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EUROZONE ECONOMIC INTEGRATION: HISTORICAL DEVELOPMENTS AND NEW CHALLENGES AHEAD

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Eurozone Economic Integration: Historical Developments and New Challenges Ahead

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Abstract

The paper yields a structural account of economic integration in the Eurozone from its inception to post-pandemic developments by considering a broad range of convergence measures. We introduce a novel FAVAR framework, extracting the structural shocks driving the Eurozone business and financial cycles directly from the cyclical components they generate. Productivity advancements have been the critical trend convergence factor, shaping long swings in real, labor market, and financial dispersion. Subdued cost-push shocks were the key driver of Eurozone nominal and competitiveness convergence throughout 2015 but have become an all-rounded divergence force since then. Fiscal discipline imposed by the Stability and Growth Pact (SGP) increased real and financial divergence during all recessionary episodes, while the ECB expansionary monetary policy was a convergence factor. The SGP suspension during the recent pandemic recession and recovery has partially counteracted divergence pressures. Looking forward, convergence will crucially depend on how productivity dynamics and economic growth will fend off further unfavorable cost-push developments, which might become pervasive in a deglobalization-driven new macroeconomic regime.

Keywords: real, nominal and financial convergence and divergence; Eurozone; economic integration; recessions; financial crises; subprime financial crisis; sovereign debt crisis; pandemic recession; FAVAR models.

JEL classification: E30, E50, C32

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1 Introduction

Twenty-five years have passed since the European Monetary Union's foundation and the introduction of the Euro as a common currency in January 1999. This critical step in the European Union integration project occurred within an overall benign macroeconomic regime characterized by moderate inflation, driven by favorable supply-side developments associated with the ongoing globalization of labor and product markets. This led to a convergence process across European economies, especially in the dynamics of inflation rates, nominal and real bond returns, and competitiveness measures. The initial convergence "success" is probably responsible for the concurrent slowdown in the pace of structural reforms to counter price and wage rigidities and improve the effectiveness of market-based adjustment mechanisms (see Mongelli 2008, for a detailed account of those facts and issues). The costs of this delay emerged when macroeconomic and financial conditions worsened. In the years from 2007 to 2013, characterized by repeated recessionary episodes and general conditions of financial distress, the convergence process came to a halt and was even reversed in the case of output levels and growth rates (Bagliano and Morana, 2011; Diaz del Hoyo et al. 2017; Franks et al. 2018), with the dispersion of unemployment rates and inflation reverting to pre-Monetary Union levels (Estrada et al., 2018). The divergence in output and employment dynamics was also enhanced by worsening general credit conditions, and further aggravated by fiscal consolidation measures, particularly in peripheral countries (Neri and Ropele, 2013; Gros, 2013; De Grauwe, 2016; see also Grande et al., 2013). In the years following this turbulent period, financial integration (Hoffmann et al., 2019), as well as the dispersion of output growth and unemployment and inflation rates, reverted to pre-crisis conditions.

More recently, a new phase of macroeconomic and financial divergence started with the onset of the pandemic recession in early 2020, quickly wiping out previous progress in Eurozone convergence (Kunovac et al., 2022). Although these recent developments are as yet underinvestigated, the available evidence points to a setback in financial integration that continued through the period of geopolitical turmoil begun in 2022 with pervasive adverse effects in the money, bond, equity and banking markets (European Central Bank, 2024). The inflation burst triggered by rising energy and food prices, supply bottlenecks, and the post-pandemic recovery led to a rise in the dispersion of inflation rates in the Eurozone to unprecedented levels. The asymmetric responses of Eurozone economies to common, composite negative supply-side shocks and the heterogeneous inflation persistence were responsible for this divergent dynamics (Coutinho and Licchetta, 2023). This episode of unprecedented nature and severity could be informative about potential future challenges to Eurozone integration. As envisaged by Goodhart and Pradhan (2020) and, more recently, Spence (2022) and Roubini (2022a,b), even a new macroeconomic regime could have emerged, characterized by permanently higher inflation, rising real natural interest rates, and slower growth. Originated from the reversal of past favorable demographic and labor supply trends, the weakening of the globalization process, and the constant deterioration of climate conditions, this regime could seriously challenge the course of Eurozone integration. Persistent inflation differentials induced by rapidly rising prices might fuel divergence in real interest rates, competitiveness, and output growth, eventually affecting labor and financial markets. Constraints on the countercyclical use of fiscal policy, such as those experiences by peripheral Eurozone countries during the sovereign debt crisis of 2011-2013, could enhance divergence even further.

In the light of the historical background and the envisaged risks, this paper provides a thorough account of macroeconomic and financial convergence in the Eurozone along a broad range of dimensions, covering real, labor, and financial markets, starting in 1999 and including the most recent developments up to 2023. We contribute to the literature by offering a structural economic interpretation of the Eurozone convergence dynamics. To this aim, we introduce a novel econometric approach allowing the disentanglement of long-run and short-run determinants of the convergence phenomenon. We estimate and give a structural economic interpretation to the common factors causing comovements in the trend and cyclical components of aggregate Eurozone macroeconomic and financial variables. The identified common factors are then included in a factor-augmented VAR ($FAVAR$) model to explore the effects of common structural disturbances on several Eurozone convergence measures at a business cycle horizon and over a longer term.

Disentangling trend and cyclical convergence dynamics is crucial to understanding how macroeconomic shocks may affect economic integration. Our main results show that productivity advancements can be singled out as the critical driver across all macroeconomic and financial convergence measures concerning trend convergence developments. Productivity fluctuations have shaped the long swings in the real, labor market, and financial conditions dispersion indicators. The dynamics of production costs were the key determinants of Eurozone inflation and competitiveness convergence trends until around 2015 and of the sharp increase in dispersion measures when adverse cost-push shocks occurred in the final part of the sample. Cyclical demand-side and supply-side developments have further reinforced these divergence pressures. We also find that the contribution of fiscal policies to Eurozone convergence is mixed, whereas the European Central Bank's monetary policy has been a constant convergence driver in all recessionary episodes from the Eurozone's inception up to the recent anti-inflationary policy turn.

The rest of the paper is organized as follows. Section 2 offer primarily descriptive insights on the Eurozone economic integration process. Section 3 (and the Appendix) introduces the econometric methodology. Sections 4 and 5 present the results of the structural analysis concerning the identification of structural shocks and their effects on the convergence dynamics in the Eurozone. Finally, Section 6 summarizes the main results and draws some policy implications.

2 The state of convergence

This Section presents a broad picture of the dynamics of convergence in the Eurozone since its inception in 1999 using indicators covering several dimensions of the convergence phenomenon. We also construct an overall indicator, providing a summary measure of Eurozone convergence. We focus on variables capturing convergence in real activity (industrial production growth), the state of the labor market (the unemployment rate), consumer price dynamics (headline CPI inflation), convergence in financial returns (on the long-term bonds and the stock markets), overall financial conditions (the ECB $CLIFS$ indicator; Duprey and Klaus, 2015), and competitiveness (real effective exchange rate changes). Monthly values of those seven macroeconomic and financial variables are collected for the twenty current members of the Eurozone from 1999 up to November 2023[1]. Details on the data and their sources are reported in Table A1 of the Appendix.

2.1 Indicators

To assess the dynamics of convergence in macro-financial variables, we use the sample standard deviation as a cross-sectional dispersion estimator. Considering the generic variable y and M countries, our estimator is, for each monthly observation, the sample standard deviation $\hat{\sigma}_y$, i.e., the positive square root of the sample variance estimator (an unbiased and consistent estimator of the population variance under the usual *i.i.d.* assumption):

$$\hat{\sigma}_y = \sqrt{\frac{1}{M-1}\sum_{i=1}^{M}\left(y_i - \frac{1}{M}\sum_{i=1}^{M} y_i\right)^2}. \tag{1}$$

Since an increase in the above statistics signals higher dispersion, i.e., higher divergence across Eurozone countries, henceforth we refer to these measures as *divergence* indicators.

The dependence of such measures on the contribution of any single cross-sectional unity (country) can be assessed by computing $\hat{\sigma}^2_y$ in up to $M-1$ subsamples, obtained by omitting each cross-sectional unity i at the time, i.e., $\hat{\sigma}^2_{y_{-i}}$, and then evaluating the discrepancy

$$\hat{\sigma}^2_{y_{i,net}} = \hat{\sigma}^2_{y_{-i}} - \hat{\sigma}^2_y. \tag{2}$$

A negative discrepancy implies that country i is a *net diverging* country, as its omission leads to a lower divergence measure than when it is included. On the contrary, a positive discrepancy implies that country i is a *net converging* country, as its inclusion in the computation lowers the dispersion measure.

We also compute corresponding GDP-weighted standard deviations, $\hat{\sigma}_{y,w}$, that underweight potentially outlying contributions from small countries, as

$$\hat{\sigma}_{y,w} = \sqrt{\frac{1}{M-1}\sum_{i=1}^{M} w_i^*\left(y_i - \frac{1}{M}\sum_{i=1}^{M} y_i\right)^2} \tag{3}$$

where $w_i^* = M \times w_i$, M being the cross-sectional sample size, and w_i the country i's contribution to total GDP, i.e., $w_i = GDP_i / \sum_{i=1}^{M} GDP_i$. The unweighted statistic in (1) implicitly assigns a unitary weight to each term in the sum. The scaling factor, i.e., the cross-sectional sample size M, makes the sum of scaled weights in (3) to match the sum of the implicit weights in (1). The weighted statistic helps to control for dispersion generated by small Eurozone players. Results obtained using the GDP-weighted measures do not differ substantially from those obtained using the unweighted measure (1), and are reported in the Online Appendix.

[1]The countries considered are: Austria, Belgium, Croatia, Cyprus, Germany, Estonia, Greece, Spain, Finland, France, Ireland, Italy, Lithuania, Latvia, Luxembourg, Malta, Netherlands, Portugal, Slovenia and Slovakia.

As mentioned above, in our application to the Eurozone the cross-sectional dimension is $M = 20$ countries, and we employ seven indicators of cross-country dispersion capturing divergence in real output (rd, based on data on industrial production growth), in the labor market performance (ld, based on the unemployment rate), in the dynamics of inflation (nd) and competitiveness (cd, based on real effective exchange rate returns) , in nominal long-term bond rates (bd) and stock market returns (sd), and in general financial conditions (fd, based on the $CLIFS$ financial condition index). As a summary measure of divergence, we also compute an overall macro-financial divergence indicator (od). The latter measure is obtained as a simple average of the seven individual indicators, after rescaling them by their average values in 1999 to obtain unit-free indexes.

By construction, our cross-sectional standard deviation measures are relatively sensitive to the presence of few outlying observations. For that reason, we also employ other measures of dispersion that all downweight observations in the tails of the distribution, namely the (Gini) absolute mean difference, the median absolute deviation, and the distance standard deviation (Székely et al., 2007). All those alternative measures are very highly correlated with the indicators based on the standard deviation, and the results of our analysis below are robust (see Tables A2-A5 in the Online Appendix). Therefore, in this section we focus on the divergence indicators based on the standard deviation.

2.2 Results

Figure 1 displays the evolution over the 1999-2023 period of the seven cross-country standard deviations and the overall summary divergence measure described above. For ease of comparison, such indicators have been normalized by their (average) 1999 values so that, in each panel of the figure, unity corresponds to the level of dispersion at the inception of the Eurozone. The dynamics of all indicators show significant fluctuations, seemingly associated with various episodes of economic and financial distress occurred in the sample under study. To investigate this relationship, we identify periods of recession or economic downturn (portrayed as dark gray shaded areas in Figure 1) and periods of financial crisis or distress (light gray shaded areas).

Concerning recessions, we follow the Eurozone's CEPR Business Cycle Dating Committee chronology and consider three major episodes (CEPR, 2024). The first corresponds to the global "Great Recession", spanning the period from March 2008 to June 2009; a second recession originated in June 2011 and lasted until March 2013, and the most recent recessionary episode was due to the COVID-19 pandemic from March to September 2020. According to this dating, in the 25-year period January 1999 - November 2023, the Eurozone was in recession in 45 months, and in a normal "expansionary" phase in the remaining 254 months.

The dating of financial crises is perhaps less straightforward, but the consensus view points to two major global financial distress episodes that severely hit the Eurozone. The first is associated with the burst of the so-called "dot-com bubble", that caused a persistent decline of the leading world stock markets indexes from April 2000 until March 2003, when a gradual but steady recovery set off. The second episode originated in the US subprime mortgage market in August 2007 and rapidly spread out to the Eurozone. Only in the summer of 2009 financial conditions eased temporarily when the functioning of the Eurozone interbank market went back to normal (Cassola and Morana, 2012).

However, starting in October 2009, a new phase of mounting financial pressure began, motivated by fears on the sovereign debt conditions of some member countries. The end of the most severe stage of this new financial crisis was in August 2012, following the implementation of a bailout package for Greece and the launch by the European Central Bank of a second long-term refinancing operation providing Eurozone banks with additional funds; this combination of events led to a permanent normalization of the Eurozone interbank market by August 2012 (Morana, 2014). Overall, the Eurozone was in a state of acute financial distress ("bust" for short) in 97 months in 1999-2023, and in normal conditions ("boom") in the remaining two-thirds of the sample. Finally, we also consider an additional period of recent geopolitical turmoil ("geo"), associated with the Russian invasion of Ukraine in February 2022 and covering 22 months until the end of the sample. Over this period, economic policies have faced the economic and financial implications of the war, that worsened the post-pandemic inflationary burst due to deteriorating supply-side conditions.

Using the dating of economic and financial crises described above, Table 1 complements the information provided by Figure 1, showing the average values of the seven divergence indicators for the whole sample, for the recessionary and expansionary periods, and for the phases of financial bust and boom; the last column reports the values over the most recent period of high geopolitical turbulence. This descriptive evidence suggests various considerations.

As shown in Figure 1, the dynamics of dispersion in industrial production growth rates (rd) show that the ongoing real convergence process has also progressed after 1999, especially during expansions, and has been only temporarily reversed during the episodes of economic and financial turmoil occurred before the 2020 recession. The only exception is an episode of increased dispersion from mid-2015 through mid-2016, mainly due to Ireland sizably outgrowing all other member countries. The onset of the pandemic recession determined a sharp and persistent increase in the divergence measure, only partially offset during the latest part of the sample. Labor market divergence dynamics (ld) show some similarities, clearly pointing to higher divergence in the recession and financial distress phases than during periods of expansion and normal financial conditions. The 2007-2009 Great Recession caused a dramatic increase in the dispersion of unemployment rates, gradually absorbed in the following years to reach very low values (around half of the initial -1999- level) in 2014-2019. Dispersion has again increased during the pandemic recession, to revert back to lower levels in the latest part of the sample.

Inflation rates converged markedly across European countries in the decade preceding the introduction of the Euro (Estrada et al., 2013). This trend was temporarily reversed in 1999-2000, as shown by the increase in the inflation divergence indicator (nd) until the onset of the dot-com financial bubble, and restored after that. A broadly similar pattern is also shown by the competitiveness divergence indicator (cd), though the latter started increasing again in the mid-2000s through early 2003. The convergence of inflation rates and competitiveness conditions in the mid-2000s was almost undone during the subprime financial crisis and the Great Recession (2007-2009) but resumed afterward. On average, both indicators deliver their lowest values over the long expansion period between the end of the sovereign debt recession and the pandemic recession (2013-2020). Since mid-2021, a new divergence phase occurs in correspondence with the inflationary burst, peaking in late 2022. Convergence has then restarted over the more recent period in the sample, concurrent with the recent disinflationary developments in the Eurozone.

Turning to financial markets, the nominal long-term interest rates (bd) and stock market returns (sd) indicators show that the integration process, already in place in the decade leading to the adoption of the Euro as a common currency, proceeded further until the outbreak of the economic and financial crisis in 2007. This pattern is broadly confirmed by the index of financial conditions developed by the European Central Bank (Duprey and Klaus, 2015): the associated divergence measure (fd) shows a downward trend in the first part of the sample, interrupted during the short period of financial distress at the turn of the century. The fact that this index combines information on the money market and on the conditions of the banking sector, along with the bond and stock markets, may explain the temporary reversal in the convergence process. The two economic recessions and the protracted financial turmoil occurred in 2007-2012 caused a sizable increase in all financial divergence indicators, followed by a gradual decline in subsequent years. The pandemic recession and the current geopolitical crisis had a limited impact on bond and stock market divergence, whereas again the dispersion of the overall financial conditions indicator increased substantially, reaching an average level comparable to previous recessions and financial crises.

Finally, the bottom plot of Figure 1 reports evidence for the overall macro-financial indicator (od), summarizing the behavior of the various divergence measures. It points to a sizable convergence in macro-financial conditions in the years from the start of the Eurozone until 2007 and again in the 2013-2019 period. This trend was temporarily reversed in 2008-2012 by economic recessions and financial distress. The pandemic recession marked a new phase of increased macro-financial divergence persisting during the current geopolitical crisis.

Overall, our set of indicators offers a varied picture of convergence dynamics across Eurozone countries since the common currency's inception. Over time, convergence has progressed along all dimensions in economic and financial expansion phases. Yet, divergence has been deeper in periods of economic contraction and financial busts, which have caused persistent setbacks in the convergence process. To investigate these effects more formally, we run the following simple regression for each divergence measure (div_t):

$$\begin{aligned} div_t &= \beta_0 + \beta_1 REC_t + \beta_2 BUST_t + \beta_3 (REC_t \times BUST_t) + \beta_4 PAND_t \\ &\quad + \beta_5 (PAND_t \times REC_t) + \beta_6 GEO_t + u_t \end{aligned} \tag{4}$$

where $div_t = rd_t, ld_t, nd_t, cd_t, bd_t, sd_t, fd_t, od_t$. $REC_t, BUST_t$ and GEO_t are dummy variables taking a unit value only during episodes of economic recessions, financial crises, and geopolitical turmoil, respectively, identified in our previous discussion.[2] We also add $PAND_t$, a step dummy taking unit values since the beginning of the pandemic recession in March 2020, to capture potentially persistent effects of the pandemic on the convergence process. In (4) the estimated parameter $\hat{\beta}_0$ captures the average level of each divergence indicator in periods of normal economic activity and orderly financial markets ($REC_t = 0$ and $BUST_t = 0$), before the pandemic and geopolitical crises ($PAND_t = 0$

[2] REC_t takes a unit value in 2008(3)-2009(6), 2011(6)-2013(3), and 2020(3)-2020(9). $BUST_t$ takes a unit value in 2000(4)-2003(3) and 2007(8)-2012(8). Finally, GEO_t takes a unit value from 2022(2) to the end of the sample, 2023(11).

and $GEO_t = 0$). Those conditions characterize half of the 1999-2023 sample (150 months out of 299). Relative to this benchmark, separate dummies deliver estimates of the average changes in the divergence measures during periods of pre-2020 economic recession but no financial distress ($\hat{\beta}_1$, with $REC_t = 1$ and $BUST_t = 0$), occurring in 7 months in the sample, and during periods of pre-2020 financial crisis without a recession ($\hat{\beta}_2$, with $REC_t = 0$ and $BUST_t = 1$), happening in 66 months. The additional effect of the joint occurrence of pre-2020 economic recessions and financial crises, occurring in 31 months of the sample, is captured by the interaction dummy and estimated as $\hat{\beta}_3$. The introduction of a dummy variable for the whole pandemic period (since February 2020) allows us to separately estimate the effects on the divergence measures (relative to "normal" pre-pandemic times) of the pandemic after the 2020 recession and before the onset of the Ukrainian war ($\hat{\beta}_4$, with $REC_t = 0$ and $GEO_t = 0$), after the start of the war ($\hat{\beta}_4 + \hat{\beta}_6$, with $REC_t = 0$ and $GEO_t = 1$), and also a specific effect of the seven-month pandemic 2020 recession ($\hat{\beta}_1 + \hat{\beta}_4 + \hat{\beta}_5$, with $REC_t = 1$ and $GEO_t = 0$).

Table 2 reports regression estimates for both the unweighted and the GDP-weighted versions of the standard deviation dispersion measures. Three main results stand out. First, most divergence indicators increase significantly during economic recessions and financial crisis episodes in the pre-2020 period, as shown by the estimated coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$, with the partial exception of the inflation and the competitiveness indicators (nd and cd), that display a convergent pattern during recessions. No significant incremental effect of the joint occurrence of recessions and financial distress is found ($\hat{\beta}_3$), with only a negative effect for stock returns. Second, the pandemic started in 2020 caused a persistent increase in divergence ($\hat{\beta}_4$) only for real activity (rd), whereas the significant rise in the unemployment rate dispersion (ld) was entirely reversed in the period of geopolitical turmoil. Finally, the level of several divergence indicators increased significantly from February 2022 ($\hat{\beta}_6$), capturing a sizable rise in the dispersion of inflation rates, competitiveness measures, and overall financial conditions.

As a final piece of descriptive evidence, we assess the dependence of our divergence indicators on the contribution of any individual country by computing each country's net contribution as defined in (2). Table 3 displays the average net contribution of each country to the divergence indicators, with negative values characterizing countries whose inclusion in the sample increases the dispersion of the overall Euro-zone measure. The main conclusion is that the group of net diverging countries is composed by countries that contribute little to the overall Euro-zone GDP. In fact, Cyprus, Estonia, Latvia, Lithuania, and Slovakia are the countries that contribute most to the divergence measures for at least five different indicators. Among larger economies, only Ireland is a net diverging country for the real output dispersion indicator (due to the 2015-2016 burst of growth, as already noticed), and Germany for the bond market dispersion measure.[3]

[3] All the results reported in this Section are largely robust to the use of alternative dispersion measures, namely the absolute mean difference, the distance standard deviation, and the median absolute deviation. See the Online the Appendix (Tables A2-A5).

3 Empirical strategy

The regression results of the previous Section suggest that macroeconomic and financial divergence in the Eurozone can be associated with both the heterogenous response of member countries to common shocks that determined business cycle episodes and financial disruptions over the sample investigated (whose relative importance is roughly captured by the R^2 of the regressions in Table 2) , as well as with idiosyncratic developments in each economy. This finding motivates a deeper investigation of the effect that structural economic forces driving macro-financial fluctuations have on divergence dynamics.

An interesting stylized fact shows that financial cycle fluctuations in advanced countries since the 1980s have shown a much longer periodicity than business cycle fluctuations. Borio et al. (2019) find that the average periodicity of the financial cycle has been between fifteen to twenty years, while the periodicity of the business cycle is estimated up to eight years, but it might have increased up to ten years recently (Beaudry et al., 2020). Hence, more than a business cycle episode can be expected to occur within a financial cycle, and more than a financial cycle within a macroeconomic regime. These features are of empirical relevance for the Eurozone (Morana, 2023; 2024). In fact, Morana (2023) shows that Eurozone medium to long-term fluctuations, occurring with periodicity longer than ten years, are associated with the evolution of the financial cycle, cost-push factors, and economic policy regimes, whereas short-term fluctuations, with periodicity shorter than ten years, are mostly related to demand-side and supply-side business cycle developments.

The same structural shocks that are behind macroeconomic and financial fluctuations can be expected to drive the dynamics of Eurozone macro-financial divergence. We carry out this structural analysis within a (σ-)divergence framework. To our knowledge, there are no similar contributions in the extant Eurozone literature.

Our empirical strategy consists of several steps that we outline in the remainder of this Section, with additional details provided in the Appendix. In the *first* step, common factors determining macroeconomic and financial comovements in the Eurozone in the long- and the short-run are estimated. The starting point is a comprehensive set of twenty-eight ($N = 28$) aggregate macroeconomic and financial variables for the Eurozone, spanning the whole 1999-2023 period and collected in vector $\mathbf{y}_t$. Each series in $\mathbf{y}_t$ is decomposed into a medium- to long-term ($\hat{\mathbf{y}}_{MLT,t}$) and a short-term ($\hat{\mathbf{y}}_{ST,t}$) component, as shown in the Appendix, such that $\mathbf{y}_t = \hat{\mathbf{y}}_{MLT,t} + \hat{\mathbf{y}}_{ST,t}$. Common medium- to long-term (MLT) factors are then extracted from $\hat{\mathbf{y}}_{MLT,t}$ as the first r principal components. A similar procedure is applied to $\hat{\mathbf{y}}_{ST,t}$, delivering s common short-term (ST) factors. The q-element vector $\hat{\mathbf{f}}_t$ (with $q = r + s$) collects the estimated MLT and ST factors, i.e. $\hat{\mathbf{f}}_t \equiv \left[\hat{\mathbf{f}}'_{MLT,t}\ \hat{\mathbf{f}}'_{ST,t}\right]'$.

In the *second* step of the procedure, in order to get insights on the structural economic interpretation of the common factors, we set up the following reduced form factor-augmented vector autoregressive ($FAVAR$) model:

$$\mathbf{E}(L)\ (\mathbf{y}_t - \boldsymbol{\mu}) = \boldsymbol{\Theta}\,\hat{\mathbf{f}}_{t-1} + \mathbf{u}_t \qquad (5)$$

$$\mathbf{C}(L)\,\hat{\mathbf{f}}_t = \mathbf{v}_t \qquad (6)$$

In (5), $\boldsymbol{\mu}$ is a $N \times 1$ mean vector, $\mathbf{u}_t$ is a $N \times 1$ vector of zero-mean serially uncorrelated idiosyncratic disturbances with contemporaneous variance-covariance matrix $\boldsymbol{\Sigma}_{\mathbf{u}}$, $\mathbf{E}(L)$

is a N-dimensional finite-order polynomial matrix in the lag operator with all the roots outside the unit circle, and $\mathbf{\Theta} = [\mathbf{\Theta}'_{MLT}\ \mathbf{\Theta}'_{ST}]'$ is a $N \times q$ matrix of factor loadings. The dynamics of the common factors are specified in (6) by means of a VAR model where $\mathbf{C}(L)$ is a q-dimensional finite-order polynomial matrix in the lag operator with all the roots outside the unit circle, and $\mathbf{v}_t$ is a q-element vector of serially uncorrelated innovations (independent of $\mathbf{u}_t$) with contemporaneous variance-covariance matrix $\mathbf{\Sigma_v}$. The reduced form model in (5) and (6) embodies the assumption that the common factors Granger-cause the macro-financial variables in $\mathbf{y}_t$, with no feedback in the opposite direction. To obtain structural common factor disturbances from the innovations in $\mathbf{v}_t$, we implement a simple Choleski factorization of $\mathbf{\Sigma_v}$, leading to the following relationship between $\mathbf{v}_t$ and a vector of (orthogonal) structural common factor disturbances $\boldsymbol{\varphi}_t$

$$\mathbf{v}_t = \mathbf{\Psi}_{0,qq}\, \boldsymbol{\varphi}_t \tag{7}$$

where $\mathbf{\Psi}_{0,qq}$ is a $q \times q$ lower-triangular matrix. The chosen recursive ordering of the reduced form innovations in $\mathbf{v}_t$ reflects the distinction between MLT, ordered first, and ST common factors, the latter following in the ordering. Under this identification scheme, and assuming a diagonal form for $\mathbf{C}(L)$, structural disturbances to the MLT factors are the only driving forces of medium- to long-term macro-financial fluctuations and affect the ST factors' dynamics. On the contrary, shocks to the latter do not influence the dynamics of MLT factors. Intuitively, shocks that generate macro-financial fluctuations at medium to long-term horizons propagate also in the short-term. Yet, shocks that generate fluctuations in the short-term do not propagate at longer horizons. The economic interpretation of the structural common factor disturbances in $\boldsymbol{\varphi}_t$ is based on the impulse responses of the macroeconomic and financial variables $\mathbf{y}_t$ to each factor shock, and the associated forecast error variance decomposition analysis. To this aim, we use the structural vector moving average representation of the $FAVAR$ model in (5) and (6) (see the Appendix for details). To preview some results discussed more extensively in the next Section, we interpret the MLT factors as mainly related to technological shocks accounting for fluctuations in productivity, potential output, and low-frequency asset prices dynamics (i.e., the "financial cycle"), and to marginal cost disturbances driving wage and price inflation. ST factors are associated with aggregate demand shocks (also attributable to monetary and fiscal policies) and to disturbances that affect short-run aggregate supply.

As the identification of the structural common shocks $\boldsymbol{\varphi}_t$ yields the identification of the common factors $\mathbf{f}_t$ (Bai and Wang, 2015), in the *third* step of the procedure we investigate the role of the identified common factors, $\widehat{\mathbf{f}_t^*} = \hat{\mathbf{\Psi}}_{0,qq}^{-1}\hat{\mathbf{f}}_t$, as drivers of the Euro-zone divergence dynamics measured by the array of indicators presented in the previous Section. To this end, the structural common factor system

$$\mathbf{\Pi}(L)\hat{\mathbf{f}}_t = \boldsymbol{\varphi}_t, \tag{8}$$

where $\hat{\mathbf{\Pi}}(L) = \hat{\mathbf{\Psi}}_{0,qq}^{-1}\hat{\mathbf{C}}(L)$, is employed together with the following reduced form $FAVAR$ model for the seven divergence measures collected in vector $\boldsymbol{\sigma}_t$

$$\mathbf{A}(L)\ (\boldsymbol{\sigma}_t - \boldsymbol{\kappa}) = \mathbf{B}\,\hat{\mathbf{f}}^*_{t-1} + \mathbf{e}_t \tag{9}$$

where $\boldsymbol{\kappa}$ is a constant mean vector, $\mathbf{e}_t$ is a vector of idiosyncratic disturbances (i.e., shocks specific to each measure of divergence), $\mathbf{B}$ is a matrix of factor loadings, and $\mathbf{A}(L)$ is a matrix of finite-order polynomial in the lag operator with $\mathbf{A}_0 = \mathbf{I}$. In (9) the common factors are assumed to Granger-cause the divergence indicators, determining part of their variability over time, whereas feedbacks in the opposite direction are ruled out by the formulation of (8). Then, the relevance of the structural MLT and ST common factors in affecting the dynamics of various dimensions of divergence within the Eurozone is evaluated on the basis of the impulse responses of $\boldsymbol{\sigma}_t$ to the disturbances in $\boldsymbol{\varphi}_t$, and on the associated forecast error variance decomposition analysis at different (business cycle and longer-run) horizons.

The results of the multi-step empirical strategy outlined above are presented in the following two Sections, starting with the estimation and interpretation of the structural common factors in Section 4. Section 5 will assess the role of common factor disturbances as driving forces of Eurozone macro-financial divergence dynamics.

4 The Eurozone macro-finance interface

The dataset used for estimation and identification of the common factors includes twenty-eight monthly variables from January 1999 through November 2023, providing a comprehensive description of the Eurozone macro-finance interface. It comprises aggregate series for real activity and labor market conditions, prices, liquidity, credit, interest rates, and a large set of indicators capturing the state of the main financial markets and of the housing market. All variables are listed in Table 1 of the Appendix, while a detailed description of the dataset is available in the Online Appendix.

As outlined in the preceding Section, each series is decomposed into a medium- to long-term and a short-term components, and principal component analysis (PCA) is applied to the two sets of variables so obtained.[4] PCA results show that the first three principal components estimated from the MLT series account for more than 80% of their total variance, and the first three principal components extracted from the ST series account for around 60%. The periodicity of the estimated PCs is also consistent with the MLT-ST decomposition, pointing to fluctuations in the range of 13.5-16 years and 3.5-4 years for the MLT and ST factors, respectively. For both sets of variables, no further component yields a sizable contribution to accounting for total variance. On this basis, we consider the first three PCs obtained from each set of series, displayed in Figure 2, as capturing the main comovements in the Eurozone macroeconomic and financial conditions, and include them as common factors, collected in vector $\hat{\mathbf{f}}_t$, in the following analysis.

In order to explore the properties of the estimated factors and proceed to their economic interpretation, we estimate the $FAVAR$ model given by (5) and (6), and apply the recursive identification scheme (7), whereby shocks to MLT factors (ordered first) are allowed to originate fluctuations in the ST factors. Impulse response functions of the MLT and ST factors to the structural shocks in $\boldsymbol{\varphi}_t$ are then estimated along with

[4] A complete set of results for the MLT-ST decomposition and PCA are reported in the Online Appendix (Tables A6-A8).

forecast error variance decompositions.[5]

Table 4 reports some selected results, showing the response of the MLT and ST common factors to each structural disturbance (from φ_1 to φ_6) at a 60-month horizon. Also the forecast error variance decomposition ($FEVD$) for the common factors at the same horizon is reported. According to the $FEVD$ results, all factors are mostly driven by a single structural shock; when a second disturbance has a sizable effect on a factor, it belongs to the same MLT or ST variety.[6] The impulse response functions detect some propagation of MLT disturbances to the ST factors, with some statistically significant responses of the latter to φ_2 and φ_3, although those effects account for less than 1% of the forecast error variance of the ST factors. Overall, those findings allow us to consider the first three disturbances (φ_1, φ_2 and φ_3) as structural shocks to the medium- to long-term factors, and the remaining elements (φ_4, φ_5 and φ_6) as structural shocks to the short-term factors.

4.1 Economic interpretation of the structural shocks

To gain some insight on the economic interpretation of the structural shocks $\boldsymbol{\varphi}_t$ we assess at the impulse response functions of the macroeconomic and financial variables $\mathbf{y}_t$ to each element in $\boldsymbol{\varphi}_t$ and the associated forecast error variance decompositions. To this purpose, we use a comprehensive sub-set of 16 (out of 28) Eurozone aggregate macro-financial series. We consider the €-coin GDP growth rate (g), the inflation rate (π), the change in the unemployment rate (u), the real wage growth rate (rw), the real overnight and long-term interest rates (ro and rl), the real M3 growth rate (rm), the credit to GDP ratio (cg), the real effective exchange rate return (rx), the current account to GDP ratio (ca), the fiscal deficit to GDP ratio (fd), the house price to rent ratio (hr), the real stock market return (mk), the New-CISS composite financial condition index (nc), the New York Fed Global Supply Chain Pressure Index (GSCPI; gs), and the real energy price growth rate (re). For each variable, Table 5 shows robust impulse responses to unitary structural shocks at various horizons (3, 12, 36, and 60 months), with standard errors in round brackets. The last two columns of each panel of the Table also report the percentage of the 60-month ahead forecast error variance accounted for by the two sets of structural shocks (MLT and ST)[7], and the fraction explained by the individual disturbances within each set. These measures yield information on the relative importance of the structural shocks in shaping the trend and cyclical components of the macro-financial series. The

[5] Based on the AIC information criterion, $\mathbf{E}(L)$ is set to order five, while the specification of $\mathbf{C}(L)$ is of order one. As detailed in the methodological Appendix, to grant robustness of our results to the lag choice and also to the ordering of the common factors disturbances, we implement a thick modelling estimation procedure, allowing for order randomization within each set of factors, and considering two additional specifications for $\mathbf{E}(L)$, with 4 and 6 lags. The (robust) IRF and $FEVD$ results of this Section are then based on median estimates, and standard errors are obtained through Monte Carlo simulation.

[6] As shown in Table 4, this happens for the second MLT factor (denoted by $\mathbf{f}_{MLT,2}$), whose 60-month ahead forecast error variance is attributed to its "own" shock φ_2 (71%) and to another structural disturbance in the MLT block φ_3 (29%), and for the third ST factor ($\mathbf{f}_{ST,3}$), where φ_5 and φ_6 account for 38% and 61% of the forecast error variance, respectively.

[7] The remaining fraction of the forecast error variance is attributed to idiosyncratic disturbances, specific to each variable in $\mathbf{y}_t$.

Online Appendix contains the impulse response plots (Figures A4-A6) and additional $FEVD$ results (Tables A9-A10).

We now look at the pattern of IRF and $FEVD$ results for each structural common factor disturbance, in order to get a broad picture of their effects on $\mathbf{y}_t$ and offer an economic interpretation.

Medium- to long-term common factor shocks. The responses triggered by the first MLT shock φ_1 suggest the interpretation as a supply-side, *productivity* disturbance: output persistently expands and unemployment declines, along with increasing real wages and a (moderate) negative effect on inflation. This shock is accommodated by an expansion in real money supply and determines an increase in real house prices and a general improvement in overall financial conditions (signalled by a decline of the New-CISS index nc). The fiscal deficit to GDP ratio increases, pointing to a procyclical fiscal policy at the trend level in the Eurozone. As φ_1 is the major driver of the first common MLT factor, which displays a periodicity of 13.5 years (Table 4), it can be considered an important determinant of macro-financial fluctuations occurring in a relatively long period. The fraction of the forecast error variances accounted for by this shock at a business cycle, 60-month horizon (1% for output growth, around 4% for real money growth and housing prices, and below 1% for all other variables), shows a small contribution of long-term productivity disturbances to cyclical fluctuations, consistent with the fact that MLT structural shocks are relevant to account for fluctuations in the trend component of the series and not for the (much more volatile) shorter-term cyclical component.

The same nature of a supply-side shock of φ_1 is shared by the second MLT structural disturbance φ_2, that elicits a strong positive response of the inflation rate along with more moderate (and delayed) negative reactions of output and real wages. These effects may qualify φ_2 as a (cost-push) *trend inflation* disturbance, determining a decline in Eurozone productivity.[8] On the monetary and financial side, we observe a tightening of real liquidity and credit conditions (rm and cg), only partly offset by decreases of real interest rates (ro and rl) pointing to a partial accommodation of the shock by monetary policy. The $FEVD$ results show that φ_2 is the most important contributor to the fluctuations in the inflation rate attributable to long-term common factor dynamics, a finding consistent with the interpretation of this disturbance as originating the supply-driven component of trend inflation.

Finally, the third MLT common factor shock φ_3 triggers a significant *fiscal* expansion from the 12-month horizon onward, along with a sizable decrease of the unemployment rate and some positive effect on real wages. The response of output is positive but not large and a moderate disinflation occurs, together with improvements of the overall financial conditions, the current account and the productivity index (gs). The resulting picture is broadly consistent with the effects of fiscal policies through a productivity channel documented for the US by Jørgensen and Ravn (2022), where a variable technology utilization can account for the above effects in an otherwise standard New-Keynesian framework. In particular, the subdued output response is compatible with the result of a reduced magnitude for the fiscal multiplier in an environment of very low interest rates. On this basis, we relate φ_3 to persistent deviations from the long-run fiscal policy rule

[8] By construction, the GSCPI index (gs) gives some indication about the dynamics of productivity in the Euro area, an increase in the index capturing a productivity decline.

(the compliance of national fiscal policies with the provisions of the Stability and Growth Pact) repeatedly occurred in the Eurozone in the period under study, particularly during the Great Recession, the sovereign debt crisis, and the recent pandemic recession.

Short-term common factor shocks. The remaining common factor structural disturbances (φ_4 to φ_6) are the major driving forces of the factors that shape comovements of the macro-financial variables at a business cycle horizon. We associate the first shock φ_4 to *aggregate demand*, given the positive responses of inflation (long-lasting), and output (absorbed within a year). The decline of the unemployment rate and real wages (due to increased inflation) are consistent with this scenario. The reduction of the real short-term (ro) and long-term (rl) interest rates, together with the depreciation of the real exchange rate (rx) suggest that a candidate underlying source of aggregate demand disturbances could be an expansionary monetary policy. The $FEVD$ results show that, at business cycle horizons, this disturbance accounts almost entirely for the forecast error variance of the inflation rate (99%) and real wages growth (90%).

The $FEVD$ analysis also detects an important role for the second ST disturbance φ_5 in accounting for the cyclical variability of output growth (around 70%) and the unemployment rate (more than 50%). The positive reaction of output associated with a negative (though small) response of inflation point to a *supply-side cyclical* nature for this shock. Different reactions by policy variables are observed, with a rise of the short-term real interest rate and an increase of the fiscal deficit measure (fd). On the financial side, the stock market (mk) responds positively and general financial conditions improve. Finally, the ST disturbance φ_6 explains the bulk of cyclical variations in the fiscal deficit ratio (72%), determining a positive response of fd along with a positive effect on output, a negative response of the unemployment rate, and no impact on inflation. We interpret it as a *cyclical fiscal* shock, capturing fluctuations in the (aggregate) policy stance at a business cycle horizon, differently from the MLT disturbance φ_3 that is related to longer-run fiscal developments. Monetary policy does not accommodate fiscal expansions (the real short-term interest rates showing a rise), and the stock market, house prices (hr) and overall financial conditions improve following output growth.

As a summary of this Section, Figure 3 presents selected results from the historical decomposition of the main macro-financial variables in order to assess the relative contribution of each MLT and ST structural shock. The contribution of φ_1 and φ_5 are plotted against output growth in two panels of the left column: the MLT disturbance φ_1 captures smooth long-run movements of output growth whereas φ_5 closely tracks shorter-run fluctuations. The long-run trend in the inflation rate (declining for most of the sample and rapidly growing in the final years) is captured by the MLT disturbance φ_2, and φ_4 tightly follows the dynamics of the real short-term interest rate. Finally, the two shocks related to fiscal policy capture the long-run evolution of the fiscal deficit to GDP ratio (φ_3) and its cyclical behavior (φ_6).[9]

[9] Additional historical decomposition results are reported in the Online Appendix (Figures A7-A10).

5 A structural analysis of macro-financial divergence in the Eurozone

Having identified some important sources of common variation in the main Eurozone macroeconomic and financial aggregates, we proceed to investigate the role of such disturbances in driving the dynamics of the divergence measures introduced in Section 2. To this aim, we combine the structural common factor model (8) with the reduced $FAVAR$ model (9) for the seven divergence indicators in vector $\boldsymbol{\sigma}_t$. The impulse responses of the various dimensions of the divergence phenomenon to each structural common factor disturbance in $\boldsymbol{\varphi}_t$ are evaluated, together with the $FEVD$ at different horizons. Moreover, we assess the contribution of each structural shock to the evolution of the divergence measures over the sample by means of the historical decompositions of the elements in $\boldsymbol{\sigma}_t$. Figure 4 and 5 show the responses of the divergence indicators to the two sets of MLT and ST common structural disturbances, whereas Table 6 collects the $FEVD$ results. In Figures 6 to 12 the contributions of the six elements in $\boldsymbol{\varphi}_t$ to each divergence measure are displayed over the whole 1999-2023 sample period. We report the historical decomposition for the overall divergence measure in the Online Appendix (Figure A11).

Divergence effects of medium- to long-term common disturbances. As shown in the plots of the left column of Figure 4, a positive *productivity*, long-run common disturbance φ_1 induces macro-financial convergence across Eurozone countries in all the dimensions covered by our set of measures, i.e., a decrease in the divergence indicators. This effect starts within one year and persists at business cycle horizons. A positive realization of φ_1 is associated with a scenario where aggregate productivity increases, leading to an expansion in output, a decline in the unemployment rate, and a moderate surge in asset prices, supported by expanding liquidity and credit within a financially stable environment. Eurozone convergence is thus fostered by favorable economic and financial conditions, as those associated with an expansion of production capacity along the growing phase of the financial cycle. The $FEVD$ results in Table 6 (Panel B) confirm that this common disturbance is the main driving force of the trend fluctuations in the divergence indicators for output growth (rd) and overall financial conditions (fd), accounting respectively for 80% and 60% of the 60-month forecast error variance attributable to MLT common factor shocks. The association of the productivity shock φ_1 with trend fluctuations in these indicators is also supported by the results of the historical decomposition, showing that this disturbance accurately tracks the long-run evolution of rd and fd (in the upper left panels of Figure 6 and 12, respectively).

A positive *trend inflation* disturbance φ_2, which captures an increase in production costs leading to a persistent rise in inflation, a short-lived output contraction, a decline in asset prices, and a worsening of overall financial conditions, is a source of divergence mainly in inflation rates (nd), competitiveness (cd), and in the financial conditions indicator, whereas bond market returns display a convergent dynamics, as shown by the impulse responses in the middle column of Figure 4. The $FEVD$ analysis in Table 6 delivers consistent results, attributing to φ_2 a large share of the forecast error variance of nd and cd accounted by MLT common shocks (46% and 32%, respectively). The historical decomposition results in the upper right panels of Figure 8, 9, 10, and 12 confirm that this shock to trend inflation is able to capture long-run tendencies in the evolution of the inflation rate and competitiveness divergence measures, and in bond market and financial conditions, too.

Finally, a positive *long-run fiscal policy* disturbance φ_3, associated with a trend fiscal expansion determining a decrease in unemployment and an improvement in financial conditions with no substantial effect on output growth, brings about convergence across most dimensions (right column of Figure 4), the exceptions being output growth, diverging in the short-term, and bond market returns, diverging at any horizon. As shown by the $FEVD$ results in Table 6, this shock accounts for large fractions of the long-run dynamics of the divergence indicators for unemployment rates (69%), competitiveness (66%), and, to a lesser extent, inflation rates (46%). The historical decompositions in the middle left plots of Figures 7, 8, and 9 support the role of φ_3 in capturing long-run fluctuations in the labour market, inflation, and competitiveness divergence measures.

Divergence effects of short-term common disturbances. As Table 6 (Panel A) documents, the short-term common factors structural disturbances (φ_4 to φ_6) account for relatively large fractions of the 60-month forecast error variances of the divergence measures, notably in the case of bond returns (65%), unemployment (46%) and inflation rates (44%), and for shares between 20% and 30% of the remaining indicators. In particular, a positive *aggregate demand* (monetary policy) shock φ_4 determines persistent increases in most divergence dimensions (Figure 5, left column), with two notable exceptions: in the case of bond market returns, divergence increases only over a two-year horizon, and, most importantly, over the same short-run horizon, output growth rates show a convergent response that vanishes in the longer term. The historical decompositions show that this common disturbance is closely associated with the short-run fluctuations of the output growth and unemployment divergence measures occurred in the late years of the sample (middle right plots of Figure 6 and 7, respectively). φ_4 also contributes importantly to the forecast error variance of the inflation rate and competitiveness divergence indicators (Table 6, Panel B), showing a dynamics that in the second half of the sample partly offsets the downward trend mainly attributable to MLT disturbances (Figure 8 and 9). A positive *cyclical fiscal* shock φ_6 induces convergence over a three-year horizon along all dimensions with the partial exception of inflation rates (Figure 5, right column). For the latter measure, as well as for the competitiveness indicator, the effect turns into an increased divergence in the long run. The $FEVD$ results in Table 6 (Panel B) show that φ_6 is the major common factor driver at business cycle horizons for the output growth and unemployment divergence measures, accounting for 68% and 37%, respectively, of the total 60-month forecast error variance attributable to ST structural disturbances. The historical decompositions of the rd and ld indicators displayed in Figure 6 and 7 (lower right plots) confirm the sizable contribution of φ_6 to cyclical fluctuations in the real and labour market divergence measures.

Finally, a positive *cyclical supply-side* shock φ_5 has a short-run convergence effect on most indicators, especially concerning output growth, unemployment, and overall financial conditions, although in some cases it is reversed over more extended horizons, as for the competitiveness and stock returns measures (Figure 5, middle column). Over the sample, the contribution of φ_5 to divergence dynamics is larger for the indicator concerning unemployment rates (Figure 7, bottom left plot), and, especially in the final part of the period, for the inflation and competitiveness measures (Figure 8 and 9).

On the whole, the results of the foregoing $FAVAR$ analysis deliver a varied and multifaceted picture of the main common determinants of divergence dynamics in the Eurozone, providing some economic content to the descriptive evidence presented in Section 2. In particular, the detected increase in most divergence indicators during the two pre-2020 recessions and the prolonged period of financial distress broadly covering the years from mid-2007 to early 2013, can be attributed to a mix of long-run and cyclical common factors. For instance, the surge in output growth divergence reflects negative shocks in the long-run productivity trend (φ_1, Figure 6), that are again important in the final part of the sample, when the pandemic recession occurred. In the latter episode, persisting throughout the geopolitical crisis, also the trend cost-push and fiscal shocks (φ_2 and φ_3) have had divergence effects. During the pandemic recession, a sizable contribution to convergence dynamics is coming also from the cyclical demand-side (monetary policy) and fiscal policy stance shocks (φ_4 and φ_6). Moreover, the latter shocks induced convergence also in overall financial conditions during the post-pandemic recovery (Figure 12). Likewise, the downward trend in the inflation divergence measure is captured by the long-run favorable behavior of production costs (φ_2, Figure 9), then reversed toward the end of the last decade, when also short-run demand and supply-side factors (φ_4, φ_5) contributed to divergence dynamics. Offsetting effects were exercised by the cyclical fiscal policy shock (φ_6). Long-run productivity dynamics plays an important role in shaping divergence also in the financial conditions indicator (φ_1, Figure 12), especially in the period of recessions and financial distress, whereas supply-side cyclical factors (φ_5) seem more closely associated with the large fluctuations of this measure during the pandemic recession and the recent geopolitical turmoil. The most recent post-pandemic macro-financial developments and their impact on divergence might be informative about the challenges ahead for the Eurozone integration process. In particular, unfavorable supply-side developments could lead to higher dispersion across member states, with an increase in inflation, output growth, and financial divergence due to adverse productivity growth dynamics and rising production costs. Fiscal policy constraints, as well as restrictive, anti-inflationary monetary policy, could also act as additional divergence factors.

6 Conclusions

This paper investigates the structural drivers of various dimensions of convergence within the Eurozone, also drawing some policy implications in the light of the serious challenges emerged since the pandemic recession and the more recent geopolitical turbulence. It proposes a novel approach to the modelling of macro-financial interlinkages, showing how structural shocks can be extracted from components directly associated with fluctuations occurring at business cycle horizons and at longer ("financial cycle") horizons, within an otherwise standard Factor-Augmented VAR ($FAVAR$) framework.

The empirical relevance of business and financial cycle fluctuations for the Eurozone, as well as for other advanced countries, is a well-established fact according to the most recent results of Borio et al. (2019), Beaudry et al. (2020), and Morana (2023, 2024). Relative to previous contributions, while our approach also exploits the data-rich structural $FAVAR$ framework for the modelling of common macro-financial features, it makes the identification of the structural shocks more accurate. According to standard economic theory, we extract structural disturbances directly from the trend (medium- to long-term) and cyclical (short-term) components that they generate. The estimated shocks have driven and shaped the historical Eurozone business and financial cycles, with estimated durations of four and fifteen years, respectively. We then investigate the common sources of Eurozone macroeconomic and financial convergence and draw policy implications concerning the potential challenges ahead.

The empirical analysis delivers some important insights on the macro-financial convergence process in the Eurozone, disentangling the role of trend and cyclical factors. Among the determinants of trend convergence, productivity dynamics can be singled out as the key factor for all macroeconomic and financial indicators. In particular, productivity fluctuations occurring along the financial cycle have shaped the long swings observed in the dispersion of output growth, unemployment, and overall financial conditions.

Subdued production costs were the crucial driver of Eurozone convergence in inflation rates and competitiveness measures throughout 2015. Subsequently, adverse cost-push shocks turned into a divergence force, determining a burst in the dispersion of most real and financial measures since the pandemic recovery. Were this reversal in supply-side conditions persistent, macro-financial divergence risk would add to the challenges already posed to economic policy within a possible new macroeconomic regime driven by adverse supply-side developments and deglobalization, such as the "Great Reversal" scenario envisaged by Goodhart and Pradhan (2019), Spence (2022), and Roubini (2022a, 2022b).

A third factor in the trend of Eurozone macro-financial dispersion is fiscal policy. The Stability and Growth Pact (SGP) and the associated excessive deficit procedure have ensured broad fiscal discipline and coordination with the area. It has, however, prevented member countries from using national fiscal policies as effective stabilization tools during recessions, apart from the recent pandemic episode. Trend fiscal policy acted as a divergence factor during all recessions in the sample especially for output growth and financial conditions. Cyclical fiscal policy, associated with the suspension of the SGP during the pandemic recession and recovery, fostered overall macro-financial convergence, reducing real, labor market, nominal, and financial dispersion. These results indicate that further progress in Eurozone convergence would be possible were the SGP be turned into a growth tool, not preventing countercyclical fiscal expansions when most needed. Finally, cyclical aggregate demand disturbances, likely related to the common monetary policy stance, have been a convergence force during all recessionary episodes since the Eurozone start, contributing to partially offset the divergent effect of supply-side and fiscal factors.

Looking forward, macro-financial convergence in the Eurozone will be the outcome of countervailing forces operating over different horizons, and will crucially depend on productivity dynamics and economic growth. Unfavorable cost-push developments will endanger it. In the absence of a genuinely pro-growth SGP, the common monetary policy will be the only offsetting policy tool to face the challenges ahead.

Appendix: Econometric implementation

Estimation of the reduced-form FAVAR model in (9) is implemented in three steps. In the first step, the common medium to long-term (MLT) and short-term (ST) Eurozone factors $\mathbf{f}_{MLT}$ and $\mathbf{f}_{ST}$ are estimated. The second step concerns their identification or structuralization. Finally, the third step delivers the estimation and identification of the FAVAR model for the divergence measures.

First step: the Eurozone common macro-financial factors

To estimate the Eurozone common macro-financial factors, we follow Morana (2023, 2024), and consider 28 aggregate series, yielding a comprehensive description of the Eurozone macro-finance interface. All series are stationary or transformed to achieve stationary. Details about the dataset are reported in Table A1 of the Appendix.

The estimation of the common MLT and ST components involves first implementing univariate $MLT-ST$ decompositions considering each of the twenty-eight series individually. Then, the estimation of the common MLT and ST components is implemented by means of Principal Components Analysis (PCA) applied to the set of estimated MLT and ST series.

The univariate MLT-ST decomposition

For each of the 28 macro-financial series in the information set, we implement the univariate decomposition

$$y_{i,t} = y_{MLT,i,t} + y_{ST,i,t}, \tag{A1}$$

using the auxiliary flexible trend model

$$y_{i,t} = \theta_{0,n} + \sum_{j=0.5}^{j^*} \theta_{sx,n,j} \sin(2\pi j x_t^*) + \theta_{cx,n,j} \sin(2\pi j x_t^*) + \epsilon_t, \tag{A2}$$

where x_t is the monthly real EA-20 GDP obtained from quarterly data through cubic spline interpolation (de Boor, C., 1978), and $x_t^* = \sum_{s=1}^{t} x_s / \sum_{t=1}^{T} x_t$ is in the interval $[0, 1]$, θ_0, $\theta_{sx,q,j}$, $\theta_{cx,q,j}$ are parameters, and ϵ_t is a zero mean weakly stationary process.

The MLT or trend function Data Generating Process (DGP) is assumed to be unknown, and approximated, according to the Weierstrass Approximation Theorem, by the Fourier expansion in (A2). It is, then, the conditional expectation $E\left[y_{i,t}|I_t\right]$, where the information set is composed by the terms in the trigonometric polynomial. The ST or cyclical component is measured by the residual component ϵ_t. Under stationarity or trend stationarity, OLS estimation of the regression function in (A2) is $\sqrt{T}$-consistent and asymptotically normal (Morana, 2024). HACSE are required for valid inference in case the residual component ϵ_t is non-spherical. Morana (2024) provides supporting Monte Carlo evidence for the Fourier decomposition approach.

The order of the Fourier expansion j^* is fixed in such a way to model fluctuations in the MLT or trend component with periodicity P^* larger than 10 years, i.e., $j^* = P^*/T$, and, therefore, yielding an ST or cyclical component associated with fluctuations of periodicity shorter than 10 years. The 10-year threshold is set according to stylized facts concerning the financial and business cycles, as in Borio (2014), Borio et al. (2019) and Beaudry et al. (2020). Their empirical evidence for advanced countries point to business cycle episodes with average historical periodicity of up to 8 or 10 years in most countries. Financial cycles show a longer periodicity, typically of 15 to 20 years. Hence, in our application $j^* = 2$, i.e., $j = 0.5, 1, 2$.

A similar decomposition approach has been proposed by Muller and Watson (2018), where the trend component is the cosine transform of the series of interest. Using Fourier (or cosine) polynomials in x_t^* (relative cumulative GDP) rather than in the linear trend, as in the proposed approach, does not alter the periodicity of the extracted components. Still, it alters their shape to reflect the fact that the accumulation of a country's wealth (cumulative income), yielded by economic growth over time, does not occur at a constant pace, differently from the linear time trend component that shows constant increments. The transformation is equivalent to allowing time to flow at a non-constant pace, i.e., to slow down when economic growth declines and accelerate when economic growth speeds up.

Hence, the empirical decomposition for the generic variable i is

$$\begin{aligned} y_{i,t} &= \hat{y}_{i,t} + \hat{\epsilon}_t, \\ &= \hat{y}_{i,MLT,t} + \hat{y}_{i,ST,t}, \end{aligned}$$

yielding the vector decomposition

$$\mathbf{y}_t = \hat{\mathbf{y}}_{MLT,t} + \hat{\mathbf{y}}_{ST,t} \tag{A3}$$

through series-by-series decomposition. Note that the linear projection $\hat{y}_{i,t}$ is the sum of the Fourier transforms up to order j^*.

The estimation of common MLT and ST components

Still following Morana (2024), we assess and estimate common MLT and ST components by PCA. At this stage, we also assume that the $\hat{\mathbf{y}}_{MLT,t}$ components are also zero-mean weakly-stationary or suitably transformed to obtain zero-mean weakly stationary. We have

$$\hat{\mathbf{f}}_{MLT,t} = \hat{\mathbf{D}}_{MLT}^{-1/2} \hat{\mathbf{Q}}'_{MLT} \hat{\mathbf{y}}_{MLT,t},$$

the $r \times 1$ vector of the common MLT factors, as estimated by the r standardized principal components for the MLT series, where $\hat{\mathbf{D}}_{MLT} = diag \left\{ \hat{\lambda}_{MLT_1}, \hat{\lambda}_{MLT_2}, ..., \hat{\lambda}_{MLT_r} \right\}$ is the $r \times r$ diagonal matrix of the non-zero ordered eigenvalues of the sample variance-covariance matrix of the MLT processes $\hat{\mathbf{\Sigma}}_{MLT}$ (rank $r < N$), $\hat{\mathbf{Q}}_{MLT}$ is $N \times r$ matrix of the associated orthogonal eigenvectors. Moreover,

$$\hat{\mathbf{f}}_{ST,t} = \hat{\mathbf{D}}_{ST}^{-1/2} \hat{\mathbf{Q}}'_{ST} \hat{\mathbf{y}}_{ST,t},$$

the $s \times 1$ vector of the common ST factors, as estimated by the s standardized principal components of the ST series, where $\hat{\mathbf{D}}_{ST} = diag \left\{ \hat{\lambda}_{ST_1}, \hat{\lambda}_{ST_2}, ..., \hat{\lambda}_{ST_s} \right\}$ is the $s \times s$ diagonal matrix of the non-zero ordered eigenvalues of the sample variance-covariance matrix of the ST processes $\hat{\mathbf{\Sigma}}_{ST}$ (rank $s < N$), $\hat{\mathbf{Q}}_{ST}$ is $N \times s$ matrix of the associated orthogonal eigenvectors.

Despite their stationarity, the common factors can be strongly persistent. Within our stationarity context, we do not disentangle trend or medium to long-term factors and cyclical or short-term factors on the basis of the traditional I(1) vs. I(0) persistence distinction. Their separation is based on stylized facts about the properties of the financial vs. the business cycle, i.e., according to their different periodicity. Another relevant distinctive element is the different volatility of their driving structural disturbances. MLT factors account for the smooth, underlying evolution over time of macro-financial variables; ST factors account for their relatively more volatile, yet systematic fluctuations. This is akin to Hodrick and Prescott (1997)'s assumption about the smoothness of the output trend induced by the process of economic growth.

Following Bai (2003), the PC estimator of the common factors $\hat{\mathbf{f}} = \begin{pmatrix} \hat{\mathbf{f}}'_{MLT} & \hat{\mathbf{f}}'_{ST} \end{pmatrix}'$ is min $\left\{\sqrt{N}, \sqrt{T}\right\}$ consistent and asymptotically normal for the space spanned by the latent factors. A conjecture in Morana (2024) suggests that the asymptotic results in Bai (2003) holds also in the case the procedure is implemented using the Fourier decomposition of the series rather than the actual series. More formally, Hellton and Thoresen (2014) show that, under additive noise, yet general covariance conditions, PCA is robust to measurement error in the data, increasing PCs variability but not their bias. Even the increase in PCs variability can, however, be taken as negligible for the components associated with the largest eigenvalues, which can be expected to dominate the variance of the noise components. Stochastic cycle plus noise models (Harvey, 1989) can be fitted to the estimated common components to assess their periodicity and the magnitude of their potential observation error. The unobserved irregular component provides a measure of the estimation errors, and its magnitude is given by its variance, which can the be assessed in relative terms using the inverse signal-to-noise ratio. The empirical condition that the latter quantity tends to zero might then be taken as evidence that the estimation error can be neglected and that the factors can be treated as observed.

Second step: the identification/structuralization of the common MLT and ST factors

Despite their economic interpretability, the $q = r + s$ common factors $\hat{\mathbf{f}}_{MLT,t}$ and $\hat{\mathbf{f}}_{ST,t}$ are not identified without further restrictions, i.e., it is always possible to premultiply the factors with an arbitrary full rank matrix of appropriate order to define a new model which is observationally equivalent to the factor model. We follow Bai and Wang (2015) and impose the needed q^2 identification restrictions on the factors innovations $\mathbf{v}_t$. This requires the explicit modelling of the dynamics in the common MLT and ST factors, consistent with the model specification. The reduced form FAVAR model for the N ($N = 28$) actual series of interest $\mathbf{y}_t$ is

$$\mathbf{E}(L)\left(\mathbf{y}_t - \boldsymbol{\mu}\right) = \mathbf{\Theta}\hat{\mathbf{f}}_{t-1} + \mathbf{u}_t \tag{A4}$$

$$\mathbf{C}(L)\hat{\mathbf{f}}_t = \mathbf{v}_t \tag{A5}$$

where $\boldsymbol{\mu}$ is the $N \times 1$ mean vector, $\mathbf{u}_t$ is a $N \times 1$ vector of zero-mean $i.i.d.$ idiosyncratic disturbances with variance-covariance matrix $\mathbf{\Sigma}_u$, $\mathbf{E}(L)$ is a diagonal polynomial matrices in the lag operator of finite order with all the roots outside the unit circle

$$\mathbf{E}(L) = diag\left(e_1(L), ..., e_2(L), ..., e_N(L)\right),$$

where $e_i(L) = 1 + e_{1,i}L + e_{2,i}L^2, ...,\ i = 1, ..., N$, $\hat{\mathbf{f}}_t = \left(\begin{array}{cc} \hat{\mathbf{f}}'_{MLT,t} & \hat{\mathbf{f}}'_{ST,t} \end{array} \right)'$ is the $q \times 1$ zero-mean vector of common factors estimated by PCA, $\mathbf{\Theta} = \left(\begin{array}{cc} \mathbf{\Theta}'_{MLT} & \mathbf{\Theta}'_{ST} \end{array} \right)'$ is the $N \times q$ factor loading matrix. The dynamics in the common factors are modelled by means of an unobserved stationary diagonal VAR(1) model (Harvey, 1989). The unobserved AR(1) model emerges as a special case of the unobserved stochastic cycle model. We use it as a parsimonious approximation to allow for estimation in a classical framework, even when the number of factors is relatively large as in our application, and control for measurement errors. Hence, $\mathbf{C}(L)$ is a diagonal polynomial matrix in the lag operator $\mathbf{C}(L)$ with all the roots outside the unit circle

$$\mathbf{C}(L) = diag\left(c_1(L), ..., c_q(L)\right),$$

where $c_i(L) = 1 + c_i L$, $i = 1, ..., q$, $\mathbf{v}_t$ is $q \times 1$ vectors of zero-mean $i.i.d.$ common factors disturbances with variance-covariance matrix $\mathbf{\Sigma}_v$, which is not diagonal, allowing, therefore, interlinkages across factors.

The reduced form model in (A4) and (A5) assumes that the common factors Granger-cause the actual series, but not the other way around. Moreover, in order to avoid multicollinearity issues, no Granger-causality is allowed across variables, i.e., no spillover of idiosyncratic innovations is allowed across variables. As the focus is on the propagation of the common MLT and ST shocks, the diagonal FAVAR model is not restrictive for our purposes.

Following Bernanke et al. (2005), consistent and asymptotically normal estimation of the FAVAR model in (A4) is performed conditional to the PCA estimates of the MLT and ST common factors. However, differently from Bernanke et al. (2005), the dynamics in the common factors in (A5) are estimated via MLE and the Kalman filter. This allows to control for measurement errors when assessing common factors dynamics. As idiosyncratic dynamics are not feeding back to the common factors, the disjoint estimation of the two equation blocks in (A4) and (A5) does not affect consistency and asymptotic normality, but only efficiency. Asymptotic efficiency is attained by joint estimation of (A4) and (A5) by restricted 3-SLS, imposing the MLE-Kalman filter estimates $\hat{\mathbf{C}}(L)$. Efficient estimation is viable in our application, as the 3SLS and the SURE estimators coincide.

The reduced form VMA representation of the FAVAR model in (A4) and (A5) is

$$\mathbf{z}_t = \mathbf{F}(L)^{-1}\mathbf{o}_t, \tag{A6}$$

where $\mathbf{z}_t = \left(\begin{array}{cc} \hat{\mathbf{f}}'_t & \mathbf{y}'_t \end{array} \right)'$, neglecting $\boldsymbol{\mu}$ for simplicity, $\mathbf{o}_t = \left(\begin{array}{cc} \mathbf{v}'_t & \mathbf{u}'_t \end{array} \right)'$ with variance-covariance matrix $\mathbf{\Sigma}_o$, and

$$\mathbf{F}(L) = \left(\begin{array}{cc} \mathbf{C}(L) & \mathbf{0} \\ -\mathbf{\Theta}L & \mathbf{E}(L) \end{array} \right), \tag{A7}$$

while its structural form is

$$\mathbf{z}_t = \mathbf{\Psi}(L)\,\boldsymbol{\epsilon}_t, \tag{A8}$$

where $\boldsymbol{\epsilon}_t = \begin{pmatrix} \boldsymbol{\varphi}_t' & \boldsymbol{\lambda}_t' \end{pmatrix}'$ is the $M = N + q \times 1$ vector of structural shock with identity $\mathbf{I}$ variance-covariance matrix.

Since the first element of $\mathbf{F}(L)$ is the identity matrix $\mathbf{I}$, equating the first term of the right-hand sides of (A6) and (A8) yields the following relationship between the reduced form and the structural shocks:

$$\mathbf{o}_t = \mathbf{\Psi}_0\,\boldsymbol{\epsilon}_t, \tag{A9}$$

where $\mathbf{\Psi}_0$ is an invertible matrix. Hence, comparison of (A8) and (A6) shows that

$$\mathbf{F}(L)^{-1}\mathbf{\Psi}_0 = \mathbf{\Psi}(L),$$

implying that $\mathbf{F}_i^{-1}\mathbf{\Psi}_0 = \mathbf{\Psi}_i$ $(\forall i > 0)$, $\mathbf{F}(1)^{-1}\mathbf{\Psi}_0 = \mathbf{\Psi}(1)$, and $\mathbf{\Sigma_o} = \mathbf{\Psi}_0'\mathbf{\Psi}_0$ since, by assumption, the structural factor shocks are orthogonal and have unit variance. This yields $M \times (M+1)/2$ restrictions.

The identification of all the structural shocks $\boldsymbol{\epsilon}_t$ would require additional $(M \times (M-1)/2)$ restrictions, as for instance, the requirement of a lower triangular structure for the impact matrix $\mathbf{\Psi}_0$, as delivered by the Cholesky decomposition of $\mathbf{\Sigma_o}$, yielding $\mathbf{\Psi}_0 = chol(\mathbf{\Sigma_o})'$.

The recursive ordering implies that structural MLT and ST shocks exercise a contemporaneous impact on the N macro-financial variables but not the other way around. The lack of propagation of the structural idiosyncratic shocks on the common factors is also what is implied by the block recursive structure in (A7). Idiosyncratic fluctuations do not affect the fundamental common factors dynamics. It also implies that MLT structural shocks can exercise a contemporaneous and dynamic impact on the ST common factors, but the MLT common factors are not affected by the ST structural shocks. The propagation of the MLT shocks starts in the short-term and continue at longer horizons, and therefore affect the ST component of macroeconomic and financial series. This is consistent with a standard view of economic fluctuations, whereby the structural trend disturbances can cause fluctuations at business cycle horizons, too, but the structural disturbances that feed cyclical fluctuations at business cycle horizons do not feed trend fluctuations: structural MLT shocks affect macro-financial variables MLT and ST components but structural ST shocks affect their ST components only. Finally, the distinction between fast-moving and slow-moving variables can help to justify the ordering of the macro-financial variables. Hence, under the identification restrictions, the $\mathbf{\Psi}_0$ matrix is

$$\mathbf{\Psi}_0 = \begin{pmatrix} \underset{(r\times r)}{\mathbf{\Psi}_{0,rr}} & \underset{(r\times s)}{\mathbf{0}} & \underset{(r\times N)}{\mathbf{0}} \\ \underset{(s\times r)}{\mathbf{\Psi}_{0,sr}} & \underset{(s\times s)}{\mathbf{\Psi}_{0,ss}} & \underset{(s\times N)}{\mathbf{0}} \\ \underset{(N\times r)}{\mathbf{\Psi}_{0,Nr}} & \underset{(N\times s)}{\mathbf{\Psi}_{0,Ns}} & \underset{(N\times N)}{\mathbf{\Psi}_{0,NN}} \end{pmatrix}, \tag{A10}$$

where also $\mathbf{\Psi}_{0,rr}$, $\mathbf{\Psi}_{0,ss}$, and $\mathbf{\Psi}_{0,NN}$ are lower triangular matrices. Their form implies a recursive ordering within each set of variables, i.e., MLT common components, ST common components, and macro-financial variables.

As we are only interested in the identification of the structural common factors and their disturbances, we can neglect the potential impact of the ordering of the macro-financial variables on $\mathbf{\Psi}_{0,Nr}$, $\mathbf{\Psi}_{0,Ns}$, $\mathbf{\Psi}_{0,NN}$. Hence, the focus is on the recursive structure on the $q \times q$ submatrix in (A10)

$$\mathbf{\Psi}_{0,qq} = \begin{pmatrix} \underset{(r\times r)}{\mathbf{\Psi}_{0,rr}} & \underset{(r\times s)}{\mathbf{0}} \\ \underset{(s\times r)}{\mathbf{\Psi}_{0,sr}} & \underset{(s\times s)}{\mathbf{\Psi}_{0,ss}} \end{pmatrix},$$

that adds $q \times (q-1)/2$ restrictions to the $q \times (q+1)/2$ yielded by the orthonormality of the structural common factor innovations, obtaining the q^2 restrictions needed in total for the identification of the common MLT and ST factors (Bai and Wang, 2015). This can be obtained through the Cholesky decomposition of the variance-covariance matrix $\mathbf{\Sigma}_v$, yielding $\mathbf{\Psi}^*_{0,qq} = chol(\mathbf{\Sigma_v})'$. The identified common factors used in the divergence analysis (third step of the procedure) are then estimated as

$$\widehat{\mathbf{f}^*}_t = \hat{\mathbf{\Psi}}^{-1}_{0,qq}\hat{\mathbf{f}}_t, \tag{A11}$$

where $\hat{\mathbf{\Psi}}^{-1}_{0,qq}$ is the upper $q \times q$ submatrix in $\hat{\mathbf{\Psi}}^{-1}_0$. The structural form of the reduced form model in (A5) is similarly estimated as

$$\hat{\mathbf{\Pi}}(L)\hat{\mathbf{f}}_t = \hat{\boldsymbol{\varphi}}_t$$

where $\hat{\mathbf{\Pi}}(L) = \hat{\mathbf{\Psi}}^{-1}_{0,qq}\hat{\mathbf{C}}(L)$.

We allow for policy analysis robustness to the ordering of the common factors by implementing a randomized triangularization, i.e., through randomizing the relative positions of the common factors within each category. Hence, still maintaining the relative ordering of the two categories, i.e., MLT common factors first, the ST common factors next, we randomly shift the MLT factors within their own set and similarly for the common ST factors. We use 1000 replications for this procedure. Following Granger and Jeon (2004), we also control for the impact of the lag order for the matrix $\mathbf{E}(L)$ and, in addition to the optimally selected lag order according to the AIC information criterion, consider two alternative lag structures by increasing and decreasing the optimal order by one lag. The median estimate of the matrix $\mathbf{\Psi}_0$, out of the 3000 computed, is then employed for the structuralization of the shocks and the impulse response analysis and the forecast error variance decomposition. The same procedure is followed for the computation of the impulse responses standard errors, considering 1000 Monte Carlo replication. In this case, the number of randomized orderings is set to 30, yielding a total of 9000 alternative impulse response structures.

Impulse responses and forecast error variance decomposition for the structural common factor innovations $\boldsymbol{\varphi}_t$ can then be computed using (A8) for the variable of interest $\mathbf{y}_t$. In this respect, the variance of the h-step forecast of the generic variable j is

$$V[y_{j,t}(h)] = \sum_{i=0}^{h-1}\sum_{l=1}^{N+q}\left(e_j'\mathbf{\Psi}_j e_l\right)^2$$

where e_j is the j-th column of $\mathbf{I}_{N+q}$. The share of forecast error variance of variable j accounted for by the generic shock l is

$$w_{jl}(h) = \frac{\sum_{i=0}^{h-1} \left(e_j' \mathbf{\Psi}_j e_l\right)^2}{V[y_{j,t}(h)]}.$$

We can further disentangle the contribution of the $r+s$ structural shocks that drive the MLT and ST common factors $\boldsymbol{\varphi}$ from the contribution of the N idiosyncratic disturbances. We then have

$$\frac{\sum_{l=1}^{r} \sum_{i=0}^{h-1} \left(e_j' \mathbf{\Psi}_j e_l\right)^2}{V[y_{j,t}(h)]} + \frac{\sum_{l=r+1}^{r+s} \sum_{i=0}^{h-1} \left(e_j' \mathbf{\Psi}_j e_l\right)^2}{V[y_{j,t}(h)]} + \frac{\sum_{l=r+s+1}^{r+s+N} \sum_{i=0}^{h-1} \left(e_j' \mathbf{\Psi}_j e_l\right)^2}{V[y_{j,t}(h)]} = 1.$$

More specifically, we can compute the relative contribution of each of the $r+s$ structural shocks as

$$s_{jl}(h)_{MLT} = \frac{\sum_{i=0}^{h-1} \left(e_j' \mathbf{\Psi}_j e_l\right)^2}{\sum_{l=1}^{r} \sum_{i=0}^{h-1} \left(e_j' \mathbf{\Psi}_j e_l\right)^2}$$

for $l = 1, .., r$ for the shocks that drive the common MLT factors and

$$s_{jl}(h)_{ST} = \frac{\sum_{i=0}^{h-1} \left(e_j' \mathbf{\Psi}_j e_l\right)^2}{\sum_{l=r+1}^{r+s} \sum_{i=0}^{h-1} \left(e_j' \mathbf{\Psi}_j e_l\right)^2}$$

for $l = r+1, .., r+s$ for the shocks that drive the common ST factors. The latter statistics yields information on the relative importance of each structural shocks in the determination of the MLT and ST components for the variable of interest j, i.e., they yield the forecast error variance decomposition for the MLT (trend) and ST (cycle) components.

Third step: the structural divergence analysis

Empirically, we start from the following (semi) reduced-form Factor-Augmented VAR model

$$\mathbf{A}(L)\left(\boldsymbol{\sigma}_t - \boldsymbol{\mu}\right) = \mathbf{B}\hat{\mathbf{f}}_{t-1}^* + \mathbf{e}_t \tag{A12}$$

$$\hat{\mathbf{\Pi}}(L)\hat{\mathbf{f}}_t = \hat{\boldsymbol{\varphi}}_t \tag{A13}$$

where $\boldsymbol{\sigma}_t$ is a $p \times 1$ vector of divergence measures, $\boldsymbol{\mu}$ is the $p \times 1$ mean vector, $\mathbf{e}_t$ is a $p \times 1$ vector of zero-mean reduced form idiosyncratic (or divergence-measure specific) disturbances with variance-covariance matrix $\mathbf{\Sigma}_e$. $\mathbf{A}(L)$ is a finite order polynomial matrix in the lag operator with all the roots outside the unit circle, $\mathbf{B}$ is a $p \times q$ factor loading matrix, and $\widehat{\mathbf{f}}^*$ are the estimated identified/structural MLT and ST common factors in (A11). Hence, while the divergence measures system in (A12) is in reduced form, the common factor system in (A13) is in structural form, as delivered by the second step in our analysis. The model in (A12) and (A13) assumes that the common factors Granger-cause the divergence measures, but not the other way around. The rationale is that structural common factor disturbances might be expected to account for at least some of the variability of the divergence measures. Yet, idiosyncratic, divergence measure-specific disturbances are not feeding to the common structural factors.

Consistent and asymptotically normal estimation of the FAVAR model in (A12) is performed conditional to the estimated identified/structural MLT and ST common factors $\hat{\mathbf{f}}^{*}$ (Bernanke et al., 2005). As idiosyncratic dynamics are not feeding to the common factors, the disjoint estimation of the two equation blocks in (A12) and (A13) does not affect consistency and asymptotic normality, but only efficiency. Asymptotic efficiency is however attained by restricted 3-SLS estimation, imposing the MLE-Kalman filter estimates $\hat{\mathbf{\Pi}}(L)$.

Upon estimation, the $n \times 1$, $n = p + q$ vector of (semi) reduced form disturbances

$$\mathbf{w}_t = \begin{pmatrix} \boldsymbol{\varphi}_t \\ \mathbf{e}_t \end{pmatrix}$$

is transformed into a full vector of structural shocks

$$\boldsymbol{\xi}_t = \begin{pmatrix} \boldsymbol{\varphi}_t \\ \boldsymbol{\kappa}_t \end{pmatrix},$$

where the structural disturbances $\boldsymbol{\kappa}_t$ accounts for *idiosyncratic* fluctuations in the divergence measures, and $\boldsymbol{\varphi}_t$ for their *fundamental* common fluctuations. As detailed in the second step, the structural common shocks $\boldsymbol{\varphi}_t$ can be further disentangled in those critically inducing medium to long-term fluctuations in economic and financial variables, i.e., $\boldsymbol{\varphi}_{i,t}$, $i = 1, .., r$, and some other critically driving their short-term fluctuations, i.e., $\boldsymbol{\varphi}_{j,t}$, , $j = r + 1, .., r + s$.

The (semi) reduced form VMA representation of the FAVAR model in (A12) and (A13) is

$$\mathbf{x}_t = \mathbf{D}(L)_t^{-1}\mathbf{w}_t, \tag{A14}$$

where $\mathbf{x}_t = \begin{bmatrix} \hat{\mathbf{f}}_t^{*\prime} & \boldsymbol{\sigma}_t^{2\prime} \end{bmatrix}'$, neglecting $\boldsymbol{\mu}$ for simplicity, and

$$\mathbf{D}(L) = \begin{pmatrix} \mathbf{\Pi}(L) & \mathbf{0} \\ -\mathbf{B}L & \mathbf{A}(L) \end{pmatrix},$$

while its full structural form is

$$\mathbf{x}_t = \mathbf{\Gamma}(L)\,\boldsymbol{\xi}_t. \tag{A15}$$

Since the first element of $\mathbf{D}(L)$ is the identity matrix $\mathbf{I}$, equating the first term of the right-hand sides of (A14) and (A15) yields the following relationship between the (semi) reduced form and the structural shocks

$$\mathbf{w}_t = \mathbf{\Gamma}_0\,\boldsymbol{\xi}_t,$$

where $\mathbf{\Gamma}_0$ is the invertible matrix

$$\mathbf{\Gamma}_0 = \begin{pmatrix} \mathbf{I}_q & \mathbf{0}_{q,p} \\ \mathbf{\Gamma}_{0,p,q} & \mathbf{\Gamma}_{0,pp} \end{pmatrix} \tag{A16}$$

Also, comparison of (A14) and (A15) shows that

$$\mathbf{D}(L)^{-1}\mathbf{\Gamma}_0 = \mathbf{\Gamma}(L),$$

implying that $\mathbf{D}_i^{-1}\mathbf{\Gamma}_0 = \mathbf{\Gamma}_i$ $(\forall i > 0)$, $\mathbf{D}(1)^{-1}\mathbf{\Gamma}_0 = \mathbf{\Gamma}(1)$, and

$$\mathbf{\Sigma_w} = \mathbf{\Gamma}_0\mathbf{\Gamma}_0'$$

since, by assumption, the structural shocks are orthogonal and have unit variance, and where

$$\mathbf{\Sigma_w} = \begin{pmatrix} \mathbf{I}_q & \mathbf{\Sigma}_{\boldsymbol{\varphi},\mathbf{e}} \\ \mathbf{\Sigma}_{\boldsymbol{\varphi},\mathbf{e}}' & \mathbf{\Sigma_e} \end{pmatrix},$$

and the $q \times p$ submatrix $\mathbf{\Sigma}_{\boldsymbol{\varphi},\mathbf{e}}$ contains the covariances between the structural common factors disturbances and the reduced form divergence measures idiosyncratic disturbances. The impact matrix $\mathbf{\Gamma}_0$ (A16) can, then, be readily obtained through the Cholesky decomposition of $\mathbf{\Sigma_w}$, i.e., $\mathbf{\Gamma}_0 = chol(\mathbf{\Sigma_w})'$.

The contemporaneous impact of the structural common factor disturbances $\boldsymbol{\varphi}$ on the divergence measures is yield by the submatrix $\mathbf{\Gamma}_{0,p,q}$. As described in the second step of the procedure, the identification of the structural common factor disturbances $\boldsymbol{\varphi}$ relies on the assumption that both short-term and medium to long-term macro-financial fluctuations can originate from the MLT structural shocks, but that ST structural disturbances can only generate short-term fluctuations. The assessment of the divergence/convergence impact of the common shocks is the focus of the paper. Hence, the additional results concerning the structural idiosyncratic divergence measures disturbances are included in the Online Appendix.

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Table A1: Dataset composition			
Eurozone disaggregate country member data			
Data	**Source**	**Data**	**Source**
Industrial production growth	Eurostat	Nominal 10-year government bond rate	ECB
Harmonized unemployment rate	Eurostat	Nominal share prices	OECD
Real broad effective exchange rate return	BIS	Composite Indicator of Financial Conditions CLIFS	ECB
Harmonized CPI	Eurostat		
Euro Area aggregate data			
Data	**Source**	**Data**	**Source**
€-coin GDP growth	BoI	Total credit to the private nonfinancial sectors-to-GDP ratio	BIS
Harmonized unemployment rate	Eurostat	House price index-to-GDP ratio	OECD
Current account-to-GDP ratio	OCED	House price index-to-net disposable income per head ratio	OECD
Fiscal deficit-to-GDP ratio	ECB	House price index-to-rent ratio	OECD
Harmonized CPI	Eurostat	Real gold price index return	IMF
Real earnings for manufacturing growth rate	OECD	Real European Fama-French market factor return	F-F
Real narrow effective exchange rate return	BIS	3-month Euribor rate - €STR spread	ECB
Global supply-chain pressure index	NY Fed	10-year government bond rate - €STR spread	ECB
Real energy price index return	IMF	Composite Indicator of Systemic Sovereign Stress SovCISS	ECB
Real Euro Short-Term Rate €STR	ECB	Euro Soxx 50 (implied) Volatility VSTOXX	Eurex
Real 3-month Euribor rate	ECB	New Composite Indicator of Systemic Stress New-CISS	ECB
Real 10-year government bond rate	ECB	Real European Fama-French size factor return	F-F
Real M3 index of notional stocks growth rate	ECB	Real European Fama-French value factor return	F-F
Excess nominal M3 growth	ECB/BoI	Real European Charart momentum factor return	F-F

The Table reports information on the data employed in the study. Details about data construction are available in Section A1 of the Online Appendix.

Table 1: Divergence statistics						
	ALL	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**
rd	5.91	6.64	5.78	6.15	5.60	7.38
ld	12.53	19.38	11.32	16.16	10.92	9.70
nd	1.55	1.56	1.55	1.80	1.21	3.30
cd	2.07	2.00	2.09	2.49	1.75	2.94
bd	1.45	2.74	1.22	2.13	1.17	0.65
sd	19.13	24.38	18.20	24.85	16.87	12.17
fd	6.76	9.74	6.23	9.40	4.90	10.51
od	0.73	0.96	0.69	0.90	0.62	0.87

This Table reports the average figures for the divergence indicators computed over the whole sample (*ALL*), recessions (*REC*) and expansions (*EXP*), financial busts (*BUST*) and booms (*BOOM*), and over the most recent period of economic and financial distress started by the war in Ukraine (GEO). Figures are for real divergence (*rd*), labor market divergence (*ld*), nominal divergence (*nd*), competitiveness divergence (*cd*), bond market divergence (*bd*), stock market divergence (*sd*), financial conditions divergence (*fd*), and overall divergence (*od*).

Table 2: Divergence indicators and economic and financial distress								
	rd		***ld***		***nd***		***cd***	
Estimated coeff. on:	***SD***	***wSD***	***SD***	***wSD***	***SD***	***wSD***	***SD***	***wSD***
Const. (β_0)	**5.108** (0.190)	**3.327** (0.144)	**10.365** (0.454)	**7.270** (0.342)	**1.222** (0.102)	**0.790** (0.057)	**1.860** (0.206)	**1.168** (0.110)
REC (β_1)	**0.470** (0.236)	-0.263 (0.285)	**4.093** (0.652)	**2.594** (0.777)	**-0.240** (0.110)	-0.069 (0.057)	**-0.731** (0.208)	**-0.278** (0.128)
BUST (β_2)	**0.980** (0.330)	**0.606** (0.212)	**3.317** (1.190)	**2.957** (1.176)	**0.574** (0.162)	**0.448** (0.110)	**0.676** (0.319)	**0.631** (0.236)
REC x BUST (β_3)	-0.261 (0.548)	0.707 (0.484)	3.675 (2.844)	4.730 (2.464)	0.265 (0.401)	0.041 (0.251)	0.603 (0.512)	0.340 (0.411)
PAND (β_4)	**3.412** (0.781)	**4.116** (0.890)	**2.206** (1.115)	**3.452** (0.961)	0.111 (0.241)	0.148 (0.154)	**-0.581** (0.297)	-0.033 (0.248)
PAND x REC (β_5)	0.217 (2.451)	2.614 (2.580)	-1.506 (1.321)	2.581 (1.989)	-0.100 (0.259)	-0.162 (0.157)	0.496 (0.298)	-0.109 (0.253)
GEO (β_6)	-1.139 (0.824)	-1.676 (0.940)	**-2.870** (1.180)	**-4.258** (1.153)	**1.969** (0.418)	**1.385** (0.270)	**1.659** (0.341)	**1.328** (0.390)
R2	0.280	0.456	0.435	0.499	0.417	0.505	0.152	0.244
R2 adj.	0.262	0.443	0.422	0.487	0.403	0.493	0.132	0.226
	bd		***Sd***		***fd***		***od***	
	SD	***wSD***	***SD***	***wSD***	***SD***	***wSD***	***SD***	***wSD***
Const. (β_0)	**1.199** (0.121)	**1.745** (0.264)	**17.094** (1.646)	**9.524** (0.731)	**4.765** (0.427)	**3.984** (0.389)	**0.601** (0.031)	**0.859** (0.037)
REC (β_1)	**1.911** (0.406)	**4.219** (0.949)	**10.046** (1.965)	**3.568** (1.950)	**3.064** (0.991)	**2.451** (0.890)	**0.197** (0.044)	**0.589** (0.173)
BUST (β_2)	**0.460** (0.212)	0.101 (0.472)	**7.132** (2.081)	**4.779** (1.262)	**3.778** (0.780)	**2.931** (0.715)	**0.229** (0.038)	**0.282** (0.070)
REC x BUST (β_3)	-0.439 (0.706)	-0.840 (1.684)	**-8.093** (3.087)	-4.066 (2.392)	-0.391 (1.644)	-0.751 (1.378)	0.030 (0.083)	0.028 (0.202)
PAND (β_4)	**-0.811** (0.124)	**-1.177** (0.268)	**-5.126** (1.771)	**-2.027** (0.829)	0.070 (0.601)	-0.142 (0.522)	0.041 (0.034)	0.169 (0.062)
PAND x REC (β_5)	**-1.690** (0.409)	**-3.933** (0.953)	**-8.339** (2.156)	-1.848 (2.25)	**-2.778** (1.131)	**-2.089** (0.970)	**-0.159** (0.076)	-0.345 (0.250)
GEO (β_6)	**0.259** (0.066)	**0.263** (0.087)	0.202 (1.194)	0.918 (0.879)	**5.672** (0.641)	**5.074** (0.648)	**0.230** (0.042)	0.180 (0.097)
R2	0.439	0.333	0.256	0.234	0.466	0.373	0.493	0.564
R2 adj.	0.425	0.317	0.238	0.216	0.452	0.358	0.481	0.553

The Table reports the regression results for the (unweighted) standard deviation (SD) and the GDP-weighted standard deviation (wSD) measures. HACSE are reported in square brackets. R2 and R2 (adj.) are the unadjusted and adjusted coefficients of determination. The figures are for various indicators: real divergence (*rd*), labor market divergence (*ld*), nominal divergence (*nd*), competitiveness divergence (*cd*), bond market divergence (*bd*), stock market divergence (*sd*), financial conditions divergence (*fd*), aggregate macro-financial divergence (*od*).

Table 3: Average country net contributions to cross-sectional variance								
	rd	***ld***	***nd***	***cd***	***bd***	***sd***	***fd***	***od***
AT	0.12	**-0.02**	0.02	0.04	0.03	0.32	0.10	0.09
BE	0.08	0.15	0.02	0.04	0.02	0.38	0.05	0.10
HR	0.08	0.10	0.03	**-0.01**	**-0.01**	0.11	0.03	0.06
CY	**-0.02**	**-0.21**	0.01	0.02	**-0.08**	**-2.98**	**-0.06**	**-0.03**
EE	**-0.14**	**-0.64**	**-0.05**	**-0.02**	**-0.04**	**-0.13**	.	**-0.20**
FI	0.08	0.18	0.02	0.03	0.03	0.15	0.10	0.10
FR	0.12	0.21	0.02	0.03	0.01	0.43	0.09	0.11
DE	0.12	0.17	0.02	0.02	**-0.29**	0.35	0.06	0.07
GR	0.02	0.03	0.00	0.01	0.03	**-0.36**	**-0.23**	0.01
IE	**-0.81**	**-0.17**	0.01	**-0.05**	0.03	0.21	**-0.51**	**-0.29**
IT	0.09	0.16	0.03	0.04	**-0.01**	0.40	0.10	0.11
LV	0.01	**-0.12**	**-0.12**	**-0.15**	**-0.01**	**-0.11**	**-0.08**	**-0.27**
LT	**-0.17**	**-0.45**	**-0.05**	**-0.07**	0.00	**-0.11**	**-0.02**	**-0.22**
LU	0.04	**-0.18**	0.02	0.03	0.03	**-0.01**	0.02	0.04
MT	**-0.11**	0.07	0.02	0.03	0.02	**-0.10**	**-0.05**	0.02
NL	0.07	0.04	0.02	0.03	0.01	0.40	0.02	0.07
PT	0.04	0.08	0.02	0.03	0.03	0.34	0.04	0.07
SK	**-0.10**	0.01	**-0.10**	**-0.20**	0.02	**-0.49**	**-0.05**	**-0.30**
SI	0.09	0.13	**-0.02**	0.04	0.04	**-0.05**	0.05	0.06
ES	0.11	0.17	0.03	0.04	0.02	0.32	0.08	0.12

The Table reports each country's average net contribution to the divergence measures, computed as in equation (2) in the text. The figures are for: real divergence (*rd*), labor market divergence (*ld*), nominal divergence (*nd*), competitiveness divergence (*cd*), bond market divergence (*bd*), stock market divergence (*sd*), financial conditions divergence (*fd*), and overall divergence (*od*). Figures in bold denote diverging countries (negative net contribution statistics). Data are for the EA-20 countries, i.e. Austria (AT), Belgium (BE), Croatia (HR), Cyprus (CY), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Luxembourg (LU), Malta (MT), the Netherlands (NL), Portugal (PT), Slovakia (SK), Slovenia (SI), Spain (ES).

Table 4: Robust impulse responses of common *MLT* and *ST* factors and forecast error variance accounted by structural shocks

	IRF	FEVD		IRF	FEVD		IRF	FEVD		IRF	FEVD		IRF	FEVD		IRF	FEVD
$f_{MLT,1}$	**60**	**60**	$f_{MLT,2}$	**60**	**60**	$f_{MLT,3}$	**60**	**60**	$f_{ST,1}$	**60**	**60**	$f_{ST,2}$	**60**	**60**	$f_{ST,3}$	**60**	**60**
φ_1	0.923 (0.028)	94.9	φ_1	-0.054 (0.069)	0.5	φ_1	0.000 (0.145)	0.0	φ_1	-0.051 (0.031)	0.0	φ_1	-0.008 (0.005)	0.0	φ_1	0.099 (0.056)	0.0
φ_2	0.000 (0.151)	0.0	φ_2	0.992 (0.127)	70.6	φ_2	0.000 (0.498)	0.0	φ_2	0.448 (0.062)	0.6	φ_2	0.008 (0.062)	0.0	φ_2	0.189 (0.170)	0.0
φ_3	-0.227 (0.165)	5.1	φ_3	-0.443 (0.284)	28.9	φ_3	0.992 (0.116)	100.0	φ_3	-0.197 (0.124)	0.3	φ_3	-0.043 (0.005)	0.2	φ_3	0.300 (0.030)	0.3
φ_4	0.000 (0.000)	0.0	φ_4	0.000 (0.000)	0.0	φ_4	0.000 (0.000)	0.0	φ_4	0.653 (0.001)	99.1	φ_4	0.000 (0.003)	0.0	φ_4	-0.027 (0.025)	0.1
φ_5	0.000 (0.000)	0.0	φ_5	0.000 (0.000)	0.0	φ_5	0.000 (0.000)	0.0	φ_5	0.000 (0.012)	0.0	φ_5	0.176 (0.031)	99.8	φ_5	0.591 (0.474)	38.3
φ_6	0.000 (0.000)	0.0	φ_6	0.000 (0.000)	0.0	φ_6	0.000 (0.000)	0.0	φ_6	0.000 (0.012)	0.0	φ_6	0.000 (0.054)	0.0	φ_6	0.748 (0.102)	61.3

The Table reports the robust impulse responses of the MLT (f_{MLT}) and ST (f_{ST}) common factors to a unitary change in the *MLT* and *ST* common structural shocks at the 60 months ahead, with standard errors in round brackets. The Table also reports the % of forecast error variance accounted by each structural shocks at the same horizon. The *MLT* structural shocks are $\boldsymbol{\varphi_1, \varphi_2,\ \varphi_3}$. The *ST* structural shocks are $\boldsymbol{\varphi_4, \varphi_5,\ \varphi_6}$.

Table 5: Robust impulse responses and % of variance accounted by structural shocks

g	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	0.186 (0.260)	0.837 (0.454	0.952 (0.457)	0.918 (0.444)		80.2
φ_2	0.486 (1.405)	-0.375 (0.645)	-0.571 (0.614)	-0.591 (0.598)	1.4	12.8
φ_3	0.454 (0.824)	0.235 (0.451)	0.246 (0.449)	0.273 (0.443)		7.0
φ_4	0.689 (0.236)	-0.121 (0.345)	-0.274 (0.312)	-0.233 (0.265)		7.4
φ_5	1.302 (0.239)	1.206 (0.312)	0.747 (0.201)	0.513 (0.141)	60.8	69.2
φ_6	0.804 (0.274)	0.574 (0.407)	0.472 (0.386)	0.419 (0.345)		23.4

π	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	-0.145 (0.148)	-0.240 (0.349)	-0.380 (0.444)	-0.401 (0.449)		5.6
φ_2	0.039 (0.772)	1.166 (0.571)	2.317 (0.598)	2.498 (0.602)	2.9	86.0
φ_3	-0.192 (0.454)	-0.346 (0.403)	-0.486 (0.451)	-0.489 (0.465)		8.4
φ_4	1.534 (0.119)	1.533 (0.235)	1.392 (0.297)	1.198 (0.275)		99.0
φ_5	0.015 (0.113)	-0.066 (0.201)	-0.113 (0.189)	-0.080 (0.145)	90.9	0.5
φ_6	-0.049 (0.135)	-0.084 (0.276)	-0.102 (0.350)	-0.092 (0.338)		0.5

u	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	-0.962 (0.727)	-2.252 (1.260)	-3.758 (1.426)	-3.862 (1.401)		53.0
φ_2	-6.104 (3.444)	-3.459 (1.822)	-1.583 (1.900)	-1.147 (1.888)	0.5	16.0
φ_3	-2.138 (2.051)	-2.297 (1.341)	-2.814 (1.438)	-3.038 (1.446)		31.0
φ_4	-0.965 (0.569)	-1.126 (0.815)	-1.094 (0.911)	-0.931 (0.797)		1.0
φ_5	-2.411 (0.553)	-7.959 (0.727)	-8.070 (0.578)	-6.046 (0.419)	94.5	51.5
φ_6	-3.857 (0.655)	-5.844 (0.979)	-7.990 (1.095)	-7.853 (1.016)		47.5

rw	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	0.224 (0.122)	0.556 (0.171)	0.559 (0.151)	0.533 (0.143)		26.0
φ_2	-0.224 (0.965)	-1.510 (0.247)	-1.347 (0.205)	-1.228 (0.193)	3.7	66.2
φ_3	0.643 (0.565)	0.446 (0.178)	0.219 (0.149)	0.170 (0.146)		7.8
φ_4	-0.567 (0.141)	-0.934 (0.144)	-0.778 (0.112)	-0.656 (0.094)		90.2
φ_5	-0.346 (0.131)	-0.252 (0.120)	-0.028 (0.066)	0.041 (0.047)	71.8	3.5
φ_6	-0.233 (0.149)	0.158 (0.165)	0.208 (0.134)	0.221 (0.118)		6.3

ro	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	-0.077 (0.176)	-0.133 (0.485)	-0.321 (0.727)	-0.324 (0.796)		5.9
φ_2	-1.359 (0.934)	-1.317 (0.865)	-1.143 (1.015)	-1.012 (1.116)	1.1	53.2
φ_3	-0.362 (0.549	0.027 (0.608)	0.803 (0.770)	1.189 (0.868)		40.9
φ_4	-1.548 (0.132)	-1.413 (0.297)	-0.853 (0.471)	-0.558 (0.506)		35.3
φ_5	0.202 (0.121)	0.617 (0.256)	1.103 (0.316)	1.154 (0.283)	90.4	30.7
φ_6	0.348 (0.152)	0.665 (0.353)	1.126 (0.563)	1.293 (0.616)		34.0

rl	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	-0.092 (0.166)	-0.224 (0.441)	-0.574 (0.653)	-0.709 (0.712)		14.8
φ_2	-1.479 (0.838)	-1.537 (0.753)	-1.826 (0.888)	-1.819 (0.961)	2.8	74.0
φ_3	-0.332 (0.497)	-0.019 (0.532)	0.505 (0.673)	0.724 (0.749)		11.2
φ_4	-1.239 (0.123)	-1.281 (0.277)	-1.144 (0.434)	-0.998 (0.461)		95.6
φ_5	-0.079 (0.115)	-0.051 (0.231)	0.039 (0.282)	0.103 (0.258)	73.4	0.3
φ_6	0.063 (0.136)	0.134 (0.308)	0.263 (0.487)	0.311 (0.537)		4.1

rm	Robust IRF (months)				FEVD	CFEVD
	3	12	60	60	60	60
φ_1	0.482 (0.247)	1.776 (0.523)	2.653 (0.597)	2.699 (0.587)		62.8
φ_2	-1.977 (1.320)	-2.406 (0.788)	-1.934 (0.788)	-1.803 (0.780)	7.3	19.1
φ_3	-0.457 (0.784)	-1.138 (0.573)	-1.476 (0.597)	-1.432 (0.600)		18.1
φ_4	-2.022 (0.217)	-1.637 (0.380)	-1.214 (0.411)	-0.993 (0.360)		66.2
φ_5	-0.103 (0.210)	0.224 (0.338)	0.023 (0.278)	-0.260 (0.204)	76.6	1.1
φ_6	-0.900 (0.256)	-0.980 (0.472)	-0.937 (0.527)	-0.872 (0.484)		32.7

cg	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	-0.204 (0.222)	0.128 (0.0770)	0.523 (0.704)	0.490 (0.717)		8.5
φ_2	-3.124 (1.834)	-3.297 (1.440)	-1.263 (0.911)	-1.112 (0.923)	1.5	81.2
φ_3	-0.732 (1.059)	-0.100 (1.003)	0.603 (0.705)	0.386 (0.727)		10.3
φ_4	-0.593 (0.209)	-1.519 (0.504)	-1.563 (0.454)	-1.314 (0.401)		85.6
φ_5	-0.260 (0.206)	-0.609 (0.462)	-0.421 (0.294)	-0.128 (0.224)	53.8	9.3
φ_6	-0.546 (0.241)	-0.156 (0.623)	0.381 (0.585)	0.353 (0.548)		5.1

Table 5 (continued): Robust impulse responses and % of variance accounted by structural shocks

rx	Robust IRF (months)				FEVD	CFEVD
	3	12	60	60	60	60
φ_1	0.133 (0.684)	0.814 (1.240)	1.074 (1.298)	1.064 (1.263)		39.5
φ_2	-3.907 (3.622)	-1.158 (1.950)	-0.390 (1.900)	-0.293 (1.849)	0.8	39.6
φ_3	-1.919 (2.138)	-0.376 (1.427)	0.381 (1.462)	0.397 (1.446)		20.9
φ_4	-1.035 (0.673)	-0.394 (1.048)	-0.107 (1.001)	-0.077 (0.853)		9.6
φ_5	0.331 (0.620)	-0.855 (0.874)	-0.995 (0.620)	-0.749 (0.442)	17.6	52.9
φ_6	-0.166 (0.712)	-0.725 (1.204)	-0.830 (1.218)	-0.751 (1.093)		39.5

ca	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	0.122 (0.117)	0.099 (0.268)	0.054 (0.403)	0.018 (0.444)		0.6
φ_2	0.946 (0.753)	-0.124 (0.456)	-1.347 (0.556)	-1.753 (0.618)	1.6	75.3
φ_3	0.381 (0.454)	0.392 (0.346)	0.503 (0.432)	0.546 (0.481)		24.1
φ_4	-0.406 (0.111)	-0.445 (0.193)	-0.582 (0.296)	-0.587 (0.314)		22.8
φ_5	0.052 (0.100)	-0.106 (0.166)	-0.590 (0.205)	-0.754 (0.190)	74.4	24.5
φ_6	0.040 (0.121)	-0.415 (0.226)	-0.895 (0.364)	-0.751 (1.093)		52.7

fd	Robust IRF (months)				FEVD	CFEVD
	3	12	60	60	60	60
φ_1	0.048 (0.054)	0.599 (0.273)	1.097 (0.319)	0.689 (0.281)		61.1
φ_2	0.062 (0.448)	-0.251 (0.676)	-0.722 (0.475)	-0.282 (0.398)	1.6	8.6
φ_3	0.027 (0.257)	0.430 (0.419)	0.770 (0.354)	0.568 (0.303)		30.3
φ_4	0.065 (0.056)	0.005 (0.020)	-0.231 (0.234)	-0.119 (0.166)		1.3
φ_5	0.201 (0.052)	0.780 (0.186)	0.831 (0.160)	0.314 (0.086)	80.5	27.0
φ_6	0.289 (0.063)	1.104 (0.246)	1.117 (0.296)	0.894 (0.221)		71.7

hr	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	0.092 (0.092)	1.533 (0.390)	2.656 (0.403)	2.454 (0.403)		96.6
φ_2	-0.456 (0.749)	-0.985 (0.761)	-0.452 (0.541)	-0.525 (0.526)	4.2	3.4
φ_3	0.030 (0.432)	0.014 (0.526)	0.027 (0.423)	0.086 (0.408)		0.0
φ_4	-0.085 (0.092)	-0.911 (0.251)	-1.341 (0.260)	-1.087 (0.220)		40.1
φ_5	0.271 (0.086)	1.513 (0.227)	1.238 (0.173)	0.521 (0.119)	81.3	53.3
φ_6	0.083 (0.102)	0.409 (0.304)	0.507 (0.329)	0.357 (0.292)		6.6

mk	Robust IRF (months)				FEVD	
	3	12	36	60	60	
φ_1	0.133 (0.148)	0.204 (0.250)	0.191 (0.237)	0.186 (0.230)		60.4
φ_2	-0.363 (0.757)	-0.015 (0.351)	-0.019 (0.324)	-0.031 (0.313)	0.1	14.2
φ_3	-0.281 (0.438)	0.003 (0.257)	0.089 (0.241)	0.103 (0.238)		25.4
φ_4	-0.022 (0.154)	-0.234 (0.227)	-0.185 (0.193)	-0.154 (0.163)		2.7
φ_5	1.386 (0.147)	1.149 (0.190)	0.660 (0.117)	0.455 (0.085)	82.0	68.9
φ_6	0.813 (0.183)	0.599 (0.267)	0.502 (0.235)	0.446 (0.209)		28.4

nc	Robust IRF (months)				FEVD	
	3	12	36	60	60	
φ_1	-0.043 (0.020)	-0.079 (0.028)	-0.087 (0.028)	-0.084 (0.026)		75.4
φ_2	-0.004 (0.081)	0.023 (0.039)	0.027 (0.039)	0.031 (0.039)	1.4	3.5
φ_3	0.008 (0.049)	-0.032 (0.030)	-0.051 (0.027)	-0.054 (0.027)		21.1
φ_4	0.020 (0.019)	0.002 (0.024)	-0.001 (0.022)	-0.001 (0.018)		0.4
φ_5	-0.186 (0.017)	-0.128 (0.020)	-0.079 (0.013)	-0.056 (0.009)	86.4	73.3
φ_6	-0.087 (0.022)	-0.069 (0.028)	-0.059 (0.026)	-0.052 (0.023)		26.3

gs	Robust IRF (months)				FEVD	CFEVD
	3	12	60	60	60	60
φ_1	0.026 (0.033)	-0.054 (0.117)	-0.082 (0.117)	-0.071 (0.115)		1.4
φ_2	0.625 (0.243)	0.857 (0.189)	0.660 (0.158)	0.641 (0.158)	9.2	63.3
φ_3	0.162 (0.141)	-0.197 (0.138)	-0.432 (0.122)	-0.392 (0.122)		35.3
φ_4	0.079 (0.033)	0.145 (0.085)	0.128 (0.083)	0.108 (0.072)		25.4
φ_5	0.035 (0.031)	0.114 (0.073)	0.021 (0.005)	-0.051 (0.036)	51.7	7.7
φ_6	-0.126 (0.039)	-0.224 (0.099)	-0.195 (0.100)	-0.177 (0.091)		66.9

re	Robust IRF (months)				FEVD	CFEVD
	3	12	36	60	60	60
φ_1	-0.286 (4.622)	2.633 (9.036)	4.378 (10.52)	4.329 (10.39)		21.8
φ_2	-1.042 (22.35)	7.710 (13.75)	12.38 (14.14)	12.22 (13.99)	0.3	76.7
φ_3	1.400 (13.18)	0.873 (10.14)	0.943 (10.87)	1.395 (10.90)		1.5
φ_4	22.5 (4.123)	5.712 (6.72)	-4.205 (7.132)	-3.991 (6.199)		16.6
φ_5	18.44 (3.677)	22.00 (5.477)	15.66 (4.387)	10.79 (3.215)	68.5	64.8
φ_6	-0.811 (4.513)	6.376 (7.637)	10.77 (8.466)	10.55 (7.775)		18.6

The Table reports robust impulse responses to unitary structural shocks at various horizons, i.e., 3, 12, 36, and 60 months ahead, with standard errors in round brackets. The Table also reports the % of forecast error variance at the 60 months ahead horizon accounted by each category of shocks (*FEVD*), i.e., $\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}$, $\boldsymbol{\varphi_3}$ and $\boldsymbol{\varphi_4}, \boldsymbol{\varphi_5}, \boldsymbol{\varphi_6}$, and the % of component (trend or cycle) forecast error variance at the 60 months ahead horizon accounted by each structural shock (*CFEVD*). The selected variables are the €-coin GDP growth rate (***g***), the change in the unemployment rate ($\boldsymbol{u}$), the real wage growth rate (***rw***), the inflation rate ($\boldsymbol{\pi}$), the real overnight and long-term interest rates (***ro, rl***), the real effective exchange rate return (***rx***), the current account to GDP ratio (***ca***), the fiscal deficit to GDP ratio ($\boldsymbol{fd}$), the house price to rent ratio ($\boldsymbol{hr}$), the real M3 growth rate (***rm***), the credit to GDP ratio ($\boldsymbol{cg}$), stock market returns (***mk***), the New-CISS composite financial condition index (***nc***), the NY Fed Global Supply Chain Pressure Index (***gs***), and the real energy price growth rate (***re***).

Table 6: Component's Forecast error variance decomposition divergence series

Panel A: Divergence series' FEVD

rd	FEVD (months)				*ld*	FEVD (months)				*nd*	FEVD (months)				*cd*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	0.0	0.3	0.7	1.1	φ_1	0.0	0.1	0.2	0.7	φ_1	0.0	0.0	0.2	0.2	φ_1	0.0	0.0	0.0	0.0
φ_2	0.1	0.1	0.1	0.1	φ_2	0.0	0.0	0.2	0.1	φ_2	0.1	0.0	0.2	1.0	φ_2	0.2	0.2	0.1	0.3
φ_3	0.0	0.0	0.1	0.2	φ_3	0.0	0.0	0.3	1.4	φ_3	0.0	0.0	0.3	1.2	φ_3	0.1	0.1	0.1	0.8
φ_4	0.1	0.5	2.7	7.5	φ_4	0.2	0.4	0.8	0.7	φ_4	0.4	2.3	10.8	27.8	φ_4	0.0	0.5	2.8	14.4
φ_5	0.0	1.8	2.0	3.2	φ_5	1.0	7.2	26.1	29.1	φ_5	0.0	0.1	1.3	14.7	φ_5	2.8	3.0	1.6	12.8
φ_6	2.2	5.2	6.8	7.9	φ_6	0.7	5.0	19.3	37.8	φ_6	2.1	2.6	2.0	1.3	φ_6	1.2	2.0	3.0	1.9

Panel B: Trend and cyclical divergence components' FEVD

rd	FEVD (months)				*ld*	FEVD (months)				*nd*	FEVD (months)				*cd*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	64.4	76.6	78.9	80.3	φ_1	59.8	28.0	30.3	28.1	φ_1	40.5	28.5	9.7	7.7	φ_1	3.3	13.7	2.6	2.5
φ_2	32.4	13.9	8.3	6.9	φ_2	24.1	24.0	6.4	3.3	φ_2	25.0	31.4	42.3	46.4	φ_2	54.9	36.9	24.4	31.7
φ_3	3.2	9.5	12.8	12.9	φ_3	16.1	48.0	63.4	68.6	φ_3	34.5	40.1	48.1	45.9	φ_3	41.8	49.4	73.0	65.8
φ_4	6.9	23.7	40.1	44.8	φ_4	3.0	1.7	1.0	1.7	φ_4	45.7	76.3	63.4	62.5	φ_4	9.0	38.4	49.4	52.5
φ_5	23.7	17.5	17.4	18.1	φ_5	57.4	56.5	43.0	34.8	φ_5	1.4	9.3	33.5	33.0	φ_5	55.3	21.4	43.9	42.8
φ_6	69.4	58.8	42.4	37.1	φ_6	39.7	41.8	56.0	63.6	φ_6	52.9	14.3	3.1	4.5	φ_6	35.7	40.2	6.7	4.7

Panel A: Divergence series' FEVD

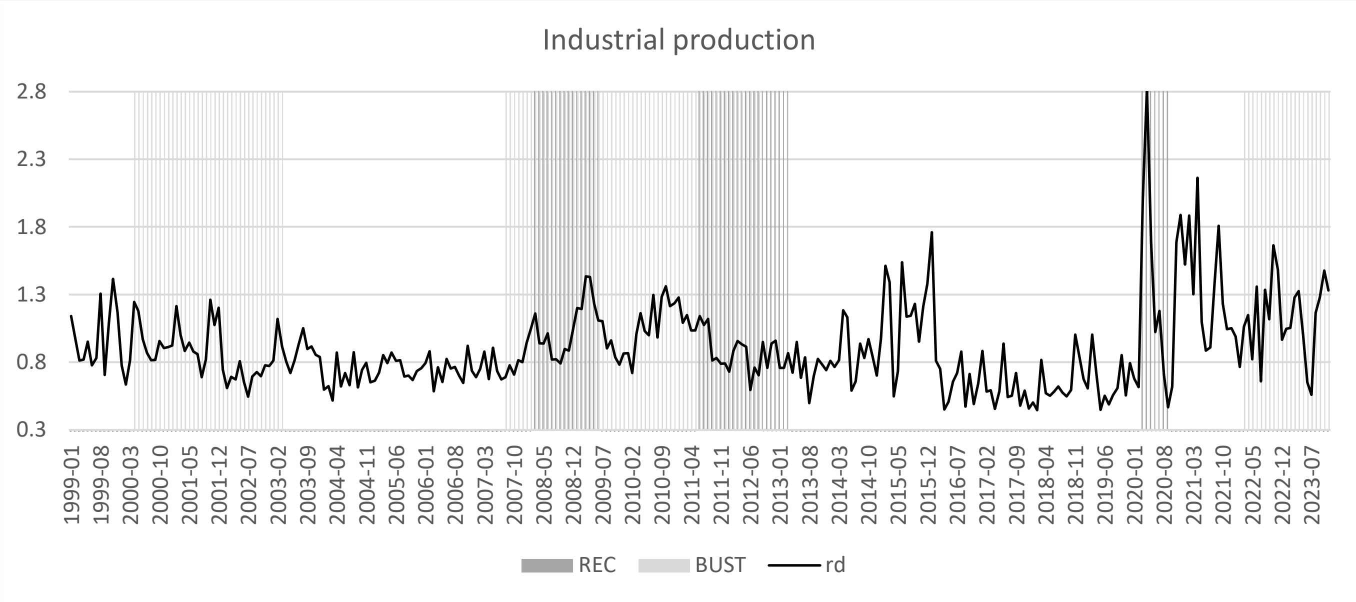
bd	FEVD (months)				*sd*	FEVD (months)				*fd*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60
φ_1	0.0	0.2	1.0	1.9	φ_1	0.0	0.0	0.1	0.6	φ_1	0.0	0.0	0.4	1.7
φ_2	0.2	0.1	0.1	0.7	φ_2	0.6	0.4	0.3	0.2	φ_2	0.1	0.1	0.1	0.2
φ_3	0.0	0.1	0.2	0.7	φ_3	0.0	0.1	0.2	0.4	φ_3	0.0	0.0	0.0	0.4
φ_4	0.1	1.5	2.3	1.4	φ_4	0.4	0.5	0.6	7.9	φ_4	0.7	0.4	1.1	6.9
φ_5	1.8	11.1	30.1	51.8	φ_5	1.3	1.2	1.0	4.0	φ_5	8.9	9.4	10.2	9.3
φ_6	0.5	1.7	4.0	11.7	φ_6	3.1	4.2	7.4	8.8	φ_6	3.2	4.6	6.4	7.4

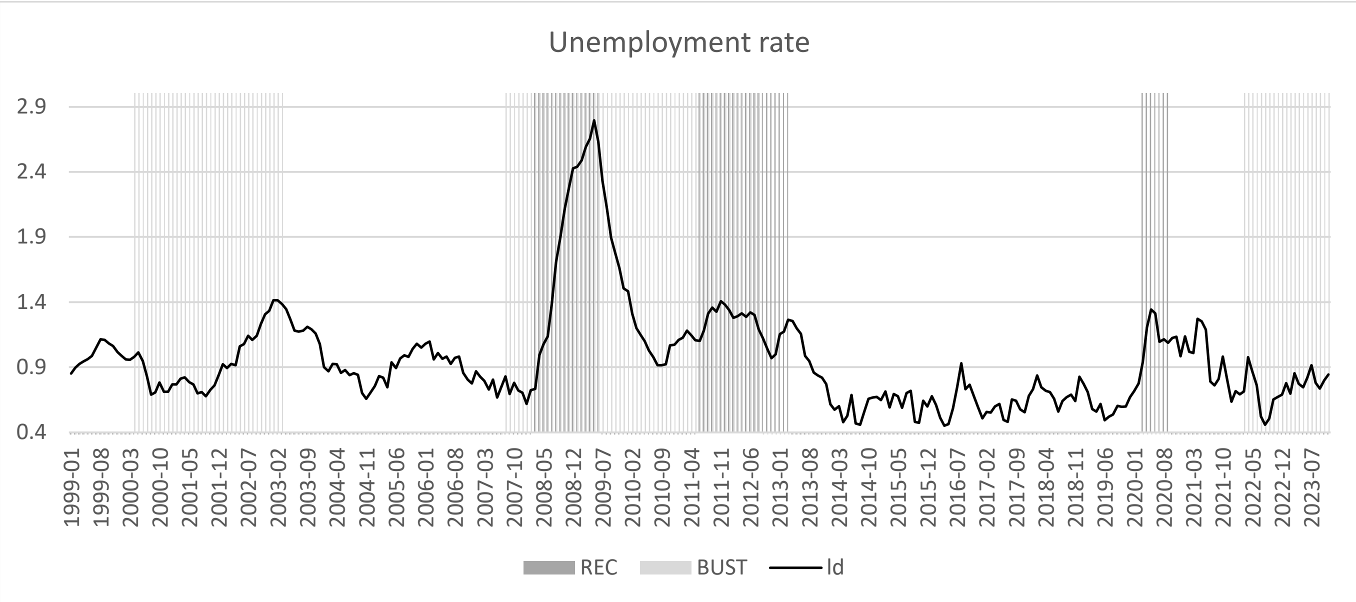
Panel B: Trend and cyclical divergence components' FEVD

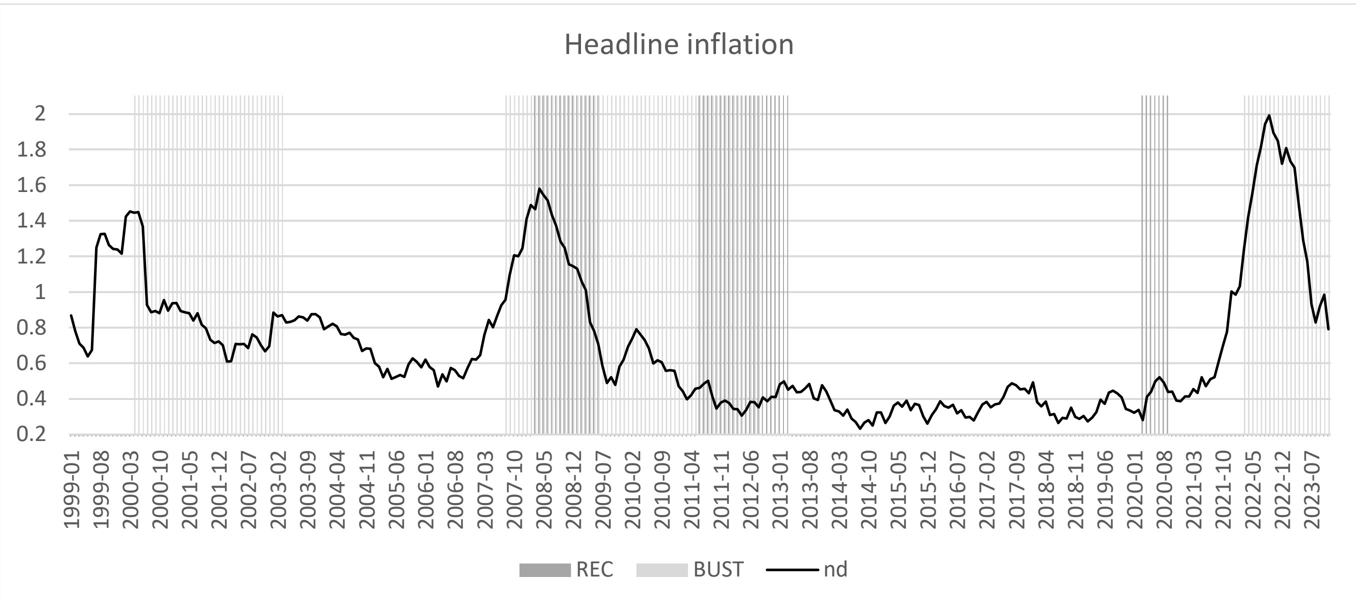
bd	FEVD (months)				*sd*	FEVD (months)				*fd*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60
φ_1	48.7	75.4	58.0	50.6	φ_1	1.1	13.5	49.7	53.0	φ_1	21.6	79.1	76.7	69.0
φ_2	30.7	7.5	21.5	27.0	φ_2	86.0	55.2	17.0	9.8	φ_2	76.2	18.1	7.1	9.4
φ_3	20.7	17.1	20.5	22.3	φ_3	12.9	31.2	33.3	37.3	φ_3	2.2	2.8	16.2	21.6
φ_4	10.2	6.4	2.2	1.6	φ_4	8.6	6.5	38.4	45.8	φ_4	2.9	6.5	29.3	43.6
φ_5	77.7	82.5	79.8	73.0	φ_5	20.2	10.8	19.3	30.1	φ_5	65.1	57.6	39.4	33.3
φ_6	12.0	11.0	18.0	25.5	φ_6	71.3	82.7	42.4	24.1	φ_6	32.1	36.0	31.3	23.0

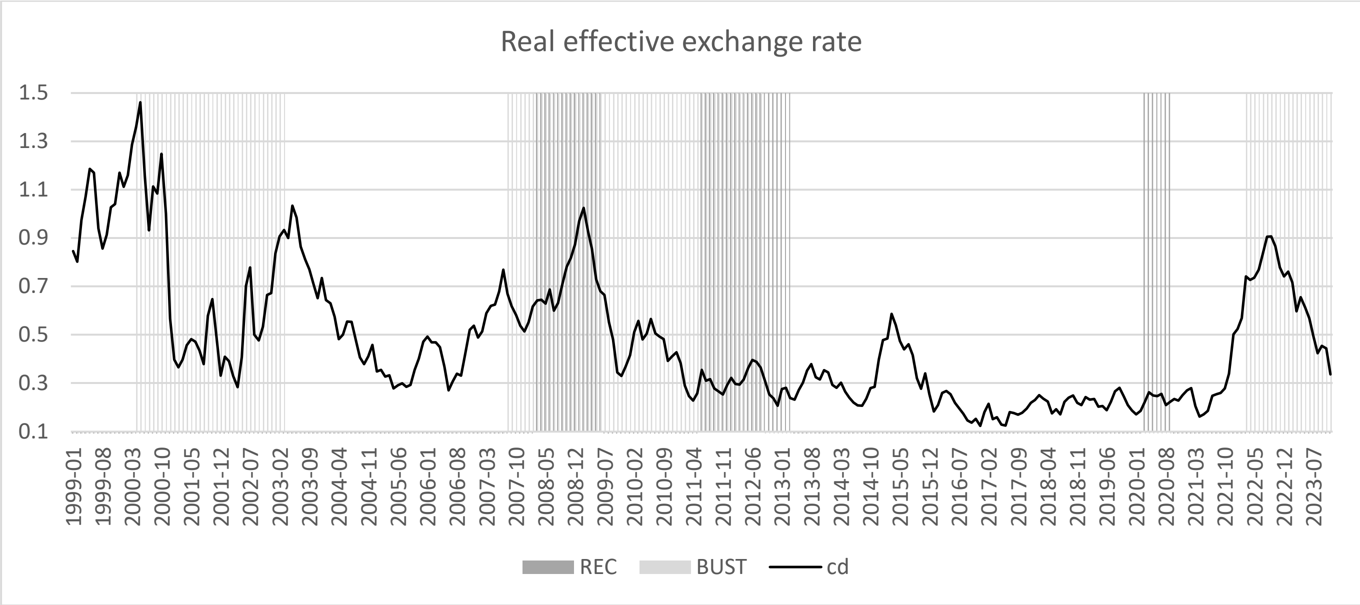
The Table reports the contributions of the structural shocks to the forecast error variance at various horizons, i.e. 3, 12, 36, and 60 months ahead for the divergence indicators (Panel A) and their trend and cyclical components. The common medium to long-term (trend) structural shocks are $\boldsymbol{\varphi_1}$, $\boldsymbol{\varphi_2}$, $\boldsymbol{\varphi_3}$, the common short-term (cyclical) structural shocks are $\boldsymbol{\varphi_4}$, $\boldsymbol{\varphi_5}$, $\boldsymbol{\varphi_6}$. The responses are computed for the real (***rd***), labor market (***ld***), nominal (***nd***), competitiveness (***cd***), bond market (***bd***), stock market (***sd***), and overall financial condition (***fd***) indicators.

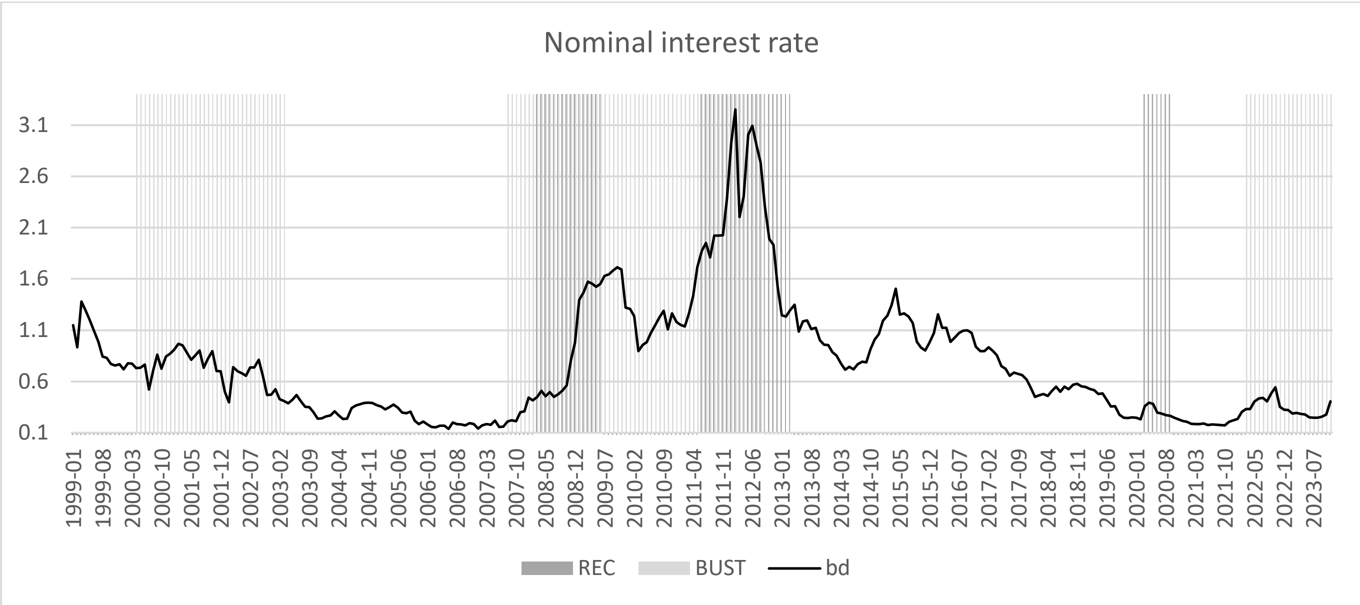
Figure 1: Divergence indicators based on the Standard Deviation measure.

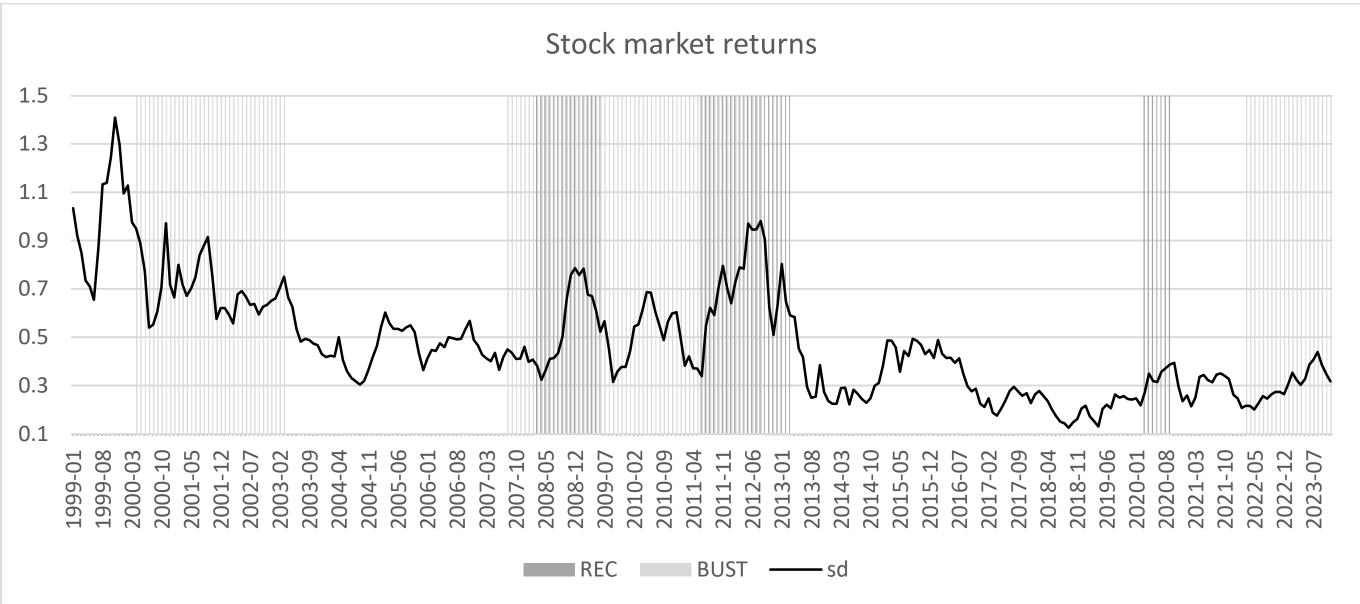


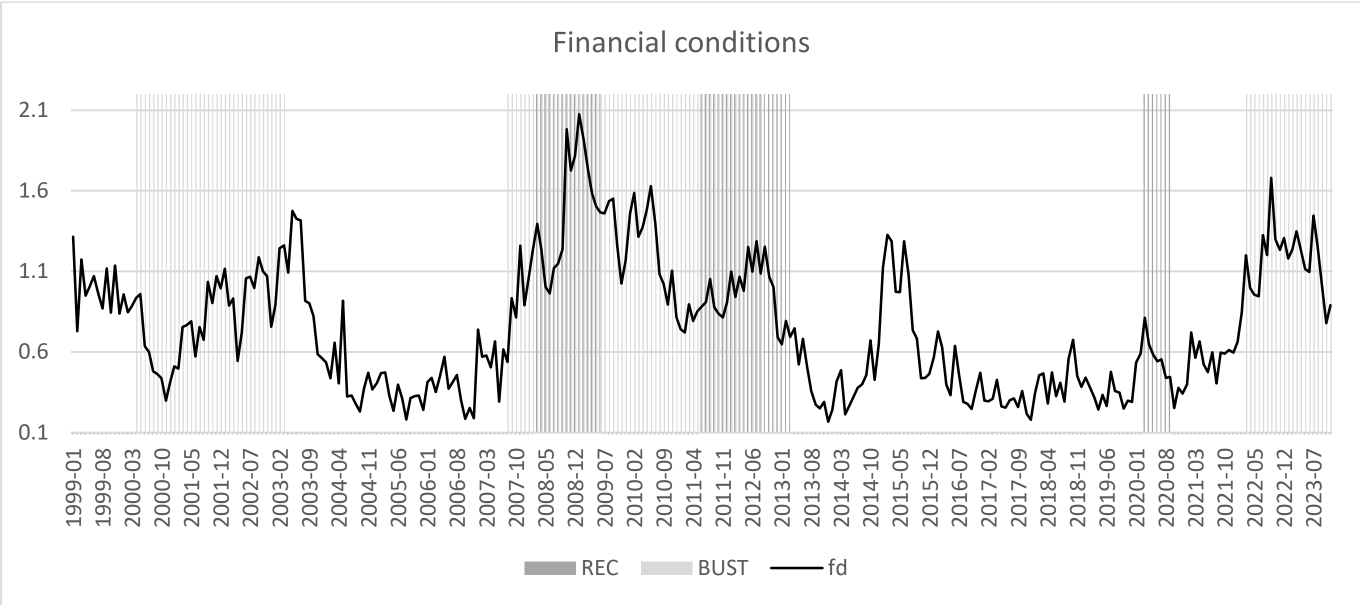


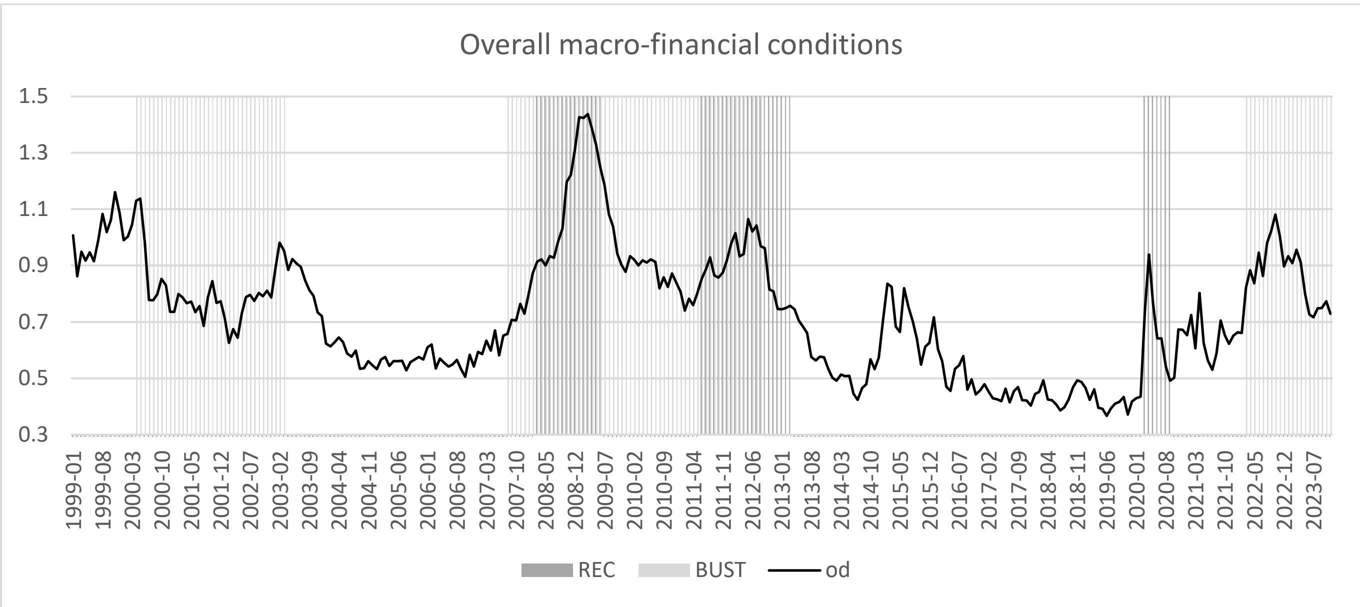



Real effective exchange rate
REC
BUST
cd


Nominal interest rate
REC
BUST
bd

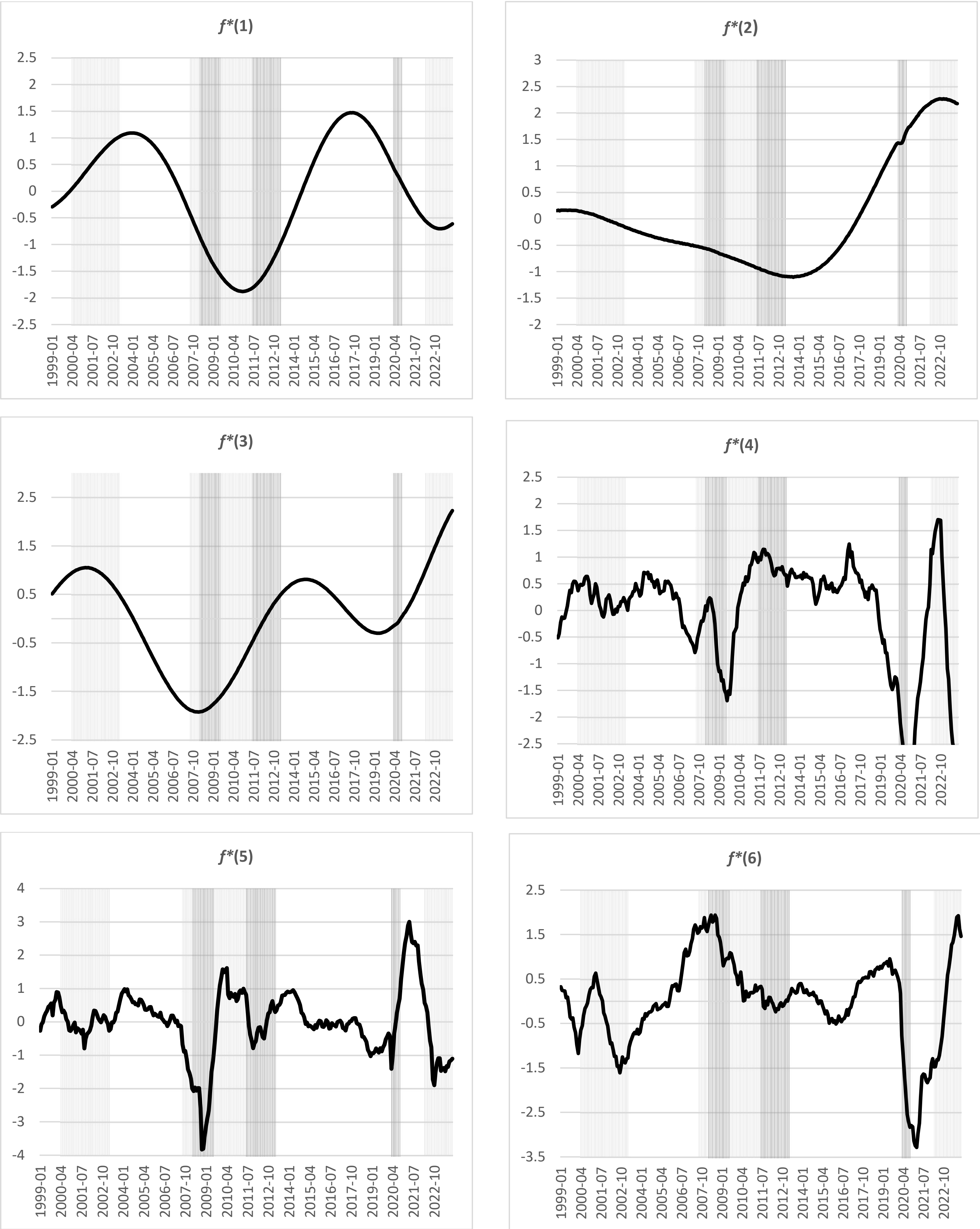

Stock market returns
REC
BUST
sd





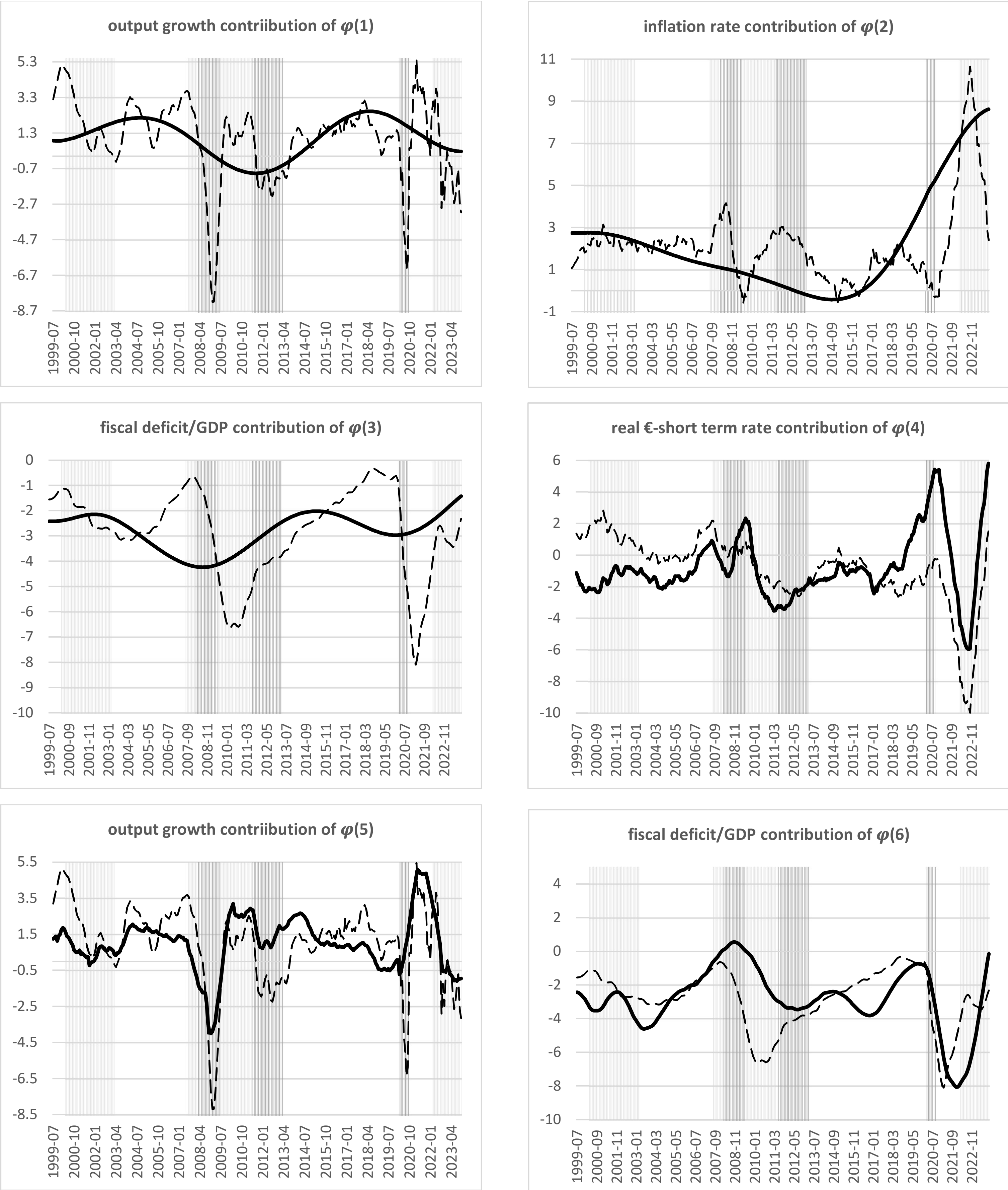
The Figure shows divergence indicators computed using the Standard Deviation measure for various variables, i.e. year-on-year monthly industrial production growth (real divergence; *rd*), year-on-year monthly rate of growth for the harmonized unemployment rate (labor market divergence; *ld*), headline HCPI inflation (nominal divergence; *nd*), year-on-year real effective exchange rate return (competitiveness divergence*; cd*), monthly nominal long term interest rate (bond market divergence*, bd*), year-on-year monthly nominal stock market returns (stock market divergence; *sd*), monthly *CLIFS* financial condition index (financial conditions divergence; *fd*), monthly overall macro-financial conditions (overall macro-financial divergence; *od*). Light-gray shaded areas in the plots refer to financial distress/crisis periods; dark-gray shaded areas refer to recession periods. In light gray, we also mark the most recent geopolitical crisis period. Figures are re-scaled to show a unitary value in 1999 on average.

Figure 2: The identified common medium to long-term and short-term factors



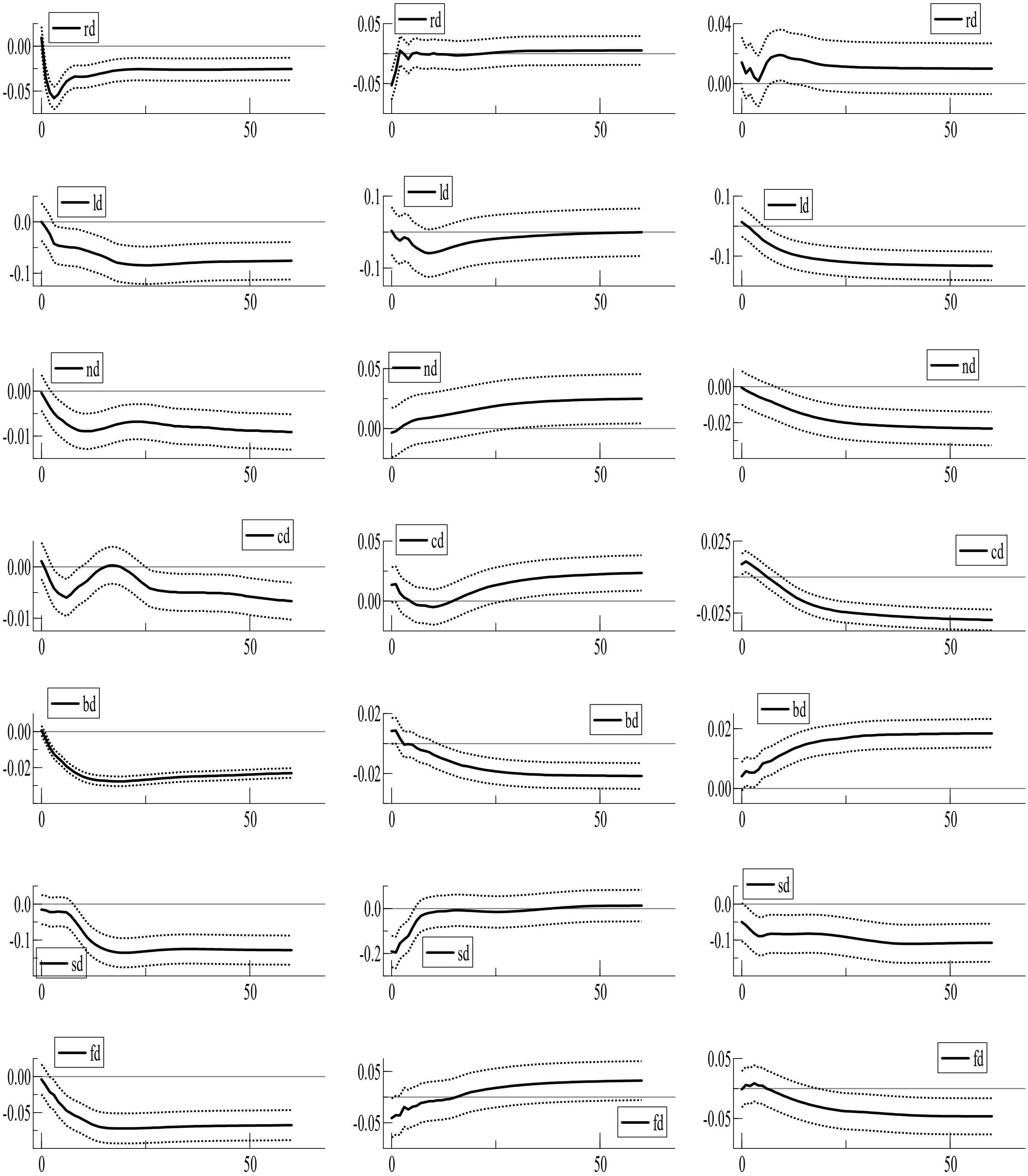
The Figure shows the identified common medium to long term (f_1^*, f_2^*, f_3^*) and short-term (f_4^*, f_5^*, f_6^*) factors.

Figure 3: Selected historical decomposition results



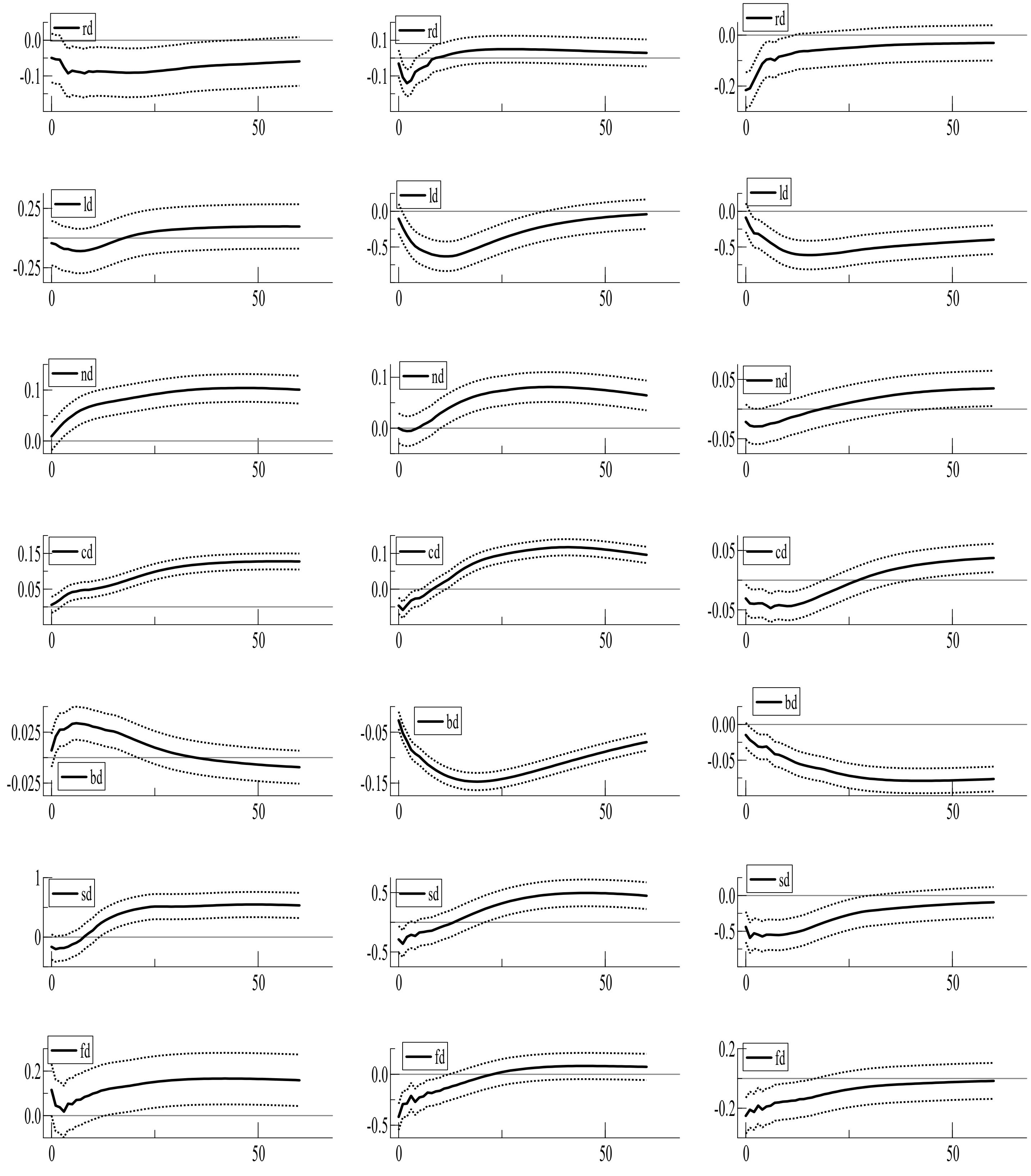
The Figure reports the contributions of the LR-AS ($\boldsymbol{\varphi_1}$) and SR-AS ($\boldsymbol{\varphi_5}$) structural shocks to aggregate Eurozone GDP growth, the contributions of the trend ($\boldsymbol{\varphi_3}$) and cyclical ($\boldsymbol{\varphi_6}$) fiscal shocks to the aggregate Eurozone fiscal deficit/GDP ratio, the contribution of the cost-push shock ($\boldsymbol{\varphi_2}$) to headline Eurozone inflation to aggregate GDP growth, and the contribution of the monetary policy shock ($\boldsymbol{\varphi_4}$) to the Eurozone real overnight interest rate.

Figure 4: Responses of divergence measures to common structural shocks



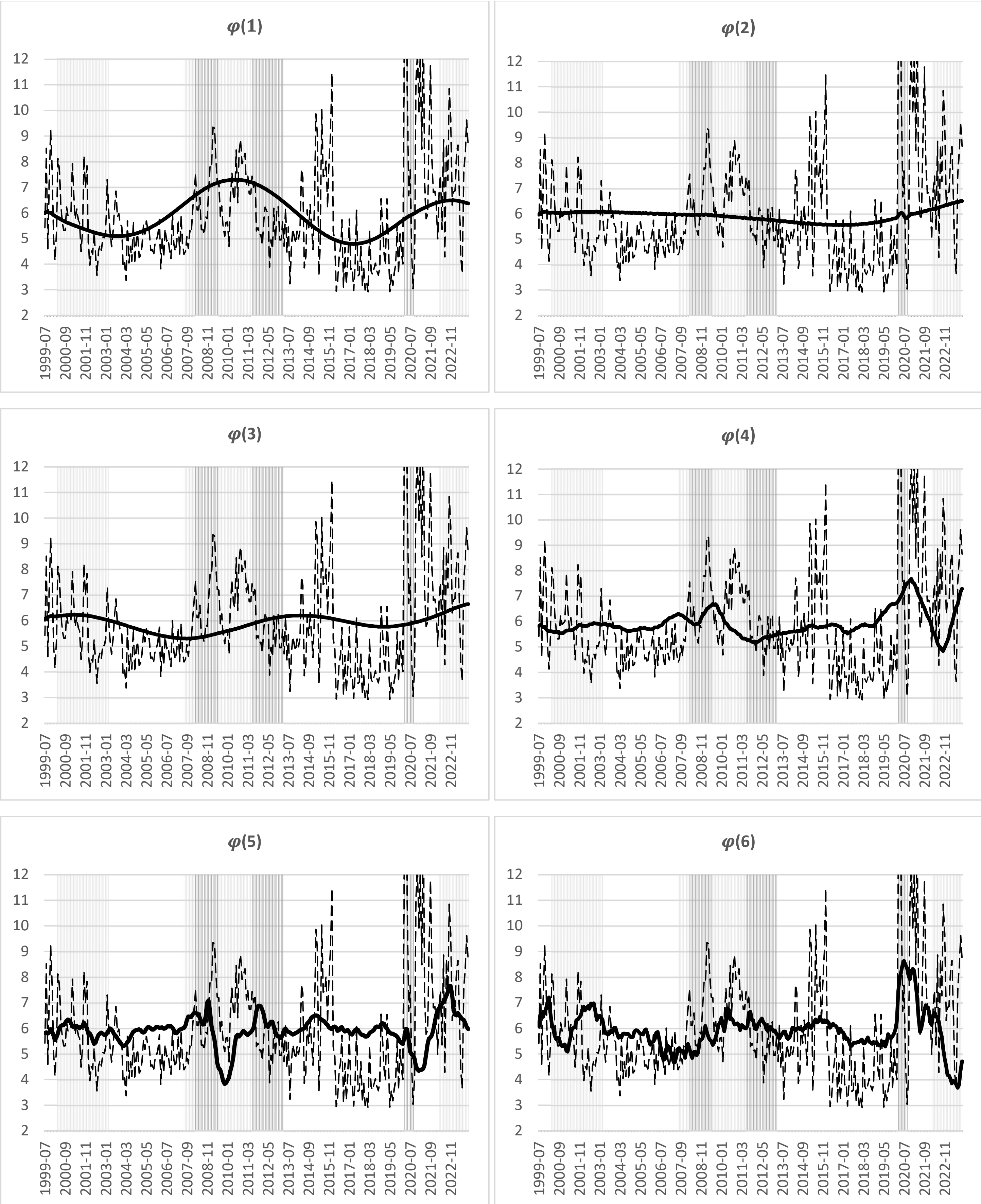
The figure reports the Impulse responses of divergence indicators to a unitary common medium to long-term structural shock. The first column reports the responses to a **LR-AS/**productivity shock $\boldsymbol{\varphi_1}$, the second column reports the responses to the cost-push shock $\boldsymbol{\varphi_2}$, the third column reports the responses to the trend fiscal shock $\boldsymbol{\varphi_3}$. The responses are computed for the real (*rd*), labor market (*ld*), nominal (*nd*), competitiveness (*cd*), bond market (*bd*), stock market (*sd*), and overall financial condition (*fd*) indicators.

Figure 5: Responses of divergence measures to common structural shocks



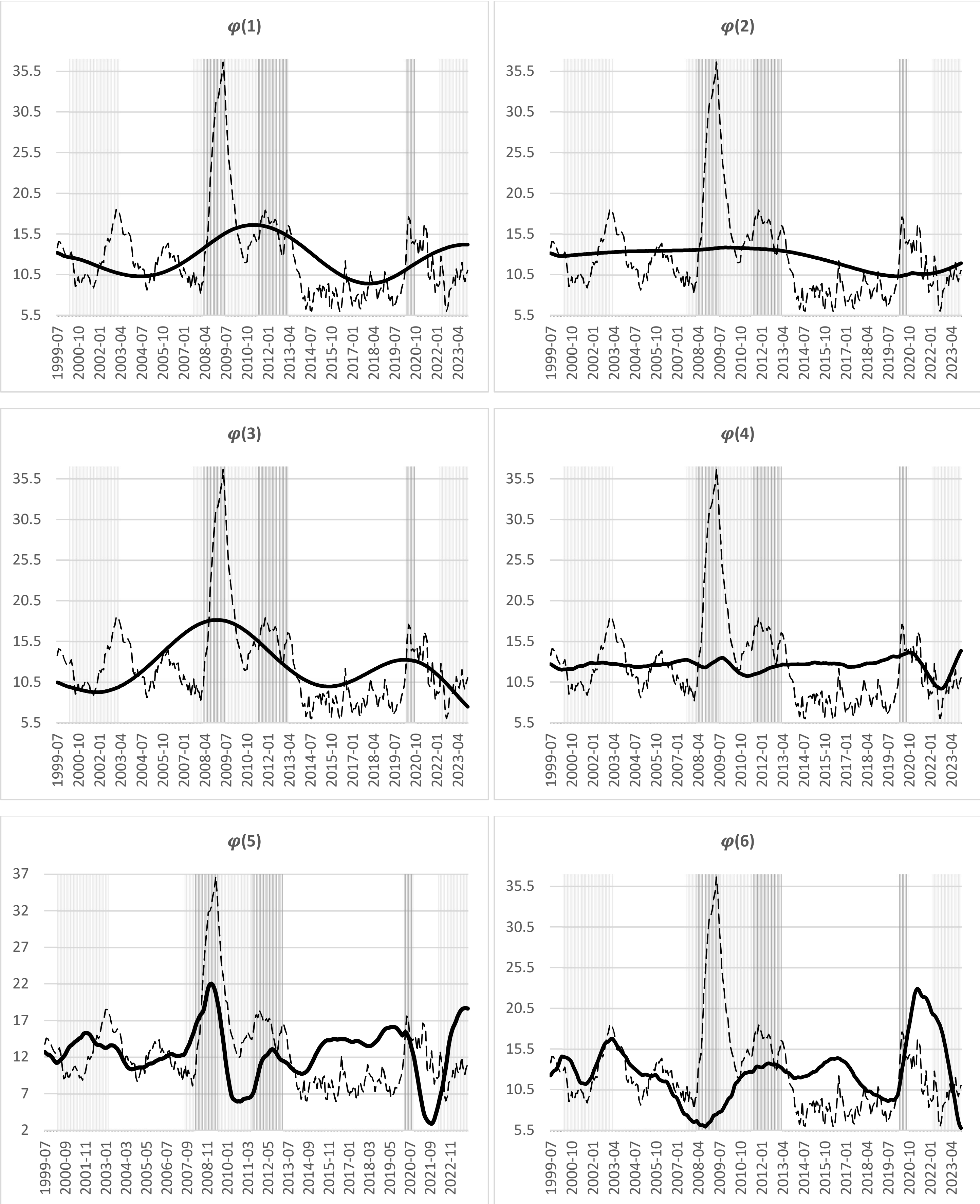
The figure reports the impulse responses of divergence indicators to a unitary common short-term structural shock. The first column reports the responses to an AD/monetary policy shock $\boldsymbol{\varphi_4}$, the second column reports the responses to the SR-AS/cyclical supply-side shock $\boldsymbol{\varphi_5}$, the third column reports the responses to the cyclical fiscal shock $\boldsymbol{\varphi_6}$. The responses are computed for the real (*rd*), labor market (*ld*), nominal (*nd*), competitiveness (*cd*), bond market (*bd*), stock market (*sd*), and overall financial condition (*fd*) indicators.

Figure 6: Historical decomposition of the real divergence indicator



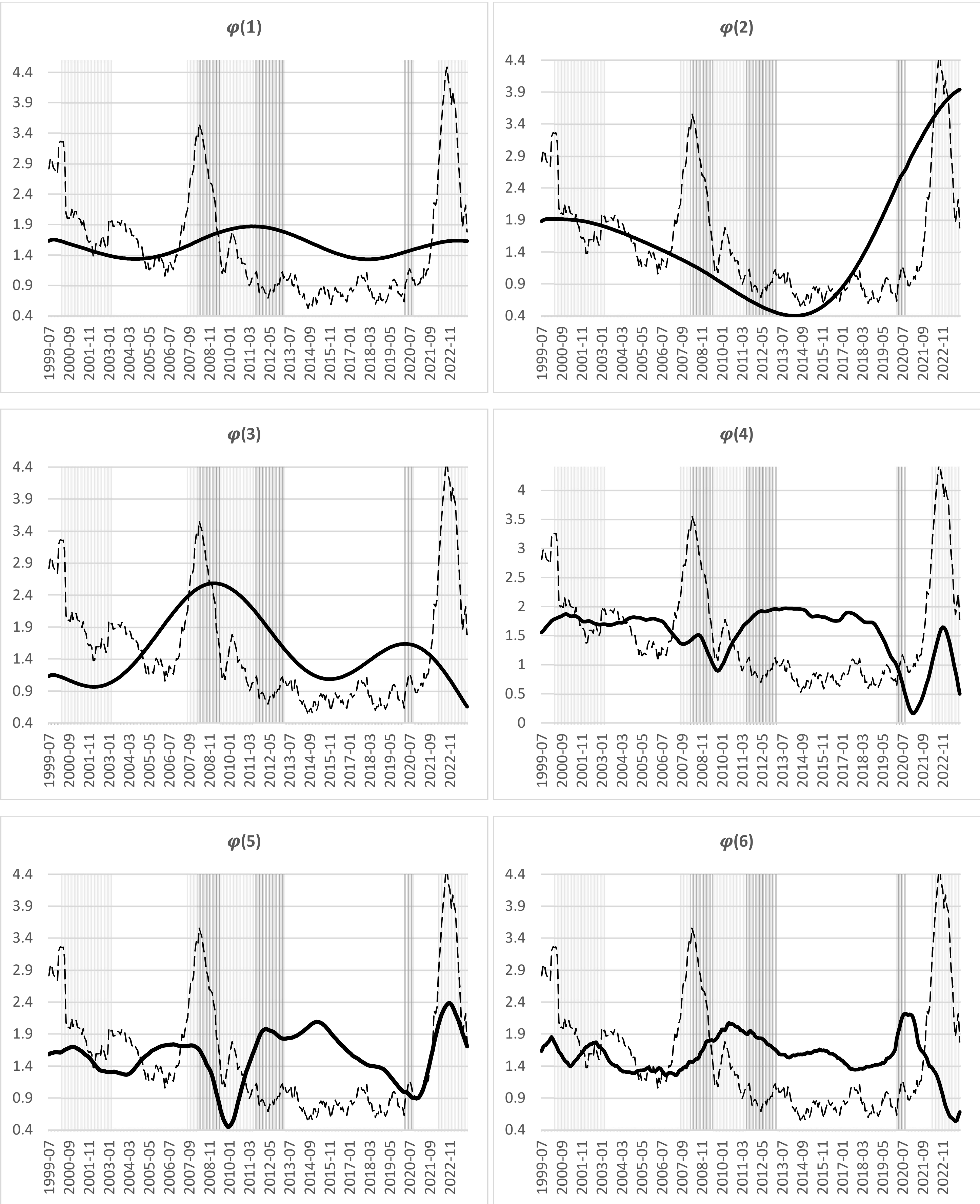
The figure reports the contribution of the common medium to long-term ($\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}, \boldsymbol{\varphi_5}, \boldsymbol{\varphi_6}$) structural shocks in the historical decomposition of the real divergence indicator.

Figure 7: Historical decomposition of the labor market divergence indicator



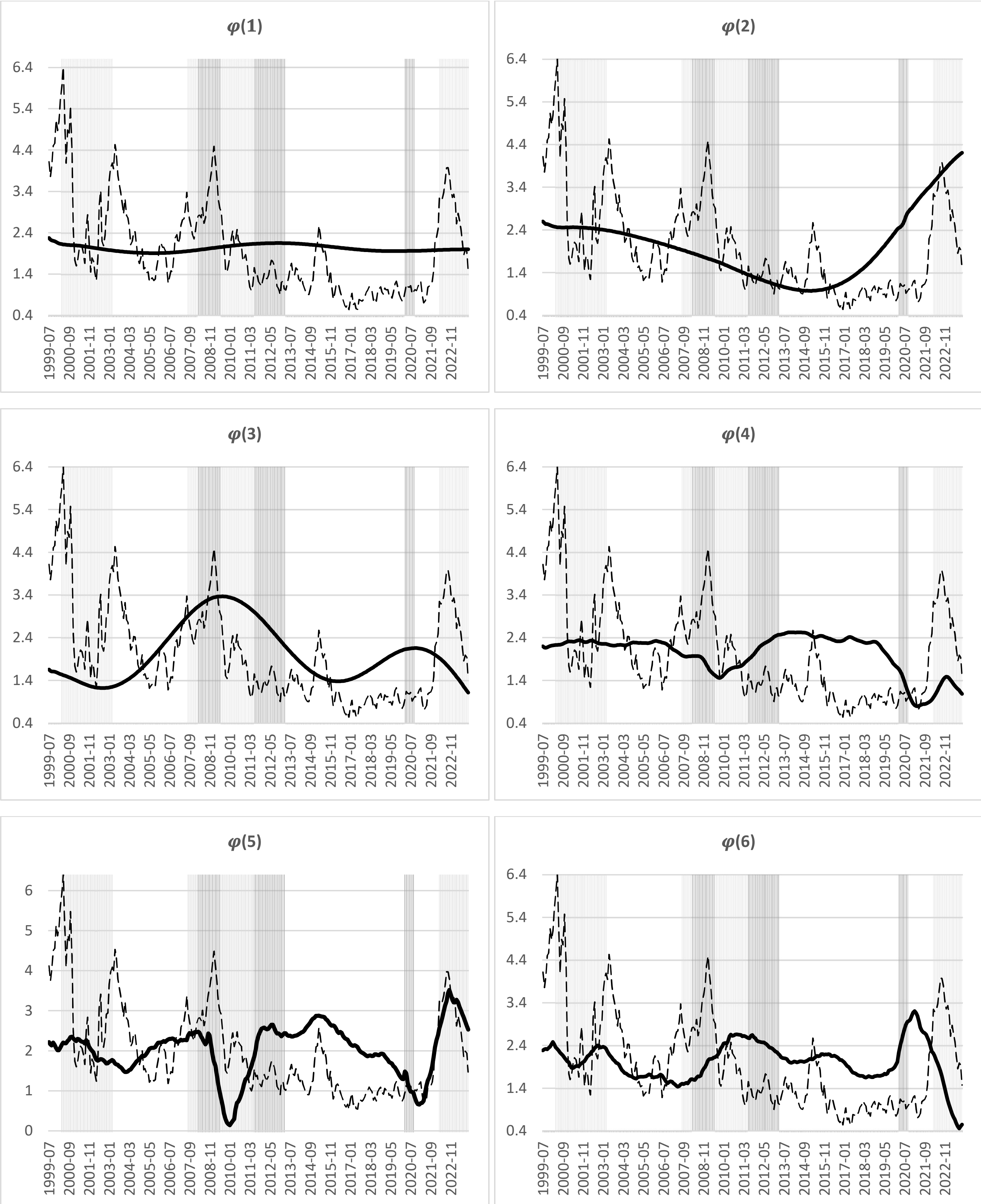
The figure reports the contribution of the common medium to long-term ($\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}, \boldsymbol{\varphi_5}, \boldsymbol{\varphi_6}$) structural shocks in the historical decomposition of the labor market divergence indicator.

Figure 8: Historical decomposition of the nominal divergence indicator



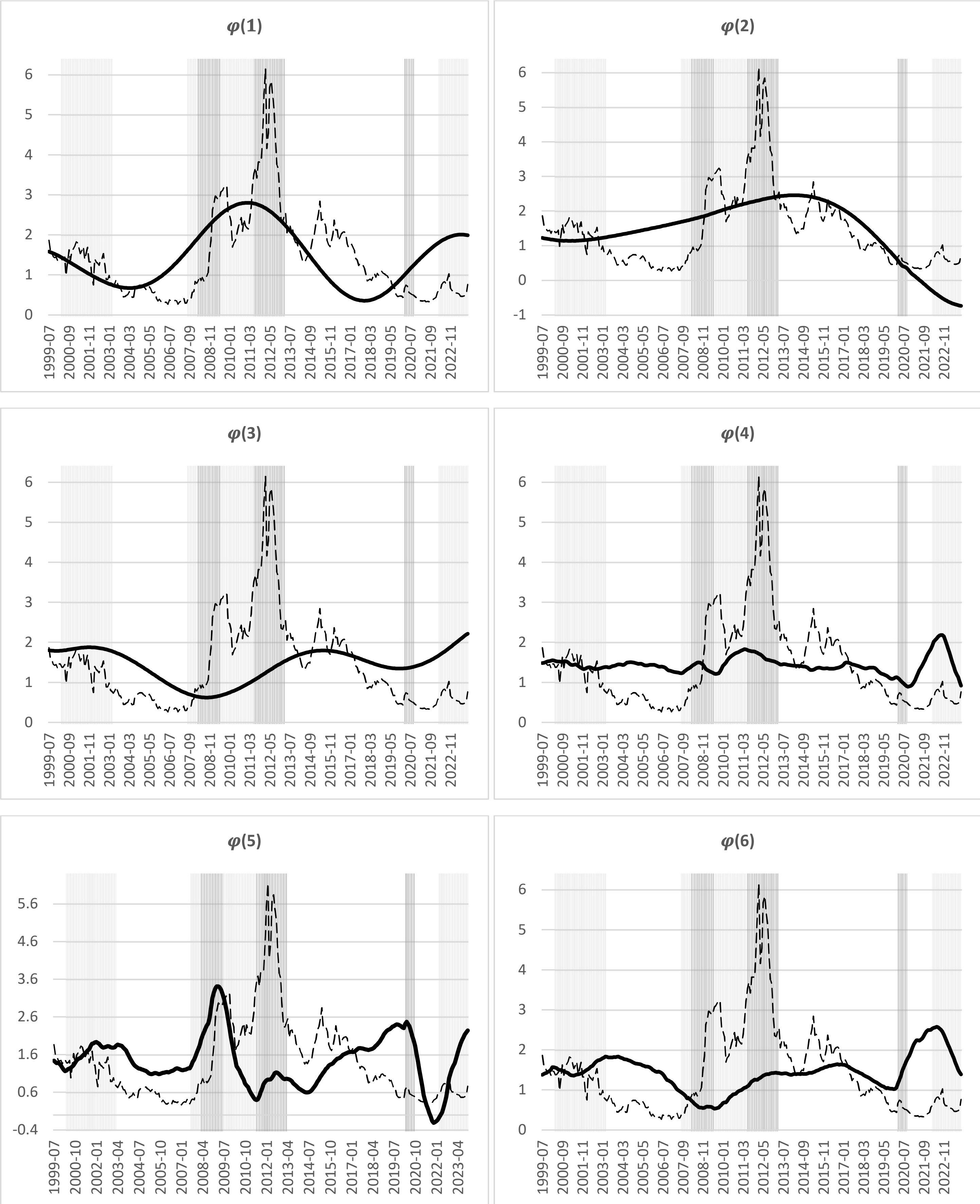
The figure reports the contribution of the common medium to long-term ($\varphi_1, \varphi_2, \varphi_3$) and short-term ($\varphi_4, \varphi_5, \varphi_6$) structural shocks in the historical decomposition of the nominal divergence indicator.

Figure 9: Historical decomposition of the competitiveness divergence indicator



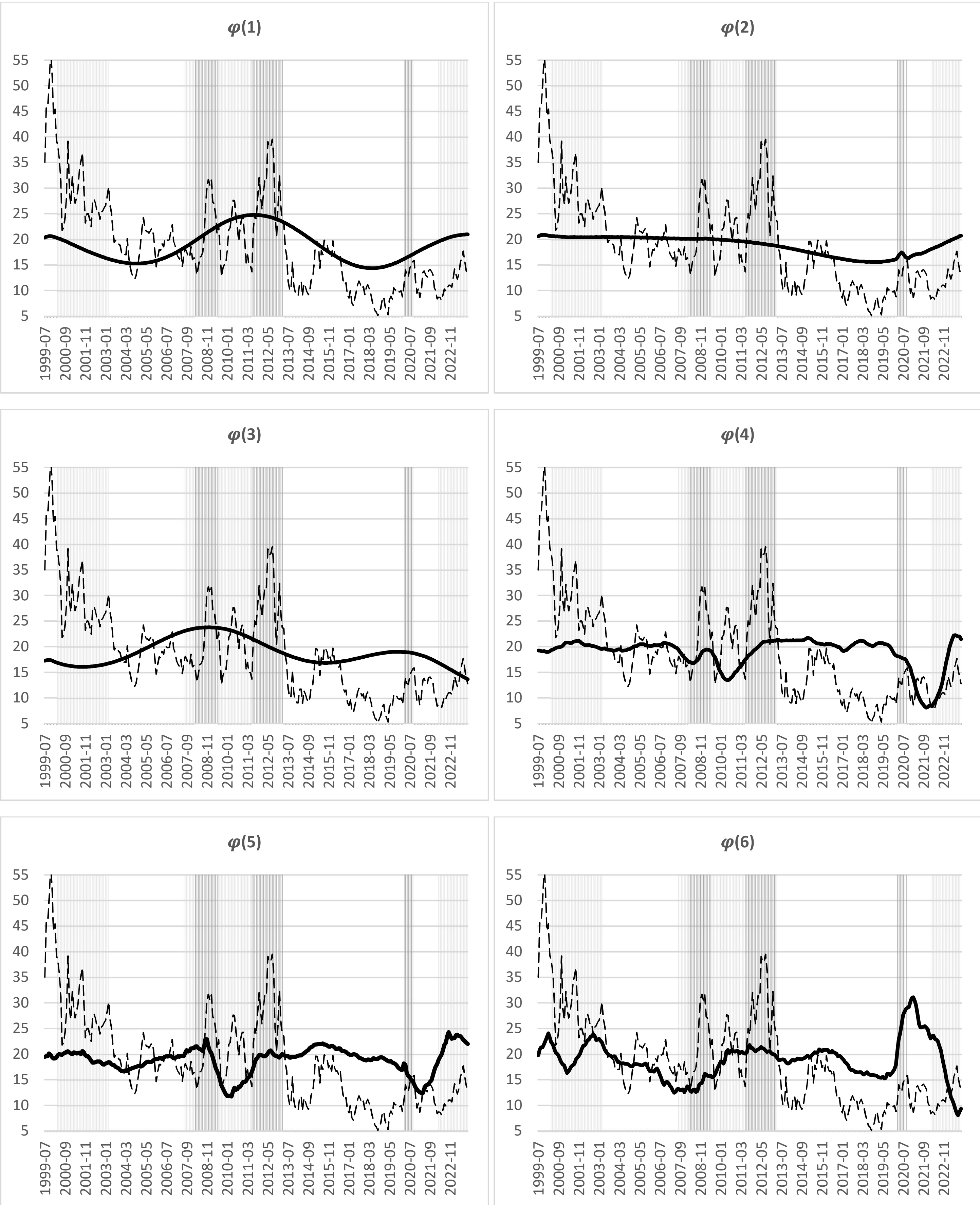
The figure reports the contribution of the common medium to long-term ($\varphi_1, \varphi_2, \varphi_3$) and short-term ($\varphi_4, \varphi_5, \varphi_6$) structural shocks in the historical decomposition of the competitiveness indicator.

Figure 10: Historical decomposition of the bond market divergence indicator



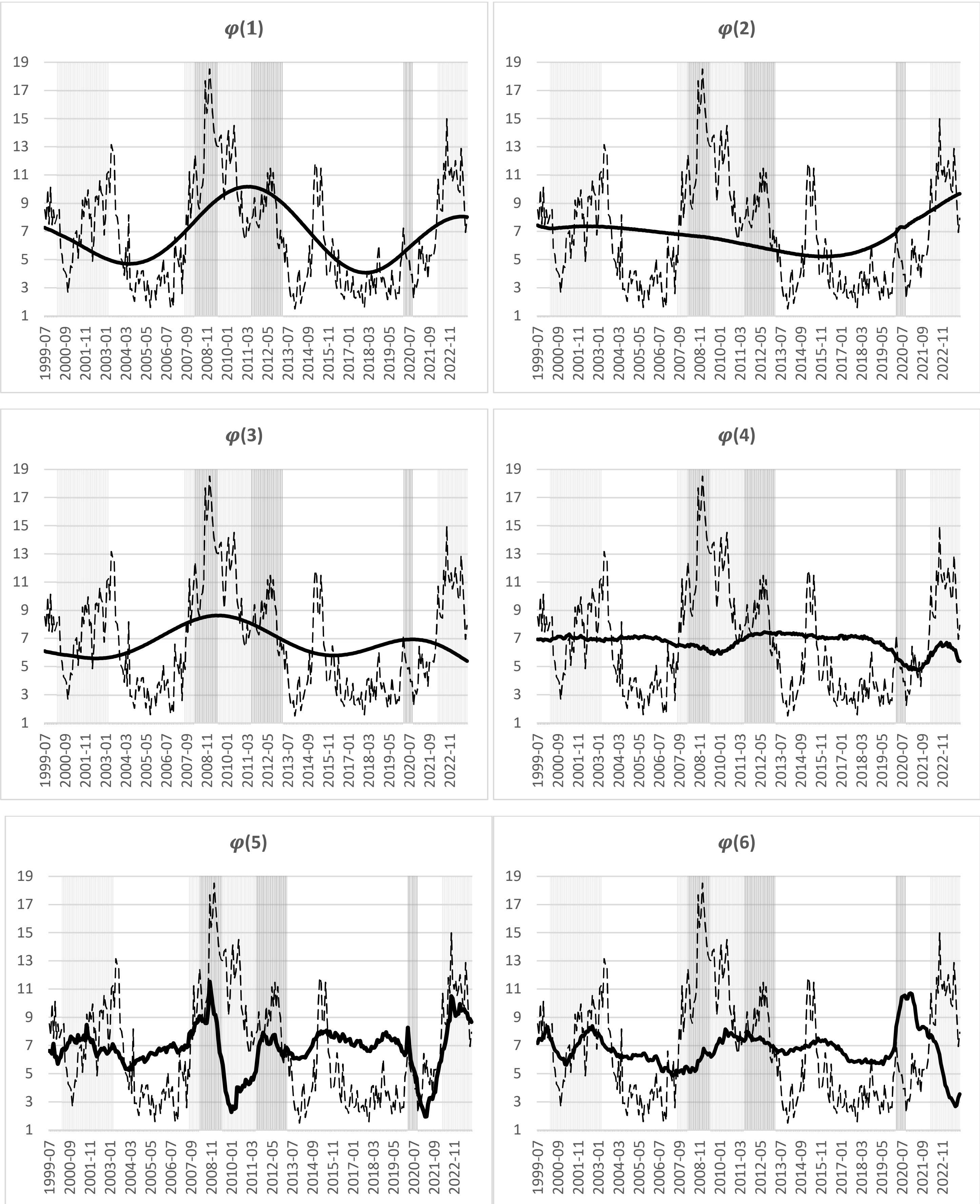
The figure reports the contribution of the common medium to long-term ($\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \ \boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}, \boldsymbol{\varphi_5}, \boldsymbol{\varphi_6}$) structural shocks in the historical decomposition of the bond market divergence indicator.

Figure 11: Historical decomposition of the stock market divergence indicator



The figure reports the contribution of the common medium to long-term ($\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}, \boldsymbol{\varphi_5}, \boldsymbol{\varphi_6}$) structural shocks in the historical decomposition of the stock market divergence indicator.

Figure 12: Historical decomposition of the financial condition divergence indicator



The figure reports the contribution of the common medium to long-term ($\varphi_1, \varphi_2, \varphi_3$) and short-term ($\varphi_4, \varphi_5, \varphi_6$) structural shocks in the historical decomposition of the financial condition divergence indicator.

Eurozone Economic Integration: Historical Developments and New Challenges Ahead (Online Appendix)

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October 2024

Abstract

This online appendix contains details on data construction, the MLT-ST decomposition, and the structural identification of the idiosyncratic divergence measures shocks.

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A1. Dataset construction

The dataset consists of monthly seasonally adjusted series for the euro area (moving composition) over the period 1999:1-2023:11. The euro area currently consists of 20 countries: Austria, Belgium, Croatia, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain.[1] If yet unavailable, euro area 19 figures are used. If needed, seasonal adjustment is performed by X-12 ARIMA. For series not available at the monthly frequency, monthly figures are obtained from cubic interpolation of their quarterly figures, using actual series for end-points. The method assigns each value in the quarterly series to the last monthly observation of the corresponding quarter. Then, it sets all intermediate monthly observations on a natural cubic spline connecting all the time points. See de Boor (1978) for details.

A1.1 Eurozone-level data

Economic conditions and external and internal balance

- Real economic activity: monthly €-coin (€g). We multiply the series by a factor of four to yield a monthly estimate of the year-on-year GDP growth rate. Source: Bank of Italy.

- Labor market tightness: monthly harmonized unemployment rate year-on-year growth rate (u). The series is backcasted over the period 1998:1-1998:3 using a U.C. model. Source: Eurostat.

- External balance: quarterly current account balance to GDP ratio (ca). A positive value means net lending to the rest of the world. The series is backcasted over the period 1998:1-1998:4 using a U.C. model. Monthly observations are obtained through interpolation and seasonally adjusted. Source: ECB.

- Internal balance: quarterly public deficit to GDP ratio (fd). A positive value means that the government has a surplus. The series is backcasted over 1998:1-2002:3 using annual figures available from Eurostat and a U.C. model. Monthly figures are obtained from cubic interpolation. Source: ECB.

Prices, interest rates, and liquidity conditions

- Price inflation: monthly year-on-year harmonized HCPI (all goods) inflation rate (π). Source: Eurostat.

- Wage inflation: quarterly year-on-year growth rate of the HICP deflated Hourly Earnings Index for Manufacturing (rw). The monthly real earnings series is computed through interpolation. Source: OECD and Eurostat.

- Competitiveness: monthly year-on-year real broad effective exchange rate return (rx). Source: BIS.

[1] Of the twenty current members of the Eurozone, eleven countries adopted the Euro in January 1999 (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain). Then, Greece joined in 2001, Slovenia in 2007, Cyprus and Malta in 2008, Slovakia in 2009, Estonia in 2011, Latvia in 2014, Lithuania in 2015, and Croatia in 2023.

- Transportation costs: monthly New York Fed Global Supply-Chain Pressure Index (gs). The index is based on various global transportation costs series and supply chain-related components of Purchase Manager Index (PMI) surveys, i.e., delivery times, backlogs, and purchased stocks, for manufacturing firms across China, the euro area, Japan, South Korea, Taiwan, the United Kingdom, and the United States. We compute an annual (MA-12) moving average of the series. Source: NY Fed.

- Energy price inflation: monthly year-on-year IMF Fuel (Energy) Index growth rate. The index comprises crude oil, natural gas, coal, and propane sub-indices. The original US index is converted into Euros using the U.S. Dollar to Euro spot exchange rate and deflated using the seasonally adjusted HICP index. Source: IMF.

- Interest rates: annualized real short- and long-term monthly interest rates. The policy/risk-free real interest rate is the real Euro short-term rate (€STR; ro), the real short-term rate is the 3-month real Euribor rate (rs), while the real long-term interest rate is the 10-year government bond rate (rl). The ECB has been publishing Euro short-term rate figures since October 2019. Starting on 2 October 2019, the EONIA rate has been calculated as the €STR plus a spread provided by the ECB on 31 May 2019 as 8.5 basis points. We compute synthetic €STR values through January 1999 by applying the same scaling backward to the available EONIA rate values. Real figures are obtained in all cases by subtracting the year-on-year harmonized HICP inflation rate. Source: ECB.

- Liquidity conditions: year-on-year monthly real money growth (rm) and excess money growth (em) rates. The former is computed as the difference between the monthly nominal M3 growth rate and the monthly HICP inflation rate; the latter is calculated as the difference between the year-on-year monthly nominal M3 growth rate and the monthly €-coin indicator. Source: ECB.

Cyclical financial market conditions

- Credit market: quarterly private credit gap, i.e., the quarterly ratio of total credit to private nonfinancial sectors to the annual moving sum of quarterly nominal gross domestic product (cg). The series is backcasted over 1998:1-1998:4 using a U.C. model and conditioning on the M3 to GDP ratio. The monthly credit gap series is computed through interpolation. Source: BIS.

- Housing market: the quarterly house price gap, i.e., the ratio of the quarterly house price index to the annual moving sum of quarterly nominal gross domestic product (hg); the quarterly house price to income ratio, i.e., the quarterly nominal house price index divided by nominal net disposable income per head (hi); the quarterly house price to rent ratio, i.e., the quarterly nominal house price index divided by the nominal rent price index (hr). We compute quarterly year-on-year growth rates for the abovementioned variables and monthly figures through cubic spline interpolation. Source: OECD

- Gold market: monthly year-on-year real gold price return (rg). The US$ per troy ounce gold price is converted into Euros and deflated by the seasonally adjusted HICP index. Source: IMF.

- Stock market: the monthly year-on-year return of the European Fama-French market factor return (mk). Source: French website.

Economic and financial uncertainty and financial condition measures

- Interbank market stress: monthly 3-month Euribor-Euro Short Term Rate spread (so), which yields an overall credit and liquidity risk measure for the interbank market. Source: ECB.
- Sovereign bond market stress: the monthly term spread, computed as the difference between the 10-year government bond rate and the Euro Short Term Rate rate (lo), which yields a measure of credit risk for the government bond market. Moreover, we use the Composite Indicator of Systemic Sovereign Stress (SovCISS; sc) by Garcia-de-Andoain and Kremer (2018), integrating credit risk, volatility, and liquidity at short-term and long-term bond maturities into a composite indicator. An increase in SovCISS points to increasing sovereign debt default risk. Figures for 1999:1-2000:8 are backcasted using the re-scaled spread between the euro area 10-year government bond rate and the 10-year Bund rate. Source: ECB.
- Stock market stress: the monthly EURO STOXX 50 (implied) Volatility (VSTOXX) (vx) is used to measure economic and financial uncertainty (stock market uncertainty). Monthly figures are averages of the available daily values. An increase in implied stock market volatility signals higher stock market uncertainty. Source: Eurex.
- Overall financial conditions: the new Composite Indicator of Systemic Stress (NewCISS; nc) by Hollo et al. (2012). It embeds information on bank and non-bank financial intermediaries, money markets, securities (equities and bonds), and foreign exchange markets. A monthly series is obtained by averaging daily figures over each month. An increase in this financial condition index points to increasing financial distress. Source: ECB.

Expectations of future economic conditions

Revisions in expectations of future economic conditions: monthly year-on-year European Fama and French (1993) size (SMB, sb) and value (HML, hl) factor returns, and Charart (1997) momentum (MOM, mm) factor returns. Unanticipated higher profitability of small and value firms might be related to favorable changes in the investment opportunity set and, therefore, to expectations of an improved macroeconomic outlook. Hence, positive size and value shocks might signal the anticipation of an economic upturn. On the other hand, a positive momentum shock yields less clear-cut information, as momentum may persist over expansions and, temporarily, over economic downturns. Source: French website.

A1.2 Country-level data

Industrial production data are for manufacturing and are available from Eurostat. We compute year-on-year monthly growth rates. Unemployment rate data are for total unemployment and are available from Eurostat. We compute year-on-year monthly growth rates. Inflation rate data are for the harmonized consumer price index and are available from Eurostat. We compute year-on-year monthly inflation rates. Broad real effective exchange rates are available from the BIS. We compute year-on-year monthly returns. Nominal government bond rates are for the ten-year maturity and are available from the ECB. Stock prices are the share price indexes available from the OECD or the national stock exchanges (Croatia, Malta, and Cyprus). We compute year-on-year monthly returns. Financial conditions are measured by the Country Level Index of Financial Stress (CLIFS) available from the ECB. In a few cases, some of the member countries data are missing or unavailable over the entire period 1999:1-2023:11. In such circumstances, the dispersion measures are computed using only the available country-level data at any given time. For instance, CLIFS data is unavailable for Estonia. Moreover, for Latvia, Lithuania, and Slovenia, CLIFS data are available from 2003, 2004, and 2002, respectively. Share prices for Cyprus are available since 2012. Bond returns are available from 2000 for Latvia, Lithuania, Malta, Slovakia, and Slovenia, and from 2006 for Croatia.

A2. MLT-ST decompositions

The results of the first step of the procedure detailed in the methodological Appendix in the main text, i.e., the $MLT - ST$ decompositions and the estimation of the common MLT and ST factors using PCA are reported in Tables A6-A8. In Table A6 we report the results for the $MLT - ST$ decompositions; we also report Becker et al. (2006) KPSS tests for the actual series and the estimated residual (cyclical) components. We plot the estimated MLT and ST components in Figures A1-A3. The decomposition is successful in all cases, as the estimated MLT components capture the underlying dynamics in all the series (Figures A1 and A2), consistent with the statistical significance of the trigonometric components. Coherently, no evidence of a trend can be gauged from the cyclical components reported in Figure A3. The coefficient of determination in the auxiliary specifications measures the contribution of MLT fluctuations to overall fluctuations. On average, across the series, the R^2 is about 0.40, pointing to a dominant contribution of the ST components. The $KPSS$ test does not detect stochastic nonstationarity in the actual series. Stationarity is also clear-cut for the estimated ST components, confirming the validity of the decompositions.

In Table A7 we report the results of the Principal Components Analysis carried out on each set of estimated components. Concerning the MLT series, we use first differences, rather than levels, for the real short and long-term interest rates and the credit gap. Even in the case of over differencing, the series would be stationary. This transformation is more economically meaningful than linear detrending as it yields the monthly variation in the series of interest, and it is akin to Bai and Ng (2004).[2] Concerning the MLT series, the first two PCs account for about 70% of the total variance (40% and 27%, respectively); the third component accounts for an additional 16% of the variance; the contribution of the fourth and fifth component is about 10% and 8%, respectively. Concerning the ST series, the first two PCs account for about 46% of the total variance (25% and 21%, respectively); the third component accounts for an additional 14% of the variance; the contribution of the fourth and fifth components is about 8% and 7%, respectively. Table A7 also reports the estimated (inverse) signal-to-noise ratio from a stochastic cycle plus noise U.C. models for the selected common MLT and ST components and their estimated periodicity. This allows one to assess the empirical relevance of PC's measurement error and confirm the

[2] The transformation slightly increases the overall correlation across series (2.3%.) and should make extracting the common components more accurate.

validity of the disentangling of the MLT and ST fluctuations. The estimated inverse signal-to-noise ratio is virtually zero for all the estimated PCs, supporting their modeling as they were observed factors and inference based on standard asymptotic theory in the FAVAR analysis. This finding is also supportive of the application of PCA to the estimated MLT and ST components of the various macro-financial variables, consistent with the theoretical results of Hellton and Thoresen (2014). The estimated periodicity is consistent with expectations, pointing to periodic fluctuations in the range of 13-21 years and 3.5-4.5 years for MLT and ST factors, respectively.

In Table A8 we also report the loadings of the first five MLT and ST factors for the various variables, in alternative to the associated eigenvectors, as delivered in PC regressions of the variables on the common factors. The estimated PCs are indexes that summarize information on a large set of variables; in the current context, they convey information about how different series' components, i.e., trend and cycle, correlates or comove, uncovering stylized facts about macro-financial fluctuations. They represent "forces that potentially affect many economic variables" (Bernanke et al., 2005, p.392). Yet, the common factors estimated by PCA are not identified without further restrictions. It is always possibly to premultiply the PCs by an arbitrary full rank matrix of suitable order to define a new observationally model.

Hence, based on the proportion of accounted overall variance we focus our analysis on the first three PCs extracted from each set of MLT and ST series, that we report in Figure 3 in the main text. Their identification and economic interpretation is carried out within the FAVAR context, following Bai and Wang (2015), as detailed in the methodological Appendix in the main text.

A3. Identification of idiosyncratic divergence shocks

Concerning the identification of the structural divergence measures idiosyncratic disturbances, the procedure imposes a lower triangular structure for the $\mathbf{\Gamma}_{0,pp}$ matrix measuring their contemporaneous impact on the divergence measures. This is equivalent to impose a recursive ordering for the divergence measures. The distinction between fast-moving and slow-moving variables can help to justify the ordering of the divergence measures. For instance, fast-moving variables divergence measures, i.e., financial variables, should follow the slow-moving variables divergence measures in the ordering. This yields, for instance

$$\begin{bmatrix} e_{nd,t} \\ e_{ld,t} \\ e_{rd,t} \\ e_{cd,t} \\ e_{bd,t} \\ e_{sd,t} \\ e_{fd,t} \end{bmatrix} = \mathbf{\Gamma}_{0,p,q} \begin{bmatrix} \varphi_{1,t} \\ \varphi_{2,t} \\ \varphi_{3,t} \\ \varphi_{4,t} \\ \varphi_{5,t} \\ \varphi_{6,t} \end{bmatrix} + \mathbf{\Gamma}_{0,pp} \begin{bmatrix} \kappa_{1,t} \\ \kappa_{2,t} \\ \kappa_{3,t} \\ \kappa_{4,t} \\ \kappa_{5,t} \\ \kappa_{6,t} \\ \kappa_{7,t} \end{bmatrix} \tag{1}$$

where we are ordering first the inflation dispersion measure (nd), followed by the labour market (ld) and industrial output (rd) measures. Next, we order competitiveness dispersion (cd) followed by the bond market (bd), stock market (sd), and overall financial condition (fd) dispersion measures. The selected ordering nd, ld, rd, cd, bd, sd, fd is consistent with the assumption that prices, unemployment, and output are the relatively slow-moving variables, and real effective exchange rates, bond, stocks, and overall financial conditions are the relatively fast-moving ones. Our thick modelling strategy ensures robustness to ordering and lag length to our policy analysis.

The results of the impulse response analysis are reported in Figures A8 and A9 for the idiosyncratic divergence structural shocks κ_1, κ_2, κ_3, κ_4, κ_5, κ_6, and κ_7. In Table A11 we report the results of the forecast error variance decomposition.

A3.1 Idiosyncratic macro-financial divergence spillovers

Table A11 (Panel A) shows that each structural idiosyncratic shock can be associated with its divergence measure, accounting for the bulk of forecast error variance within one year. The accounted $FEVD$ share at this horizon is larger than 80% for all the indicators but the financial condition indicator (73%). The evidence of cross-measure interactions and the contribution of the cyclical, structural shocks to overall series fluctuations increases with the horizon. At business cycle horizons, the $FEVD$ share accounted by the own shock is much lower for the nominal, stock market, and financial condition indicators (35%-50%) and lowest for the labor market, competitiveness, and bond market indicators (14%-25%). The real divergence indicator is an exception (70%), which is not surprising given its much higher noisiness, as shown in Figure 1. Even at business cycle horizons, cross-measure spillovers are most relevant for the competitiveness, bond, stock, and financial condition indicators, particularly nominal divergence spillovers to these measures (7%-25%). Overall, in the light of $FEVD$ results, macroeconomic spillovers appear more relevant to financial divergence than vice versa.

The impulse response analysis yields further insights on these interlinkages. As shown in Figure Figures A12-A13, the idiosyncratic structural spillovers, in general, are short-lived and not significant beyond one year in most cases.

For instance, a positive real divergence shock κ_1 yields an increase in labor market dispersion ld within three months; the impact is also positive on bonds, stocks, and financial conditions divergence bd, sd, and fd, albeit not significant even in the very short-term for this latter series. A negative effect can be noted on competitiveness dispersion cd (Figure A12, top panel). Similar results hold for a positive labor market divergence shock κ_2, increasing output (rd), bonds, stocks, financial condition divergence, and competitiveness divergence (Figure A12, center panel). More persistent appears the effect of a positive nominal divergence shocks κ_3, impacting nonlinearly on real and labor market divergence, i.e., negatively within six months/one year, yet positively within three years. The impact is positive even at business cycle horizons on competitiveness, stocks, and financial condition divergence but negative on bond market divergence (Figure A12, bottom panel).

Similarly persistent appears the effects of a competitiveness divergence shock κ_4, leading to an increase in real, bonds, and financial condition divergence within six months and an increase in labor, nominal, and stocks divergence within three years (Figure A13, top panel). Differently, a positive bond market diverges shock κ_5 leads to a reduction of real, labor, and competitiveness divergence within eighteen months, yet an increase in stock market and financial condition divergence within six months and two years, respectively (Figure A13, upper center panel). Finally, similar effects hold for the stocks and financial condition divergence shocks κ_6 and κ_7, yielding to a short-lived increase in financial/stock market divergence, as well as in competitiveness and real divergence, while exercising a negative impact on bond market divergence within one year (Figure A13, lower center and bottom panels).

Overall, the evidence points to interesting interlinkages across the various divergence measures, showing how idiosyncratic diverging developments in one measure, in general, generate a diverging response also in the other macro-financial measures. Bond market developments show some exceptions regarding macroeconomic divergence.

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Table A2: Correlation of divergence statistics (synthetic Eurozone)													
ld							***cd***						
		SD	**GMD**	**DSD**	**MAD**	**wSD**			**SD**	**GMD**	**DSD**	**MAD**	**wSD**
	SD		1.00	0.99	0.93	0.92		**SD**		0.99	0.98	0.88	0.85
	GMD	0.94		0.99	0.95	0.92		**GMD**	0.99		0.99	0.93	0.87
rd	**DSD**	0.93	0.98		0.92	0.92	***nd***	**DSD**	0.98	1.00		0.92	0.90
	MAD	0.68	0.88	0.88		0.87		**MAD**	0.84	0.91	0.90		0.86
	wSD	0.86	0.83	0.85	0.65			**wSD**	0.95	0.96	0.96	0.87	
sd							***od***						
		SD	**GMD**	**DSD**	**MAD**	**wSD**			**SD**	**GMD**	**DSD**	**MAD**	**wSD**
	SD		0.98	0.98	0.81	0.76		**SD**		0.99	0.91	0.57	0.75
	GMD	0.99		0.99	0.91	0.80		**GMD**	0.98		0.93	0.65	0.77
bd	**DSD**	0.99	0.99		0.89	0.82	***fd***	**DSD**	0.98	0.99		0.58	0.69
	MAD	0.83	0.89	0.83		0.78		**MAD**	0.91	0.97	0.97		0.82
	wSD	0.93	0.93	0.89	0.88			**wSD**	0.90	0.91	0.91	0.88	

The Table reports correlation coefficients for the divergence indicators computed over the sample. The indicators are the standard deviation (*SD*), the Gini mean absolute deviation (G*MD*), the distance standard deviation (*DSD*), the median absolute deviation (MAD), and the GDP-weighted standard deviation (*wSD*). In each of the four panels, figures below the main diagonal refer to *rd*, *nd*, *bd*, and *fd*; figures above the main diagonal refer to *ld*, *cd*, *sd*, and *od*.

Table A3: Divergence statistics (synthetic Eurozone)													
			rd							***Ld***			
	ALL	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**		**ALL**	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**
SD	5.91	6.64	5.78	6.15	5.60	7.38	**SD**	12.53	19.38	11.32	16.16	10.92	9.70
GMD	6.26	7.45	6.05	6.84	5.84	7.28	**GMD**	14.09	21.53	12.77	18.06	12.32	10.99
DSD	3.82	4.60	3.68	4.19	3.56	4.39	**DSD**	8.86	14.07	7.93	11.53	7.66	6.81
MAD	4.79	6.25	4.54	5.60	4.35	4.92	**MAD**	11.45	16.50	10.56	14.14	10.26	9.30
wSD	4.12	5.02	3.96	4.08	3.95	5.77	**wSD**	9.39	16.10	8.20	12.57	8.03	6.46
			nd							***Cd***			
	ALL	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**		**ALL**	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**
SD	1.55	1.56	1.55	1.80	1.21	3.30	**SD**	2.07	2.00	2.09	2.49	1.75	2.94
GMD	1.64	1.64	1.64	1.88	1.28	3.60	**GMD**	2.22	2.16	2.23	2.65	1.86	3.32
DSD	1.02	1.06	1.02	1.19	0.78	2.35	**DSD**	1.38	1.36	1.38	1.65	1.15	2.12
MAD	1.19	1.14	1.19	1.31	0.95	2.63	**MAD**	1.65	1.62	1.65	1.90	1.39	2.73
wSD	1.05	1.06	1.04	1.23	0.80	2.32	**wSD**	1.45	1.54	1.44	1.82	1.14	2.46
			bd							***Sd***			
	ALL	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**		**ALL**	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**
SD	1.45	2.74	1.22	2.13	1.17	0.65	**SD**	19.13	24.38	18.20	24.85	16.87	12.17
GMD	1.38	2.57	1.17	1.99	1.13	0.73	**GMD**	20.31	23.94	19.66	26.50	17.82	13.15
DSD	0.93	1.67	0.80	1.37	0.76	0.45	**DSD**	12.44	14.68	12.04	16.18	10.97	7.81
MAD	0.81	1.56	0.68	1.09	0.69	0.62	**MAD**	15.34	16.58	15.12	20.31	13.28	10.17
wSD	2.07	4.66	1.62	2.93	1.76	0.83	**wSD**	10.91	12.98	10.54	14.14	9.46	8.41
			fd							***od (scaled)***			
	ALL	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**		**ALL**	**REC**	**EXP**	**BUST**	**BOOM**	**GEO**
SD	6.76	9.74	6.23	9.40	4.90	10.51	**SD**	0.73	0.96	0.69	0.90	0.62	0.87
GMD	7.38	10.73	6.79	10.25	5.29	12.13	**GMD**	0.77	1.02	0.73	0.96	0.65	0.94
DSD	4.77	6.67	4.43	6.53	3.45	7.99	**DSD**	0.80	1.02	0.76	0.97	0.67	1.21
MAD	5.93	8.77	5.42	8.14	4.18	10.77	**MAD**	1.26	1.90	1.15	1.59	1.07	1.41
wSD	5.51	7.59	5.14	7.46	4.07	8.92	**wSD**	1.07	1.63	0.97	1.34	0.91	1.21

The Table reports the average figures for the divergence indicators computed over the whole sample (*ALL*), recessions (*REC*), expansions (*EXP*), financial busts (*BUST*), booms (*BOOM*), and over the most recent period of economic and financial distress started by the Russian's war in Ukraine (GEO). The indicators are the standard deviation (*SD*), the Gini mean absolute deviation (G*MD*), the distance standard deviation (*DSD*), the median absolute deviation (MAD), and the GDP-weighted standard deviation (*wSD*). The figures are for: real divergence (*rd*), labor market divergence (*ld*), nominal divergence (*nd*), competitiveness divergence (*cd*), bond market divergence (*bd*), stock market divergence (*sd*), financial conditions divergence (*fd*), and overall divergence (*od*).

Table A4: Divergence indicators and economic and financial distress (synthetic Eurozone)

	rd			*ld*			*nd*			*cd*		
	GMD	*DSD*	*MAD*	*GMD*	*DSD*	*MAD*	*GMD*	*DSD*	*MAD*	*GMD*	*DSD*	*MAD*
Const	**5.324**	**3.237**	**3.930**	**11.661**	**7.244**	**9.643**	**1.277**	**0.775**	**0.925**	**1.969**	**1.210**	**1.439**
	(0.146)	(0.089)	(0.096)	(0.482)	(0.298)	(0.349)	(0.088)	(0.054)	(0.046)	(0.200)	(0.126)	(0.112)
REC	**0.870**	**0.482**	**1.212**	**4.967**	**3.138**	**4.702**	-0.159	-0.098	0.038	**-0.692**	**-0.426**	**-0.366**
	(0.224)	(0.161)	(0.246)	(0.693)	(0.485)	(0.481)	(0.102)	(0.062)	(0.062)	(0.203)	(0.127)	(0.115)
BUST	**1.385**	**0.855**	**1.484**	**3.782**	**2.328**	**2.937**	**0.612**	**0.395**	**0.422**	**0.709**	**0.451**	**0.475**
	(0.334)	(0.186)	(0.269)	(1.333)	(0.872)	(1.084)	(0.142)	(0.096)	(0.077)	(0.305)	(0.192)	(0.169)
REC x BUST	-0.464	-0.180	-0.634	3.231	3.004	0.185	0.143	0.157	-0.165	0.594	0.395	0.333
	(0.605)	(0.388)	(0.550)	(2.892)	(2.335)	(1.438)	(0.362)	(0.249)	(0.153)	(0.501)	(0.323)	(0.284)
PAND	**3.111**	**1.944**	**2.077**	**2.721**	**1.781**	**2.667**	0.204	0.125	0.276	**-0.532**	-0.313	-0.232
	(0.628)	(0.372)	(0.677)	(1.239)	(0.732)	(1.046)	(0.254)	(0.158)	(0.183)	(0.311)	(0.191)	(0.224)
PAND x REC	0.892	0.753	1.263	-2.238	-1.669	-2.666	-0.182	-0.093	-0.243	0.443	0.260	0.205
	(2.706)	(1.739)	(2.454)	(1.500)	(0.996)	(1.196)	(0.276)	(0.170)	(0.199)	(0.312)	(0.191)	(0.225)
GEO	-1.154	**-0.793**	-1.084	**-3.391**	**-2.215**	**-3.012**	**2.120**	**1.450**	**1.428**	**1.880**	**1.223**	**1.526**
	(0.656)	(0.388)	(0.734)	(1.338)	(0.825)	(1.170)	(0.428)	(0.305)	(0.283)	(0.371)	(0.233)	(0.278)
R2	0.324	0.333	0.338	0.448	0.436	0.441	0.518	0.520	0.653	0.183	0.192	0.277
R2bar	0.308	0.317	0.322	0.434	0.423	0.427	0.506	0.509	0.644	0.164	0.172	0.260

	bd			*sd*			*fd*			*od*		
	GMD	*DSD*	*MAD*	*GMD*	*DSD*	*MAD*	*GMD*	*DSD*	*MAD*	*GMD*	*DSD*	*MAD*
Const	**1.138**	**0.769**	**0.654**	**18.216**	**11.180**	**13.612**	**5.134**	**3.367**	**4.048**	**0.631**	**0.640**	**1.023**
	(0.109)	(0.077)	(0.074)	(1.570)	(1.012)	(0.938)	(0.437)	(0.299)	(0.358)	(0.028)	(0.023)	(0.042)
REC	**1.926**	**1.154**	**1.639**	**4.202**	**2.988**	-1.173	**3.684**	**2.200**	**3.337**	**0.235**	**0.222**	**1.173**
	(0.306)	(0.198)	(0.125)	(1.795)	(1.167)	(1.121)	(1.036)	(0.628)	(0.739)	(0.041)	(0.030)	(0.084)
BUST	**0.435**	**0.354**	**0.190**	**8.431**	**5.166**	**7.657**	**4.156**	**2.659**	**3.227**	**0.254**	**0.264**	**0.379**
	(0.201)	(0.135)	(0.135)	(2.102)	(1.352)	(1.531)	(0.835)	(0.553)	(0.676)	(0.037)	(0.032)	(0.092)
REC x BUST	-0.608	**-0.391**	**-0.863**	-4.670	-3.509	-1.840	-0.680	-0.612	-0.629	-0.007	-0.025	**-0.587**
	(0.625)	(0.393)	(0.404)	(2.834)	(1.787)	(2.381)	(1.779)	(1.098)	(1.403)	(0.080)	(0.079)	(0.226)
PAND	**-0.700**	**-0.492**	**-0.276**	**-4.867**	**-3.008**	**-2.900**	-0.062	-0.093	-0.287	0.039	0.127	-0.055
	(0.111)	(0.079)	(0.076)	(1.687)	(1.085)	(1.057)	(0.659)	(0.430)	(0.637)	(0.034)	(0.038)	(0.053)
PAND x REC	**-1.676**	**-0.972**	**-1.453**	-2.026	-1.062	**3.746**	**-3.012**	**-1.898**	**-2.289**	**-0.164**	**-0.171**	**-0.945**
	(0.311)	(0.201)	(0.132)	(2.017)	(1.349)	(1.303)	(1.246)	(0.796)	(1.066)	(0.083)	(0.082)	(0.144)
GEO	**0.289**	**0.177**	**0.241**	-0.200	-0.365	-0.538	**7.063**	**4.721**	**7.011**	**0.268**	**0.447**	**0.440**
	(0.067)	(0.035)	(0.042)	(1.192)	(0.691)	(0.872)	(0.741)	(0.419)	(0.716)	(0.043)	(0.087)	(0.057)
R2	0.441	0.430	0.371	0.274	0.257	0.333	0.498	0.470	0.509	0.558	0.646	0.548
R2 adj.	0.427	0.416	0.356	0.256	0.239	0.317	0.486	0.458	0.497	0.547	0.637	0.537

The Table reports the estimated regressions for the Gini mean difference (GMD), the distance standard deviation (DSD), and the median absolute deviation (MAD). HACSE are reported in square brackets. R2 and R2 (adj.) are the unadjusted and adjusted coefficients of determination. The figures are for: real divergence (*rd*), labor market divergence (*ld*), nominal divergence (*nd*), competitiveness divergence (*cd*), bond market divergence (*bd*), stock market divergence (*sd*), financial conditions divergence (*fd*), aggregate macro-financial divergence (*od*).

Table A5: Average country net contributions to SD, GMD, and DSD (synthetic Eurozone)

	rd				*ld*				*nd*				*cd*		
	SD	**GMD**	**DSD**		**SD**	**GMD**	**DSD**		**SD**	**GMD**	**DSD**		**SD**	**GMD**	**DSD**
AT	0.12	0.14	0.13	**AT**	**-0.02**	**-0.01**	**0.06**	**AT**	0.02	0.03	0.03	**AT**	0.04	0.06	0.05
BE	0.08	0.08	0.09	**BE**	0.15	0.21	0.20	**BE**	0.02	0.03	0.03	**BE**	0.04	0.06	0.05
HR	0.08	0.09	0.09	**HR**	0.10	0.15	0.16	**HR**	0.03	0.02	0.03	**HR**	**-0.01**	**-0.02**	0.00
CY	**-0.02**	**-0.03**	**0.01**	**CY**	**-0.21**	**-0.24**	**-0.05**	**CY**	0.01	0.01	0.02	**CY**	0.02	0.03	0.03
EE	**-0.14**	**-0.18**	**-0.07**	**EE**	**-0.64**	**-0.72**	**-0.44**	**EE**	**-0.05**	**-0.07**	**-0.05**	**EE**	**-0.02**	**-0.03**	**-0.01**
FI	0.08	0.10	0.10	**FI**	0.18	0.26	0.25	**FI**	0.02	0.02	0.03	**FI**	0.03	0.04	0.03
FR	0.12	0.16	0.13	**FR**	0.21	0.29	0.27	**FR**	0.02	0.03	0.03	**FR**	0.03	0.04	0.04
DE	0.12	0.15	0.13	**DE**	0.17	0.21	0.23	**DE**	0.02	0.03	0.03	**DE**	0.02	0.03	0.03
GR	0.02	0.01	0.04	**GR**	0.03	0.07	0.14	**GR**	0.00	0.00	0.01	**GR**	0.01	0.01	0.02
IE	**-0.81**	**-0.63**	**-0.34**	**IE**	**-0.17**	**-0.24**	**-0.09**	**IE**	0.01	0.01	0.02	**IE**	**-0.05**	**-0.06**	**-0.01**
IT	0.09	0.12	0.11	**IT**	0.16	0.22	0.20	**IT**	0.03	0.05	0.04	**IT**	0.04	0.06	0.05
LV	0.01	0.00	0.02	**LV**	**-0.12**	**-0.18**	**-0.11**	**LV**	**-0.12**	**-0.11**	**-0.07**	**LV**	**-0.15**	**-0.17**	**-0.10**
LT	**-0.17**	**-0.18**	**-0.08**	**LT**	**-0.45**	**-0.57**	**-0.38**	**LT**	**-0.05**	**-0.07**	**-0.04**	**LT**	**-0.07**	**-0.09**	**-0.06**
LU	0.04	0.04	0.06	**LU**	**-0.18**	**-0.21**	**-0.06**	**LU**	0.02	0.03	0.03	**LU**	0.03	0.04	0.04
MT	**-0.11**	**-0.13**	**-0.03**	**MT**	0.07	0.10	0.13	**MT**	0.02	0.02	0.03	**MT**	0.03	0.02	0.03
NL	0.07	0.08	0.09	**NL**	0.04	0.09	0.13	**NL**	0.02	0.02	0.02	**NL**	0.03	0.04	0.03
PT	0.04	0.05	0.07	**PT**	0.08	0.10	0.12	**PT**	0.02	0.03	0.03	**PT**	0.03	0.04	0.03
SK	**-0.10**	**-0.11**	**-0.03**	**SK**	0.01	0.05	0.11	**SK**	**-0.10**	**-0.09**	**-0.05**	**SK**	**-0.20**	**-0.18**	**-0.10**
SI	0.09	0.11	0.10	**SI**	0.13	0.17	0.18	**SI**	**-0.02**	**-0.03**	**-0.01**	**SI**	0.04	0.05	0.05
ES	0.11	0.14	0.11	**ES**	0.17	0.18	0.20	**ES**	0.03	0.04	0.03	**ES**	0.04	0.05	0.05

	bd				*sd*				*fd*				*od (scaled)*		
	SD	**GMD**	**DSD**		**SD**	**GMD**	**DSD**		**SD**	**GMD**	**DSD**		**SD**	**GMD**	**DSD**
AT	0.03	0.05	0.04	**AT**	0.32	0.36	0.35	**AT**	0.10	0.13	0.14	**AT**	0.09	0.12	0.19
BE	0.02	**-0.01**	0.01	**BE**	0.38	0.51	0.44	**BE**	0.05	0.05	0.09	**BE**	0.10	0.12	0.19
HR	**-0.01**	**-0.03**	**-0.01**	**HR**	0.11	0.04	0.13	**HR**	0.03	0.05	0.07	**HR**	0.06	0.05	0.12
CY	**-0.08**	**-0.10**	**-0.06**	**CY**	**-2.98**	**-2.45**	**-1.41**	**CY**	**-0.06**	**-0.07**	**-0.01**	**CY**	**-0.03**	**-0.03**	**0.04**
EE	**-0.04**	**-0.01**	**-0.01**	**EE**	**-0.13**	**-0.20**	**-0.06**	**EE**	.	.	.	**EE**	**-0.20**	**-0.23**	**-0.21**
FI	0.03	0.04	0.03	**FI**	0.15	0.11	0.20	**FI**	0.10	0.08	0.11	**FI**	0.10	0.11	0.18
FR	0.01	0.01	0.02	**FR**	0.43	0.58	0.49	**FR**	0.09	0.10	0.11	**FR**	0.11	0.14	0.21
DE	**-0.29**	**-0.22**	**-0.13**	**DE**	0.35	0.48	0.41	**DE**	0.06	0.06	0.08	**DE**	0.07	0.10	0.18
GR	0.03	0.03	0.03	**GR**	**-0.36**	**-0.56**	**-0.20**	**GR**	**-0.23**	**-0.16**	**-0.06**	**GR**	0.01	0.02	0.08
IE	0.03	0.03	0.03	**IE**	0.21	0.25	0.30	**IE**	**-0.51**	**-0.47**	**-0.23**	**IE**	**-0.29**	**-0.23**	**-0.14**
IT	**-0.01**	**-0.01**	0.00	**IT**	0.40	0.53	0.46	**IT**	0.10	0.13	0.13	**IT**	0.11	0.16	0.22
LV	**-0.01**	**-0.01**	0.00	**LV**	**-0.11**	**-0.17**	**-0.02**	**LV**	**-0.08**	**-0.09**	**-0.03**	**LV**	**-0.27**	**-0.26**	**-0.25**
LT	0.00	0.01	0.02	**LT**	**-0.11**	**-0.11**	0.02	**LT**	**-0.02**	**-0.03**	0.01	**LT**	**-0.22**	**-0.25**	**-0.24**
LU	0.03	0.04	0.04	**LU**	**-0.01**	**-0.03**	0.11	**LU**	0.02	0.01	0.06	**LU**	0.04	0.05	0.12
MT	0.02	0.03	0.02	**MT**	**-0.10**	**-0.15**	0.07	**MT**	**-0.05**	**-0.04**	0.02	**MT**	0.02	0.01	0.10
NL	0.01	**-0.01**	0.01	**NL**	0.40	0.57	0.48	**NL**	0.02	0.04	0.07	**NL**	0.07	0.09	0.14
PT	0.03	0.03	0.03	**PT**	0.34	0.43	0.40	**PT**	0.04	0.06	0.08	**PT**	0.07	0.09	0.15
SK	0.02	0.02	0.02	**SK**	**-0.49**	**-0.63**	**-0.30**	**SK**	**-0.05**	**-0.05**	0.00	**SK**	**-0.30**	**-0.25**	**-0.20**
SI	0.04	0.04	0.04	**SI**	**-0.05**	**-0.06**	0.07	**SI**	0.05	0.06	0.07	**SI**	0.06	0.06	0.13
ES	0.02	0.04	0.03	**ES**	0.40	0.50	0.46	**ES**	0.08	0.10	0.11	**ES**	0.12	0.14	0.21

The Table reports each country's net contribution to the standard deviation, Gini mean difference (GMD), and distance standard deviation (DSD) divergence measure. The figures are for real divergence (*rd*), labor market divergence (ld), nominal divergence (*nd*), competitiveness divergence (*cd*), bond market divergence (*bd*), stock market divergence (*sd*), financial conditions divergence (*fd*), aggregate divergence (*od*). Figures in bold denote diverging countries (negative net contribution statistics). Data are for the EA-20 countries, i.e., Austria (AT), Belgium (BE), Croatia (HR), Cyprus (CY), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Luxembourg (LU), Malta (MT), the Netherlands (NL), Portugal (PT), Slovakia (SK), Slovenia (SI), Spain (ES).

Table A6: MLT-ST decompositions

	g	u	rw	π	em	ro	rs	rl	sb
$\boldsymbol{\theta_0}$	1.014 (0.252)	-1.617 (1.089)	0.444 (0.160)	2.136 (0.176)	4.328 (0.397)	-0.920 (0.200)	-0.652 (0.203)	0.752 (0.150)	0.165 (0.071)
$\boldsymbol{\theta_{s,0.5}}$	-	-	-	-	-	-	-	-	-
$\boldsymbol{\theta_{s,1}}$	-1.604 (0.589)	3.782 (1.544)	-1.903 (0.497)	2.711 (0.514)	1.098 (0.5344)	-1.458 (0.669)	-1.220 (0.656)	-1.752 (0.490)	-
$\boldsymbol{\theta_{s,2}}$	-	-	-	-	-1.418 (0.657)	-	-	-	0.212 (0.110)
$\boldsymbol{\theta_{c,0.5}}$	1.945 (0.577)	-	2.315 (0.592)	-2.737 (0.650)	-	3.423 (0.834)	3.280 (0.809)	3.968 (0.630)	–
$\boldsymbol{\theta_{c,1}}$	0.736 (0.364)	-4.607 (1.589)	-0.595 (0.254)	1.049 (0.280)	-	-	-	-1.109 (0.253)	-
$\boldsymbol{\theta_{c,2}}$	-0.646 (0.246)	3.157 (1.120)	-0.593 (0.207)	-0.809 (0.222)	-1.600 (0.443)	-0.594 (0.289)	-0.503 (0.283)	-	-0.270 (0.087)
$\boldsymbol{R^2}$	0.206	0.251	0.409	0.546	0.252	0.584	0.580	0.772	0.169
$\boldsymbol{\bar{\bar{R}}^2}$	0.196	0.244	0.402	0.540	0.244	0.580	0.575	0.769	0.163
$\boldsymbol{KPSS}$	0.276	0.216	0.200	0.370	0.110	*0.060*	*0.070*	*0.246*	0.179
$\boldsymbol{KPSSn}$	0.028	0.027	0.040	0.033	0.034	0.034	0.037	0.023	0.027
$\boldsymbol{KPSSa}$	0.024	0.051	0.029	0.026	0.048	0.045	0.067	0.024	0.089

	hl	mm	rx	ca	ls	fd	hg	hi	hr
$\boldsymbol{\theta_0}$	0.244 (0.126)	0.794 (0.151)	-0.105 (0.622)	0.828 (0.094)	1.672 (0.101)	-2.802 (0.199	0.243 (0.353)	0.938 (0.266)	1.859 (0.276)
$\boldsymbol{\theta_{s,0.5}}$	-	-	–	-	-	-	-	–	-
$\boldsymbol{\theta_{s,1}}$	1.676 (0.393)	–	5.465 (2.025)	-1.057 (0.264)	-	-1.689 (0.520)	-0.048 (0.440)	–	-
$\boldsymbol{\theta_{s,2}}$	0.949 (0.200)	0.307 (0.257)	2.582 (1.256)	0.758 (0.155)	-	-	-	-	-
$\boldsymbol{\theta_{c,0.5}}$	-1.207 (0.480)	-	-5.394 (2.160)	-0.653 (0.329)	0.280 (0.144)	1.786 (0.620)	-	-	-
$\boldsymbol{\theta_{c,1}}$	0.508 (0.198)	-	-	-0.299 (0.146)	-0.820 (0.145)	-	1.268 (0.560)	1.283 (0.452)	2.793 (0.488)
$\boldsymbol{\theta_{c,2}}$	-	-	-2.107 (0.810)	-0777 (0.105)	0.592 (0.139)	-1.146 (0.239)	-2.208 (0.447)	-2.104 (0.414)	-2.254 (0.411)
									-
$\boldsymbol{R^2}$	0.392	0.033	0.185	0.727	0.482	0.354	0.330	0.429	0.599
$\boldsymbol{\bar{\bar{R}}^2}$	0.385	0.030	0.174	0.776	0.476	0.348	0.323	0.425	0.597
$\boldsymbol{KPSS}$	0.375	0.104	0.066	*0.180*	0.295	0.153	0.145	0.214	0.282
$\boldsymbol{KPSSn}$	0.042	0.021	0.030	0.052	0.053	0.051	0.043	0.040	0.032
$\boldsymbol{KPSSa}$	0.024	0.038	0.043	0.024	0.047	0.064	0.079	0.147	0.060

Table A6: MLT-ST decompositions (continued)										
	rg	***mk***	***rm***	***cg***	***vx***	***sc***	***so***	***nc***	***gs***	***re***
$\boldsymbol{\theta_0}$	6.733 (1.592)	0.447 (0.212)	3.212 (0.348)	1.207 (0.305)	23.513 (0.946)	0.165 (0.012)	0.269 (0.020)	0.183 (0.021)	0.0712 (0.071)	11.882 (5.115)
$\boldsymbol{\theta_{s,0.5}}$	-	-	-		-	-	-	-	-	–
$\boldsymbol{\theta_{s,1}}$	-	-	-3.265 (0.892)	-3.052 (0.752)	-	0.114 (0.026)	-	-	-	-10.50 (7.704)
$\boldsymbol{\theta_{s,2}}$	-9.616 (2.530)	-	-1.750 (0.619)	-1.956 (0.562)	-	-0.043 (0.020)	-0.184 (0.032)	-0.087 (0.036)	-0.491 (0.070)	-
$\boldsymbol{\theta_{c,0.5}}$	5.233 (2.041)	-	4.733 (0.750)	5.933 (0.717)	3.264 (1.326)	-0.115 (0.031)	0.129 (0.032)	-	-0.612 (0.117)	-
$\boldsymbol{\theta_{c,1}}$	-3.058 (2.233)	-	-	-	–	-0.071 (0.018)	-0.144 (0.033)	-	0.481 (0.114)	15.46 (8.103)
$\boldsymbol{\theta_{c,2}}$	-	-0.328 (0.219)	-3.054 (0.412)	-	3.606 (1.035)	0.095 (0.015)	0.085 (0.026)	0.096 (0.021)	0.235 (0.101)	-
$\boldsymbol{R^2}$	0.239	0.150	0.529	0.517	0.151	0.613	0.526	0.240	0.681	0.100
$\boldsymbol{\bar{\bar{R}}^2}$	0.231	0.142	0.523	0.512	0.145	0.606	0.519	0.235	0.677	0.094
$\boldsymbol{KPSS}$	0.114	0.057	0.269	*0.041*	0.338	0.290	0.298	0.120	*0.202*	0.101
$\boldsymbol{KPSSn}$	0.044	0.031	0.049	0.042	0.044	0.039	0.056	0.049	0.042	0.028
$\boldsymbol{KPSSa}$	0.025	0.054	0.039	0.031	0.039	0.025	0.030	0.214	0.044	0.085

The Table reports the estimated econometric models employed for decomposing the various variables. HACSE standard errors are reported in square brackets. R^2 and $\bar{\bar{R}}^2$ are the unadjusted and adjusted coefficients of determination, respectively. KPSS and KPSSa are the Kwiatkowski-Phillips-Schmidt-Shin tests for stationarity or trend stationarity conducted on the actual variables and the estimated residuals, respectively. The asymptotic critical values for the null hypothesis of stationarity (*trend stationarity*) are 0.739, 0.463, and 0.347 (0.216, 0.146, and 0.119) for the 1%, 5%, and 10% levels, respectively. KPSSn is the Becker-Enders-Lee test for second-order nonlinear trend stationarity conducted on the actual variables. The asymptotic critical values for the null hypothesis of non-linear trend stationarity are 0.162, 0.102, and 0.077 for the 1%, 5%, and 10% levels, respectively. Bartlett Kernel and Newey-West bandwidth are employed to compute the various KPSS tests. The variables are the €-coin GDP growth rate (***g***), the change in the unemployment rate ($\boldsymbol{u}$), the real wage growth rate (***rw***), the inflation rate (**π**), the excess money growth rate (***em***), the real overnight, short- and long-term interest rates (***ro, rs, rl***), the Fama-French size, value and market factors (***sb***, ***hl***, ***mk***), the Charart momentum factor (***mm***), the real effective exchange rate return (***rx***), the current account to GDP ratio (***ca***), the fiscal deficit to GDP ratio ($\boldsymbol{fd}$), the term spread (***lo***), the house price to GDP ratio ($\boldsymbol{hg}$), the house price to income ratio ($\boldsymbol{hi}$), and the house price to rent ratio ($\boldsymbol{hr}$), the real gold price return (***rg***), and the real M3 growth rate (***rm***), the credit to GDP ratio ($\boldsymbol{cg}$), the VSTOXX implied volatility index (***vx***), the New-CISS composite financial condition index (***nc***), the Euribor-Eonia spread (***so***), the composite indicator of systemic sovereign stress (***sc***); the monthly NY Fed Global Supply Chain Pressure Index (***gs***), and the real energy price growth rate (***re***).

Table A7: Principal Components Analysis								
Panel A: Selected estimated eigenvalues, medium to long-term components								
	$PC_{M,1}$	$PC_{M,2}$	$PC_{M,3}$	$PC_{M,4}$	$PC_{M,5}$	$PC_{M,6}$	$PC_{M,7}$	$PC_{M,8}$
EigenVa	11.19	7.54	4.37	2.77	2.10	0.02	0.00	0.00
% var	39.98	26.94	15.62	9.91	7.51	0.05	0.00	0.00
% cum	39.98	66.92	82.53	92.44	99.94	100.00	100.00	100.00
$(\mathbf{s/n})^{-1}$	0.0000	0.0000	0.0000	0.0000	0.0000	-	-	-
years	13.46	16.00	15.00	21.09	13.09			
Panel B: Selected estimated eigenvalues, short-term components								
	$PC_{S,1}$	$PC_{S,2}$	$PC_{S,3}$	$PC_{S,4}$	$PC_{S,5}$	$PC_{S,6}$	$PC_{S,7}$	$PC_{S,8}$
EigenVa	6.96	5.83	3.84	2.31	1.94	1.23	1.10	0.86
% var	24.85	20.81	13.71	8.26	6.92	4.38	3.93	3.06
% cum	24.85	45.66	59.38	67.64	74.56	78.94	82.86	85.93
$(\mathbf{s/n})^{-1}$	0.0000	0.0000	0.0000	0.0000	0.0000	-	-	-
years	3.60	4.04	3.44	4.28	4.57			

Panel A in the Table reports the sample eigenvalues (*EigenVa*) corresponding to the largest eight PCs ($\boldsymbol{PC_{M,1}}, \dots, \boldsymbol{PC_{M,8}}$) of the medium to long-term components, their percentage of the accounted total variance (% *var*), the cumulative percentage of the accounted total variance (% *cum*), the inverse signal-to-noise ratios $(\mathbf{s/n})^{-1}$ and the periodicity of the estimated unobserved cyclical components. Panel B reports the same statistics for the short-term components ($\boldsymbol{PC_{S,1}}, \dots, \boldsymbol{PC_{S,8}}$).

Table A8: Regressions of demeaned actual variables on standardized PCs

	g	*u*	*rw*	π	*em*	*ro*	*rs*	*rl*
$PC_{M,1}$	**0.767**	**-3.619**	**0.464**	**-0.582**	**0.511**	**0.562**	**0.429**	**0.087**
	(0.083)	(0.325)	(0.071)	(0.031)	(0.112)	(0.035)	(0.040)	(0.041)
$PC_{M,2}$	0.052	**-1.912**	**-0.676**	**0.885**	**0.891**	**-0.992**	**-1.003**	**-1.506**
	(0.115)	(0.341)	(0.109)	(0.046)	(0.104)	(0.034)	(0.039)	(0.037)
$PC_{M,3}$	0.124	**-1.773**	**-0.284**	**0.326**	**-1.114**	**-0.514**	**-0.633**	**-0.609**
	(0.112)	(0.337)	(0.076)	(0.034)	(0.075)	(0.032)	(0.034)	(0.038)
$PC_{M,4}$	**0.252**	**1.218**	**-0.134**	**0.540**	**0.443**	**0.843**	**0.852**	**0.742**
	(0.085)	(0.238)	(0.042)	(0.026)	(0.099)	(0.034)	(0.035)	(0.034)
$PC_{M,5}$	**0.598**	**-1.133**	**0.496**	**-0.426**	**-0.348**	**0.880**	**0.888**	**0.890**
	(0.064)	(0.281)	(0.046)	(0.023)	(0.078)	(0.063)	(0.062)	(0.060)
$PC_{S,1}$	**0.661**	**-4.267**	**-0.974**	**1.102**	**-0.823**	**-1.258**	**-1.214**	**-0.959**
	(0.139)	(0.292)	(0.124)	(0.041)	(0.097)	(0.027)	(0.027)	(0.034)
$-PC_{S,2}$	**1.189**	0.714	-0.094	**-0.415**	**-1.088**	**-0.095**	**-0.192**	**0.128**
	(0.127)	(0.381)	(0.105)	(0.049)	(0.085)	(0.034)	(0.041)	(0.031)
$-PC_{S,3}$	**0.833**	**-3.545**	-0.014	0.060	**-1.929**	**0.323**	**0.301**	**0.127**
	(0.136)	(0.273)	(0.056)	(0.037)	(0.120)	(0.032)	(0.034)	(0.034)
$PC_{S,4}$	**0.651**	**-4.440**	0.046	-0.016	0.007	**0.363**	**0.406**	-0.017
	(0.100)	(0.277)	(0.054)	(0.027)	(0.089)	(0.034)	(0.036)	(0.043)
$PC_{S,5}$	0.004	**-2.297**	**-0.197**	**0.185**	**1.430**	**0.135**	**0.106**	**-0.254**
	(0.113)	(0.336)	(0.075)	(0.032)	(0.083)	(0.030)	(0.032)	(0.040)
R2	**0.81**	**0.90**	**0.82**	**0.97**	**0.92**	**0.98**	**0.98**	**0.98**

	sb	*hl*	*mm*	*rx*	*Ca*	*lo*	fd	hg
$PC_{M,1}$	**0.209**	**0.192**	0.108	**1.435**	**0.680**	**-0.475**	**0.996**	**1.613**
	(0.026)	(0.073)	(0.095)	(0.378)	(0.043)	(0.032)	(0.058)	(0.058)
$PC_{M,2}$	**-0.121**	-0.091	**-0.190**	0.000	**-0.148**	**-0.515**	**-0.170**	**0.773**
	(0.030)	(0.059)	(0.089)	(0.309)	(0.053)	(0.028)	(0.064)	(0.064)
$PC_{M,3}$	-0.028	0.139	0.064	-0.381	**0.392**	**-0.095**	-0.114	**-0.394**
	(0.028)	(0.074)	(0.092)	(0.357)	(0.038)	(0.040)	(0.061)	(0.061)
$PC_{M,4}$	**0.059**	**0.638**	0.031	**0.874**	**-0.997**	**-0.101**	-0.058	**0.087**
	(0.029)	(0.090)	(0.101)	(0.314)	(0.044)	(0.033)	(0.043)	(0.043)
$PC_{M,5}$	-0.079	-0.130	-0.003	**-1.410**	**-0.414**	0.010	**0.469**	**0.466**
	(0.043)	(0.120)	(0.106)	(0.246)	(0.044)	(0.052)	(0.062)	(0.062)
$PC_{S,1}$	**-0.050**	**0.256**	0.006	**-1.466**	**-0.320**	**0.300**	**0.232**	**-0.175**
	(0.021)	(0.046)	(0.077)	(0.266)	(0.050)	(0.023)	(0.023)	(0.064)
$-PC_{S,2}$	**0.439**	-0.006	**-0.307**	-0.011	**0.415**	**0.223**	**-1.087**	**1.872**
	(0.024)	(0.060)	(0.085)	(0.364)	(0.042)	(0.037)	(0.037)	(0.069)
$-PC_{S,3}$	**-0.139**	**0.306**	**-0.519**	-0.009	0.081	**-0.196**	**0.528**	**-1.344**
	(0.024)	(0.069)	(0.093)	(0.306)	(0.050)	(0.033)	(0.033)	(0.052)
$PC_{S,4}$	-0.017	**-0.470**	**0.400**	**-3.012**	**-0.197**	**-0.380**	**0.296**	-0.059
	(0.035)	(0.077)	(0.104)	(0.359)	(0.035)	(0.034)	(0.034)	(0.052)
$PC_{S,5}$	-0.043	**0.341**	**0.366**	**2.159**	**0.123**	**-0.389**	**0.207**	-0.072
	(0.026)	(0.083)	(0.091)	(0.300)	(0.039)	(0.041)	(0.041)	(0.062)
R2	**0.78**	**0.57**	**0.50**	**0.70**	**0.92**	**0.90**	**0.92**	**0.95**

Table A8 (continued): Regressions of standardized target variables on selected PCs

	hi	***hr***	***rg***	***mk***	***Rm***	***cg***	***vx***	***sc***
$PC_{M,1}$	**1.561**	**1.977**	**-2.255**	0.154	**1.860**	0.210	**-2.443**	**-0.101**
	(0.062)	(0.083)	(0.659)	(0.083)	(0.094)	(0.151)	(0.524)	(0.005)
$PC_{M,2}$	**0.664**	**1.372**	**2.779**	0.032	0.057	**-0.595**	-0.839	0.007
	(0.136)	(0.084)	(0.620)	(0.078)	(0.075)	(0.178)	(0.540)	(0.004)
$PC_{M,3}$	**-0.348**	**0.170**	**-4.649**	-0.135	**-1.315**	**-0.883**	0.224	**-0.028**
	(0.079)	(0.070)	(0.781)	(0.079)	(0.094)	(0.155)	(0.455)	(0.005)
$PC_{M,4}$	**0.266**	**0.619**	0.649	-0.011	0.155	**0.994**	**1.671**	**-0.018**
	(0.084)	(0.065)	(0.769)	(0.090)	(0.090)	(0.126)	(0.515)	(0.004)
$PC_{M,5}$	**0.322**	**0.501**	0.276	**-0.280**	**0.676**	**1.349**	**1.592**	**-0.028**
	(0.074)	(0.082)	(0.828)	(0.102)	(0.087)	(0.108)	(0.329)	(0.003)
$PC_{S,1}$	**0.530**	**1.276**	-0.330	0.086	**-1.264**	**-1.163**	-1.013	**0.031**
	(0.114)	(0.073)	(0.523)	(0.086)	(0.089)	(0.187)	(0.589)	(0.004)
$-PC_{S,2}$	**1.161**	**1.017**	-0.358	**1.204**	**0.517**	**0.469**	**-2.976**	**-0.065**
	(0.139)	(0.078)	(0.868)	(0.071)	(0.075)	(0.205)	(0.549)	(0.006)
$-PC_{S,3}$	**-1.161**	**-0.607**	**-3.696**	**0.701**	**-1.156**	**-1.080**	**-5.478**	**-0.025**
	(0.115)	(0.060)	(0.628)	(0.089)	(0.094)	(0.162)	(0.796)	(0.004)
$PC_{S,4}$	**0.289**	**0.691**	**6.381**	**0.149**	**0.674**	**0.446**	**-1.060**	**-0.012**
	(0.071)	(0.060)	(0.776)	(0.092)	(0.092)	(0.135)	(0.365)	(0.004)
$PC_{S,5}$	0.067	**0.446**	**-7.472**	0.053	**1.249**	-0.079	0.118	**-0.008**
	(0.084)	(0.068)	(0.730)	(0.092)	(0.096)	(0.148)	(0.476)	(0.005)
R2	**0.91**	**0.96**	**0.76**	**0.77**	**0.95**	**0.81**	**0.68**	**0.93**
	so	***nc***	***gs***	***re***				
$PC_{M,1}$	**-0.133**	**-0.096**	**-0.230**	-3.920				
	(0.011)	(0.009)	(0.026)	(2.238)				
$PC_{M,2}$	-0.012	0.004	**0.655**	**11.54**				
	(0.012)	(0.009)	(0.025)	(2.608)				
$PC_{M,3}$	**-0.119**	**-0.033**	**0.175**	0.701				
	(0.012)	(0.007)	(0.025)	(2.988)				
$PC_{M,4}$	0.008	-0.004	**-0.200**	3.518				
	(0.010)	(0.008)	(0.028)	(2.243)				
$PC_{M,5}$	0.009	**0.022**	**-0.142**	**9.431**				
	(0.015)	(0.008)	(0.021)	(3.108)				
$PC_{S,1}$	**0.045**	**0.018**	**0.346**	**24.88**				
	(0.010)	(0.007)	(0.026)	(2.546)				
$-PC_{S,2}$	**-0.097**	**-0.102**	**-0.144**	**15.49**				
	(0.013)	(0.009)	(0.025)	(3.371)				
$-PC_{S,3}$	**-0.022**	**-0.077**	**-0.169**	-0.324				
	(0.010)	(0.009)	(0.026)	(3.392)				
$PC_{S,4}$	**0.044**	-0.009	-0.034	**8.690**				
	(0.011)	(0.007)	(0.027)	(2.414)				
$PC_{S,5}$	**-0.028**	**-0.035**	**0.065**	1.205				
	(0.012)	(0.007)	(0.028)	(2.599)				
R2	**0.78**	**0.83**	**0.94**	**0.71**				

The Table reports the results of the estimated PC regressions for any of the demeaned monthly variables in the data set on the first five standardized PCs extracted from the MLT ($PC_{M,i}$) and ST ($PC_{S,i}$) series. The figures in bold are statistically significant at the 5% level. Figures in round brackets refer to Newey-West consistent t-ratio p-values. ***R2*** is the coefficient of determination. The variables are the €-coin GDP growth rate (***g***), the change in the unemployment rate (u), the real wage growth rate (***rw***), the inflation rate (π), the excess money growth rate (***em***), the real overnight, short- and long-term interest rates (***ro, rs, rl***), the Fama-French size, value and market factors (***sb***, ***hl***, ***mk***), the Charart momentum factor (***mm***), the real effective exchange rate return (***rx***), the current account to GDP ratio (***ca***), the fiscal deficit to GDP ratio (fd), the term spread (***lo***), the house price to GDP ratio (hg), the house price to income ratio (hi), and the house price to rent ratio (hr), the real gold price return (***rg***), and the real M3 growth rate (***rm***), the credit to GDP ratio (cg), the VSTOXX implied volatility index (***vx***), the New-CISS composite financial condition index (***nc***), the Euribor-Eonia spread (***so***), the composite indicator of systemic sovereign stress (***sc***); the monthly NY Fed Global Supply Chain Pressure Index (***gs***), and the real energy price growth rate (***re***).

Table A9: Forecast error variance decomposition for macro-financial series

g	FEVD (months)				π	FEVD (months)				*u*	FEVD (months)				*rw*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	0.0	0.2	0.7	1.1	φ_1	0.0	0.0	0.1	0.2	φ_1	0.0	0.1	0.2	0.3	φ_1	0.0	0.3	0.7	1.0
φ_2	0.0	0.0	0.1	0.2	φ_2	0.0	0.2	1.5	2.5	φ_2	0.8	0.4	0.1	0.1	φ_2	0.0	0.9	2.0	2.5
φ_3	0.0	0.1	0.1	0.1	φ_3	0.0	0.1	0.2	0.2	φ_3	0.2	0.2	0.1	0.2	φ_3	0.2	0.4	0.3	0.3
φ_4	5.5	3.5	3.9	4.5	φ_4	75.2	82.2	88.7	90.1	φ_4	1.1	1.2	1.0	0.9	φ_4	5.2	31.3	57.5	64.7
φ_5	12.8	27.0	39.8	42.1	φ_5	0.0	0.1	0.3	0.4	φ_5	3.5	38.6	52.6	48.6	φ_5	2.4	4.3	3.3	2.5
φ_6	5.6	8.2	11.8	14.2	φ_6	0.1	0.2	0.4	0.4	φ_6	15.6	28.1	37.6	44.9	φ_6	1.5	1.4	3.1	4.5
ro	FEVD (months)				*rl*	FEVD (months)				*rm*	FEVD (months)				*cg*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	0.0	0.0	0.0	0.1	φ_1	0.0	0.0	0.2	0.4	φ_1	0.0	0.6	2.9	4.6	φ_1	0.0	0.0	0.1	0.1
φ_2	0.8	0.7	0.7	0.6	φ_2	1.0	1.1	1.6	2.1	φ_2	0.5	0.8	1.2	1.4	φ_2	1.1	1.4	1.3	1.2
φ_3	0.2	0.1	0.2	0.4	φ_3	0.2	0.1	0.1	0.3	φ_3	0.0	0.2	0.9	1.3	φ_3	0.1	0.1	0.1	0.2
φ_4	71.6	65.9	45.3	31.9	φ_4	52.8	58.0	66.3	70.2	φ_4	42.0	47.9	51.4	50.7	φ_4	2.5	10.5	35.3	46.0
φ_5	0.7	4.9	19.8	27.7	φ_5	0.2	0.2	0.1	0.2	φ_5	0.5	0.4	0.7	0.8	φ_5	0.5	1.9	5.4	5.0
φ_6	2.8	7.4	21.0	30.8	φ_6	0.1	0.3	1.6	3.0	φ_6	8.8	13.3	21.3	25.0	φ_6	2.6	1.4	1.9	2.7
rx	FEVD (months)				*ca*	FEVD (months)				*fd*	FEVD (months)				*hr*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	0.0	0.0	0.2	0.3	φ_1	0.0	0.0	0.0	0.0	φ_1	0.0	0.2	0.8	1.0	φ_1	0.0	0.7	2.7	4.1
φ_2	0.3	0.3	0.3	0.3	φ_2	0.7	0.3	0.7	1.2	φ_2	0.0	0.0	0.1	0.1	φ_2	0.1	0.2	0.1	0.1
φ_3	0.2	0.2	0.2	0.2	φ_3	0.1	0.2	0.4	0.4	φ_3	0.0	0.1	0.4	0.5	φ_3	0.0	0.0	0.0	0.0
φ_4	1.7	1.8	1.8	1.7	φ_4	5.8	10.3	16.6	17.0	φ_4	0.5	0.1	0.7	1.1	φ_4	0.2	7.5	24.5	32.6
φ_5	0.6	1.0	6.3	9.3	φ_5	0.5	1.3	10.8	18.2	φ_5	4.3	12.8	24.1	21.7	φ_5	2.6	25.6	48.9	43.3
φ_6	0.0	0.7	4.0	6.6	φ_6	0.5	4.3	28.4	39.2	φ_6	9.2	24.1	52.1	57.7	φ_6	0.3	1.8	4.8	5.4
mk	FEVD (months)				*nc*	FEVD (months)				*gs*	FEVD (months)				*re*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	0.0	0.0	0.1	0.1	φ_1	0.0	0.2	0.7	1.1	φ_1	0.0	0.0	0.1	0.1	φ_1	0.0	0.0	0.0	0.1
φ_2	0.1	0.0	0.0	0.0	φ_2	0.0	0.0	0.0	0.0	φ_2	1.9	3.0	4.8	5.8	φ_2	0.0	0.0	0.1	0.2
φ_3	0.1	0.0	0.0	0.0	φ_3	0.0	0.0	0.2	0.3	φ_3	0.4	0.2	2.1	3.2	φ_3	0.0	0.0	0.0	0.0
φ_4	0.1	0.6	1.8	2.2	φ_4	1.0	0.7	0.4	0.4	φ_4	2.0	4.8	10.8	13.2	φ_4	25.0	19.0	12.7	11.4
φ_5	34.2	51.1	56.9	56.5	φ_5	52.6	61.7	64.7	63.3	φ_5	0.4	2.5	4.6	4.0	φ_5	10.8	24.6	42.0	44.4
φ_6	13.4	15.5	20.0	23.3	φ_6	11.7	14.5	19.4	22.8	φ_6	5.9	12.9	28.1	34.6	φ_6	0.3	0.9	7.1	12.7

The Table reports the contributions of the structural shocks that drive the medium to long-term (trend) components, i.e., φ_1, φ_2, φ_3, and the structural shocks that drive the short-term (cyclical) components, i.e., $\varphi_4, \varphi_5, \varphi_6$, to the forecast error variance at various horizons, i.e. 3, 12, 36, and 60 months ahead for the variables of interest. The selected variables are the €-coin GDP growth rate (***g***), the change in the unemployment rate ($\boldsymbol{u}$), the real wage growth rate (***rw***), the inflation rate (**π**), the real overnight and long-term interest rates (***ro, rl***), the real effective exchange rate return (***rx***), the current account to GDP ratio (***ca***), the fiscal deficit to GDP ratio ($\boldsymbol{fd}$), the house price to rent ratio ($\boldsymbol{hr}$), the real M3 growth rate (***rm***), the credit to GDP ratio ($\boldsymbol{cg}$), the New-CISS composite financial condition index (***nc***), the NY Fed Global Supply Chain Pressure Index (***gs***), and the real energy price growth rate (***re***).

Table A10: Components' forecast error variance decomposition for macro-financial series

g	FEVD (months)				π	FEVD (months)				*u*	FEVD (months)				*rw*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	5.4	63.7	80.0	80.2	φ_1	21.1	10.3	6.1	5.6	φ_1	1.9	16.7	44.1	53.0	φ_1	9.2	19.3	24.1	26.0
φ_2	46.7	14.1	12.0	12.8	φ_2	34.9	68.4	83.9	86.0	φ_2	80.7	58.5	26.7	16.0	φ_2	3.4	57.2	65.6	66.2
φ_3	47.8	22.2	8.0	7.0	φ_3	43.9	21.2	10.0	8.4	φ_3	17.4	24.8	29.3	31.0	φ_3	87.4	23.6	10.3	7.8
φ_4	23.0	9.1	7.0	7.4	φ_4	99.8	99.7	99.2	99.1	φ_4	5.5	1.7	1.1	1.0	φ_4	56.5	84.5	90.0	90.2
φ_5	53.6	69.7	71.7	69.2	φ_5	0.1	0.1	0.4	0.5	φ_5	17.2	56.9	57.7	51.5	φ_5	26.7	11.7	5.2	3.5
φ_6	23.4	21.2	21.3	23.4	φ_6	0.1	0.2	0.4	0.5	φ_6	77.3	41.4	41.2	47.6	φ_6	16.8	3.8	4.8	6.3
ro	FEVD (months)				*rl*	FEVD (months)				*rm*	FEVD (months)				*cg*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	0.5	1.1	5.1	5.9	φ_1	0.5	2.0	9.6	14.8	φ_1	5.5	36.5	57.8	62.8	φ_1	1.0	0.3	4.7	8.5
φ_2	82.9	91.2	75.7	53.2	φ_2	86.9	92.2	84.4	74.0	φ_2	88.7	48.2	23.8	19.1	φ_2	87.9	95.8	87.1	81.2
φ_3	16.5	7.7	19.2	40.9	φ_3	12.5	5.8	6.0	11.2	φ_3	5.8	15.3	18.4	18.1	φ_3	11.1	3.9	8.2	10.3
φ_4	95.4	84.2	52.6	35.3	φ_4	99.4	99.1	97.5	95.6	φ_4	82.0	77.7	70.0	66.2	φ_4	44.3	75.6	82.8	85.6
φ_5	0.9	6.3	23.0	30.7	φ_5	0.4	0.3	0.2	0.3	φ_5	0.9	0.7	1.0	1.1	φ_5	9.2	14.0	12.7	9.3
φ_6	3.7	9.5	24.4	34.0	φ_6	0.2	0.6	2.3	4.1	φ_6	17.1	21.6	29.0	32.7	φ_6	46.5	10.3	4.4	5.1
rx	FEVD (months)				*ca*	FEVD (months)				*fd*	FEVD (months)				*hr*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	0.2	4.7	25.8	39.5	φ_1	2.4	3.8	1.5	0.6	φ_1	41.1	65.8	62.1	61.1	φ_1	5.6	77.7	94.7	96.6
φ_2	64.5	64.1	50.2	39.6	φ_2	80.7	55.3	63.9	75.3	φ_2	47.2	3.6	9.6	8.6	φ_2	92.9	22.3	5.3	3.4
φ_3	35.2	31.2	24.0	20.9	φ_3	16.9	40.9	34.6	24.1	φ_3	11.7	30.7	28.3	30.3	φ_3	1.5	0.1	0.0	0.0
φ_4	74.0	52.0	14.6	9.5	φ_4	85.1	64.4	29.8	22.8	φ_4	3.5	0.4	1.0	1.3	φ_4	6.5	21.5	31.3	40.1
φ_5	25.2	28.5	52.2	52.9	φ_5	7.4	8.4	19.4	24.5	φ_5	30.7	34.6	31.3	27.0	φ_5	84.9	73.3	62.6	53.3
φ_6	0.2	4.7	25.8	39.5	φ_6	7.5	27.1	50.8	52.7	φ_6	65.8	65.0	67.7	71.7	φ_6	8.5	5.2	6.1	6.6
mk	FEVD (months)				*nc*	FEVD (months)				*gs*	FEVD (months)				*re*	FEVD (months)			
	3	12	36	60		3	12	36	60		3	12	36	60		3	12	36	60
φ_1	5.1	25.1	52.0	60.4	φ_1	51.1	83.9	78.6	75.4	φ_1	0.6	0.4	1.2	1.4	φ_1	12.0	18.1	21.5	21.8
φ_2	44.1	34.2	20.0	14.2	φ_2	3.1	2.6	3.2	3.5	φ_2	83.6	94.2	69.2	63.2	φ_2	73.3	72.5	77.0	76.7
φ_3	50.9	40.6	28.0	25.4	φ_3	45.8	13.5	18.2	21.1	φ_3	15.8	5.4	29.6	35.3	φ_3	14.8	9.4	1.5	1.5
φ_4	0.3	0.9	2.3	2.7	φ_4	1.6	0.9	0.5	0.4	φ_4	24.8	23.7	24.9	25.4	φ_4	69.2	42.7	20.6	16.6
φ_5	71.6	76.0	72.4	68.9	φ_5	80.6	80.2	76.6	73.3	φ_5	4.3	12.4	10.6	7.7	φ_5	29.9	55.3	68.0	64.8
φ_6	28.1	23.0	25.4	28.4	φ_6	17.9	18.9	22.9	26.3	φ_6	70.9	63.9	64.5	66.9	φ_6	0.9	2.0	11.4	18.6

The Table reports the contributions of the structural shocks that drive the medium to long-term (trend) components, i.e., $\boldsymbol{\varphi_1}$, $\boldsymbol{\varphi_2}$, $\boldsymbol{\varphi_3}$, and the structural shocks that drive the short-term (cyclical) components, i.e., $\boldsymbol{\varphi_4}$, $\boldsymbol{\varphi_5}$, $\boldsymbol{\varphi_6}$, to the forecast error variance at various horizons, i.e. 3, 12, 36, and 60 months ahead for the variables of interest. The selected variables are the €-coin GDP growth rate (***g***), the change in the unemployment rate ($\boldsymbol{u}$), the real wage growth rate (***rw***), the inflation rate ($\boldsymbol{\pi}$), the real overnight and long-term interest rates (***ro, rl***), the real effective exchange rate return (***rx***), the current account to GDP ratio (***ca***), the fiscal deficit to GDP ratio ($\boldsymbol{fd}$), the house price to rent ratio ($\boldsymbol{hr}$), the real M3 growth rate (***rm***), the credit to GDP ratio ($\boldsymbol{cg}$), the New-CISS composite financial condition index (***nc***), the NY Fed Global Supply Chain Pressure Index (***gs***), and the real energy price growth rate (***re***).

Table A11: Forecast error variance decomposition of divergence series

Panel A: Divergence series' FEVD

Rd	**FEVD (months)**				***ld***	**FEVD (months)**				***nd***	**FEVD (months)**				***cd***	**FEVD (months)**			
	3	**12**	**36**	**60**		**3**	**12**	**36**	**60**		**3**	**12**	**36**	**60**		**3**	**12**	**36**	**60**
κ_1	96.3	86.9	77.2	69.5	κ_1	0.0	1.6	1.1	0.7	κ_1	0.0	0.7	3.0	2.4	κ_1	0.0	1.8	5.4	3.9
κ_2	0.5	0.8	2.2	2.0	κ_2	98.1	84.8	48.0	23.8	κ_2	0.0	0.7	0.8	0.4	κ_2	0.2	0.6	4.8	2.4
κ_3	0.6	0.9	1.7	2.0	κ_3	0.0	0.5	2.2	3.9	κ_3	97.4	88.2	66.3	35.7	κ_3	4.5	11.1	25.9	24.8
κ_4	0.0	0.2	1.4	1.3	κ_4	0.0	0.0	0.7	0.7	κ_4	0.0	2.0	6.8	5.7	κ_4	88.0	74.5	37.8	20.8
κ_5	0.0	0.1	0.7	0.9	κ_5	0.0	0.2	0.3	0.2	κ_5	0.0	0.6	1.1	0.7	κ_5	0.0	0.1	3.3	1.7
κ_6	0.0	1.1	1.9	1.7	κ_6	0.0	0.2	0.4	0.3	κ_6	0.0	0.2	1.8	4.9	κ_6	0.4	2.6	9.0	10.3
κ_7	0.0	2.1	2.4	2.5	κ_7	0.0	0.0	0.4	0.6	κ_7	0.0	2.5	5.5	4.1	κ_7	2.5	3.6	6.3	5.7
φ_1	0.0	0.3	0.7	1.1	φ_1	0.0	0.1	0.2	0.7	φ_1	0.0	0.0	0.2	0.2	φ_1	0.0	0.0	0.0	0.0
φ_2	0.1	0.1	0.1	0.1	φ_2	0.0	0.0	0.2	0.1	φ_2	0.1	0.0	0.2	1.0	φ_2	0.2	0.2	0.1	0.3
φ_3	0.0	0.0	0.1	0.2	φ_3	0.0	0.0	0.3	1.4	φ_3	0.0	0.0	0.3	1.2	φ_3	0.1	0.1	0.1	0.8
φ_4	0.1	0.5	2.7	7.5	φ_4	0.2	0.4	0.8	0.7	φ_4	0.4	2.3	10.8	27.8	φ_4	0.0	0.5	2.8	14.4
φ_5	0.0	1.8	2.0	3.2	φ_5	1.0	7.2	26.1	29.1	φ_5	0.0	0.1	1.3	14.7	φ_5	2.8	3.0	1.6	12.8
φ_6	2.2	5.2	6.8	7.9	φ_6	0.7	5.0	19.3	37.8	φ_6	2.1	2.6	2.0	1.3	φ_6	1.2	2.0	3.0	1.9

Panel B: Trend and cyclical divergence components' FEVD

Rd	**FEVD (months)**				***ld***	**FEVD (months)**				***nd***	**FEVD (months)**				***cd***	**FEVD (months)**			
	3	**12**	**36**	**60**		**3**	**12**	**36**	**60**		**3**	**12**	**36**	**60**		**3**	**12**	**36**	**60**
φ_1	64.4	76.6	78.9	80.3	φ_1	59.8	28.0	30.3	28.1	φ_1	40.5	28.5	9.7	7.7	φ_1	3.3	13.7	2.6	2.5
φ_2	32.4	13.9	8.3	6.9	φ_2	24.1	24.0	6.4	3.3	φ_2	25.0	31.4	42.3	46.4	φ_2	54.9	36.9	24.4	31.7
φ_3	3.2	9.5	12.8	12.9	φ_3	16.1	48.0	63.4	68.6	φ_3	34.5	40.1	48.1	45.9	φ_3	41.8	49.4	73.0	65.8
φ_4	6.9	23.7	40.1	44.8	φ_4	3.0	1.7	1.0	1.7	φ_4	45.7	76.3	63.4	62.5	φ_4	9.0	38.4	49.4	52.5
φ_5	23.7	17.5	17.4	18.1	φ_5	57.4	56.5	43.0	34.8	φ_5	1.4	9.3	33.5	33.0	φ_5	55.3	21.4	43.9	42.8
φ_6	69.4	58.8	42.4	37.1	φ_6	39.7	41.8	56.0	63.6	φ_6	52.9	14.3	3.1	4.5	φ_6	35.7	40.2	6.7	4.7

Panel A: Divergence series' FEVD

Bd	**FEVD (months)**				***sd***	**FEVD (months)**				***fd***	**FEVD (months)**			
	3	**12**	**36**	**60**		**3**	**12**	**36**	**60**		**3**	**12**	**36**	**60**
κ_1	0.1	0.2	1.7	1.1	κ_1	0.2	0.7	1.0	1.1	κ_1	0.1	0.7	2.0	2.0
κ_2	0.2	0.6	2.8	1.2	κ_2	3.5	8.3	7.1	5.2	κ_2	0.0	1.0	3.1	2.6
κ_3	0.1	2.0	18.3	11.0	κ_3	2.9	4.7	6.3	6.5	κ_3	0.2	6.7	15.6	17.7
κ_4	0.1	0.5	0.3	0.7	κ_4	0.0	1.1	7.8	10.3	κ_4	0.0	1.1	1.4	1.3
κ_5	96.9	79.3	34.9	14.2	κ_5	0.0	0.2	4.2	3.6	κ_5	0.8	1.5	1.1	1.1
κ_6	0.0	2.6	1.8	1.6	κ_6	88.0	78.1	62.8	50.3	κ_6	0.0	1.5	1.3	1.2
κ_7	0.0	0.2	2.6	2.0	κ_7	0.0	0.5	1.3	1.2	κ_7	86.1	72.9	57.4	48.3
φ_1	0.0	0.2	1.0	1.9	φ_1	0.0	0.0	0.1	0.6	φ_1	0.0	0.0	0.4	1.7
φ_2	0.2	0.1	0.1	0.7	φ_2	0.6	0.4	0.3	0.2	φ_2	0.1	0.1	0.1	0.2
φ_3	0.0	0.1	0.2	0.7	φ_3	0.0	0.1	0.2	0.4	φ_3	0.0	0.0	0.0	0.4
φ_4	0.1	1.5	2.3	1.4	φ_4	0.4	0.5	0.6	7.9	φ_4	0.7	0.4	1.1	6.9
φ_5	1.8	11.1	30.1	51.8	φ_5	1.3	1.2	1.0	4.0	φ_5	8.9	9.4	10.2	9.3
φ_6	0.5	1.7	4.0	11.7	φ_6	3.1	4.2	7.4	8.8	φ_6	3.2	4.6	6.4	7.4

Panel B: Trend and cyclical divergence components' FEVD

Bd	**FEVD (months)**				***sd***	**FEVD (months)**				***fd***	**FEVD (months)**			
	3	**12**	**36**	**60**		**3**	**12**	**36**	**60**		**3**	**12**	**36**	**60**
φ_1	48.7	75.4	58.0	50.6	φ_1	1.1	13.5	49.7	53.0	φ_1	21.6	79.1	76.7	69.0
φ_2	30.7	7.5	21.5	27.0	φ_2	86.0	55.2	17.0	9.8	φ_2	76.2	18.1	7.1	9.4
φ_3	20.7	17.1	20.5	22.3	φ_3	12.9	31.2	33.3	37.3	φ_3	2.2	2.8	16.2	21.6
φ_4	10.2	6.4	2.2	1.6	φ_4	8.6	6.5	38.4	45.8	φ_4	2.9	6.5	29.3	43.6
φ_5	77.7	82.5	79.8	73.0	φ_5	20.2	10.8	19.3	30.1	φ_5	65.1	57.6	39.4	33.3
φ_6	12.0	11.0	18.0	25.5	φ_6	71.3	82.7	42.4	24.1	φ_6	32.1	36.0	31.3	23.0

The Table reports the contributions of the structural shocks to the forecast error variance at various horizons, i.e. 3, 12, 36, and 60 months ahead for the divergence indicators (Panel A) and their trend and cyclical components. The common medium to long-term (trend) structural shocks are $\varphi_1, \varphi_2, \varphi_3$, the common short-term (cyclical) structural shocks are $\varphi_4, \varphi_5, \varphi_6$, the structural idiosyncratic divergence shocks are $\kappa_1, \kappa_2, \kappa_3, \kappa_4, \kappa_5, \kappa_6, \kappa_7$. The responses are computed for the real (***rd***), labor market (***ld***), nominal (***nd***), competitiveness (***cd***), bond market (***bd***), stock market (***sd***), and overall financial condition (***fd***) indicators.

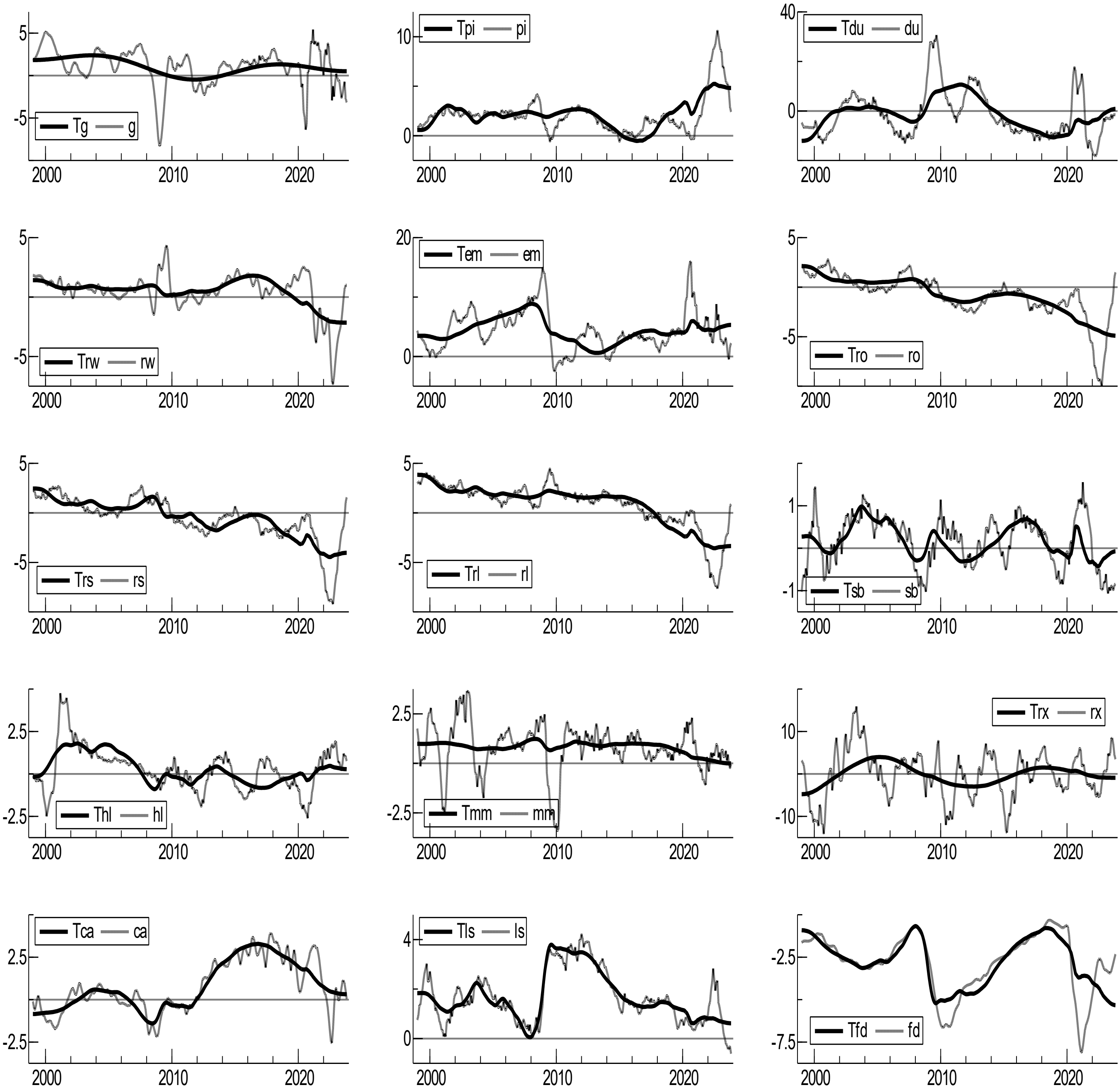


Figure A1: Actual series (dashed) and their medium to long-term components (solid). The series are real €-coin GDP growth (*g*), the change in the unemployment rate (*u*), real wage growth (*rw)*, inflation (*pi*), excess money growth (*em*), the real ECB overnight/ short-term rate (€STR; *ro*), the real 3-month Euribor rate (*rs*), the real 10-year government bond rate (*rl*), he Euro Fama-French size (*sb*) and value (*hl*) factors, the Euro Carhart momentum factor (*mm*), the euro real effective exchange rate return (*rx*), the current account/GDP ratio (*ca*), the term spread (*ls*), and the fiscal deficit/GDP ratio (*fd*).

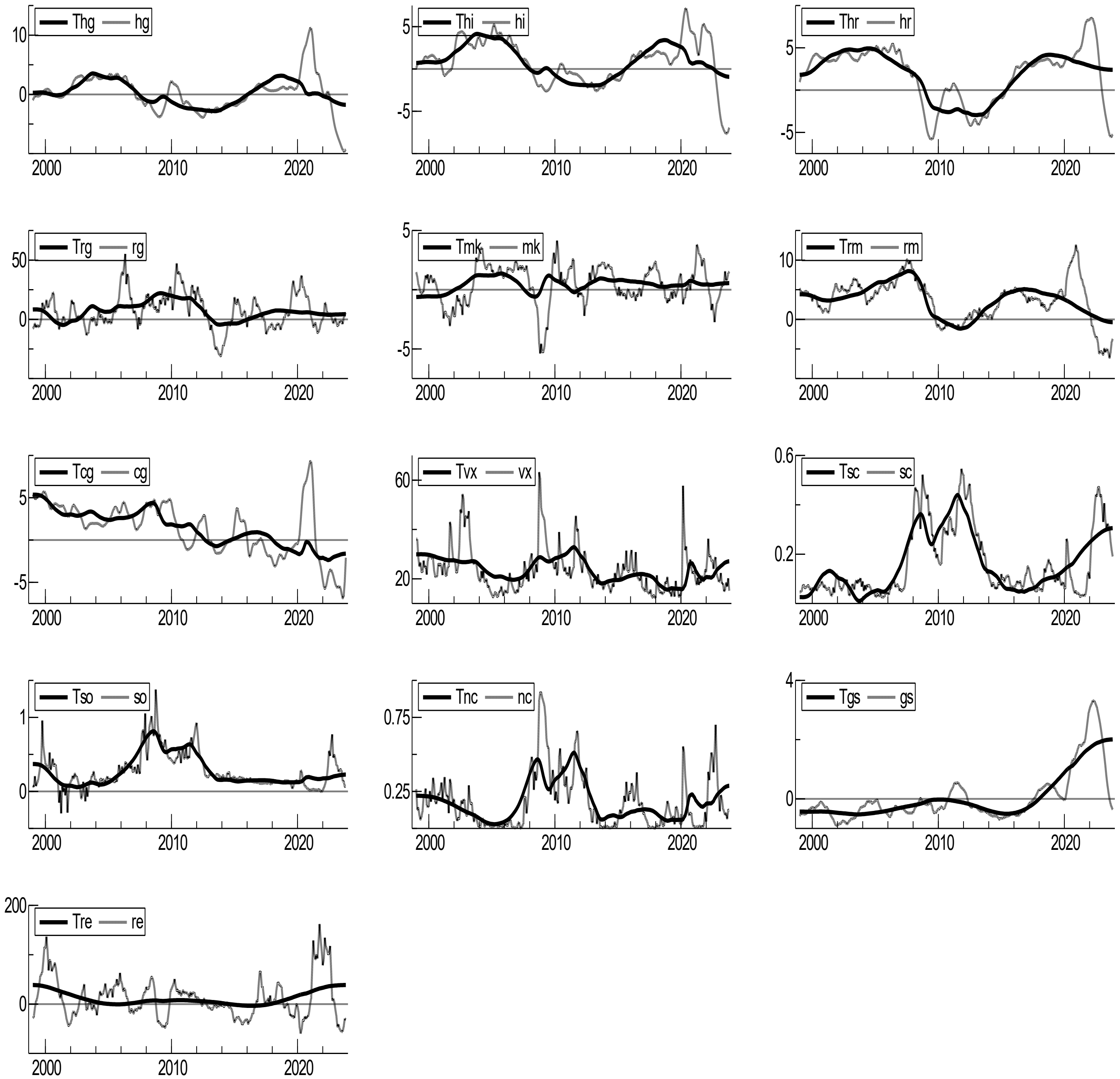


Figure A2: Actual series (dashed) and their medium to long-term components (solid). The series are the change in the house price/GDP ratio (*hg*), the house price to income ratio (*hi*), the house price to rent ratio (*hr*), real gold price returns (*rg*), the FF market factor return (*mk*), the real money growth rate (*rm*), the private credit/GDP ratio (*cg*), the VSTOXX implied volatility index (*vx*), and the Sov-CISS index (*sc*), the 3-month Euribor-Euro Short Term Rate spread (*so*), the New-CISS index (*nc*), the global supply chain pressure index (*gs*), the real energy price return (*re*).

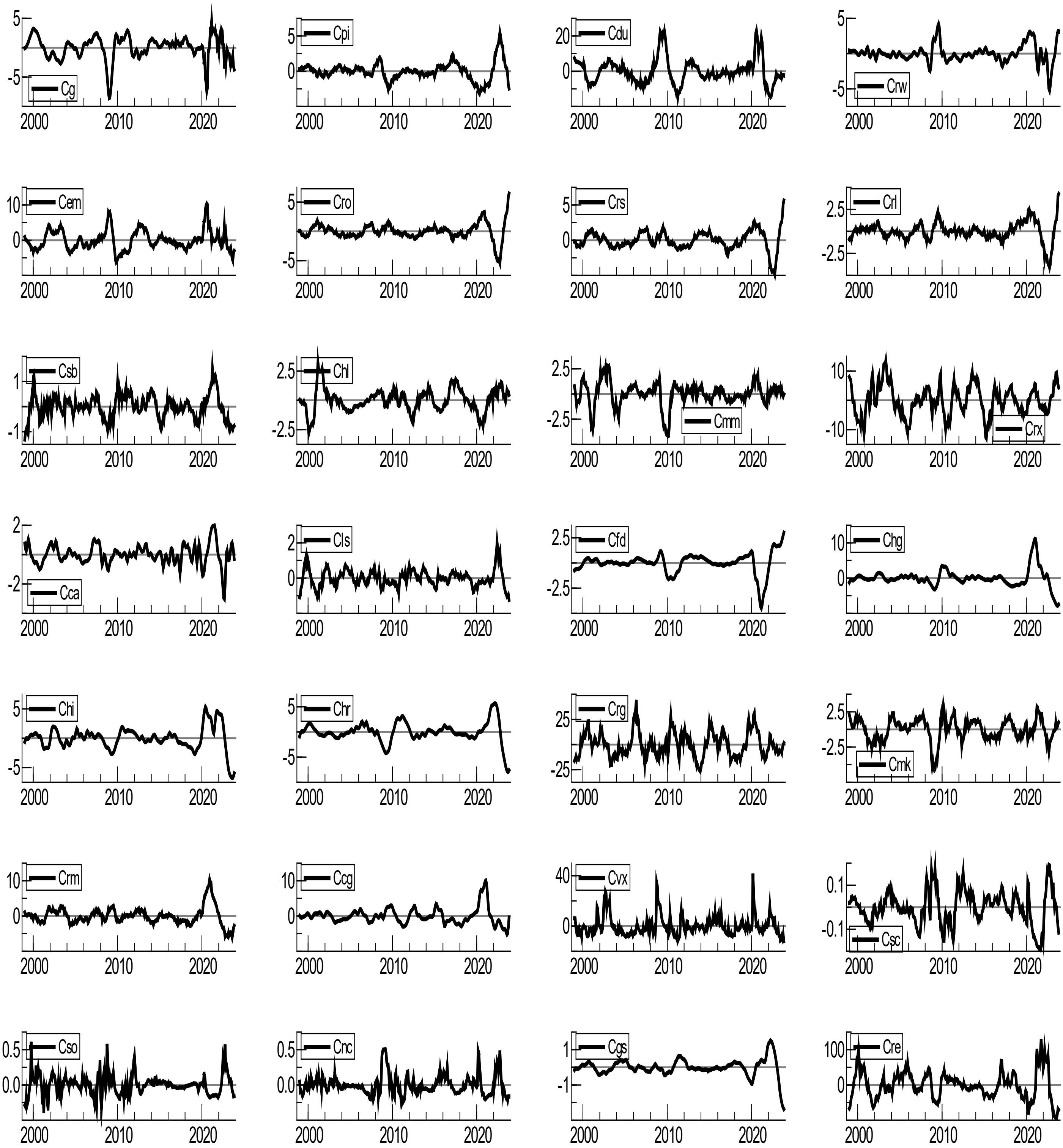
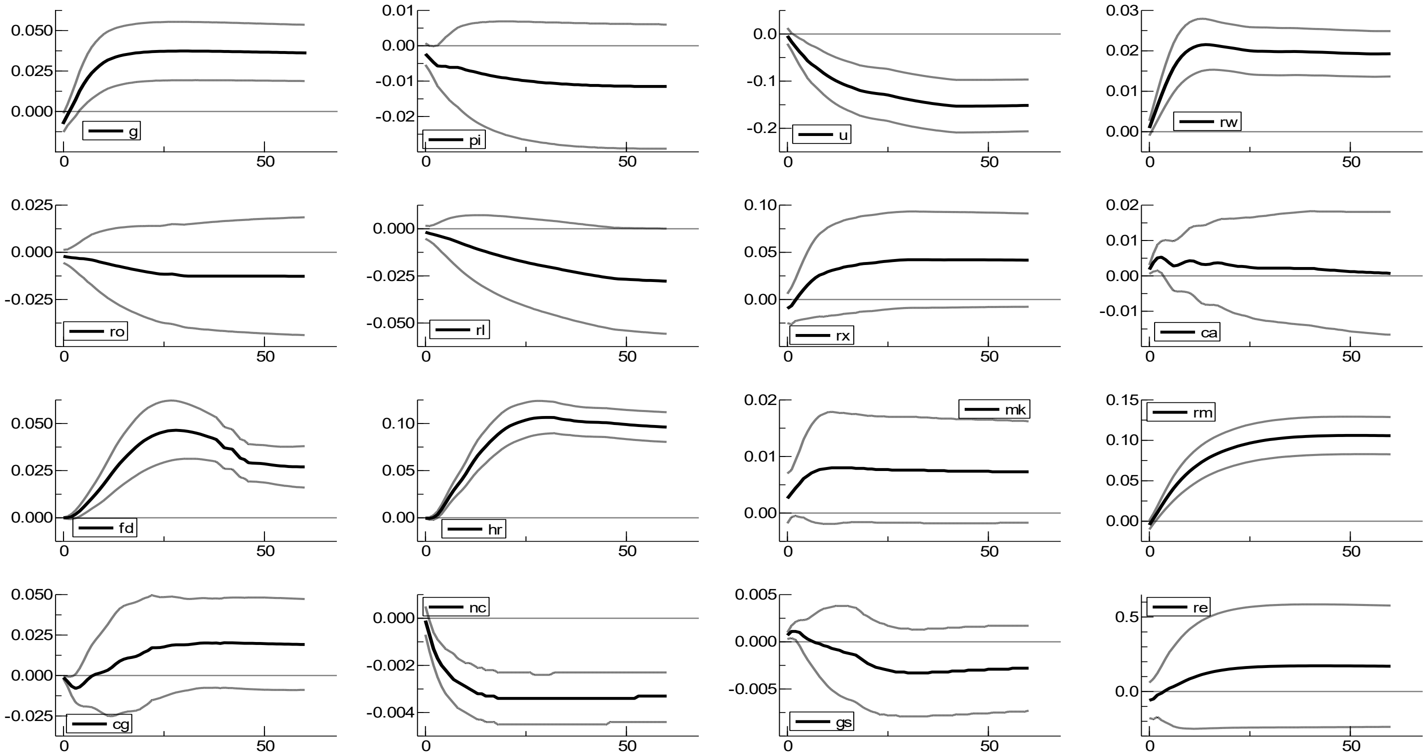


Figure A3: Short-term components (solid). The series are real €-coin GDP growth (*g*), the change in the unemployment rate (*u*), real wage growth (*rw)*, inflation (*pi*), excess money growth (*em*), the real ECB overnight/ short-term rate (€STR; *ro*), the real 3-month Euribor rate (*rs*), the real 10-year government bond rate (*rl*), he Euro Fama-French size (*sb*) and value (*hl*) factors, the Euro Carhart momentum factor (*mm*), the euro real effective exchange rate return (*rx*), the current account/GDP ratio (*ca*), the term spread (*ls*), the fiscal deficit/GDP ratio (*fd*), the change in the house price/GDP ratio (*hg*), the house price to income ratio (*hi*), the house price to rent ratio (*hr*), real gold price returns (*rg*), the FF market factor return (*mk*), the real money growth rate (*rm*), the private credit/GDP ratio (*cg*), the VSTOXX implied volatility index (*vx*), and the Sov-CISS index (*sc*), the 3-month Euribor-Euro Short Term Rate spread (*so*), the New-CISS index (*nc*), the global supply chain pressure index (*gs*), the real energy price return (*re*).

Responses to φ_1 (LR-AS/productivity shock)



Responses to φ_2 (cost-push shock)

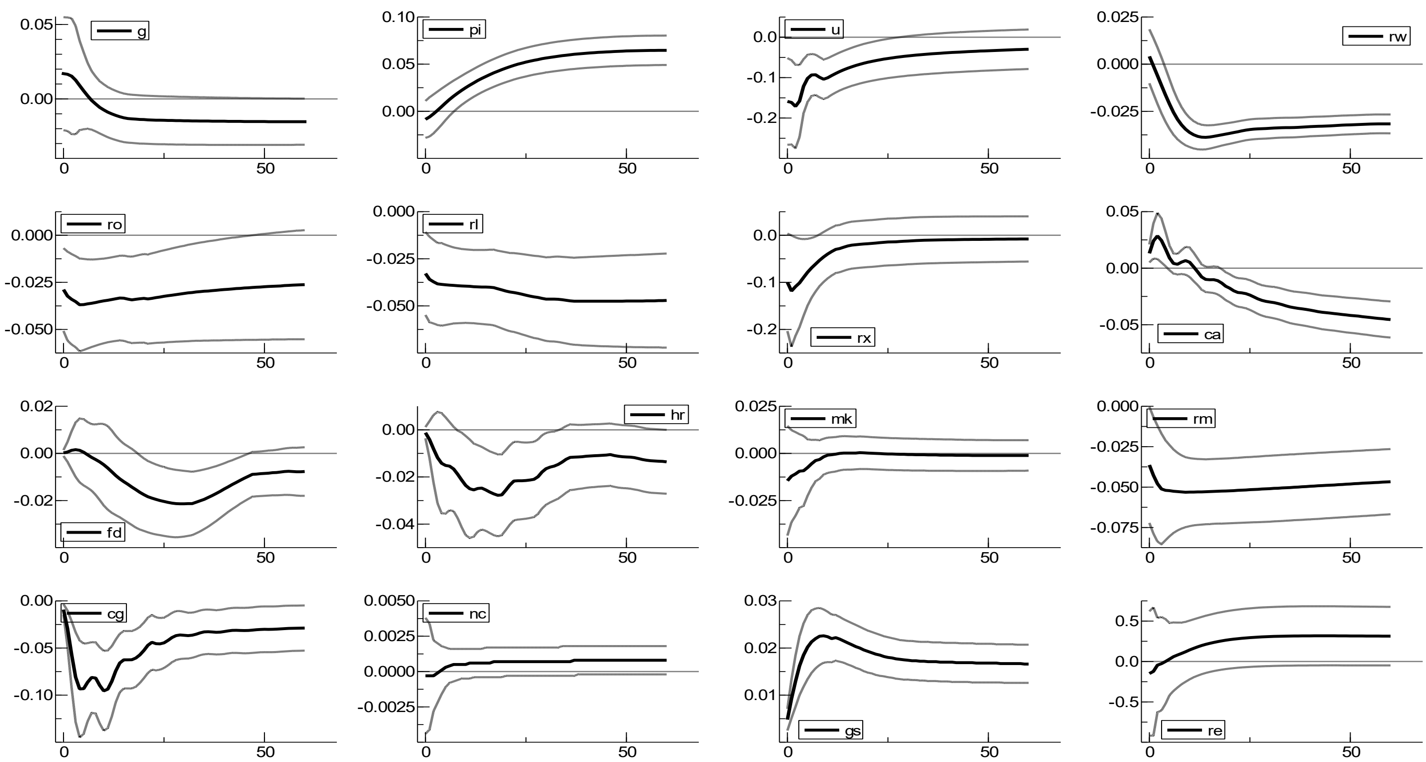


Figure A4: Responses of selected macro-financial series to a one standard error increase in the structural common MLT shock φ_1 (LR-AS/productivity shock) (top plots block) and φ_2 (cost-push shock) (bottom plots block). The selected variables are the €-coin GDP growth rate (***g***), the change in the unemployment rate (***u***), the real wage growth rate (***rw***), the inflation rate (**π**), the real overnight and long-term interest rates (***ro, rl***), the real effective exchange rate return (***rx***), the current account to GDP ratio (***ca***), the fiscal deficit to GDP ratio (***fd***), the house price to rent ratio (***hr***), the real M3 growth rate (***rm***), the credit to GDP ratio (***cg***), the New-CISS composite financial condition index (***nc***), the NY Fed Global Supply Chain Pressure Index (***gs***), and the real energy price growth rate (***re***).

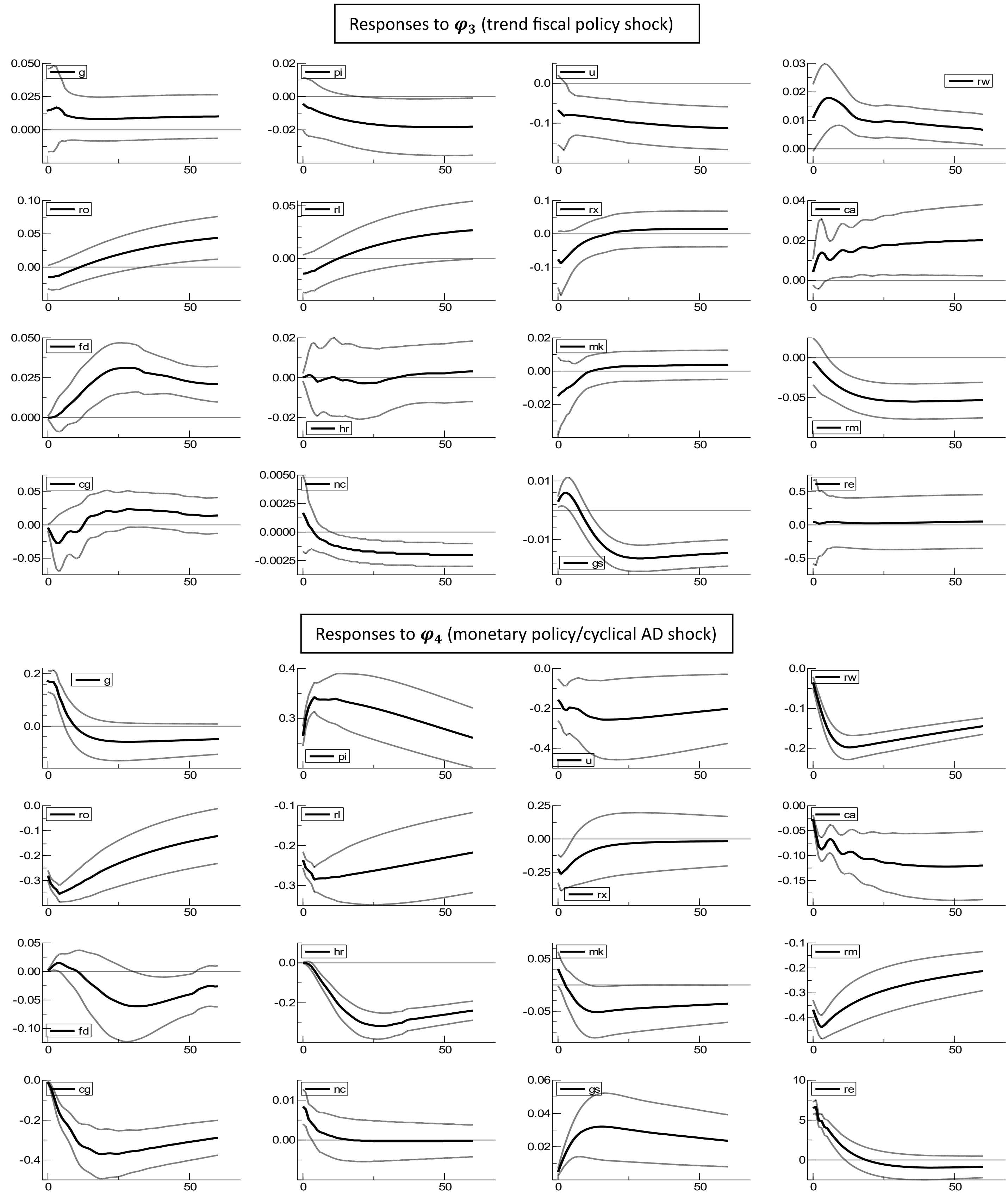


Figure A5: Responses of selected macro-financial series to a one standard error increase in the structural common MLT shock φ_3 (trend fiscal policy shock) (top plots block) and the structural common ST shock φ_4 (monetary policy/cyclical AD shock) (bottom plots block). The selected variables are the €-coin GDP growth rate ($\boldsymbol{g}$), the change in the unemployment rate ($\boldsymbol{u}$), the real wage growth rate (***rw***), the inflation rate ($\boldsymbol{\pi}$), the real overnight and long-term interest rates (***ro, rl***), the real effective exchange rate return (***rx***), the current account to GDP ratio (***ca***), the fiscal deficit to GDP ratio ($\boldsymbol{fd}$), the house price to rent ratio ($\boldsymbol{hr}$), the real M3 growth rate (***rm***), the credit to GDP ratio ($\boldsymbol{cg}$), the New-CISS composite financial condition index (***nc***), the NY Fed Global Supply Chain Pressure Index (***gs***), and the real energy price growth rate (***re***).

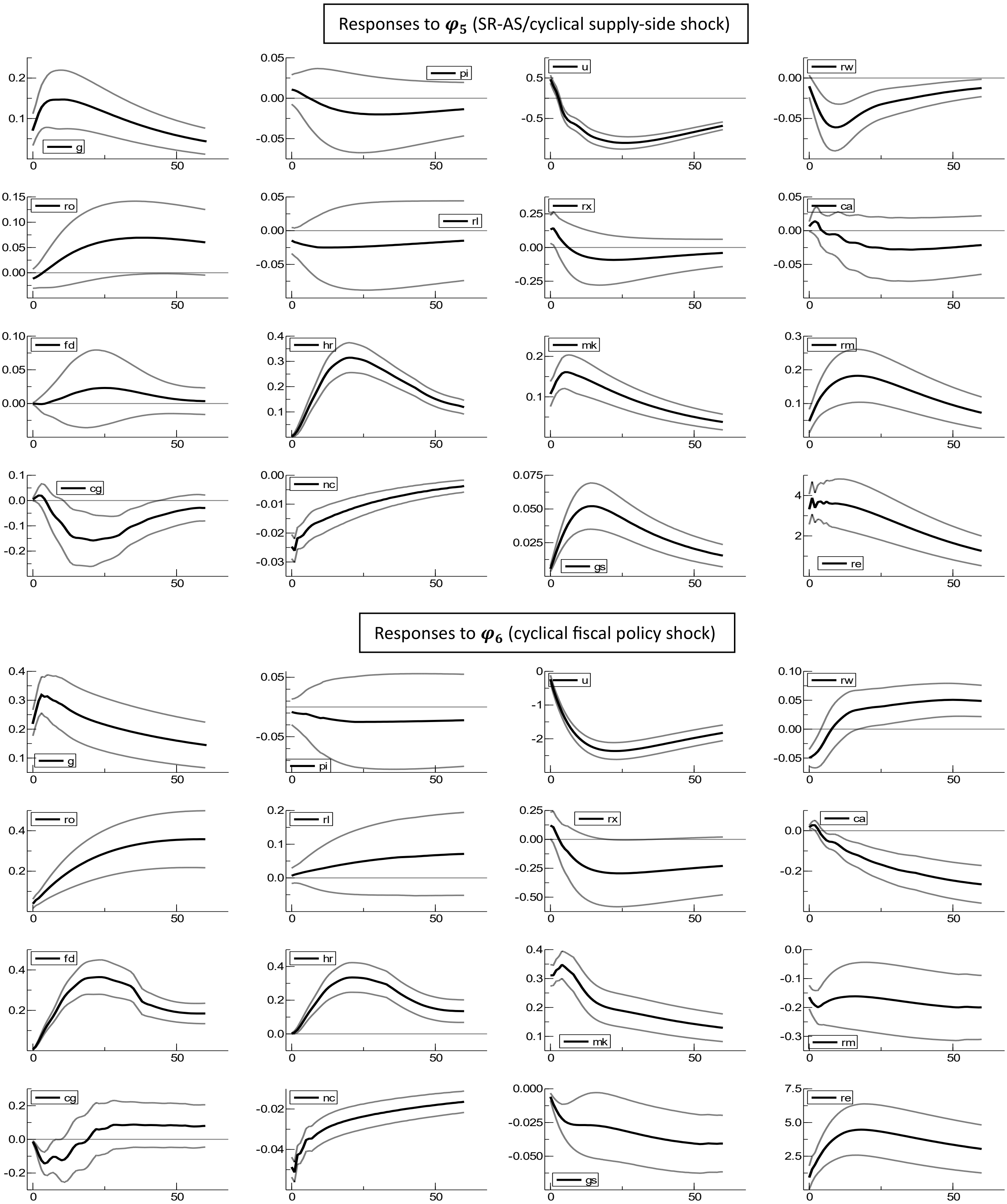


Figure A6: Responses of selected macro-financial series to a one standard error increase in the structural common ST shock $\boldsymbol{\varphi_5}$ (SR-AS/cyclical supply-side shock) (top plots block) and $\boldsymbol{\varphi_6}$ (cyclical fiscal policy shock) (bottom plots block). The selected variables are the €-coin GDP growth rate ($\boldsymbol{g}$), the change in the unemployment rate ($\boldsymbol{u}$), the real wage growth rate (***rw***), the inflation rate ($\boldsymbol{\pi}$), the real overnight and long-term interest rates (***ro, rl***), the real effective exchange rate return (***rx***), the current account to GDP ratio (***ca***), the fiscal deficit to GDP ratio ($\boldsymbol{fd}$), the house price to rent ratio ($\boldsymbol{hr}$), the real M3 growth rate (***rm***), the credit to GDP ratio ($\boldsymbol{cg}$), the New-CISS composite financial condition index (***nc***), the NY Fed Global Supply Chain Pressure Index (***gs***), and the real energy price growth rate (***re***).

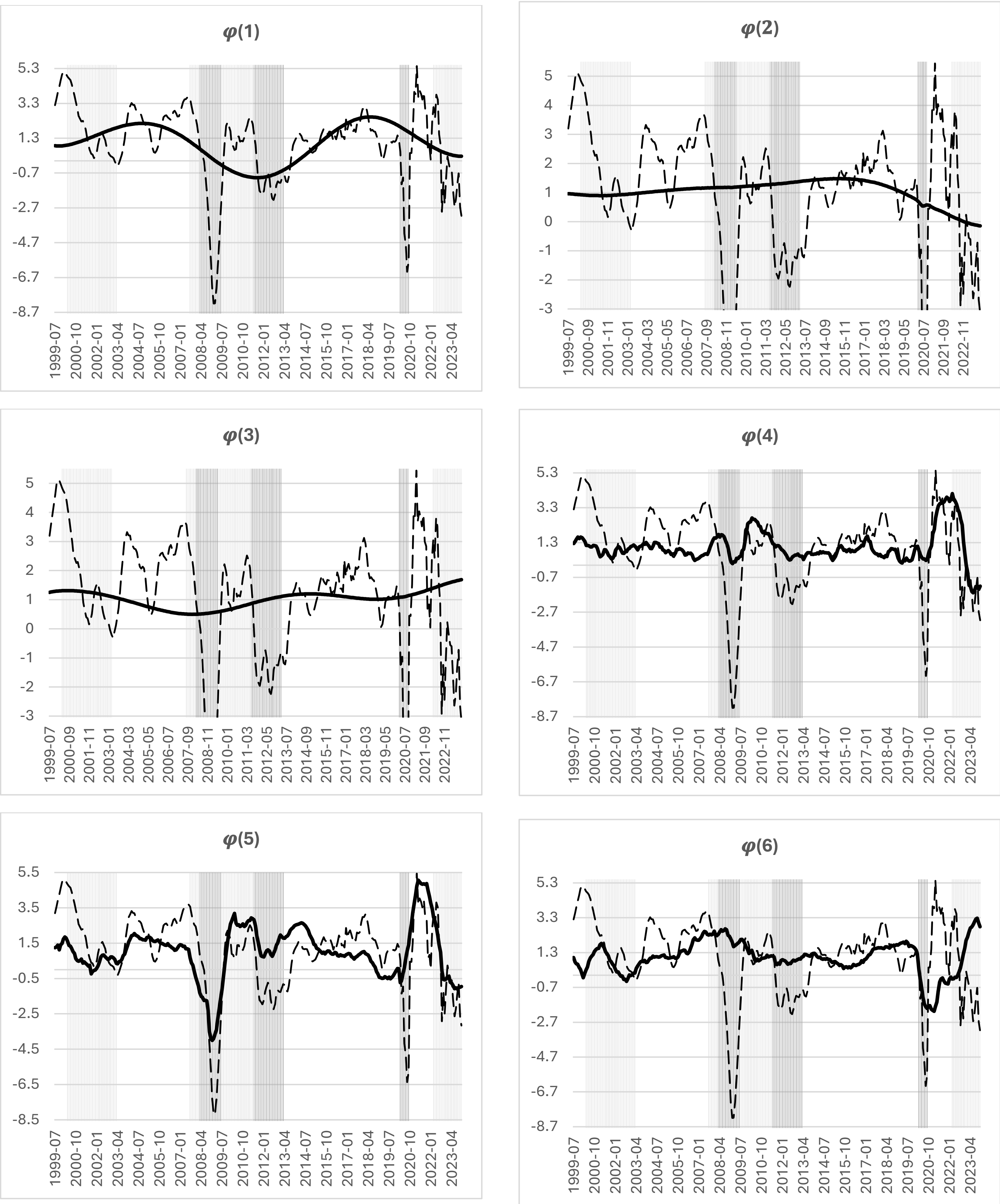


Figure A7: Historical decomposition of the €-coin GDP growth rate. Contribution of the common medium to long-term ($\boldsymbol{\varphi_1}$, $\boldsymbol{\varphi_2}$, $\boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}$, $\boldsymbol{\varphi_5}$, $\boldsymbol{\varphi_6}$) structural shocks.

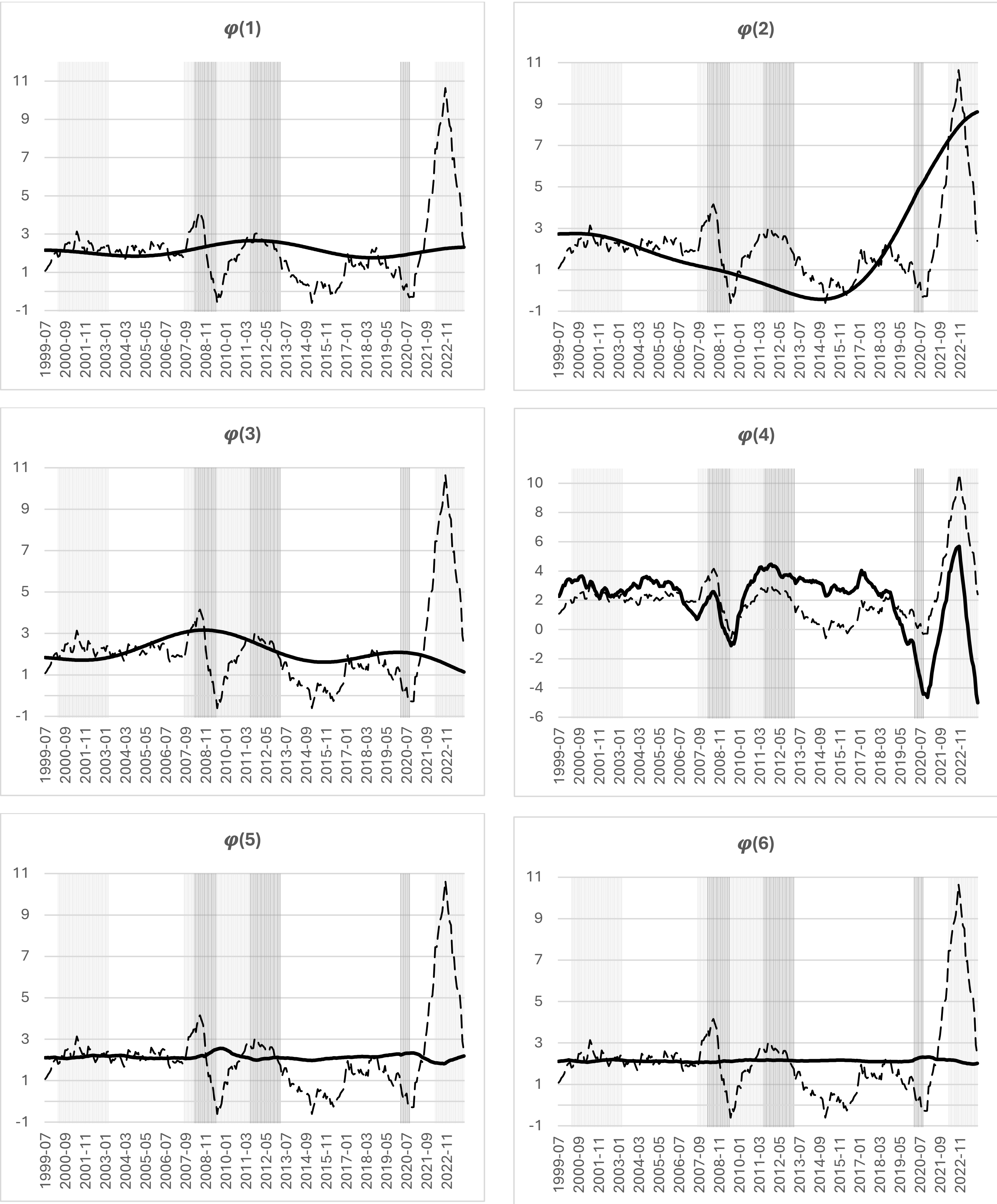


Figure A8: Historical decomposition of the headline inflation rate. Contribution of the common medium to long-term ($\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}, \boldsymbol{\varphi_5}, \boldsymbol{\varphi_6}$) structural shocks.

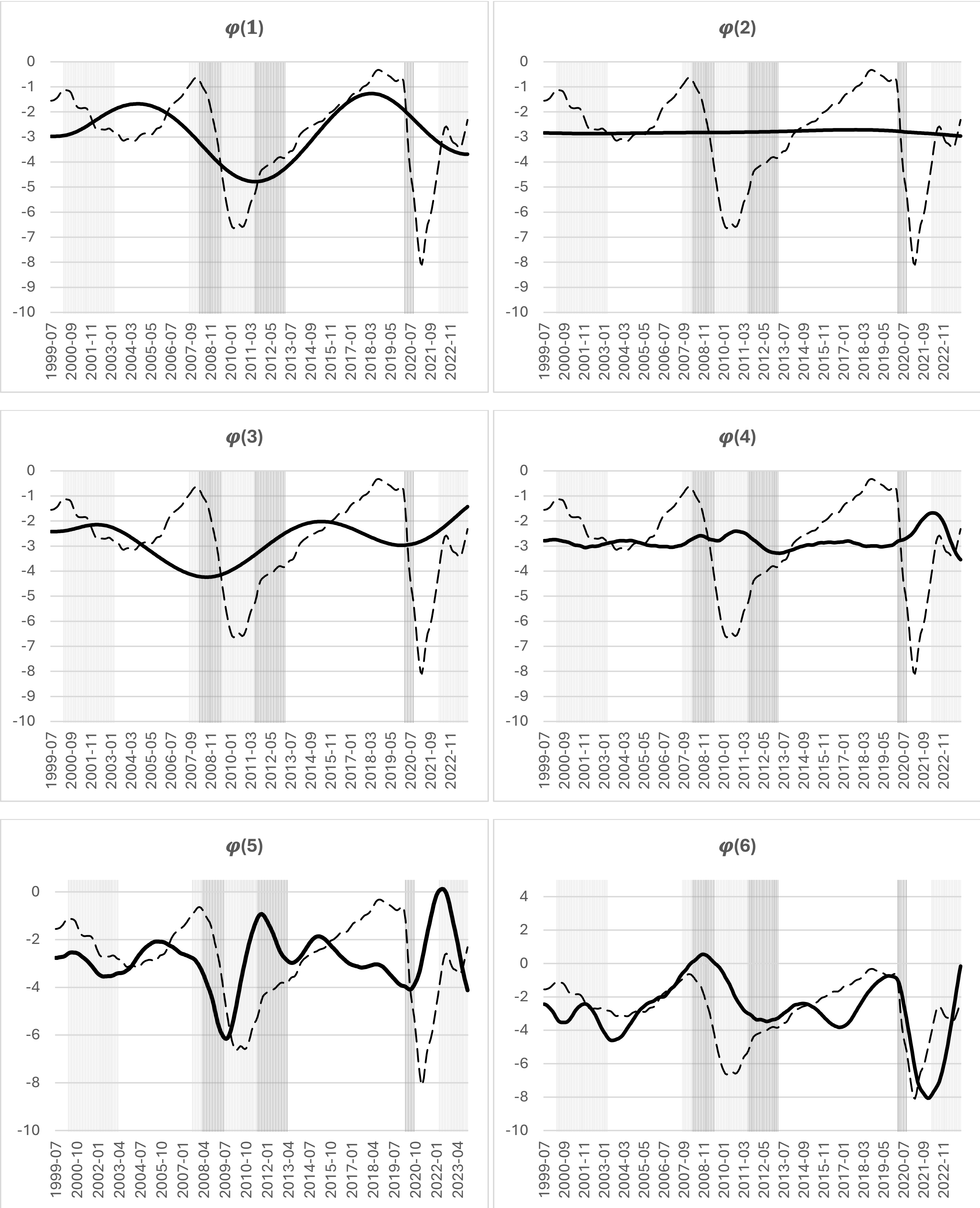


Figure A9: Historical decomposition of the fiscal deficit to GDP ratio. Contribution of the common medium to long-term ($\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}, \boldsymbol{\varphi_5}, \boldsymbol{\varphi_6}$) structural shocks.

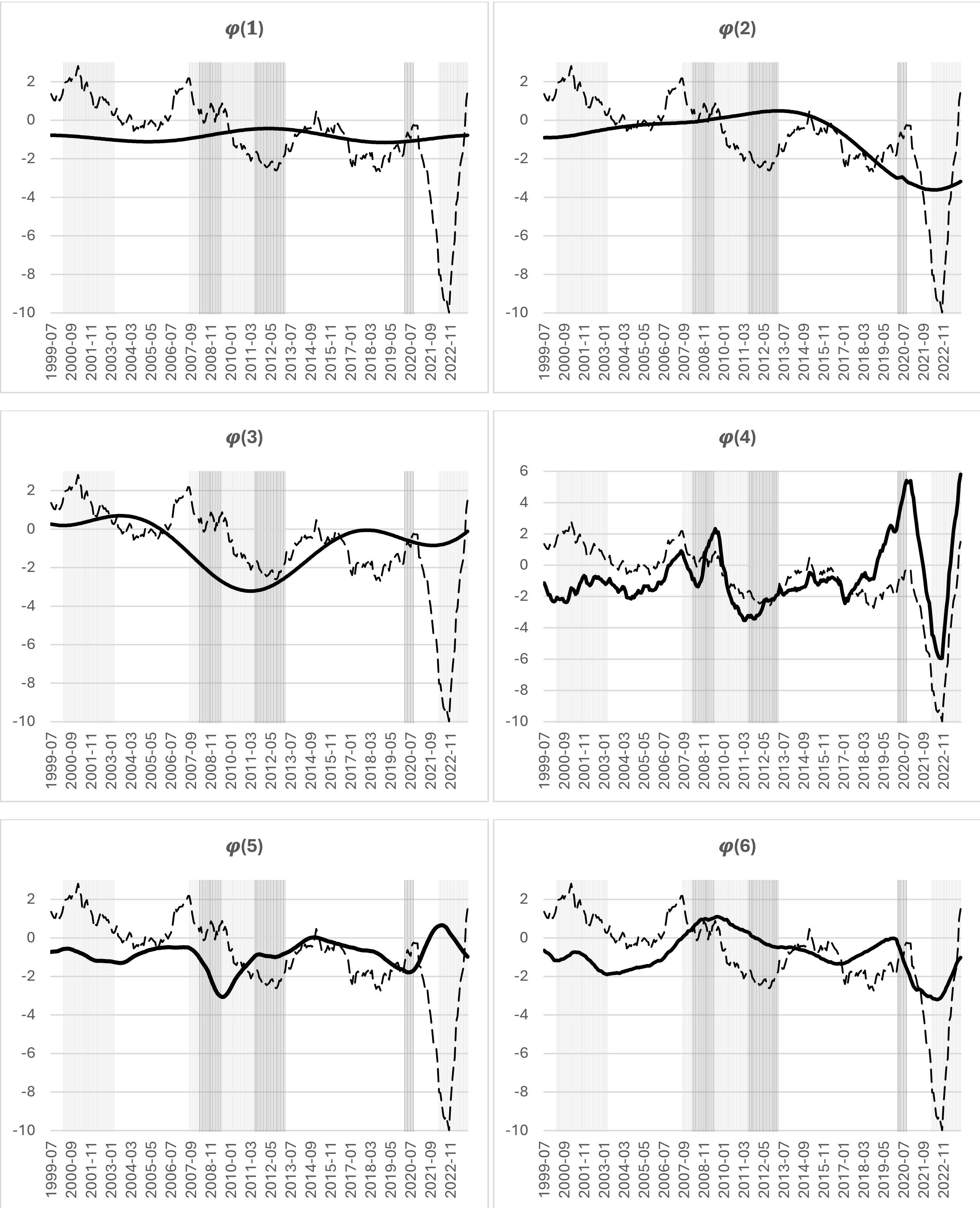


Figure A10: Historical decomposition of the real overnight interest rate. Contribution of the common medium to long-term ($\boldsymbol{\varphi_1}, \boldsymbol{\varphi_2}, \boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}, \boldsymbol{\varphi_5}, \boldsymbol{\varphi_6}$) structural shocks.

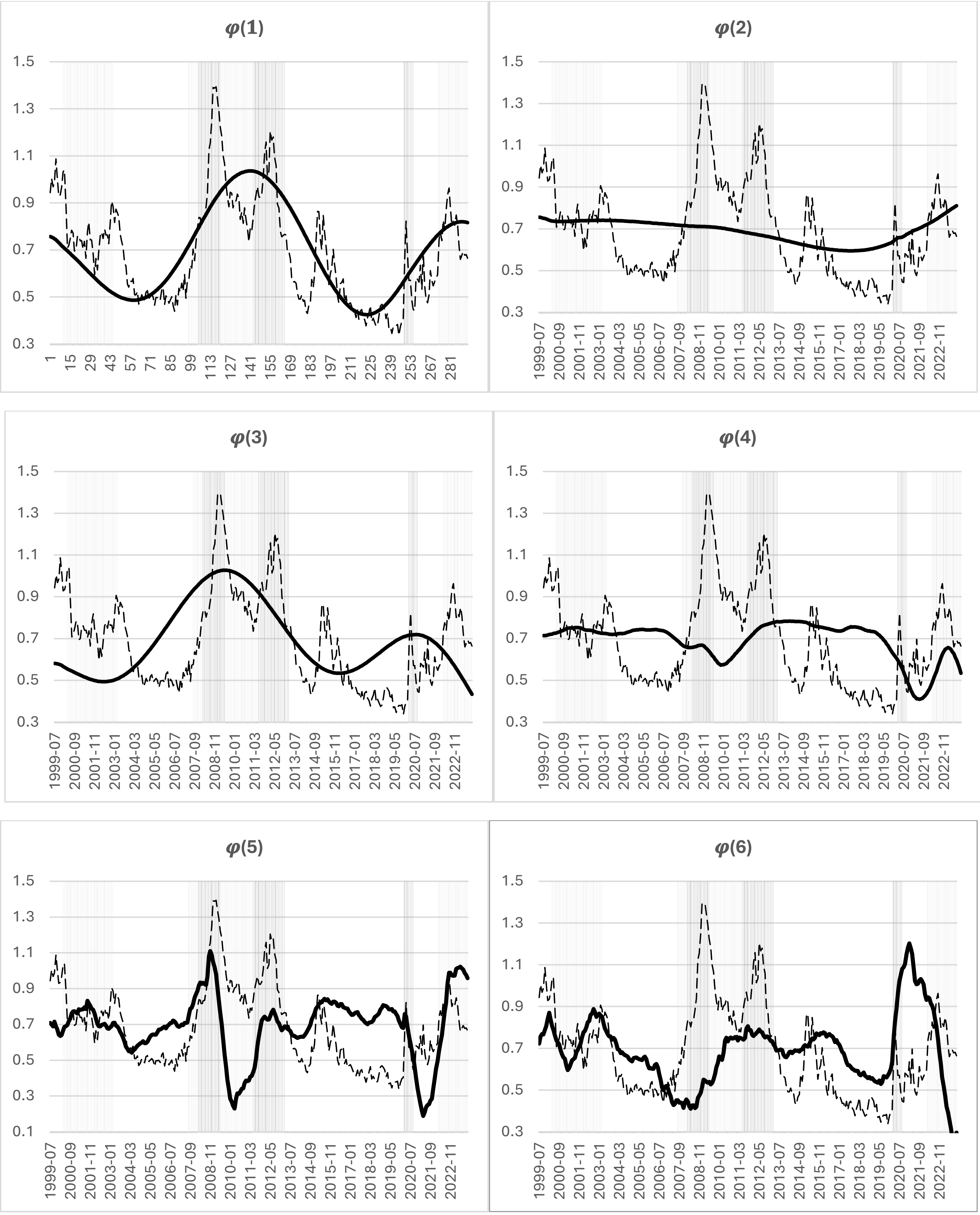
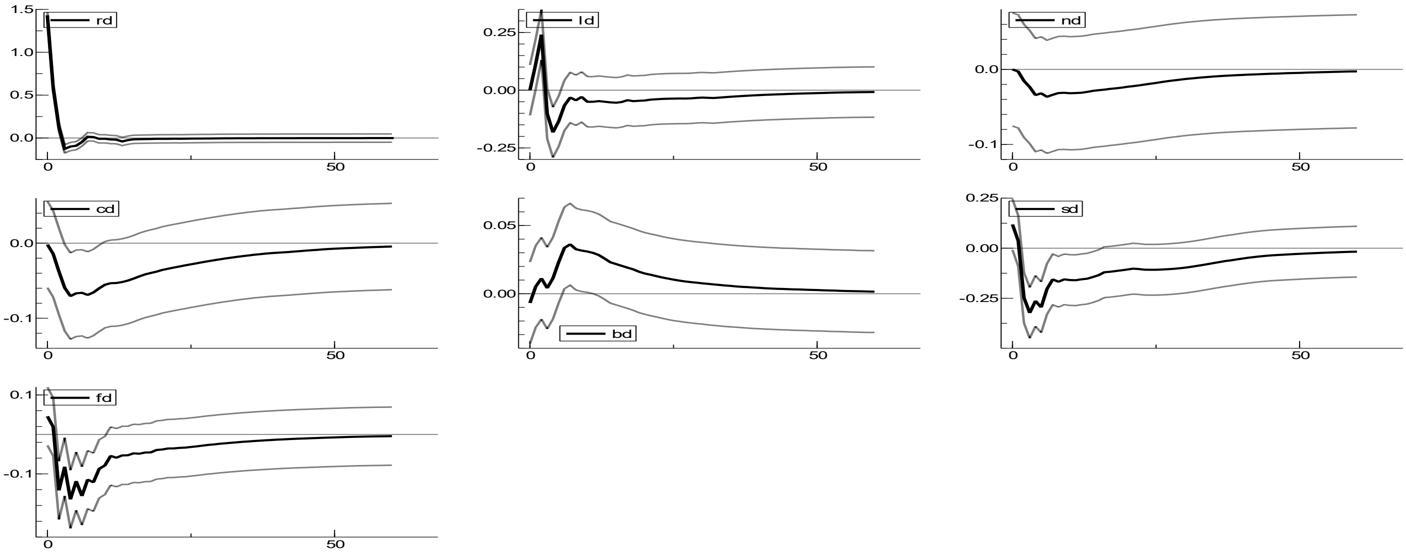
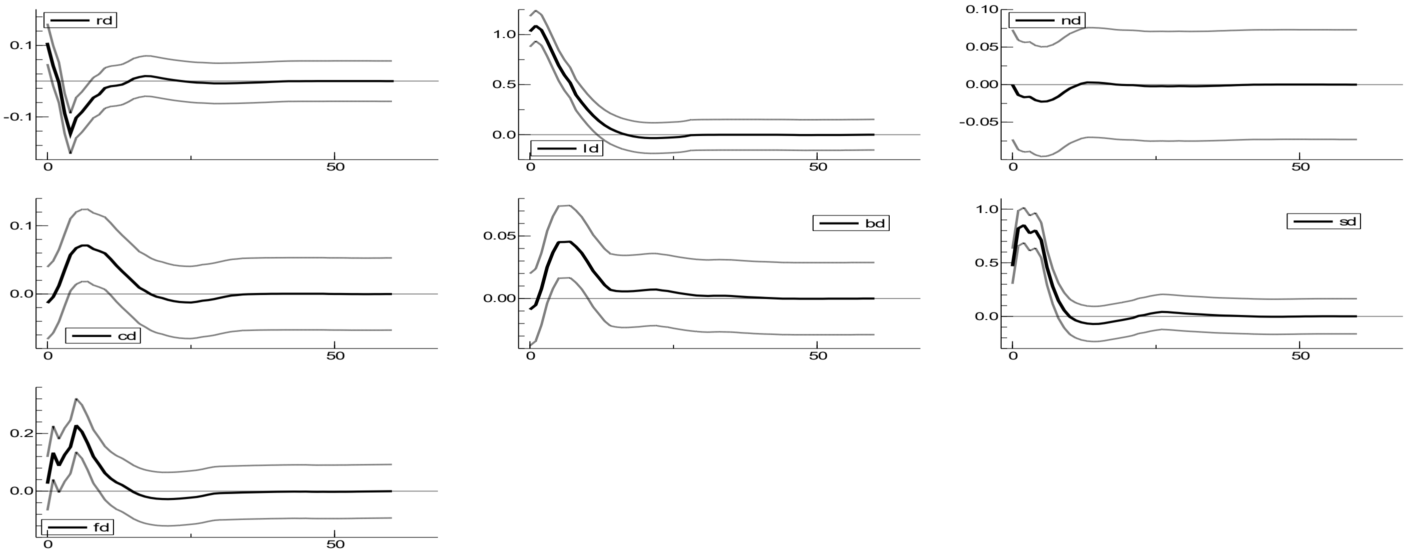


Figure A11: Historical decomposition of the overall macro-financial indicator. Contribution of the common medium to long-term ($\boldsymbol{\varphi_1}$, $\boldsymbol{\varphi_2}$, $\boldsymbol{\varphi_3}$) and short-term ($\boldsymbol{\varphi_4}$, $\boldsymbol{\varphi_5}$, $\boldsymbol{\varphi_6}$) structural shocks.

Responses to ***rd* shock k_1**



Responses to ***ld* shock k_2**



Responses to ***nd* shock k_3**

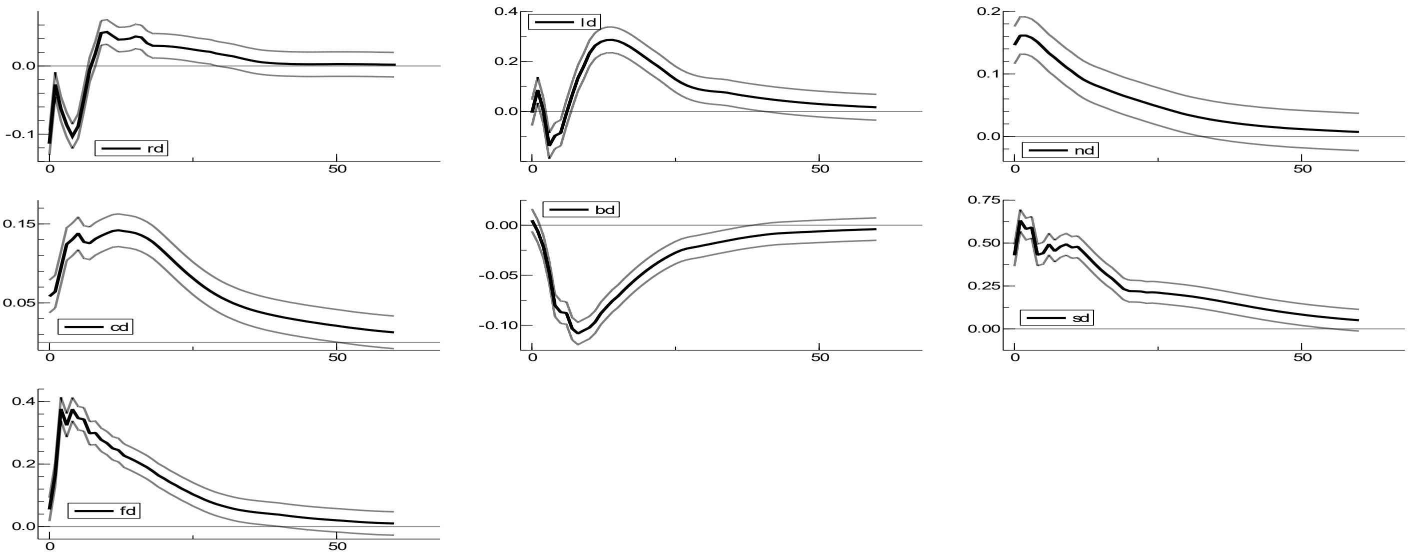
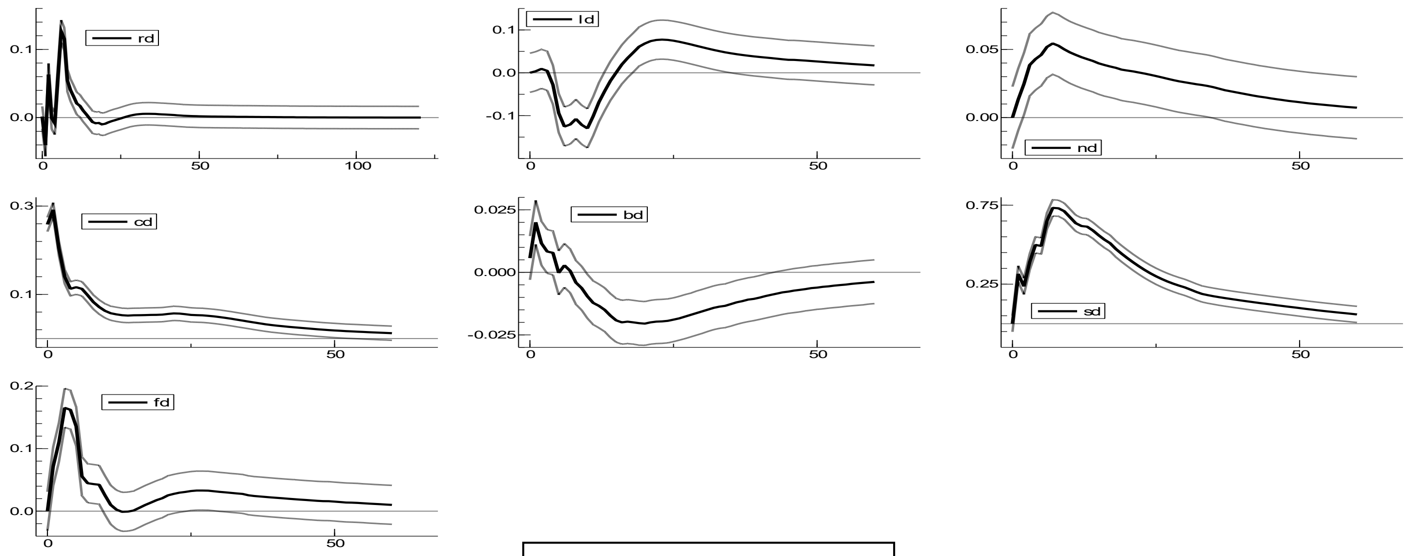
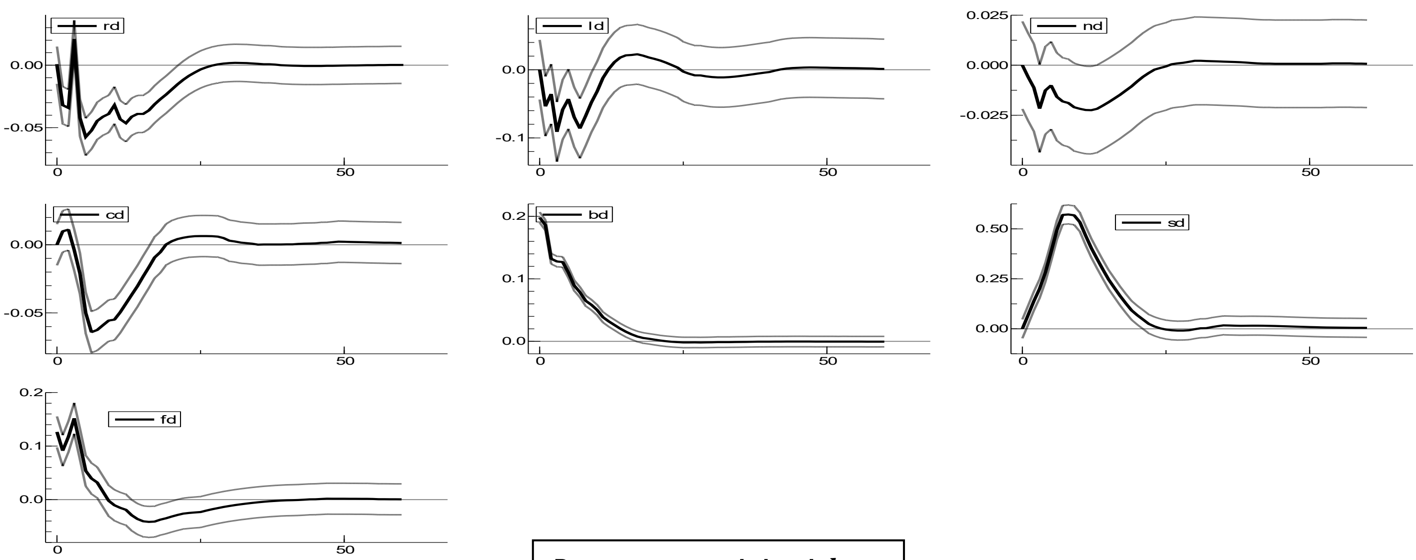


Figure A12: Impulse responses of divergence indicators to a unitary idiosyncratic real (k_1), labor market (k_2), and nominal (k_3) divergence structural shock. The responses are computed for the real (***rd***), labor market (***ld***), nominal (***nd***), competitiveness (***cd***), bond market (***bd***), stock market (***sd***), and financial condition (***fd***) indicators.

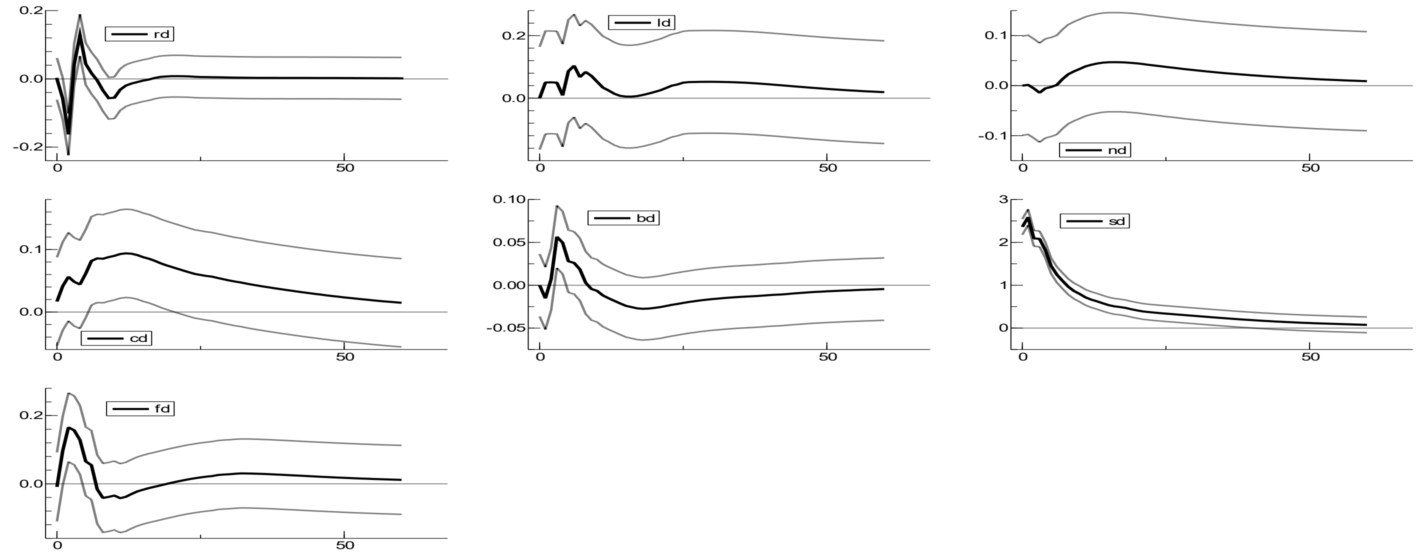
Responses to ***cd*** **shock** $\boldsymbol{k_4}$



Responses to ***bd*** **shock** $\boldsymbol{k_5}$



Responses to ***sd*** **shock** $\boldsymbol{k_6}$



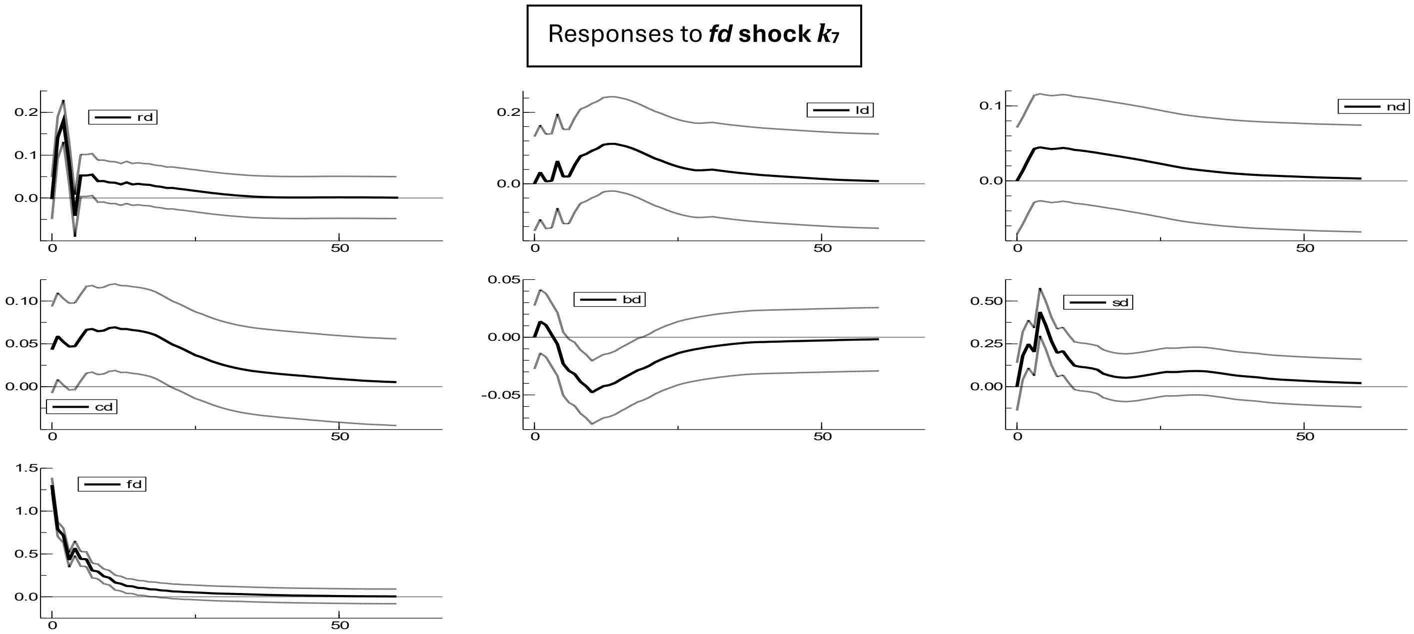


Figure A13: Impulse responses of divergence indicators to a unitary idiosyncratic competitiveness (k_4), bond market (k_5), stock market (k_6), and financial condition (k_7) divergence structural shock. The responses are computed for the real (***rd***), labor market (***ld***), nominal (***nd***), competitiveness (***cd***), bond market (***bd***), stock market (***sd***), and financial condition (***fd***) indicators.