Macro-Financial Interactions in a Changing World*

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Abstract

We measure the time-varying strength of macro-financial linkages within and across the US and euro area economies by employing a large set of information for each region. In doing so, we rely on factor models with drifting parameters where real and financial cycles are extracted, and shocks are identified via sign and exclusion restrictions. The main results show that the euro area is disproportionately more sensitive to shocks in the US macroeconomy and financial sector, resulting in an asymmetric cross-border spillover pattern between the two economies. Moreover, while macro-financial interactions have steadily increased in the euro area since the late 1980s, they have oscillated in the US, exhibiting very long cycles of macro-financial interdependence.

Keywords: Macro-Financial Linkages, Dynamic Factor Models, TVP-VAR.

JEL Codes: E44, C32, C55, F44, E32, F41

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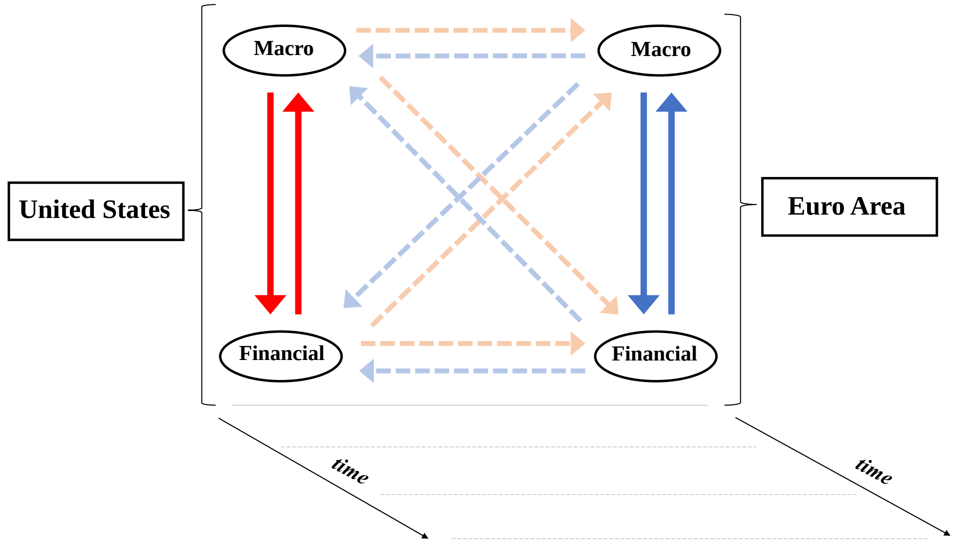
1 Introduction

The eagerness to understand macro-financial linkages has been brisk and unprecedented over the recent years. Much of this has been driven by the desire to comprehend the forces that lead to the Great Recession, including the deep and long-lasting consequences from the financial downturn that began in 2007. In particular, recent research on macro-finance has focused on the role of the financial sector as a generator of shocks, which are transferred to the overall economy via macro-financial linkages. Less (albeit some) effort has been put in understanding how the macroeconomy can create and transmit shocks to the financial sector. Moreover, very little effort has been invested in grasping the role that linkages themselves may play as amplifier and feedback loop for shocks generated inside the linkages as well as elsewhere. Yet, the prospect for a full recovery seems bleach at present. Despite unprecedented monetary expansion and supportive fiscal policy, per-capita income growth has stagnated in many jurisdictions, including the US and euro area. Therefore, understanding how macro-financial interactions can condition a potential recovery has become crucial for policy makers.

Figure 1 shows a diagram that illustrates the complexities embedded in macro-financial interactions. Each economy in the figure has two sectors, macroeconomic and financial. Domestic spillovers between the sectors in the US (euro area) are denoted by red (blue) solid arrows. In parallel, cross-border interactions between the sectors are denoted with dashed arrows. Moreover, all these relationships may be subject to potential fundamental changes over time due to a number of reasons, opening an additional dimension to the problem. One outcome from Figure 1 is that the study of international macro-financial dynamic interactions, albeit crucial for policy makers, is challenging due to all the possible ways in which shocks could be transmitted. The aim of this paper is to provide a robust assessment of these interactions by taking into account all these underlying dimensions.

The first part of the problem involves defining what the macroeconomic and financial cycles are. Yet, in the empirical literature there is still a wide debate on the exact definition of a real cycle and how different and more complete it is from the standard business cycle. For the financial counterpart, there is even less consensus on what constitutes a financial cycle, its statistical characterization, and how similar it is to the real cycle. The

Figure 1: International Macro-Financial Dynamic Interactions



Note: Solid red (blue) arrows denote the domestic macro-financial interactions for the US (euro area). Dashed red arrows make reference to the spillovers from the US to the euro area. Dashed blue arrows denote the spillovers from the euro area to the US

existing definitions, usually, tend to be narrow (normally incorporating just a few variables in order to capture the multi-faceted nature of the real or financial sectors), exogenously pre-determined (constructed such that they reproduce pre-determined statistical characteristics), or based on short time series samples.[1]

Recognising the above short-comings, this paper attempts to provide a comprehensive definition of real and financial cycles using dynamic factor models. Unlike previous studies, our empirical framework allows for an endogenous and time-varying selection of variables in the construction of each of the latent cycles, selecting from a large dataset of real activity and financial indicators, for each economy. These variables include information about output, employment, production, consumption, etc., on the real side, and information regarding balance sheets, credit, foreign financial activity, etc., on the financial side of the economy. The motivation for including this feature in our modelling strategy relies on the need for robustness in the determination of the most relevant variables driving the financial cycle over time, given the lack of consensus about its definition.

The second part of the problem consists of measuring the intensity of the evolving

[1]Section 2 provides a detailed review of the literature on the study of macro-financial linkages.

macro-financial interactions. To quantify the degree of time variation and profundity in linkages, the cycles are allowed to endogenously evolve according to a structural VAR model with drifting coefficients. Also, in order to provide robust assessments, the identification of real and financial shocks is based on a wide range of schemes that assume exclusion, sign and timing restrictions on the impulse response functions. To the best of our knowledge this is the first study of macro-financial spillovers between the US and the euro area, each as single economic units, that covers a period starting in the 1980s. In particular, the sample starts in 1981:II for the case of the euro area, which is considerably longer than the sample analyzed in any of the previous studies that focus on macro-financial linkages in this region. Equally, due to good data availability, for the US we can go as far back as 1960:I.

Moreover, we measure the linkages between macroeconomic and financial conditions in a number of ways in order to provide a comprehensive assessment. Besides the qualitative comparison of the real and financial cycles, and the computation of their time-varying correlation, we examine the mutual impact and propagation of structural shocks over time, calculate the time-varying forecast error variance decomposition at different horizons to assess the predictive power that one cycle has on another, and examine the time-varying factor loadings for the real as well as financial cycle to measure the strength of common patterns inside each sector.

Lastly, the third part of the problem focuses on quantifying the intensity of cross-border spillovers in the macro-financial sphere. In doing so, we propose a joint (two-economy) model which basically nests the two single-economy models. Considering that US and the euro area top the list of global GDP figures, it is of global relevance to understand their dynamics and cross-border propagation of shocks. Moreover, the topic is of high policy relevance considering the recent attempts to bring the two economies closer by creating special economic agreements (such as TTIP*), foster deeper financial cross-border flows (global banks, EU passport in banking and market financing in euro area), and enforce regulatory harmonization (transatlantic mutual recognition of regulation in securities and derivatives, Basel III and FSB).[2]

[2] *=Transatlantic Trade nd Investment Partnership

With longer and smoother financial cycles compared to the macroeconomic, both in the euro area and in the US, our results robustly uncover a number of highly policy-relevant features about the evolution of international macro-financial interactions. First, while the euro area has exhibited increasing commonalities in the financial sector since the early 2000s, the strength of commonalities in the US financial sector has remained relatively steady over time. In particular, euro area private sector liabilities have become increasingly determinant for the shape and evolution of financial cycles. Second, while in the euro area, macro-financial interactions have steadily increased since late 1980's, in the US, they have oscillated, exhibiting very long cycles of macro-financial interdependence. Moreover, the integration of the financial sector in the overall economy and the increase in the interplay between the two sectors has been more intense in the US, while more solid and gradual in the euro area. Third, we unveil significant differences in the transmission of mutual shocks. In the euro area, the propagation of shocks has increased in both directions, that is, from financial to real, and real to financial, but in the US, it has only increased in the first direction, from financial to real. Likewise, the degree of responsiveness of the financial sector to macroeconomic shocks is comparatively higher in the US, suggesting a deeper integration between the two sectors. Fourth, the intensity in transmission of macro-financial shocks across borders is highly asymmetric, mainly going from US to euro area. In particular, there is a dimension of asymmetry whereby unexpected deteriorations in the US economy are detrimental for euro area financial conditions, while, unexpected deteriorations in the euro area economy could be beneficial for the financial conditions in the US. These asymmetries increased over time, until the Great Recession.

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature that helps to identify our contributions. Section 3 describes the employed empirical framework. Section 4 analyzes domestic macro-financial linkages. Section 5 studies international spillovers. Section 6 concludes.

2 Contacts with the literature

The financial turmoil of 2008 sparked an interest in studying the structural interplay between financial cycles and the broader economy. While the questions raised in those studies were not necessarily new, and build on the arguments laid out in the 1930's and 1970's (Fisher (1933) and Minsky (1977)), the scope of the pre-Great Recession studies were much narrower, focusing either on a few cycles, particular aspect, or a particular segment of the financial sector. For instance, there were studies that showed the procyclical nature of the financial system (Borio et al. (2001) and Borio and Lowe (2002)). Others have tried to find long-run regularities in financial crises and the factors leading up to them (Reinhart and Rogoff (2009)).[3]

The recent empirical studies examining the interplay between macroeconomic and financial cycles can generally be divided in two main strands. The first one focuses on the measurement of both cycles, which presents challenges, especially, when defining a financial cycle. Instead, the second strand focuses on assessing changes over time in the relationship between macroeconomic and financial cycles. Next, we proceed to briefly review the two strands of the literature to elucidate the contributions of this paper.

In first place, studies that have focused on the measurement of the cycles can be grouped into four categories. The first category uses frequency-based filters to extract the cyclical components of macroeconomic and financial variables, and to describe their similarities and differences. Most of these studies find that financial cycles are longer in length and larger in amplitude than business cycles, but with an increasing synchronization over time (Drehmann et al. (2012), Aikman et al. (2015), Gerba (2015), Schueler et al. (2017) and Gerba et al. (2017b)). However, since these measures are not based on a given theory or model, the analysis of their interdependence can return spurious results, as it is shown in Phillips and Jin (2015).[4] This is also the case for the second category, which focuses on extracting cycles in frequency domain (Strohsal et al. (2015) and Schueller et al. (2017)).[5]

[3]In a recent work Jorda et al. (2017) document a set of historical features of macro-financial linkages, pointing to the prominent role that financial factors should have in macroeconomic models.

[4]Moreover, these studies either assume that the frequency between the two types of series is similar, or that financial is *ex ante* longer than the business cycle.

[5]These studies also find that financial cycles, in general, are longer than real cycles, but show evidence for both short- and medium-term cycles in real credit growth

An important short-coming of this method is that since it requires stationarity, it makes it difficult to endogenously account for potential structural brakes, which may result in a lengthening or shortening of the cycles. Third, a less restrictive way of depicting the two cycles is by relying on turning points identification, by using the Bry-Boschan algorithm (Harding and Pagan (2002), (2006)).[6] The main drawback with this method is that it is excessively agnostic, and therefore, also has very limited theory to explain the results. Fourth, to overcome some of the drawbacks of non-parametric or agnostic filters, model-based filters have been employed. This method is usually based on unobserved component models used to extract cycles by relying on the Kalman filter (Galati et al. (2016) and Ruenster and Vlekke (2016)).

In parallel, different empirical strategies have been employed to infer potential changes in the relationship between macroeconomic and financial variables. The most employed tool has been the vector autoregressions (VARs) subject to parameter instabilities. Blake (2000) and Calza and Sousa (2006) use Threshold VAR models to measure the effect of credit shocks on real activity, for the US and euro area, respectively. Both studies show evidence of a stronger impact occurring under low credit growth regimes. For similar purposes, Davig and Hakkio (2010), Hubrich and Tetlow (2015), and Nason and Tallman (2015) use Markov-switching VAR models to study the relationship between financial stress and US economic activity.[7] All these studies agree in that the propagation of financial shocks to the real economy is different during high financial stress regime in comparison to normal times.[8] Other studies allow for instabilities in the VAR models that are smoother than sudden changes of regimes, that is, by allowing parameters to evolve according to random walks. For example, Prieto et al. (2016) use a time-varying parameter (TVP) VAR model to analyze the contribution of credit spread shocks to the US economy. Gambetti and Musso (2017) follow a similar approach to investigate the effect of credit supply shocks. Ciccarelli et al. (2016) investigate commonalities and spillovers in macro-financial linkages by using

[6] As show in Claessens et al. (2011) and Drehmann et al. (2012) financial cycles are also found to be longer than business cycles, although Cagliarini and Price (2017) don't find sufficient evidence. Moreover, they find that business cycles display a higher degree of synchronisation with credit and house price cycles than with equity prices.

[7] Kaufmann and Valderrama (2010) apply a similar framework to also assess the case of the euro area.

[8] In a recent work, Leiva-Leon et al. (2018) evaluate changes in the propagation of shocks between credit sentiment and the macroeconomy by relying on a multivariate Markov-switching framework.

a panel VAR model with drifting coefficients.[9] An important drawback of these studies is that the employed measure of financial cycles is based on one or a few financial variables, which usually are related to credit activity only. This is because of the computational problems arising in estimating such models using a large number of variables. However, this limitation precludes the estimation of a broad measure of the financial cycle, which is a crucial feature, given its complexity and lack of consensus about its definition.

The two strands of the literature described above have been somehow disconnected. This paper intends to unify them by, first, extracting both macroeconomic and financial cycles from a large set of information with Kalman filtering techniques, and second, casting those extracted cycles into a structural VAR model with time-varying parameters to assess changes in the propagation of their shocks. This modelling strategy, which consists of a joint estimation procedure, described in Section 3 and Appendix A, allows us to infer changes in macro-financial linkages from a robust and broader perspective than previous studies. Additionally, we allow for a changing and flexible selection of variables driving both the financial and real cycle, and identify real and financial shocks with a strategy that is based on sign, exclusion and timing restrictions on the impulse response functions.

We also incorporate an international dimension to our analysis by looking at cross-border spillovers between the US and the euro area, both within the sectors, and across. In this regard, most of the studies have looked at the US outward spillover, finding that US financial and real shocks matter significantly for the rest of the world. Using a structural VAR model for pre-2008 data, Bayami and Thahn Bui (2010) find that international business cycles are largely driven by US financial shocks, with minor role for shocks from other advanced economies. Miranda-Agrippino and Rey (2018) equally find that there are large financial spillovers from the US to the rest of the world.

Our framework is more extensive than previous studies since it allows to identify outward as well as inward spillovers in the US and the euro area, both within the sector as well as across them. Moreover, we allow the degree of spillover effects between the two regions to exhibit potential changes over time. Therefore, we provide a full spectrum of international macro-financial interactions, that is, across regions (US and euro area), across sectors

[9] Also, Abbate et al. (2016) purse a similar goal, but from an international perspective.

(Macroeconomic and Financial), and over time. The related literature is relatively limited, and most of related works assess the degree of financial crises spill-overs across markets, without considering the across sectors aspect (real economy), or the non-crises times.[10]

3 Empirical framework

This section describes the econometric framework used to jointly (i) extract macroeconomic and financial cycles from large datasets and (ii) assess the evolving interdependence between these cycles. Let F_t be a vector that contains n_f indicators of financial conditions and R_t be a vector containing n_r indicators of real activity for a given economy. Our aim is to provide a framework that allows for a flexible selection of the variables driving both cycles over time, and that also accounts for potential changes in the propagation of real and financial shocks.

3.1 One-economy model

We rely on a dynamic factor model with drifting loadings and where the factors evolve according to a VAR model with time-varying coefficients. Accordingly, consider the model described in the following equations,

$$\begin{bmatrix} F_t \\ R_t \end{bmatrix} = \begin{bmatrix} \Lambda_{f,t} & 0 \\ 0 & \Lambda_{r,t} \end{bmatrix} \begin{bmatrix} f_t \\ r_t \end{bmatrix} + \begin{bmatrix} v_{f,t} \\ v_{r,t} \end{bmatrix}, \tag{1}$$

$$\begin{bmatrix} f_t \\ r_t \end{bmatrix} = \Phi_{1,t} \begin{bmatrix} f_{t-1} \\ r_{t-1} \end{bmatrix} + \cdots + \Phi_{k,t} \begin{bmatrix} f_{t-k} \\ r_{t-k} \end{bmatrix} + \begin{bmatrix} u_{f,t} \\ u_{r,t} \end{bmatrix}, \tag{2}$$

where f_t and r_t denote the financial conditions and real activity factors, respectively.[11] The idiosyncratic innovations, $\mathbf{v}_t = (v_{f,t}, v_{r,t})'$, are assumed to be orthogonal between them and normally distributed, $\mathbf{v}_t \sim N(0, diag(\mathbf{\Omega}))$. The reduced form innovations from the VAR, $\mathbf{u}_t = (u_{f,t}, u_{r,t})'$, are also assumed to be normally distributed, $\mathbf{u}_t \sim N(0, \mathbf{\Sigma})$. To be

[10] For instance, Gravelle et al. (2006) find evidence of shift-contagion across currency markets, but not bond markets. Dungey et al. (2010) find that the degree of shift-contagion depends on the crisis, with higher levels during subprime US 2007 crises or the 1998 Russian/LTCM crisis.

[11] In the empirical applications, we assume $k = 2$.

able to assess the propagation of real and financial shocks, we let $\mathbf{u}_t = \mathbf{A}^{-1}\boldsymbol{\varepsilon}_{\mathbf{t}}$, where the vector $\boldsymbol{\varepsilon}_t = (\varepsilon_{f,t}, \varepsilon_{r,t})'$, denotes the underlying structural shocks, such that $E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t^{'}) = I$, and $E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_{t-k}^{'}) = 0$, $\forall k$, and $\mathbf{A}$ denotes the impact multiplier matrix. Although, our benchmark specification assumes homoskedastic residual associated to the VAR equation, we also account for changes in the covariance matrix Σ in alternative specifications for robustness purposes.[12]

To allow for changes over time in the information contained in the cycles and in the propagation of shocks between real and financial cycles, we let both the autoregressive coefficients $\boldsymbol{\phi}_t = vec(\Phi_t)$, where $\Phi_t = [\Phi_{1,t}, ..., \Phi_{k,t}]$, and the factor loadings $\boldsymbol{\lambda}_t = vec(\boldsymbol{\Lambda}_t)$, where $\boldsymbol{\Lambda}_t = [\Lambda_{f,t}, \Lambda_{r,t}]'$, to be time-varying by following random walk dynamics,

$$\boldsymbol{\phi}_t = \boldsymbol{\phi}_{t-1} + \boldsymbol{w}_t, \tag{3}$$

$$\boldsymbol{\lambda}_t = \boldsymbol{\lambda}_{t-1} + \boldsymbol{\omega}_t. \tag{4}$$

The innovations $\boldsymbol{w}_t$ and $\boldsymbol{\omega}_t$ are white noise Gaussian processes with zero mean and constant covariances, $\boldsymbol{\Psi}_w$ and $\boldsymbol{\Psi}_\omega$, respectively.

To identify macroeconomic and financial shocks previous studies have mainly relied on simple recursive, or Cholesky, identification strategy (Davig and Hakkio (2010), Hubrich and Tetlow (2015), Nason and Tallman (2015), Abbate et al. (2016), Ciccarelli et al. (2016), Prieto et al (2016)), which can be highly controversial. In a recent work, Gambetti and Musso (2017) relied on the use of large set of sign restrictions to identify loan supply shocks. In this paper, we rely on a recent work by Arias et al. (2018) and use a combination of a few sign, exclusion and timing restrictions to identify macroeconomic and financial shocks. Additionally, we use an alternative identification strategy as robustness exercise, proposed by Bai and Wang (2015).

Regarding the strategy based on the combination of restrictions, first, we assume that real activity and financial conditions are persistent processes by assuming positive signs

[12] In particular, we account for breaks in the volatility associated to the so-called "Great Moderation". Allowing for more general modelling choices of heteroskedasticity such as stochastic volatility generates complications to obtain draws of the autoregressive coefficients that yield a stationary process. This is because (i) the structural shocks are set identified, and (ii) the variables involved in the VAR are latent, and therefore, also treated as random variables.

in the off-diagonal entries of the impact multiplier matrix, A^{-1}. Second, we assume that positive real activity shocks have positive contemporaneous effect on financial conditions, but that a shock in financial conditions does not have a contemporaneous effect on real activity. As noticed in Prieto et al. (2016) (and many other studies), this assumption implies that macroeconomic variables react with a delay to financial shocks, possibly because of wealth effects and other effects which involve financial intermediaries that take time to materialize. In contrast to financial variables, that may react instantaneously to macroeconomic shocks. Third, consequently, we assume that it would take at least one period for real activity to react to a shock in financial conditions. Therefore, we postulate that a positive unexpected change in the financial cycle positively affects the real cycle with a one period lag. Although, in the two-economy model, described in the next section, the restriction on the non-contemporaneous effect of financial on macroeconomic conditions is relaxed and financial shocks are allowed to contemporaneously influence real activity. The combination of these restrictions is summarized in Table 1.

Table 1: Sign, Exclusion and Timing Restrictions for the One-economy model

	Financial Shock	Real Shock
	h=0	
Financial Cycle	+	+
Real Cycle	0	+
	h=1	
Financial Cycle	$*$	$*$
Real Cycle	+	$*$

Note: The symbol $*$ indicates that no restriction is imposed in the corresponding relationship, and "h" denotes the horizon of the impulse response.

Bai and Wang (2015) proposed a way to perform structural analysis in a context of dynamic factor models with factors that are governed by a vector autoregressive structure. This identification strategy simply consists of directly restricting the variance-covariance matrix of the reduced form innovations to be an identity matrix, that is, $\Sigma = I$. It is important to notice that, unlike previous studies that measure macro-financial linkages based on VAR models that contain observed data, our framework relies on a VAR system that only includes latent variables. This particular feature facilitates the identification of the underlying macroeconomic and financial shocks. This is because the shocks are jointly estimated with the rest of the parameters of the model, and by imposing this restriction, the rest of elements in the model are adjusted in a way that the resulting innovations $\mathbf{u}_t$ have a structural interpretation by construction. As a robustness exercise, we alternatively employ this approach to assess the propagation of shocks between macroeconomic and financial cycles. This information corresponds to the solid arrows, red for US and blue for euro area, in Figure 1. The use of all these alternative identification schemes would allow us to provide robust assessments on the evolving nature of macro-financial interactions.

3.2 Two-economy model

The factor model described above is estimated for the two economies, US and euro area, separately in order to provide a deep and accurate understanding of their corresponding macro-financial linkages. However, we are also interested in identifying potential changes in the cross-border spillovers between the two economies. In particular, we are interested in estimating the time-varying effect of (i) financial shocks in the US to the financial cycle in the euro area, (ii) real shocks in the US to the real cycle in the euro area, (iii) financial shocks in the US to the real cycle in the euro area, (iv) real shocks in the US to the financial cycle in the euro area, (v) financial shocks in the euro area to the financial cycle in the US, (vi) real shocks in the euro area to the real cycle in the US, (vii) financial shocks in the euro area to the real cycle in the US, and (viii) real shocks in the euro area to the financial cycle in the US This information corresponds to the dashed arrows in Figure 1, red for spillovers from US to the euro area, and blue for spillovers from euro area to US.

In order to address these issues, we propose an extended, or joint, model that nests each of the two models for individual economies. Accordingly, consider the following US-euro area dynamic factor model:

$$\begin{bmatrix} F_t^{US} \\ R_t^{US} \\ F_t^{EA} \\ R_t^{EA} \end{bmatrix} = \begin{bmatrix} \Lambda_{f,t}^{US} & 0 & 0 & 0 \\ 0 & \Lambda_{r,t}^{US} & 0 & 0 \\ 0 & 0 & \Lambda_{f,t}^{EA} & 0 \\ 0 & 0 & 0 & \Lambda_{r,t}^{EA} \end{bmatrix} \begin{bmatrix} f_t^{US} \\ r_t^{US} \\ f_t^{EA} \\ r_t^{EA} \end{bmatrix} + \begin{bmatrix} v_{f,t}^{US} \\ v_{r,t}^{US} \\ v_{f,t}^{EA} \\ v_{r,t}^{EA} \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} f_t^{US} \\ r_t^{US} \\ f_t^{EA} \\ r_t^{EA} \end{bmatrix} = \Psi_{1,t} \begin{bmatrix} f_{t-1}^{US} \\ r_{t-1}^{US} \\ f_{t-1}^{EA} \\ r_{t-1}^{EA} \end{bmatrix} + \cdots + \Psi_{k,t} \begin{bmatrix} f_{t-k}^{US} \\ r_{t-k}^{US} \\ f_{t-k}^{EA} \\ r_{t-k}^{EA} \end{bmatrix} + \begin{bmatrix} u_{r,t}^{US} \\ u_{f,t}^{US} \\ u_{r,t}^{EA} \\ u_{f,t}^{EA} \end{bmatrix} \tag{6}$$

where F_t^{US} and R_t^{US} denote the set of information on financial and real activity, respectively, for the US economy. Similarly, F_t^{EA} and R_t^{EA} denote the same set of information but for the euro area economy. Notice that, consequently, this joint model would extract four latent factors associated to the financial and real cycles for the US (f_t^{US} and r_t^{US}) and for the euro area (f_t^{EA} and r_t^{EA}). The main advantage of this joint model is that we allow for the four latent factor to be endogenously interrelated in a VAR fashion. Moreover, we also allow for time variation in the parameters of the VAR in order to identify changes in the cross-border propagation of macroeconomic and financial shocks. The dynamics of the evolving parameters are assumed to be of the same nature as the ones detailed in the region-specific models, that is, following independent random walks.

The reduced form innovations, $\mathbf{u}_t^* = (u_{r,t}^{US}, u_{f,t}^{US}, u_{r,t}^{EA}, u_{f,t}^{EA})'$, and structural innovations, $\boldsymbol{\varepsilon}_t^* = (\varepsilon_{r,t}^{US}, \varepsilon_{f,t}^{US}, \varepsilon_{r,t}^{EA}, \varepsilon_{f,t}^{EA})'$, are linked through the impact multiplier matrix, that is, $\mathbf{u}_t^* = B^{-1}\boldsymbol{\varepsilon}_t^*$. The main challenge associated to the joint model arises when defining the restrictions to identify cross-border spillovers. As noticed in Prieto et al. (2016), structural (DSGE) models are still not available in a form to derive meaningful and widely accepted sign restrictions to disentangle real and financial shocks (see Eickmeier and Ng (2011) for a discussion). However, we take advantage of the fact that the model incorporates two economies instead of only one in order to define a set of restrictions that help us to identify the underlying structural shocks. In particular, we assume that, within each region, there is a positive and contemporaneous response of real activity and financial conditions to both real and financial shocks. Next, we assume that euro area developments, in general, have no contemporaneous impact on US developments, with only one exception. We allow for the possibility that the financial conditions in the US and euro area contemporaneously influence each other. Finally, we assume that positive US real shocks are favorable for both real and financial conditions in the euro area. However, a positive financial shock in the US would take at least one period to generate a positive influence on the euro area macroeconomic conditions. This set of restrictions can be summarized in Table 2.

Table 2: Sign and Exclusion Restrictions for the Two-economy model

	Fin. Shock E.A.	Real Shock E.A.	Fin. Shock US	Real Shock US
Financial Cycle E.A.	+	+	$*$	+
Real Cycle E.A.	+	+	0	+
Financial Cycle US	$*$	0	+	+
Real Cycle US	0	0	+	+

Note: The symbol $*$ indicates that no restriction is imposed in the corresponding relationship.

For robustness purposes, we additionally estimate the model by assuming an alternative shock identification strategy, which consists of a Cholesky factorization in Table 5 of Appendix A.2. In doing so, we assume the following order of the latent factors. We order first the US real cycle, followed by the US financial cycle, and by the real cycle of the euro area, leaving at the end the financial cycle of the euro area. Notice that this order implies that (i) financial shocks take at least one period to affect macroeconomic conditions, and (ii) US developments could affect contemporaneously euro area developments, but not vice versa.

For further validation purposes, we re-estimate the model using a mixture of recursive and sign-restrictions as outlined in Table 6 of Appendix A.2. It consists of three parts: (i) recursive restrictions within each block; (ii) euro area shocks do not contemporaneously impact the US; (iii) leave unrestricted the effects that US shocks have on euro area. This is an alternative scheme that is sufficiently broad to incorporate the empirical results contained in the current international macro-financial literature.

The overall output retrieved by the models described in this section provides a comprehensive analysis of macro-financial interactions along the following dimensions: (i) within sectors of a given economy (ii) across sectors within a given economy, (iii) across sectors and across economies, and (iv) over the time dimension. Moreover, we provide a series of additional exercises for robustness purposes, altering the estimation method of the latent cycles, the identification of structural shocks, and potential changes in the volatility of macroeconomic and financial cycles. In sum, given the high complexity of measuring macro-financial linkages at the international level, we adopt a series of alternative exercises with the only aim of gathering main messages that describe, from a robust and meaningful way, how macroeconomic and financial shocks propagate across borders.

4 Macro-financial linkages

This section provides a comprehensive overview of the time-varying interactions between macroeconomic and financial sectors, for the US and euro area. In doing so, we provide different pieces of information designed to study these interactions from various perspectives, for each economy separately. First, we assess the evolving strength of commonalities within each of the two sectors, that is, macroeconomic and financial. This is done by jointly characterizing the underlying cycles and inferring the segments of the real and financial sectors that are most important for driving those cycles over time. Second, we provide a characterization of the joint propagation of macroeconomic and financial shocks. This is performed by examining the time-varying correlation between the cycles, and analyzing information contained in impulse responses and forecast error variance decompositions. We aim to provide a discussion that is comparative in nature, consequently, the description of the results is structured per type of features, and not per economy. Notice that in the analysis, we use the terms *linkages* and *interactions* interchangeably, treating them as synonyms for deep and dynamically evolving relations between the two sectors. This is in contrast to the commonly used word *nexus* or *link* that we interpret as not profoundly changing over time.

4.1 Data

The description of the variables for the US economy is reported in Table 3, and was retrieved from St. Louis Fed database. The sample spans from 1960:I until 2017:IV, covering four very distinct episodes in US contemporaneous economic history including the Golden Age, stagflation and oil shocks, Great Moderation, and the Great Recession. The list of variables used in the analysis of the euro area is reported in Table 4. The data spans the period between 1980:I and 2014:IV, covering the pre-Single Market episode, as well as the Single Market and the monetary union era. The data is gathered from the work of Gerba et al. (2018a), in turn collected from a variety of international sources. One set of variables comes from the ECB's euro area Wide Model including variables F1-F3, F9-F11, R1-R5 in Table 4. Variables F4-F7 come from Datastream, while F8 and R6-R7 come from OECD World Economic outlook. The remaining variables are retrieved from two BIS sources: F12-F19 and R8 from BIS Market data, and F20-F21 from BIS International Financial Statistics database. For the pre-EMU period, the series have been backward extrapolated using weights from euro area-12, and then adjusted as the new members joined the monetary union. Thus, the country weights for the pre-euro area period reflect the relative economic strength of the member states in the union around the time of the introduction of the physical euro coins in 2002.

All variables, except for ratios and spreads are expressed in growth rates in our model. Financial ratios and spreads are expressed in levels. Our data sample is extensive and wide-ranging enough to encompass many aspects of the financial and real sectors. On the financial side, we have included price as well as quantity variables. Price variables include corporate financing spreads, financial ratios of firms, and stock market indices. Quantities include assets and liabilities of banks (including their subcomponents), assets and liabilities of households and firms (along with their subcomponents), credit, monetary system net foreign assets and liabilities, monetary aggregates, and velocity of money. On the real side, our sample comprises of aggregate as well as disaggregate macroeconomic measures. Included are GDP and its aggregate demand components, labour market indicators, and variables capturing productivity and the supply side of the economy such as real output per hour, unit labor costs, and compensation to employees.

Since the set of information used for each economic region is not exactly the same due to their idiosyncrasies and availability, our intention here is to be empirically as broad and comprehensive as possible in order to capture the multi-faceted nature of the contemporary financial sector and the macroeconomy. In addition, because of frictions and imperfections, fluctuations and alterations in quantities may not always show up in prices. Equally, fluctuations and alterations in the banking system may not always result in corresponding movements in the private sector, even if it is the counterparty. That is why we require a sufficient and diverse set of indicators to capture these complexities. For that reason, on the financial side we have expanded on the usual credit-and asset price variables to include indicators of other entries in the balance sheets of private sector and banks (including but not only securities, liabilities, net worth, profits after tax, savings), monetary system, corporate financial ratios and different corporate (default) spreads. In a similar manner, we expand our macroeconomic side to include information beyond the usual business cycle (or GDP). That is why we include detailed information on consumption capacity, labor market, firm inputs, productivity, and the supply side in general. As a result, we expect to have a more comprehensive account of the multi-layered character of macro-financial linkages across all segments of the contemporary advanced economies.

4.2 Strength of commonalities within sectors

The estimated real and financial cycles of the US are plotted in Figure 2. It shows that the financial cycle lasts much longer than the macroeconomic one. While financial activity underwent two larger contractions during our sample period (1992 and 2008), macroeconomic activity experienced many more (albeit shorter) downturns. The first corresponds to the global economic downturn in the Western world in the early 1990's, including the US savings & loan crisis and a restrictive monetary policy. The second date corresponds to the onset of the Great Recession. Also, the dynamics of the financial cycle is smoother than the real one, experiencing much less of the very short-run variation. Moreover, the financial cycle experienced a profound change in frequency around 1990. While the average length of a financial cycle was 5-7 years in the pre-1990 sample, it increased to 7-10 years in the subsequent period. The macroeconomic cycle, on the other hand, has an average length of 2-5 years throughout the entire sample period.[13]

These attributes also apply to the euro area cycles, as can be seen from Figure 3. Although the frequency of the financial cycle is again lower, there are some differences with respect to the US case. While in the first half of the sample (1980-1996), the financial cycle is largely below the trend, the real cycle had completed a full phase by that time. Also, while the first boom phase in the financial cycle lasted for around 7 years (1996-2003), that of the macroeconomy was 2 years shorter. It is also important to notice that there is a stronger co-movement between both cycles starting from mid-1990's, with boom and bust phases roughly coinciding, albeit the timing and magnitude is not entirely identical.

On the whole, there are significant differences in the nature of the two cycles. Financial cycles are longer and smoother, in particular since 1990's, while real cycles have lower amplitude and are more erratic. Also, it seems that higher and longer build-ups in the financial sector have resulted in higher peaks, while more frequent reversals in the real economy have resulted in deeper troughs for the macroeconomic cycle, relatively speaking. Additionally, there seems to be a significant co-movement between the two cycles, in particular for the euro area. The next section explores this feature in further detail. For robustness purposes, we also compute the underlying cycles using principal components (PC) and plot them in Figures 15 and 16 of the Appendix. Although PC provides consistent estimation of the factors, this method is not able to endogenously assess potential instabilities in factor loadings. The results show that the factors estimated by PC follow a similar pattern to the factors estimated with Bayesian methods, with the later exhibiting smoother and more stable dynamics, confirming our inferences on the two cycles.

Compared to alternative composite measures of financial activity, such as the National Financial Conditions Index (NFCI) of Brave and Butters (2012), or the non-financial and credit-to-GDP cycles, we find similarity to the non-financial leverage cycle (see Figure 18 of Appendix A.4). The long cycles and the long build-ups in particular since the 1990s are visible in both. However, the reversals are sharper in our financial cycle, and the flexibility in our framework allows for long-term movement in the trend, in parallel. In addition, like the leverage cycle, our financial cycle is a good lead indicator and could serve as an

[13] In line with the Great Moderation literature, documented by McConnell and Perez-Quiros (2000), there is a decline in the volatility of the real cycle since mid-1980s.

early warning signal for financial stress. The swings in the cycle anticipate those of credit-to-GDP and the business cycle (see Figure 17 of Appendix A.4). In comparison to the adjusted NFCI, the information contained in our financial cycle is more informative on the particular phase of the cycle and the probability and severity of a subsequent reversal. The NFCI, on the other hand, is better suited for risk monitoring and analysis of risk build-up.

We proceed to assess the durability in commonalities within each sector, defined as the contemporaneous relationship between real and financial indicators with its corresponding cycle (or factor). This evolving relationship is measured by the time-varying factor loadings. This information is useful to identify potential changes in the composition of both cycles, and therefore, to interpret them in a more accurate manner.

For the US case, the dynamic correlation between the financial indicators and the financial cycle is plotted in Figure 4, while Figure 5 plots the correlation between the real indicators and the real cycle. A couple of features deserve to be mentioned. First, most of the factor loadings associated to financial indicators are sizeable and statistically significant over time, validating the underlying pattern of commonalities across different segments of the financial sector. This is also the case for the loadings associated to real activity. Second, with only a few exceptions, the degree of variability over time in the factor loadings has remained relatively stable, both types of indicators. This result indicates that the composition of US real and financial cycles has remained, in general, relatively unchanged.

The case of the euro area is somewhat different. Figure 6 plots the evolving relationship between financial indicator and the financial factor, while Figure 7 plots the same for real activity. The results indicate a clear change in the composition of the euro area financial cycle. On the one hand, indicators containing information about credit and balance sheet variables have increased their correlation with the financial cycle over time. This includes variables such as loans to non banks by deposit institutions, loans to non governmental sector and monetary aggregates, but also others such as net foreign assets and net foreign liabilities. Conversely, other set of financial indicators have exhibited a decreasing correlation with the financial cycle over time. These variables contain information about the financial position of firms, such as, price-earning ratios of non financial firms or price-book ratio of financial firms. Regarding the real sector, commonalities have remained relatively steady. It is important to notice that the increasing convergence of most of the variables to financial cycle is significantly larger than the decoupling exhibited by a few other financial variables, pointing to overall increasing commonalities in the financial sector.

These features point to our first main result, that patterns in macro-financial linkages between the two economies are diverging. The euro area has exhibited increasing commonalities in the financial sector since early 2000s. On the other hand, the strength of the US financial sector has remained relatively steady over time. Despite those divergences, there are also similarities between the two economies. Macroeconomic indicators have exhibited a relatively stable importance in shaping the real cycle. Furthermore, balance sheet- (stocks) and credit variables that have become more relevant in shaping the financial cycles can be grouped into the liability side of the non-financial sector. In other words, private sector liabilities have become increasingly determinant for the shape and evolution of financial cycles.

4.3 Depth of linkages across sectors

This section focuses on measuring the evolving interaction between macroeconomic and financial cycles from different perspectives to provide robust assessments. We start by computing the time-varying correlation between the two cycles for each economy.[14] For the case of the US that correlation has varied significantly over time, as it is shown in Figure 8. In particular, between 1963 and 1992, the correlation consistently declined and attained a record low of 0.4. Yet, this lost ground over 30 years was quickly recovered during the subsequent period, and by 2009 the correlation was at a historical peak of above 0.67.

The growth rate in the correlation during 1990's and 2000's was more than twice as high as the rate of decline in the previous episode. This particular period was characterized by heavy deregulation in the US financial system, both across activities/segments and geographically. Also during this time, an intense financial deepening involving many of the

[14]Since the cycles, proxied by the factors, evolve according to a vector autoregression, we compute the unconditional variance-covariance matrix of the elements in the VAR, i.e. f_t and r_t, and not of its innovations. Next, we compute the corresponding correlation coefficient. Since this measure is only a function of the parameters of the VAR, the same procedure is applied for each period of time to obtain the desired time-varying correlation.

known financial innovations occurred during this period. As a result, competition between financial institutions intensified. The US financial system opened up heavily during this period and attracted a lot of foreign capital. That capital fuelled two market bubbles: first in the corporate financing market (dot-com boom), and then in the housing market (subprime). On the real side, during this time inflation was significantly reduced and there was seemingly stable and moderate growth. Apart from a very brief downturn in early 90's and early 2000's, the rest of these two decades was characterized by a solid expansion. The increased liquidity in the system also lead to increased consumption and investment, and solid employment and productivity figures. These changes potentially explain the rapid increase in correlation between the two cycles over this period.

Next, when one also takes into account that the Great Recession, characterized by a reversal in financial sector activity, outflow of capital, inflation volatility, and weak growth, interrupted this trend and lead to a decline in the correlation between the two types of cycles (down to 0.5 at the end of 2017).

The corresponding time-varying correlation for the euro area has behaved somewhat differently. Figure 9, indicates that macro-financial interactions have continuously risen, with the exception of the pre-Maastricht Treaty period between 1984-1991. After the Single European Act in 1987, the correlation started to steadily grow, surpassing a historical record of 0.7 by 2011. Notice that the collapse of the European Stability Mechanism in 1992 did not interrupt this long-term trend of macro-financial deepening. In general, since the formal adoption of the Euro, the correlation has grown slower compared to the previous growth phase. These results indicate that the establishment of the Economic and Monetary Union (EMU) and the adoption of the currency is associated with long-lasting stronger interactions between the financial sector and the real economy.

Altogether, the correlation between the macroeconomic and financial cycles is high in both economies, albeit with different time patterns. Our second main result shows that while in the euro area, macro-financial interactions have steadily increased since late 1980's, in the US, they have oscillated around a mean of approximately 0.5, exhibiting very long cycles of macro-financial interdependence. Additionally, over the past 25 years, the correlation coefficient has been higher in the euro area, while the rate of change of the correlation has been much larger in the US This implies that the integration of the financial sector in the overall economy and the increase in the interplay between the two has been more intense in the US, while more solid and gradual in the euro area.

We perform two types of robustness exercises associated with the vector autoregression that provides further basis for measurement of macro-financial interactions. First, instead of identifying the structural shocks with the baseline scheme, that is, by imposing sign, exclusion and timing restrictions in the impulse responses, we directly estimate orthogonal innovations in the VAR, as in Bai and Wang (2015). The time-varying correlation between macroeconomic and financial cycles based on orthogonal innovations is plotted in Figure 19, for the US, and in Figure 20, for the euro area, of the Appendix A.3. The results show estimates that are qualitatively similar to the ones obtained with the baseline identification scheme, providing robustness to our assessments. Second, for the case of the US, we also account for the Great Moderation episode by imposing a break in the variance-covariance matrix of the VAR innovations in 1985 in the baseline scheme. Figure 21 plots the time-varying correlation, again showing qualitatively similar dynamics. However, notice that the inclusion of the break in volatility is associated with an overall decline in the strength of macro-financial linkages.

Next, we turn to potential changes over time in the propagation of real and financial shocks for both economies. The top chart of Figure 10 plots the response of real activity to a financial shock in a three-dimensional graph, while the bottom chart plots the response of financial conditions to a real shock, for the US economy. The results show a couple of salient asymmetric patterns. First, while the sensitivity of financial conditions to real shocks has remained relatively unchanged over time, the sensitivity of real activity to financial shocks started to increase in the early 2000s. This finding explains the substantial deterioration of the macroeconomy as a result of the financial shocks of the Great Recession, between 2007 and 2009. Second, the effects of real shocks on financial conditions lasted significantly longer than the effects of financial shocks on real activity. These patterns are more visible in the two-dimensional graphs of dissected impulse responses, which are reported in the Appendix A.3 to conserve space. Figure 22 plots the time-varying cumulated responses at pre-determined horizons, showing that, in general, the effects of real shocks are not only larger, but also, more variable over time compared to financial shocks.

The transmission of shocks in the euro area, shown in Figure 11, presents a couple of important differences when comparing it with the case of US First, the effect of financial shocks to real activity has also increased over time. However, the increase started much earlier than in the US, in particular, since the early 1990s. Also, notice that around that time, financial conditions in the euro area also started to become more sensitive to real shocks. These features are consistent with the sustained increase in synchronization between macroeconomic and financial euro cycles shown in Figure 9. Second, the sensitivity of real activity to financial shocks in the euro area is small on impact but long-lasting, while in the US that sensitivity is large on impact but short-lasting, in relative terms. These features can be seen in detail in the dissected impulse responses plotted in Figure 23 of the Appendix A.3. Also, notice that the response that has exhibited the largest variation over time is the one regarding the effects of real shocks on financial conditions.

Accordingly, our third main finding unveils asymmetric shock propagation patterns in both economies. In the euro area, the interactions have increased in both directions, from financial to real, and vice versa, but in the US, they have increased in only one direction, from financial to real. Also, the financial sector of the US presents a sensitivity to macroeconomic shocks that is of higher magnitude and of shorter duration than in the euro area. These asymmetries in macro-financial linkages remain even when we change the identification scheme of structural shocks, by directly assuming orthogonality in the innovations of the VAR equation, see Figure 24, for the US, and Figure 25, for the euro area, in Appendix A.3.

These results persist even when we assume a break in volatility of the US economy in 1985,. However, some features deserve to be commented. Figure 26 shows that the Great Moderation period is associated with a slight increase in responsiveness of the macroeconomy to financial shocks, but also with a substantial reduction in the sensitivity of the financial sector to real shocks. This implies that when the structural reduction in business cycle fluctuations took place, real shocks not only became smaller but their ability to influence financial conditions also diminished.

Next, we focus on measuring the predictive ability that developments in one sector, that is, macroeconomic or financial, may have on the other. In doing so, we follow the line of Diebold and Yilmaz (2009) and rely on the notion of the Forecast Error Variance Decomposition (FEVD) obtained from the VAR equation of the model.[15] We report the corresponding results in Appendix A.3 for the sake of space. Figure 27 plot the FEVD over time for the US economy showing that, in general, there have not been significant changes in the contribution of shocks in one sector to future developments of the other, with one important exception. Since the Great Recession, the information contained in financial conditions increased its ability to predict future short-term developments of the macroeconomy, as can be seen in the left plot of Chart (b) in Figure 27. For the case of the euro area, the situation is rather different. Since the early 1990s, real activity dynamics started to increase its ability to predict future long-term developments in the financial conditions, as is shown in Chart (c) of Figure 28. Also around that time, euro area financial conditions started to become less predictable based on its own past dynamics.

5 International spillovers

Once we have defined the time-varying macro-financial interactions within an economy, we proceed to examine the intensity of cross-border spillovers between the two economies, both across the sectors and in-between them. As described by the dashed arrows in Figure 1, there are eight possible ways to consider cross-border interactions in macro-finance. These different dimensions of spillovers are measured with the "global" two-economy model, described in Section 3.2. The estimated factors obtained with the two-economy model follow similar patterns as the ones associated to the one-economy model, as can be seen in Figure 29 of Appendix A.3. This provides additional robustness for our measurement of both types of cycles.

First, we compute the cross-border and cross-sector time-varying correlations, and report them in Figure 12. The figure shows clear patterns associated to gradual, but sus-

[15] A recent literature (Cotter et al (2017) and Korobilis and Yilmaz (2018), among others) focuses on using the network approach proposed in Diebold and Yilmaz (2009) to measure the degree of interconnectedness between international financial market segments (equity, sovereign credit, financial firms). Although these papers focus on other aspects of interest, such as, networks, market monitoring, index performance evaluations, and non-structural volatility.

tained, increases in the correlation between (i) US and E.A. financial activity, (ii) US and E.A. real activity, and (iii) US financial and E.A. real activity. Such an increasing interdependence pattern persisted until the end of the Great Recession, and slightly declined afterwards. The only exception is the correlation between the US real and E.A. financial activity, which has remained fairly stable over time.[16]

Although correlation measures are useful to address the overall strength of bilateral cross-border macro-financial relationships, they remain silent about the asymmetric effects between sectors and economies. Therefore, we proceed to evaluate the impulse response functions retrieved from the two-economy model. Figure 13 shows the effect that shocks generated in the US economy have on the euro area, while Figure 14 shows how shocks generated in the euro area could affect the US economy. The shocks are identified by relying on the combination of sign and exclusion restrictions reported in Table 2. A clear pattern emerges from the estimated joint model. The impact of US shocks is much larger than the one associated to shocks coming from euro area. Real as well as financial shocks originating from the US have statistically and economically significant impact on euro area macroeconomic and financial cycles, as can be seen in the dissected impulse responses shown in Figure 31 of Appendix A.3.[17] Notice that the largest increase over time is the one of US real activity on E.A. financial conditions. Instead, shocks from the euro area tend to produce either small or short-lasting effects on the U.S economy (in line with Jensen (2019)). In particular, real euro area shocks have an effect on US real activity that only last one quarter. Also, the point estimates responses show that when the financial or real conditions deteriorate (improve) in the euro area, the financial condition in the US improve (deteriorate). However, as shown in Figure 32 of Appendix A.3, this negative impact is estimated with substantial uncertainty.

It is important to notice that the intensity in the transmission of shocks increases over time, at least until the Great Recession. This is consistent with the increasing correlation

[16]Notice that the two-economy model also delivers the time-varying correlations associated to sectors within a given economy. Such estimated correlations are qualitatively similar to the ones obtained with the one-economy model, as can be seen in Figure 30 of Appendix A.3.

[17]This finding is in line with the findings of Berg and Vu (2019) and Kose et al. (2017), who find economically and statistically significant effects on the world economy from US financial volatility. Giorgiadis (2016) find similar results for US conventional and unconventional monetary policy.

pattern between the factor across sector and regions, shown in Figure 12. Also, there seems to be no evidence about an intensification in transmission of E.A. shocks to the US since the formal introduction of the Euro, at least not as a clearly visible change in pattern since 2000. These results suggest that the hegemony of the US in the international monetary and financial system has been highly dominant (and increasing over time). The introduction of the Euro did not manage to alter it (in line with the discussion in Gourinchas et al. (2019)).

There is however a subtle but important change in the transmission to E.A. financial conditions over 2000's. In particular, after around 2002, transmission of shocks arriving from the US seem to weaken somewhat, having persistently risen previously. Even if it is not enough evidence to establish a causal relation, this coincides with the full introduction of the euro on 1 January 2002. Hence, although the monetary union may not have resulted in an increase in cross-border spillovers of real or financial activity, it seems to have somewhat weakened the transmission of US shocks by creating a tighter net and core, at least in the financial sphere.

Another relevant finding is that since the Great Recession, the transmission of US shocks has weakened, meanwhile the negative transmission of E.A. shocks have also been reduced. This can be interpreted as a small change in the US global role since the financial crisis of 2007-08, whereby the weakening of its economy and the protectionism that followed has reduced its' international exposure and role as producer of cross-border (in)stability. Cuaresma et al. (2019) also find that the transmission of US monetary policy shocks has weakened in the aftermath of the global financial crisis in a Global VAR framework.

To assess the validity of the results obtained with our baseline specification, we re-estimate the joint model using two alternative identification schemes described in tables 5 and 6 of Appendix A.2. Figures 33-34, and 35-36 of Appendix A.3 plot the impulse response patterns associated to the (i) recursive and (ii) alternative sign restrictions identification schemes, respectively. Notice that in both cases the impulse responses are qualitatively similar to the ones obtained with the benchmark identification scheme. The only difference in magnitude we find is that with these alternative identifications, transmission of US financial and E.A. real shocks is more intense, while those of US real are of slightly smaller magnitude. Moreover, the negative effects of E.A. shocks on US financial conditions are also somewhat stronger in these alternative specifications. One could say that adverse (favourable) shocks in euro area developments could be beneficial (damaging) for the US financial conditions. An explanation for this pattern is that the US may act as a hub that attracts investments and (financial) capital when conditions are adverse in Europe. Since the financial deregulation in early 1980's and geographical liberalisation in financial services, the flow of capital to US has continuously increased. However, this positive trend broke with the near financial meltdown in 2008 and the deep contraction in the US financial sector. That could explain why the negative transmission from E.A. to US financial system has debilitated.

Our international analysis reveals a number of important facts regarding the relation between the euro area and the US since the financial liberalization and trade integration in 1980's. First and most firmly, we find that the transmission of macro and financial shocks across borders is largely asymmetric, going from the US to the euro area. Previous literature hints towards this asymmetry, but does not fully model the bidirectional spillovers, or does it for only one policy or aspect. For instance, Jarocinski (2019) show using a SVAR that Fed monetary policy has much stronger effects on ECB's monetary policy , while euro area's has negligible impact on the US. Second, we find that the intensity of transmissions across borders increased over time. However, since the Great Recession, this positive trend has been reversed, and transmission of US shocks has been weakened. This could be a result from the weakened dominance of the US economy globally, or because of the protectionism that followed the financial crisis of 2007-08. Third, we find a negative relation in transmission between EA shocks and US financial conditions. One could say that adverse (favourable) shocks in euro area developments could be beneficial (damaging) for the US financial conditions. However, this pattern has also been weakened following the near financial meltdown in the US in 2008. Previous works (Berg and Vu (2019), Gourinchas et al. (2019), Jarocinski (2019), Giorgiadis (2016)) have advocated for a dominant position of the US in the international financial, monetary, or macroeconomic sphere. However, as far as we are aware, this is the first study to formally establish it in a structural empirical model with (i) full bidirectional spillovers between two of the largest global economies, (ii) along macroeconomic and financial dimensions simultaneously, and (iii) covering a relatively large time span that allows for long-term interpretations.

6 Conclusions

The relation between the financial sector and the rest of the economy has undergone tremendous changes since the 1990's. The impact of the financial crises that began in 2007, and its aftermath has spurred an interest in the study of the degree of their linkages, and the extent to which each poses a threat to the stability of the other. Our understanding has significantly improved over the past decade, but there are still many unanswered questions, in particular related to a possible feedback mechanism between the two, both domestically and across borders. This paper attempts to fill this gap by analysing the macro-financial interactions within a structural time-varying framework using a large dataset for two of the largest world economies. Our study includes three dimensions: US, euro area, and cross-border spillovers.

Further investigation into the current macro-financial structure, in particular the feedback mechanism between the two is much needed. Currently, there are significantly more studies who focus on the transmission of financial disturbances, or papers that only investigate one side of the macro-financial linkages. As our findings show, the transmissions go in both directions, and are at times asymmetric or uneven. Subsequent studies should take this into account, and examine in-depth the feedback mechanism between the two sectors, preferably in structural models. Besides, it would be highly relevant to further explore the relative differences in impact versus persistence in impulse responses between financial-and real shocks. One level deeper, we have unveiled how correlations between variables and cycles has changed over time. Correlation of private sector liabilities to financial cycles has significantly increased. Their role in shaping the macro-financial cycles need to be examined more systematically, including their drift.

We also show that the correlation between euro area macro-financial cycles has been higher to that of the US economy. Structural factors underlying this difference should be examined in further detail, as well as the impact and potential constraint on future economic growth in both economies. Finally, much more effort will be required to understand the cross-border spillovers of macro-financial linkages. We have established the dominance of US financial developments on euro area. Yet, exactly how and via what channels these are transmitted to euro area need to be explored further.

References

[1] Abbate, A., Eickmeier, S., Lemke, W., and M. Marcellino. (2016), "The Changing International Transmission of Financial Shocks: Evidence from a Classical Time-Varying FAVAR" *Journal of Money, Credit and Banking*, 48(4): 573601.

[2] Aikman D, AG Haldane and BD Nelson (2015), "Curbing the Credit Cycle", *The Economic Journal*, 125(585): 10721109.

[3] Arias, J., Rubio-Ramiez, J., and Waggoner, D. (2018), "Inference Based on Structural Vector Autoregressions Identified with Sign and Zero Restrictions: Theory and Applications" *Econometrica*, 86(2): 685720.

[4] Bai, J., and Wang, P. (2015), "Identification and Bayesian Estimation of Dynamic Factor Models" *Journal of Business & Economic Statistics*, 33(2): 221240.

[5] Balke N. (2000), "Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks", *The Review of Economics and Statistics*, 82(2): 344349.

[6] Bayoumi, T. and Thanh Bui, T. (2011), "Deconstructing the International Business Cycle: Why Does a US Sneeze Give the Rest of the World a Cold?" IMF Working Paper No. 10/239.

[7] Berg, K. A., and Vu, N. T. (2019). "International spillovers of US financial volatility", *Journal of International Money and Finance*, 97: 19-34.

[8] Borio, C. (2014), "The Financial Cycle and Macroeconomics: What Have we Learnt?" *Journal of Banking and Finance* 45: 182-198.

[9] Borio, C., Disyatat, P., and Juselius, M. (2017), "Rethinking Potential Output: Embedding Information About the Financial Cycle", *Oxford Economic Papers* 69(3): 655-677

[10] Borio C and P Lowe (2002), "Asset Prices, Financial and Monetary Stability: Exploring the Nexus", BIS Working Papers No 114.

[11] Borio C, C Furfine and P Lowe (2001), "Procyclicality of the Financial System and Financial Stability: Issues and Policy Options", in *Marrying the Macro- and Microprudential Dimensions of Financial Stability*, BIS Papers No 1, BIS, Basel, pp 157.

[12] Cagliarini, A. and Price, F. (2017), "Explaining the Link Between the Macroeconomic and Financial Cycles". Royal Bank of Australia Conference Volume 2017

[13] Calza A., and J. Sousa (2006), "Output and Inflation Responses to Credit Shocks: Are There Threshold Effects in the euro area?", *Studies in Nonlinear Dynamics & Econometrics*, 10(2): 3.

[14] Ciccarelli M., Ortega E. and T. Valderrama (2016), "Commonalities and cross-country spillovers in macroeconomic-financial linkages", *BE Journal of Macroeconomics*, 16(1): 231-275.

[15] Claessens S, MA Kose and ME Terrones (2011), "Financial Cycles: What? How? When?", IMF Working Paper No WP/11/76.

[16] Comunale, M. and Hessel, J. (2012), "Current Account Imbalances in the euro area: Competitiveness or Financial Cycle?" De Nederlandsche Bank Working Paper No. 443

[17] Cotter, J., Hallam, M., and Yilmaz, K. (2017), "Mixed-frequency macro-financial spillovers", Koc University mimeo.

[18] Crowley, P.M. and Hughes Hallett,m A. (2016), "Correlations Between Macroeconomic Cycles in the US and UK: What Can a Frequency Domain Analysis Tell Us?" *Italian Economic Journa;* 2(1): 5-29

[19] Crespo Cuaresma, J., Doppelhofer, G., Feldkircher, M., and Huber, F., (2019), "Spillovers from US monetary policy: evidence from a time varying parameter global vector autoregressive model". *Journal of the Royal Statistical Society: Series A (Statistics in Society).*

[20] Davig T., and C. Haikko (2010), "What is the effect of financial stress on economic activity?", *Federal Reserve Bank of Kansas City Economic Review*, 95: 35-62.

[21] Diebold, F. X., and K. Ylmaz. (2015), "Financial and macroeconomic connectedness: A network approach to measurement and monitoring", Oxford University Press, USA.

[22] Drehmann, M., Borio, C.E.V., and K. Tsatsaronis. (2012), "Characterizing the Financial Cycle: Don't Lose Sight of the Medium Term, BIS Working Paper No. 380

[23] Dungey, M., Fry, R., Martin, V., Tang, C. and Gonzalez-Hermosillo, B. (2010), "Are financial crises alike?" IMF Working Paper 10/14.

[24] Eickmeier, S. and T. Ng. (2011), "How do credit supply shocks propagate internationally? A GVAR approach", *European Economic Review*, 74: 128145.

[25] Fisher I (1933), "The Debt-Deflation Theory of Great Depressions", *Econometrica*, 1(4): 337357.

[26] Galati G., Hindrayanto I., Koopman S.J., and M. Vlekke (2016), "Measuring Financial Cycles with a Model-Based Filter: Empirical Evidence for the United States and the euro area", De Nederlandsche Bank Working Paper No 495.

[27] Gambetti L., and A. Musso (2017), "Loan supply shocks and the business cycle", *Journal of Applied Econometrics*, 32: 764-782.

[28] Gerba E. (2015), "Financial Cycles and Macroeconomic Stability: How Secular is the Great Recession?" LAP Lambert Academic Publishing, Saarbruecken, Germany. ISBN 978-3-659-68911-6

[29] Gerba, E., Jerome, H., and Zochowski, D. (2018a), "Structural Changes in the euro area: Evidence from a New Dataset", Forthcoming in ECB Working Paper Series.

[30] Gerba, E., Jerome, H., and Zochowski, D. (2018b), "How Profound are euro area Macro-Financial Linkages? Stylized Facts from a Novel Dataset", Forthcoming in ECB Working Paper Series.

[31] Georgiadis, G. (2016), "Determinants of global spillovers from US monetary policy", *Journal of International Money and Finance*, 67: 41-61.

[32] Gravelle, T., Kichian, M. and Morley, J. (2006), "Detecting shift-contagion in currency and bond markets", *Journal of International Economics* 68 pp: 409423.

[33] Gourinchas, P.O., Rey, H. and Sauzet, M. (2019),"The international Monetary and Financial System", NBER Working Paper No. 25782

[34] Harding D and A Pagan (2002), "Dissecting the Cycle: A Methodological Investigation", *Journal of Monetary Economics*, 49(2): 365381.

[35] Harding. D., and A. Pagan (2006), "Synchronization of Cycles", *Journal of Econometrics*, 132(1): 5979.

[36] Hellbling, T., Berezin, P, Kose, A., Kumhof, M., Laxton, D., and Spatafora, N. (), "Decoupling the Train? Spillovers and Cycles in the Global Economy".

[37] Hubrich K., and R. Tetlow (2015), "Financial stress and economic dynamics: the transmission of crises", *Journal of Monetary Economics*, 70: 100-115.

[38] Jansen, D. J. (2019), "Did Spillovers From Europe Indeed Contribute to the 2010 US Flash Crash?", DNB Working Paper 622.

[39] Jarocisnki, M (2019), "International spillovers of the Fed and ECB monetary policy surprises", Unpublished memo.

[40] Jorda O, M Schularick and AM Taylor (2017), "Macrofinancial History and the New Business Cycle Facts", in M Eichenbaum and JA Parker (eds), *NBER Macroeconomics Annual 2016*, Vol 31, University of Chicago Press, Chicago, pp 213263.

[41] Kaufmann S., and M. Valderrama (2010), "The role of credit aggregates and asset prices in the transmission mechanism: a comparison between the euro area and the US", *The Manchester School*, 78(4): 345-377.

[42] Korobilis, D., and Yilmaz, K. (2018), "Measuring Dynamic Connectedness with Large Bayesian VAR Models", Koc University mimeo.

[43] Kose, A., Lakatos, C., Ohnsorge, F. L., and Stocker, M., (2017), "The global role of the US economy: Linkages, policies and spillovers" The World Bank.

[44] Leiva-Leon D., Perez-Quiros G., Sapriza H. and E. Zakrajsek (2018), "Credit-market Sentiment and the Macroeconomy: A Nonlinear Approach", *Mimeo.*

[45] McConnell M., and G. Perez-Quiros (2000), "Output Fluctuations in the Unites States: What Has Changed since the Early 1980s?", *American Economic Review*, 90(5): 1464-1476.

[46] Minsky HP (1977), "A Theory of Systemic Fragility", in EI Altman and AW Sametz (eds), *Financial Crises: Institutions and Markets in A Fragile Environment*, John Wiley and Sons, New York, pp 138152.

[47] Miranda-Agrippino, S., and Rey, H. (2018), "US Monetary Policy and the Global Financial Cycle, NBER Working Paper No. 21722.

[48] Nasson J., and E. Tallman (2015), "Business cycles and financial crises: the roles of credit supply and demand shocks", *Macroeconomic Dynamics*, 19: 836-882.

[49] Prieto, E., Eickmeier, S., and Marcellino, M. (2016), "Time Variation in MacroFinancial Linkages", *Journal of Applied Econometrics*, 31(7)': pp. 1215-1233.

[50] Phillips P.C.B. and S Jin (2015), "Business Cycles, Trend Elimination, and the HP Filter", Cowles Foundation Discussion Paper No 2005.

[51] Reinhart CM and KS Rogoff (2009), "This Time is Different: Eight Centuries of Financial Folly", Princeton University Press, Princeton.

[52] Runstler G and M Vlekke (2016), "Business, Housing and Credit Cycles", European Central Bank Working Paper Series No 1915.

[53] Schuler YS, PP Hiebert and TA Peltonen (2017), "Coherent Financial Cycles for G-7 Countries: Why Extending Credit Can Be an Asset", European Systemic Risk Board Working Paper Series No 43.

[54] Strohsal T, CR Proano and J Wolters (2015), "Characterizing the Financial Cycle: Evidence from a Frequency Domain Analysis", Bundesbank Discussion Paper No 22/2015, Deutsche Bundesbank, Frankfurt am Main.

Table 3: List of variables for the US

ID	Trans.	Description
F1	2	Nonfinancial Corporate Business; Net Worth, Billions of Dollars
F2	2	Nonfinancial Corporate Business: Profits After Tax (without IVA and CCAdj), Billions of Dollars
F3	2	Private Residential Fixed Investment, Billions of Dollars
F4	2	Households and Nonprofit Organizations; Net Worth, Billions of Dollars
F5	2	Nonfinancial Corporate Business; Credit Market Instruments; Liability, Billions of Dollars
F6	2	Households and Nonprofit Organizations; Credit Market Instruments; Liability, Billions of Dollars
F7	2	Households and Nonprofit Organizations; Home Mortgages; Liability, Billions of Dollars
F8	2	All Sectors; Commercial Mortgages; Asset, Billions of Dollars
F9	2	Households and Nonprofit Organizations; Total Time and Savings Deposits; Asset, Level, Billions of Dollars
F10	2	Households and nonprofit organizations; corporate equities; asset, Level, Billions of Dollars
F11	2	Federal Government; Credit Market Instruments; Liability, Level, Billions of Dollars
F12	2	S&P500
F13	2	M1 Money Stock, Billions of Dollars
F14	2	Velocity of M1 Money Stock, Ratio
F15	2	Velocity of M2 Money Stock, Ratio
F16	2	M2-M1 Money Stock, Billions of Dollars
F17	2	Velocity of MZM Money Stock, Ratio
F18	1	AAA-spread
F19	1	BAA-spread
F20	1	Corporate risk spread
F21	1	10-Year Treasury Constant Maturity Rate, Percent
F22	2	Total Consumer Credit Owned and Securitized, Outstanding, Billions of Dollars
F23	2	Households and Nonprofit Organizations; Consumer Credit; Liability, Billions of Dollars
R1	2	Real Gross Domestic Product, Billions of Chained 2009 Dollars
R2	2	Real Personal Consumption Expenditures, Billions of Chained 2009 Dollars
R3	2	Nonfarm Business Sector: Real Compensation Per Hour, Index 2009=100
R4	2	Real Gross Private Domestic Investment, Billions of Chained 2009 Dollars
R5	2	Real Disposable Personal Income, Billions of Chained 2009 Dollars
R6	2	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing, Hours
R7	2	All Employees: Manufacturing, Thousands of Persons
R8	2	Nonfarm Business Sector: Real Output Per Hour of All Persons, Index 2009=100
R9	2	Gross Fixed Capital Formation in United States, Billions of United States Dollars

Note. The column "Trans." of the table indicates the transformation made to the corresponding variable prior to include it in the model. "Trans.=1" indicates that the variable is expressed in levels. "Trans.=2" indicates that the variable is expressed in growth rates.

Table 4: List of variables for the euro area

ID	Trans.	Description
F1	1	Firm price-book ratio
F2	2	Savings rate hshlds
F3	1	Firm dividend yield
F4	1	Price-earning ratio of non-financial firms EMU
F5	1	Price-earning ratio of financial firms EMU
F6	1	Price-earning ratio of non-financial firms US
F7	1	Price-earning ratio of financial firms US
F8	1	Current account balance
F9	1	Price-book ratio financial firms
F10	1	Price-book ratio non-financials
F11	1	Firms price-cash flow ratio
F12	2	Depository corp. excl. CB, assets, loans to non-banks, M-end
F13	2	OMFI, assets, credit to non fin. corporations, total, M-end
F14	2	Banks (MFI), loans to non-financial corporations (MU), M-end - outstanding amount at the end of period
F15	2	Claims of monetary syst. on non-govt. sect., loans (MU11-17), M-end
F16	2	Depository corp. excl. CB, assets, loans to non-banks, M-end
F17	1	Bank liabs, non-monetary, LT (MU11-17), total, M-end
F18	2	Monetary system net foreign assets, assets (MU11-17), M-end
F19	2	Monetary system net foreign assets, liabs. (MU11-17), M-end
F20	2	Money stock m2 (MU11-17), M-end
F21	2	Money stock m3 (MU11-17), M-end
R1	2	Real GDP
R2	2	Private consumption
R3	2	Government consumption
R4	2	Gross investment
R5	2	Labor force
R6	2	Total employment
R7	2	Unit labor cost
R8	2	Compensation to employees

Note. The column "Trans." of the table indicates the transformation made to the corresponding variable prior to include it in the model. "Trans.=1" indicates that the variable is expressed in levels. "Trans.=2" indicates that the variable is expressed in growth rates.

Figure 2: Estimated factors of the US

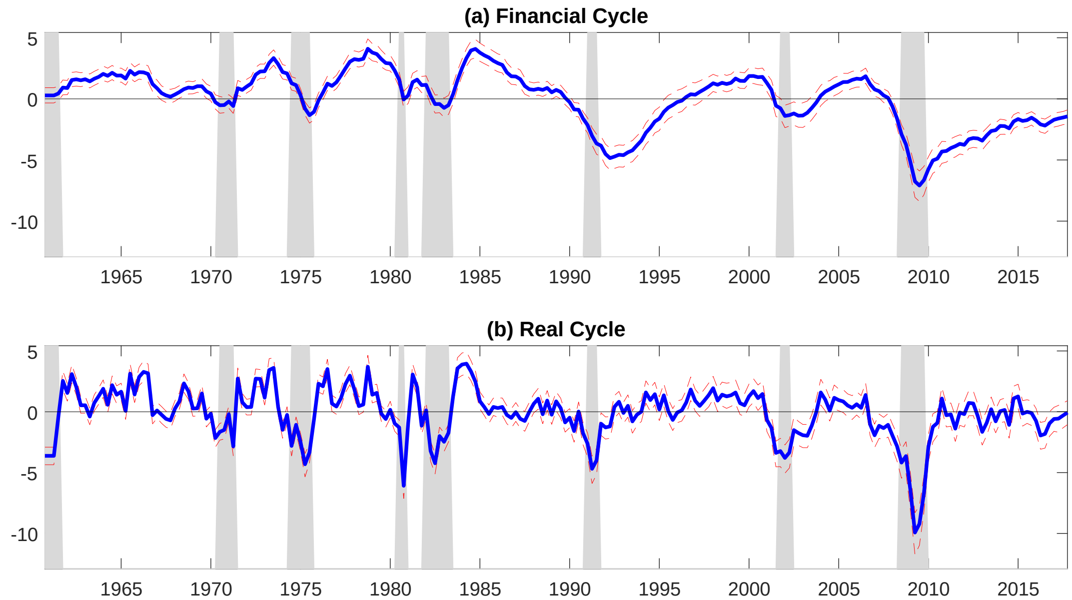
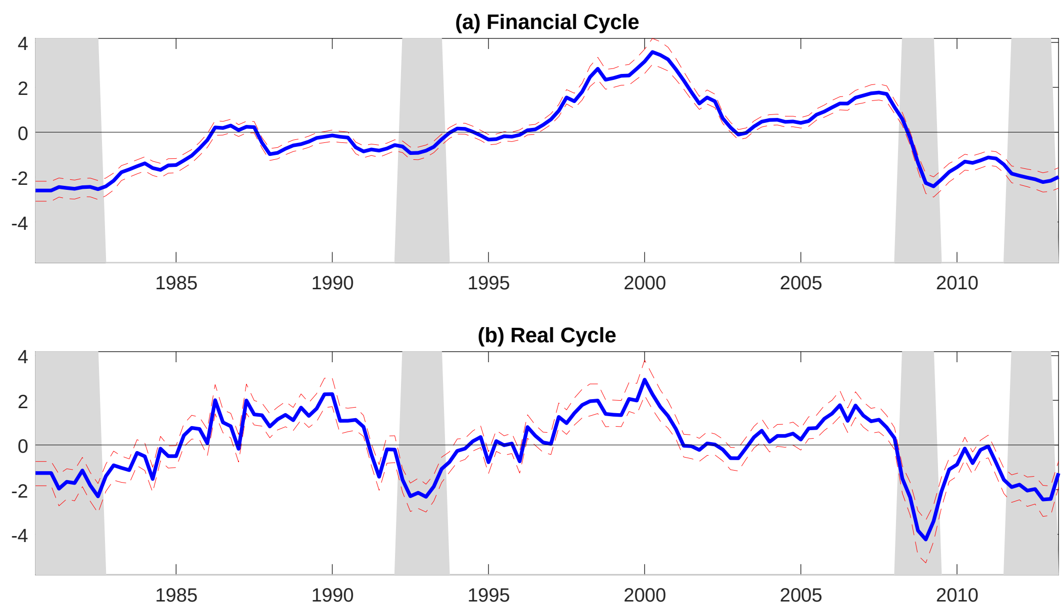
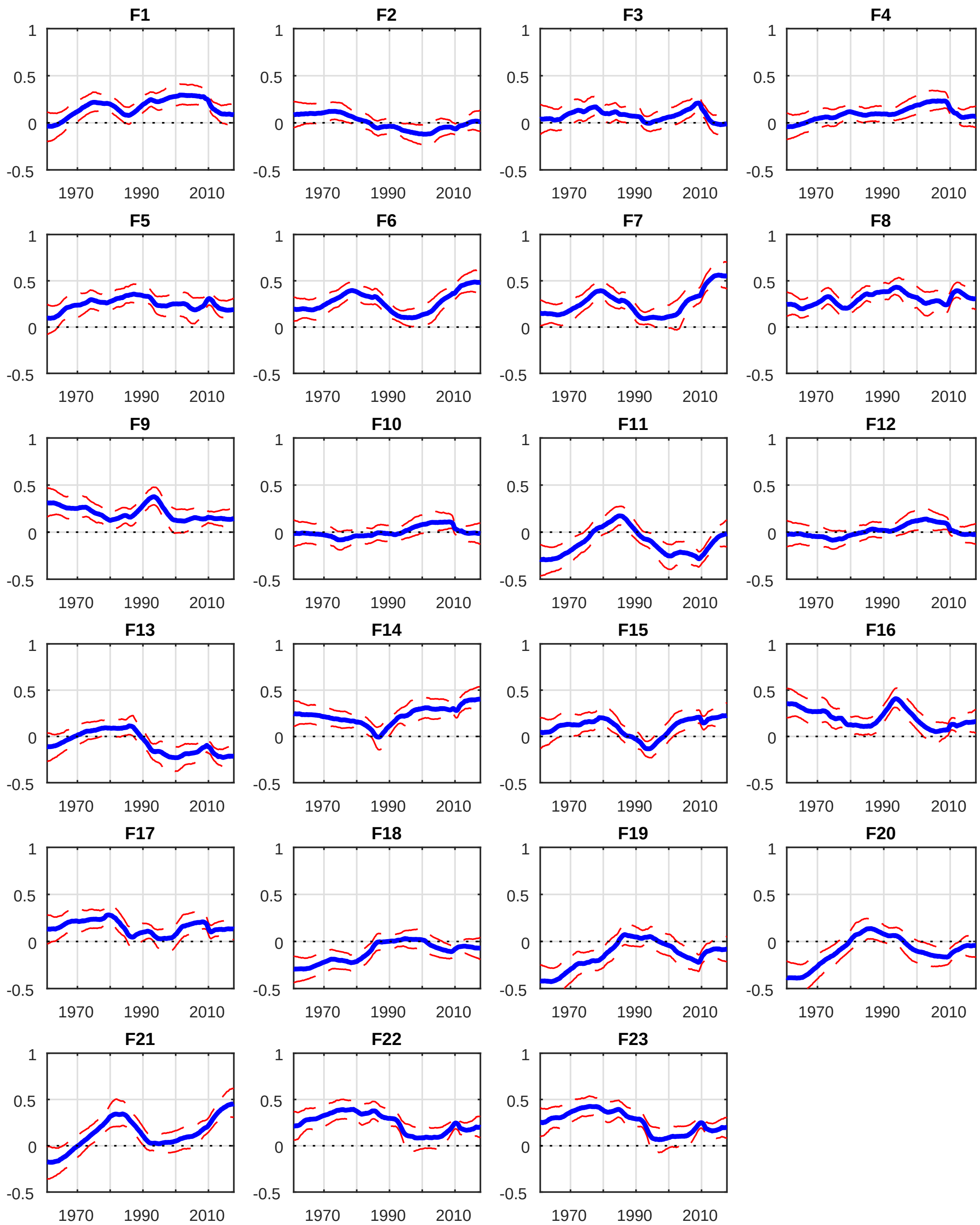


Figure 3: Estimated factors of the euro area



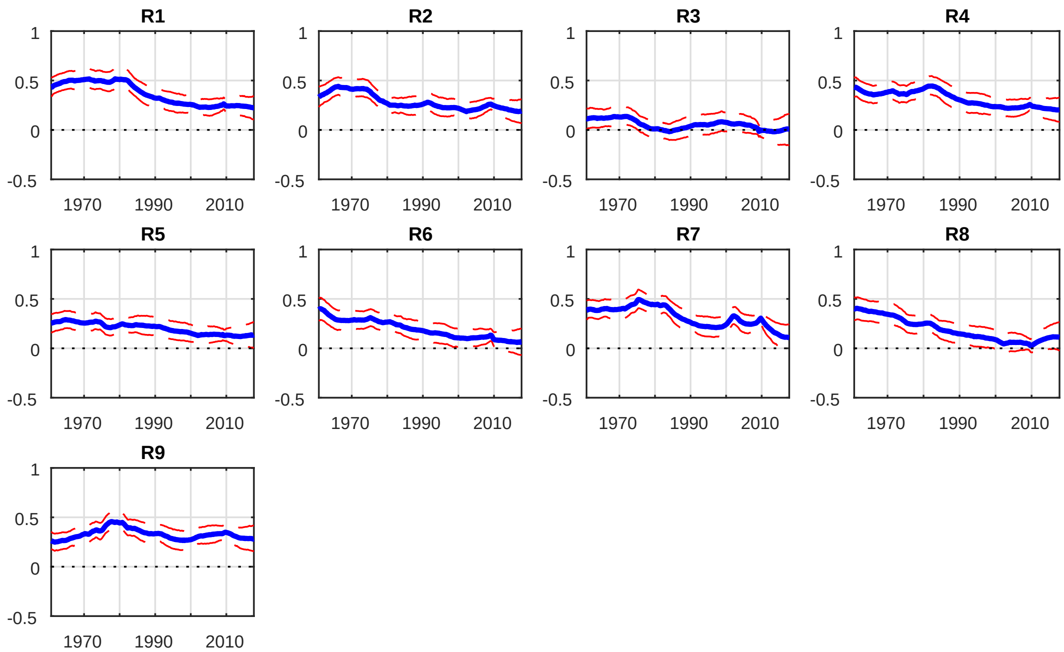
Note: The figures plot the estimated real and financial cycles. The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution. The grey areas denote the NBER and CPER recession dates for the US and euro area, respectively.

Figure 4: Time-varying factor loadings of financial conditions for the US



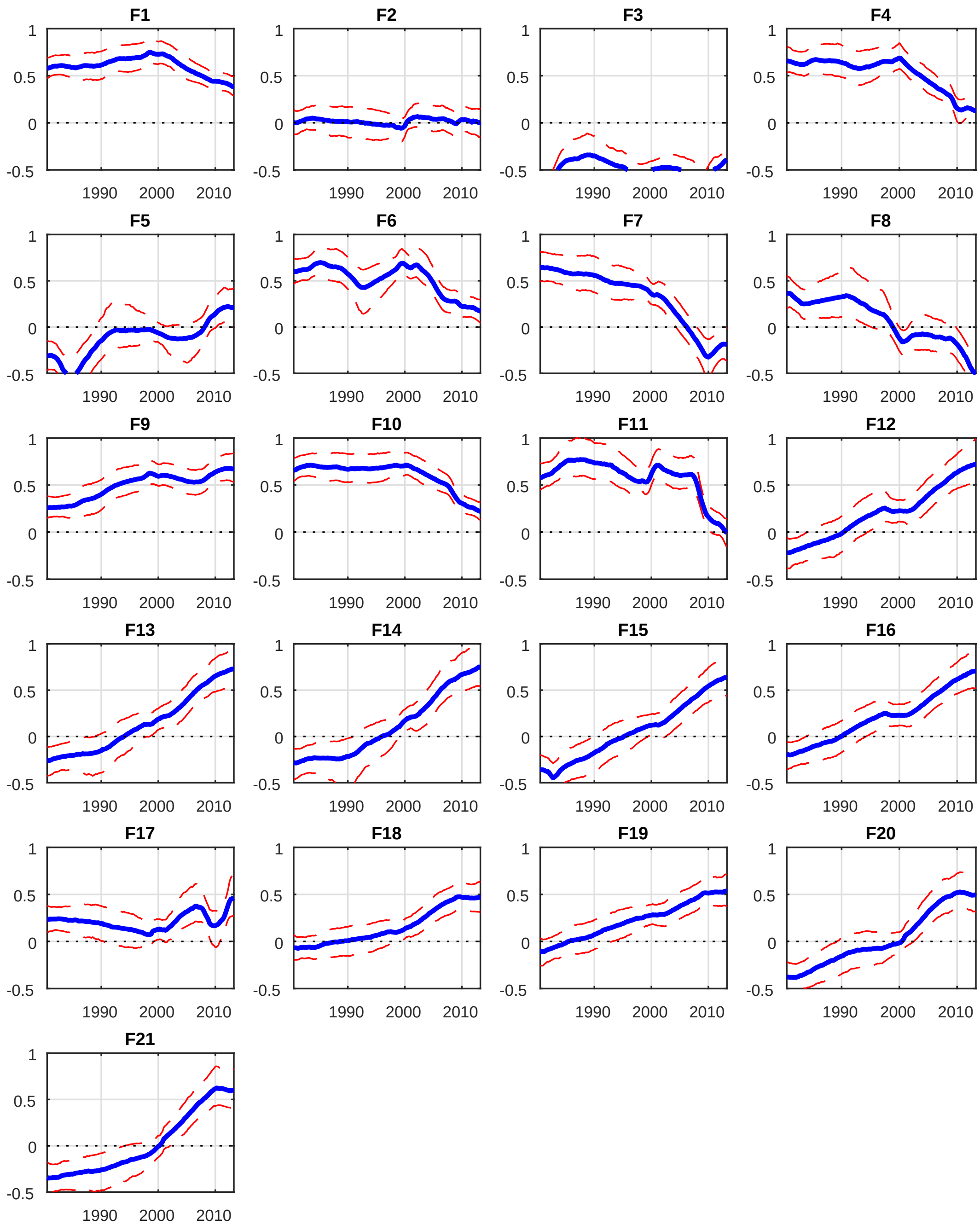
Note: The figure plots the estimated time-varying factor loadings of variables associated to the real activity factor. The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 5: Time-varying factor loadings of real activity for the US (cont.)



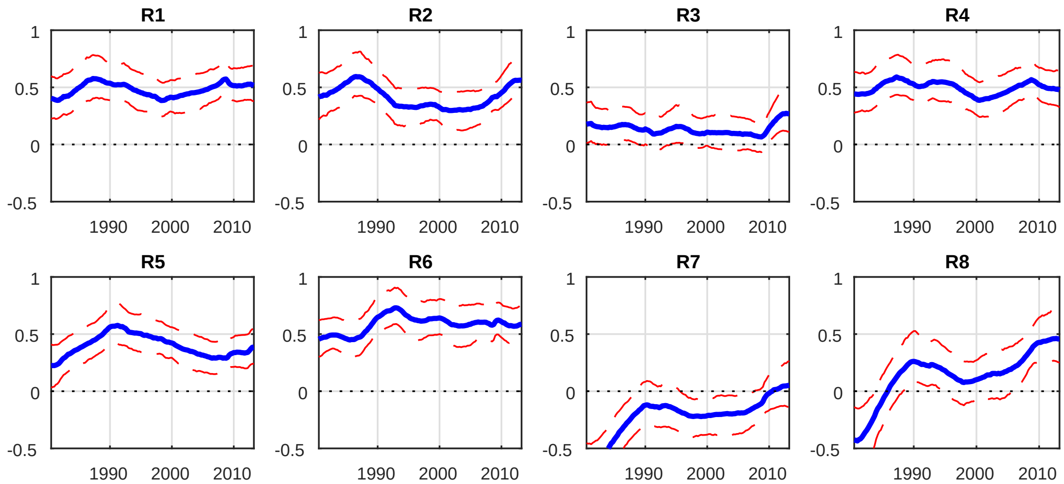
Note: The figure plots the estimated time-varying factor loadings of variables associated to the financial conditions factor. The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 6: Time-varying factor loadings of financial conditions for the euro area



Note: The figure plots the estimated time-varying factor loadings of variables associated to the real activity factor. The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 7: Time-varying factor loadings of real activity for the euro area (cont.)



Note: The figure plots the estimated time-varying factor loadings of variables associated to the financial conditions factor. The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 8: Estimated correlation between factors of the US

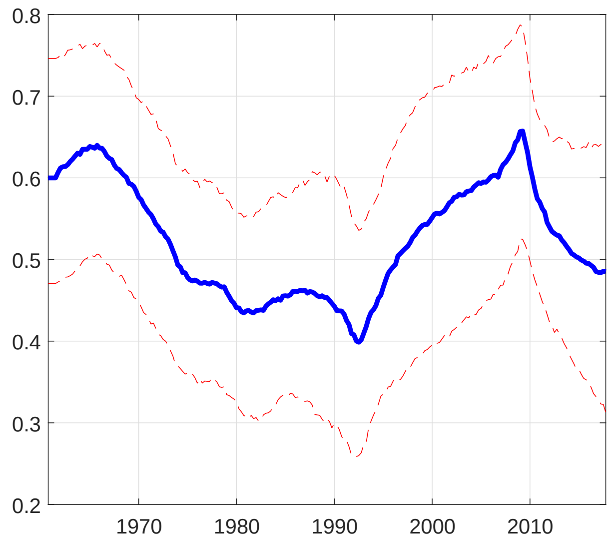
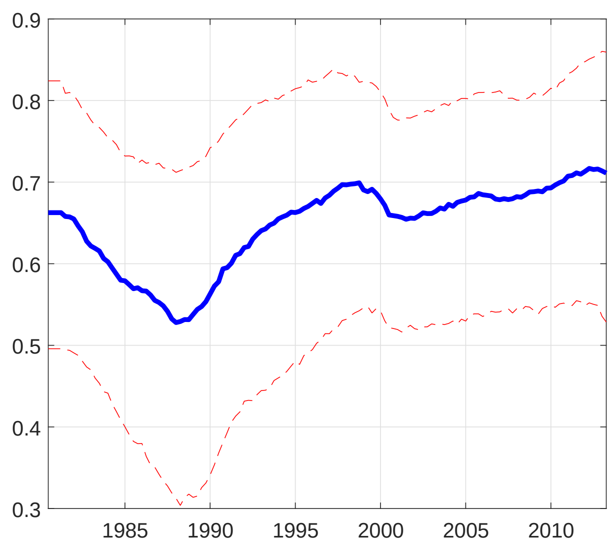
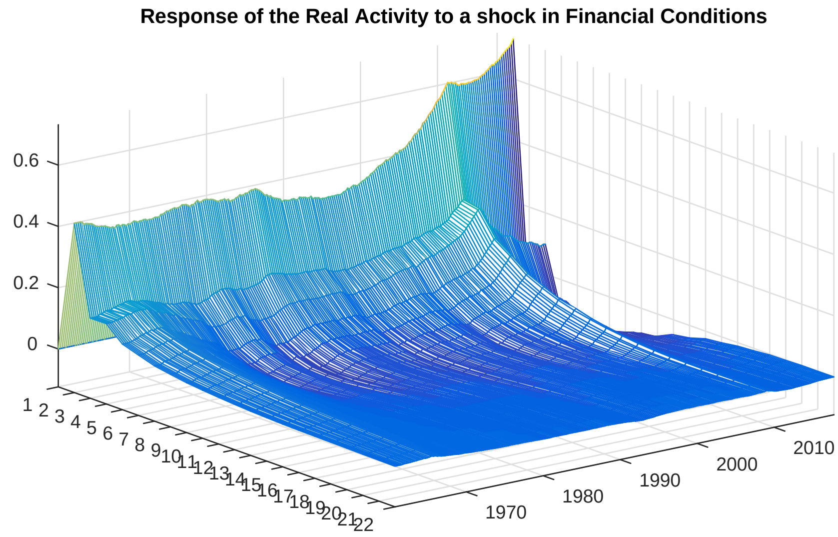


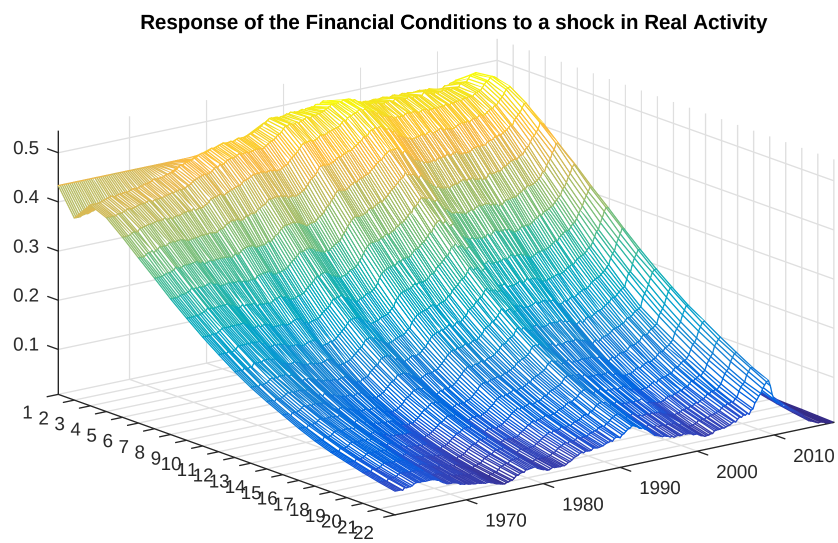
Figure 9: Estimated correlation between factors of the euro area



Note: The figures plot the estimated time-varying correlation between the real and financial cycle. The solid blue line makes reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

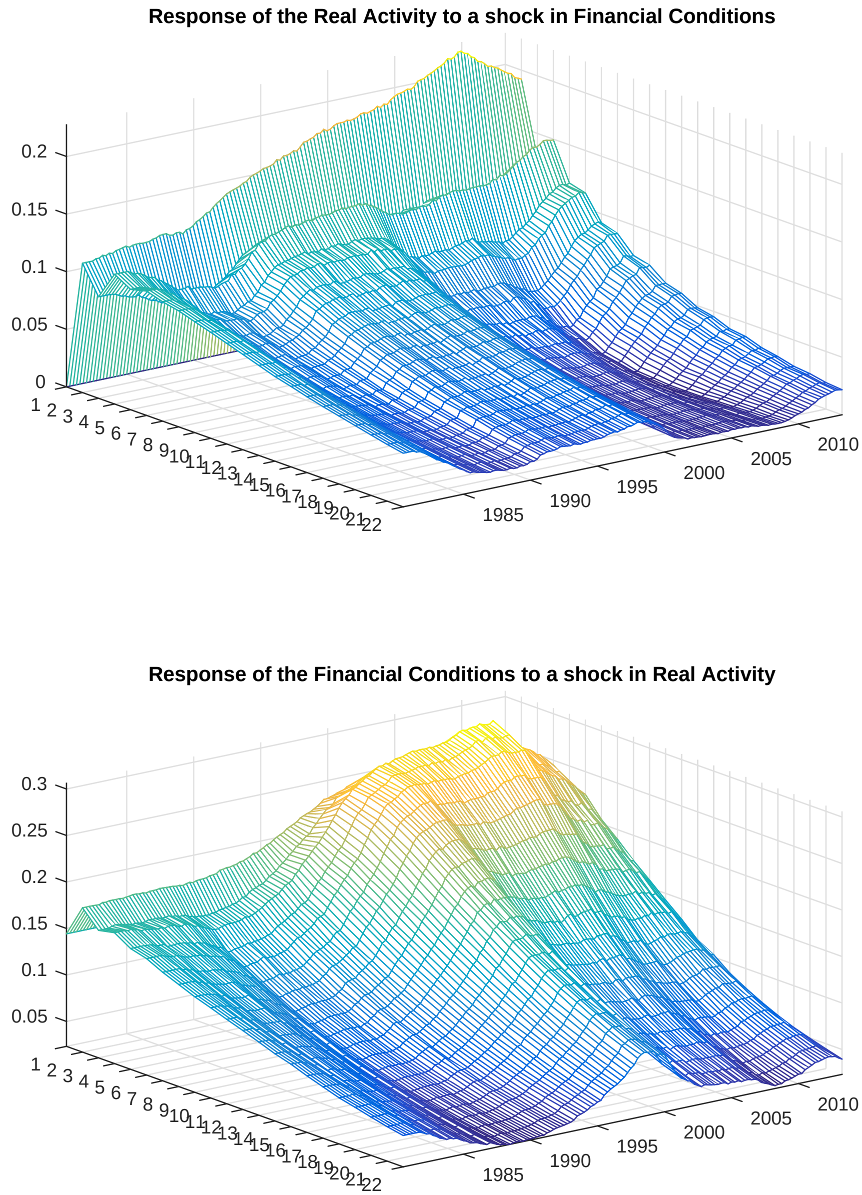
Figure 10: Impulse Responses Between Real and Financial Cycles for US





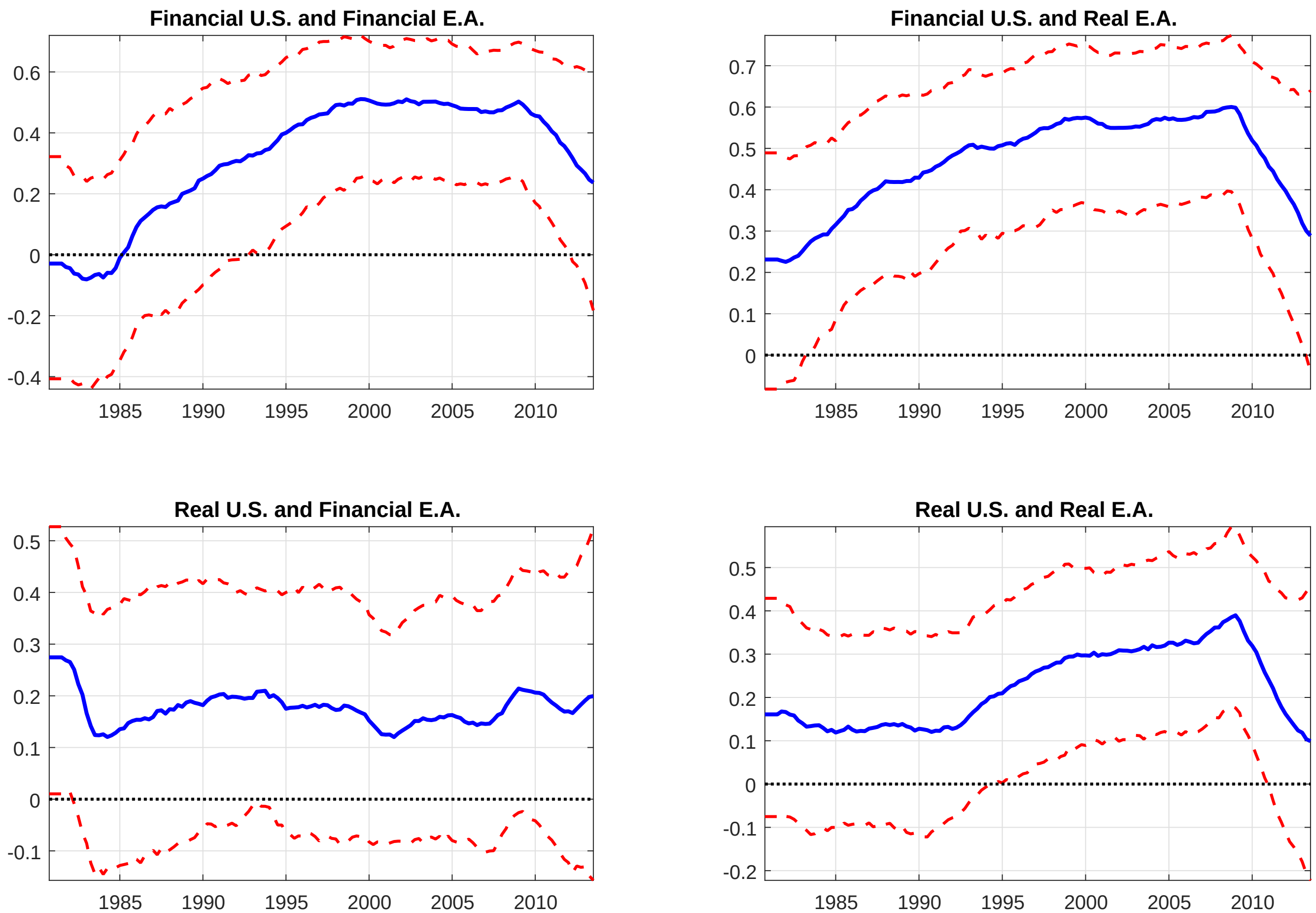
Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution.

Figure 11: Impulse Responses Between Real and Financial Cycles for euro area



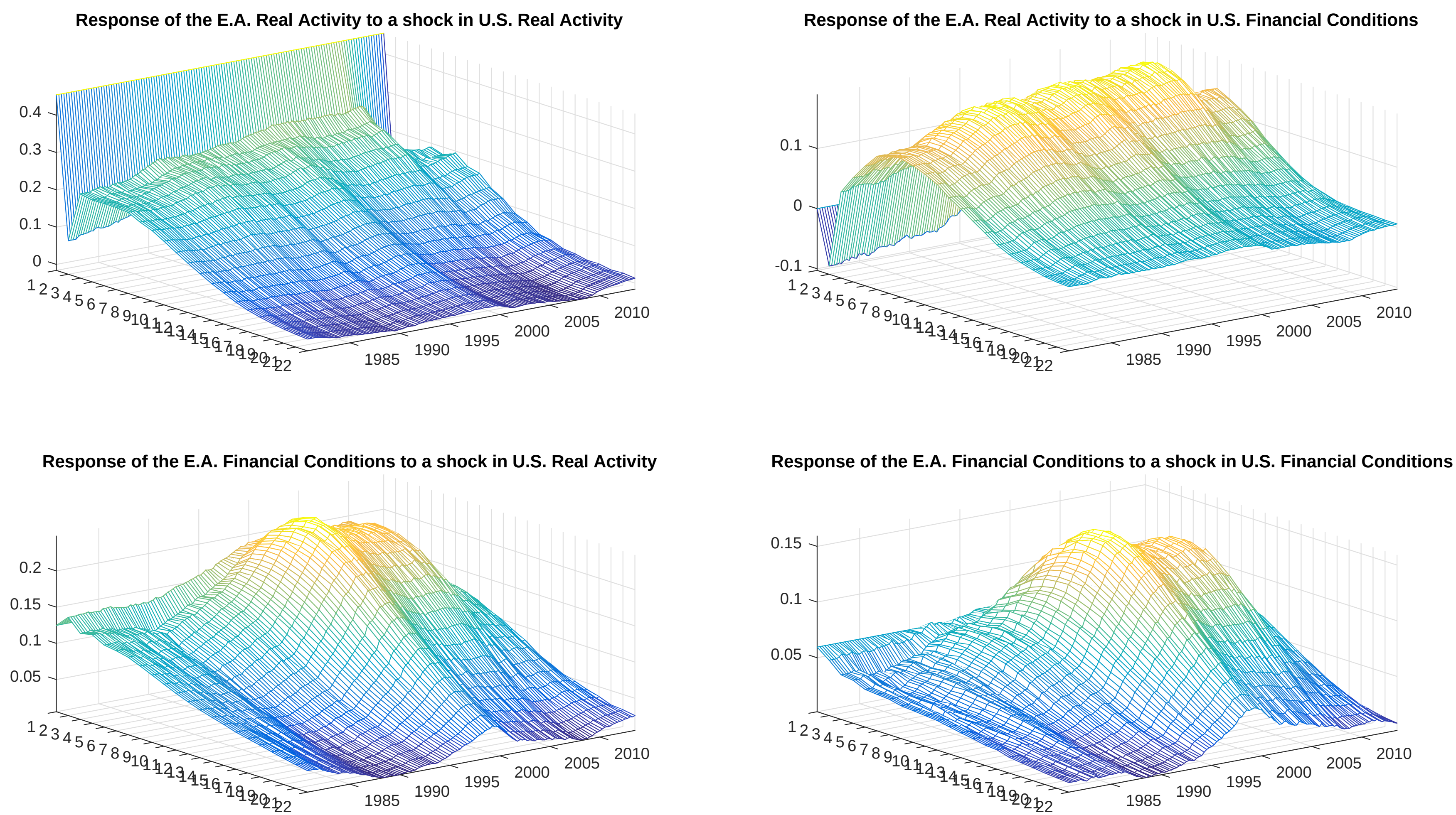
Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution.

Figure 12: Estimated correlation between real and financial factors of US and E.A. (Two-economy model)



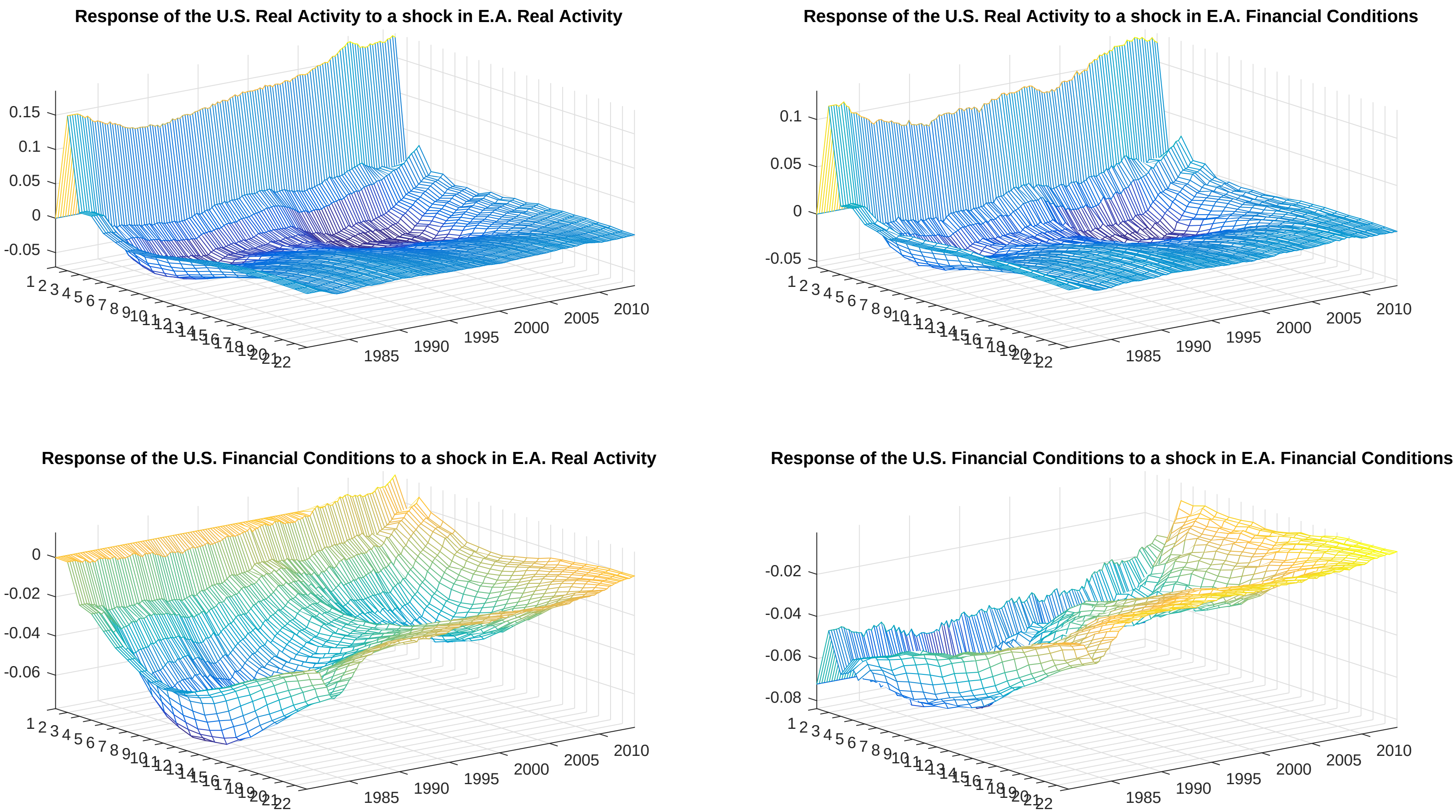
Note: The figures plot the estimated time-varying correlation between the real and financial cycle associated to the US and euro area. The solid blue line makes reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 13: Macro-financial spillovers from the US to the euro area over time (Two-economy model)



Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by using sign and exclusion restrictions in the impact multiplier matrix to identify the structural shocks.

Figure 14: Macro-financial spillovers from the euro area to the US over time (Two-economy model)



Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by using sign and exclusion restrictions in the impact multiplier matrix to identify the structural shocks.

A Online Appendix for "Macro-Financial Interactions in a Changing World"

A.1 Estimation Algorithm

The proposed algorithm relies on Bayesian methods and uses the Gibbs sampler to simulate the posterior distribution of parameters and latent variables involved in the time-varying parameter factor model. Define the following vectors containing information on the $n_f$and $n_r$financial and real activity variables, respectively, $\widetilde{Y}_T = \{F_{1_f,t}, ..., F_{n_f,t}, R_{1_r,t}, ..., R_{n_r,t}\}_{t=1}^T$, real activity index, $\widetilde{f}_T = \{f_t\}_{t=1}^T$, financial conditions index, $\widetilde{r}_T = \{r_t\}_{t=1}^T$, factor loadings, $\widetilde{\Lambda}_{x,T} = \{\Lambda_{x,t}\}_{t=1}^T$, where $\Lambda_{x,t} = (\lambda_{1_x,t}, ..., \lambda_{n_x,t})'$, for $x = \{f, r\}$, and autoregressive coefficients, $\widetilde{\Phi}_T = \{vec(\Phi_{1,t}), ..., vec(\Phi_{k,t})\}_{t=1}^T$. The algorithm consists of the following steps:

- ***Step 1***: Sample $\widetilde{f}_T$, and $\widetilde{r}_T$ from $P(\widetilde{f}_T, \widetilde{r}_T | \widetilde{\Lambda}_{x,T}, \widetilde{\Phi}_T, \Sigma, \Omega, \Psi_\omega, \Psi_w, \widetilde{Y}_T)$

The model in equations (1)-(2), with $k = 2$, can be casted in a state space representation with measurement equation given by,

$$\begin{bmatrix} F_{1_f,t} \\ \vdots \\ F_{n_f,t} \\ R_{1_r,t} \\ \vdots \\ R_{n_r,t} \end{bmatrix} = \begin{bmatrix} \lambda_{1_f,t} & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \lambda_{n_f,t} & 0 & 0 & 0 \\ 0 & \lambda_{1_r,t} & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \lambda_{n_r,t} & 0 & 0 \end{bmatrix} \begin{bmatrix} f_t \\ r_t \\ f_{t-1} \\ r_{t-1} \end{bmatrix} + \begin{bmatrix} v_{1_f,t} \\ \vdots \\ v_{n_f,t} \\ v_{1_r,t} \\ \vdots \\ v_{n_r,t} \end{bmatrix}, \tag{7}$$

and transition equation defined as,

$$\begin{bmatrix} f_t \\ r_t \\ f_{t-1} \\ r_{t-1} \end{bmatrix} = \begin{bmatrix} \phi^{(1)}_{ff,t} & \phi^{(1)}_{fr,t} & \phi^{(2)}_{ff,t} & \phi^{(2)}_{fr,t} \\ \phi^{(1)}_{rf,t} & \phi^{(1)}_{rr,t} & \phi^{(2)}_{rf,t} & \phi^{(2)}_{rr,t} \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_{t-1} \\ r_{t-1} \\ f_{t-2} \\ r_{t-2} \end{bmatrix} + \begin{bmatrix} u_{f,t} \\ u_{r,t} \\ 0 \\ 0 \end{bmatrix}. \tag{8}$$

Conditional on $\widetilde{\Lambda}_{x,T}$ and $\widetilde{\Phi}_T$, equations (7)-(8) constitute an linear and Gaussian state-space model and the Carter and Kohn simulation smoother is applied to generate inferences of the factors.

- ***Step 2***: Sample Ψ_w from $P(\Psi_w|\widetilde{\Phi}_T, \widetilde{Y}_T)$

To sample the variance of the time-varying autoregressive coefficient innovations we use an inverse Wishart prior distribution, $IW(\underline{\eta}, \underline{v})$, with $\underline{\eta} = \tau$ and $\underline{v} = \kappa^2 \times \tau \times \Psi_w^{OLS}$, where $\tau = 80$ is the size of the training sample, Ψ_w^{OLS} is the variance of the autoregressive coefficient matrix estimated by OLS based on the training sample, and $\kappa = 0.2$ is a scaling factor. Hence, draws of Ψ_w are generated from the posterior distribution,

$$\Psi_w \sim IW(\bar{\eta}, \bar{v}),$$

where

$$\begin{aligned}
\bar{\eta} &= \underline{\eta} + T \\
\bar{v} &= \underline{v} + (\boldsymbol{\phi}_t - \boldsymbol{\phi}_{t-1})'(\boldsymbol{\phi}_t - \boldsymbol{\phi}_{t-1}).
\end{aligned}$$

- ***Step 3***: Sample $\widetilde{\Phi}_T$ from $P(\widetilde{\Phi}_T|\widetilde{f}_T, \widetilde{r}_T, \Psi_w, \Sigma, \widetilde{Y}_T)$

Conditional on the factors, the time-varying coefficients VAR model that drives the dynamics of the factors can be compactly expressed in the following state-space form,

$$\begin{aligned}
\boldsymbol{y}_t &= \boldsymbol{X}_t'\boldsymbol{\phi}_t + \boldsymbol{v}_t, \quad \boldsymbol{v}_t \sim N(\mathbf{0}, \Sigma) \\
\boldsymbol{\phi}_t &= \boldsymbol{\phi}_{t-1} + \boldsymbol{w}_t, \quad \boldsymbol{w}_t \sim N(\mathbf{0}, \Psi_w)
\end{aligned}$$

where $\boldsymbol{y}_t = (f_t, r_t)'$, $\boldsymbol{X}_t = I_m \otimes [1, \boldsymbol{y}_{t-1}', ..., \boldsymbol{y}_{t-k}']$ are observed, with $m = 2$ being the number of factors, and $\boldsymbol{\phi}_t$ is the latent vector. Therefore, as in Step 1, the Carter and Kohn algorithm is applied to generate draws of $\widetilde{\Phi}_T$. To achieve stability in the system, this step is repeated until it generates a draw of $\boldsymbol{\phi}_t$ that fulfills with the stationarity conditions for all time periods in the sample.

- ***Step 4***: Sample Σ from $P(\Sigma|\widetilde{f}_T, \widetilde{r}_T, \widetilde{\Phi}_T, \Psi_w, \widetilde{Y}_T)$

To sample the variance of reduced form innovations we use an inverse Wishart prior distribution, $IW(\underline{m}, \underline{\nu})$, with $\underline{m} = m+1$ and $\underline{\nu} = I_m$. Hence, draws of Σ are generated from the posterior distribution,

$$\Sigma \sim IW(\bar{m}, \bar{\nu}),$$

where

$$\begin{aligned} \bar{m} &= \underline{m} + T \\ \bar{\nu} &= \underline{\nu} + (\boldsymbol{y}_t - \boldsymbol{X}_t' \boldsymbol{\phi}_t)'(\boldsymbol{y}_t - \boldsymbol{X}_t' \boldsymbol{\phi}_t). \end{aligned}$$

- ***Step 5***: Sample $\widetilde{\Lambda}_{x,T}$ from $P(\widetilde{\Lambda}_{x,T} | \widetilde{f}_T, \widetilde{r}_T, \Omega, \Psi_\omega, \widetilde{Y}_T)$

Given that Ω is assumed to be a diagonal matrix, each time-varying loading can be sampled independently. Accordingly, we use the following state-space representation,

$$\begin{aligned} X_{i_x,t} &= \lambda_{i_x,t} x_t + v_{i_x,t}, \quad v_{i_x,t} \sim N(0, \Omega_{[i_x,i_x]}) \\ \lambda_{i_x,t} &= \lambda_{i_x,t-1} + \omega_{i_x,t}, \quad \omega_{i_x,t} \sim N(0, \Psi_{\omega,[i_x,i_x]}) \end{aligned}$$

for observed variables $X = F, R$, latent factors $x = f, r$, and $i = 1, ..., n$. Next, the Carter and Kohn algorithm is applied to generate draws of the elements in $\widetilde{\Lambda}_{x,T}$.

- ***Step 6***: Sample Ψ_ω from $P(\Psi_\omega | \widetilde{\Lambda}_{x,T}, \widetilde{Y}_T)$

To sample, independently, the variance of the time-varying loading innovations we use an inverse Gamma prior distribution, $IG(\underline{u}, \underline{z})$, with $\underline{u} = 0.1 \times T$ and $\underline{z} = 0.1^2$. Hence, draws of Ψ_w are generated from the posterior distribution,

$$\Psi_w \sim IG(\bar{u}, \bar{z}),$$

where

$$\begin{aligned} \bar{u} &= \underline{u} + T \\ \bar{z} &= \underline{z} + (\lambda_{i_x,t} - \lambda_{i_x,t-1})'(\lambda_{i_x,t} - \lambda_{i_x,t-1}). \end{aligned}$$

- ***Step 7***: Sample Ω from $P(\Omega|\widetilde{f}_T, \widetilde{r}_T, \widetilde{\Lambda}_{x,T}, \widetilde{Y}_T)$

To sample, independently, the variance of the idiosyncratic terms we use an inverse Gamma prior distribution, $IG(\underline{l}, \underline{o})$, with $\underline{l} = 0$ and $\underline{o} = 0$. Accordingly, draws of the entries in the diagonal of Ω are generated from the posterior distribution,

$$\Omega_{i_x} \sim IG(\bar{l}, \bar{o}),$$

for $i = 1, ..., n$, $X = F, R$, and $x = f, r$, where

$$\begin{aligned} \bar{l} &= \underline{l} + T \\ \bar{o} &= \underline{o} + (X_{i_x,t} - \lambda_{i_x,t} x_t)'(X_{i_x,t} - \lambda_{i_x,t} x_t). \end{aligned}$$

To approximate the posterior distribution of both the parameters and latent variables involved in the model, each step of the algorithm is recursively repeated $M = 22,000$ times, discarding the first $m = 20,000$ iterations to ensure convergence.

A.2 Alternative Identification Schemes

Table 5: Recursive Identification for the Two-economy model

	Fin. Shock E.A.	Real Shock E.A.	Fin. Shock US	Real Shock US
Financial Cycle E.A.	$*$	$*$	$*$	$*$
Real Cycle E.A.	0	$*$	$*$	$*$
Financial Cycle US	0	0	$*$	$*$
Real Cycle US	0	0	0	$*$

Note: The symbol $*$ indicates that no restriction is imposed in the corresponding relationship.

Table 6: Alternative Sign and Exclusion Restrictions for the Two-economy model

	Fin. Shock E.A.	Real Shock E.A.	Fin. Shock US	Real Shock US
Financial Cycle E.A.	$+$	$+$	$*$	$*$
Real Cycle E.A.	0	$+$	$*$	$*$
Financial Cycle US	0	0	$+$	$+$
Real Cycle US	0	0	0	$+$

Note: The symbol $*$ indicates that no restriction is imposed in the corresponding relationship.

A.3 Additional Figures

Figure 15: Estimated factors of the US - Principal Component

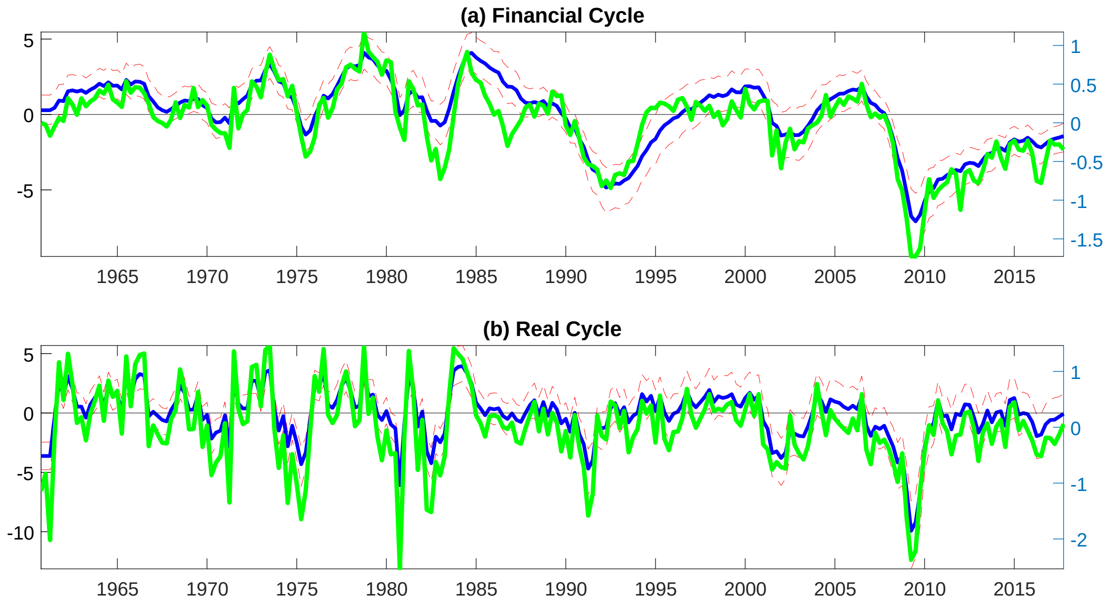
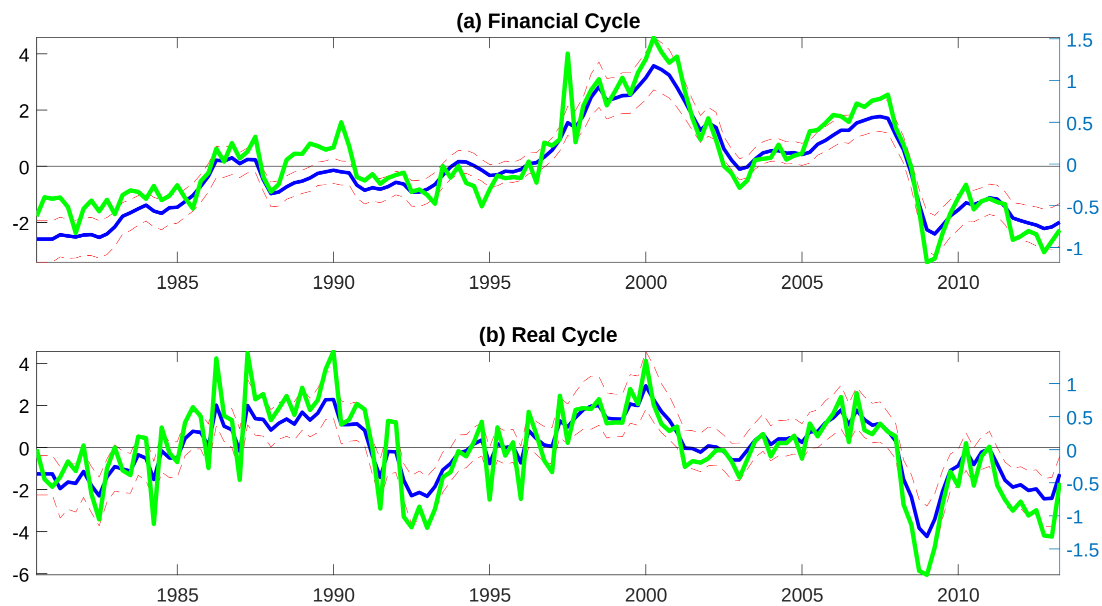
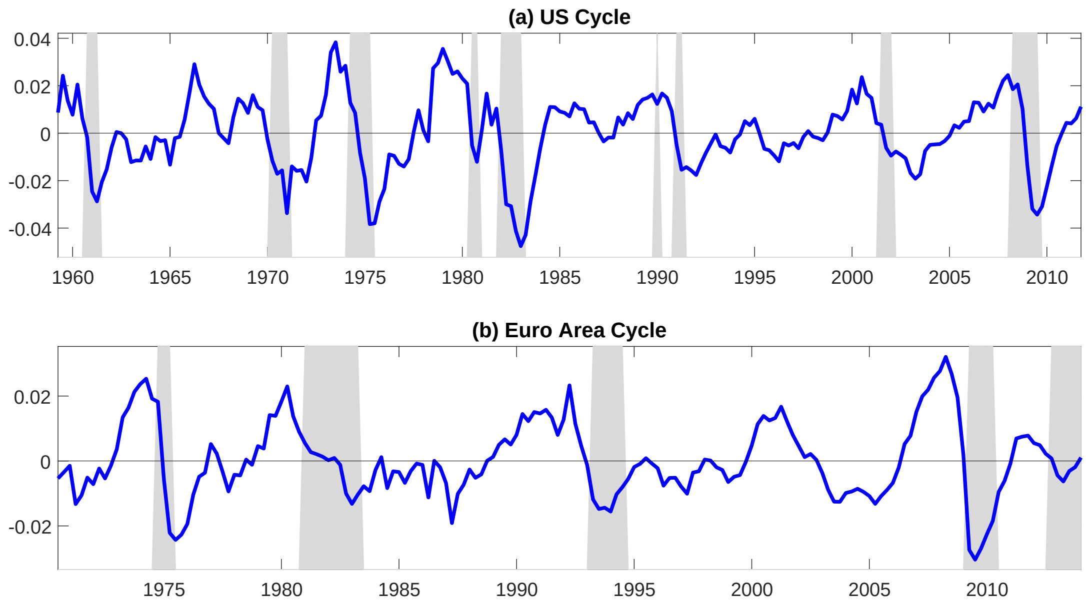


Figure 16: Estimated factors of the euro area - Principal Component



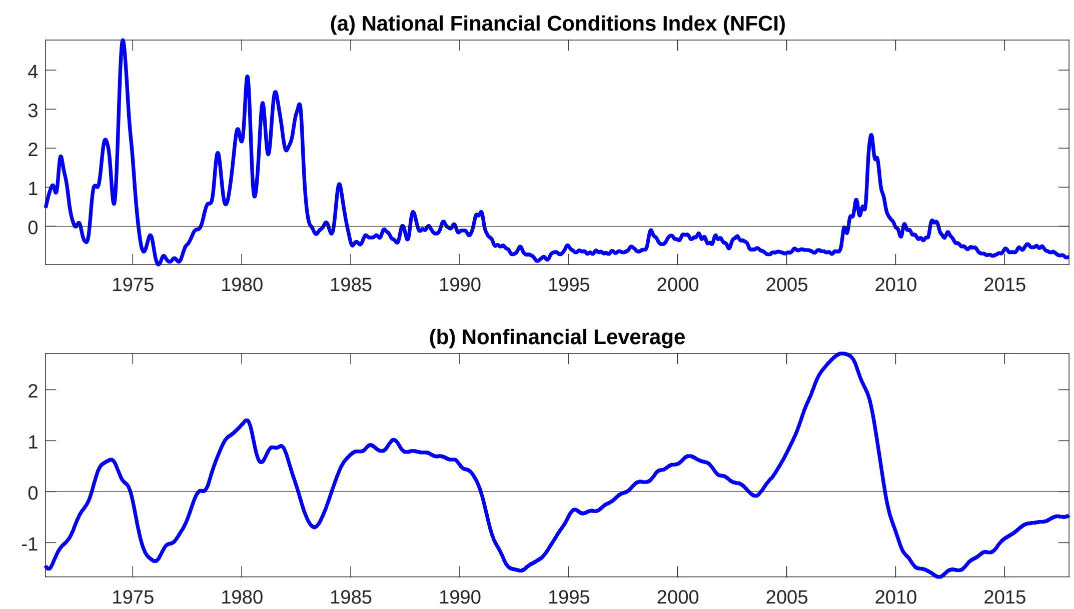
Note: The figures plot the estimated real and financial cycles. The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 5 and 95 of the posterior distribution, and the solid green line plots the corresponding factor estimated with principal components, and aligned with the right axis.

Figure 17: Output Gap Based on Real GDP



Note: The figures plots the business cycles in the US and euro area based on real GDP. The cycles have been extracted using the HP filter with lambda of 1,600 (quarterly frequency). The recession dates are marked in grey and come from the official sources: NBER for the US and CEPR for the euro area.

Figure 18: Financial Conditions in the US



Note: Chart A plots the National Financial Conditions Index. Chart B plots the detrended non-financial leverage cycle. These data are taken from the Federal Reserve Bank of Chicago (Brave and Butters (2012)).

Figure 19: Estimated correlation between factors of the US - Orthogonal Innovations

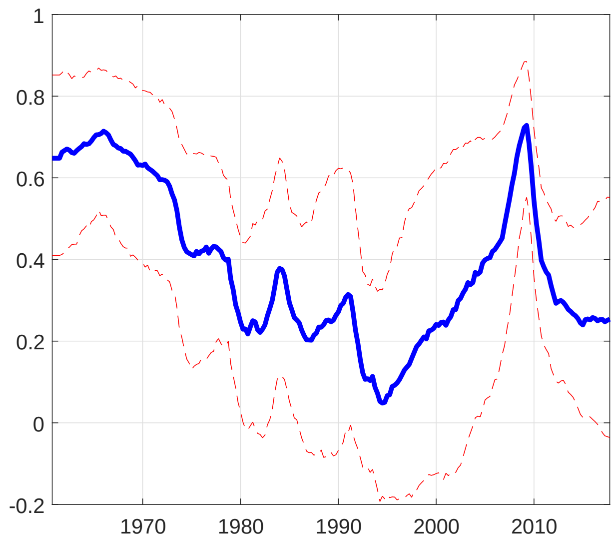
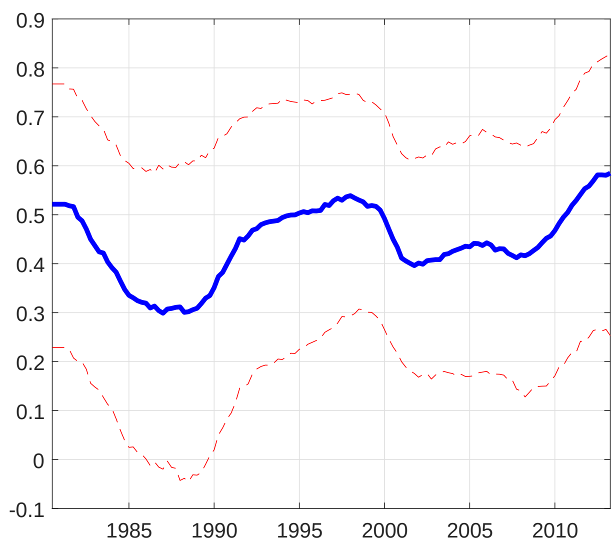
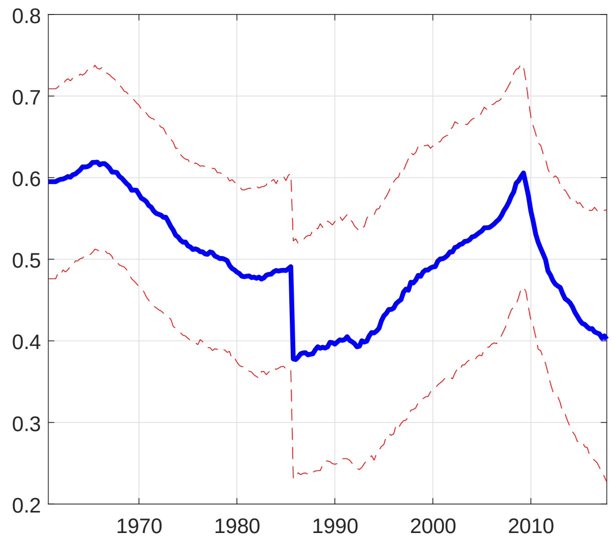


Figure 20: Estimated correlation between factors of the euro area - Orthogonal Innovations



Note: The figures plot the estimated time-varying correlation between the real and financial cycle. The solid blue line makes reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution. The estimates are obtained by assuming orthogonality in the innovations of the factors.

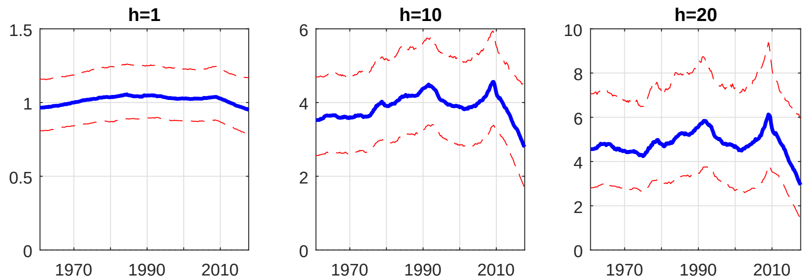
Figure 21: Estimated correlation between factors of the US - Break in Volatility



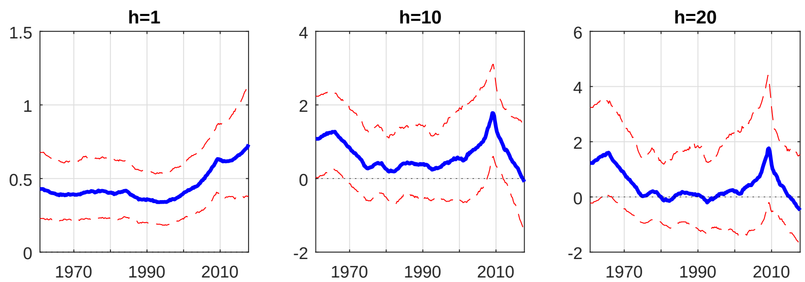
Note: The figure plots the estimated time-varying correlation between the real and financial cycles. The solid blue line makes reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution. The estimates are obtained by assuming a break in the volatility of the factors occurred in 1985.

Figure 22: Cumulated Impulse Response Patterns for US

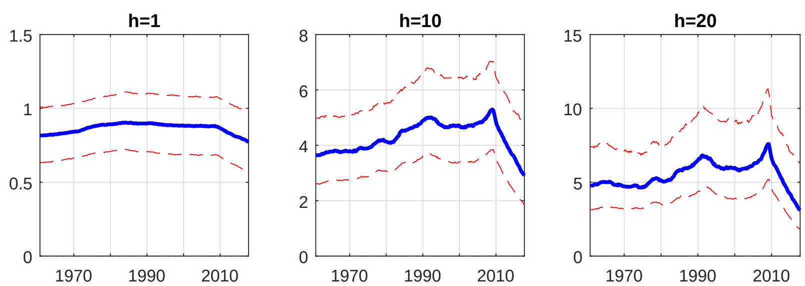
(a) Response of financial conditions to a financial shock



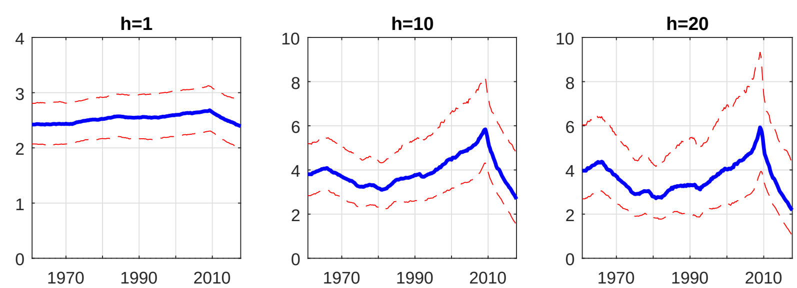
(b) Response of real activity to a financial shock



(c) Response of financial conditions to a real shock



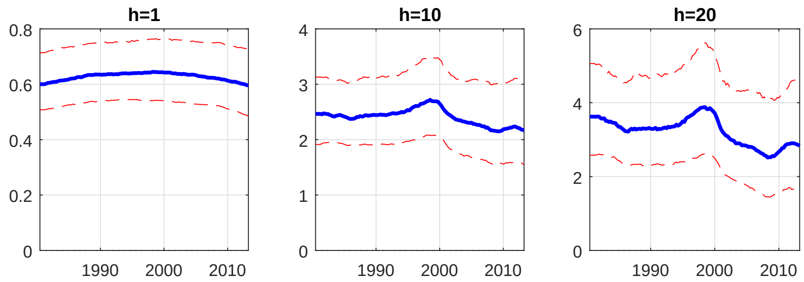
(d) Response of real activity to a real shock



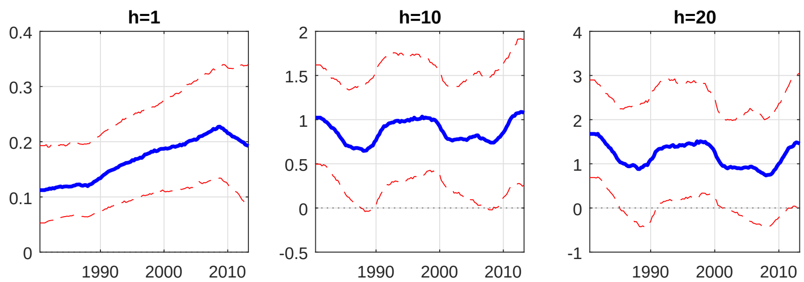
Note: The figure plots the estimated time-varying cumulated impulse responses for different horizons (h). The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 23: Cumulated Impulse Response Patterns for euro area

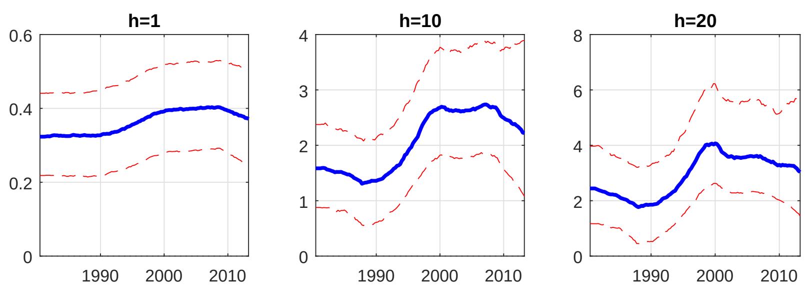
(a) Response of financial conditions to a financial shock



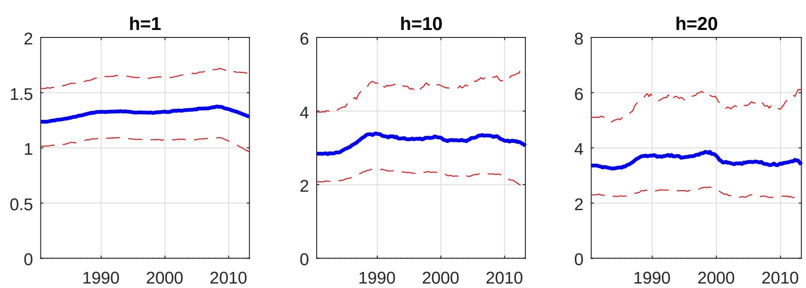
(b) Response of real activity to a financial shock



(c) Response of financial conditions to a real shock

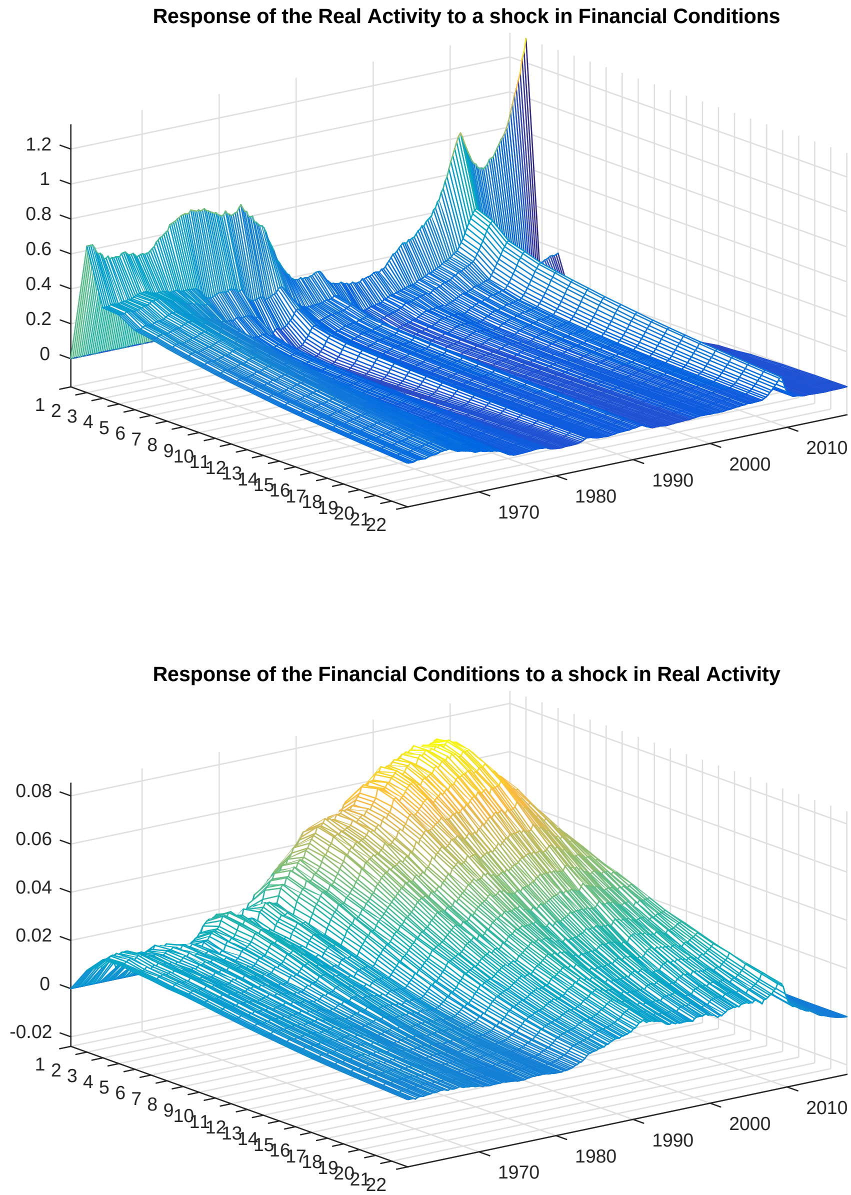


(d) Response of real activity to a real shock



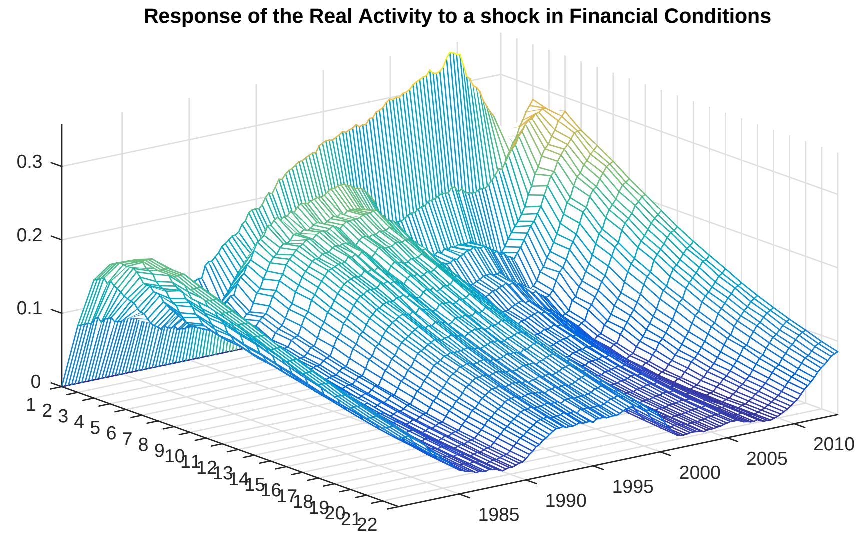
Note: The figure plots the estimated time-varying cumulated impulse responses for different horizons (h). The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

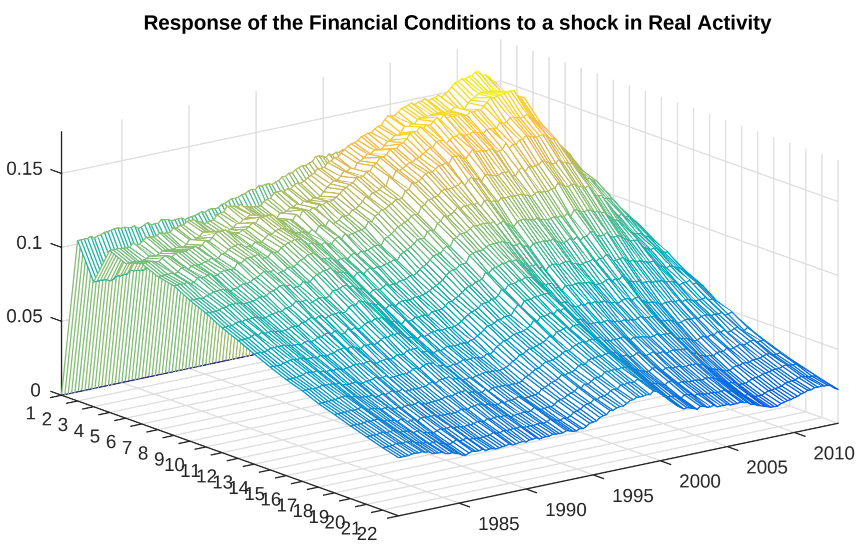
Figure 24: Impulse Responses Between Real and Financial Cycles for US - Orthogonal Innovations



Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by assuming orthogonality in the innovations of the factors.

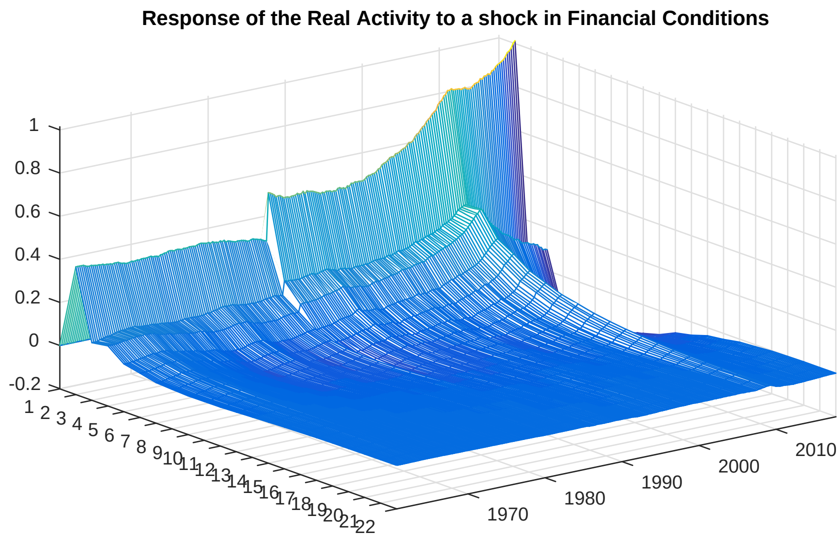
Figure 25: Impulse Responses Between Real and Financial Cycles for euro area - Orthogonal Innovations

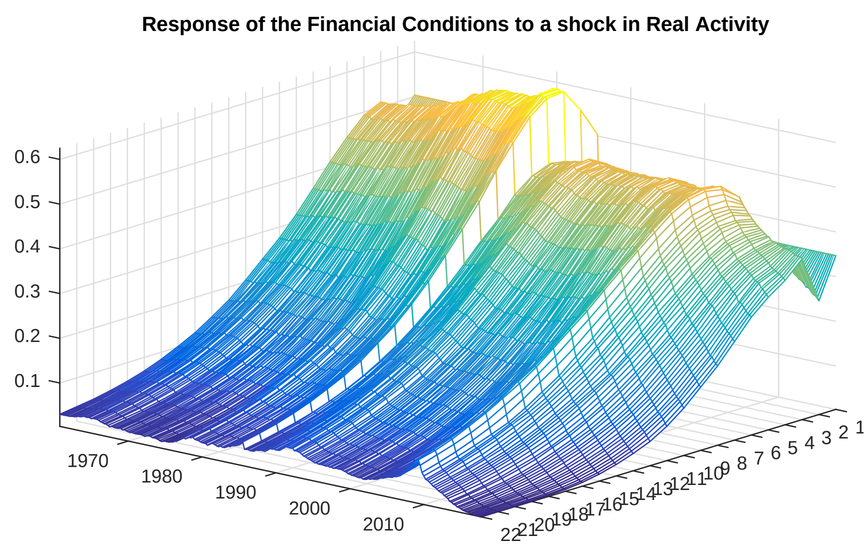




Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by assuming orthogonality in the innovations of the factors.

Figure 26: Impulse Responses Between Real and Financial Cycles for US - Break in Volatility

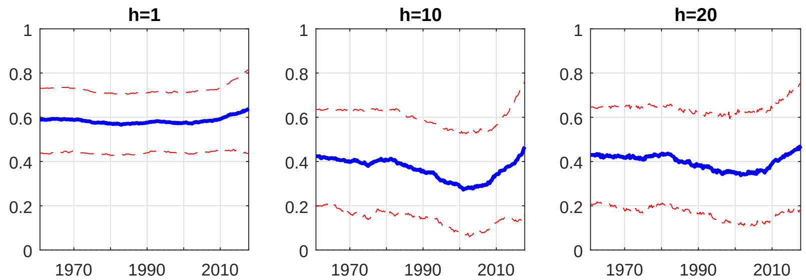




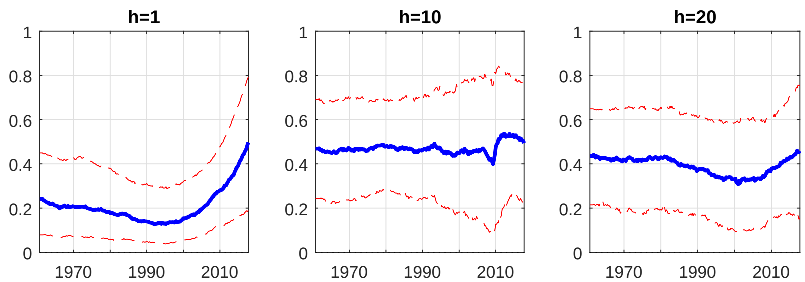
Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by assuming a break in the volatility of the factors occurred in 1985.

Figure 27: Forecast Error Variance Decomposition for US

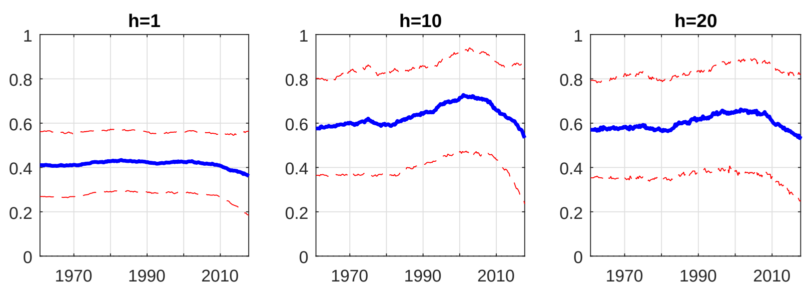
(a) Contribution of financial shocks to financial conditions



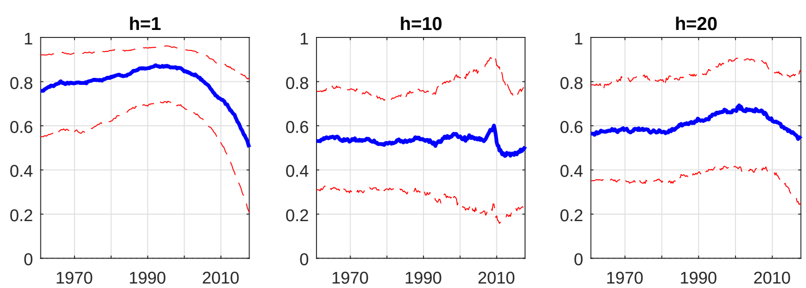
(b) Contribution of financial shocks to real activity



(c) Contribution of real shocks to financial conditions



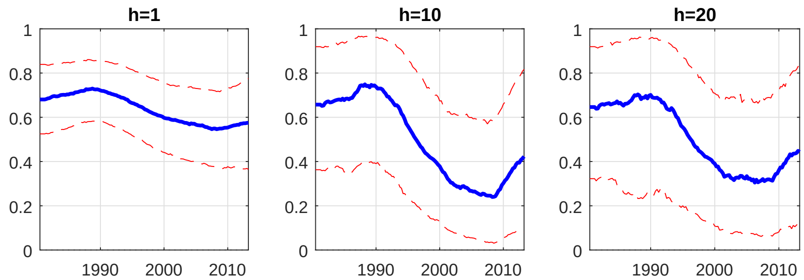
(d) Contribution of real shocks to real activity



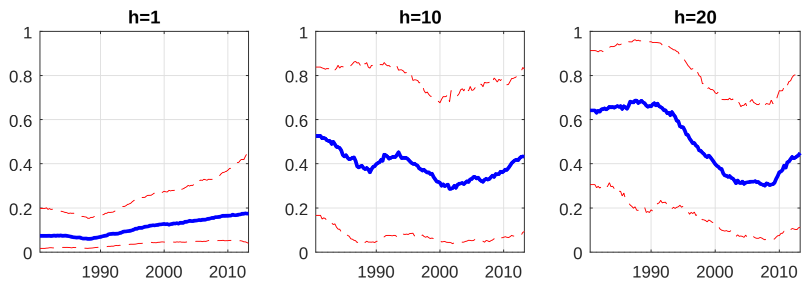
Note: The figure plots the estimated time-varying forecast error variance decomposition for different horizons (h). The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 28: Forecast Error Variance Decomposition for euro area

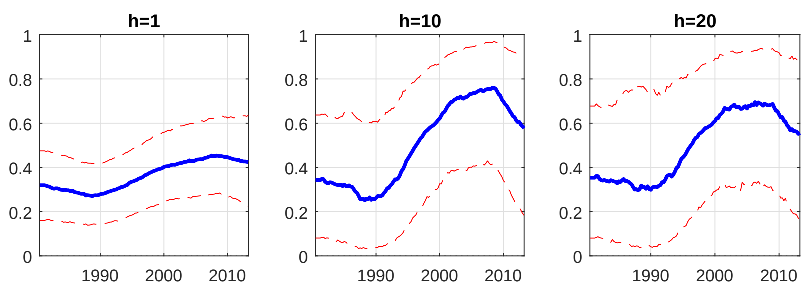
(a) Contribution of financial shocks to financial conditions



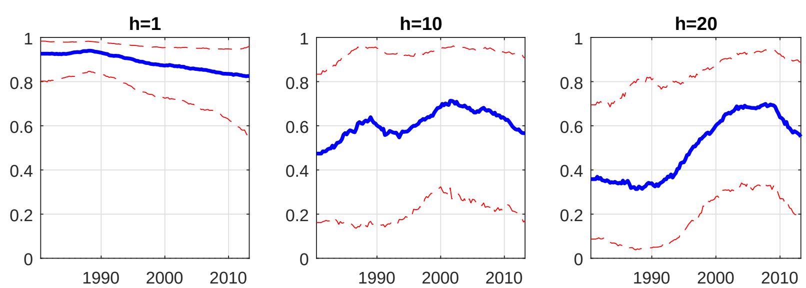
(b) Contribution of financial shocks to real activity



(c) Contribution of real shocks to financial conditions

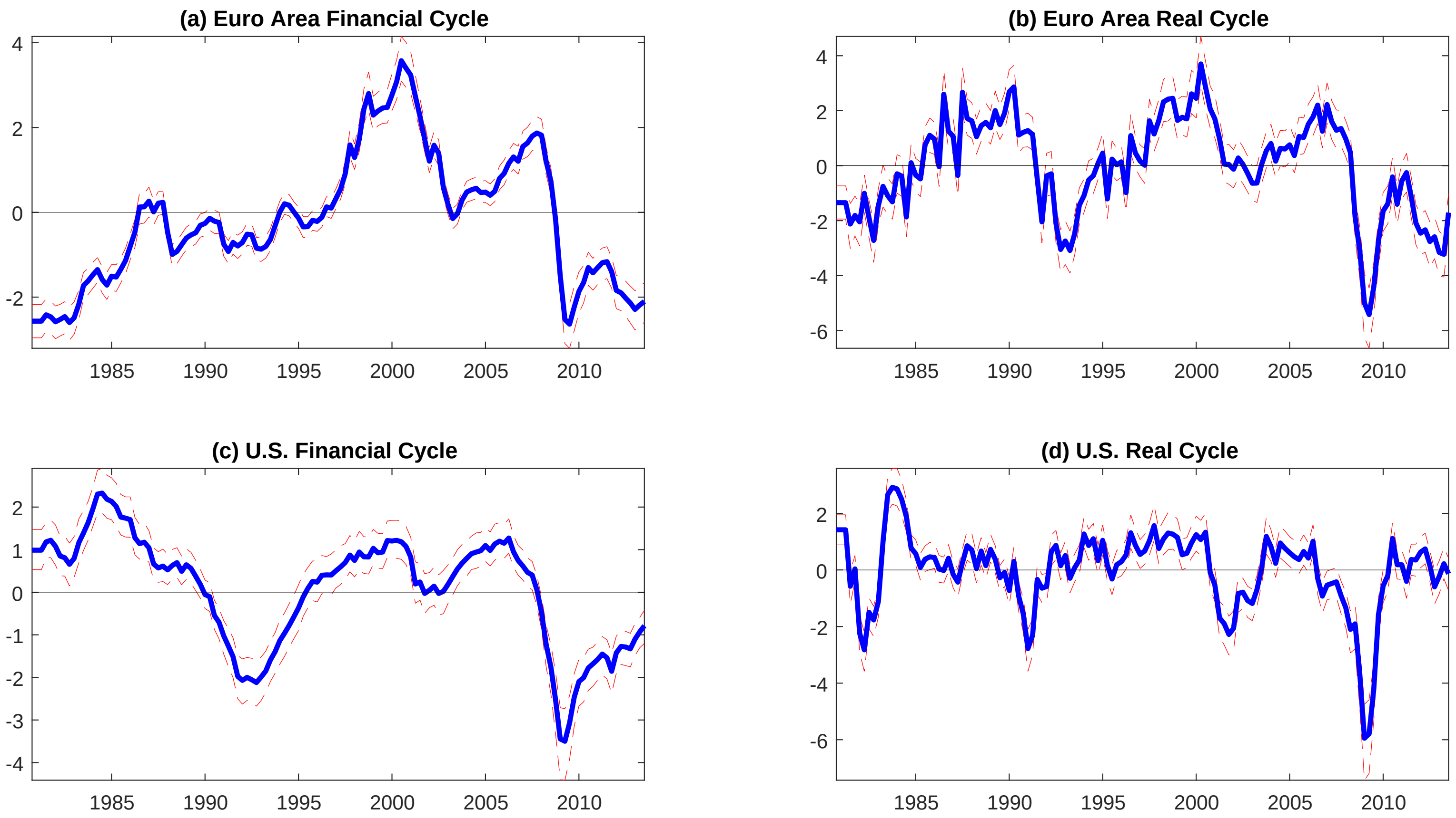


(d) Contribution real shocks to real activity



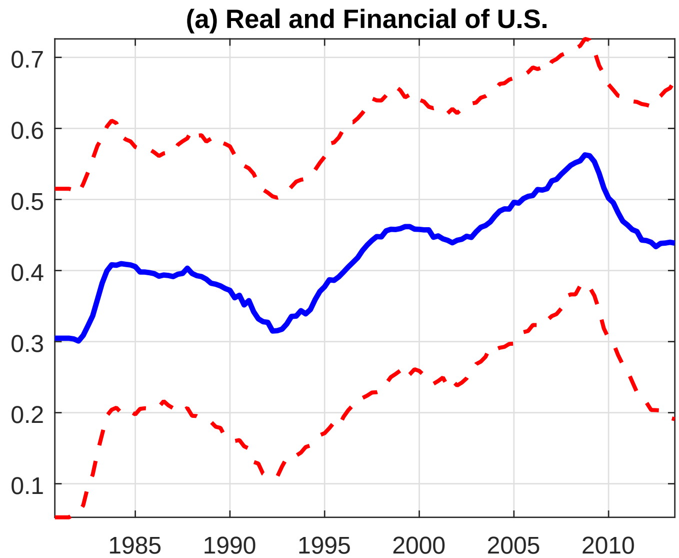
Note: The figure plots the estimated time-varying forecast error variance decomposition for different horizons (h). The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

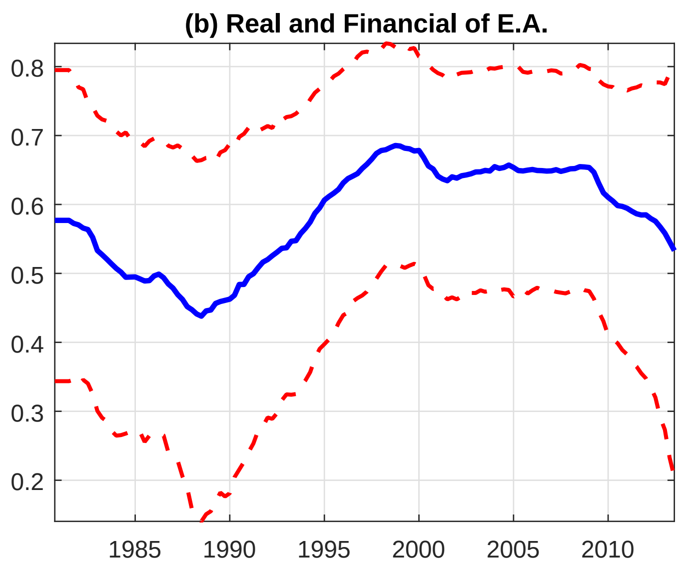
Figure 29: Estimated factors of the US and euro area (Two-economy model)



Note: The figures plot the estimated real and financial cycles for the US and euro area obtained with the (joint) two-economy model. The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 30: Estimated correlation between factors associated to a given economy (Two-economy model)

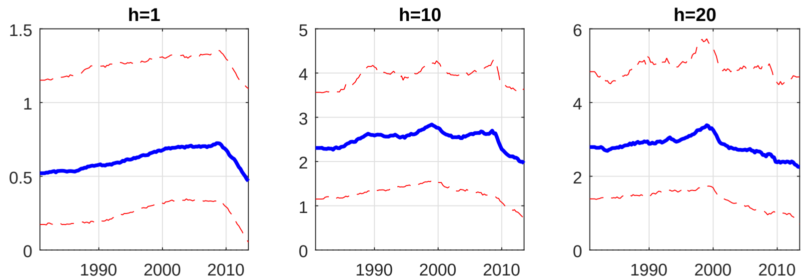




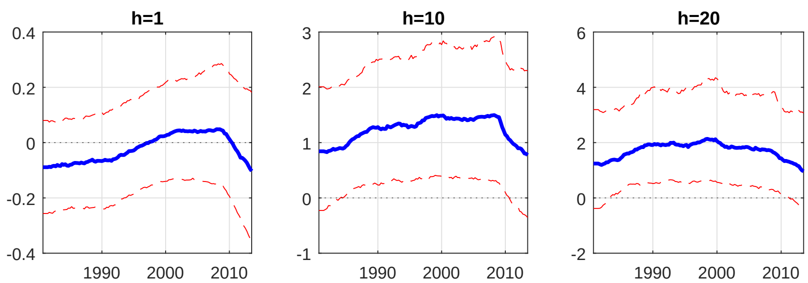
Note: The figure plots the estimated time-varying correlation between the business and financial cycles associated to a given economy. The solid blue line makes reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 31: Cumulated Impulse Response Patterns: Effect of US on E.A.

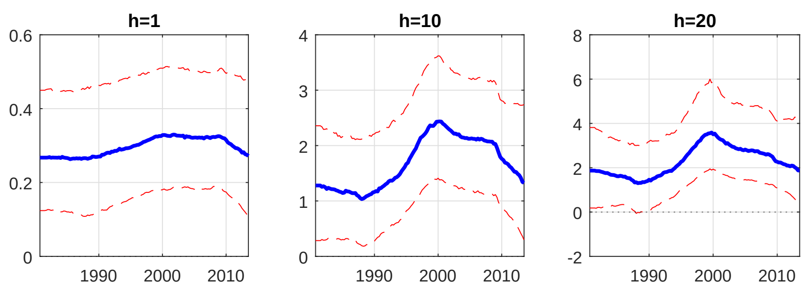
(a) Response of the E.A. Real Activity to a shock in US Real Activity



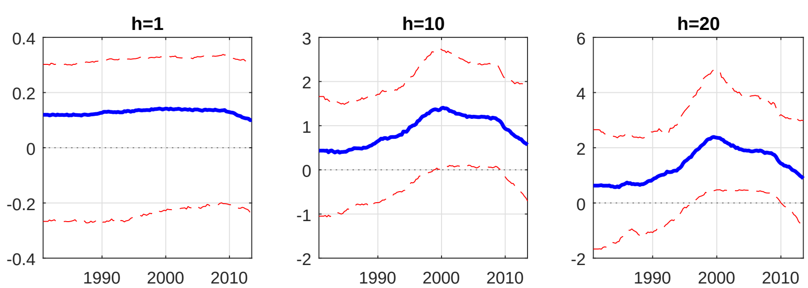
(b) Response of the E.A. Real Activity to a shock in US Financial Conditions



(c) Response of the E.A. Financial Conditions to a shock in US Real Activity



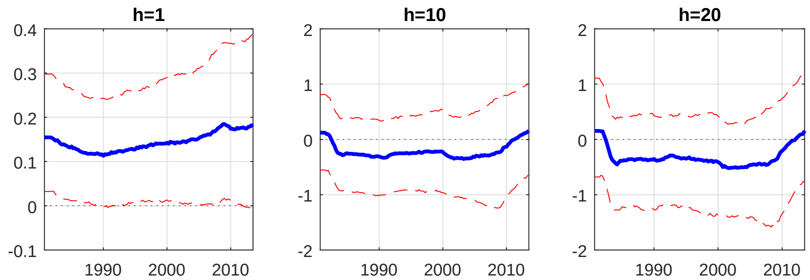
(d) Response of the E.A. Financial Conditions to a shock in US Financial Conditions



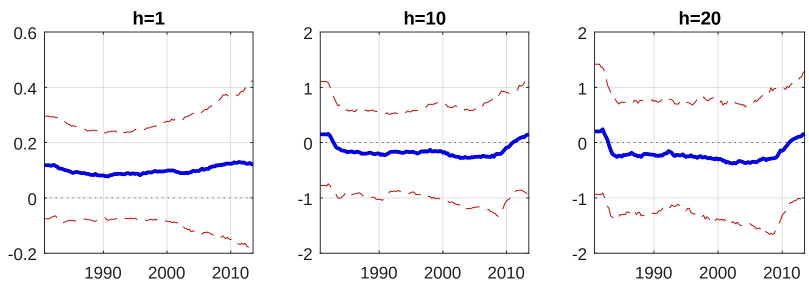
Note: The figure plots the estimated time-varying cumulated impulse responses for different horizons (h). The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 32: Cumulated Impulse Response Patterns: Effect of E.A. on US

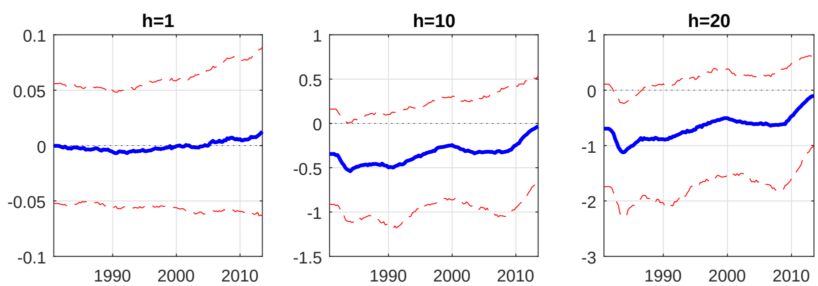
(a) Response of the US Real Activity to a shock in E.A. Real Activity



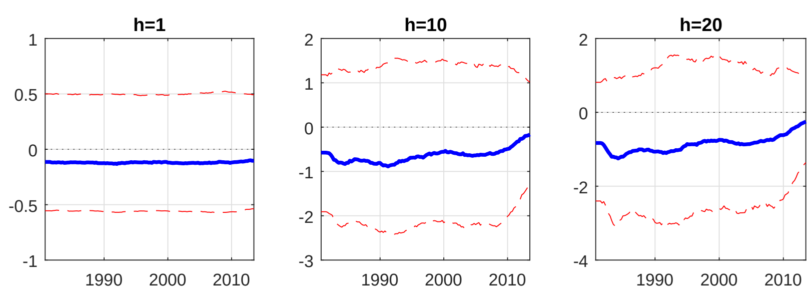
(b) Response of the US Real Activity to a shock in E.A. Financial Conditions



(c) Response of the US Financial Conditions to a shock in E.A. Real Activity

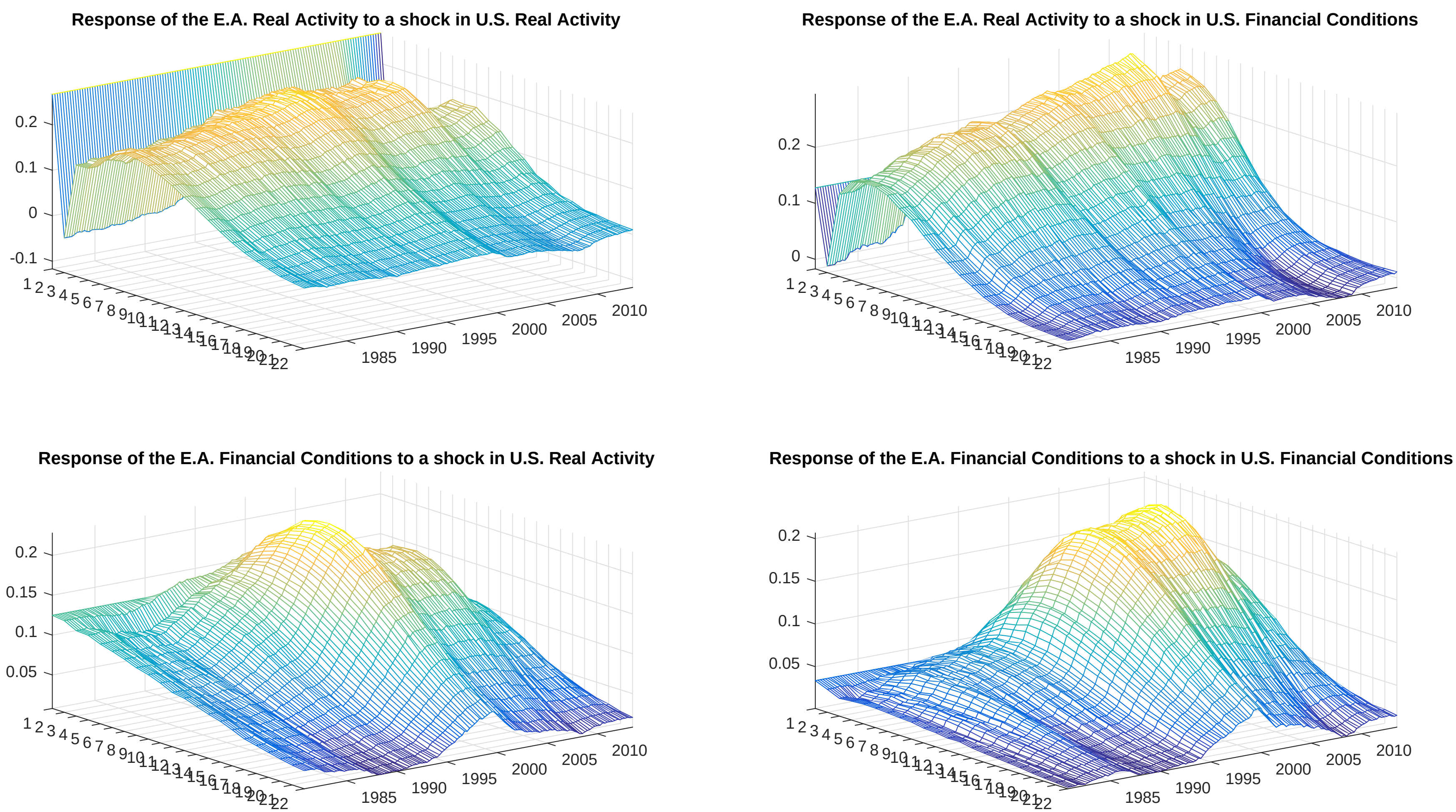


(d) Response of the US Financial Conditions to a shock in E.A. Financial Conditions



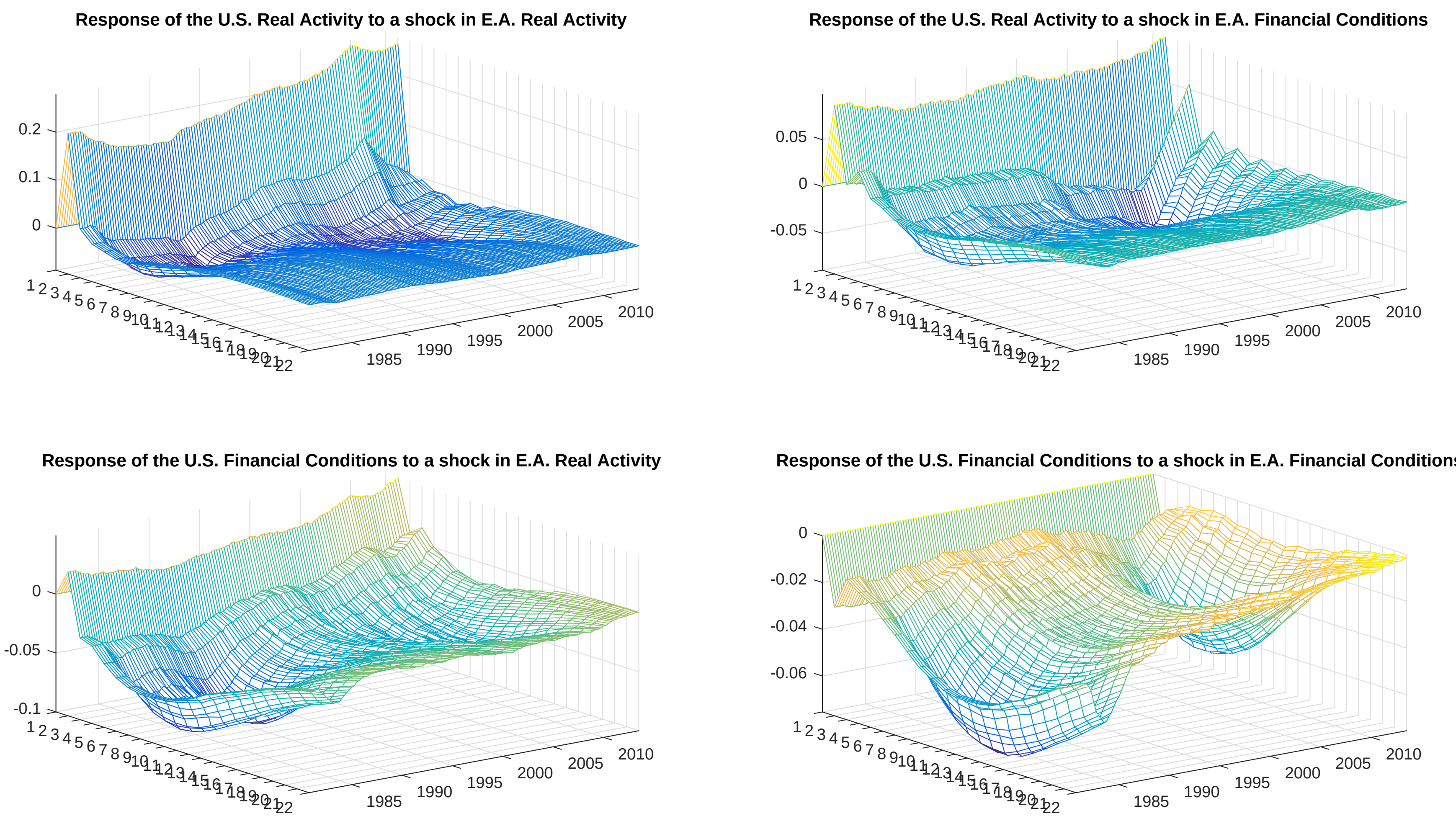
Note: The figure plots the estimated time-varying cumulated impulse responses for different horizons (h). The solid blue lines make reference to the median of the posterior distribution, while the dashed red lines indicate the percentile 16 and 84 of the posterior distribution.

Figure 33: Macro-financial spillovers from the US to the euro area over time - Cholesky



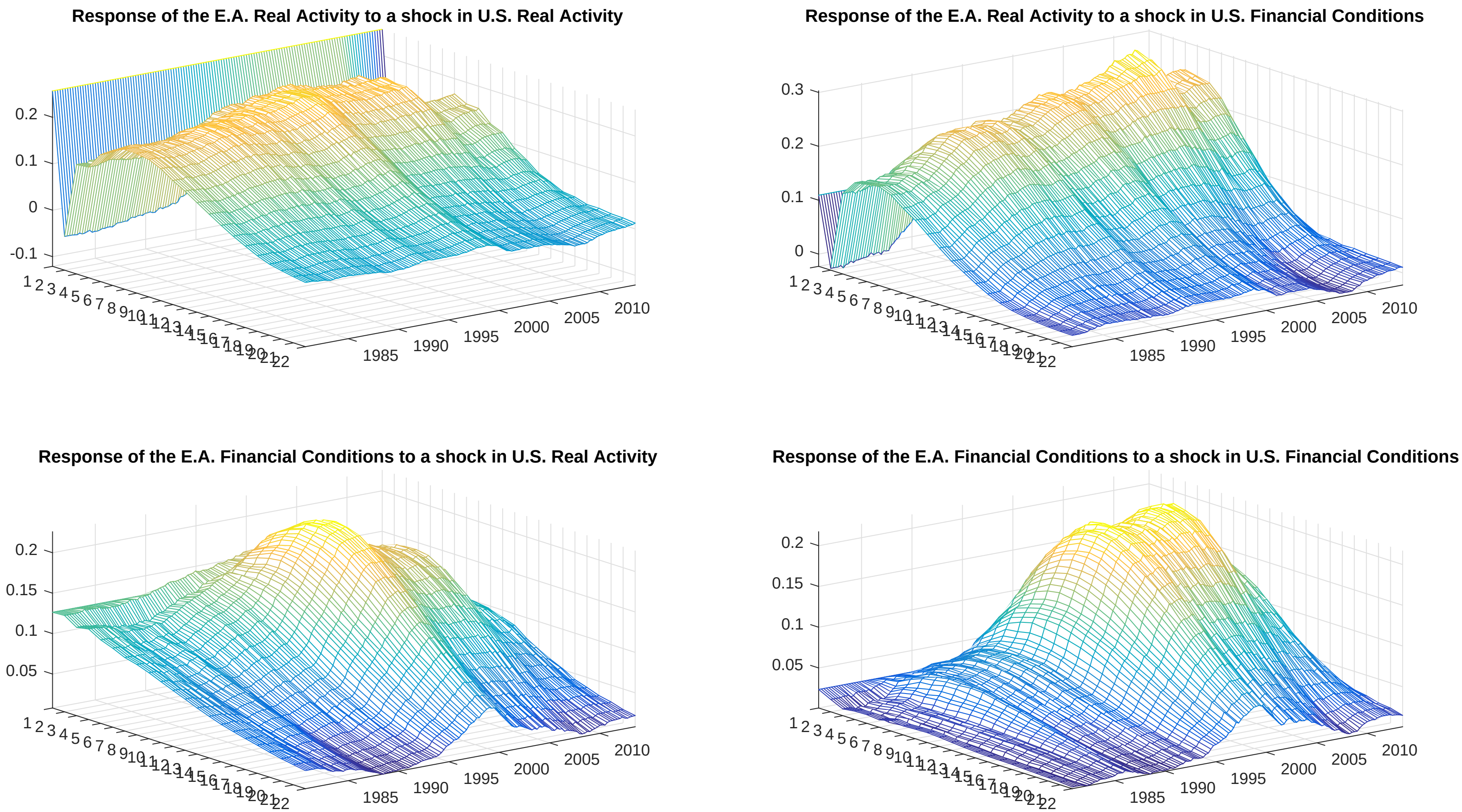
Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by using Cholesky factorization to identify the structural shocks.

Figure 34: Macro-financial spillovers from the euro area to the US over time - Cholesky



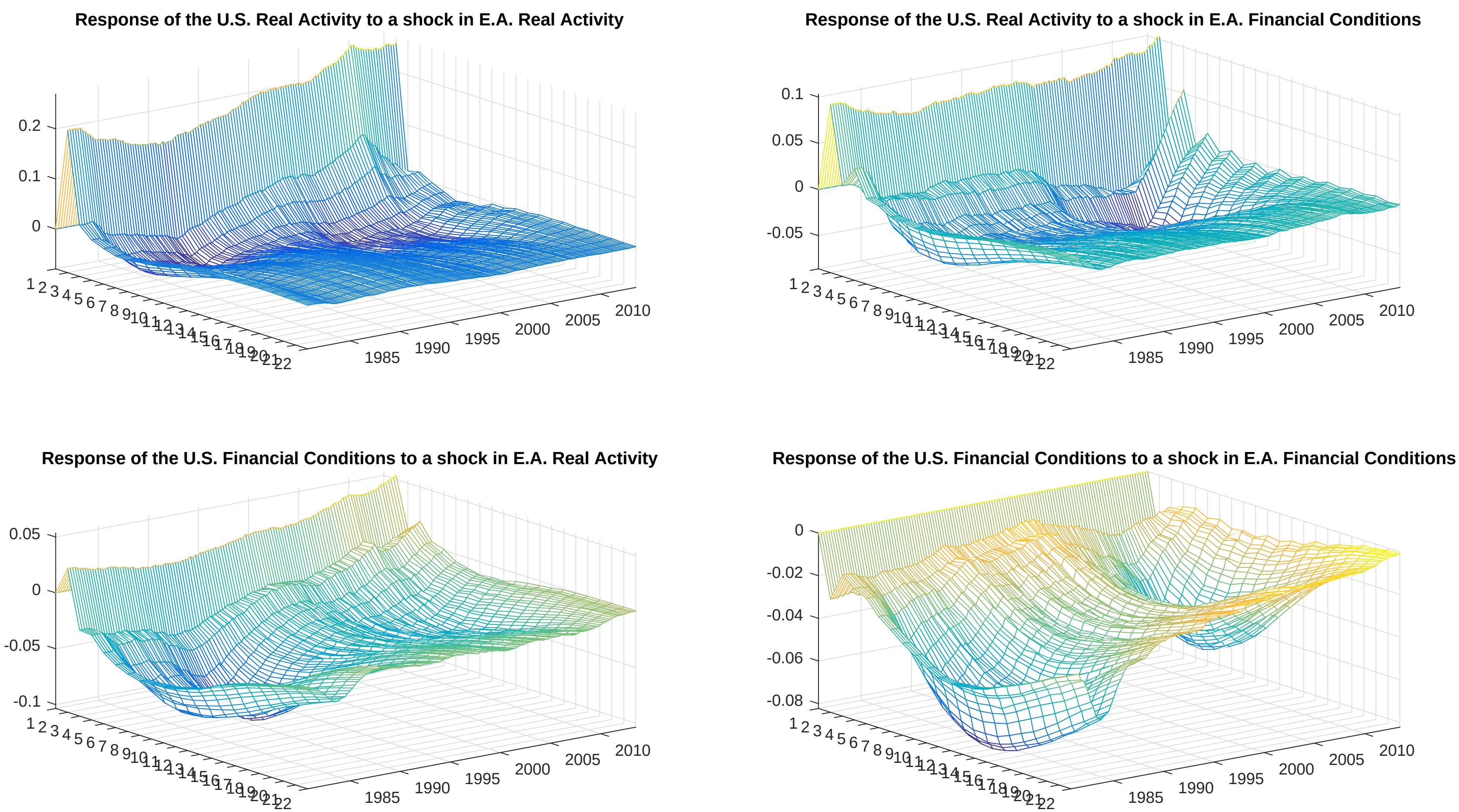
Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by using Cholesky factorization to identify the structural shocks.

Figure 35: Macro-financial spillovers from the US to the euro area over time - Alternative sign and exclusion restrictions



Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by using Cholesky factorization to identify the structural shocks.

Figure 36: Macro-financial spillovers from the euro area to the US over time - Alternative sign and exclusion restrictions



Note: The figure plots the estimated time-varying impulse responses for different horizons (h). The surface makes reference to the median of the corresponding posterior distribution. The estimates are obtained by using Cholesky factorization to identify the structural shocks.