

Essays on Macroeconomics and Financial Stability



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Declaration

I hereby declare that the work described in this dissertation is, except where otherwise stated, entirely my own work and has not been submitted as an exercise for a degree at this or any other university. Chapter two was jointly co-authored with Prof. Efthymios Pavlidis and Prof. Ivan Paya and published at the Special Issue “Housing Unaffordability: An International Economic Problem”, New Zealand Economic Papers, 55 (1), pp. 105-123. Chapter three was jointly co-authored with Dr. Kostas Vasilopoulos.

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Dedicated to the memory of my mother

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Abstract

This thesis is composed by three chapters. The first chapter examines how cross-country spillovers in the Euro Area affect the *risk-taking channel* of monetary policy. Our empirical evidence suggests that the impact of monetary surprises on systemic risk changes after the period of the Zero Lower Bound, and that a significant fraction of the response can be attributed to the high degree of financial contagion in the Euro Area. Chapter two focuses on the systemic risk in the real estate sector and its determinants. We find that sustainable house prices positively contribute to the stability of the financial sector; whilst house price exuberance and rapid increases in housing unaffordability amplify systemic risk. In the third chapter, we explore the non-linearities in the impact of a housing demand shock on the macro-financial environment. In periods of housing stress, an unexpected drop in house prices leads to a decline in consumption and financial instability while on the contrary, the impact is weaker under normal times.

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Introduction

This thesis is composed by three chapters that focus on two topics that have attracted considerable attention since the financial crisis of 2007, the housing market and systemic risk. The first chapter examines the systemic risk spillovers across the Euro Area. To capture systemic risk, we present a new country-level index based on micro-data and the $\Delta CoVaR$ methodology by [Adrian & Brunnermeier \(2016\)](#), which we then incorporate into a GVAR model to investigate the degree of contagion in Euro Area economies. Our findings suggest that there are strong systemic risk spillovers in the Core region, which are not spreading out to the Periphery. On the other hand, peripheral economies are affected mostly by domestic factors and they are a source of systemic risk for the Euro Area. Finally, systemic risk shocks in small economies have a sizeable effect on the other member countries, which highlights the need for monitoring financial risk not only at the aggregate level. A union systemic risk shock drives down Euro Area economic activity, with cross-country spillovers to account for two thirds of the response.

In this chapter we also study the relationship between monetary policy and systemic risk. The literature suggests that expansionary monetary policy shocks result in a more risky behaviour, and as a consequence, higher systemic risk. We incorporate high-frequency monetary surprises into the model and we find evidence of the *risk-taking channel* of monetary policy in the period before the Zero Lower Bound. However, the relationship is reversed after 2009, when expansionary shocks mitigate systemic risk. The GVAR model allows us to decompose the direct and indirect impact of monetary surprises. We find that a significant fraction (17.4%) of systemic risk responses following a monetary surprise can be attributed to the indirect

(spillovers) channel. We also focus on different forms of unconventional monetary policy and their role in financial stability. Near term guidance reduces systemic risk, whereas the initiation of the QE program has the opposite effect. Finally, the effectiveness of monetary policy exhibits significant asymmetries, with core countries driving the union response. Most importantly, the evidence suggests that neglecting cross-country spillovers would underestimate the impact of monetary policy shocks, since they account for a substantial fraction of the systemic risk responses.

The following two chapters focus on the relationship between the housing market and financial stability. Chapter two employs the $\Delta CoVaR$ method to estimate the systemic risk in the UK real estate sector. Our findings indicate that there is strong dependency between downside risk in the financial system and the real estate sector. In particular, when the real estate sector is under distress, the *value-at-risk* of the entire financial system is higher by 74%. In addition, firm characteristics and macro variables appear to play a role in the tail dependency between real estate and financial sector. Our findings show that there is a negative relationship between house prices and systemic risk. In other words, sustainable house price growth results in a more stable financial system. However, in periods of exuberance in the housing market, systemic risk in the real estate market is significantly higher. Finally, we employ an alternative version of $\Delta CoVaR$ to quantify the exposure of the largest UK banks to the real estate sector downside risks.

Chapter three sheds further light into the time-varying dynamics between housing and financial markets. The aim of this chapter is to examine whether the impact of housing demand shocks vary depending on the phase of the housing cycle. More specifically, we employ a non-linear VAR model to examine the effect of house prices on consumption, residential investment, and financial stability. In order to define periods of distress in the housing market, we adopt the *at-risk* framework by [Adrian et al. \(2019\)](#). The framework has been on the centre of ECB's policymakers agenda as a new approach to quantify tail risks in macroeconomy and

financial market. More specifically, the *at-risk* framework estimates the dynamic distribution of house prices growth using quantile regressions and a set of financial variables. We define the stress threshold by focusing on the left quartile of the estimated distribution of house price growth. Our findings indicate that in periods of housing stress, the response of consumption to a housing demand shock is greater by 34% and residential investment is more than two times higher. With regards to financial stress, a negative housing demand shock leads to greater financial stress, in line with the findings in chapter two. However the effect is mostly driven by periods of housing stress, while on the contrary, the link between the two markets is weak under normal times. We then focus on the role of household credit. We find a positive relationship between consumption's response (following a housing demand shock) and credit availability, whereas the relationship with financial stress exhibits significant non-linearities in periods of limited or excessive credit.

Both chapters provide valuable insights about the non-linear relationship between the financial and housing markets. House prices are considered one of the best predictors of macroeconomic tail risks. The housing market frequently experiences overvaluation and bubbles, which according to our findings, drive the effect on financial stress and economic activity, and strengthens the case for close monitoring of the fluctuations in the housing market.

Chapter 1

The role of systemic risk spillovers in the transmission of Euro Area monetary policy

1.1 Introduction

In the aftermath of the 2008 financial crisis, the international transmission of financial stress has been a focal point of research and policy analysis. In 2011, [Christine Lagarde](#), the then Managing Director of the IMF, argued that international financial exposures were “*transmitting weakness and spreading fear*” across markets and countries. Similarly, [Grant \(2016\)](#) suggests that the cross-country financial linkages (and not the trade relationships) were the main stress transmission mechanism in both the US subprime mortgage and the Eurozone debt crises.¹ Euro area is a special case because, on the one hand there is significant heterogeneity amongst countries and on the other hand, there is a single monetary authority and high financial integration. The latter, despite all the direct and indirect benefits, could lead to more costly crises, since economies are exposed to both domestic and currency union shocks. A country level systemic risk event may become aggravated, due to strong financial contagion in the euro

¹In addition, [Brutti & Sauré \(2015\)](#) argue that cross-border financial exposures were an important transmission channel and they argue that a fragile foreign banking system could constitute a liability to the rest of the union members.

banking system, and lead to a widespread adverse effect on the union-wide financial stability (Allen et al., 2011).

The aim of this chapter is twofold. First, to quantify the systemic risk spillovers across the Euro area and, second, to examine how these affect the transmission of common monetary policy and the systemic *risk-taking channel*. According to the joint report of Financial Stability Board (FSB), International Monetary Fund (IMF) and Bank for International Settlements (BIS), systemic risk is defined as the disruption of the flow of financial services, caused by an institution or by a part of the financial system, that could have an adverse effect on the real economy. To capture systemic risk, we adopt the $\Delta CoVaR$ risk measure, introduced by Adrian & Brunnermeier (2016).² We extend the methodology to the country level by employing an aggregate version for a market capitalization weighted portfolio of financial institutions. $\Delta CoVaR$ is one of the most widely used measures and its main advantage is that is based on micro-data, so it is more informative than country-level measures that are based on government securities.³ For robustness purposes, we also employ as an alternative indicator, the market-based Composite Index of Systemic Sovereign Stress (henceforth *SovCISS*). The index was created by Garcia-de Andoain & Kremer (2017) and the data series are provided by the ECB Statistical Data Warehouse.⁴

We then incorporate this systemic risk index in a euro area Global VAR (GVAR) model to allows us to capture the cross-countries spillovers. There are different methodological approaches in the literature to capture interconnectedness among firms or countries, such as market data-based (systemic risk) measures (Billio et al. 2012, Gómez-Puig & Sosvilla-Rivero

²Numerous studies focus on the estimation of systemic risk, however there is no commonly accepted measure in the literature. Bisias et al. (2012) present an extended survey of the different measures grouped by their features. Each group captures a different aspect of systemic risk, such as contagion, volatility, liquidity, macroeconomic environment and institution-specific measures

³For the estimation we include financial firms beyond the banking sector such as insurance companies, real estate firms and financial services institutions. See also the recent work from Jin & De Simone (2020) and Pavlidis et al. (2021) who expand the analysis of the euro systemic risk beyond the banking sector by focusing on investment funds and real estate firms respectively.

⁴ECB Statistical Data Warehouse also provides time-series data for the Composite Index of Systemic Stress (*CISS*) by Hollo et al. (2012), but not for all the examined countries in our sample.

2014) and network analysis (Hüser 2015, Covi et al. 2019). Our approach differs from the other papers in the literature since we capture contagion by analysing (exogenous) shocks amongst member countries or union regions. The GVAR framework is a common approach to model financial linkages amongst countries (Galesi & Sgherri 2009, Doornik & van Roye 2014)⁵ and has been extended to the Euro area financial markets.⁶ More specifically, Bicu & Candelon (2013) apply the model based on balance sheet data and sectoral CDS premia, to estimate the interconnectedness of the Eurozone banking sectors. Moreover, Caporale & Girardi (2013) uses the GVAR framework to find a strong link between euro area spreads and they show how the fiscal imbalances lead to financial imbalances.

All of the papers in the euro area GVAR literature argue that there are significant spillovers in terms of economic activity and financial stability. To measure the degree of interconnectedness and its drivers, we quantify the impact of country-level systemic risk shocks to the union aggregate level. Our empirical evidence suggests that Italy, Spain and Germany are the most systemically important countries in the monetary union. However, shocks in some of the smaller countries (Ireland) can also have a sizeable impact at the union level. We observe that core countries are highly interconnected but their spillovers to the rest of the union members are low. On the other hand, the systemic risk shocks in the peripheral countries have a considerably larger effect on all the EMU members. In addition, we examine the impact of systemic risk shocks on the macroeconomy. The results indicate that an unexpected increase in the Euro Area aggregate systemic risk leads to a slowdown in economic activity, of which two thirds of its variation can be attributed to cross-country spillovers.

The second part of the chapter focuses on the role of spillovers on the *risk-taking channel* of monetary policy. Much of the existing literature supports that low interest rates lead to excessive risk taking by financial institutions, the so-called *risk-taking channel*. Various studies have

⁵Other papers also analyse the financial spillovers by focusing on the transmission of liquidity and credit shocks (see Chudik & Fratzscher, 2011 and Eickmeier & Ng, 2015).

⁶The GVAR literature has also been extended to the various Euro area-focused contexts such as fiscal policy (Hebous & Zimmermann, 2013 and Ricci-Risquete & Ramajo-Hernández, 2015), monetary policy (Burriel & Galesi, 2018) trade (Bussière et al., 2009) and house prices (Vansteenkiste & Hiebert, 2011).

covered different indicators of risk-taking activity and they find evidence for the transmission channel.⁷ However, there is no extended literature in terms of financial stability and the “*systemic risk-taking channel*”. [Kabundi & De Simone \(2020\)](#) identify this gap in the literature and analyse the systemic risk responses following conventional and unconventional monetary policy shocks identified using sign restrictions and they find evidence of the *risk-taking channel*. Similarly, [Faia & Karau \(2019\)](#) include systemic risk measures in a VAR model and shadow rates as instruments of monetary policy. They present similar results but also evidence of a price puzzle, which indicates that the identification of the monetary shock is problematic.

We adopt the high-frequency monetary surprises by [Altavilla et al. \(2019\)](#) that overcome this issue and also allows us to examine the impact of other forms of monetary policy (such as forward guidance and QE) on systemic risk. This is the first paper, to the best of our knowledge, that incorporates high-frequency shocks into the GVAR framework. The results indicate that the impact of monetary policy is not homogeneous across time. We find that during the ZLB, expansionary shocks result in a decrease in systemic risk. Most importantly, we isolate the systemic risk response coming from the spillover channel. The results indicate that cross-country spillovers play an important role in the transmission of monetary policy shocks accounting for more than 17% of the systemic risk and 13% of GDP responses’ variation. Our findings suggest that there are significant asymmetries amongst countries with core economies to benefit the most in terms of growth and financial stability. We also find that the effect is also heterogeneous across the different types of surprises. An expansionary near term guidance (*timing*) shock to mitigate systemic risk, whereas QE shocks to have the opposite effect. Our empirical results are in line with [Leitner et al. \(2021\)](#) who examine the impact of monetary policy shocks on CISS for the period after 2007 and [Kapinos \(2020\)](#) who finds that expansionary monetary news shocks lead to a decrease in systemic risk in the US.

⁷[Neuenkirch & Nöckel \(2018\)](#) and [Dell’Ariccia et al. \(2014\)](#) use data from lending surveys and argue that low interest rates result to greater bank risk-taking in the EMU and the US respectively. Similar findings are presented by [Delis & Kouretas \(2011\)](#) who use a large panel dataset related bank-lending channel.

The remainder of the chapter proceeds as follows. In Section 1.2, we present the $\Delta CoVaR$ methodology and the construction of the systemic risk index. Section 1.3 describes the GVAR methodology and model specification. In Section 1.4, we discuss the empirical findings on the transmission of systemic risk shocks at the regional and euro area level. Section 1.5 focuses on the relationship between systemic risk and monetary policy. Finally, Section 1.6 discusses the conclusion and the main policy implications.

1.2 Measuring systemic risk

A number of different systemic risk measures have been proposed in the literature, however there is not a commonly accepted approach. For our analysis, we construct a systemic risk country index by employing one of the most popular systemic risk methodologies, $\Delta CoVaR$, proposed by [Adrian & Brunnermeier \(2016\)](#). $\Delta CoVaR$ is a widely-used measure and has been applied in a variety of contexts such as measuring the systemic importance of the Eurozone financial sub-sectors ([Bernal et al., 2014](#)) and the European sovereign debt markets ([Reboredo & Ugolini, 2015](#)). The method builds on the concept of Value-at-Risk (VaR), which is arguably one of the most widely used risk measures for investors and policymakers. However it cannot be used for macroprudential purposes since it does not take into consideration the links amongst firms. To capture this aspect of risk, [Adrian & Brunnermeier \(2016\)](#) develop the concept of $CoVaR_q^{s|i}$, defined as the VaR_q of the entire financial system when the firm i is under distress (returns equal to its VaR_q).

The VaR of an institution at $q\%$ confidence level, is defined by:

$$P(R^i \leq VaR_q^i) = q, \quad (1.1)$$

The $CoVaR$ of the system when the institution i is under distress is defined as:

$$P(R^s \leq CoVaR_q^{s|i} \mid R^i = VaR_q^i) = q, \quad (1.2)$$

In Equation 1.2, R^i and R^s denote the returns of institution i and of the financial system index respectively. The systemic importance of an institution can be measured by focusing on its marginal contribution to financial system's risk. For this purpose they define $\Delta CoVaR$ as the difference between the $CoVaR_q$ with the one estimated in normal times ($q = 0.5$).⁸ $\Delta CoVaR$ captures the risk spillovers from a firm across the financial system. For the cross-country analysis, we estimate the level of systemic risk at the country level by introducing an aggregate version of the $\Delta CoVaR$ measure. Therefore, we compute the systemic risk for a market capitalization weighted portfolio of financial firms including banks, financial services, real estate and insurance companies.⁹

A similar approach has been adopted by Rodríguez-Moreno & Peña (2013) for a portfolio of European and US stocks. The estimation of systemic risk is at the national and not the European level, to isolate potential cross-border externalities at this stage.¹⁰ At this stage we do not want the stock market variation of the other union members included in the aggregate union index to affect the country level estimation of systemic risk. Figure 1.1(i) compares the euro area $\Delta CoVaR$ index and the *SovCISS* index from the ECB database. The estimation of *SovCISS* integrates yield and liquidity spreads along with volatility into an overall measure of sovereign market stress.¹¹ Although the estimation methods are different, we observe that they provide a similar pattern. Figure 1.1(ii) illustrates the systemic risk index for the ten examined economies divided into two union regions, Core and Periphery.

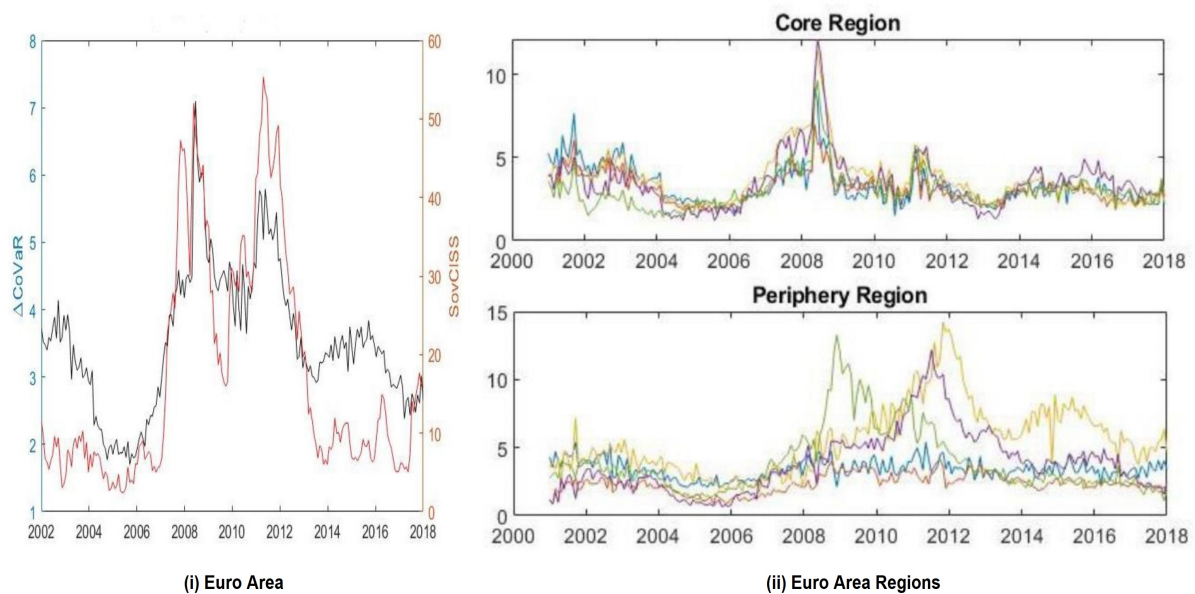
⁸For a detailed description of the $\Delta CoVaR$ estimation, see Appendix, section A.1.

⁹The data series are provided by Datastream and for the selection of the financial institutions we used the constituents of the countries' DS Financials Index. For robustness, we use weights based on a 6 month moving-average Market Capitalization and the systemic risk indices is identical. In addition, we remove REITs from our sample and this does not change our results.

¹⁰See Buch et al. (2019) for the differences and the drivers of euro area systemic risk at the national and European level.

¹¹See García-de Andoain & Kremer (2017, 2018) for the detailed estimation of the index.

Figure 1.1 Systemic risk in the Euro Area



Note: The figure reports the systemic risk estimation for the euro area based on two alternative measures. The black line illustrates the $\Delta CoVaR$ country-level risk index and the red line, the *SovCISS* provided by ECB Statistical Data Warehouse. The examined period is 2001m1-2018m12. On the right-hand side charts, we divide our sample of 10 Euro Area economies to two regions, namely Core and Periphery based on the systemic risk variation they exhibited in the examined time period.

We observe that the Great Recession in 2008 and the sovereign debt crisis in 2012 both led to a considerable increase in systemic risk. The definition of the two union regions depends on two distinctive patterns that are observed in individual countries systemic risk variation. Core countries, namely Germany, France, the Netherlands, Belgium and Austria, affected mostly by the 2008 global financial crisis, whereas the increase in 2012 was considerable weaker in those countries. These countries present a very high degree of interconnectedness and co-movement for the entire examined period. On the other hand, for peripheral countries, namely Italy, Spain, Greece, Portugal and Ireland, present high level of risk in both periods, with the peak values to be observed in 2012.

1.3 The GVAR framework

The GVAR methodology is a multi-country model that allows us to take into consideration the international financial spillovers across the Euro area. The framework was introduced by Pesaran et al. (2004) and extended by Dees et al. (2007). This is the first paper, to the best of our knowledge, that includes systemic risk measures to account for financial stability. We incorporate ten Euro area countries¹² and three macroeconomic variables for each country (Y); logGDP¹³, Prices (logHICP) and the systemic risk index. As shown in the Equation 1.3, each country is modelled as a small open economy with an error-correction model that includes domestic and foreign variables. The mathematical representation of the VAR model with exogenous variables (VARX (p, q)) is:

$$Y_{i,t} = a_i + \sum_{j=1}^p A_{i,j} Y_{i,t-j} + \sum_{j=0}^q B_{i,j} Y_{i,t-j}^* + \sum_{j=0}^q C_{i,j} X_{t-j} + \varepsilon_{i,t} \quad (1.3)$$

In Equation 1.3, i stands for each country and $A_{i,j}$ is a matrix of coefficients related to the lags of the domestic variables. To capture spillovers across the monetary union, each national economy is also affected by a weighted matrix of foreign variables (Y^*) as presented in Equation 1.4. The foreign variables include all three domestic variables weighted by the level of GDP for the examined period.¹⁴ The GVAR model also allows for global variables (X) that are included in all country models. $B_{i,j}$ and $C_{i,j}$ are the matrices of coefficients for foreign and global variables respectively. Country specific shocks (ε_i) are assumed to be serially uncorrelated mean zero with a non-singular covariance matrix.

¹²These ten economies account for around 95% of Euro Area GDP for period 2002-2018.

¹³We estimate the monthly GDP based on Chow-Lin interpolation using the quarterly GDP data provided by Eurostat and the (monthly) industrial production index provided by FED of St.Louis.

¹⁴See Table A3. The weights are adjusted for the sub-period analysis. Additionally, in line with Dovern & van Roye (2014), we use an alternative weighting scheme based on cross-country claims from the Consolidated Banking Statistic provided by BIS. The data present some missing values, which are filled with zeros or the claims of the other counterpart to the examined country if available. Both weighting schemes provide similar findings.

To ensure consistency, the foreign variables are treated as weekly exogenous, which implies that each country is treated as a small economy with the domestic macroeconomic variables to have no long-run impact to foreign variables, allowing however short-run feedback effects. Therefore, the international spillovers could have a short-term effect but not a long-term impact on the examined domestic economy.

$$Y_{i,t}^* = \sum_{i \neq j}^{N=10} w_{i,j} Y_{j,t}, \quad \text{with } \sum_{i \neq j}^{N=10} w_{i,j} = 1 \quad (1.4)$$

Monetary policy, captured by the shadow rate by [Wu & Xia \(2016\)](#), is the common factor (X_t) for all the countries and can affect the real economy directly and indirectly through spillovers from the other euro area members. It is modelled as a function of a set of union aggregate variables (\tilde{Y}) such as output, prices and systemic risk to capture the ECB's response to macroeconomic developments in the union.¹⁵

$$X_t = b_x + \sum_{j=1}^{p_x} D_j X_{t-j} + \sum_{j=1}^{q_x} \tilde{Y}_{t-j} + u_{x,t} \quad (1.5)$$

The novelty of this work is that we additionally incorporate high-frequency monetary surprises in the framework. In this case, when we analyse monetary policy shocks, the surprises enter the model as exogenous variables, allowing no feedback from the domestic macro-financial environment and ordered first in the model. The modelling approach is based on [Paul \(2020\)](#) that shows that the structural estimation of a proxy SVAR model could be carried out by using the shock series ordered first in a standard recursive VAR model. With regards to the estimation steps, we firstly estimate each individual country's VARX separately (see [Equation 1.3](#)). We select the lag order based on the Akaike Information Criterion (AIC) and

¹⁵Similar approach has been adopted by [Burriel & Galesi \(2018\)](#) and [Georgiadis \(2015\)](#).

we impose a limit to the number of lags for both domestic ($p_{max} = 4$) and foreign variables ($q_{max} = 1$) to secure model stability.¹⁶

In the second step, all the country models are stacked in to create the GVAR model where all the variables are endogenous. Specifically, Z_t is a vector of all variables included $(Y_t, Y_t')'$:¹⁷

$$A_{i,0}Z_{i,t} = a_0 + \sum_{j=1}^p A_{i,j}Z_{t-j} + \varepsilon_{i,t} \quad (1.6)$$

We then use the weights (w), that capture bilateral exposure across countries, to express Y_t' as function of Y_t and we define $G = A_i w_i$ to obtain:

$$G_0 Y_{i,t} = a_0 + \sum_{j=1}^p G_j Y_{t-j} + \varepsilon_{i,t} \quad (1.7)$$

Multiplying both parts of equation (1.7) by G_0^{-1} , we obtain:

$$Y_{i,t} = b_0 + \sum_{j=1}^p F_j Y_{t-j} + \eta_{i,t} \quad (1.8)$$

where $b_0 = G_0^{-1}a_0$, $F_j = G_0^{-1}G_j$ and $\eta_t = G_0^{-1}\varepsilon_t$

The dynamic properties of the model are analyzed by using Generalized Impulse Response Functions (GIRFs), introduced by [Koop et al. \(1996\)](#) and adapted to VAR framework in [Pesaran & Shin \(1998\)](#). We follow [Smith & Galesi \(2017\)](#) SGIRF methodology, who identify structural shocks in a country by using the triangular approach by [Sims \(1980\)](#). Country shocks ($\varepsilon_{i,t}$) are assumed to be uncorrelated with shocks in the common variable equation (u_t). Alternative ordering of the variables should not affect the outcome as long as the contemporaneous correlations remain unrestricted. For a more detailed description of the model, we refer to [Smith & Galesi \(2017\)](#) and [Chudik & Pesaran \(2016\)](#).¹⁸

¹⁶In the [Appendix, Table A4](#) presents the optimal ordering based on the Akaike information criterion (AIC). The results are robust to different lag selection based on the Schwarz Bayesian criterion (SBC).

¹⁷We neglect the global variables (X_t) for simplicity and we only use the domestic lags (p) since by construction are always greater than the foreign variables lags (q).

¹⁸For the estimation of the model, we use the Matlab codes from the GVAR Toolbox by Vanessa Smith.

1.4 Systemic risk spillovers

In this section we present the empirical findings on the transmission of systemic risk shocks across the Euro Area. We employ monthly data for the period 2004m09 to 2018m09 to take advantage of the fact that all the countries had adopted the common currency and they appertain to the ECB's monetary authorities' regulations.¹⁹ This is one of the first papers to look at cross-country spillovers, whereas most of the existing literature analyzes the monetary union as a whole or it only focuses on the largest economies. Our results shed light on the systemic importance at regional and country level and the direction of the risk transmission. For the identification of the systemic risk shock, we use the standard Cholesky decomposition similarly to [Dovern & van Roye \(2014\)](#) who adopt this approach to identify financial stress shocks in the GVAR framework. Initially, we analyse the macroeconomic impact of an unexpected increase in the aggregate euro area systemic risk, in other words when all countries experience an unexpected one standard error (s.e.) increase in the level of risk. We then decompose the effect coming from domestic and foreign developments to examine the importance of cross-country spillovers. Finally, we investigate which countries drive the union systemic risk by presenting the peak responses after a country and a euro-regional shocks.

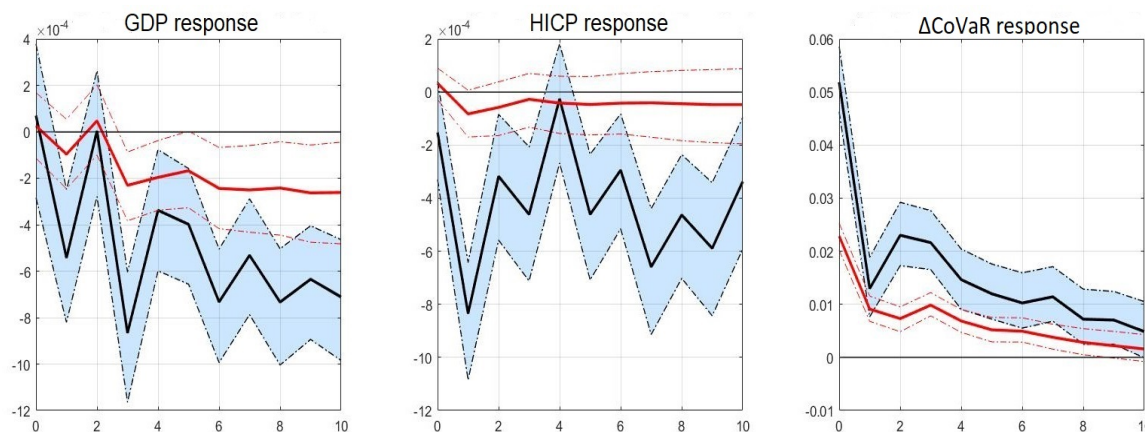
1.4.1 The impact of a EA systemic risk shock and the role of spillovers

The 2008 financial crisis highlighted how a systemic event, such as the collapse of Lehman Brothers, can substantially affect real economic activity. Monitoring financial stress has become a major concern for regulators especially since the Great Recession and the European sovereign debt crisis. The relationship between financial stress and business cycles is widely-documented in the literature (see [Kremer, 2016](#)). To examine the relationship between the systemic risk

¹⁹In the [Appendix, Table A1](#) describes the data series and their sources. The main data limitation comes from the shadow rate series that starts at 2004m09.

in financial markets and economic activity, we analyse the responses of output and prices following an unexpected increase in the aggregate level of systemic risk in the Eurozone.²⁰

Figure 1.2 Euro Area systemic risk shock



Note: The figure reports the SGIRFs of the Euro Area output, prices and systemic risk following a (positive) systemic risk shock. The identification strategy is based on the Cholesky decomposition. The lag selection is based on the Akaike information criterion (AIC). The shaded area represents the 68% confidence level, which is based on 200 bootstrap iterations.

Our empirical findings in Figure 1.2 indicate that an unexpected increase in systemic risk results in a persistent slowdown in economic activity. To decompose the effect coming from foreign developments, we present the responses when there is no direct spillover effect amongst countries with the red line and confidence interval. The findings indicate that spillovers account for two thirds of GDP's response, which highlights the importance of the spillovers that amplify the impact of systemic risk shocks.²¹ In the second column, prices present a similar pattern. Finally, by construction, the effect of foreign systemic risk shocks have a simultaneous impact on the union aggregate systemic risk. In both cases, we apply a shock to all euro area countries, however the initial aggregate response is almost twice as large in the presence of spillovers.

²⁰Dovern & van Roye (2014) examine the international transmission of a global financial stress shock on 20 major economies and its effect on economic activity.

²¹One of the important costs of financially integrated markets is that domestic economies are exposed to foreign credit shocks (Allen et al. 2011).

The results suggest that spillovers play an important role in the transmission of a systemic risk shock. To investigate the exposure of Eurozone economies to the rest of the union members, we look into the country SGIRFs.²² The results for both systemic risk measures, $\Delta CoVaR$ and *SovCISS* indices suggest that there is an unambiguous strong contagion amongst Eurozone economies. In the case of the micro-data based $\Delta CoVaR$, the transmission of the shock has immediate effect on the union members' financial systems and it fades out 10 periods after its occurrence. The initial response is similar for the market-based *SovCISS* with the only difference to be that the effect is more long lasting in the case of output.

The degree of interconnectedness is considerably higher in core countries, which are more exposed to systemic risk shocks at the union level. The responses of the countries in the Periphery are also significant but smaller in magnitude on average. The responses in this region are driven mostly by domestic factors, whereas the exposure to core economies and the spillover effect are weak or insignificant. Therefore, our results support that the main transmission channel of systemic risk is running from peripheral to core countries. Our findings are consistent with [Gorea & Radev \(2014\)](#) who estimate the market-perceived probability of joint default of the Euro Area countries and they find evidence of an active contagion transmission channel from the Periphery towards the Core region. Financial risk spillovers is one of the main disadvantages of the high degree of financial integration in the monetary union, which in this case appears to be less beneficial for core economies.

The most exposed country, both in terms of the increase in systemic risk and output losses, is Greece, which was vulnerable due to the government debt crisis (see [Grammatikos & Vermeulen, 2012](#)). In the vast majority of countries, the spillover effect plays an important role and results in deeper recessions. Italy and Spain present also considerable exposure to the union shock, which is, however, mostly driven by domestic factors, whereas the spillover effect has an insignificant or negative effect at the countries' risk level. On the other hand, the decline in GDP of France and Germany is close to the Euro Area average. When we introduce the

²²see [Appendix, Figure A1a and A1b](#).

foreign variables matrix and the spillover channel, their output losses are significantly higher than the rest of the union members. It is worth noticing that in some core economies, namely the Netherlands, Belgium and Austria, when we mute the foreign variables from the country equation, the impact of systemic risk shocks on output is insignificant or even positive.

Our findings are in line with the previous empirical evidence which indicates that core economies are exposed to systemic risk spillovers from the Periphery, whereas the latter is more affected by the domestic macro-financial environment. Most importantly, we find that systemic risk shocks have a sizeable adverse effect on the economic activity and that the high degree of financial contagion is a strong mechanism through which domestic shocks are propagated to other economies.²³ Spillovers play an important role in the transmission of the shock, which highlights the need for close monitoring of systemic risk at the country level but also the financial contagion across the union members.²⁴

1.4.2 Which countries drive EA systemic risk contagion?

In this section we examine the systemic importance of two Euro Area regions and individual countries. Table 1.1 illustrates the peak systemic risk responses following regional and country specific shocks.²⁵ A shock in the two Euro Area regions has a quantitatively similar effect on the union aggregate, however, Periphery only accounts for 22% of union's cross-country claims (based on BIS data) and one third of the union's GDP that indicates that they are disproportionately systemically important in comparison to core countries. In line with our findings in previous sections, we observe that spillovers are stronger from periphery to core economies than from core to the periphery. Italy is the most systemically important country in

²³However, as noted by Allen et al. (2011), spillovers should not undermine the rationale of financial integration in the euro area since the gains from diversification and risk sharing outweigh potential costs. In addition, they support that some of the costs arisen from the contagion effects can be attributed to the lack of policy coordination and they can be avoided.

²⁴Hollo et al. (2012) document a sharp decline in economic activity following a CISS shock, especially in period of distress.

²⁵In the vast majority of the cases, the transmission of the systemic risk is immediate and the peak response is being observed in the first period after the occurrence of the shock.

the euro area, followed by Spain.²⁶ The largest economy in the monetary union, Germany, is also systemically important, especially across core countries. We observe that core countries are highly interconnected with a country level shock having a strong impact on the rest of the economies of the region but a weak effect on peripheral economies.²⁷

Table 1.1 Country and regional systemic risk shocks

Systemic risk:	$\Delta CoVaR$			SovCISS		
Regional Shocks	Euro Area	Core	Periphery	Euro Area	Core	Periphery
Core	3.32**	●	0.83**	2.04**	●	1.23**
Periphery	3.31**	3.52**	●	3.08**	2.34**	●
Country Shocks	Euro Area	Core	Periphery	Euro Area	Core	Periphery
DEU	1.82**	3.10**	-0.36**	1.26**	1.77**	0.30
FRA	2.19**	3.00**	0.73*	0.87**	1.42**	-0.10**
NDL	1.70**	2.51**	0.70*	1.06**	1.08**	1.03**
BEL	0.96**	1.23**	0.47*	0.81**	0.78**	0.87**
AUS	0.74**	0.94**	0.39*	0.62**	0.60**	0.67**
ITA	2.86**	2.96**	2.68**	2.74**	2.07**	4.06**
ESP	2.35**	2.84**	1.68**	2.07**	1.54**	3.25**
GRE	1.19**	1.32**	0.96**	0.90**	0.70**	1.26**
POR	0.70**	0.86**	0.49**	0.62**	0.48**	0.90**
IRE	1.50**	1.83**	0.94**	0.57**	0.45**	0.85**

Note: The table illustrates the (positive) peak regional SGIRF for systemic risk following an one standard error increase in the systemic risk at regional and country level. For the identification of the shock we apply the Cholesky decomposition with the ordering being GDP, Prices and systemic risk. For the vast majority of the cases, the impact of systemic risk is immediate and the peak response is being observed in the first period after the shock occurs. Notation of ** and * indicate statistically significant results at 90% and 68% respectively.

²⁶To quantify the systemic importance of a country, we look at the increase of the euro area aggregate systemic risk index following a country level shock as depicted in the first column of Table 1.1.

²⁷Eller et al. (2017) apply a GVAR model to examine the international impact of a fiscal policy shock in Germany. Similarly to our findings they found that mostly core economies affected by the positive cross-border spillovers. The effect is positive but weaker for Periphery. They also recognize that the transmission of the shock is through the financial channel.

On the other hand, peripheral economies' shocks affect both regions. It is worth noticing that small economies appear to be also systemically important. Portugal and Ireland account together for less than 4% of Eurozone's GDP,²⁸ but their contribution to aggregate systemic risk is significant. The results are qualitatively similar if we use *SovCISS* instead of $\Delta CoVaR$. Overall, the evidence suggests that peripheral countries are a significant source of systemic risk for the euro area. The need for monitoring the spillovers from the periphery has been documented before in the literature. According to [Constancio \(2012\)](#), contagion from the peripheral countries has contributed to union-wide financial stress, especially after July 2011 and the sovereign debt crisis. He also highlighted the strong degree of stress transmission from Italy and Spain to Greece, Portugal and Ireland's government bonds. Similarly, [Caporale & Girardi \(2013\)](#) analyse the spillovers in terms of borrowing cost from fiscal imbalances in the euro area economies. They find that negative externalities from Italy and other peripheral countries could lead to crowding out effects for the euro area consumption and an increase in the government bond rates in all countries and regions.

1.5 Monetary policy and systemic risk

Central banks have a pivotal role in supervising and supporting financial stability. An extensive literature has focused on the *risk-taking channel* of monetary policy that suggests that accommodative monetary policy encourages more risk-taking behavior of financial institutions ([Borio & Zhu, 2012](#)).²⁹ However in the period of the ZLB the empirical evidence is mixed and another strand of the literature argues that expansionary unconventional monetary policy supported the financial system during the crisis (see [Gambacorta et al., 2014](#) and [Boeckx et al., 2017](#)).³⁰

²⁸The percentage is estimated based on the average quarterly GDP for the examined period 2001-2018.

²⁹[Neuenkirch & Nöckel \(2018\)](#) argue that euro area expansionary monetary policy shocks lead to a decrease in the banks' lending standards and consequently to an increase in systemic risk. More recently, [Faia & Karau \(2019\)](#) find evidence of the *risk-taking channel* in the US, whereas in the euro area there is evidence of the price puzzle and the systemic risk responses are insignificant. They apply a Panel VAR to analyse the effect of monetary policy shocks on $\Delta CoVaR$, using [Wu & Xia \(2016\)](#) shadow rate to capture unconventional policies.

³⁰Both papers use the assets of the ECB balance sheet as an instrument of monetary policy and they argue that these policies do not increase the volatility of the financial system (VIX) or systemic stress (CISS) respectively.

This paper sheds light on the non-linear relationship between monetary policy and systemic risk and empirically investigates the role of cross-country spillovers in the transmission of monetary policy shocks. We divide the sample period into two sub-periods with the cutting point being when the shadow rate becomes negative. The specific sub-samples are being selected so we can analyse the impact of the monetary policy before and after the period of the ZLB. For the first sample period, our results below are in line with the *risk-taking channel*, whereas in the second period of the ZLB and of the unconventional monetary policies, expansionary policy shocks lead to a decline in systemic risk. Our findings are in line with [Leitner et al. \(2021\)](#) who find that in the period after 2007, expansionary conventional monetary policy, near term guidance and forward guidance result in a decline in systemic risk whereas QE shocks increase systemic risk.³¹ Most importantly, we find that spillovers, amongst Eurozone economies, amplify the effectiveness of monetary policy, with their effect however to be heterogeneous across time and Euro Area regions.

1.5.1 Identification of monetary policy shocks

In our analysis, to account for changes in the monetary policy stance, we use the shadow rate by [Wu & Xia \(2016\)](#), which is being modeled as a common (global) variable. However, the identification of a monetary policy shock using the shadow rate as a policy instrument and Cholesky decomposition is problematic, since it results in a price puzzle (see [Sims, 1992](#)) as in [Faia & Karau \(2019\)](#). In other words, an expansionary monetary policy shock to result in lower prices and in a drop in economic activity. To address this issue we follow the new strand of the literature that uses the central bank's announcements to identify monetary policy shocks. For that purpose, we use data from [Altavilla et al. \(2019\)](#) who construct a Euro Area event-study database of monetary surprises (EA-MPD) by measuring the asset price changes following a policy announcement window. By looking at the press release window and the very short-end

³¹[Kapinos \(2020\)](#) finds that expansionary news shocks result in lower systemic risk during the zero lower bound period.

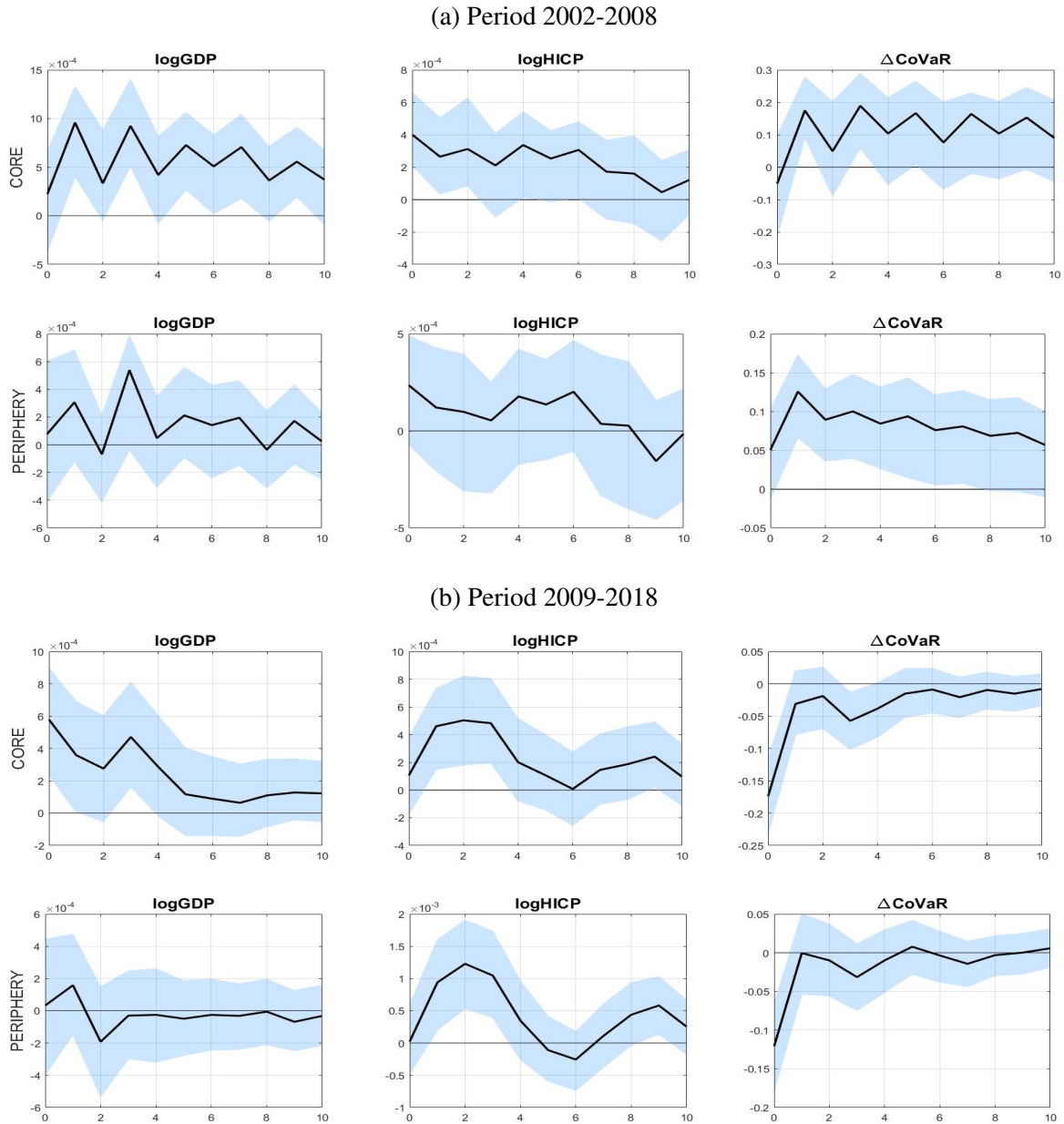
of the yield curve, they identify the ‘*target*’ surprises following the work of [Gurkaynak et al. \(2004\)](#). The main advantage of this methodology is that it identifies more precisely monetary surprises by capturing new policy tools, such as Forward Guidance (FG) and Quantitative Easing (QE).

This is one of the first papers that incorporates high-frequency shocks into the GVAR model.³² For that purpose, we follow [Paul \(2020\)](#) who shows that the structural estimation of a proxy SVAR model could be carried out by using the monetary policy shock series ordered first in a standard recursive VAR model. Therefore, we include the externally identified shock in the model as an exogenous variable that has a contemporaneous effect on the macroeconomic variables and systemic risk. Similar analysis has been carried by [Plagborg-Møller & Wolf \(2021\)](#), [Miranda-Agrippino \(2016\)](#) and [Jarociński & Karadi \(2020\)](#) who also incorporate high-frequency surprises ordered first in a VAR model. Since all the variables in the model are also expressed in levels and not in differences, in line with [Coibion \(2012\)](#) and [Barakchian & Crowe \(2013\)](#), we use the cumulative shock series to identify the policy shocks and we let the series to take values equal to zero for months with no announcements.

[Figure 1.3](#) presents the responses following an expansionary monetary policy shock for the two examined time periods. Target monetary surprises used for the estimation capture the market expectations about changes in policy rates. By incorporating the high-frequency shocks into the model the price puzzle disappears. For the first period, an accommodative policy shock results to an increase in GDP and prices. In accordance with the results shown above, the regional and country responses are not homogeneous. The impact is stronger in core countries and drive the Euro Area aggregate response, whereas the peripheral economies present insignificant results. The consequence of an unexpected monetary expansion is the increase in systemic risk in both regions, which is line with the “*risk-taking channel*”.

³²[Goodhead \(2021\)](#) uses the EA-MPD surprises in a Proxy SVAR to study the effect of forward guidance and yield curve compression surprises on Euro Area macro-financial variables. [Alzuabi et al. \(2020\)](#) use monetary policy shocks series constructed based on the shocks series by [Romer & Romer \(2004\)](#) for the US economy in the GVAR framework.

Figure 1.3 Monetary policy shock: Sub-period analysis



Note: The figure reports the SGIRFs of output, prices and systemic risk following an expansionary monetary policy shock. The shock is defined as one s.e. decrease in the exogenous cumulative target surprises series provided by [Altavilla et al. \(2019\)](#) and the identification strategy is based on the Cholesky decomposition. The first two rows present the responses of the sub-period 2002-2008 and the last two of the second sub-period until 2018. The lag selection is based on the Akaike information criterion (AIC). The shaded area represents the 68% confidence level, which is based on 200 bootstrap iterations.

On the second period, that shadow rates become negative, the empirical evidence underlines the asymmetric transmission of monetary policy across the Euro Area, not only in terms of output, but also with regards to financial stability. A negative monetary policy shock, as captured by *target* surprises, mitigates systemic risk significantly in both regions. In other words, an unexpected monetary expansion from ECB leads to a reduction of the Euro Area systemic risk aggregate. The results also support that monetary policy, especially in the period of the ZLB, exhibit significant cross-country heterogeneity, since it affects primarily the Core region. Output and price level increase following a negative monetary policy shock, with only the results for core economies being statistically significant.

This paper contributes to the literature of monetary policy's transmission asymmetries. [Georgiadis \(2015\)](#) apply a GVAR model for the euro area to analyse the impact of monetary policy on output and inflation. He finds significant heterogeneity amongst countries driven by structural characteristics such as the industry structure and more specifically the percentage of output associated with sectors sensitive to interest rate but also labor market variables. [Burriel & Galesi \(2018\)](#), in a euro-area GVAR model, find union-wide significant asymmetries in the transmission of monetary policy with countries with less fragile banking system to benefit the most.³³ Other characteristics such as the ease of doing business or the low level of GDP per capita result in higher output gains. However, the literature is limited regarding the potential asymmetries of ECB's monetary policy on the financial variables. According to the aforementioned literature, the reasons that could explain the heterogeneity of responses is the structure of the financial system and the domestic macroeconomic environment, since core economies were not affected considerably by the sovereign debt crisis.

For robustness purposes, we employ *SovCISS* as an alternative indicator for systemic risk. The results using an alternative measures of systemic stress such as *SovCISS*. In both cases similar patterns are being observed. The main difference in the responses between the two

³³[Ciccarelli et al. \(2013\)](#) find asymmetries on the effect of monetary policy on output across countries and they suggest that the monetary transmission mechanism depends on the financial fragility of the sovereigns, banks, firms and households.

different specifications is the timing of the responses. The micro data-based, $\Delta CoVaR$, leads to an immediate decrease of systemic risk, whereas in the case of *SovCISS* the lowest point was reached after 2 quarters. In addition, we control for macroprudential policies which could impact systemic risk. We employ the data series index constructed by [Cerutti et al. \(2017\)](#), which enters the model as a domestic variable for the eleven examined economies. We re-run the model for the two sub periods and in both cases the inclusion of the new variable does not change the results. Although the analysis of macroprudential policy shocks is out of the scope of this paper, it is worth noticing that prudential policies appear to effectively mitigate systemic risk.³⁴ Cross-country spillovers of prudential policies account for a significant fraction of these responses and is a topic that is worth exploring further in future research.

1.5.2 The role of systemic risk spillovers

In previous sections we showed that there are considerable systemic risk spillovers across the monetary union. Contagion and interconnectedness amongst financial institutions play an important role in the transmission of the monetary policy (see [Kabundi & De Simone, 2020](#)). For that reason, we re-run the model when muting the cross-country spillovers across countries to decompose the effect of monetary policy into the direct and the indirect component.³⁵ [Figure 1.4](#) illustrates the importance of taking into consideration the potential cross-country risk spillovers for the conduction of monetary policy. We present the Euro Area responses following an expansionary monetary policy shock for the period after 2009. In the first column, the spillovers account for 13% of the variation of the Euro Area GDP aggregate response.

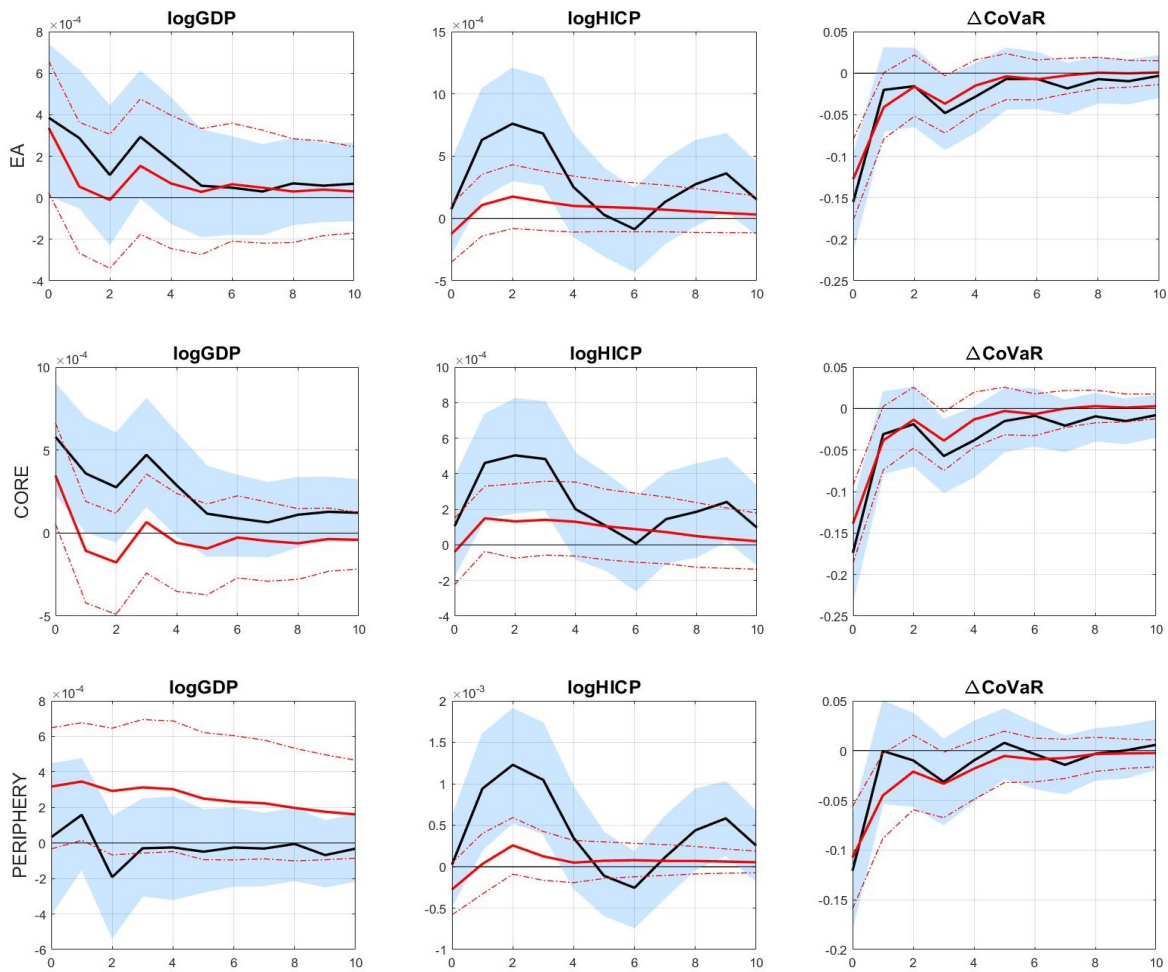
The role of spillovers however varies across the two regions. In core economies, the interconnectedness appears to be beneficial in terms of output gains with spillovers to account

³⁴[Cerutti et al. \(2017\)](#) suggest that macroprudential policies have a significant effect on credit development. Similarly, [Fernandez-Gallardo & Paya \(2020\)](#) find that macroprudential policy results in a decline in CISS and credit growth.

³⁵Similarly, [Burriel & Galesi \(2018\)](#) attribute a considerable fraction of the monetary shocks' impact on the spillovers amongst countries, which amplifies the aggregate effect.

for a fraction of 40% of GDP SGIRFs. On the other hand, peripheral countries that suffered from severe recessions during the examined period, present negative externalities across the region. When we take into consideration the spillover channel the impact is insignificant and less than half than before.

Figure 1.4 Monetary policy shock: Spillovers effect



Note: The figure reports the SGIRFs of output, prices and systemic risk following an expansionary monetary policy shock. The shock is defined as one s.e. decrease in the exogenous cumulative target surprises series provided by Altavilla et al. (2019) and the identification strategy is based on the Cholesky decomposition. The black line stands for the benchmark model and the red line when we mute the cross-country spillovers. The responses include the aggregate euro area and two regions; core and periphery. The examined period is 2009m1–2018m9. The lag selection is based on the Akaike information criterion (AIC). The shaded area represents the 68% confidence level, which is based on 200 bootstrap iterations.

With regards to the impact on systemic risk, spillovers account for 17.4% of the response. In this case the contagion channel has a positive effect across both regions. In core economies, a fraction of more than 20% can be attributed to the cross-country spillovers, whereas in the case of the peripheral economies this percentage is at 11.6%. Our empirical findings highlight how misleading can be, for the policymakers, to ignore the spillovers across the monetary union, both in terms of the macroeconomic impact but also the response of the financial markets.

1.5.3 How QE affects systemic risk?

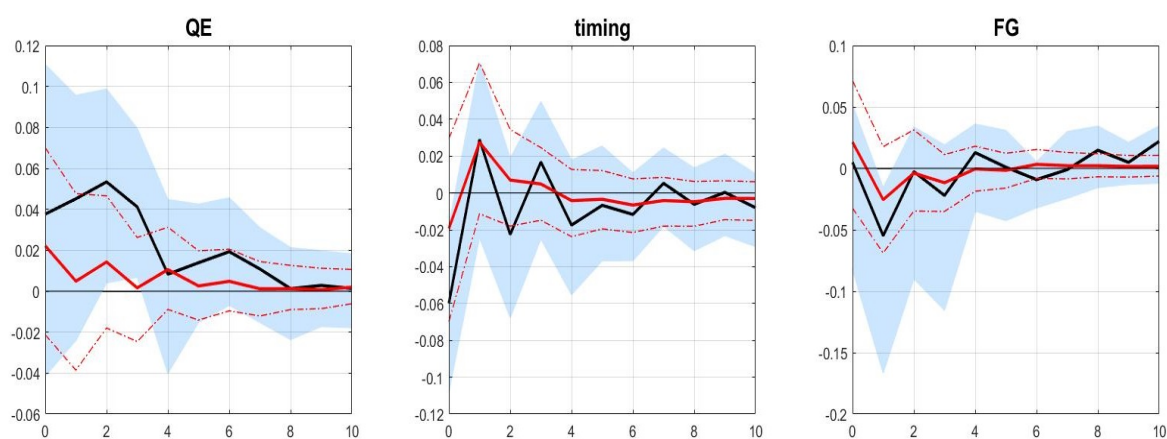
Target surprises were dominant in the policy decision announcement window, however [Altavilla et al. \(2019\)](#) extend the analysis to capture press conference window surprises. The first two factors are ‘*timing*’ and ‘*forward guidance*’, which capture the market expectations channel in the short run and medium run respectively. They also isolate the QE surprises by using the method of [Swanson \(2017\)](#) in the post-2014 period. Following their work, we focus on the period after 2014 and we incorporate one instrument at a time to extrapolate each component separately and to examine how they affect systemic risk. The modelling approach is identical to the ‘*target*’ surprises as the cumulative shock series are modelled as exogenous variables in the GVAR model structure.

Our results indicate that the expectation channel has a positive relationship with systemic risk. In other words, expansionary monetary policy announcements lead to a systemic risk reduction. The effect of the ‘*timing*’ shock, that refers to the short-term expectations has an immediate strong effect and it results to an increase in output and a decrease in systemic risk, but also causes inflationary pressures. The ‘*forward guidance*’ factor presents similar results leading to a decline in systemic risk a few months after the occurrence of the shock.³⁶ It is worth noticing though that in both channels we observe considerable heterogeneity across regions, in

³⁶See [Zlobins \(2020\)](#) who examines the macroeconomic effects of the ECB’s forward guidance (FG) in the euro area and [Möller \(2020\)](#) studies the role of ECB communication as a determinant of Eurozone’s banking system systemic risk.

line with the previous findings. The euro area systemic risk response is predominately driven by core economies, whereas peripheral countries experience in some cases higher systemic risk, inflationary pressures and weak growth. The findings are consistent with [Fendel et al. \(2020\)](#), who document that ECB communication affects the economies differently. Most specifically, economies with a low solvency rating are affected across different maturities, whereas the impact for countries with a high solvency rating is significant only in short term.

Figure 1.5 Conference window surprises



Note: The figure reports the SGIRFs of systemic risk following an expansionary monetary policy shock. The shock is defined as one s.e. decrease in the exogenous cumulative target surprises series provided by [Altavilla et al. \(2019\)](#) and the identification strategy is based on the Cholesky decomposition. The first column refers to QE surprises followed by timing and Forward Guidance shocks. The examined period is 2014m1-2018m9. The lag selection is based on the Akaike information criterion (AIC). The shaded area represents the 68% confidence level, which is based on 200 bootstrap iterations.

The findings from QE shocks indicate that the asset purchases program led to an increase in the aggregate systemic risk. The first column in [Figure 1.5](#) presents the systemic risk responses following a QE shock, which is increasing across the euro area with the highest responses observed in core economies providing evidence of the *risk-taking channel* similarly to expansionary shocks in normal times. In terms of output, the shock results to a positive but statistically insignificant effect in most of the countries.³⁷

³⁷Detailed results available upon request.

Our findings indicate that the initiation of the QE program creates a trade-off for the ECB between economic growth and financial stability. In 2016, [Mario Draghi](#), the then president of the ECB, recognized this adverse effect and he clarified that is not the goal of the ECB to ensure the profitability of any particular institutions. More specifically, QE programs can reduce the profitability of financial institutions such as insurance companies which are exposed to the decline in interest rates.³⁸ Part of the literature also emphasizes the negative impact of QE on financial stability. [Gern et al. \(2015\)](#) and [Claeys & Leandro \(2016\)](#) support that prolonged expansionary monetary policies encourage risk-taking beyond the socially desirable. Additionally, it may result in asset prices disconnecting from the fundamentals and fueling asset price bubbles, which can trigger a banking crisis in the medium or long term. In conclusion, the different channels of unconventional forms of monetary policy present mixed results regarding their impact on systemic risk. Despite the increase in systemic risk caused by the adoption of the QE program, expansionary monetary policy shocks (signalling and target/policy rate surprises) appear to be an important tool for mitigating systemic risk.³⁹

Finally, we decompose the response coming from domestic factors and the spillover channel. The empirical evidence, as presented in [Figure 1.5](#), highlights the important role that contagion plays on the transmission of the signalling shocks. In both cases of timing and forward guidance, if we do not take into consideration the spillover effect the systemic risk responses, become insignificant. When the contagion effect is muted, the effect of a QE shock also becomes insignificant. Therefore, similarly to policy rate announcements, cross-country spillovers play an important role in the transmission of conference window surprises.

³⁸In our sample insurance companies account for 26% of the firms' Market Capitalization, therefore we expect that the asset purchase program will result to a deterioration of the financial sector index. See [Table A2](#) presents the composition of the portfolio of financial firms that are being used for the systemic risk index.

³⁹Similarly to [Claeys & Darvas \(2015\)](#) who support that the overall benefits of the UMP outweigh the potential risks.

1.6 Conclusions

Since the financial crisis, systemic events have become a major concern for regulators and policymakers. According to the [ECB Report \(2009\)](#), the analysis of systemic risk should consider both endogenous and exogenous sources of risk. In this paper we quantify the financial exposure of euro area economies to other union members and its impact on economic activity. To capture systemic risk, we present a new country-level index based on micro-data and the $\Delta CoVaR$ methodology, which we then incorporate into a GVAR model to examine the spillovers across euro area economies. Our empirical evidence suggests that there are considerable systemic risk spillovers across the union. More specifically, we observe high degree of financial contagion amongst core countries, which is not spreading out to the Periphery. On the other hand, peripheral economies are affected mostly by domestic factors and they are a source of systemic risk for the EA. At the country level, systemic risk shocks in small economies have a sizeable effect on the other member countries, which highlights the need for monitoring financial risk not only at the aggregate level. Additionally, we study the impact of systemic risk on economic activity. Our findings suggest that a euro area systemic risk shock results in a significant drop in GDP across the union and that the responses are mostly driven by the spillover channel that accounts for around two thirds of the responses' variation.

Our results indicate that spillovers also play an important role in the transmission of monetary policy. We find that in normal times a monetary contraction reduces systemic risk. However, during the ZLB period, when the unconventional forms of policy were introduced, the relationship is reversed, and expansionary monetary shocks lead to a decrease in the risk level. We also find that during the conference window surprises, near term guidance mitigates systemic risk, whereas the opposite effect is being observed for QE shocks. Most importantly, the evidence suggests that neglecting cross-country spillovers would underestimate the impact of monetary policy shocks, since they account for a substantial fraction of the systemic risk responses.

Chapter 2

House prices, (un)affordability and systemic risk

Joint with Efthymios Pavlidis and Ivan Paya

2.1 Introduction

The financial crisis of 2007/08 and the Great Recession that followed have led to a vast interest in housing and its effect on the economy. A substantial amount of research has been devoted to better understand the role of housing markets in the lending sector and its effect on the macroeconomy (e.g. [Favilukis et al. 2017](#), [Piazzesi & Schneider 2016](#), [Jordà et al. 2016](#), [Guerrieri & Iacoviello 2017](#), [Gertler & Gilchrist 2018](#)). Another strand of literature has examined the impact of housing unaffordability on socio-economic outcomes such as labour supply and demand, consumption, savings, education, health and income inequality (e.g. [Quigley & Raphael 2004](#), [Campbell & Cocco 2007](#), [Zabel 2012](#), [Gabriel & Painter 2018](#)). Policymakers have also expressed their concern about the issue of unaffordability. For instance, in the UK, the housing market has been defined as a broken market by the government in the White Paper issued by [Department for Communities & Local Government](#) in 2017.

In this chapter, we focus on the impact of the housing market and, in particular, housing unaffordability on financial stability. The literature in this area argues that imbalances in the housing market can directly affect the stability of the entire financial system. The banking sector is the main channel of this effect and there are two transmission mechanisms. The first one, the so-called collateral channel, implies a positive relationship between house prices and financial stability (see [Kiyotaki & Moore 1997](#), [Goodhart & Hofmann 2008](#), [Daglish 2009](#), [Niinimäki 2009](#)). The argument is that rising house prices increase the value of the collateral held by banks enhancing their total capital. This increase in the value of the collateral in turn has two effects. First, the supply of credit to the real estate sector increases. Second, the probability of default drops. Likewise, increasing house prices significantly reduce the probability of default of mortgage borrowers and potential losses to lenders, resulting in a more stable banking industry. The second effect, the deviations hypothesis, implies a negative relationship between persistent deviations of house prices from fundamentals, or house price bubbles, and financial stability (see [Bernanke & Gertler 1995](#), [Allen & Gale 2000](#), [Allen & Carletti 2013](#)). This effect is due to an increase in moral hazard problems, and to excessive risk taking and high risk accumulation.¹ [Koetter & Poghosyan \(2010\)](#), in their analysis of regional house prices and banks in Germany, test for these two transmission mechanisms. Their results support both hypotheses and conclude that increases in house prices result in a more stable banking system, but that in periods when prices deviate from fundamental values, the probability of distress is higher.

Overall, the existing literature on housing markets and financial stability has focused on issues such as default rates but it has not yet explored the relationship between the real estate (RE) sector and systemic risk. We argue that the real estate sector contributes to the systemic risk of the financial sector, partly through its impact on the banking sector.² In this chapter,

¹[Ferrari et al. \(2015\)](#) consider the housing market as an important source of systemic risk and they present a novel graphical approach to identify early signs of real estate related crisis. They conclude that overvalued properties and increasing household debt are early indicators of a crisis.

²[Li et al. \(2016\)](#) use Contingent Claims Analysis to measure systemic risk in the RE sector in China. They find that a systemic risk shock results in a negative but temporary effect on banking returns. [Meng et al. \(2014\)](#) use

we quantify for the first time the systemic risk of the real estate sector and examine the role of unaffordability in its build-up. As we previously discussed in the first chapter, although a vast literature on systemic risk has emerged in the last decade and systemic risk is nowadays a widely accepted concept, there is still no consensus about its exact definition, neither a universally accepted measure. [Adrian & Brunnermeier \(2016\)](#) argue that losses at the firm level that threaten the capacity of the entire system and potentially harm the real economy could be described as systemic risk. On the basis of this definition, the authors propose a systemic risk measure, $\Delta CoVaR$, which we employed in the previous chapter focusing at the country level risk. In this chapter, $\Delta CoVaR$ will be our measure of systemic risk, however in this case we focus only on the real estate market and not the importance of other financial institutions. Moreover, our empirical analysis focuses on the UK because of the importance of its financial sector in the international financial system and because, as mentioned above, its housing sector presents increasing challenges for the public and for policymakers.

To estimate the $\Delta CoVaR$ of the UK RE sector, we use a large sample of RE firms listed on the London Stock Exchange. Overall, the results of our analysis suggest that there is a strong tail dependency between the RE and the financial sector, with a $\Delta CoVaR$ of 8.4%. At the cross-sectional level, we find that systemic risk is associated with firm characteristics, in particular, with firms' size and systematic risk as measured by the CAPM beta. Movements of $\Delta CoVaR$ over time, on the other hand, are associated to a number of housing variables, the macroeconomic environment, and firm characteristics. In line with the collateral and deviations hypotheses, our findings suggest that, while sustainable real house price changes are associated with a decline in systemic risk, house price exuberance (as measured by the *GSADF* test of [Phillips et al. \(2015a,b\)](#)) and rapid increases in housing unaffordability are associated with higher levels of systemic risk. With respect to macroeconomic variables, we find that increases in the Bank of England base rate as well the unconventional monetary policies adopted since

Random Matrix Theory to investigate the systemic risk and spatiotemporal dynamics of the US housing market. Their findings suggest that the increasing risk since early 1977 resulted to the 2007 bubble.

2009 are inversely related to systemic risk. Finally, undertaking the analysis separately for commercial and for residential real estate companies yields qualitatively similar results.

The rest of the chapter is organised as follows. Section 2.2 presents the methodology to measure systemic risk, the data employed in the cross-sectional analysis, and the corresponding results. Section 2.3 describes the dynamic model, the variables employed in the time series analysis, and the main results of the chapter. Finally, section 2.4 provides brief conclusions.

2.2 Methodology

2.2.1 Measuring systemic risk

As previously stated, the estimation of systemic risk is based on the *CoVaR* methodology by [Adrian & Brunnermeier \(2016\)](#). *CoVaR* builds on the concept of value at risk, *VaR*, but also accounts for possible interactions between financial institutions. Our analysis focuses on a portfolio of UK real estate firms and the Conditional *VaR* is defined as the *VaR* of the financial system (s) given that the examined real estate firm (i) is under distress.

The mathematical representation of *CoVaR* is:

$$P(R^s \leq CoVaR_q^{s|i} | R^i = VaR_q^i) = q,$$

where R stands for the year-on-year return and q is the confidence level. *CoVaR* captures the association between the risk of the overall financial sector and a particular institution's stress event and it can be used to inform prudential policies.³ The methodology has already become a

³We note that the systemic risk measure *CoVaR* examines the system's stress conditional on an individual firm's (or portfolio of firms) stress. This implies that the conditioning set to compute the system's stress varies cross-sectionally. The focus is therefore on the behaviour of the financial system's returns assuming a RE firm (or portfolio of firms) is in distress and to measure their tail dependency employing $\Delta CoVaR$. This approach differs from alternative measures of systemic risk that examine a firm's stress conditional on systemic risk (or on a systemic event such as a financial crisis). This is the case of the Systemic Expected Shortfall (SES) measure developed by [Acharya et al. \(2017\)](#). The attractive feature of SES is that the conditioning set is held constant across firms (as a way of ranking the systemic risk of firms), while *CoVaR* has the advantage of keeping the analysis within the standard regulatory tool of *VaR*.

popular estimation method of systemic risk and has been employed in many applications (see [Fong et al. 2009](#), [Borri et al. 2014](#), [Gauthier et al. 2012](#), [de Mendonça & da Silva 2018](#)).

The marginal contribution of a particular real estate firm to the system's risk, $\Delta CoVaR$, is computed by comparing the $CoVaR_q$ with the one in normal times, at the median ($q = 0.5$)⁴:

$$\Delta CoVaR_q^i = CoVaR_q^{s|R^i=VaR_q} - CoVaR_q^{s|R^i=VaR_{0.5}}.$$

To estimate the aggregate systemic risk in the real estate sector, we construct the RE portfolio using a market-capitalisation weighted average of 81 UK real estate firms listed in the London Stock Exchange.⁵ The list of companies together with descriptive statistics are displayed in [Appendix, section B.2](#). The financial system index consists of all the banks, insurers, real estate companies, general financial services firms and investment trusts in the FTSE350 index. The banking sector index is constructed by using data for all the banks included in the FTSE350 index. The frequency of the data is monthly and the sample period is from June 2002 until July 2018.⁶

Table 2.1 Data description of sector indices and RE portfolio

Index	Mean Returns	St.Deviation	$VaR_{95\%}$
Financial Sector	0.50%	4.43	7.15%
Banking Sector	-0.45%	6.69	11.41%
RE Portfolio	0.35%	5.46	8.59%
Systemic Risk Estimates			
$CoVaR_{95\%}^{fin RE}$	$\Delta CoVaR_{95\%}^{fin RE}$	$CoVaR_{95\%}^{bank RE}$	$\Delta CoVaR_{95\%}^{bank RE}$
12.42%	8.43%	16.72%	8.46%

Note: The table reports summary statistics for the market indices and the real estate portfolio. The sample period is 2002m6-2018m7 and all the quantities are expressed in monthly frequency. All the estimates of risk are expressed in absolute values.

⁴In the [Appendix, section A.1](#), we present a detailed description of the step-by-step estimation of $\Delta CoVaR$.

⁵This data is obtained from Datastream and Morningstar.

⁶The frequency and period of the analysis is restricted by some of the variables needed to implement the dynamic model described in the next section.

In Table 2.1 reports descriptive statistics together with the VaR of the RE portfolio, the financial system, and the banking sector. As can be seen from this table, the overall financial system index is the more diversified of the three, and displays the highest average return and the lowest variability and tail risk for this sample period. The unconditional 95th percentile VaR of the financial system index is 7.15%. Conditioning on the RE sector being under stress, the VaR increases by 74%. These statistics suggest a strong tail dependency between the RE sector and the financial system. The RE sector is therefore *systemic as a herd*. Following the theoretical arguments and stylised facts discussed in the introduction, we conjecture that this association between stress in RE firms and the overall risk of the financial system is possibly transmitted through the banking sector. The last row of table shows that the risk of the banking sector is significantly higher when the RE sector risk is high,⁷ providing support to this argument.⁸ Overall, the results in this section already endorse the ECB's recommendation in their 2015 report of close supervision to the RE sector and the convenience of macroprudential tools designed for this purpose. We proceed with the cross-sectional analysis of systemic risk and RE firm characteristics.

2.2.2 Systematic, idiosyncratic and systemic risks

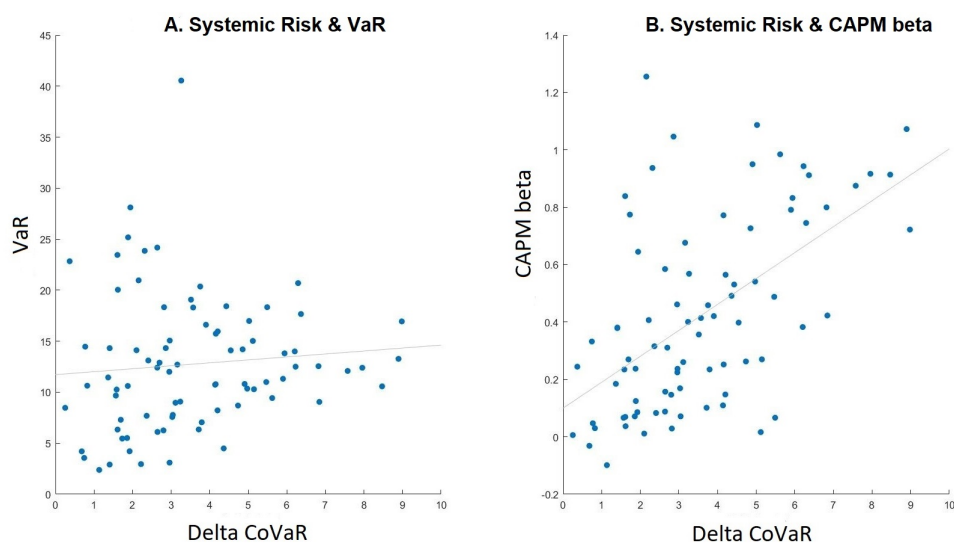
Idiosyncratic and systemic risk are different concepts. The former only affects a particular firm and will not ripple out to the rest of the system, while the latter is about the risk that a particular firm induces to the overall financial system. Figure 2.1a shows that there is no strong cross-sectional connection between the VaR and systemic risk. This highlights the importance of having indicators that can capture systemic rather than idiosyncratic risk for macroprudential

⁷As a robustness exercise, we have also computed the systemic risk measures using the FTSE350 RE index instead of the portfolio of the 81 RE firms described above. The results are similar. We decided to employ the portfolio of 81 companies instead of only the ones in the FTSE350 RE index in our main analysis in order to have a more comprehensive and representative sample of the sector.

⁸The banking sector's VaR increases by 47% conditional on the RE market being under distress. We have also reversed the analysis to check if in periods when banks are stressed, the RE firms' risk increases. The $\Delta CoVaR_{bank}^{RE}$ is 6.78%. Although the effect is sizeable, we note that it is lower than $\Delta CoVaR_{RE}^{bank}$, which may be indicative that the effect of the correlation runs from the real estate sector to the banking institutions.

purposes. The findings are in line with [Adrian & Brunnermeier \(2016\)](#) who support that there is only a weak link between an institution's risk in isolation (VaR), and its marginal contribution to systemic risk. However, they point out that there is a strong positive time series relationship. They argue that a potential explanation behind the lack of cross-section correlation between the two measures of risk is the interlinkages of each firm with the rest of the financial system.

Figure 2.1 Systemic risk, VaR and CAPM beta



Note: Figure reports the average systemic risk of the examined real estate firms against their idiosyncratic (VaR) and systematic risk (CAPM beta). The estimation is based on year-on-year monthly returns and the period 2002m6 to 2018m7.

For example, we observe that Harworth Group and Capital & Regional have the highest VaR values of the sample with 24.17% and 23.85%, respectively. However, the values of $\Delta CoVaR$ for these two firms are low, 2.63% and 2.35%. Therefore, when the two RE firms are in distress, the VaR of the system only increases slightly. On the other hand, British Land and Land Securities, two of the biggest RE firms in the UK market, contribute significantly to the systemic risk (8%), but the VaR of both of them is relatively low at 10.6% and 12.4%, respectively. Similarly, there is a difference between systemic and systematic or market risk. Systematic risk is the inherent part of the risk of an asset coming from the market that cannot

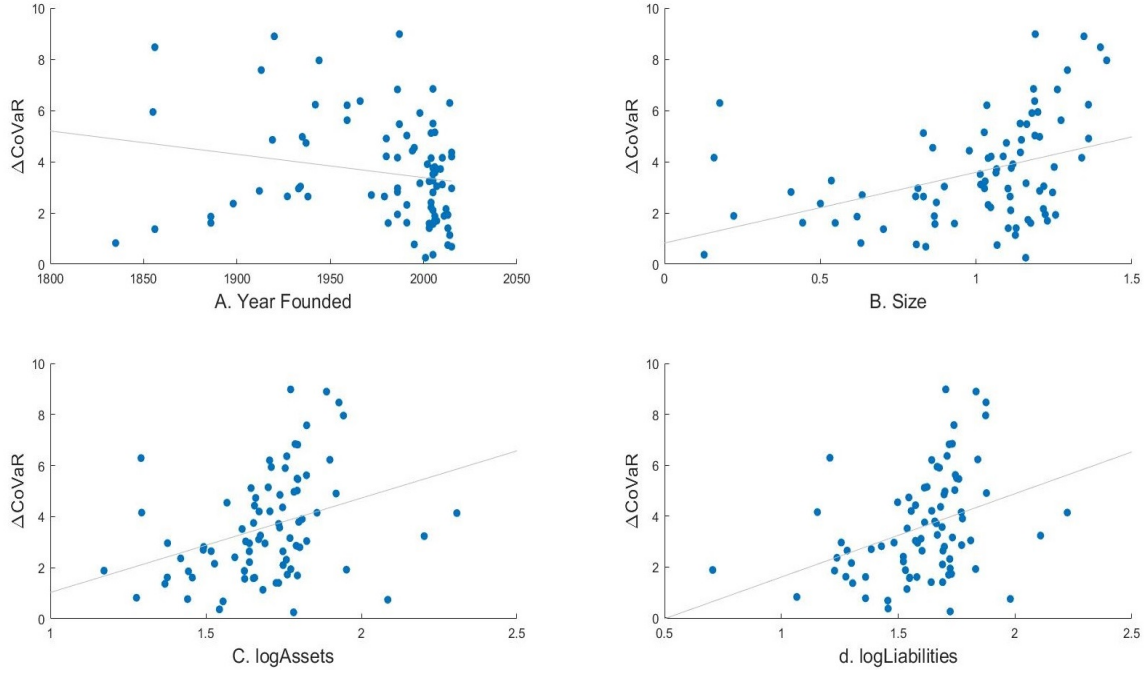
be diversified away. [Figure 2.1b](#) shows the relationship between $\Delta CoVaR$ and CAPM beta, the most common measure of market risk. We observe a positive and significant relationship between these two types of risk.⁹ Firms that are closely related with the market (high systematic risk) also present high values of $\Delta CoVaR$. For instance, the RE companies that carry the highest systemic risk, such as British Land, Land Securities, Segro, Derwent London and Workspace, also present the highest values for market risk, between 0.7 and 1.

2.2.3 Firm characteristics

We first examine if the years that a company is on operation affects the value of $\Delta CoVaR$. The results presented in [Figure 2.2a](#) show that this is not the case in our sample. On the other hand, size, measured by the log of the average market capitalisation divided by the cross sectional average, has a statistically significant positive relationship with systemic risk (see [Figure 2.2b](#)). This result is further validated by the use of assets and liabilities as can be seen in [Figures 2.2c](#) and [2.2d](#). Therefore, the greater the magnitude of the firm's operations the more prominent its systemic risk is. Another firm characteristic that has been typically employed in analyses about systemic risk is leverage (debt/capital or debt/equity ratios). We find a positive relationship with $\Delta CoVaR$ but the results are statistically insignificant.

Overall, the results presented in this section suggest that returns in the RE sector and in the UK financial system have a significant left-tail correlation. Furthermore, they suggest that certain factors at the firm level, such as systematic risk and size, affect the value of systemic risk. However, these results are not informative about the time variation in systemic risk since the *CoVaR* measure provides an estimate of systemic risk of the RE firms over the whole sample period. To study the time-variation in systemic risk and the variables that contributed to its build up before the financial crisis, we introduce a dynamic model of *CoVaR* in the next section.

⁹All the regression analyses of this section are available upon request.

Figure 2.2 Firm characteristics and $\Delta CoVaR^{fin}$ 

Note: The Figure reports the average systemic risk of the examined real estate firms against balance sheet characteristics. Figure A presents the year each firm's was founded, Figures B, C and D presents the relationship between systemic importance and firm's size captured by Market Capitalization, Assets and Liabilities. The estimation is based on year-on-year monthly returns and the period 2002m6 to 2018m7.

2.3 House prices, affordability and systemic risk

To examine the effect of house prices and housing affordability on systemic risk, we adopt a regression model, similar to that of [Brunnermeier et al. \(2017, 2020\)](#) in their analysis of the banking sector of the OECD economies:

$$|\Delta CoVaR_t^{s|i}(q)| = \alpha_i + \beta H_{t-1} + \gamma C_{i,t-1} + \delta M_{t-1} + \varepsilon_{i,t}. \quad (2.1)$$

The dependent variable is expressed in absolute values so that higher values of $\Delta CoVaR_t^{s|i}(q)$ correspond to a larger contribution of institution i to systemic risk. H represents the variables related to housing, C denotes firm characteristics, and M refers to the macroeconomic variables.

Starting with firm characteristics, C , these include idiosyncratic risk (VaR_i) and size (log of market capitalisation of firm i).¹⁰ The exogenous aggregate macroeconomic risk factors, M , are controlled for by the growth rate of GDP in the UK, growth of credit and investments, the rate of inflation, returns on the selective stock market index FTSE100, leverage, and the stance of monetary policy. Leverage is measured by net debt divided by the market capitalization of the UK financial sector index provided by Datastream.¹¹ The stance of monetary policy is measured by two variables due to the presence of the zero lower bound. We employ the Bank of England base rate up until 2009 to capture conventional monetary policy, and from then onward, we include the shadow rate computed using the method by [Wu & Xia \(2016\)](#) to control for unconventional policies. Monthly GDP is calculated using the Chow-Lin interpolation method and data for quarterly Real GDP from the FRED database (Federal Reserve Bank of St. Louis) and the monthly Industrial Production index from Bank of England statistics. The inflation rate is computed using the consumer price index (CPI) from the OECD Main Indicators. Finally, to capture credit cycles we use data on investments and credit obtained from the International Financial Statistics (IFS) database and the Bank of England, respectively.¹²

The set of housing market factors, H , includes three variables that are constructed using data from the International House Price Database of the Federal Reserve Bank of Dallas (see [Mack et al. 2011](#), [Pavlidis et al. 2016](#)). The first variable is real house prices. The second is a housing exuberance dummy that takes the value of unity when the recursive right-tail unit root test statistic, $BSADF$, of [Phillips et al. \(2015a,b\)](#) exceeds the corresponding critical value. The last variable is a measure of housing affordability. Despite its importance, the measures of affordability available are few (see survey by [Meen 2018](#)). These measures are

¹⁰While there is no significant cross-section relationship between VaR and $\Delta CoVaR$, there is indeed a relationship between those two variables at the time series dimension as can be seen in [Figure B.3](#). However, these two variables provide different information. For most of the period $\Delta CoVaR$ is above VaR , and specially noteworthy is the difference in the build up of the financial crisis.

¹¹We have also considered an alternative measure of leverage, the Leverage Index provided by the Center of Risk Management Lausanne. The results with this alternative measure of financial leverage, available upon request, were similar to the ones reported below and we have therefore omitted them.

¹²These two variables have been adjusted to monthly frequency using cubic spline interpolation.

based on either low frequency data, a specific part of the population such as first-time buyers, or regional indices. This makes them non-applicable in our context because our aim is to examine affordability at the nationwide level and at a relatively high frequency. To deal with this issue we focus on the time series properties of real house prices to disposable income. Specifically, we construct a housing unaffordability dummy variable which, similarly to the housing exuberance dummy, takes the value of one when the *BSADF* statistic of the ratio of real house price to real disposable income exceeds the corresponding critical value.

2.3.1 Empirical results

Table 2.2 presents estimation results for the dynamic model. Overall, the results are in line with both the “*collateral*” and “*deviation*” channels. In particular, the relationship between $|\Delta CoVaR|$ and house prices is negative and statistically significant, which supports the *collateral channel*. That is, during periods of increasing prices, the financial system is more stable. However, during periods when house prices display explosive dynamics, their impact on systemic risk reverses and turns positive. The positive impact on systemic risk is even higher when we employ the measure of unaffordability. In this case, the estimated coefficient is significantly larger. These latter results are consistent with the *deviation hypothesis*.¹³

Our results also suggest that firm characteristics relate to systemic risk. First, we find that a firm’s idiosyncratic risk (*VaR*) is positively correlated with systemic risk. A positive relationship between these two measures of risk is in line with the work of Adrian & Brunnermeier (2016) for the banking sector. In our case, this suggests that systemic risk closely follows the time-variation of the idiosyncratic risk carried by the RE firms. Second, our results suggest that the larger the size of the firm the higher its systemic risk. Turning to the set of variables that control

¹³We have also considered an alternative approach to the one of having three separate regressions for each of the variables in the set of housing market factors, *H*, as reported in Table 2.2. This approach involved having two separate regression specifications. The first specification included real house prices and the housing exuberance dummy in the same model and the second real house prices and housing affordability. In both cases, the macroeconomic risk factors, *M*, and the firm characteristic factors, *C*, remained the same as in Table 2.2. The results not reported here, but available upon request.

for the macroeconomic environment, we observe that they all have the expected sign. The growth rate of real GDP has a negative effect on systemic risk. Credit booms increase the level of risk, and the Investment-to-GDP ratio is negatively related to $|\Delta CoVaR|$. The estimates of the effect of these control variables are in line with the findings of [Brunnermeier et al. \(2017\)](#).

Table 2.2 Systemic risk of the RE sector ($\Delta CoVaR_{RE}^{Fin}$)

Variables	Model 1	Model 2	Model 3
$\ln HPI_{(t-1)}$	-2.931 (0.000)		
House Price Exuberance $_{(t-1)}$		1.041 (0.000)	
Unaffordability $_{(t-1)}$			1.448 (0.000)
$VaR_{RE,(t-1)}$	0.059 (0.000)	0.058 (0.000)	0.056 (0.000)
Size $_{(t-1)}$	0.909 (0.000)	0.800 (0.000)	0.823 (0.000)
GDP growth $_{(t-1)}$	-0.147 (0.000)	-0.132 (0.000)	-0.124 (0.000)
Inflation $_{(t-1)}$	-0.042 (0.584)	-0.036 (0.643)	-0.056 (0.464)
$\Delta Investments_{(t-1)}$	-0.124 (0.000)	-0.114 (0.000)	-0.121 (0.000)
$\Delta Credit_{(t-1)}$	0.624 (0.000)	0.719 (0.000)	0.682 (0.000)
$\ln Leverage_{(t-1)}$	1.227 (0.000)	1.645 (0.000)	1.648 (0.000)
MP base rate $_{(t-1)}$	-0.342 (0.000)	-0.350 (0.000)	-0.328 (0.000)
Shadow rate $_{(t-1)}$	0.314 (0.000)	0.290 (0.000)	0.289 (0.000)
Stock Market $_{(t-1)}$	-0.311 (0.000)	-0.310 (0.000)	-0.304 (0.000)
R^2	0.45	0.45	0.45

Note: This table reports the coefficients from panel regressions of $|\Delta CoVaR_i^{fin}|$ for the sample of the 81 UK RE firms on firm characteristics, housing and macroeconomic variables. The exuberance indicator dummy variables are estimated based on the *BSADF* approach. The firm size is measured by the log of Market Capitalisation divided by the sector's average. P-values are displayed in parentheses.

In addition, we find that higher levels of financial leverage are associated with higher systemic risk, which is in line with existing literature (Acharya & Thakor 2016). The positive coefficient on leverage is the expected one given that the (negative) externality of the RE sector on the financial sector is expected to be larger under a less well capitalised system. Regarding the impact of monetary policy, we find that while tightening in normal times would reduce the level of systemic risk, during periods of zero-lower-bound, measures of unconventional monetary policies help to tame the risk in the system. The results are in line with the findings in the first chapter. Finally, a bear stock market would increase the correlation between downside risk in RE firms and the financial sector.

Table 2.3 Systemic risk of the RE sector: Analysis by type of business

Group:	Residential RE	Commercial RE
$\ln HPI_{(t-1)}$	-2.937 (0.000)	-3.251 (0.000)
$RHPI\ Exuberance_{(t-1)}$	0.971 (0.000)	1.129 (0.000)
$Unaffordability_{(t-1)}$	1.427 (0.000)	1.337 (0.000)

Note: This table reports the coefficients from panel regressions of $|\Delta CoVaR_i^{fin}|$ for two sub-samples of the RE sector (residential and commercial) on firm characteristics, housing and macroeconomic variables. The rest of the variables are not presented since the estimates are qualitatively similar to the previous table. P-values are displayed in parentheses.

So far we have not differentiated RE firms according to their type of business: commercial or residential.¹⁴ The distinction between the two groups of RE firms is relevant for policy analysis purposes. This is so because, compared to Residential RE firms (RRE), Commercial RE companies (CRE) account for a larger share of GDP, and are more vulnerable to the business cycles exhibiting higher default rates. We analyse whether our results differ across these two

¹⁴In [Appendix, section B.4](#) we provide information about the composition of the RE companies by type of business and their corresponding systemic risk measures.

groups of RE firms and present the results in [Table 2.3](#).¹⁵ Overall, we observe only small differences. House prices appear to amplify more the tail dependency between CRE firms and the financial sector. However, when housing unaffordability rapidly rises, the increase in systemic risk is greater for RRE than for CRE firms.

2.3.2 Exposure of UK banks to the housing market

In the introduction, we conjectured that the transmission mechanism that makes the RE sector systemically important is the banking sector. Several empirical studies have already provided evidence about the effect of the RE sector on banks' profitability and stability. For instance, [Elyasiani et al. \(2010\)](#) examine the relationship between commercial banks and real estate investment trusts (REITs). They find that financial intermediaries' returns are highly sensitive to the real estate market. A shock to REITs' returns spillovers to the banking sector, as well as to insurance companies and savings and loans companies. [Martins et al. \(2011\)](#) find that the housing market has a significant impact on the profitability and default risk of banks, specially of small size.

We contribute to this growing literature by quantifying the association between stress in RE companies and the banking sector. To do so we run the following regression of $\Delta CoVaR_i^{bank}$ on housing and macroeconomic variables, as well as firm characteristics. Similarly to the previous model, the housing variables include house prices and exuberance indicators. The results are presented in [Table 2.4](#). First, the coefficient on house prices is negative, implying that sustainable house price growth is associated with less risk in the banking sector, and drop in prices with higher risk, possibly due to more vulnerable balance sheets caused by the exposure to mortgages and properties used as collateral. Second, during periods of house price exuberance, or bubbles, this relationship is reversed.

¹⁵The coefficients of the variables that control for firm characteristics, C , and macroeconomic environment, M , barely change and are therefore not reported here.

Table 2.4 Dependency between RE and banking sector ($\Delta CoVaR_{RE}^{bank}$)

Variables	Model 1	Model 2	Model 3
$\ln HPI_{(t-1)}$	-3.175 (0.000)		
House Price Exuberance $_{(t-1)}$		1.348 (0.000)	
Unaffordability $_{(t-1)}$			1.996 (0.000)
$VaR_{RE,(t-1)}$	0.076 (0.000)	0.075 (0.000)	0.073 (0.000)
Size $_{(t-1)}$	1.660 (0.000)	1.565 (0.000)	1.605 (0.000)
GDP growth $_{(t-1)}$	-0.313 (0.000)	-0.304 (0.000)	-0.295 (0.000)
Inflation $_{(t-1)}$	0.234 (0.028)	0.263 (0.013)	0.243 (0.021)
$\Delta Investments_{(t-1)}$	-0.260 (0.000)	-0.254 (0.000)	-0.265 (0.000)
$\Delta Credit_{(t-1)}$	0.695 (0.000)	0.825 (0.000)	0.784 (0.000)
$\ln Leverage_{(t-1)}$	1.801 (0.000)	2.275 (0.000)	2.287 (0.000)
MP base rate $_{(t-1)}$	-0.414 (0.000)	-0.432 (0.000)	-0.406 (0.000)
Shadow rate $_{(t-1)}$	0.420 (0.000)	0.383 (0.000)	0.378 (0.000)
Stock Market $_{(t-1)}$	-0.500 (0.000)	-0.499 (0.000)	-0.490 (0.000)
R^2	0.48	0.48	0.48

Note: This table reports the coefficients from panel regressions of $|\Delta CoVaR_i^{bank}|$ for the sample of the 81 UK RE firms on firm characteristics, housing and macroeconomic variables. The exuberance indicator dummy variables are estimated based on the *BSADF* approach. The firm size is measured by the log of Market Capitalisation divided by the sector's average. P-values are displayed in the parentheses.

Furthermore, unaffordability plays a role, increasing the dependency of the RE firms and banks in periods of distress.¹⁶ The effect of the firm characteristics and macroeconomic

¹⁶Similarly to the analysis reported in Table 2.2 and discussed in footnote 13, we have estimated two alternative regression model specifications. One with real house prices and the housing exuberance dummy, and another

environment is qualitatively similar to the one shown in the previous table of results. We have also examined, as we did in the previous section, whether the effects of house prices and affordability on the co-movement in the tails between RE companies and the banking sector depends upon the type of business. The results in [Table 2.5](#) show that the coefficients on the housing variables, H , are larger for CRE than for RRE firms. House price bubbles and unaffordability strengthen the degree of correlation between banks and CRE companies more than for RRE firms.

Overall, our findings not only contribute to a better understanding of the links between the RE and the banking sector but also provide additional information about the systemic risk of the banking sector which has been extensively researched in recent times. In addition to this, we provide in [Appendix](#) and [section B.5](#) an analysis about the dependency between risk in the Big Four banks in the UK (Lloyds Banking Group, RBS (Natwest Group), Barclays, and HSBC) and the RE sector. We find that while the tail dependency between the RE sector and these four banks is substantial, it decreases with the level of international diversification.

Table 2.5 Dependency between RE sector and banking sector:
Analysis by type of business

Group:	Residential RE	Commercial RE
$\ln HPI_{(t-1)}$	-2.409 (0.000)	-4.272 (0.000)
$RHPI \text{ Exuberance}_{(t-1)}$	1.081 (0.000)	1.653 (0.000)
$Unaffordability_{(t-1)}$	1.684 (0.000)	2.278 (0.000)

Note: This table reports the coefficients from panel regressions of $|\Delta CoVaR_i^{bank}|$ for two sub-samples of the RE sector (residential and commercial) on firm characteristics, housing and macroeconomic variables. The rest of the variables are not presented since the estimates are qualitatively similar to the previous table. P-values are displayed in parentheses.

where we included real house prices and housing affordability. The results, available upon request, were similar to the ones in [Table 2.4](#) for the former specification. For the latter, real house prices were not statistically significant.

2.4 Conclusions

Two of the topics that have attracted considerable attention since the financial crisis of 2007-08 are housing and systemic risk. This chapter is at the intersection of these two fields and contributes to them by quantifying the systemic risk of the real estate sector. We focus on the UK due to the importance of its financial sector in the international financial system and the role that housing plays in the determination of socio-economic outcomes. Our findings indicate that there is strong dependency between downside risk in the financial system and the real estate sector. In particular, when returns in the real estate sector are in distress, the value-at-risk of the entire financial system is higher by 74%. Looking at the determinants of systemic risk, we find that while moderate house prices movements positively relate to the level of financial stability, exuberance in house prices and housing unaffordability are associated with higher levels of systemic risk. In addition, firm characteristics and macro variables appear to play a role in the tail dependency between real estate and financial sector.

Chapter 3

The asymmetric effect of housing demand shocks and the role of credit

Joint with Kostas Vasilopoulos

3.1 Introduction

The role of housing on the business cycle has been a focal point of research, especially in the aftermath of the US housing market collapse and the subsequent Great Recession. Housing is considered a consumption good but also serves as collateral and long-term investment for both households and firms. Specifically, housing demand shocks are used in macroeconomic models as a primary source of the house price movements and, can drive macroeconomic fluctuations through the collateral channel ([Liu et al. 2013, 2019](#)). Moreover, housing represents a significant fraction of household's lifetime consumption and variation in house prices directly affect housing wealth, which just like financial wealth, plays a crucial role in household's spending ([Muellbauer & Murphy 2008](#)).¹

¹[Case et al. \(2005\)](#) find that changes in housing wealth has a significant impact on household consumption, whereas the effect of financial wealth is rather weak. [Campbell & Cocco \(2007\)](#) use micro-data for the UK economy and find that a rise in house prices would result in an increase in households' wealth and more relaxed borrowing constraints. [Disney et al. \(2010\)](#) examine the impact of housing capital gains on consumption using

As we discussed in the previous chapter, a critical aspect of the dynamics between house prices and the macro-financial environment is that they are not homogeneous over time since the phase of the housing cycle is crucial for the transmission of house price shocks. Housing market variation matters more during the bust phase of the cycle than during booms due to the asymmetric effects on collateral constraints (Guerrieri & Iacoviello 2017).² The loosened constraints have a positive but weak effect on consumption, whereas the subsequent collapse in 2008 resulted in a prolonged recession (Mian et al. 2013, Zhu et al. 2019). To illustrate these potential asymmetries in the transmission of housing shocks, we present in Figure 3.1 the change in consumption³ and financial stress against lagged house prices for the periods before (blue) and after (red) 2006.⁴ We observe that the relationship changes significantly between the two periods. In the after-2006 period, the slope becomes steeper, which indicates that variation in the housing market has a more substantial impact on consumption and financial stress. Therefore, as highlighted by Duca & Muellbauer (2013), and Musso et al. (2011), a linear model will yield non-robust findings since it does not take into account potential non-linearities across boom and bust periods.

Understanding these asymmetries is important since they drive the effect of housing demand shocks. This is the main goal of this paper. We shed light on the dynamic impact of housing demand shocks by employing a non-linear (Interacted) Panel VAR that captures the evolving dynamics between the housing market and the macroeconomy. The model allows us to distinguish between different regimes such as periods of high/low housing stress and constrained/excessive credit. To define periods of high stress, we adopt the novel *at-risk* framework by Adrian et al. (2019) to estimate downside risks in the housing market through a macro-model and predictive quantile regressions. Our results indicate that housing demand shocks have a weak effect on

data from the British Household Panel Survey. They find evidence of a positive relationship between house prices and consumption but significant heterogeneity of responses between owners and renters.

²Pavlidis et al. (2009) support that house prices impact consumption mostly during bubble periods.

³Nominal consumption series are provided by OECD Statistics and are seasonally adjusted.

⁴We choose 2006 as the reference year because the sharp decline in US house prices was the impetus for the subprime mortgage crisis and the subsequent 2008 Great Recession.

GDP growth and consumption during normal times. However, a (negative) shock in a stressed period has severe effects resulting in a sizeable drop in economic activity. We find that the effect is driven by the asymmetric response of consumption, the effect of which is 34% higher in periods of distress in the housing market. The responses of residential investment present a similar pattern since their peak response is two times higher when the housing market is at its *at-risk* region.

Figure 3.1 Consumption, financial stress and house prices



Note: The left panel shows house prices growth and consumption growth, and the right panel house prices growth and *CLIFS* for our sample of 11 countries. The solid lines show the fitted values of a regression of consumption growth on house prices growth broken down into post- and pre-2006.

The focus of the paper also extends to the interlinkages between the housing and financial markets. Our findings suggest that the variation in the housing market matters in terms of financial stability only during periods of distress, whereas under normal times the impact is rather weak. As we discussed in the previous chapter, the effect of house price shocks on financial stress comes through two different channels of opposite direction, which results in non-linearities. First, the so-called “*financial accelerator mechanism*” (Kiyotaki & Moore 1997), which consists of the positive relationship between house prices and the value of the real estate portfolio of the financial institutions (“*collateral value hypothesis*”).⁵ In other words, a

⁵Niinimäki (2009) argued that an increase in the housing market decrease the probability of a bank being under distress. In addition, Goodhart & Hofmann (2008) suggest that an increase in house prices directly affects banks’ balance sheet, resulting in a rise in credit supply.

drop in house prices results in decline in the balance sheet value of financial institutions and to an increase in financial stress, in line with our benchmark model results. On the other hand, a prolonged period of high growth in house prices would result in accumulation of risk due to excessive lending to risky investments⁶ at very low rates (Bernanke & Gertler 1995). As we discussed in the previous chapter, the second channel is defined as the “*deviation hypothesis*”. When we control for periods of excessive or limited lending, we find the relationship changes, and increases in house prices result in higher financial stress, whereas the opposite effect is observed in the rest of the periods.⁷

The rest of this chapter is organised as follows. Section 3.2 describes the empirical model and its main applications. In section 3.3 we describe the *at-risk* modelling framework and we define the housing stress regime. Section 3.4 provides the empirical findings and explores the role of credit in the transmission of housing demand shocks. Finally, we examine the presence of heterogeneity between positive and negative house price changes and section 3.5 concludes.

3.2 Methodology

3.2.1 The IPVAR model

To examine the time-varying impact of housing demand shocks, we employ an Interacted Panel VAR model as introduced by Towbin & Weber (2013):

$$J_{i,t}Y_{i,t} = \tilde{C}_i + \sum \tilde{A}_k Y_{i,t-k} + \tilde{C}^1 X_{i,t} + \sum \tilde{B}_k^1 X_{i,t} Y_{i,t-k} + \tilde{u}_{i,t} \quad (3.1)$$

$$t = 1 \dots T \quad \tilde{u}_{i,t} \sim N(0, \tilde{\Sigma})$$

⁶Excessive developments in the housing market have contributed to systemic risk and financial stability (Ferrari et al. 2015). In addition, Allen & Carletti (2013) show that in bubble periods, speculators enter the market. These information asymmetries make banks unable to assess potential risks and contribute to excessive risk-taking.

⁷Pan & Wang (2013) find evidence of a negative relationship between non-performing loans and increases in house prices, which is stronger in recession periods. On the other hand, deviations from their long-run fundamental values result in an increase in banks' instability.

$Y_{i,t}$ is a vector of explanatory variables which includes GDP growth, consumption, residential investment, real house prices, the short-term interest rate⁸ and the financial stress index.⁹ The model allows for a time-varying effect of a shock in house prices by including an interaction term, $X_{i,t}$ that influences the dynamic relationship between the endogenous variables. In our model specification, $X_{i,t}$ is a dummy variable that will take the value equal to one when we are in a stressed periods and zero otherwise.

To identify housing demand shocks, we use a standard recursive approach. The recursive identification of housing demand shock in a VAR model is common in the literature (see [Goodhart & Hofmann, 2008](#) and [Prieto et al., 2016](#)). In line with the literature, we order house prices after the macroeconomic variables and before the fast-moving financial index. The latter implies that a housing demand shock has a contemporaneous effect in the financial markets. $J_{i,t}$ is a lower triangular matrix with unity in the diagonal.¹⁰ Equation 3.1 implies that $\tilde{\Sigma}$, the covariance matrix, is diagonal.

The standard reduced form obtained by multiplying both sides by $J_{i,t}^{-1}$:

$$Y_{i,t} = C_i + \sum A_k Y_{i,t-k} + C^1 X_{i,t} + \sum B_k^1 X_{i,t} Y_{i,t-k} + u_{i,t} \quad (3.2)$$

$$t = 1 \dots T, \quad u_{i,t} \sim N(0, \Sigma_{i,t})$$

To estimate the model, we use OLS equation-by-equation¹¹ and we allow for fixed effects to account for heterogeneity across countries. Finally for the estimation of the confidence intervals, we follow the bootstrapping method by [Towbin & Weber \(2013\)](#) with 200 replications.

⁸We include the interest rate in the model to account for changes in monetary policy. Alternatively, we use the interest rate spread as a proxy for monetary policy and the results are quantitatively similar. The spread is defined as the difference between the short-term and long-term interest rate series provided by the OECD database.

⁹To capture financial stress, we use the Country Level Index of Financial Stress (*CLIFS*) for the EU countries and the Composite Indicator of Systemic Stress (*CISS*) for the US, both provided by ECB's Statistical Data Warehouse.

¹⁰Housing demand shocks are often assumed to have no contemporaneous effect on real GDP or consumption, so as to rule out a more fundamental type of shocks such as a positive technology shock ([Jarocinski & Smets 2008](#), [Iacoviello & Neri 2010](#), [Musso et al. 2011](#)).

¹¹As noted by [Towbin & Weber \(2013\)](#), the error terms are not correlated across equations by construction. Therefore, the equation by equation estimation will not result to loss in efficiency.

The IPVAR framework allows us to analyse the factors that drive the potential asymmetries in the impact of housing shocks with the nonlinear impact is allowed but not forced (see [Caggiano et al., 2017](#)).¹² For a more detailed description of the methodology, we refer to the IPVAR Matlab Toolbox by [Towbin & Weber \(2011a\)](#).

3.2.2 Data

The panel data consists of 11 large European countries and the US. Real house prices are provided by the OECD database. Similarly, most of the series that we use in the empirical analysis section, such as the short and long-term interest rates and GDP growth rates, can also be found in the OECD database. The private consumption expenditure data are from the FED Reserse Bank of St. Louis (FRED) and the country level financial stress index (*CLIFS*) and the Composite Index of Systemic Stress (*CISS*) can be found in the ECB database. The financial stress index was the main limitation of our sample, since ECB has calculated *CLIFS* only a few countries. Finally, residential investment series are provided by Dallas FED. The data are of quarterly frequency and expands from 1990Q1 to 2019Q4.¹³

3.2.3 IPVAR literature

The IPVAR model was first introduced by [Towbin & Weber \(2013\)](#) to examine the asymmetric impact of external shocks in a panel of 101 countries under fixed and flexible exchange rate regime. The framework has been applied to various contexts. For instance, [Aastveit et al. \(2017\)](#) and [Balcilar et al. \(2017\)](#) show that monetary policy has a significantly smaller effect on economic activity in periods of high economic policy uncertainty for the US and the Euro

¹²Alternatively, other model specifications could have been used such as a Threshold-VAR model, for which we would need to run the model twice for the two different regimes. This would not be possible in our case since the stressed periods consists of a small number of observations. On the other hand, the IPVAR uses all the available observations and capture the regime dynamics via the interaction term.

¹³See [Appendix, Table C1](#). We chose to exclude the COVID-19 period because of the lack of sufficient data at the time that this paper is being written and also due to the plethora of fiscal support programs that are in place, since the start of the pandemic does not allow us to make inference for this period.

area, respectively. [Caggiano et al. \(2017\)](#) apply an Interacted VAR model for the US economy and they find that this nonlinear relationship is bidirectional with the impact of an uncertainty shock to be larger in the periods of the ZLB. More recently, [Kim & Lim \(2020\)](#) employ an IPVAR with 23 countries to examine the role of household indebtedness on the effectiveness of monetary policy.¹⁴ Their empirical evidence suggests that the impact on consumption and investment is stronger in high household debt levels and that contractionary policy stance is more effective than the expansionary regime. Finally, another strand of the literature examines the role of the market structure in the transmission of shocks. [Leroy & Lucotte \(2019\)](#) deploy an IPVAR model and a panel of 16 European countries and show that monopolistic regimes increase make credit cheaper and increase macroeconomic volatility. Similarly, [Kouretas et al. \(2020\)](#) using the framework and EU data, find that residential mortgages and consumer loans are significantly higher in a less competitive market environment or when the sector is dominated by foreign banks.

3.3 *Housing market-at-risk*

The impact that house price fluctuations have on the economy depends on the stress in the housing market ([Aron et al., 2012](#)). For that purpose, we need to identify when the market is under distress and when it is in normal times. The importance of identifying housing stressed periods is highlighted by [Reinhart & Rogoff \(2013\)](#) and [Allen & Carletti \(2013\)](#) who point out that house and asset price bubbles typically precede banking crises. In order to define periods of distress in the housing market, we adopt the *at-risk* framework by [Adrian et al. \(2019\)](#). The framework has been on the centre of ECB's policymakers agenda as a new approach to quantify tail risks in macroeconomy and financial markets ([Figueres & Jarociński 2020](#)). It has also been applied to the residential housing market by [Deghi et al. \(2020\)](#) to identify downside risks in 32 advanced and emerging economies.

¹⁴[Nickel & Tudyka \(2014\)](#) employ an IPVAR to investigate the effect of indebtedness, measured by Debt to GDP ratio, in the asymmetries in the transmission of fiscal policy shocks.

Their model estimates the dynamic distribution of house prices growth using quantile regressions and a set of financial variables.¹⁵ They find that the variation on the tail of the distribution contributes significantly to the tail risk of output and financial stability. In our model, year-on-year house price growth (ΔY) is the dependent variable and the set of explanatory variables (X) includes credit growth and *CLIFS* to capture financial conditions, and GDP growth to account for the macroeconomic environment. In addition, we include past house prices growth and house price misalignment¹⁶ to control for the housing market developments. For the estimation we use one year ahead horizon ($h = 4$) and we focus on the 5%, 25%, 75% and 95% quantiles. The mathematical representation of the model is as follows:

$$\Delta_h Y_{i,t+h,q} = \alpha_{i,h,q} + \beta_{i,h,q} X_{i,t} + e_{i,t+h,q} \quad (3.3)$$

Figure 3.2 presents the actual year-on-year house price growth and their predicted distribution based on the estimates of the quantile regression model. We observe that there is a degree of co-movement across the markets in line with the literature¹⁷ and that the Great Recession coincides with the stressed housing market periods, with the actual growth to be between the 25% and 5% left tail predicted distribution region. To define the stress threshold and the stress regime, we estimate the average value of the left quartile of house prices growth rate.¹⁸ The regime interaction term, in the IPVAR model, takes the value equal to one when house price growth is below this level and zero otherwise.¹⁹ For robustness purposes, we use the historical distribution of house prices growth, and we estimate the “*at-risk*” value at the left quartile and the results are quantitatively similar.

¹⁵See also Alter & Mahoney (2021) for regional residential housing markets and Kennedy et al. (2021) for the analysis of the tail risks in the commercial real estate market.

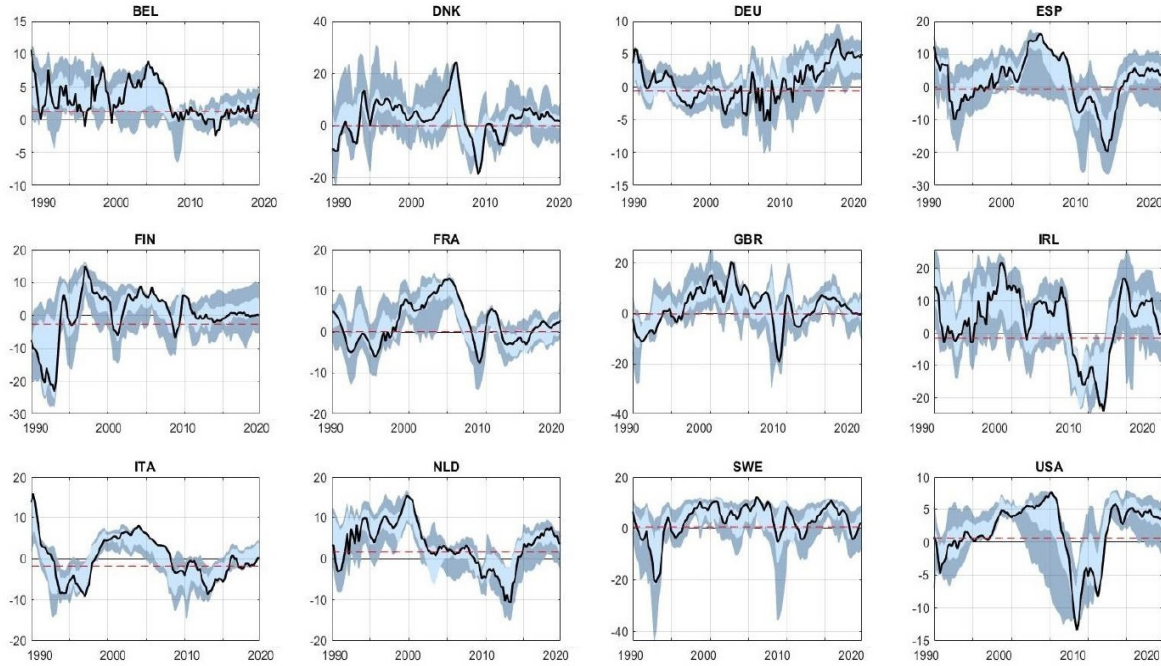
¹⁶The misalignment index is defined as the Real Personal Disposal Income to Real House Prices ratio.

¹⁷Cesa-Bianchi (2013) examines the international transmission of housing demand shocks in a GVAR model. The findings suggest that there are significant spillovers across countries and that a US shock can be quickly transmitted to the global economy.

¹⁸We select the left quartile as a threshold to have a big enough sample during the periods of distress. The results are robust to alternative thresholds such as 20%, 10% and 5%. The latter case requires a smaller number of lags to obtain statistically significant results.

¹⁹In the Appendix, Figure C1b illustrates the two regimes against the house price growth.

Figure 3.2 Housing market-at-risk



Note: The figure presents the actual year-on-year house prices growth together with their predicted distribution based on the estimates from the quantile regression model. The dark shaded area represents the 5%-95% lower and upper tail of the distribution and light shaded area stands for the 25%-75% region. The red dotted line stands for the average 25% tail growth rate.

3.4 Empirical analysis

3.4.1 Impulse response functions

To analyse the heterogeneity across different phases of the housing cycle, we focus on the negative housing demand shocks which corresponds to a 1% decline in house prices. We generate cumulative Impulse Response Functions (IRFs) for each regime together with the 90% probability bands obtained from bootstrap with 200 repetitions similar to [Towbin & Weber \(2011b\)](#). As we explained in the model section we use the recursive approach to identify housing demand shocks and we order house prices after the macroeconomic variables, but before the financial stress index. We consider alternative strategies where housing demand shocks are considered completely exogenous, thus we order the house prices first. Although

the response to the house prices itself is affected by the contemporaneous effects, the rest of the model variables are robust to the alternative specification. [Figure 3.3](#) displays the responses following a negative house demand shock in stressed period (in red) and normal times (in blue).

The response of consumption: The relationship between house prices and consumption is robust and well-documented in the aforementioned literature. An unexpected drop in house prices directly affects household's wealth and life-time consumption and at the same time weakens their ability to borrow against their properties ([Suari-Andreu 2021](#)). In this section we provide empirical evidence that the relationship exhibits non-linearities and that the impact of house price shocks vary depending on the stress in the housing market. More specifically, our results indicate that one percentage point unanticipated decrease in house prices leads to 1.7% drop in consumption, ten periods after the occurrence of the shock, when the house prices are at their “*at-risk*” region. Under normal times, the impact is considerably smaller (1.3%) highlighting the non-linearities in the transmission of housing demand shocks. Similarly, the effect on GDP growth is 21% greater when the housing market is under distress.

The response of housing supply: The most direct effect of housing market variation on economic activity is through residential investment ([Goodhart & Hofmann 2008](#)). Significant growth in house prices relative to construction cost makes investments more profitable (the *Tobin q* for residential investment). To examine the effects of demand shocks in the housing cycle (supply) and their role as a driver of the previously documented asymmetries, we investigate their impact on the residential investment channel. During periods of distress in the housing market, investments on residential properties decline on average by 1.4%, whereas for the rest of the period the average growth rate is just 1.1%. Similarly, building permits decline by 0.13% in periods of housing stress compared to an average positive change of 0.11% in the rest of the sample. [Figure 3.3](#) shows that residential investment exhibit significant asymmetries

following a housing demand shock. An unexpected decline in house prices results in a 1.5% drop in investments in *at-risk* periods compared to just -0.7% under normal times.²⁰

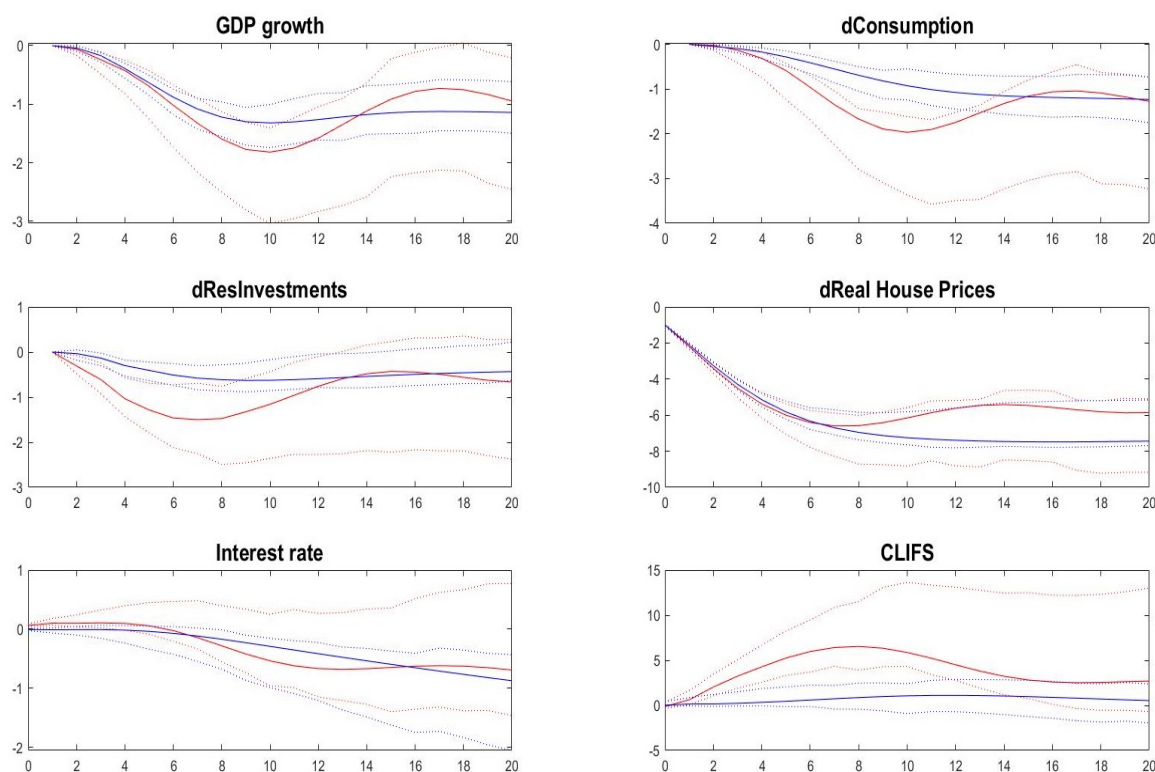
However, the relationship is bidirectional with a shock in residential investment to have a positive effect on house prices²¹, which is three times stronger in distressed periods (2% and 0.7% respectively). Residential investment is one of the best early warning signs of an upcoming recession contributing 26% to the drop of economic activity in the period before recessions (Leamer 2007). According to 2020 OECD data, private consumption and investments on dwellings and other buildings and structures account for 70.67% of the 2020 UK's GDP. Our findings in Figure 3.3 indicate that residential investment together with consumption play an important role in the transmission of housing demand shock on economic activity. They also highlight that housing demand shocks have a strong asymmetric effect on the supply side depending on the phase of the housing cycle, which consequently contributes to the asymmetric effect on macroeconomy.

The response of financial stress: Finally, we focus on the relationship between house prices and financial stability. Our methodological approach allows for non-linearities in the transmission of housing demand shocks and provides some valuable insights on the dynamics between the two markets. In normal periods, housing and financial markets exhibit weak co-movements with housing demand shocks to have an insignificant effect on *CLIFS*. However, when the housing market is in distress, a negative shock would cause a significant increase in the financial stress index (7.2% increase). The negative relationship between the two markets is in accordance with the *collateral hypothesis*, that suggests that a reduction in house prices results in a drop in the value of the real estate portfolio held by financial institutions. The increased exposure of the financial market indicates a significant nonlinear relationship between the two sectors and highlights the need for close monitoring of the residential real estate market.

²⁰Similarly, Jarocinski & Smets (2008) apply a BVAR model for the US and the period before 2007 and they also find that house price shocks have a positive relationship with residential investment.

²¹See Appendix, Figure C2 for the responses following a housing supply shock.

Figure 3.3 Cumulative IRFs following a housing demand shock



Note: Cumulative IRFs following a housing demand shock conditional on periods of housing distress. To define the stressed periods, we employ the *at-risk* modelling approach and we set the threshold as the average value of the predicted lower 25% tail. The red line stands for the responses during stressed periods, whereas the blue line when the housing market experiences no distress. The identification of the shock is based on the standard recursive approach. The shaded areas represent the 90% probability bands generated by bootstrapping with 200 iterations.

For robustness purposes, we employ alternative indicators of financial conditions such as the stock market index returns²² and credit growth and they both provide quantitatively similar responses. With regards to the latter, credit plays an important role in the transmission of housing demand shocks not only in terms of financial stability, but also in terms of the households' response. The impact of house prices on consumption comes from the direct effect on the borrowing ability of households and their access to credit. [Iacoviello & Neri \(2010\)](#) support that the link between house prices and the macroeconomy is primarily driven by credit-constrained households that use their property as collateral. This is in line with our

²²See [Appendix, Figure C3](#) for the asymmetric response of the stock market index to a housing demand shock.

previous findings, since in the periods of housing distress the credit growth is weak (0.74%) compared to normal times (2.58%). In addition, an unexpected house prices drop leads to decline in credit growth and the effect is 30% greater in periods of housing distress.

3.4.2 The role of credit

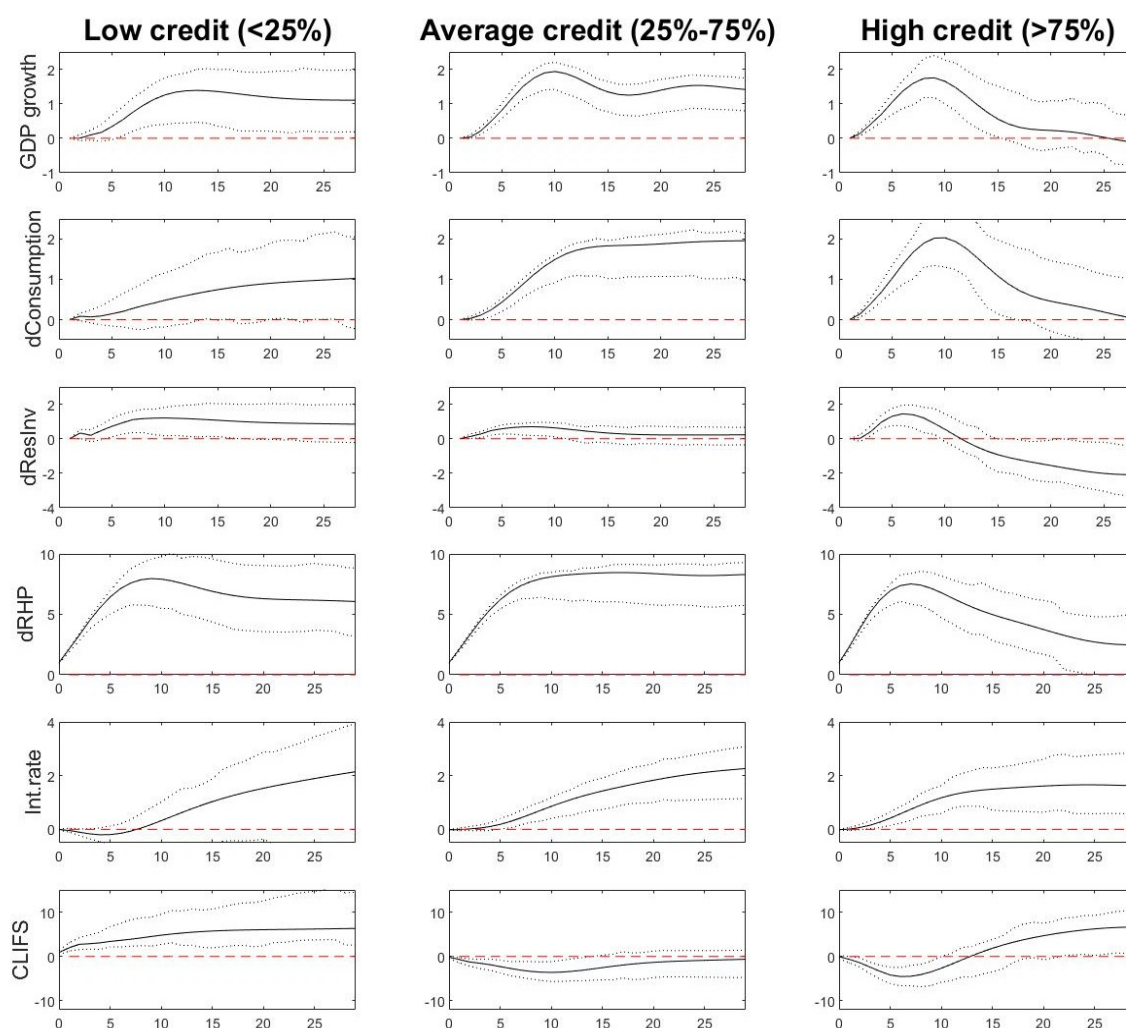
In this section we construct a credit-depending regime for the IPVAR model to explore the role of credit as a channel that can mitigate or amplify the impact of housing shocks. Specifically, we examine how different levels of household credit cause asymmetries in the transmission of the house price shocks. The bottom quartile of each country's household credit to GDP distribution is defined as periods of low available credit, while the right quartile of the distribution is defined as periods of high credit. Normal times is represented by the median values. The model specification is similar to the benchmark model and includes GDP growth, consumption, residential investment, the interest rate and the financial stress index (*CLIFS*).

Our empirical findings suggest that in periods of low credit, the impact of housing demand shocks on GDP, consumption and residential investment is weak and close to zero. These periods are characterised by lending constraints and the inability of households to access credit that weakens the *collateral channel* mechanism (Iacoviello & Neri 2010). The provision of household credit depends on financial institutions and these periods at the left tail of the credit distribution coincides with the recession phase of the business cycle and with low GDP growth. As a result, further increases in house prices cause higher stress in the financial markets.

Higher credit levels strengthen the impact size of housing demand shocks. An unexpected increase in house prices during periods of average credit increase consumption growth by 1.9% and the change rate of residential investment by 0.6%. In the right tail of the credit distribution (high credit), the effect is stronger with consumption and residential investment rising by 2% and 1.4%, respectively, following one percentage point increase in house prices. In addition, the response of financial stress exhibits significant non-linearities. In normal times,

the relationship between house prices and *CLIFS* is negative with increases in property prices reducing the probability of default of financial institutions and financial risk. However, in periods of excessive lending, an unexpected increase in house prices results in a decline in stress by 4.5%, which is at around 30% greater than normal times.

Figure 3.4 Housing demand shocks under alternative credit regimes



Note: Cumulative IRFs following a housing demand shock conditional on the level of household credit. We define three periods of credit availability, namely limited credit (left quartile), excessive credit (right quartile) and normal times. The identification of a housing demand shock is based on the standard recursive approach. The shaded areas represent the 90% probability bands generated by bootstrapping with 200 iterations.

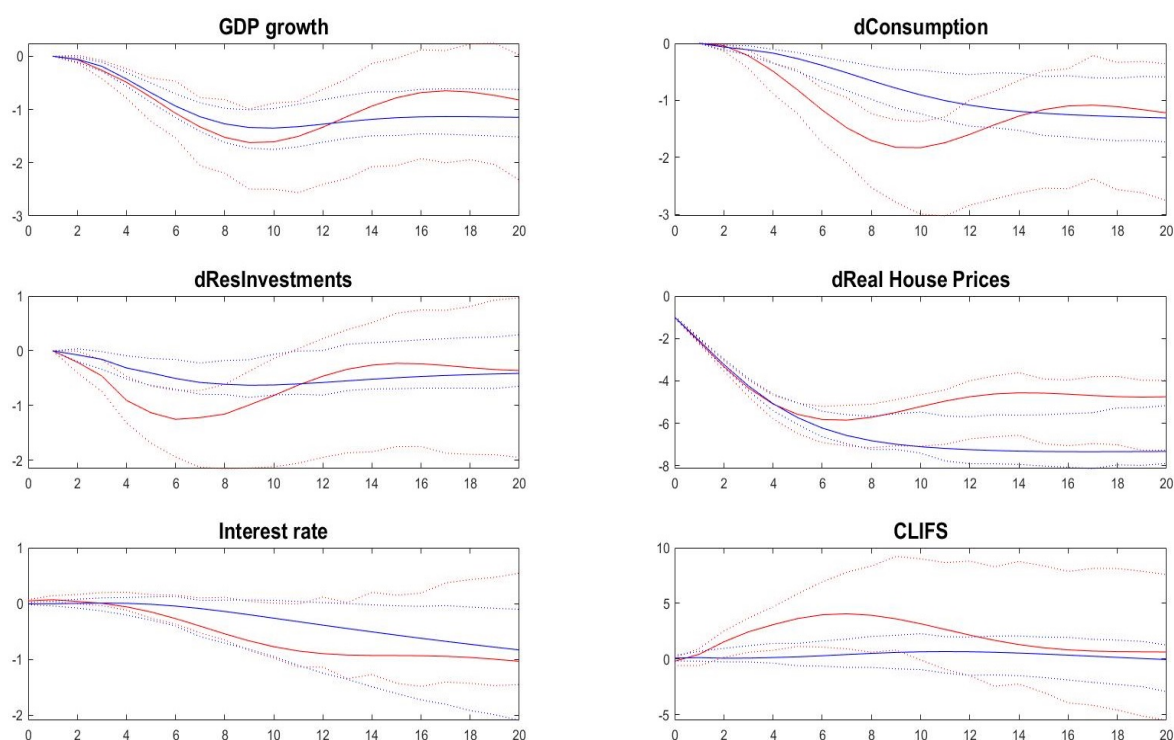
In the medium term, the response changes and *CLIFS* increases by 6.6%. This pattern is similar to the medium term response of residential investment, that decline by 2% after the initial boost by the housing demand shock. Our findings are in line with [Koetter & Poghosyan \(2010\)](#), who support that rising house prices increase the net wealth of borrowers and reduce the probability of credit default and financial stress. In contrast, persistent deviations from the fundamentals lead to an adverse selection problem with risky investors receiving excessive lending ([Pan & Wang 2013](#)). The latter mechanism can support our findings, where it suggests that in periods of excessive lending and financial stress, the relationship between house prices and financial stability is reversed as we observe in the medium term responses of *CLIFS*. Our results suggest that a baseline linear model can not capture the complex dynamics between the variation in the housing market and financial stability, and necessitate the need to employ non-linear modelling techniques to understand this dynamic and time-varying relationship.

3.4.3 Positive vs. negative movements

In this section we simplify our method to determine the regime. We now postulate that the asymmetric impact of a housing demand shock is stemming from positive and negative changes in house prices. Numerous papers document a significant heterogeneity between housing gains and losses. For example, [Engelhardt \(1996\)](#) examines the link between house price changes and savings, and he finds that housing capital losses and not potential gains drive households' behaviour. More recently, [Prieto et al. \(2016\)](#) apply a TV-VAR model to analyse the role of housing in the US economy, and they find that adverse shocks have a more significant impact on the US economy than the positive. The non-linear relationship is also documented in [Guerrieri & Iacoviello \(2017\)](#), where they argue that negative shocks have more significant impact on consumption since they reduce the households' borrowing capacity and, consequently, lead to lower demand for labour and a decline in hours worked. To investigate this non-linear relationship, we isolate the positive and negative changes in the country-level house prices

index. Figure 3.5 illustrates the cumulative responses of consumption, residential investment and the financial stress index. In line with the literature, negative changes have a greater effect on economic activity than positive movements.

Figure 3.5 Cumulative IRFs: Positive vs. negative movements



Note: Cumulative IRFs following a housing demand shock conditional on the sign of the year-on-year change. The red-shaded area represents the responses following a negative movement in house price growth, whereas the blue-shaded area depicts the positive changes. The shocks are normalised for comparison purposes. The shaded areas represent the 90% probability bands generated by bootstrapping with 200 iterations.

One per cent increase in house prices leads to a rise in consumption by 1.3% and a 0.6% upward change in residential investment. On the other hand, a negative shock has a more severe impact on both variables, with consumption dropping by 1.8% and investments by 1.2%. With respect to financial stress, the findings indicate that the relationship is driven by negative movements, whereas a positive change in house prices has no effect on the financial stress index. As described above, negative changes have a stronger effect on collateral-constrained

households. This effect can be transmitted through the mortgage market and the real estate portfolios of financial institutions to the financial stress index.

The factors that cause these asymmetries between positive and negative shocks have been the subject of considerable interest. [Disney et al. \(2010\)](#) use data from the British Household Panel Survey, and they find that the heterogeneity in the responses is being attributed to the fact that negative equity induces precautionary savings, and increases in house prices lift households out of negative equity and lead to a sizeable consumption response. Similarly, [Christelis et al. \(2019\)](#) provide a simulation analysis of a model with income risk and precautionary saving and they show that in the presence of liquidity constraints the response of consumption in response to a negative income shock is larger than to a positive shock. Finally, [Case et al. \(2013\)](#) find that home sellers behave differently for psychological reasons to a negative and a positive change in house prices. They argue that the (negative) wealth effect from declines in house prices is larger than the positive effect from an increase.

3.4.4 Alternative specification

In this section, we conduct a variety of robustness checks; however, we only report the figures of a few salient robustness checks and provide the rest in an online appendix. First we focus on the financial stress index. *CLIFS* have been well established in the literature as a measure of financial stability and it is being used by ECB and the European System of Central Banks. The selection of *CLIFS* ensure consistency in terms of measuring financial stress across our sample, since ECB estimates the index for all the examined economies, with USA to be the only exception. In that case, we use *CISS*. For robustness purposes, we also document the results for stock market index returns, provided by OECD database, as an alternative indicators that capture developments in financial conditions. As presented in [Figure C3](#), an unexpected drop in house prices results in a 6% decline in the stock market returns during periods of housing stress, whereas the impact is weaker (3.6%) under normal times. Regarding the regimes selection

for the housing stress periods we use the average bottom quartile of the estimated house price growth distribution. The results are similar if instead we use the historical distribution of house prices and we focus on the 10% and 20% tail of the growth distribution. That provide similar results, but they require a smaller number of lags or, otherwise, not all the results are statistically significant. The benchmark estimation of the model is based on 4 lags, however, alternative specification of 2,6,8 and 12 lags provides similar results.

3.5 Conclusions

This chapter examines the asymmetric effects of housing demand shocks and the non-linear transmission channel of house prices on consumption, residential investment, and financial stability. Our findings indicate that in periods of housing stress, as defined by the *at-risk* modelling approach, the impact following a housing demand shock is significantly higher. During normal times, an unexpected drop in house prices has a weak impact on consumption and does not affect the financial markets. On the other hand, in periods of distress, a negative surprise house price movement increases financial stress and results in a 34% greater adverse effect on consumption. In addition, the results show that negative changes to house prices are more important than positive movements, which align with previous findings and indicate that the severe impact of the housing demand shocks is driven by the periods of stress in the housing market. From the policy-maker's point of view, our paper provides valuable insights. The housing market is considered one of the best indicators to predict future downturns in the macroeconomy with its downturn fluctuations to result in severe repercussions for the macro-financial stability. The housing market frequently experiences overvaluation and bubbles, which according to our findings, could result in a severe effect in terms of financial stress and economic activity. This paper quantifies this asymmetric effect that housing demand shocks have on the macro-financial environment and strengthens the case for close monitoring of the fluctuations in the housing market.

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Appendix A

The role of systemic risk spillovers in the transmission of EA monetary policy

A.1 ΔCoVaR methodology

[Adrian & Brunnermeier \(2016\)](#) developed the concept of *CoVaR* building on one of the most popular measures of a firm's risk is its value at risk, *VaR*. *CoVaR* captures the association between the risk of the overall financial sector and a particular institution's stress event.

The *VaR* of institution i is defined by:

$$P(R^i \leq VaR_q^i) = q,$$

where R^i stands for the return of institution i , and q denotes the confidence level. The Conditional *VaR* (*CoVaR*) is, in turn, defined as the *VaR* of the financial system given that institution i is under distress. The mathematical expression of the *CoVaR* is:

$$P(R^s \leq CoVaR_q^{s|i} | R^i = VaR_q^i) = q,$$

$$\Delta CoVaR_q^i = CoVaR_q^{s|R^i=VaR_q^i} - CoVaR_q^{s|R^i=VaR_{0.5}^i}.$$

where R^s is the return of the financial system. The marginal contribution of a particular institution to the system's risk, $\Delta CoVaR$, is computed by comparing the *CoVaR* _{q} with the one in

normal times, at the median ($q = 0.5$). The estimation of the $\Delta CoVaR$ is done through quantile regressions.¹ The procedure is described in the following 3 steps:

1. Run the Quantile Regressions: $R_t^s = a_q + b_q R_t^i + e_t$
2. Use the estimates of a_q and b_q , \hat{a}_q and \hat{b}_q , to obtain: $CoVaR_q^{s|i} = \hat{a}_q + \hat{b}_q VaR_q^i$
3. Compute the systemic risk: $\Delta CoVaR_q^{s|i} = CoVaR_q^{s|i} - CoVaR_{0.5}^{s|i}$

Adding time variation

Following [Adrian & Brunnermeier \(2016\)](#), we allow the returns of the examined firms and of the sector as a whole to depend on a set of state variables, S_t . We note that these variables are not considered to be factors of systemic risk, but they are used because they can capture time variation in the conditional moments of the returns. These variables should be highly liquid and tractable and the choice of them depends on data availability.²

The estimation procedure of the dynamic model for the $\Delta CoVaR$ is described by the following five steps:

1. Run the quantile regression: $R_t^i = a_q + c_q S_{t-1}^i + e_t$
2. Use the estimates $(\hat{a}_q^i, \hat{c}_q^i)$ to obtain the dynamic VaR , $VaR_t^i(q) = \hat{a}_q^i + \hat{c}_q^i S_{t-1}^i$
3. Run the quantile regression: $R_t^s = a_q^{s|i} + b_q^{s|i} VaR_t^i(q) + c^{s|i} S_{t-1} + u_t$
4. Use the estimates $(\hat{a}_q^{s|i}, \hat{b}_q^{s|i}$ and $\hat{c}^{s|i})$ to obtain the Conditional VaR:

$$CoVaR_t^{s|i}(q) = \hat{a}_q^{s|i} + \hat{b}_q^{s|i} VaR_t^i(q) + \hat{c}^{s|i} S_{t-1}$$
5. Compute the systemic risk: $\Delta CoVaR_t^{s|i}(q) = CoVaR_t^{s|i}(q) - CoVaR_t^{s|i}(0.5)$

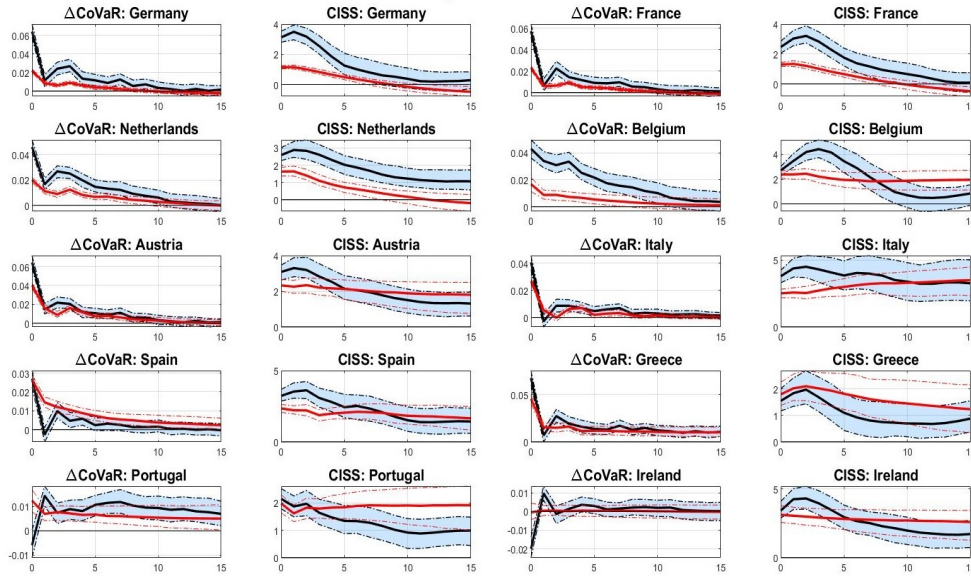
¹There are alternative methods to obtain the $\Delta CoVaR$. In [Appendix, section B.1](#) we present the multivariate GARCH modelling approach by [Girardi & Ergün \(2013\)](#).

²For the Euro Area systemic risk index, we use the term spread, the change in the 3 month interest rate, the difference between the government bond and EURIBOR and each country's stock market index (see [Table A1](#)). For the UK economy and Chapter 2, we employ changes in the three-month yield, changes in the yield curve, the TED spread, credit spread, FTSE100 volatility (VIX), and returns of the FTSE100 (See [Table B2](#)).

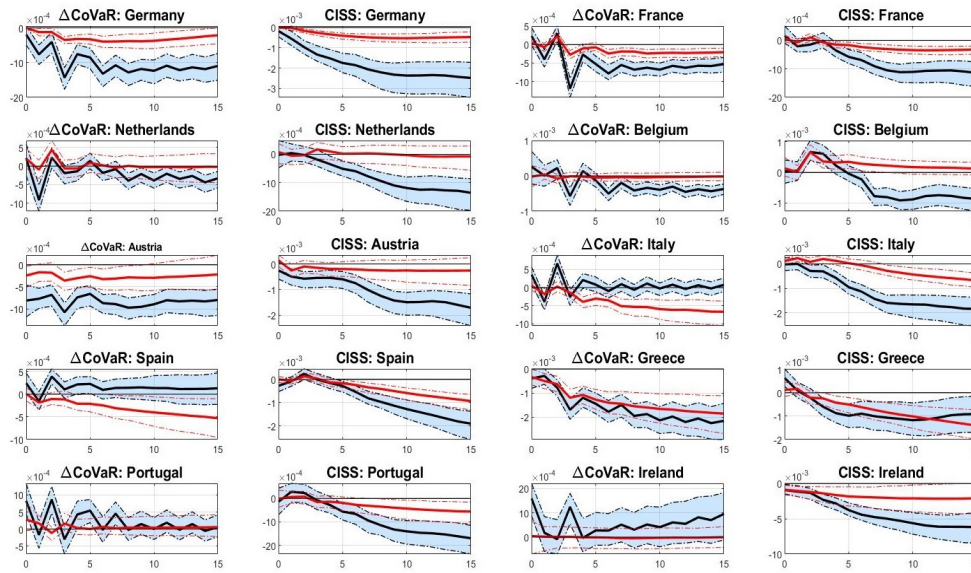
A.2 Figures & Tables

Figure A1 Euro Area systemic risk shock: Country responses

(a) Systemic risk response



(b) GDP response



Note: The figure reports the SGIRFs of the Euro Area systemic risk (a) and output (b) following a (positive) systemic risk shock. The identification strategy is based on the Cholesky decomposition. The lag selection is based on the Akaike information criterion (AIC). The shaded area represents the 68% confidence level, which is based on 200 bootstrap iterations.

Table A1 Chapter 1: Data description

Variable series	Frequency	Source
Gross Domestic Product (GDP)	Quarterly	Eurostat
Industrial Production	Monthly	FED of St. Louis (FRED)
Harmonised Consumer Price Index (HCIP)	Monthly	Eurostat
Shadow Rate	Monthly	Wu & Xia (2016)
High-Frequency Monetary Surprises	Monthly	Altavilla et al. (2019)
Sovereign Composite Systemic Stress Index	Monthly	Eurostat
Price and Market Capitalisation	Monthly	Datastream
State Variables		
3 month Government Bond	Monthly	FRED, Datastream, IMF
10 year Government Bond	Monthly	FRED
EURIBOR	Monthly	FRED
Stock Market Index	Monthly	Datastream

Note: The table illustrates the sources of the economic and financial series used in the GVAR model estimation. We also report the state variables sources used for the systemic risk index estimation. For countries where the 3 month government bond is not available, we use alternatively the Datastream series: TR EURO GVT 3MO.

Table A2 Euro Area ΔCoVaR estimation: Data

Financial Sectors					
	no.	MV(%)		no.	MV(%)
Banks	55	44.65%	Financial Services	81	13.52%
Insurance	25	26.05%	Real Estate	100	15.79%
Countries					
Core	no.	MV(%)	Periphery	no.	MV(%)
DEU	49	22.21%	ITA	29	12.62%
FRA	48	22.86%	ESP	25	14.33%
NDL	31	11.00%	GRE	13	0.58%
BEL	32	6.62%	POR	7	0.32%
AUS	13	3.28%	IRE	9	1.64%
FIN	5	4.62%	Total	261	1

Note: The table reports the data used to estimate the ΔCoVaR index. For that purpose, we collect Price and Market Capitalization data from Datastream for 261 active Euro Area financial firms. Data for 'dead' companies are not available, leading potentially to a survivorship bias. The sectoral division is based on Datastream reports. We observe that banks account for almost 45% of the Market Capitalization of the Euro Area financial system. We include firms that consists the (country) DS Financial sector as presented by the data source. The estimation period is 2001m1-2018m12.

Table A3 GVAR weights

	DEU	FRA	ITA	ESP	NDL	BEL	AUS	GRE	POR	IRE
DEU		0.37	0.35	0.32	0.31	0.30	0.29	0.29	0.29	0.29
FRA	0.31		0.27	0.25	0.24	0.23	0.23	0.22	0.22	0.22
ITA	0.25	0.22		0.20	0.19	0.18	0.18	0.18	0.18	0.18
ESP	0.16	0.15	0.14		0.13	0.12	0.12	0.12	0.12	0.12
NDL	0.10	0.09	0.08	0.08		0.07	0.07	0.07	0.07	0.07
BEL	0.06	0.05	0.05	0.04	0.04		0.04	0.04	0.04	0.04
AUS	0.05	0.04	0.04	0.04	0.03	0.03		0.03	0.03	0.03
GRE	0.03	0.03	0.03	0.03	0.03	0.02	0.02		0.02	0.02
POR	0.03	0.02	0.02	0.02	0.02	0.02	0.2	0.02		0.02
IRE	0.03	0.03	0.02	0.02	0.02	0.02	0.2	0.02	0.02	

Note: The table illustrates the weights for the GVAR model. Each column illustrates the decomposition of the foreign variables matrix for the 10 Euro Area economies. The estimation is based on the average quarterly GDP data provided by Eurostat for the period 2001-2018.

Table A4 GVAR lag order selection

	Full Period	Period A	Period B	Foreign var.
DEU	3	3	3	1
FRA	3	3	3	1
ITA	4	3	4	1
ESP	3	4	2	1
NDL	4	4	2	1
BEL	3	3	3	1
AUS	3	1	1	1
GRE	3	3	3	1
POR	3	1	3	1
IRE	1	2	1	1

Note: The table reports the optimal lag selection for the GVAR model based on the Akaike information criterion (AIC) for the full time period (first column) and two sub-periods (second and third column). The last column stands for the lag of the foreign variables, which is set to be equal to 1 by construction in line with the GVAR literature.

Appendix B

House prices, (un)affordability and systemic risk

B.1 Alternative methodology: A GARCH approach

An alternative procedure to estimate the dynamic $\Delta CoVaR$ is to use a bivariate GARCH model.

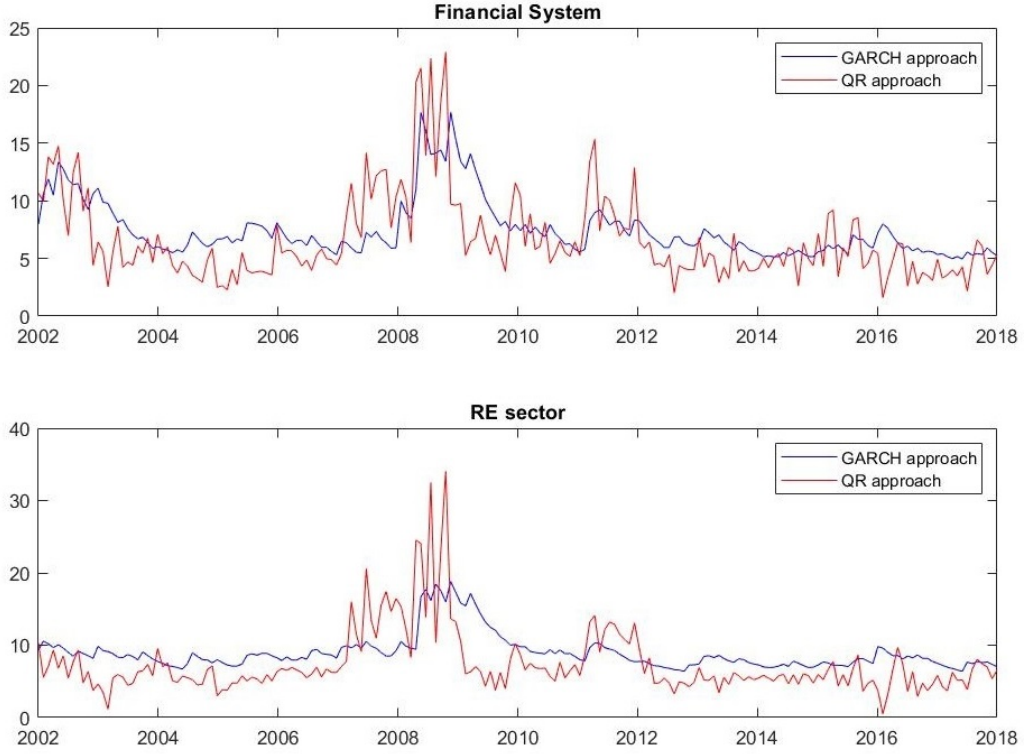
The first step is to estimate the dynamic VaR using a GARCH(1,1) model.

The main assumptions are:

1. $R_{t+1} = \mu + e_{t+1}$
2. $\sigma_{t+1}^2 = \alpha_0 + \alpha_1 e_{t+1}^2 + \beta \sigma_t^2$
3. $e_{t+1} = \sigma_{t+1} z_{t+1}$, where $z \sim N(0, 1)$
4. $|VaR_{t+1}| = \hat{\mu} + \hat{\sigma}_{t+1} F_a^{-1}$

Figure B1 illustrates the VaR obtained by using the two alternative methodologies. For the financial sector, the results are similar for most of the period. The most significant deviation is observed during 2007-2009, when the state variables model implies a higher systemic risk than the one produced with the GARCH method. This pattern is similar for the RE sector.

Figure B1 Dynamic VaR: Alternative methodologies



We now specify the bivariate GARCH model for returns of the financial system and the RE sector that is required to estimate $\Delta CoVaR$. We assume that returns follow a bivariate normal distribution:

$$(R_t^i, R_t^S) \sim N(0, \begin{bmatrix} \sigma_{i,t}^2 & \rho \sigma_t^i \sigma_t^S \\ \rho \sigma_t^i \sigma_t^S & \sigma_{S,t}^2 \end{bmatrix})$$

$$\text{Therefore, } R_t^S | R_t^i \sim N\left(\frac{R_t^i \sigma_{S,t} \rho_t^i}{\sigma_{i,t}}, (1 - \rho_t^i)(\sigma_{S,t}^2)\right)$$

$$\text{By the definition of } CoVaR_t^{S|i}(q) : P\left(R^S | R^i = VaR_t^i(q) \leq CoVaR_t^{S|i}(q)\right) = q\%$$

From the properties of the bivariate normal distribution, it follows that:

$$P\left(\left(R_t^S - \frac{R_t^i \sigma_{S,t} \rho_t^i}{\sigma_{i,t}}\right) / \sigma_{S,t} \sqrt{1 - \rho^2} \mid R_t^i = VaR_q^i(t) \leq \left(CoVaR_q^i(t) - \frac{R_t^i \sigma_{S,t} \rho_t^i}{\sigma_{i,t}}\right) \sigma_{S,t} \sqrt{1 - \rho^2}\right) = q\%$$

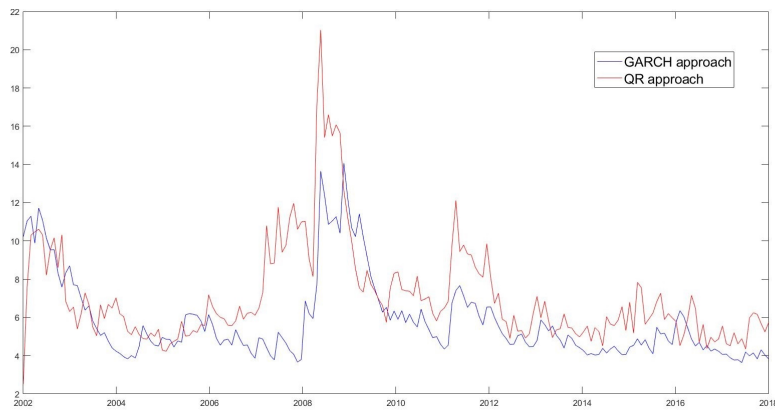
Since $\left(R_t^S - \frac{R_t^i \sigma_{S,t} \rho_t^i}{\sigma_{i,t}}\right)$ & $\left(CoVaR_q^i(t) - \frac{R_t^i \sigma_{S,t} \rho_t^i}{\sigma_{i,t}}\right)$ are $N(0,1)$ random variables:

$$VaR_q^i(t) = \Phi(q\%)^{-1} \sigma_{i,t} \text{ and } CoVaR_q^i(t) = \Phi(q\%)^{-1} \sigma_{i,t} \sqrt{1 - \rho_{i,t}^2} + \Phi(q\%)^{-1} \rho_{i,t} \sigma_{S,t}$$

$$\text{Therefore: } \Delta CoVaR_q^i(t) = \Phi(q\%)^{-1} \rho_{i,t} \sigma_{i,t}$$

We note that the main factors affecting the value of systemic risk are the correlation coefficient (ρ_i) and the dynamic volatility of the financial system ($\sigma_{S,t}$). Both the time-varying correlation coefficient and the standard deviation are estimated with a DCC specification. The figure below illustrates the dynamic $\Delta CoVaR$ estimated with both methods. We observe that the estimated systemic risk employing the GARCH method increases only right at the inception of the financial crisis. The method employing state variables better captures the build up of systemic risk ahead of the crisis and that this is another reason we employ it in our main analysis of the paper.

Figure B2 Dynamic $\Delta CoVaR$: Alternative methodologies



B.2 Static $\Delta CoVaR$: Individual Real Estate firms

Table B1 Static $\Delta CoVaR$ estimates

Name	Mnem.	VaR	CoVaR ^{fin}	$\Delta CoVaR^{fin}$	CoVaR ^{bank}	$\Delta CoVaR^{bank}$
Land Securities Group	LAND	12.40%	13.08%	7.78%	15.47%	6.91%
British Land	BLND	10.57%	13.71%	8.29%	16.3%	7.56%
Segro	SGRO	13.26%	12.91%	8.61%	15.78%	8.42%
Hammerson	HMSO	12.50%	11.22%	6.17%	18.23%	7.69%
Derwent London	DLN	12.09%	11.78%	7.41%	17.74%	8.63%
Shaftesbury	SHB	12.55%	11.71%	6.60%	17.30%	8.47%
Intu Properties	INTU	10.81%	9.78%	4.83%	16.49%	7.00%
Capital & Counties Prop	CAPC	10.78%	8.26%	4.18%	14.37%	6.31%
Unite Group	UTG	16.98%	9.59%	4.78%	15.55%	5.41%
Great Portland Estates	GPOR	9.43%	10.07%	5.16%	19.71%	10.29%
Workspace Group	WKP	16.94%	13.84%	8.83%	20.00%	11.02%
Big Yellow Group	BYG	11.31%	10.57%	5.6%	15.82%	5.65%
Assura	AGR	14.32%	7.57%	1.35%	11.74%	1.96%
Grainger	GRI	14.33%	8.80%	2.71%	13.61%	3.45%
Savills	SVS	13.81%	11.30%	5.71%	15.05%	5.20%
Purplebricks Group	PURP	20.96%	6.88%	2.08%	11.05%	3.39%
Safestore	SAFE	12.71%	10.11%	3.07%	13.72%	2.56%
CLS Holdings	CLI	10.9%	11.02%	5.46%	16.31%	6.34%
Daejan Holdings	DJAN	10.35%	10.11%	5.01%	14.65%	5.65%
St Modwen Prop.	SMP	17.66%	11.69%	6.35%	16.77%	7.82%
RDI Reit	RDI	16.61%	9.75%	4.10%	16.02%	6.30%
Londonmetric Prop.	LMP	7.29%	8.45%	1.61%	14.30%	2.96%
Hansteen Holdings	HSTN	9.05%	12.26%	6.77%	20.67%	9.31%
Urban Civic	UANC	18.43%	11.79%	4.41%	15.57%	5.37%
Helical Reit	HLCL	14.20%	12.02%	4.74%	15.19%	4.64%
Mountview Estate	MTVW	8.69%	11.47%	4.71%	15.64%	5.33%
Capital & Regional	CAL	24.17%	8.85%	2.63%	14.81%	3.89%
Harworth Group	HWG	23.85%	9.89%	2.35%	15.87%	3.59%
Mucklow A&J Group	MKLW	12.00%	10.96%	3.11%	15.32%	4.39%
U & I Group	UAI	15.96%	10.02%	3.97%	17.40%	6.64%

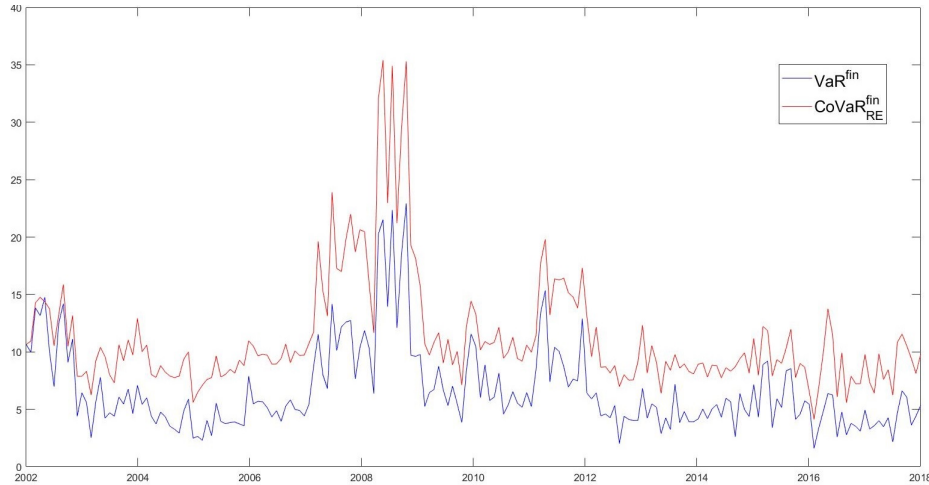
Name	Mnem.	VaR	CoVaR ^{fin}	$\Delta CoVaR^{fin}$	CoVaR ^{bank}	$\Delta CoVaR^{bank}$
LSL Properties	LSL	20.36%	10.32%	4.03%	14.94%	3.33%
Countrywide	CWD	28.11%	5.10%	1.82%	8.97%	1.18%
McKay Securities	MCKS	8.96%	8.66%	2.89%	14.35%	3.66%
Foxtons Group	FOXT	23.46%	4.96%	1.46%	8.66%	1.31%
Conygar Invest.	CIC	10.26%	8.34%	1.59%	13.18%	2.34%
Palace Capital	PCA	22.84%	6.75%	0.14%	14.09%	3.69%
Town Centre Securities	TOWN	14.00%	11.81%	6.15%	16.77%	7.80%
Inland Homes	INL	19.08%	9.43%	3.30%	14.31%	3.75%
Lok'n Stores Group	LOK	14.10%	11.43%	4.41%	15.95%	5.67%
Real Estate Investors	RLE	13.11%	9.10%	2.34%	15.28%	4.56%
Newriver Reit	NRR	6.35%	8.26%	3.65%	14.60%	5.50%
Highcroft Investments	HCFT	6.11%	9.30%	2.72%	13.56%	2.65%
Property Franchise Group	TPFG	15.06%	6.15%	2.80%	11.48%	4.34%
Caledonian Trust	CNN	12.89%	9.76%	2.67%	14.40%	3.25%
London & Assocs. Prop.	LAS	12.41%	10.06%	2.43%	12.52%	2.17%
Cardiff Properties	CDFF	5.51%	9.22%	1.88%	14.60%	3.14%
Wynnstay Prop	WSP	6.33%	9.58%	1.66%	14.28%	2.67%
Hunters Property	HUNT	11.45%	5.47%	12.24%	9.82%	0.82%
HML Holdings	HMLH	20.04%	8.08%	1.58%	13.94%	2.33%
M Winkworth	WINK	10.64%	6.49%	0.77%	10.91%	1.11%
Safeland	SAF	18.33%	10.11%	2.61%	12.52%	1.58%
Steward & Wight	STE	7.69%	10.73%	2.37%	12.69%	1.22%
Fletcher King	FLK	15.73%	10.64%	4.11%	16.53%	5.44%
Belvoir Lettings	BLV	14.47%	4.58%	0.73%	11.09%	2.32%
Panther Securities	PNS	7.57%	10.52%	3.18%	13.29%	2.02%
Secure Inc. Reit	SIR	7.78%	6.38%	2.96%	9.24%	1.23%
GCP Students Lettings	DIGS	2.91%	5.32%	1.34%	8.95%	1.22%
Local Shop Reit	LSR	15.03%	9.97%	5.10%	13.26%	2.23%
AEW UK Reit	AEWU	3.09%	6.85%	2.83%	11.34%	4.00%
Alpha Real Trust	ARTL	10.61%	9.52%	1.89%	16.42%	4.23%

Name	Mnem.	VaR	CoVaR ^{fin}	Δ CoVaR ^{fin}	CoVaR ^{bank}	Δ CoVaR ^{bank}
Axa Property Trust	APT	9.67%	7.52%	0.61%	11.07%	0.25%
Custodian Reit	CREI	2.38%	5.54%	1.07%	11.84%	2.20%
Drum Inc. Reit	DRIP	4.21%	5.29%	0.65%	9.23%	0.78%
Ediston Prop.	EPIC	2.95%	6.22%	2.09%	12.29%	4.87%
F&C Com. Prop.	FCPT	6.26%	8.69%	2.78%	14.45%	4.28%
KCR Residential Reit	KCR	20.69%	8.69%	2.78%	14.45%	4.28%
Picton Prop. Trust	PCTN	14.12%	8.08%	2.12%	13.87%	3.78%
Regional Reit	RGL	4.49%	7.54%	4.12%	10.39%	3.97%
UK Com. Prop Trust	IKCM	7.05%	12.22%	3.47%	12.60%	1.72%
Tritax Big Box Reit	BBOX	4.21%	5.63%	1.84%	9.21%	1.71%
Target Healthcare Reit	THRL	3.56%	3.17%	0.63%	7.04%	0.94%
Std.Lf.Inv.Prop.Inc Trust	SLI	9.08%	8.84%	3.22%	13.85%	4.03%
F&C UK Rlst. Inv.	FCRE	10.73%	9.47%	4.13%	14.91%	5.04%
Summit Germany	SMTG	5.46%	5.74%	1.64%	12.05%	3.30%
Raven Russia	RUS	18.33%	11.20%	5.33%	16.18%	6.90%
Sirius Real Estate	SRE	18.30%	10.35%	3.70%	18.55%	5.13%
Vordere	VOR	25.18%	2.07%	1.77%	6.16%	2.65%
Alpha Pyrenees Trust	ALPH	40.55%	10.06%	3.33%	12.80%	2.80%
Globalworth Reit	GW	8.47%	10.06%	3.23%	12.80%	2.80%
Macau Prop.Opp. Fund	MPO	10.29%	11.45%	4.92%	16.51%	6.86%
Schroder Reit	SERE	8.22%	2.21%	3.95%	1.66%	7.91%

Note: The table reports the average systemic risk contribution of individual UK RE firms. The examined period is 2002m6-2018m7 and all the observations are obtained from Datastream. The system indices are FTSE350 financial system that includes all banks, investment funds, general financial, insurance and RE companies and FTSE350 Banks to measure the dependency with the banking sector. The measures of risk are estimated for the 95% quantile, and they expressed in absolute values.

B.3 Dynamic estimation of CoVaR & state variables

Figure B3 VaR and CoVaR of the financial system index



Note: The figure shows the dynamic VaR of the UK financial system compared to its $CoVaR$ when the Real Estate market is under distress. The estimation of both measures is based on quantile regressions and a set of state variables. The area between the two lines is the additional tail risk coming from the Real Estate market.

Table B2 State variables summary statistics

Variables	Mean	Std Dev	Skewness	Min	Max
Three month yield (change)	-2.63	20.86	-8.47	-178.8	26.20
Yield Curve (change)	-0.19	24.44	1.39	-52.3	121.7
TED Spread	25.18	31.08	3.37	0.813	215.12
Credit Spread	1.04	29.47	3.64	-95.9	225.87
FTSE100 Volatility (VIX)	18.83	7.94	1.61	9.55	54.15
FTSE100 Returns	0.20	3.94	-0.76	-13.96	8.30

Note: The table reports summary statistics for the state variables employed to estimate the dynamic model of systemic risk. The spreads and changes in spreads are expressed in monthly basis points, and the returns in monthly percentages.

B.4 Residential and commercial Real Estate firms

We distinguish between firms that focus on commercial property and those that focus on residential property. In the first group we include all the industrial and retail RE firms. These firms hold portfolios of warehouses, shopping centres, hotels, restaurants, storage facilities and medical centres. The second group own and manage properties available for occupation and for no-business purposes, and they are also involved in property development and trading. [Figure B4](#) shows the weights of each group in the construction of the RE portfolio. The commercial real estate firms constitute more than 50% of the index, while only one in four firms is residential-focused. For the rest of firms, 16% have a mixed portfolio of commercial and residential and 9% are classified separately as international firms. These are mostly RE companies that are traded in the London Stock Exchange (LSE) but their asset are located in foreign countries. [Table B.3](#) shows that the systemic risk of commercial RE (CRE) and residential RE (RRE) companies is very similar around 8%, although it is higher for CRE firms when the impact is measured only on the banking sector. This result provides support to the analysis of the ECB's report in 2015 that suggests that CRE companies have higher loan-to-value (LTV) ratios and strong cyclicalities leading to higher default risk.

Figure B4 Constituents of the Real Estate portfolio

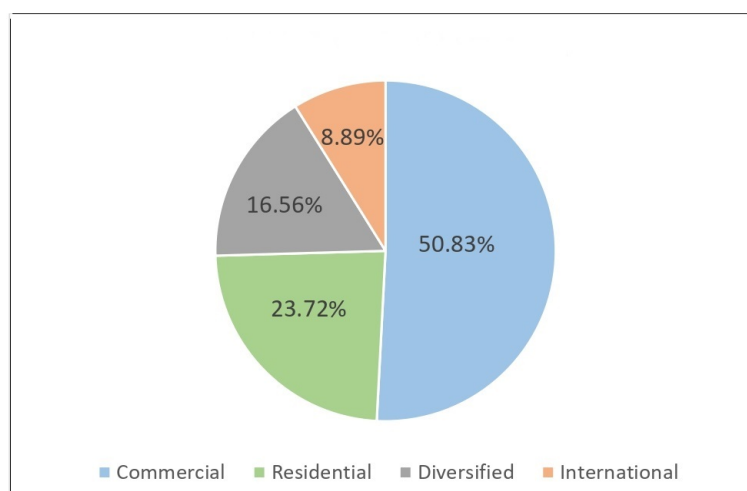


Table B.3: RE systemic risk by type of business

Group	No of Firms	Market Cap	VaR	ΔCoVaR^{fin}	$\Delta\text{CoVaR}^{bank}$
All Companies	81	100%	8.59%	8.32%	8.46%
All excl. International	73	91.11%	8.49%	8.38%	8.49%
Commercial	39	50.83%	9.17%	7.87%	9.11%
Residential	21	23.72%	10.41%	7.94%	10.43%
Diversified	13	16.56%	8.12%	5.69%	7.98%
International	8	8.89%	8.07%	3.40%	4.61%

Note: The table reports the estimates for the systemic risk measures for different sub-sectors of the RE sector. The examined period is 2002m6-2018m7 and all the quantities are expressed in monthly frequency. All the estimates of risk are expressed in absolute values.

B.5 The effect on the Big Four

We apply the ΔCoVaR methodology to examine the impact of the real estate market to individual UK banking institutions. For this analysis, we employ the four systemically important banks in the UK, namely, Lloyds Banking Group, Barclays, Royal Bank of Scotland and HSBC. These four companies own around 45% of the mortgage market share.¹

Table B.4: UK mortgage market lending market shares

Bank	2017	2016	2015	2014
Lloyds Banking Group	16%	15.6%	17.5%	19.5%
Royal Bank of Scotland	12%	12.9%	11.2%	9.7%
Barclays	9%	8.4%	8.6%	10%
HSBC	7.1%	6.4%	5.8%	6.2%
Total	44.1%	43.3%	43.1%	45.4%

*Source: UK Finance and CML

Table B.4 presents the market shares of each bank for the UK mortgage gross lending based on the data provided by UK Finance and CML. We first confirm that these four banks are systemically important in the UK by computing their ΔCoVaR_j^i , or the level of risk of the financial system when these banking institutions are under distress.

¹Nationwide is the second largest mortgage lender (12.3%), but it is a building society hence not in the London Stock Exchange. We also leave out Santander because this company is not traded in the UK stock market either.

In Table B.5 we can observe that the systemic importance of the banks is related to their share in the mortgage market. Lloyds and RBS have higher ΔCoVaR than the other two institutions. To examine the exposure of the banks to the real estate market, we estimate the $\Delta\text{CoVaR}_{RE}^i$, that is, the VaR of each individual bank when the RE portfolio is under distress. RBS and Lloyds are the most vulnerable to the housing market. When the returns of the real estate portfolio are at their $\text{VaR}_{95\%}$, the risk measure of the two banks increases by 24.42% and 17.5%, respectively. The exposure of Barclays and HSBC is lower, as expected, due to their more international focus on different banking operations such as investment and corporate banking.

Table B.5: UK systemic banks

Bank	$\text{VaR}_{95\%}$	$\Delta\text{CoVaR}_i^{FIN}$	$\Delta\text{CoVaR}_{RE}^i$
Lloyds Banking Group	19.95%	7.99%	17.5%
Royal Bank of Scotland	20.59%	6.10%	24.42%
Barclays	16.01%	5.42%	11.80%
HSBC	10.18%	5.61%	5.51%

Note: The table reports the estimates for the ΔCoVaR measures of the banking sector. The examined period is 2002m6-2018m7 and all the quantities are expressed in monthly frequency. All the estimates of risk are expressed in absolute values.

Appendix C

The asymmetric effect of housing demand shocks and the role of credit

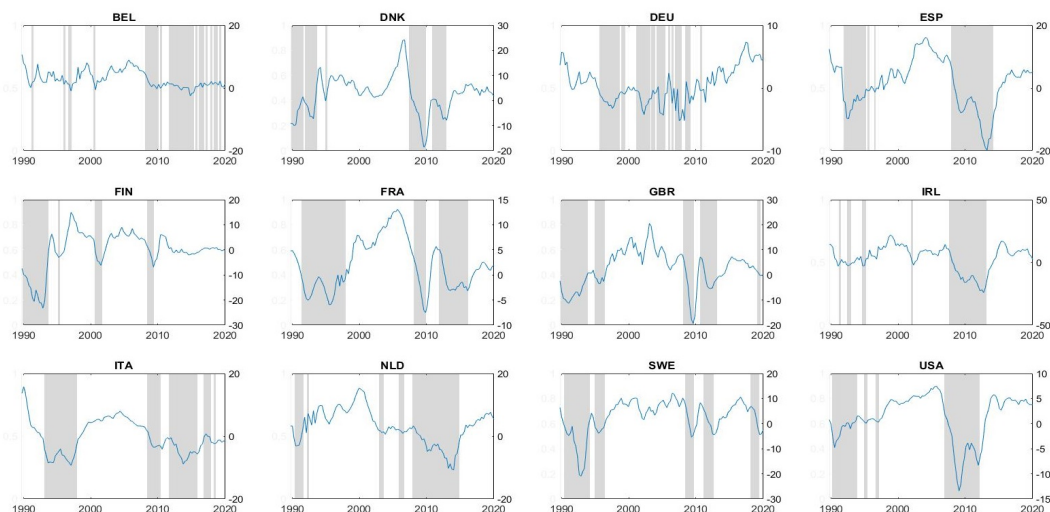
C.1 Figures & Tables

Table C1 Chapter 3: Data description

Variable series	Source
Gross Domestic Product growth (y0y)	OECD data
Private consumption expenditure	OECD data
Residential investment	Dallas FED
Real house prices	OECD data
Inflation (CPI)	OECD data
Country Level Index of Financial Stress (CLIFS)	ECB Data Warehouse
Composite Systemic Stress Index (CISS)	ECB Data Warehouse
Credit-to-GDP	BIS data
Share prices index	OECD data
Short-term interest rate	OECD data
Long-term interest rate	OECD data

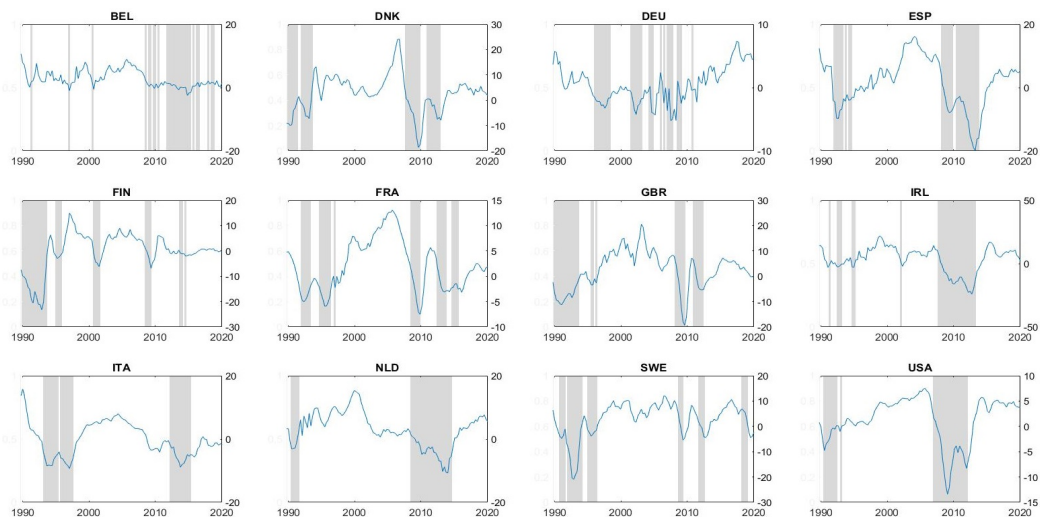
Note: The table illustrates the sources of the time-series used in the empirical analysis. All series are transformed to year-on-year growth rates, except from the indices of stress (CLIFS and CISS) and the interest rates.

Figure C1 Housing stress regime

(a) *At-Risk* Modelling Approach

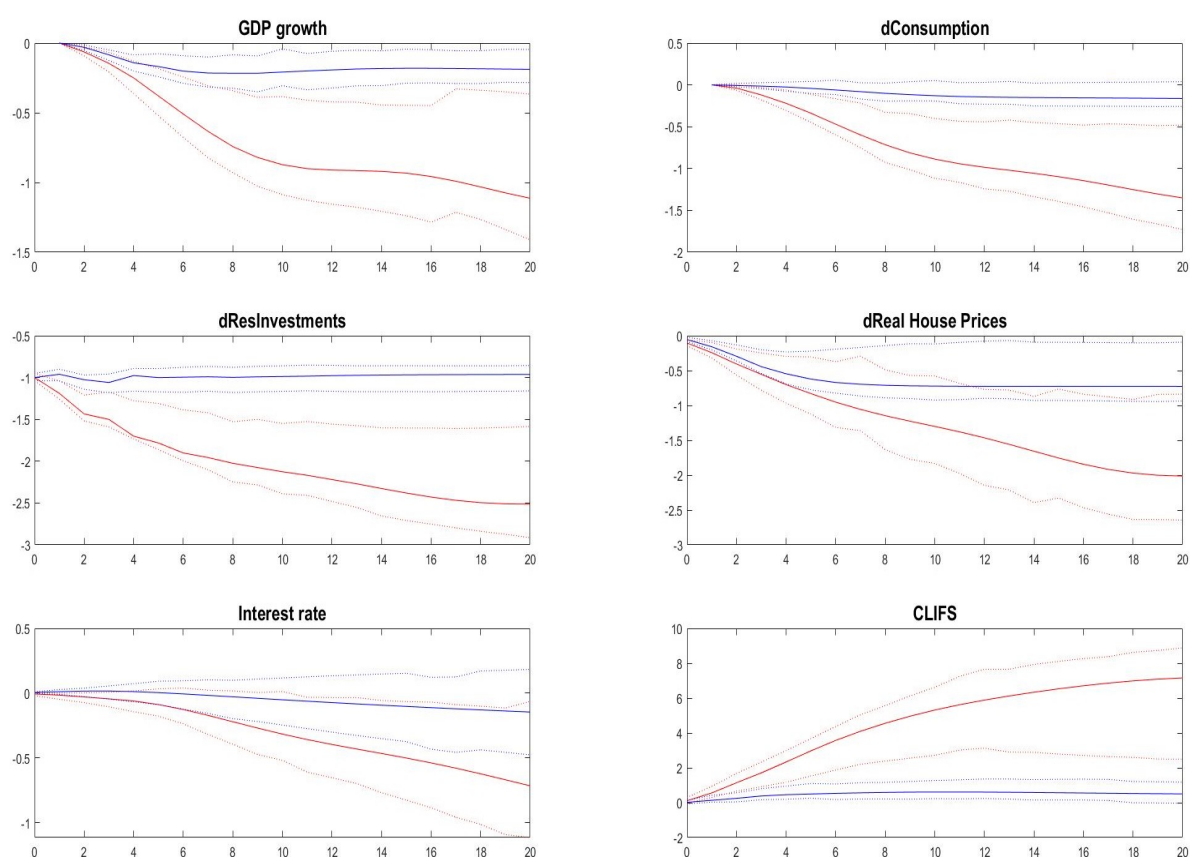
Note: The Figure illustrates the year-on-year growth in real house prices together with the grey shaded area, which indicates the periods of distress as identified by the *at-risk* modelling approach and a predictive quantile regression model.

(b) Historical House Prices Distribution



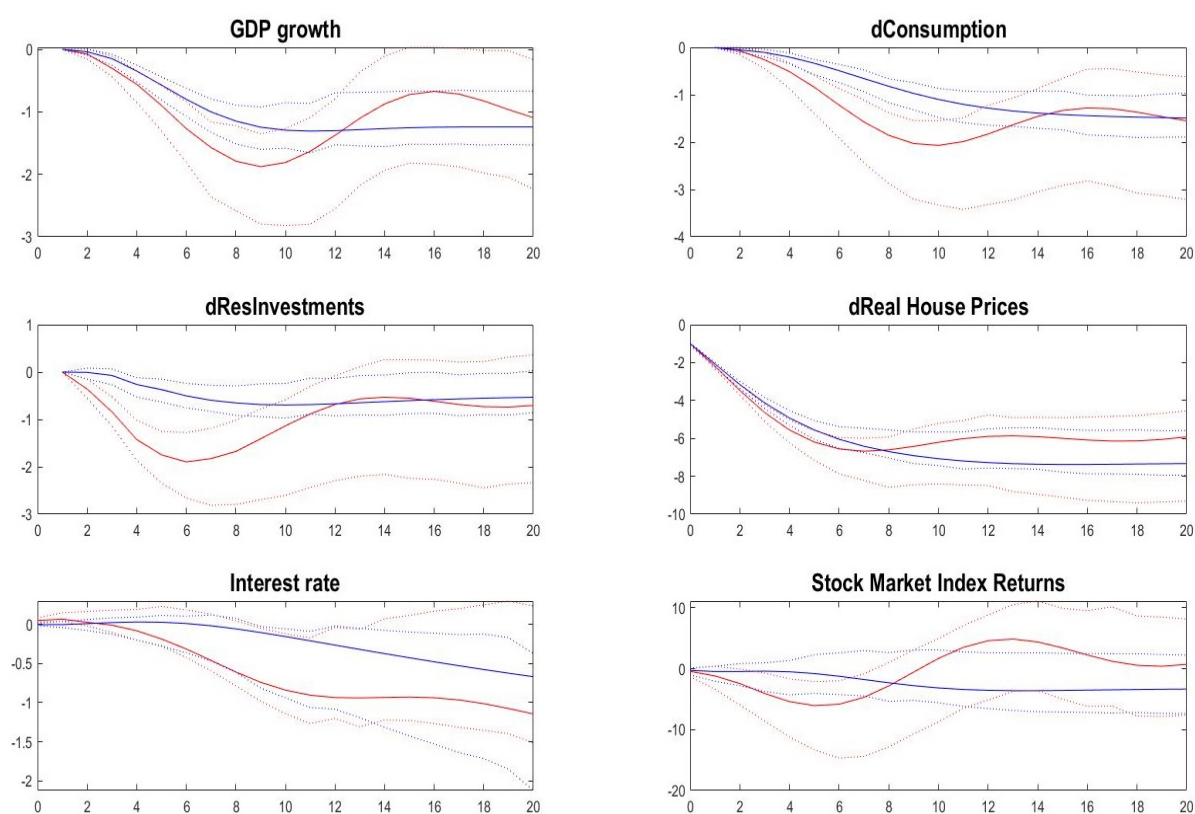
Note: The Figure illustrates the year-on-year growth in real house prices together with the grey shaded area, which indicates the periods of distress as identified by the 25% left tail of house prices distribution.

Figure C2 Cumulative IRFs: Housing supply shock



Note: Cumulative IRFs following a housing supply shock conditional on periods of housing distress. To define the stressed periods, we employ the *at-risk* modelling approach and we set the threshold as the average value of the predicted lower 25% tail. The identification of the shock is based on residential investment growth and the standard recursive approach. The shaded areas represent the 90% probability bands generated by bootstrapping with 200 iterations.

Figure C3 Cumulative IRFs: Stock market index returns



Note: Cumulative IRFs following a housing demand shock conditional on periods of housing distress. To define the stressed periods, we employ the *at-risk* modelling approach and we set the threshold as the average value of the predicted lower 25% tail. The identification of the shock is based on the standard recursive approach. The shaded areas represent the 90% probability bands generated by bootstrapping with 200 iterations.