchronicity measure and the rolling correlation are calculated using a rolling window of $w = 53$ months.

Non-EU countries generally exhibited lower synchronicity and correlation over the past two decades, accompanied by larger absolute business cycle differences compared to EU countries. Bosnia and Herzegovina experienced a steady increase in synchronicity throughout the sample period. Negative spikes in the rolling correlation were driven by diverging business cycle dynamics during the GFC and the euro crisis. North Macedonia saw an increase in synchronicity following the euro crisis, after periods of moderate synchronicity and negative correlation. This change likely reflects time-shifted business cycle dynamics, which became less pronounced after 2015. The magnitude of absolute business cycle differences in North Macedonia was the largest in our sample, particularly evident during the initial COVID-19 shock. Finally, Serbia's dynamics show a steady increase in synchronicity over time. The rolling correlation reached its highest value in 2020, signaling strong alignment during the moderation period. Initially, Serbia displayed sizable absolute differences, but these were followed by moderate deviations starting in 2010 and continuing through the end of the sample.

To complement our analysis of synchronicity and correlation, we now address questions about the volatility of the business cycles, which were not explicitly covered by our previous measures. To do so, we estimate the time-varying volatility of the cyclical components for each country. Following Kastner (2019a), we model the cyclical component for each country, c_t, within a stochastic volatility (SV) framework, defined as:

$$c_t = \nu_t, \quad \nu_t \sim \mathcal{N}(0, \omega_t^2), \tag{2.10}$$

where ν_t represents a Gaussian shock with zero mean and time-varying variance ω_t^2. We model ω_t as following a flexible stochastic volatility process:

$$h_t = \log \omega_t = \rho_h h_{t-1} + u_{h,t}, \quad u_{h,t} \sim \mathcal{N}(0, \sigma_h^2), \quad h_0 \sim \mathcal{N}\left(0, \frac{\sigma_h^2}{1-\rho_h^2}\right), \tag{2.11}$$

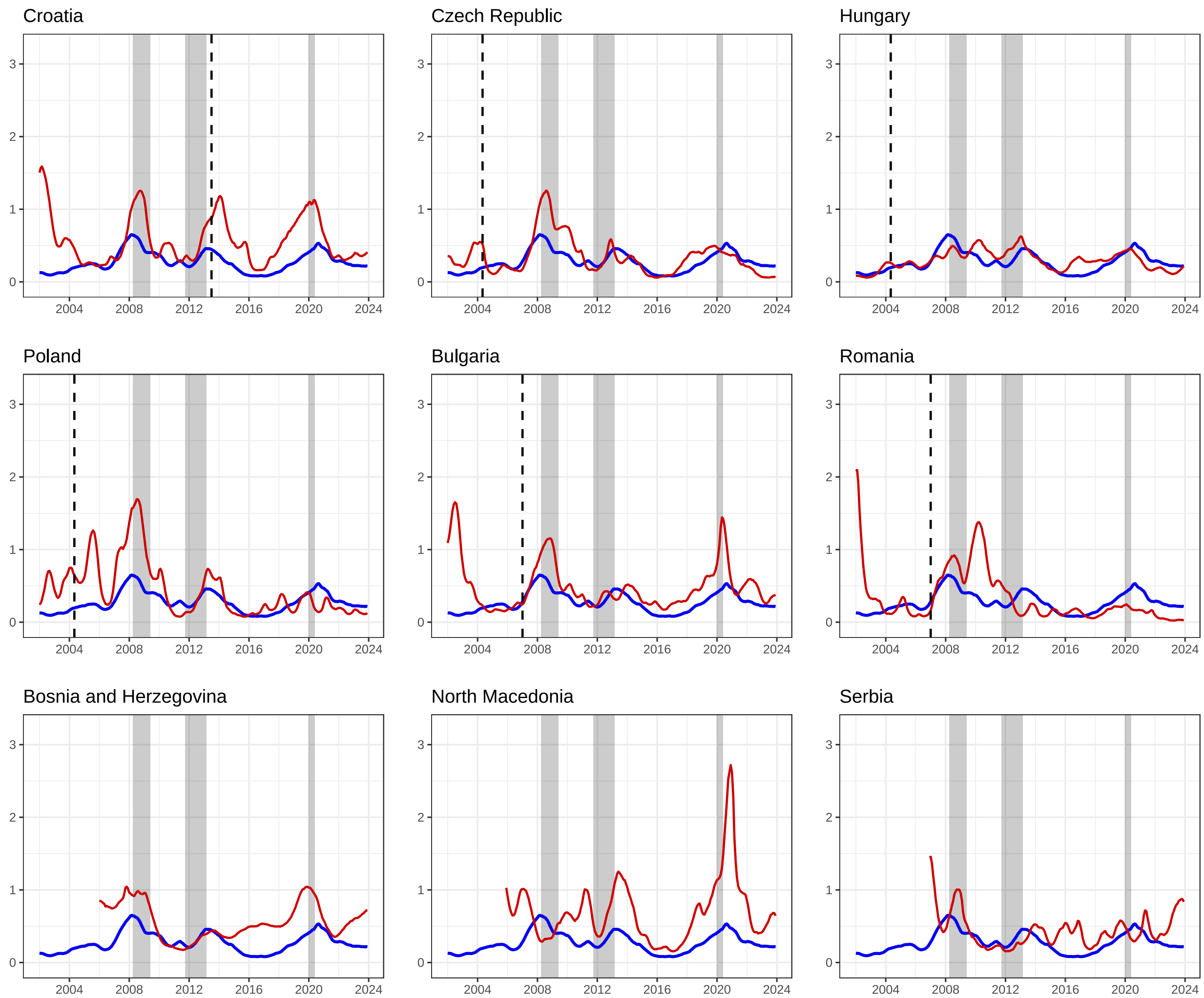
where the logarithm of ω_t, denoted as h_t, is assumed to follow a stationary autoregressive process of order one (AR(1)).[9] Here, ρ_h is the persistence parameter, σ_h^2 is the error variance, and h_0 is the initial state of the log-volatility process. Hence, in this model, the volatility evolves according to an autoregressive process.

We plot the estimated time-varying standard deviation, ω_t, in Figure 4 and compare the country-wise results (red) with the euro area (blue). The overall dynamics align with the findings from our previous measures. In many countries within our sample, volatility has converged to match that of the euro area. The volatility patterns of most CESEE countries closely resemble those of the euro area. While Croatia aligns well with the euro area after 2020, we still observe clear time shifts and larger magnitudes in the business cycle dynamics of the preceding two decades. Czechia, Hungary, and Poland exhibit patterns remarkably similar to the euro area, especially following the euro crisis. However, prior to that, Czechia and Poland experienced notably higher business cycle volatility. Over time, the Visegrád group has converged toward greater alignment with the euro area. Bulgaria shows volatility patterns similar to the euro area, although substantial differences were present before 2010. Additionally, Bulgaria experienced a much larger response to COVID-19, resulting in higher volatility magnitudes during that period. Romania, on the other hand, displayed considerable business cycle volatility until the euro crisis, after which volatility declined significantly.

The non-EU countries, however, remain slight outliers. In addition to differences in the magnitude of volatility, we also observe time shifts in their volatility patterns. Bosnia and Herzegovina exhibited stronger responses to both the GFC and the COVID-19 shock, leading to higher volatility during these periods. North Macedonia's economy experienced significantly greater volatility at various points in time compared to the

[9] Note that this model assumes that the data-generating process features time-variation in the variances, which stands in contrast to the constant-variance assumption of the local level model in Eq. (2.1). However, we adopt this two-step approach deliberately, as allowing for time-varying variance in both the trend and the error components would introduce identification challenges, making it difficult to disentangle the signal from the noise in a reliable way. As such, the model presented here should be viewed as a second-step diagnostic exercise and thus an extension of the baseline specification in Eq. (2.1), designed to explore higher-order properties of the estimated cycle.

Figure 4: Time-varying standard deviation of the euro area (blue) and the respective CESEE country (red).



Notes: This figure presents estimates of the time-varying standard deviation of the business cycles for the respective CESEE countries (red) and the euro area (blue), as derived from Eq. (2.11). The dashed black line indicates the date of each country's accession to the European Union, while the shaded grey areas represent recessions, as defined by the EABCN. The vertical axis displays the time-varying standard deviation, and the horizontal axis represents time in months.

euro area. As mentioned previously, the initial COVID-19 shock led to major labor market disruptions, which is clearly reflected in the graph. Serbia shows volatility patterns that are somewhat similar to those of the euro area in terms of magnitude, although time shifts are still apparent. These patterns of volatility are indicative of differing economic dynamics, which we now explore further through the lens of the Phillips curve.

3 Assessing synchronization of the Phillips curve slope coefficients

To motivate our consecutive analysis, which enriches the previous analysis of synchronization, consider the following example. During a global demand shock, traditional synchronization measures might indicate that countries are moving in the same cyclical phase. However, if one economy exhibits a steep Phillips curve while another remains flat, this implies differing inflationary responses. By extension, this would require monetary policy actions with different strength. Conversely, convergence in PC slopes, even with modest output co-movement, can signal increasing structural alignment in wage-price dynamics and labor market behavior, thereby refining assessments of business cycle synchronization beyond mere aggregate co-movement.

The literature supports the view that the slope of the Phillips curve declined markedly, altering the inflation-real activity link (see, e.g., Del Negro et al., 2020; Benigno and Eggertsson, 2023; 2024). This insight suggests that even if countries experience common shocks, their inflation dynamics and thus their broader macroeconomic policy environments may diverge substantially. PC-based comparisons can thus refine synchronization analysis by revealing whether countries not only move together in real terms, but also share similar inflation sensitivities. Especially in a monetary union, where only one monetary policy authority exists, similar policy transmission channels are of utmost importance.

Thus, we proceed with a country-wise reduced-form Phillips curve estimation, focusing on the time-variation of the relationship between inflation and unemployment. The obtained slope coefficients provide further insight into the underlying drivers of the business cycles. In this context, similar slope coefficients across countries could indicate close economic alignment and a shared capacity for shock absorption.

In recent decades, characterized by a moderation in interest rates and economic activity, the slope of the Phillips curve has declined, alongside a diminished ability to respond to inflation. However, the significant economic shocks of 2020, combined with strong inflationary pressures and rapidly rising policy rates worldwide, may have revitalized the Phillips curve (see, e.g., Hazell et al., 2022; Ari et al., 2023; Hobijn et al., 2023). As shown previously, preliminary evidence presented in Section 1 supports the notion of time-variation in the Phillips curve. Consequently, we argue that constant-parameter models may overlook important time-varying dimensions of the Phillips curve and are not well-suited for our analysis. To address this limitation, we adopt a time-varying parameter (TVP) regression to estimate the slope of the Phillips curve independently for each country in our sample.

3.1 Estimating the Phillips curve: model setup and data

We estimate the country-specific models with core inflation as the dependent variable, regressing it on our measure of economic slack, i.e., the business cycle estimated in Section 2.1. The model is then given by

$$y_t = \beta_t c_t + z_t \gamma_t + \varepsilon_t, \quad \varepsilon \sim \mathcal{N}(0, \sigma^2) \tag{3.1}$$

where y_t represents core inflation, c_t is our measure of economic slack (the business cycle estimated in Section 2.1), and z_t contains a set of control variables. Details of the variables and their abbreviations are provided in Appendix A. Core inflation excludes volatile components, such as energy and food prices, offering a clearer representation of persistent inflationary pressures, which aligns with the Phillips curve relationship. Our primary focus is the relationship between core inflation and the measure of economic slack (`SLACK`), as derived in Section 2. Specifically, we are interested in the slope coefficient of the Phillips curve, β_t. For a detailed overview of the estimation process, which we carry out with Bayesian techniques, refer to Appendix B.2.

We define our set of controls in z_t as follows. To take expectations into account, PC specifications typically include a forward-looking inflation term. However, to the best of our knowledge, monthly inflation expectation measures are unavailable for most countries in our sample. While such variables are now available for the euro area for a limited time span, differences in predictors could undermine comparability across the sample. Consequently, we rely on a purely backward-looking Phillips curve specification, incorporating lagged inflation. This approach implies that inflation at time t depends not only on $t-1$ but also on a broader time span. Hence, following Forbes et al. (2021), we take the 12-month average of inflation, lagged by one period, as our backward-looking inflation term (L_INFL).[10]

Given the openness of the countries in our sample to global economic influences, we include four additional variables to account for exposure to global shocks. The Global Economic Conditions indicator (GECON), developed by Baumeister et al. (2022), provides a snapshot of current global economic dynamics by aggregating various measures of real activity, financial conditions, and uncertainty. This indicator also captures global recessionary and expansionary dynamics, enabling us to account for the global economic cycle. To reflect supply chain frictions and their associated inflationary pressures – particularly pronounced after the COVID-19 pandemic – we include the Global Supply Chain Pressure Index (GSCPI), compiled by the Federal Reserve Bank of New York. Recent supply chain disturbances have significantly contributed to inflation surges in the euro area and globally (see, e.g., De Santis, 2024; Ascari et al., 2024).

Finally, to proxy the impact of production inputs and control for second-round effects, we include two additional variables: the Brent crude oil price (OIL) and the real Commodity Price Factor (COMMODITY), as developed by Baumeister and Guérin (2021). The latter captures price comovement driven by demand-related global fluctuations. In summary, we include two country-specific predictors (SLACK and L_INFL) and four global variables (GECON, GSCPI, OIL, and COMMODITY) to control for domestic and foreign price pressures, respectively. Additional details on data sources and transformations are provided in Appendix A.

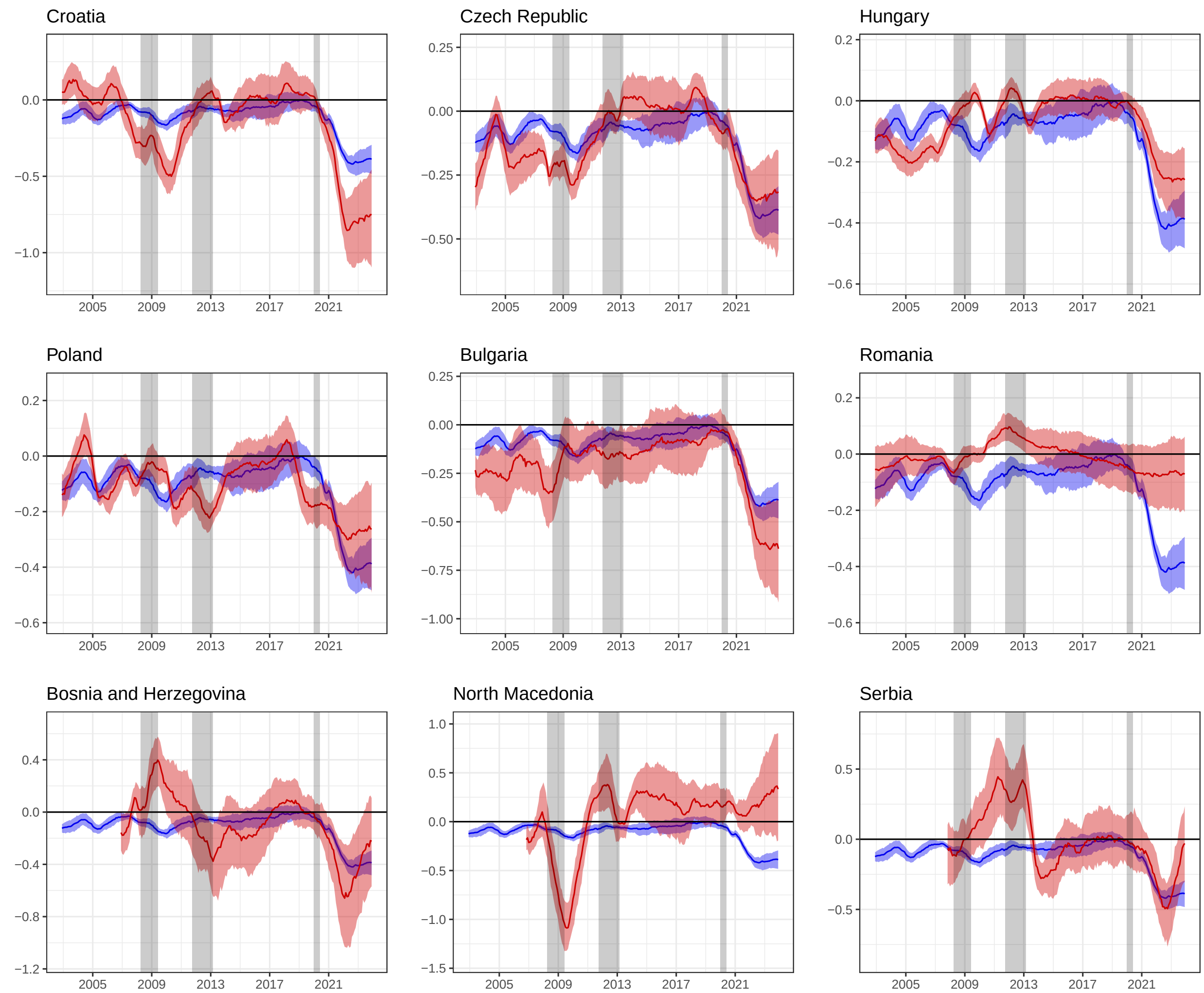
3.2 Analyzing the Phillips curve slope over time

Figure 5 presents the posterior median and the respective 16th and 84th quantiles of the time-varying coefficient of our economic slack variable. Each subfigure shows the estimate for the respective country (red) compared to the estimate for the euro area (blue). The results support the findings from our overall business cycle analysis in Section 2. Before the period of moderation following the euro crisis, the Phillips curve relationships were significant for most countries in our sample. During periods of low interest rates and low inflation, the curve flattened in every CESEE country, aligning with the euro area. From 2020 onward, the Phillips curve relationship reemerges, with significant negative coefficient estimates for most CESEE countries. In terms of magnitude, post-crisis estimates closely resemble those of the euro area. Overall, most CESEE EU countries exhibit greater alignment with the euro area than CESEE non-EU countries.

First, we focus on the estimates for the euro area. The relationship between cyclical unemployment and core inflation remained stable but slightly negative until 2015. Between 2015 and 2020, the Phillips curve flattens, with the posterior distributions of the slope coefficients becoming increasingly centered around zero

[10]Due to the 12-month moving average calculation, the sample used for estimating the TVP model starts one year after the dates reported in this section.

Figure 5: Slack coefficient in the Phillips curve of CESEE countries (red) and the euro area (blue)



Notes: Time-varying estimates of the slack coefficient across sample countries. In each plot, the blue line represents the euro area, while the red line represents the respective country. Shaded areas indicate the 68% credible interval.

and the 68% credible intervals including zero. These results align with those of Eser et al. (2020). Following the initial shock of the COVID-19 pandemic, the slope coefficient becomes significantly negative again, peaking in 2022. During that period, a 1 percentage point decline in the unemployment rate (relative to trend) is associated with an estimated 0.4 percentage point increase in core inflation. This finding supports the recent resurgence of the Phillips curve in the euro area and highlights the importance of accounting for time variation in its relationship.

Croatia exhibits similar dynamics to the euro area but with greater magnitudes during the GFC and the economic shocks of the 2020s. The Czech Republic and Hungary also align closely with the euro area, particularly after 2013. For Hungary, moderate differences emerge during the GFC and euro crisis, where the posterior distribution of the PC slope includes zero. Following the COVID-19 shocks, the slope coefficient turns negative with a lag and a slightly smaller magnitude. Poland's PC slope remained muted for a shorter period in the 2010s and turned negative two years before the COVID-19 shock. This early resurgence may be attributed to a faster recovery from the previous moderation, which preceded the euro area's recovery. Bulgaria's PC relationship remained muted from 2009 to 2020, with estimates exhibiting higher overall uncertainty. From 2021 onward, the magnitude of the coefficient slightly exceeds that observed for the euro area. However, Romania's Phillips curve dynamics deviate from broader euro area trends. The estimates' credible intervals include zero for most of the sample period, with no indication of a resurgence in the PC relationship. Our reduced-form specification does not offer an explanation for this pattern. A structural approach may be more appropriate to uncover underlying factors, such as labor market characteristics or labor force dynamics, that could contribute to persistently low unemployment.

Bosnia and Herzegovina experienced high volatility in core inflation during the sample period, alongside persistently high unemployment. During the GFC, slack coefficient estimates are positive but mostly muted thereafter. From 2021 to 2023, estimates turn negative and approximately align with the euro area. However, we interpret the outcomes for Bosnia and Herzegovina with caution given data quality concerns. North Macedonia exhibits a strongly negative slope during the GFC; however, estimates are mostly close to zero for the rest of the sample. In Serbia, coefficient estimates are positive before 2014. During this period, economic turbulence resulted in high unemployment and double-digit inflation. During the recovery, the slope briefly turns negative before flattening and aligning with the euro area through 2022.

The relationship between cyclical unemployment and core inflation in CESEE EU countries is well aligned with that of the euro area, especially after the euro crisis. Romania is the only exception in our sample. These findings suggest that close economic ties with the euro area are reflected in similar underlying economic relationships. In contrast, our results indicate that CESEE non-EU countries are less aligned with the euro area, as reflected in the slope of the Phillips curve. This highlights open questions for further (structural) research aimed at exploring the underlying differences between EU and non-EU members that drive these divergent results.

4 Concluding remarks

In this study, we examine business cycle synchronization and the Phillips curve relationship across Central, Eastern, and Southeastern European (CESEE) economies, providing updated insights into their economic alignment with the euro area. To extract the business cycle, we use the unemployment rate as a proxy for economic activity and apply a Kalman filter. This approach offers a more robust trend extraction method compared to alternatives such as the Hodrick-Prescott and Hamilton filters, as it avoids sample shortening and end-point biases.

Our findings indicate a general increase in business cycle alignment over time, particularly among CESEE countries seeking to join the euro area. However, significant heterogeneities remain, especially during periods of major economic disruption, such as the global financial crisis, the euro crisis, and the COVID-19 pandemic. CESEE EU countries show closer synchronization with the euro area than their non-EU counterparts, underscoring the role of institutional and economic integration in fostering convergence. Furthermore, estimating the time-varying volatility of business cycles using a stochastic volatility framework reveals that most CESEE economies have exhibited volatility patterns similar to those of the euro area, particularly in recent years.

To complement the synchronization analysis, we examined the Phillips curve relationship, which was weak or insignificant before the COVID-19 pandemic but steepened notably in the post-pandemic period across nearly all countries in our sample. Time-varying parameter regression models reveal dynamic shifts in the slope of the Phillips curve, with many CESEE countries increasingly aligning with the euro area's Phillips curve dynamics.

Overall, the results indicate that stronger economic ties with the euro area contribute to greater synchronization of business cycles and labor market dynamics, particularly among EU member states. These findings provide important insights for policymakers and researchers concerned with economic integration and stability within the European Union. Future research could explore the long-term implications of these convergence trends, especially in light of evolving monetary and fiscal policies in the EU. Additionally, examining the structural factors behind cross-country differences in Phillips curve dynamics can further enrich the literature on economic synchronization.

Conflicts of interest

The authors declare that they have no relevant financial or non-financial conflicts of interest.

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Appendix A Data

All series were obtained from the sources listed below, including Eurostat, the Federal Reserve Bank of New York, and the Federal Reserve Bank of St. Louis. Since the registered unemployment rate is not seasonally adjusted, we apply X-13ARIMA-SEATS, the seasonal adjustment software developed by the U.S. Census Bureau, which is openly available as an R package (see Sax and Eddelbuettel, 2018).

Table A.1: Variable description

Variable	Mnemonic	Description	Trans	Source
Core inflation	CORE	Harmonised Consumer Price Index (HICP) excluding energy and unprocessed food, seasonally adjusted.	3	Eurostat
Cyclical unemployment	SLACK	Cyclical component of the seasonally adjusted unemployment rate. Obtained by estimating the trend using the Kalman filter and calculating the cycle as the difference between observed unemployment data and the trend. Due to data limitations, both the ILO estimate (EA, Poland, and Hungary) and the registered unemployment rate (rest) is used.	0	Eurostat
Backward-looking inflation term	L_INFL	12-month average of core inflation, lagged by one month.	0	Author's calculation
Global Supply Chain Pressure Index	GSCPI	The GSCPI is a comprehensive summary of potential supply chain disruptions and includes data from the Baltic Dry Index (BDI), the Harpex index, airfreight cost indices and the Purchasing Managers' Index (PMI) surveys.	1	Federal Reserve Bank of New York.
Global Economic Conditions Indicator	GECON	The GECON is based on 16 variables and measures aggregate fluctuations of the world economy.	0	Baumeister et al. (2022)
Global Commodity Price Factor	COMMODITY	A factor extracted from a large cross-section of real commodity prices. The factor captures demand driven global fluctuations in prices.	0	Baumeister and Guérin (2021)
Oil price	OIL	Brent crude oil price for Europe	1	Federal Reserve Bank of St. Louis

Notes: Trans indicates the transformation applied to each variable. (0) = no transformation, (1) = first differences in levels, (2) = log-difference transformation, (3) = % year-on-year changes. For the robustness check, we obtain the cyclical unemployment using a trend estimate from a two-sided HP filter with $\lambda = 14400$, which corresponds to a business cycle length of approximately 68 months (Maravall et al., 2001).

Appendix B Technical appendix

B.1 The Kalman filter

The Kalman filter (Kalman, 1960) is a Bayesian-based method for making accurate predictions about a system's state over time. It refines estimates by combining prior predictions with new observations. The process consists of two steps: prediction and update, where forecasts are adjusted based on incoming data. Notably, the Kalman filter relies only on information available up to the current time t, without incorporating future data.

To provide a formal intuition for the filter, consider a univariate state space model with the measurement equation:

$$y_t = z\beta_t + v_t, \quad v_t \sim \mathcal{N}(0, r), \quad t = 1, \ldots, T, \tag{B.1}$$

where y_t is a scalar time series, v_t is a Gaussian error term with constant variance r, and z links the latent states β_t to the measurement. The latent state evolves according to the state equation:

$$\beta_t = h\beta_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, q), \tag{B.2}$$

where h is the state transition coefficient, and η_t is a Gaussian error term with constant variance q.The **prediction step** uses state information from time $t-1$ to predict the state at time t. The a priori state estimate is given by $\hat{\beta}_{t|t-1} = h\hat{\beta}_{t-1}$, and the a priori covariance estimate is denoted by $P_{t|t-1} = h^2 P_{t-1} + q$. The **update step** improves the a priori estimates with new information gained at time t. The a posteriori state estimate is given by

$$\hat{\beta}_t = \hat{\beta}_{t|t-1} + K_t \tilde{y}_t, \tag{B.3}$$

and the updated estimate of the state covariance is

$$P_t = P_{t|t-1} - K_t z P_{t|t-1}. \tag{B.4}$$

The two a posteriori equations rely on three helper equations:

The measurement residual:	$\tilde{y}_t = y_t - z\hat{\beta}_{t|t-1},$
The innovation covariance matrix:	$S_t = z^2 P_{t|t-1} + r,$
The Kalman gain:	$K_t = P_{t|t-1} z S_t^{-1}.$

The Kalman gain is a crucial component of the filter, determining the weight assigned to new measurements when updating the estimate of the system's state. It balances the uncertainty in the prediction with the uncertainty in the measurement, ensuring the updated estimate is optimally weighted. Thus, high (low) measurement noise leads to a lower (higher) Kalman gain, while high (low) uncertainty in the predicted state results in a larger (smaller) Kalman gain. To estimate the Kalman filter, we simplify our model by setting $z = 1$ and $h = 1$. Setting $z = 1$ assumes a direct measurement of the state, as z links the state to the observation. Additionally, a state transition coefficient of $h = 1$ implies a random walk model for state evolution.

B.2 The time-varying parameter model

The standard time-varying parameter (TVP) model is given by

$$y_t = \boldsymbol{x}_t \boldsymbol{\beta}_t + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2), \tag{B.5}$$

where y_t is the dependent variable of interest, and $\boldsymbol{x}_t$ is a vector of K predictors. The model assumes homoscedastic errors centered around zero with variance σ^2. Unlike in a standard linear regression, where coefficients are fixed over time, the TVP model allows $\boldsymbol{\beta}_t$ to evolve dynamically. This flexibility is particularly useful for capturing structural changes in economic relationships. To model this time variation, we assume that the coefficients follow a random walk process:

$$\boldsymbol{\beta} t = \boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Omega}), \tag{B.6}$$

where $\boldsymbol{\Omega} = \text{diag}(\omega_1, \ldots, \omega_K)$. The diagonal structure of $\boldsymbol{\Omega}$ implies that the innovations $\boldsymbol{\eta}_t$ are conditionally independent across predictors. Each ω_k governs the extent to which the corresponding coefficient β_{kt} fluctuates over time, with larger values indicating more pronounced time variation.

We follow Frühwirth-Schnatter and Wagner (2010) and adopt the non-centered specification of our regression model, which improves estimation properties, particularly in hierarchical Bayesian models. Under this approach, the measurement equation takes the form

$$y_t = \boldsymbol{x}_t \boldsymbol{\beta}_0 + \boldsymbol{x}_t \tilde{\boldsymbol{\Omega}} \tilde{\boldsymbol{\beta}} t + \epsilon_t, \tag{B.7}$$

where $\tilde{\boldsymbol{\Omega}} = \text{diag}(\sqrt{\omega_1}, \ldots, \sqrt{\omega_K})$. The corresponding state equation is given by

$$\tilde{\boldsymbol{\beta}}_t = \tilde{\boldsymbol{\beta}}_{t-1} + \boldsymbol{v}_t, \quad \boldsymbol{v}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}). \tag{B.8}$$

This approach assumes that the regression coefficients fluctuate around a baseline component. Specifically, a typical element in $\tilde{\boldsymbol{\beta}}_t$ is given by

$$\tilde{\beta}_{jt} = \frac{\beta_{jt} - \beta_{j0}}{\sqrt{\omega_j}}, \tag{B.9}$$

meaning that deviations from the baseline β_{j0} are scaled by the square root of the state innovation variance. This reformulation allows for a direct assessment of parameter evolution: if our estimation yields $\omega_j = 0$, the j-th coefficient remains constant over time, while a positive ω_j indicates smooth parameter variation. Consequently, ω_j serves as a key indicator of temporal dynamics in the regression coefficients.

Since we estimate the model in a Bayesian framework to address computational challenges, we briefly describe our choice of priors. Given the low dimensionality of the model (i.e., K is small), we place a non-informative prior on the constant part of the model, assuming that each j-th coefficient follows a standard normal distribution:

$$\beta_{j0} \sim \mathcal{N}(0, 1). \tag{B.10}$$

However, in TVP models, excessive flexibility can lead to overfitting and spurious variations in parameter estimates. To mitigate this, we impose shrinkage on the time-varying coefficients (see, e.g., Kalli and Griffin, 2014). To achieve this, we adopt a global-local shrinkage prior on the standard deviations of the state innovations, allowing for data-driven regularization of time variation. Specifically, we rely on the hierarchical Normal-Gamma prior, which has been widely used in econometric applications due to its adaptability in controlling sparsity (see, e.g., Griffin and Brown, 2017; Huber and Feldkircher, 2019; Kastner, 2019b). This prior effectively shrinks small coefficients toward zero while allowing relevant coefficients to remain flexible, making it well suited for capturing smooth structural changes without excessive noise. For each regression model, we impose a hierarchical Normal-Gamma prior on the state innovation variances, given by

$$\sqrt{\omega_j} | \xi_j^2, \phi \sim \mathcal{N}\left(0, \frac{2}{\phi}\xi_j^2\right), \quad \xi_j^2 \sim \mathcal{G}(a_\xi, a_\xi), \quad \phi \sim \mathcal{G}(c_\xi, d_\xi), \tag{B.11}$$

where the set of hyperparameters, $\theta = (a_\xi, c_\xi, d_\xi)$, governs the global and local shrinkage behavior and is chosen a priori by the researcher.[11] Here, ϕ acts as a global scaling parameter, influencing the overall level of shrinkage across all coefficients. Meanwhile, ξ_j^2 determines local shrinkage, allowing individual coefficients to adaptively shrink or remain flexible depending on the data. As shown in Griffin and Brown (2017), this hierarchical structure provides adaptive regularization, making it well-suited for models with sparse or time-varying parameters. In practice, this prior effectively shrinks small coefficients toward zero while allowing significant coefficients to remain dynamic, striking a balance between flexibility and parsimony.

For estimation, we set the global shrinkage parameter to $a_\xi = 0.1$, $c_\xi = 0.01 + a_\xi K$, and $d_\xi = 0.01 + a_\xi \sum_{k=1}^{K} \frac{\sqrt{\omega_k}}{2}$. These choices balance global and local shrinkage, ensuring that smaller coefficients are shrunk aggressively while allowing significant coefficients to remain flexible. Specifically, c_ξ scales with the number of predictors (K), while d_ξ accounts for the prior variability of the state innovation variances ω_k. To estimate the model, we employ a Gibbs sampler, an efficient Markov Chain Monte Carlo (MCMC) algorithm well-suited for hierarchical Bayesian models. After discarding 5,000 draws as burn-in, we generate 10,000 posterior draws from the full conditional distribution of the parameters. The Gibbs sampler iteratively samples from the conditional posteriors of (i) the regression coefficients, (ii) the state innovation variances, and (iii) the shrinkage parameters. The complete sampler setup is outlined in Appendix B.3.

[11]For further discussion on the effect of a_ξ on global shrinkage, see Brown and Griffin (2010).

B.3 Posterior simulation

Here, we provide a sketch of our Gibbs sampling algorithm. This sampler efficiently estimates the posterior distributions of the model parameters by iteratively sampling from their full conditional distributions. A similar approach, though designed for a multivariate setting with heteroscedastic errors, can be found in Feldkircher et al. (2017).

(i) Obtain the full history of $\{\tilde{\boldsymbol{\beta}}_t\}_{t=1}^T$ using Forward Filtering Backward Smoothing (FFBS), conditional on the remaining model parameters. The FFBS algorithm, originally introduced by Carter and Kohn (1994) and Frühwirth-Schnatter (1994), is widely used for estimating state-space models, of which the TVP model is a special case.

(ii) Draw $(\boldsymbol{\beta}_0, \omega_1, \ldots, \omega_K)'$ from $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{V})$, with $\boldsymbol{\mu} = \boldsymbol{V}(\boldsymbol{Z}\tilde{\boldsymbol{y}})$ and $\boldsymbol{V} = (\boldsymbol{Z}\boldsymbol{Z}' + \bar{\boldsymbol{V}}^{-1})$. We define $\boldsymbol{Z}$ as a $T \times (2K)$ matrix, with a typical row $[\boldsymbol{x}_t', (\boldsymbol{\beta}_t \odot \boldsymbol{x}_t)'] \frac{1}{\sqrt{\sigma^2}}$, $\tilde{\boldsymbol{y}}$ is a T-dimensional vector with a typical element $y_t \frac{1}{\sqrt{\sigma^2}}$ and $\bar{\boldsymbol{V}}$ is a $(2K) \times (2K)$ diagonal prior variance covariance matrix. The first K elements on the diagonal of $\bar{\boldsymbol{V}}$ correspond to the linear coefficients and the second K elements correspond to the innovation variances.

(iii) Sample ξ_j^2 from a generalized inverse Gaussian distribution (GIG). The GIG distribution results from combining the Gamma prior on ξ_j with a Normal likelihood (for more details see Huber et al., 2019):

$$\xi_j^2|\bullet \sim \mathcal{GIG}\left(a_\xi - \frac{1}{2}, \sqrt{\omega_j}^2, a_\xi \phi\right), \tag{B.12}$$

where $\bullet$ denotes the remaining model parameters.[12]

(iv) The global shrinkage parameter, ϕ is sampled from a Gamma distribution:

$$\phi|\bullet \sim \mathcal{G}\left(0.01 + a_\xi K, 0.01 + a_\xi \sum_{k=1}^{K} \frac{\sqrt{\omega_k}}{2}\right). \tag{B.13}$$

(v) Finally, we draw the inverse of σ^2 from a gamma distribution,

$$\sigma^{-2}|\bullet \sim \mathcal{G}(\gamma_0, \gamma_1), \tag{B.14}$$

with $\gamma_0 = 0.01 + \frac{T}{2}$ and $\gamma_1 = 0.01 + \frac{\sum_{t=1}^T (y - \boldsymbol{\beta}_t \boldsymbol{x}_t)^2}{2}$.

Appendix C Additional Results

C.1 Data plots: Core inflation and unemployment rate

[12]To efficiently sample from this distribution, we use the R package GIGrvg (see Leydold and Hörmann, 2017).

Figure C.1: Core inflation (% y-o-y) across the sample countries

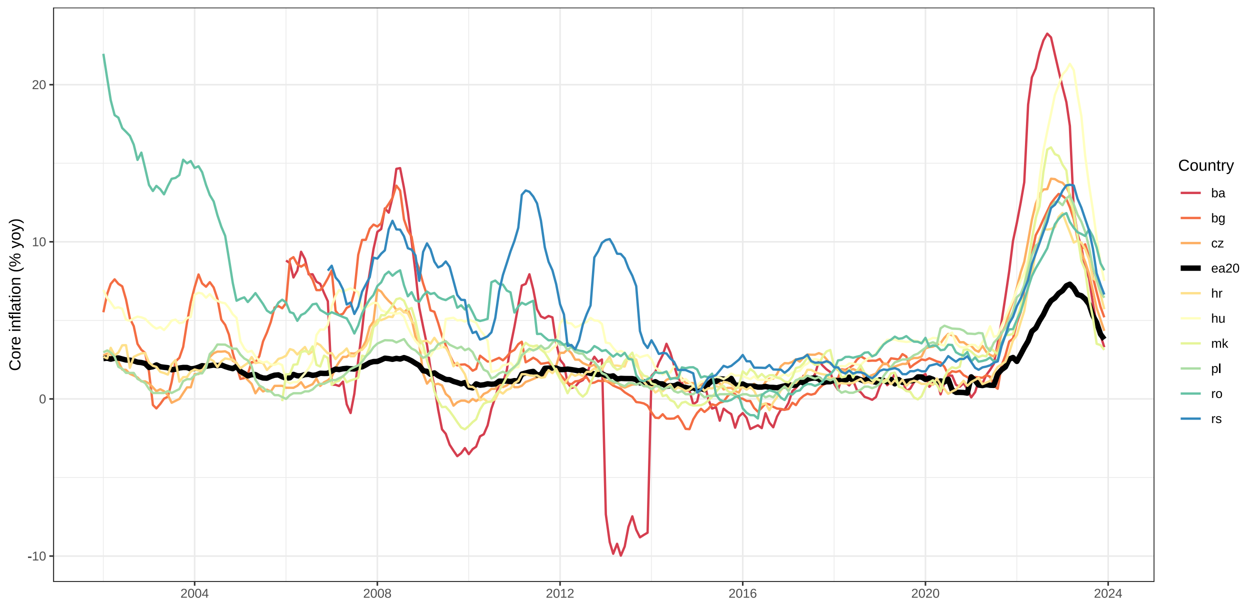
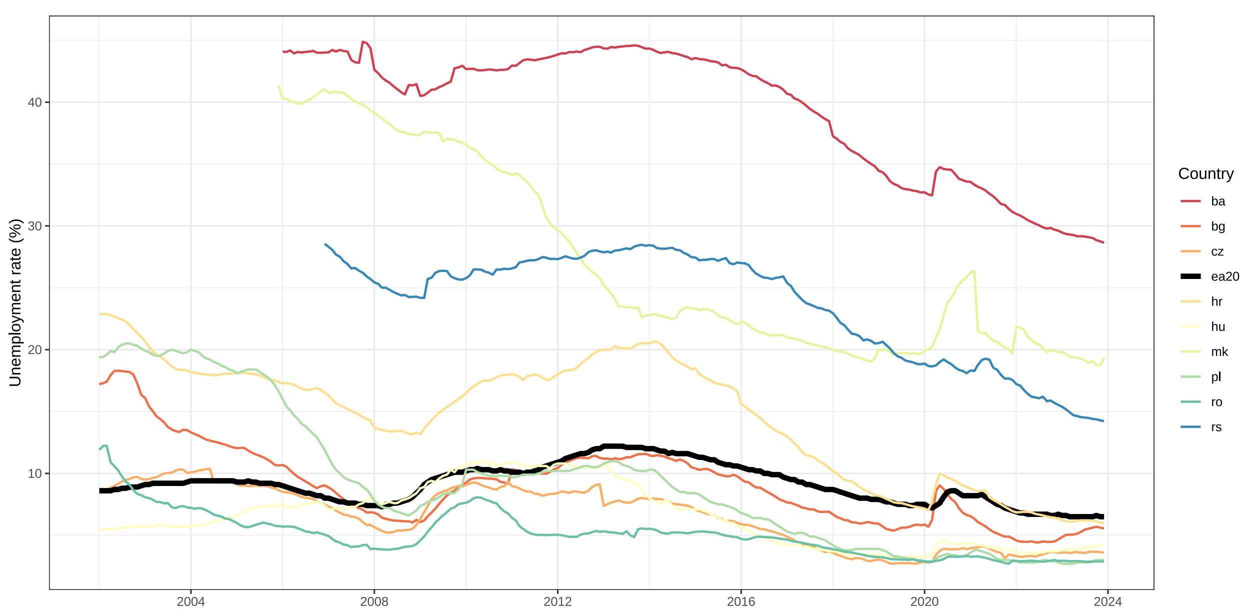
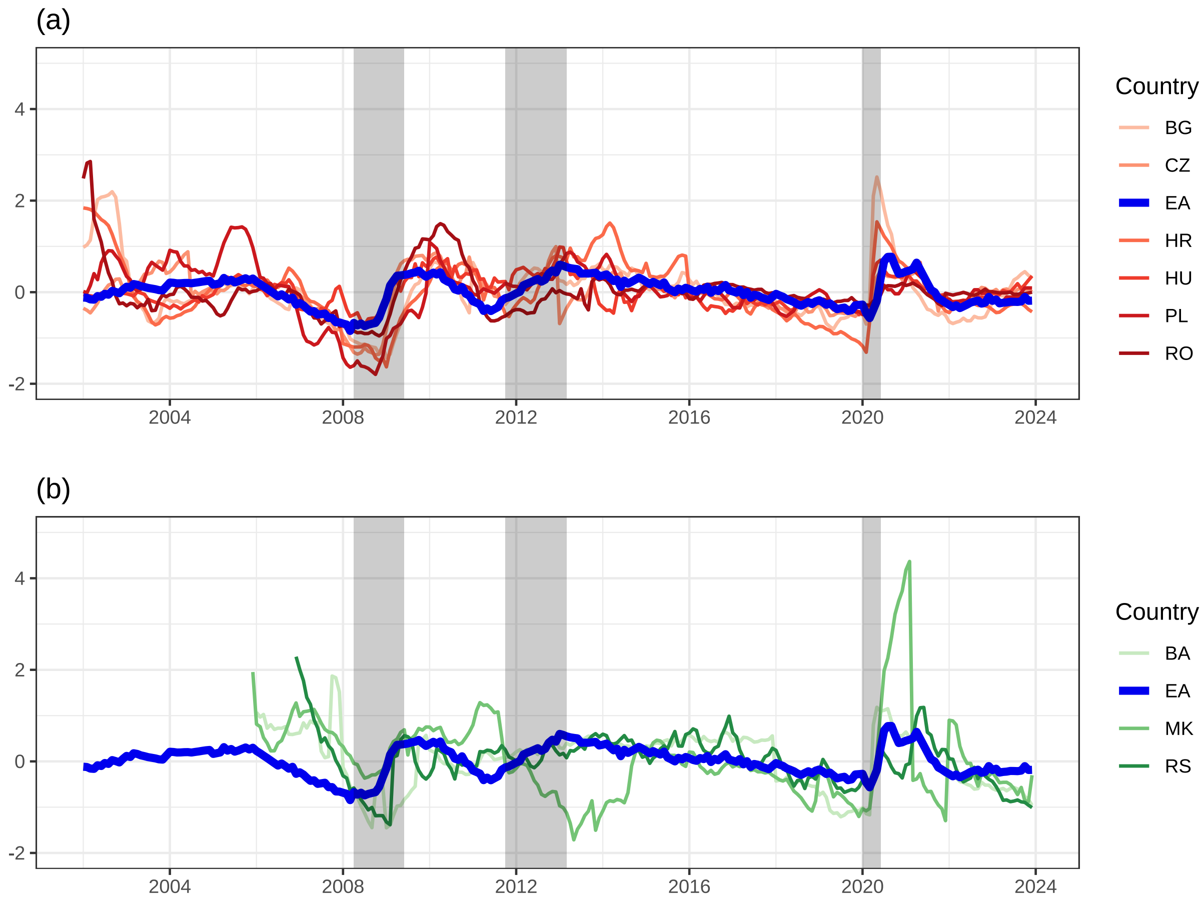


Figure C.2: Unemployment rate across the sample countries



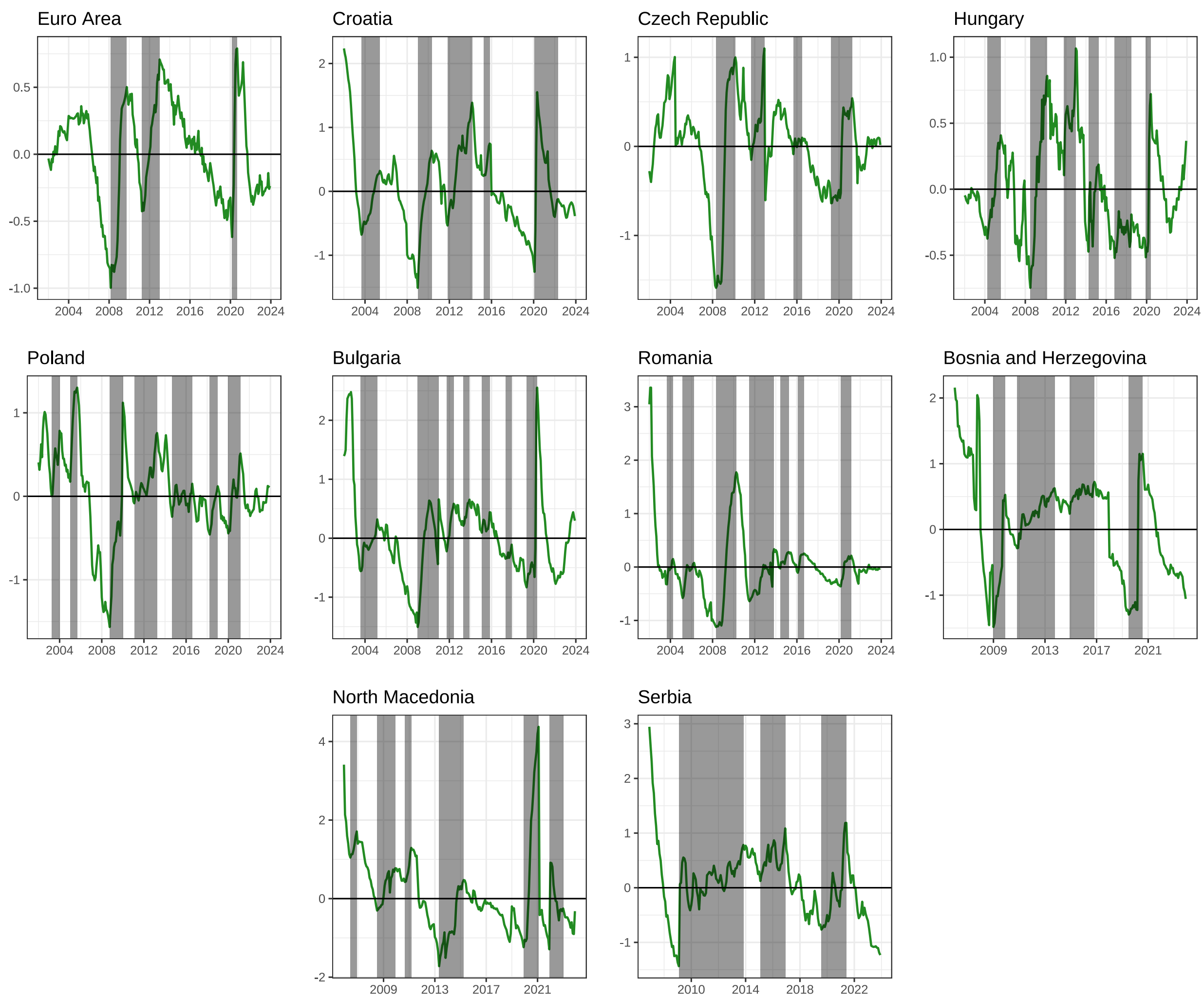
C.2 Business cycle dates

Figure C.3: Comparing cycles of euro and EU candidates with the euro area



Notes: Cyclical component of the unemployment rate of each country. Panel (a) shows the comparison of euro candidates to the euro area, while panel (b) shows the comparison of EU candidates to the euro area.

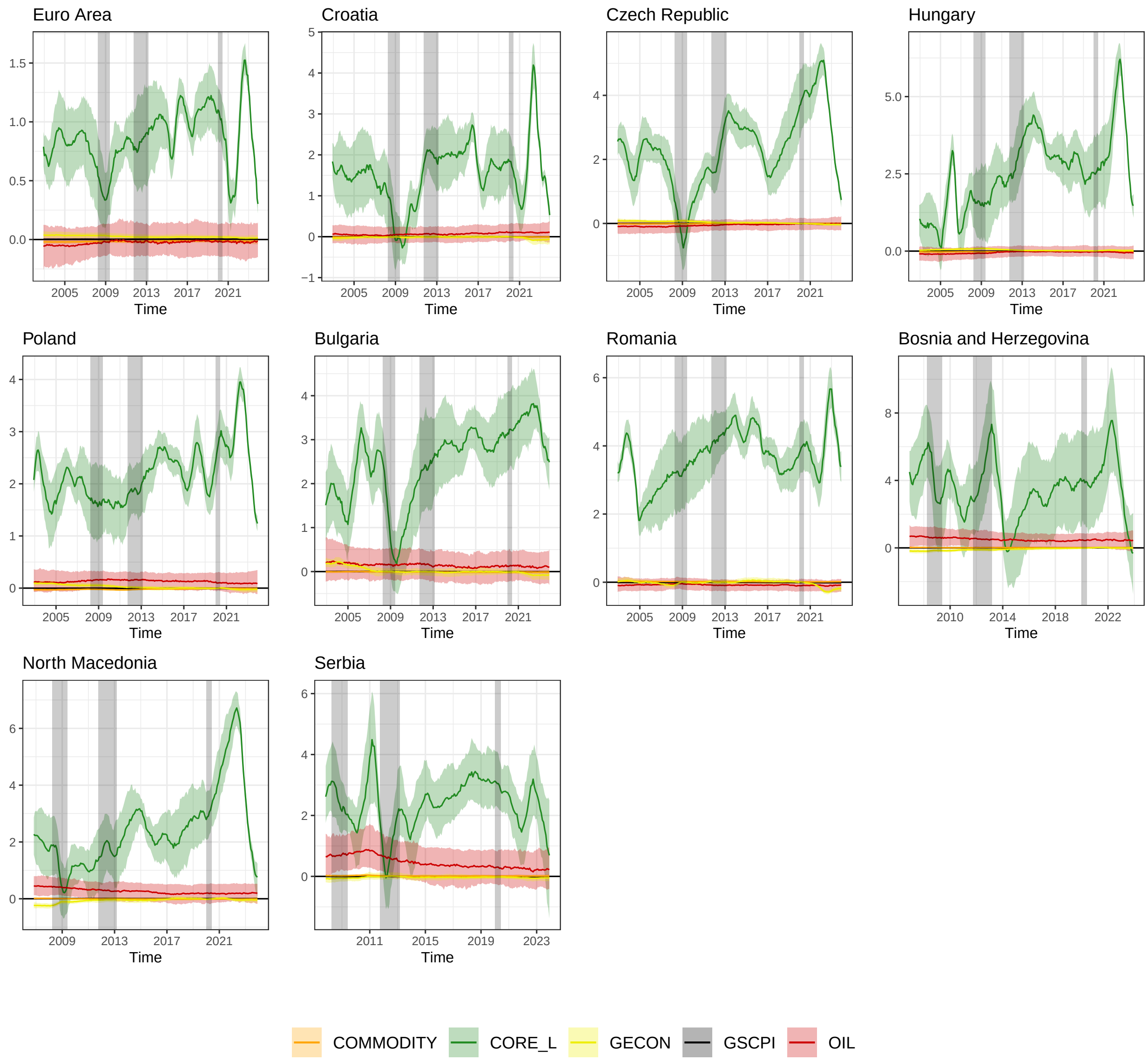
Figure C.4: Business cycle dating for the euro area and the CESEE region



Notes: We calculate the dates for peaks and troughs for each country using the algorithm proposed by Harding and Pagan (2002). The solid line represents the business cycle of the respective country, the grey shaded areas correspond to the calculated recessionary periods. The algorithm can be easily implemented using the R-package BCDating, which is available at `https://CRAN.R-project.org/package=BCDating`. We set the minimum business cycle length to 15 months and the minimum business cycle phase length to 6 months. This corresponds to the quarterly settings used in the original paper.

C.3 Additional regression results

Figure C.5: Results for other regression coefficients

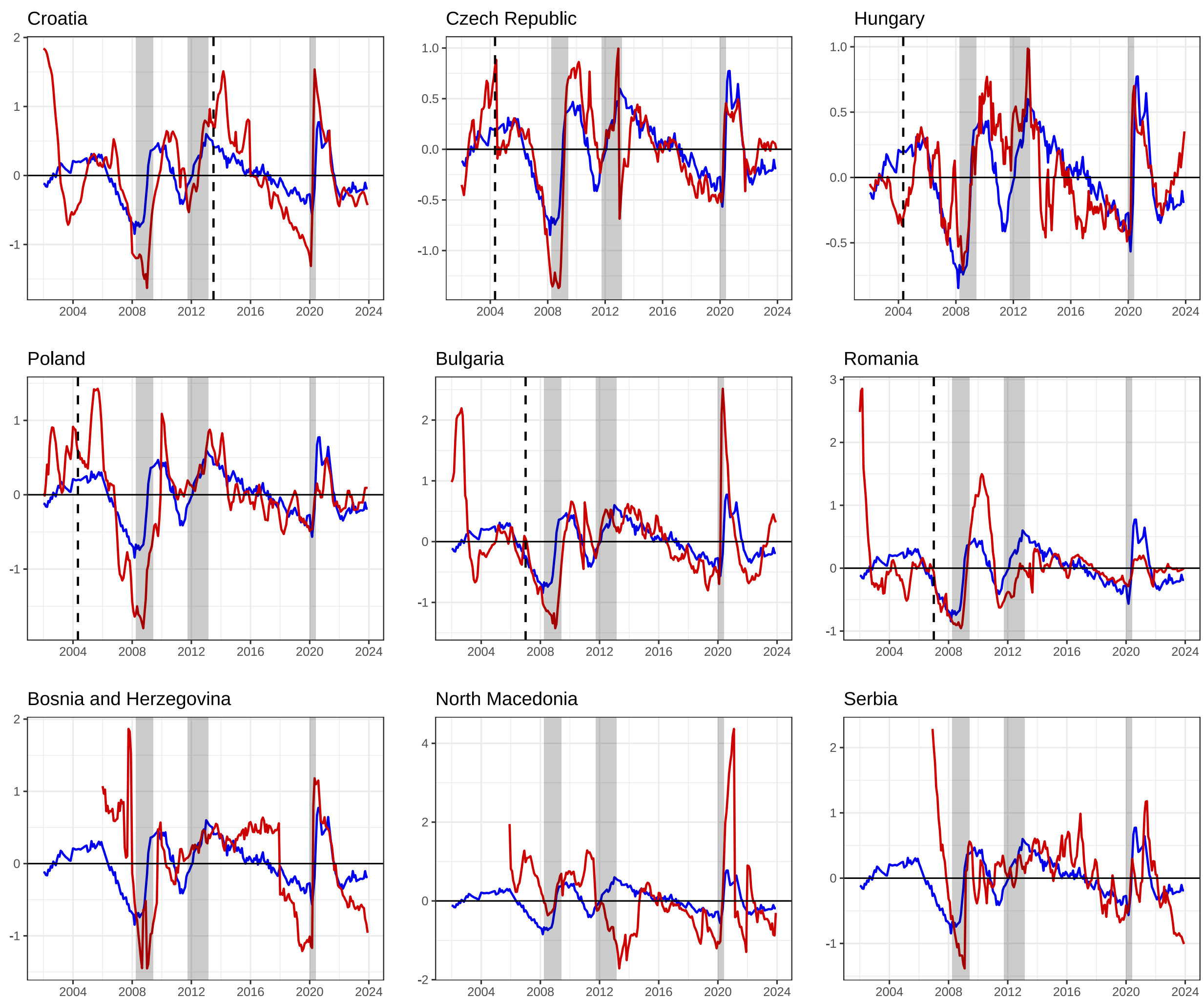


Notes: Time-varying estimate of the other coefficients in the model. Shaded areas correspond to the 68% credible interval.

Appendix D Robustness checks

This section presents empirical results using the HP-filtered cyclical components as our measure of economic slack in the Phillips curve. Figure D.1 displays country-wise business cycle estimates obtained through the HP filter. Overall, the business cycle dynamics appear remarkably similar across the sample, suggesting broadly synchronized economic fluctuations. The largest discrepancies occur at the beginning and end of the sample, likely due to the HP filter's end-point bias. Nevertheless, our findings suggest that the choice of filtering method does not drive the results.

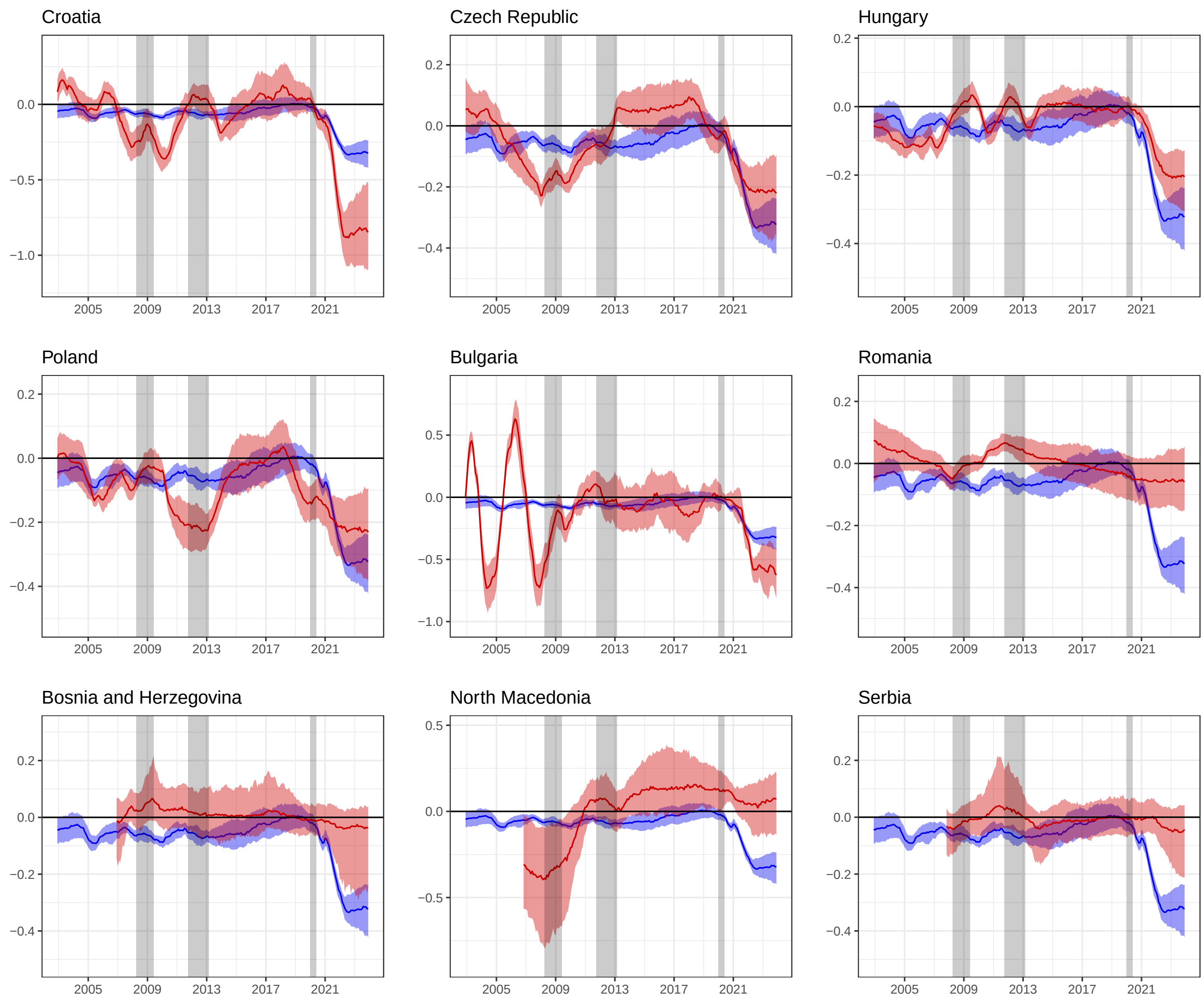
Figure D.1: CESEE business cycles (red) in comparison to the euro area (blue).



Notes: This figure illustrates the business cycle dynamics for the euro area (blue) and each respective country (red). The business cycle is measured as the difference between the observed unemployment rate and its HP-filtered trend component. The dashed black line marks the date of EU accession for each country. Shaded grey areas indicate recessions, as defined by the EABCN. The vertical axis represents the deviation from the trend (in percentage points). The horizontal axis measures time in months.

The results of the Phillips curve estimation, using business cycles extracted via the HP filter with $\lambda = 14400$, are shown in Figure D.2. The overall picture remains similar to the results obtained using Kalman-filtered cycles in Figure 5. However, notable differences appear toward the beginning and end of the sample period. One possible explanation for this is the end-point bias inherent to the HP filter, as discussed in Hamilton (2018).

Figure D.2: Slack coefficient of respective countries (red) and the euro area (blue)



Notes: Time-varying estimate of the slack coefficient across the sample countries. For each plot, the blue line represents the euro area and the red line represents the respective country. Shaded areas correspond to the 68% credible interval. The business cycles have been extracted using the HP filter with $\lambda = 14400$.

Table D.1: Explained variance of the trend estimate of the respective filters in %.

	`Kalman`	`HP`	`Hamilton`
EA20	73.60	89.48	45.96
BA	86.09	97.24	79.67
MK	87.73	97.22	82.68
CZ	81.78	91.46	57.41
BG	76.24	92.71	39.51
HR	87.48	95.42	69.02
HU	84.45	95.51	72.81
PL	91.09	96.53	78.43
RO	70.74	85.43	23.72
RS	84.43	97.23	81.45

Notes: We compute the estimate as the ratio of the variance of the trend to the variance of the time series (i.e., the unemployment rate), multiplied by 100. For the Hamilton filter, we follow the settings proposed in Hamilton (2018). As a result, the sample for the Hamilton filter estimate begins three years after the sample for the other filters. `Kalman` denotes the Kalman filter, `HP` the Hodrick-Prescott filter, and `Hamilton` the Hamilton filter.

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