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Risky mortgages, credit shocks and cross-border spillovers

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Abstract

This paper describes a novel methodology of measuring risky and conservative mortgage credit using household survey data for 18 European Union countries and the United Kingdom. In addition, we construct time series for both types of credit and embed them into a global vector autoregressive (GVAR) model, so as to study how shocks to both variables affect domestic output and propagate across countries through cross-border banking exposures. The results show that a decrease in risky credit can have long-lasting positive effects on GDP, both in the originating country and its most exposed peers, while a fall in conservative credit is detrimental. In some geographies, negative shocks to both types of credit reduce output, a feature linked to the lower relevance of homeownership which implies that mortgage credit plays a less prominent role in the domestic economy.

Keywords: Mortgage rating, LTV limits, borrower-based measures, cross-border spillovers.

JEL codes: C32, F47, G21, G51.

1 Introduction

In recent years, topics related to macroprudential policy have been high on the agenda, with an emphasis on the need to prevent fluctuations in financial cycles. This trend has given rise to a number of policy instruments aimed at preserving financial stability. In the European Union, macroprudential instruments have been well anchored in the Capital Requirements Regulation (CRR), whereby some measures are directly embedded in the Union's legal system, and the Capital Requirements Directive (CRD IV), which depicts a second set of instruments to be transposed into national law. The scope of macroprudential policies is very broad and encompasses four main financial stability risks[1]: misaligned incentives and moral hazard (e.g. capital buffers for significant banking institutions), concentration of credit risk (e.g. exposure limits), market illiquidity (e.g. liquidity ratios) and -last but not least- excessive credit growth and leverage (e.g. the countercyclical capital buffer).

Within the latter, so-called borrower-based measures are particularly known to the general public as they directly determine the access to bank financing and its volume. The epitomes of borrower-based instruments are limits on the loan-to-value (LTV), loan-to-income (LTI) or debt-service-to-income (DSTI) ratios for loans to the private sector, typically on mortgages. In general, borrower-based measures are understood as effective if they succeed in reducing the volume of low-quality credit, with banks engaging in transactions for which credit risk is lower; at some point, the behavior of borrowers might also shift towards demanding loans with more reasonable conditions (e.g. with lower LTV ratios).

In parallel, economies around the world are becoming increasingly interlinked through the bank lending channel. Financial integration is apparent, for instance, by looking at cross-border ownership of assets by banking institutions. For EU countries, this phenomenon is particularly relevant: as displayed in Figure 1, eleven out of 28 territories have more than half of their bank assets in the hands of foreign institutions. Abstracting from the potential gains from integration, two major risks arise: firstly, the transmission of financial shocks in such an environment becomes much more difficult to track; secondly, banking systems largely dependent on foreign institutions to supply credit could "import" a funding shortfall or tighter financing conditions.

[Figure 1 here]

It follows that the effects of macroprudential measures implemented in one country may spill over other geographies: for instance, they might induce regulatory arbitrage, whereby banking groups - through foreign branches and subsidiaries- benefit from either not being subject to the same local macroprudential regulation as domestic banks or these policies being laxer than in the country

[1] Following the classification in ESRB (2019).

where the parent is located. In consequence, transnational implications shall be accounted for when gauging the effectiveness of any policy action.

Measuring potential cross-border spillovers requires information on individual banking institutions in order to quantify credit risk exposures via branches and subsidiaries. In the EU, national regulators as well as the ECB can resort to supervisory reporting (FINREP/COREP) where information is consistent across countries and banks, although there are some limitations which might lead to underestimation of the true volume of cross-border transactions[2]. However, the only feasible alternative with public data is to use the results from the EBA supervisory stress tests; the exercises include a subsample of banks from each country, in a way such that circa 70% of total consolidated banking assets in the EU are covered but substantial heterogeneity across countries prevails[3]. The time series dimension remains unusable as only three rounds of the exercise are available to date (2014, 2016, 2018) and the disaggregation level is not uniform across them.

However, there is an additional dimension that not even supervisory data captures comprehensively: loan quality within non-deteriorated credit. For instance, while the volume of non-performing exposures is known for each loan segment, country, institution and reporting period, no information exists on the LTV ratio distribution within performing exposures; individual banks will certainly calculate it internally yet it falls out of the scope of regulatory data submissions. The implementation of IFRS 9 accounting standards shed some light as a distinction now exists between Stage 1 (ordinary) and Stage 2 (with a significant increase in credit risk) assets; in fact, the 2020 EBA stress test templates include information on LTV ratios for S1 and S2 assets, but the exercise has been postponed to 2021 due to the Covid-19 health crisis. Nevertheless, the S1/S2 distinction is a posteriori, as risk is measured with respect to the moment that the loan entered into the bank's balance sheet. Therefore, at present it is unfeasible to create a proxy for "conservative" and "risky" credit granted by banking institutions, whether through public or supervisory information, let alone build a uniform measure for a number of countries. This data gap has important implications, as the conclusions of any empirical model will be drawn on the grounds of broad credit aggregates lacking the required degree of granularity.

The situation becomes even more apparent in the realm of dynamic macro models. Consider a multivariate time-series setup built to calculate the dynamic response of GDP to a negative shock in credit, the latter originating due to a borrower-based macroprudential measure. Ideally, conservative credit -which encourages sustainable economic growth- should remain unaffected, while risky credit

[2] In the current COREP setting, banks only have to report cross-border exposure if the latter exceeds 10% of total exposure, although national supervisors may set a lower threshold for banks established in their jurisdiction. Besides, institutions with material focus on the domestic market are not required to report.

[3] For example, Germany counts more then 350 savings banks (*Sparkassen*) making up more than 25% of total bank assets, but all of them are classified as less significant institutions (LSIs) and thus not covered by the EBA stress test.

should fall: the effect on output should then be transient and manageable. Unfortunately, this distinction is very difficult to make due to the aforementioned data gap.

The purpose of this paper is twofold. Firstly, we construct measures of “conservative” and “risky” mortgage credit for a number of EU countries. Specifically, we use the Eurosystem’s Household Finance and Consumption Survey (HFCS) to extract LTV, LTI and DSTI ratios for each loan in the sample, and then calculate time-varying shares of conservative/risky credit using thresholds in line with the borrower-based measures in place in most European countries. These shares are applied to aggregate mortgage lending data from the BIS to construct the final time series.

Secondly, we use our measures of conservative and risky mortgages along with real output in a Global Autoregressive (GVAR) framework, in order to have a first check on the validity of our artefacts. In particular, we profit from this setup as well as cross-country banking exposures data to evaluate the potential spillover effects of borrower-based macroprudential measures within the Euro Area countries.

The results of our simulation exercise show that a negative shock to risky credit can increase real output in the long run while the effect of a contraction in conservative credit is pervasive, in line with our intuition. Nevertheless, in some geographies a contraction in credit, whether conservative or risky, increases real output. These countries are found to have a different homeownership structure with a more prominent role of the rental market, in a way such that the positive long-run effect of deleveraging on output prevails.

The remainder of the paper is organized as follows: a brief literature review can be found in Section 2; Section 3 describes the construction of conservative and risky mortgage weights. Section 4 depicts the structure of the GVAR model, the data used and our specification, then presents the main results. Finally, Section 5 concludes.

2 Related literature

To the best of our knowledge, no study exists to date analysing conservative and risky credit from a time series perspective. The literature on macroprudential policy employs aggregate credit statistics or supervisory data, but the two have not yet been combined to study differences in credit quality among performing borrowers, and how the latter feeds into macroeconomic variables. Our methodology, though simple and constrained by data availability, constitutes an initial attempt to be perfected in future research.

Having said this, by exploring the cross-border propagation of credit shocks induced by borrower-based macroprudential measures, our paper echoes several strands of literature which have been active in recent years. The first one is the conceptual work related to capital- and borrower-based macroprudential policies, and the channels through which they are expected to work (see, for example, Cerutti et al., 2017 or IMF, 2013). Focusing on the latter, Mendicino (2012) develops a business cycle model with credit frictions and shows that countercyclical LTV ratios in response to credit growth can smooth the credit cycle. Precisely, a number of early studies such as Lamont and Stein (1999) or Almeida et al. (2006) had find evidence that the business cycle is more sensitive to house price movements if LTV ratios are higher.

On the policy evaluation front, Lim et al. (2011) assess the efficiency of macroprudential tools, such as LTV caps, in reducing systemic risk using data from 49 countries. Crowe et al. (2011), using data from the US, find a positive relationship between LTV and price appreciation. Ravn (2016) highlights that LTV caps are an effective macroprudential policy tool in order to reduce the additional volatility caused by endogenous changes in lending standards; this is an important result as it is well known that banking margins are countercyclical[4]. By geographical areas, impact assessments are also abundant for individual countries[5], yet only a few studies include a multinational dimension: Kim and Mehrotra (2018) analyse four countries in the Asia-Pacific region, while Richter et al. (2019) construct a panel of 56 countries. For the Euro Area, Gross and Población (2017) develop an integrated micro-macro model framework to assess the efficacy of borrower-based instruments and quantify the macroeconomic feedback effects. In doing so, they employ household-level data from the Household Finance and Consumption Survey (HFCS) that is also the cornerstone of our study; however, the objects of study are regulatory parameters (Default probabilities and losses given default -PD and LGD) rather than credit volumes.

Turning to the implications of cross-border banking, the 2008 financial crisis gave rise to a strand of literature studying how foreign branches and subsidiaries altered their lending behaviour contingent on the parent institutionś: two prominent examples are Cerutti and Claessens (2017) and Hoggarth et al. (2013). The relative importance of foreign business for the banking group also affects credit supply in these markets, a feature studied in Cetorelli and Goldberg (2012). In the case of the Euro Area, ESRB (2019) is a comprehensive reference on this issue.

Finally, the advances in macroprudential regulation in latest years have prompted a deeper examination of the potential cross-border spillovers of these policies, with conceptual frameworks deployed as in FSC, Kok and Reinhardt (2020). The workhorse of the vast majority of them is a DSGE model: Rubio (2020) or Darracq Pariès, Kok and Rancoita (2019) present a two-country setup -the euro area versus the rest of the world-, similarly to Rubio (2020) where calibration is done for the US. Kang et al. (2017) use the 40-country DSGE in Kang et al. (2017) which includes a parsimonious financial intermediation sector with cross-border spillovers through trade flows,

[4] See, for example, Aliaga-Diaz & Oliveiro (2011).

[5] See Gerlach and Peng (2005) or Wong et al. (2016) for Hong Kong, Cussen et al. (2015) for Ireland, Price (2014) for New Zealand, or Tillmann (2015) and Kim et al. (2020) for Korea.

exchange rates and other financial variables; all studies conclude that these effects are significant, although their magnitude is strongly dependent upon the pair of countries considered and the business structure of the individual banking institutions. In a different vein, Kok, Gross and Zochowski (2016) use a mixed cross-section GVAR model to assess the effect of bank capital shocks (i.e. capital-based macroprudential measures) on different Euro area countries, an approach which we rely on by adding two contributions: disentangling the effects of high- and low-quality credit and using an up-to-date, more refined country weighting scheme with information from FSC (2020) or Cantone, Wildmann and Rancoita (2019). This is in the spirit of the broader work by Sgherri and Galesi (2009), who study the transmission of financial shocks across European economies linked through financial weights, although in their work asset prices play a prominent role.

Lastly, concerning the regulatory dimension, most studies suggest that foreign affiliates of domestic banks will increase lending in their host countries if macroprudential regulation is laxer than in the parent, a phenomenon known as regulatory arbitrage. This phenomenon is examined in Avdjiev et al. (2017), Caccavaio et al. (2017), Hills et al. (2017), Ohls et al. (2017), Reinhardt and Sowerbutts (2015) or Aiyar et al. (2014).

3 Risky versus conservative mortgages

A limitation of most papers is that they use data at the aggregate level and rely on the use of average indicators in their cross- or single-country analysis. Therefore, they miss the intricate effects of LTV limits on borrower behavior in the credit and housing markets, a feature which can only be tested accounting for intra-country borrower-specific variation. In this paper, we use comprehensive loan-level data on mortgages to distinguish between two types of credit, which we dub ”risky” and ”conservative”.

We start by extracting loan-level data from the Household Finance and Consumption Survey (HFCS), a joint initiative of all the Eurosystem national central banks, the central banks of three EU countries that have not yet adopted the euro, and several national statistical institutes aimed at collecting comparable micro-level data on households’ balance sheets. The HFCS is therefore a unique and harmonized survey that provides detailed information on households’ socio-economic and demographic background, liabilities, consumption, income, and wealth across 19 euro area countries as well as Croatia, Hungary and Poland.

Our dataset includes the three available HFCS survey waves which took place mainly during 2010, 2014 and 2017, and covers 17 of the aforementioned countries, as some key variables are missing for Croatia, Finland, Hungary, Lithuania, and Malta. It contains information on housing characteristics for the household main residence (HMR) and other real estate properties, as well as mortgages or loans using such properties as collateral taken out by a total of 40,686 households.

The data refers to the initial mortgage and subsequent refinancing. For the HMR, we calculate the LTV at loan inception using the property value at the time of acquisition and the initial mortgage. Otherwise, where the loan has been refinanced, information relates to the total amount refinanced and the year the current loan was most recently refinanced; but the collateral value at that given year is unknown as respondents are asked to price their residence only at the time of purchase and when the survey comes about. In such cases, we estimate the collateral's value using residential property price statistics from the Bank for International Settlements. For properties other than the HMR, the collateral value is only available for the year at which the survey took place; therefore, we extrapolate it using property prices back to the year when the loan was contracted.

One important observation is that borrowers might have an incentive to take out more than one mortgage backed by the same collateral, whether because they want to circumvent the regulatory limits to LTV ratios -if in place- or benefit from more favorable lending conditions. Therefore, in order to avoid misclassification, when households engage in more than one mortgage during the same year we calculate the factual LTV by adding the total amounts borrowed. In a final step, we discard all mortgages with an LTV ratio below 10% or above 200%[6] and restrict our analysis to the year 2000 onwards, as data for the GVAR model is only available since that point in time. After all the aforementioned transformations, we are left with 162,756 loans. A summary of available mortgages for each country and year is shown in Table 1.

[Table 1 here]

Once we have calculated and adjusted the LTV for each mortgage in our sample, we classify the mortgage as "risky" -as opposed to "conservative"- if it exhibits an LTV ratio beyond a preset value. We use three alternative cutoffs (85, 90 and 95 percent) in line with the regulatory limits in place in most European countries, as described in Appendix A. This allows us to compute the shares of risky credit for using two different measures: by taking the volume of risky mortgages over the total amount borrowed in one country at a given year, or by plainly counting the number of risky loans over the total number of mortgages.

In addition, we create matrices for risky and conservative credit based on debt-service-to-income (DSTI) as well as loan-to-income (LTI) ratios, which are extensively used in recently announced measures. To this end, we profit from two derived variables in the HFCS dataset which register mortgages with DSTI ratios over 40% and LTI ratios with an income multiple over 3. Once again, these cutoff values are in line with those in place in Europe to date. In this case, the sample of mortgages is larger, with 254,000 observations.

[6] After visual inspection of the dataset, we discovered that loans out of the range [10%,200%] are frequently misreported, with missing or extra zeros in the amounts leading to errors in the LTV ratio.

Because of its relevance for banking systems across the European Union -as analysed subsequently in this paper- it makes sense to include the United Kingdom in our country sample. However, as neither the Office for National Statistics nor the Bank of England are members of the HFCS cluster, we have computed risky and conservative credit shares relying upon other data sources. In particular, the Financial Conduct Authority (FCA) publishes the quarterly statistics on Mortgage Lending and Administration Return (MLAR) which feature a distribution of mortgage loans by LTV ratio and income multiple (i.e. the LTI ratio); we are thus able to compute the share of loans with LTV ratios above 90%, on one hand, and with LTI ratios greater than 3, on the other[7].

Last but not least, it may occur that too few mortgages are available in our dataset for a given country and year to compute meaningful shares of risky and conservative credit. When the number of observations falls below our *ad hoc* threshold of 50, we fill the missing values by taking moving averages of the following (resp. preceding) years, if this happens at the beginning (resp. end) of the sample, or by using linear interpolation, if the blanks lie within two available observations. For 2018 and 2019, which are not available in the HFCS sample because the 3^{rd} wave took place in 2017, we use the last computed value.

The full matrices with conservative and risky credit shares for all countries in the period 2000-2019 can be found in Appendix B; a graphical summary is depicted in Figure 2. With our methodology, risky credit appears to constitute a smaller share of total mortgages than conservative loans. This said, substantial heterogeneity prevails across countries; in particular, economies most hit by the 2008 financial crisis (e.g. Spain, Ireland, Italy, Portugal) seem to have reduced more clearly the share of risky credit over time.

[Figure 2 here]

4 An application: Cross-border spillovers of LTV limits

This section presents a simple exercise where we embed our estimates of conservative and risky credit into a multivariate time series framework, allowing us to gauge how credit shocks induced by borrower-based macroprudential measures can propagate to foreign economies via cross-border exposure of banking institutions. We start by describing our workhorse, the GVAR model, then narrate how our data and the econometric specification are constructed in the abridged spirit of Sgherri and Galesi (2009); finally, we discuss our results.

[7] More concretely, this information is contained in MLAR Table 1.31. We use the total of regulated plus unregulated mortgages; for the LTI threshold, we consider both single and joint income.

4.1 The GVAR model

The GVAR approach was originally proposed by Pesaran et al. (2004)[8] and since the very first moment after its appearance, it has been very well accepted and echoed among researchers and practitioners. The GVAR is a simple but effective methodology of modelling interactions in a system with many dimensions such as the global economy avoiding the curse of dimensionality (see, for example, Chudik et al. (2011)). GVAR modelling can be seen as a two-stage procedure. In the first step, country-specific models are estimated conditional on the rest of the world, which enters the equations in the form of weighted cross-section averages of foreign variables that are treated as weakly exogenous. The latter are generated from the domestic variables using a weight matrix that can reflect trade volumes (the original formulation of GVAR), banking sector features or any other desired cross-country interaction. In the second step, individual country models are stacked and solved simultaneously as one global, reduced-form VAR model. The solution can be used for shock scenario analysis and forecasting as in an ordinary low-dimensional VAR.

We present a succinct mathematical formulation of the model following Kok, Gross and Zochowski (2016). Initially, consider an ordinary VARX structure (possibly with a deterministic trend) with exogenous variables for each of the countries $i = 1, 2, ..., N$. Assume there are d_i endogenous variables grouped in a vector $y_{i,t}$ and f_i foreign variables in a vector $y^*_{i,t}$. While domestic variables enter the model with P lags at most, foreign variables are considered both contemporaneously and with up to R lags:

$$y_{it} = a_{i,0} + a_{i,1}t + \sum_{p=1}^{P} \Phi_{i,p} y_{t-p} + \sum_{r=0}^{R} \Gamma_{i,r} y^*_{t-r} + \varepsilon_{i,t} \tag{1}$$

where $\varepsilon_{i,t} \sim iid(0, \Sigma_i)$. Note that there exists the possibility of contemporaneous cross-country dependence of shocks, that is, $E\left[\varepsilon_{i,t}\varepsilon'_{j,t}\right] = \operatorname{cov}\left(\varepsilon_{i,t}\varepsilon'_{j,t}\right)$.

Foreign variables for the N countries are constructed using an $N \times N$ weight matrix W in which the relevance of country j for country i is captured by element w_{ij} and the main diagonal of W is zero, meaning that $y^*_i = \sum_{j=1}^{N} y_j$ and $\sum_j w_{ij} = 1$. Within each country VARX model, one key assumption is weak exogeneity of the foreign variables, which entails that short-run interaction between domestic and foreign variables is permitted but the former cannot influence the latter in the longer term.

Now assume $P = R$ for simplicity, stack all of the country variables in a single vector $z_{i,t} = \left(y_{i,t}\, y^*_{i,t}\right)'$ sized $(d_i + f_i) \times 1$ and rewrite the country models as:

$$A_{i,0} z_{i,t} = a_{i,0} + a_{i,1}t + \sum_{p=1}^{P} A_{i,p} z_{i,t-p} + \varepsilon_{i,t} \tag{2}$$

[8] It was also developed in seminal contributions by Pesaran and Smith (2006), Pesaran et al. (2006) and Dées et al. (2007).

where $A_{i,0} = (I_{d_i}, -\Gamma_{i,0})$ and $A_{i,p} = (\Phi_{i,p}, \Gamma_{i,p})$.

If the endogenous variables in the cross-section are stacked into one global vector y_t of dimension $d = d_1 + ... + d_N$, we can establish a mapping of the domestic variable vectors $z_{i,t}$ into the global vector by means of a series of link matrices L_i of dimension $(d_i + f_i) \times d$, so that $z_{i,t} = L_i y_t$. This allows the model to be reformulated as:

$$A_{i,0} L_i y_t = a_{i,0} + a_{i,1} t + \sum_{p=1}^{P} A_{i,p} L_i y_{t-p} + \varepsilon_{i,t} \tag{3}$$

The global model can now be constructed by stacking the the country-specific models:

$$G_0 y_t = G_0^{-1} \left(a_0 + a_1 t + \sum_{p=1}^{P} G_p y_{t-p} + \varepsilon_t \right) \tag{4}$$

$$G_i = \begin{pmatrix} A_{01} L_1 \\ A_{02} L_2 \\ \vdots \\ A_{0N} L_N \end{pmatrix}, G_p = \begin{pmatrix} A_{p1} L_1 \\ A_{p2} L_2 \\ \vdots \\ A_{pN} L_N \end{pmatrix} \tag{5}$$

This is the model that will be used for simulation and impulse response analysis. It is important to bear in mind that the GVAR produces generalized IRFs in the sense that it allows error terms to be correlated.

Aside from the weak exogeneity of foreign variables in each country model, there are three additional conditions that the GVAR has to satisfy in order to be valid and well-behaved: Firstly, the eigenvalues of the matrices $H_p = G_0^{-1} G_p$ have to be smaller or equal than one in module to ensure stability; secondly, the elements ot W have to be relatively small. Finally, the cross-dependence of the idiosyncratic shocks must be sufficiently low.

4.2 Data and estimation

By combining the annual risky/conservative credit[9] weights described in the previous section with aggregate household credit statistics from the Bank of International Settlements, we are able to create time series of risky and conservative credit, assuming that their sum equals the aggregate figure reported by the BIS[10]. We apply country-specific correction factors to scale down aggregate credit depending on the relevance of mortgages, as detailed in Appendix D.

[9] Henceforth, we use "credit" and "mortgages" indistinctly.

[10] Weights from the HFCS are computed annually while the BIS statistics are quarterly; we thus multiply each quarter in the year for the same weight. An alternative would be to interpolate quarterly weights.

The domestic block of each country model includes three quarterly time series spanning from 2000Q1 to 2019Q2: real GDP, risky and conservative credit, the latter both deflated by the consumer price index. All variables enter the model in logs; the details of the series can be found in Appendix D. We conduct Augmented Dickey-Fuller tests (ADF) on both domestic and foreign variables so as to ascertain whether the series have a unit root[11]. The test is run on levels, first and second differences; as shown in Tables 2 and 3, most variables in our model are found to be I(1).

[Table 2 here]

[Table 3 here]

In order to construct the foreign variables for each country, we use two weight matrices: For GDP, we resort to the traditional trade approach where cross-country weights are derived from bilateral imports/exports; in contrast, for the credit variables we build a matrix based on the information in FSC (2020), which includes information on cross-border bank exposures built upon supervisory reporting at the highest level of consolidation for end-2018, for a sample of circa 400 banks supervised by the SSM. Because of data availability in the construction of our credit aggregates, we must recompute the individual weights excluding Finland, Lithuania, Malta and Sweden. Final weight matrices are provided in Appendix C.

As regards the individual country VAR specification, we incorporate a maximum of two lags for each domestic variable -with the lowest AIC as the decision rule- and only one for foreign terms. Regarding the latter, de-activate foreign risky credit for all countries: the rationale for this choice is that, while an increase in risky credit might have immediate financial stability consequences for the host economy, it is likely that the impact on foreign economies through cross-border banking exposures will happen through changes in the business model or the amount of loans granted, which is more visible in conservative credit[12].

The individual country VARX* models are estimated in error-correcting form (VECMX*). The number of cointegrating relationships is determined through the reduced-rank regression procedure[13] and is reported in Table 4 along with the selected lag orders; note that country models with zero cointegration rank are estimated in differences. Also, for each country model, we test whether the foreign variables are weakly exogenous by evaluating the joint significance of the foreign terms in each VECMX*; for countries where the cointegration rank is zero, foreign variables are directly considered weakly exogenous. The test results, which are presented in Table 5, show that weak

[11] The lag order of the test statistics is determined by minimizing the Akaike IC with a limit of 2 lags.

[12] We also rule out conservative credit for Cyprus, Greece, Latvia and Slovenia, owing to the reduced availability of data to compute weights in the HFCS sample.

[13] Both the trace and maximum eigenvalue statistics are derived by letting the intercept coefficients to be unrestricted in levels and not including a deterministic trend in the reduced rank regressions.

exogeneity is assured for all series except for GDP in Slovakia; we thus consider our setup sufficiently well-grounded for the analysis.

[Table 4 here]

[Table 5 here]

Aside from the weak exogeneity, the rest of conditions needed to ensure stability of the global model are verified in our setup: The elements of the financial weight matrix are sufficiently small and the all the model eigenvalues lie on or within the unit circle. An additional way of checking model stability is to look at the persistence profiles (PPs), which gauge the effect of shocks on the long-run (cointegrating) relationships. The PPs should converge relatively fast to zero, something that happens for our model, as Figure 3 shows.

[Figure 3 here]

As a last condition, the system's idiosyncratic shocks must be weakly correlated, so that the shocks to both conservative and risky credit employed in our analysis can be considered idiosyncratic and country-specific. In a way, the foreign variables in each country VECMX* model act as common latent factors which help reducing the dependence among all domestic variables in the GVAR; therefore, the residuals of foreign variables should exhibit low correlation. We compute the pairwise cross-country correlations for foreign output and conservative credit, which are displayed in Table 6, reporting the values for the series in levels and first differences as well as for the country VECMX* residuals. The calculations show that the dependence, initially high in levels, dampens considerably after taking differences and shrinks further in the equation residuals to generally negligible values. Only risky credit series exhibit a slightly higher -though still very low- correlation.

4.3 Results

In this subsection, we present selected dynamic features of our GVAR specification. In particular, we are interested in measuring how economies respond to shocks in risky and conservative credit and how the latter propagate across foreign countries. With our methodology to build risky and conservative credit, more stringent borrower-based macroprudential measures such as LTV ratio limits are univocally linked to a reduction in risky credit; moreover, cross-border spillovers of macroprudential policy imply that the contraction might feed to other geographies where the banking institutions of the home country are exposed via branches or subsidiaries. In our simplified GVAR setup, we would expect all of the former to manifest in two simultaneous ways: Firstly, a negative shock to risky credit favours output in the long run by preventing an excessive build-up of credit risk for financial institutions; conversely, a fall in conservative credit hampers the country's economy by weakening the leverage-growth channel. Secondly, this behavior will affect the banking systems of other geographies where parent institutions affected by domestic shocks play a significant role.

We choose to illustrate our results using pairs of countries with significant cross-border bank exposures, measured by the weight matrices found in Appendix C. In particular, we use the simulation suite by Galesi and Smith (2014) focusing on three cases in which the share of domestic credit granted by foreign institutions is large: The exposure of Spanish banks in Portugal (74%) and the UK (40%), of Italian banks in Austria (54%) and of French banks in Belgium (53%), Italy (61%) and Luxembourg (58%). Figure 4 shows generalized impulse response functions (GIRFs) of real GDP to negative, one-standard deviation shocks to risky and conservative credit in Spain and Italy. Output reacts in a distinct fashion to both perturbations, in line with our intuition: conservative credit has a persistent positive effect on domestic output while risky credit has negative consequences. Regarding the magnitude, both types of credit induce a similar behavior of GDP in absolute value for the case of Spain, while in Italy the response to risky mortgages is twice as large as for conservative mortgages. Cross-border effects are also sizeable for countries significantly exposed to the Spanish and Italian banking sectors, although varying across geographies: for instance, the reaction of output in the UK is more muted than the domestic reaction in Spain, while for Portugal some amplification is at play; this might be due to foreign GDP being weighted by trade flows in the GVAR as trade linkages between Spain and Portugal are particularly strong.

[Figure 4 here]

However, not all countries exhibit behaviors in line with our intuition. Figure 5 plots the domestic impulse responses to credit shocks in France: the results are at odds with those observed for Spain and Italy as the domestic response of GDP is similar in magnitude and has a positive sign for both risky and conservative deleveraging, thus suggesting that *any* reduction in credit will favor output in the long run. The cross-country effects are, again, contingent upon the relevance of cross-border ties in terms of trade flows and financial exposure; moreover, it appears that the range of amplification effects is broader for conservative credit. One plausible explanation arises by looking at the weight matrices: the share of conservative mortgages in Luxembourg and Italy, which exhibit the largest amplification, is much larger than in France[14].

[Figure 5 here]

In order to understand why output might expand due to a reduction in conservative credit, the flow of which should be beneficial for an economy, we explore the homeownership structure across geographies in the model: where rental plays a more important role, mortgage credit should be less

[14]The divergence in responses to credit shocks in Spain, illustrated in Figure 4, also fits into this hypothesis.

relevant as its bulk is devoted to house purchase and, more broadly, secured on immovable property. In such cases, the distinction between risky and conservative mortgages could become secondary in favor of the beneficial effects of deleveraging for the aggregate economy. As shown in Figure 6, Spain and Italy -where the response of risky credit is distinct- have a much higher homeownership rate than France.

[Figure 6 here]

4.4 Robustness checks

We verify the soundness of our results using credit shocks in Spain as a benchmark. Firstly, we use alternative cutoff values of the LTV ratio to compute country weights and the resulting conservative/risky credit time series to be inserted in the GVAR. Figure 7 illustrates that responses to credit shocks under different LTV thresholds preserve the sign of the baseline case, with magnitude varying non-linearly: decreasing the cutoff has more-than-proportional effects on the GIRFs.

[Figure 7 here]

Secondly, we compute the shares of conservative and risky weights by country and year by considering the volume of mortgage credit, rather than the number of mortgages, above the LTV cutoff value. The response of GDP to a shock in volume-based risky credit are very similar to the baseline case using the number of loans, whereas the reaction of output to a shock in conservative credit is amplified considerably. Finally, we employ an alternative weight matrix for the creation of foreign credit variables in the GVAR, relying on the work on direct or branch-directed cross-border bank exposures by Cantone, Wildmann, and Rancoita (2019). Again, we have to adjust the data to exclude some countries not present in our GVAR specification. A correlation analysis with the baseline matrix, which can be found in Appendix C, suggests that the country-specific distribution of exposures is very similar in the majority of cases. As Figure 8 depicts, the impulse responses in our model appear robust to the choice of financial weight matrices.

[Figure 8 here]

5 Conclusions

In this paper, we introduce a novel, simple methodology to fill an existing gap in publicly available macro-financial data: time-series information of loan quality within performing mortgage credit in European countries. For that purpose, we classify mortgage credit into “risky” and “conservative” by exploiting loan-level data from harmonized household surveys at the European level. In order to do so, given that borrower-based macroprudential measures are widely used in most European countries, we compute LTV, DTI and LTI ratios for individual mortgages, which we use as cutoff values for our classification.

We frame our contribution in the context of increasing financial linkages across countries by considering cross-border banking exposure data. The latter allows us to quantify the potential outward spillover effects of borrower-based measures. To this end, we construct a GVAR model to evaluate how shocks to both types of credit -related to a tightening of the macroprudential stance- can potentially affect output, both domestically and in other countries.

Our results suggest that a decrease in risky credit can have long-lasting positive effects on GDP, both in the originating country and its most exposed peers, while a fall in conservative credit is detrimental. In some geographies, negative shocks to both types of credit reduce output, a feature linked to the lower relevance of homeownership which implies that mortgage credit plays a less prominent role in the domestic economy.

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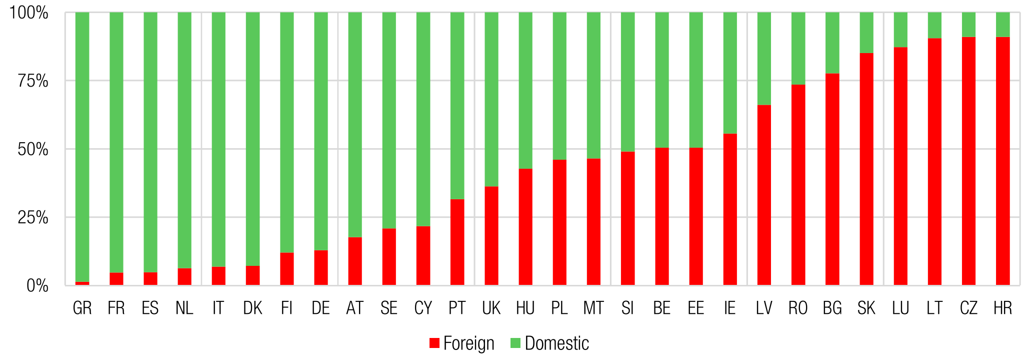
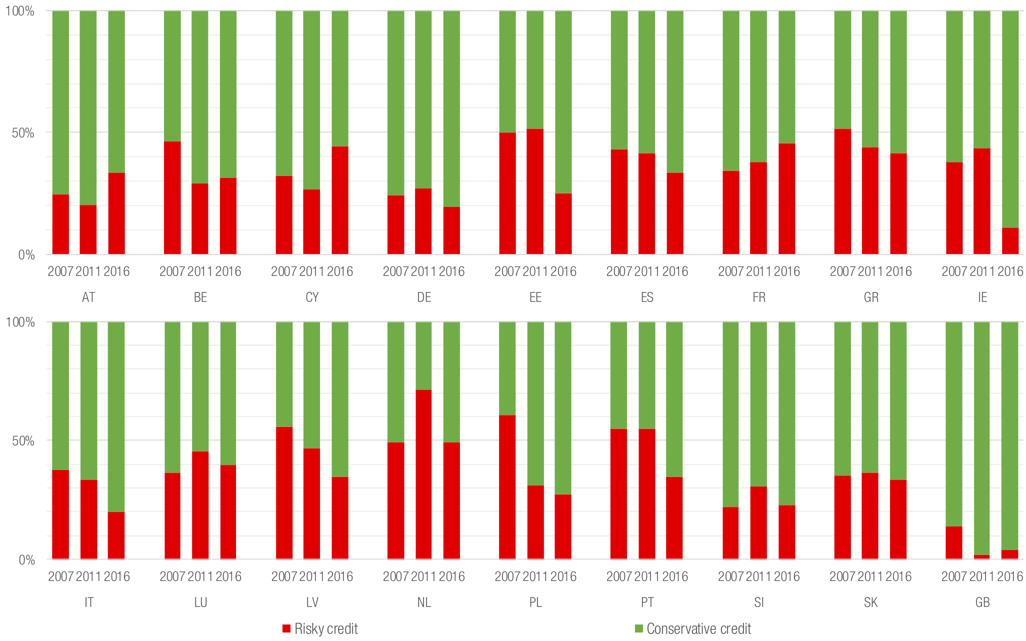
Figures and tables



Source: ECB Statistical Data Warehouse, DD dataset. Foreign banking groups include branches and subsidiaries.

Figure 1: Total consolidated bank assets by bank ownership (2019).



Results for the 90% LTV ratio threshold, using the number of mortgages (baseline case).

Figure 2: Conservative and risky credit by country in 2007, 2011 and 2016.

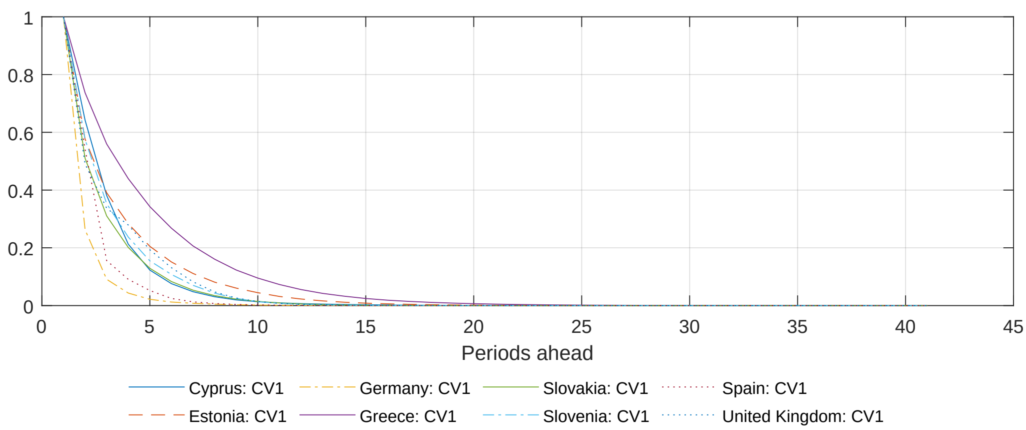


Figure 3: Persistence profiles for the cointegrating vectors: Median bootstrap estimates.

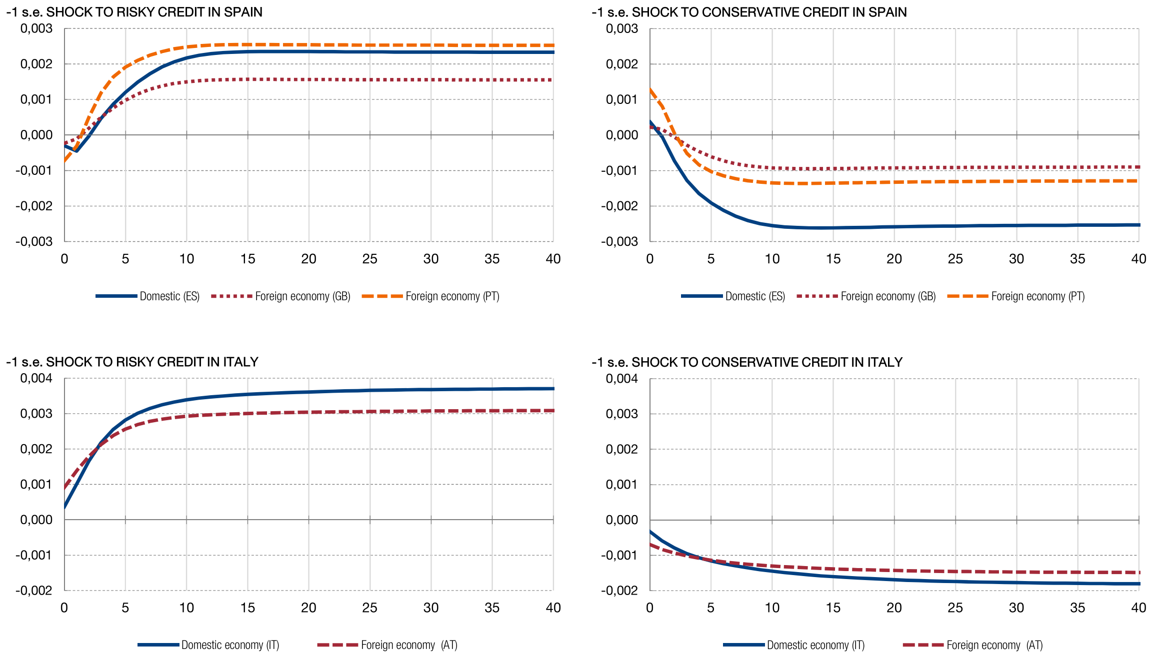


Figure 4: GDP responses to credit shocks in Spain and Italy.

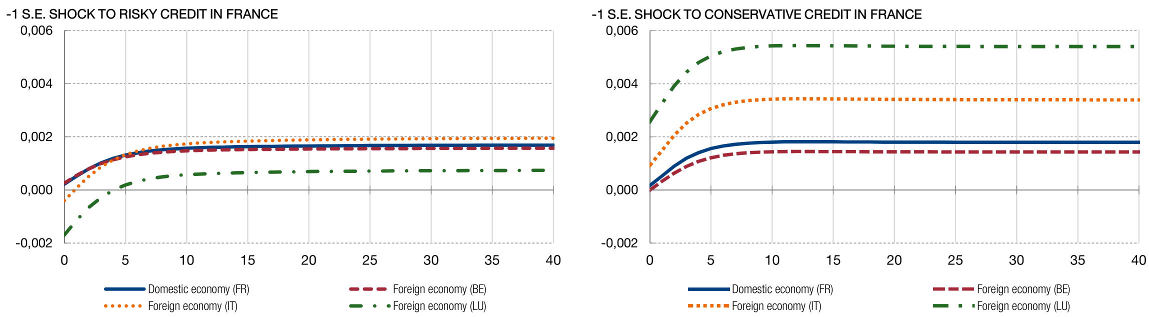
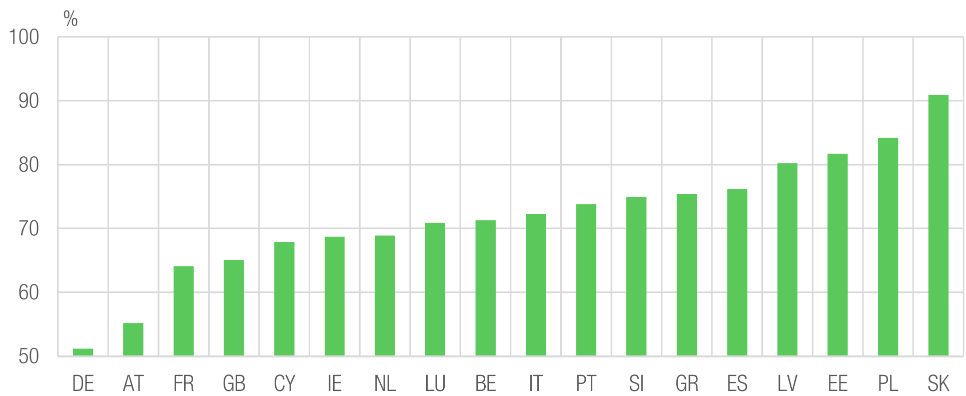


Figure 5: GDP responses to credit shocks in France.



Source: Eurostat, ilc_lvho02 *dataset.*

Figure 6: Homeownership rate (2019) in the GVAR countries.

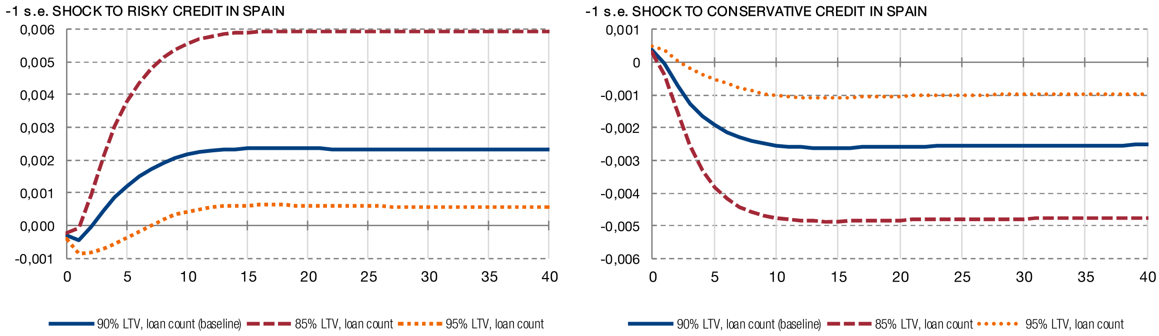


Figure 7: Spain: GDP response to domestic credit shocks under alternative LTV cutoffs.

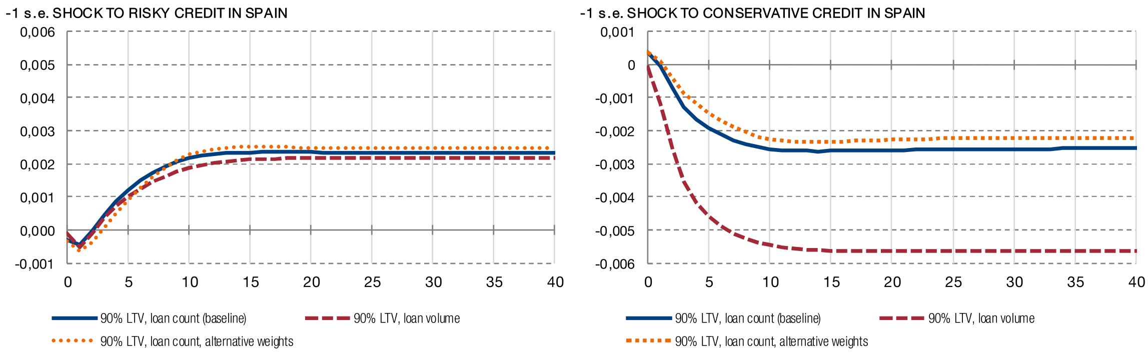


Figure 8: Spain: GDP response to domestic credit shocks under alternative weightings.

Year	AT	BE	CY	DE	EE	ES	FR	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
2000	174	336	168	384	552	948	612	306	480	372	216	*0*	348	*6*	1242	*6*	78
2001	186	318	126	318	348	738	660	180	510	486	234	*0*	408	*18*	1560	*6*	*24*
2002	186	342	228	342	486	888	768	204	558	444	348	*0*	276	*42*	1698	*6*	60
2003	162	498	342	480	618	954	1056	216	834	576	264	*0*	324	54	1218	*6*	108
2004	276	426	444	486	648	1002	1320	438	1284	660	294	*6*	252	90	1290	*36*	138
2005	282	564	510	666	870	1182	1722	444	1842	684	336	*36*	324	72	1362	66	198
2006	342	528	666	702	972	1074	1896	336	2124	648	384	*12*	498	108	1176	90	204
2007	294	648	912	846	912	810	2250	384	1986	714	480	108	696	258	1626	162	222
2008	312	504	816	948	498	468	1908	354	1704	618	414	150	690	438	1638	138	240
2009	300	612	474	1110	186	672	1974	192	960	588	420	168	744	348	1998	120	222
2010	330	606	438	1044	246	582	3186	144	822	600	564	120	738	378	1374	132	210
2011	330	312	204	1038	222	276	3012	*24*	372	306	396	54	588	330	1446	156	132
2012	198	342	264	1146	222	174	2430	*30*	552	246	456	*30*	498	414	1362	198	246
2013	198	318	306	1170	222	54	2508	*18*	318	234	402	60	372	480	378	96	306
2014	132	330	192	996	180	114	2904	*12*	300	252	408	66	396	330	180	54	156
2015	96	516	60	840	444	*18*	5124	*0*	366	150	282	72	342	306	144	*36*	114
2016	108	456	54	684	360	*0*	6552	*0*	276	120	348	*48*	342	306	138	*36*	216
2017	*0*	90	*6*	378	150	*0*	4578	*6*	270	*0*	378	*6*	384	*0*	144	*18*	*48*

Note: Red cells indicate less than 50 observations available.

Table 1: Number of available mortgages in the sample by country and year

	y(t)	y	Δy	Δ^2y	cons(t)	cons	Δcons	Δ^2cons	risk(t)	risk	Δrisk	Δ^2risk
Cr.Val.	**-3,45**	**-2,89**	**-2,89**	**-2,89**	**-3,45**	**-2,89**	**-2,89**	**-2,89**	**-3,45**	**-2,89**	**-2,89**	**-2,89**
AT	-2,63	-0,67	-3,85	-5,31	-1,35	-1,96	-6,41	-12,2	-4,61	-2,36	-5,85	-9,63
BE	-2,64	-0,78	-5,02	-6,69	-1,65	-0,98	-5,78	-7,34	-2,42	-2,16	-5,85	-6,10
CY	-2,37	-1,98	-2,08	-10,7	-1,18	-1,90	-5,11	-8,24				
DE	-2,83	-0,12	-4,65	-6,50	-2,40	-2,35	-6,00	-9,03	-2,49	-1,79	-6,17	-11,7
EE	-2,36	-1,64	-2,67	-10,6	-0,66	-2,35	-4,05	-7,29	-1,15	-2,92	-2,78	-7,76
ES	-2,02	-1,47	-2,23	-8,26	-1,32	-1,96	-5,06	-4,85	-2,38	-2,51	-6,30	-4,64
FR	-2,45	-0,65	-3,82	-7,11	-0,95	-1,23	-5,52	-10,9	-2,26	-1,75	-6,02	-7,82
GB	-2,89	-1,28	-4,35	-6,10	-1,25	-2,18	-5,82	-8,31	-1,33	-1,18	-5,72	-10,5
GR	-1,94	-1,24	-2,17	-12,4	-0,54	-2,40	-5,01	-10,7				
IE	-0,60	0,64	-6,30	-9,50	-1,09	-2,56	-4,90	-9,30	-1,04	-1,24	-5,59	-10,5
IT	-2,59	-2,47	-4,49	-6,10	-1,40	-1,68	-5,60	-9,91	-2,48	-2,61	-6,10	-10,8
LU	-2,79	-0,44	-4,91	-8,74	-2,12	-0,82	-5,56	-9,98	-1,24	-1,54	-5,90	-8,18
LV	-2,36	-1,95	-2,35	-9,90								
NL	-1,83	-0,28	-4,26	-7,34	-3,19	-2,67	-5,92	-9,42	-1,99	-2,11	-6,00	-5,35
PL	-1,63	0,21	-4,14	-9,46	-1,72	-1,74	-5,58	-10,8	-1,12	-1,77	-5,66	-9,55
PT	-1,43	-1,05	-4,01	-9,41	-1,48	-2,25	-5,57	-8,13	-1,74	-1,85	-6,08	-10,8
SI	-1,89	-1,27	-3,82	-8,35	-0,97	-1,19	-4,87	-7,06				
SK	-1,23	-1,44	-6,03	-9,58	-1,36	-1,26	-5,57	-10,8	-1,36	-0,79	-5,11	-9,59

(t): Test with trend; Δ: 1st difference; Δ^2: 2nd difference.

Table 2: Unit root tests (ADF) for the domestic variables at the 5% significance level

	y(t)	y	Δy	Δ^2y	cons(t)	cons	Δcons	Δ^2cons	risk	Δ^2risk
Cr.Val.	**-3,45**	**-2,89**	**-2,89**	**-2,89**	**-3,45**	**-2,89**	**-2,89**	**-2,89**	**-2,89**	**-2,89**
AT	-2.94	-0.41	-4.32	-8.37	-1.39	-1.73	-5.56	-9.23	-2.27	-11.4
BE	-2.49	-0.41	-3.87	-7.34	-1.59	-1.63	-5.67	-8.98	-1.93	-12.8
CY	-1.92	-1.94	-3.36	-9.05	-0.77	-2.14	-5.26	-9.59	-1.77	-12.3
DE	-2.38	-0.64	-3.94	-6.03	-1.21	-1.69	-5.40	-8.82	-2.02	-12.0
EE	-3.01	-1.22	-2.63	-6.71	-1.47	-1.69	-5.60	-9.03	-2.01	-12.3
ES	-2.78	-0.65	-4.03	-7.16	-1.28	-1.64	-5.55	-8.90	-1.87	-12.7
FR	-2.62	-0.67	-4.02	-7.34	-1.38	-1.89	-5.32	-8.36	-1.52	-12.9
GB	-2.09	-0.24	-3.91	-7.97	-1.15	-1.87	-4.97	-8.75	-1.93	-5.15
GR	-2.48	-0.69	-3.83	-7.13	-1.13	-1.71	-5.37	-9.00	-1.88	-12.5
IE	-2.84	-0.78	-3.92	-6.63	-1.05	-1.78	-5.44	-9.01	-1.45	-9.84
IT	-2.56	-0.57	-3.89	-7.27	-0.98	-1.44	-5.34	-9.75	-1.88	-12.0
LU	-3.16	-0.48	-4.30	-7.44	-1.10	-1.46	-5.51	-9.60	-1.89	-12.3
LV	-2.62	-0.85	-3.62	-7.42	-1.15	-1.80	-5.32	-8.62	-1.84	-11.9
NL	-2.98	-0.49	-4.12	-7.53	-1.07	-1.58	-5.41	-9.65	-1.75	-12.1
PL	-2.80	-0.55	-4.18	-8.03	-1.35	-1.85	-5.32	-8.64	-1.84	-5.56
PT	-2.22	-0.92	-3.65	-7.38	-1.22	-1.90	-4.96	-9.12	-2.30	-4.77
SI	-2.75	-0.67	-3.97	-7.35	-1.02	-1.73	-5.74	-10.8	-2.12	-10.4
SK	-3.01	-0.36	-3.86	-7.29	-1.04	-1.79	-5.93	-11.3	-2.20	-9.92

(t): Test with trend; Δ: 1st difference; Δ^2: 2nd difference.

Table 3: Unit root tests (ADF) for the foreign variables at the 5% significance level

		VARX* order		# Coint. Rel.
		p (domestic)	q (foreign)	
Austria	AT	1	1	0
Belgium	BE	1	1	0
Cyprus	CY	2	1	1
Germany	DE	1	1	1
Estonia	EE	1	1	1
Spain	ES	2	1	1
France	FR	1	1	0
United Kingdom	GB	2	1	1
Greece	GR	1	1	1
Ireland	IE	1	1	0
Italy	IT	1	1	0
Luxembourg	LU	1	1	0
Latvia	LV	1	1	0
Netherlands	NL	1	1	0
Poland	PL	1	1	0
Portugal	PT	1	1	0
Slovenia	SI	2	1	1
Slovakia	SK	1	1	1

Table 4: Country VARX* models: Lag order and cointegration rank

Country		F-test	Critical value	Real GDP	Conservative credit
Austria	AT	*F(0,69)*	-	-	-
Belgium	BE	*F(0,69)*	-	-	-
Cyprus	CY	*F(1,69)*	**3.98**	1.04	0.04
Germany	DE	*F(1,68)*	**3.98**	0.01	0.94
Estonia	EE	*F(1,68)*	**3.98**	0.00	0.02
Spain	ES	*F(1,68)*	**3.98**	1.22	2.93
France	FR	*F(0,69)*	-	-	-
United Kingdom	GB	*F(1,68)*	**3.98**	0.86	1.54
Greece	GR	*F(1,69)*	**3.98**	1.57	0.04
Ireland	IE	*F(0,69)*	-	-	-
Italy	IT	*F(0,69)*	-	-	-
Luxembourg	LU	*F(0,69)*	-	-	-
Latvia	LV	*F(0,71)*	-	-	-
Netherlands	NL	*F(0,69)*	-	-	-
Poland	PL	*F(0,69)*	-	-	-
Portugal	PT	*F(0,69)*	-	-	-
Slovenia	SK	*F(1,69)*	**3.98**	0.72	1.39
Slovakia	SI	*F(1,68)*	**3.98**	***5.86***	2.15

Table 5: Weak exogeneity test for the foreign variables

		Real GDP			Conservative credit			Risky credit		
		Levels	1st diff.	Res.	Levels	1st diff.	Res.	Levels	1st diff.	Res.
Austria	AT	0.79	0.48	0.05	0,79	0,28	0.02	0.20	0.02	-0.09
Belgium	BE	0,78	0,48	0,05	0,86	0,25	0,07	0,48	0,02	***-0,12***
Cyprus	CY	0,77	0,35	0,00	0,85	0,32	-0,04			
Germany	DE	0,73	0,43	***-0,18***	0,78	0,40	-0,03	-0,03	0,14	***0,13***
Estonia	EE	0,79	0,40	0,05	0,91	0,36	-0,04	0,61	0,23	***0,16***
Spain	ES	0,80	0,54	0,04	0,87	0,34	-0,04	0,54	0,16	***0,18***
France	FR	0,79	0,53	-0,01	0,90	0,43	-0,01	0,49	0,20	***0,15***
United Kingdom	GB	0,78	0,45	-0,03	0,85	0,41	0,06	-0,38	-0,06	-0,07
Greece	GR	-0,20	0,29	0,00	0,91	0,43	0,06			
Ireland	IE	0,74	0,17	-0,02	0,91	0,38	0,00	0,47	0,25	***0,16***
Italy	IT	0,09	0,55	0,03	0,90	0,37	-0,06	0,45	0,15	***0,19***
Luxembourg	LU	0,77	0,29	-0,01	0,85	0,32	0,05	0,52	0,16	0,09
Latvia	LV	0,78	0,31	-0,05						
Netherlands	NL	0,80	0,50	-0,02	0,78	0,22	-0,08	0,54	0,11	***0,11***
Poland	PL	0,75	0,15	-0,01	0,84	0,09	0,09	0,54	0,10	-0,04
Portugal	PT	0,57	0,41	0,00	0,85	0,28	0,01	0,43	0,10	0,01
Slovenia	SI	0,82	0,53	0,03	0,90	0,30	0,04			
Slovakia	SK	0,78	0,35	-0,03	0,84	0,18	0,00	0,50	0,12	-0,01

Table 6: Average pairwise cross-section correlations: variables and residuals

Appendix

A Borrower-based measures in Europe

Table A.1 presents a simplified overview of the borrower-based macroprudential measures implemented in European countries, based on the European Systemic Risk Board's database in December 2020. For the sake of our argument, we do not distinguish between enforceable limits and guidelines, neither do we include the particular cases (e.g. first-time buyers, second residence...) which tweak the headline limit upwards or downwards.

Country	LTV ratio	DSTI ratio	DTI ratio
Austria	80%	30 – 40%	..
Belgium	90%	50%	9
Cyprus	70 – 80%	80%	..
Czech Republic	80 – 90%	45 – 50%	9
Denmark	95%	..	4 – 5
Estonia	85 – 90%	50%	..
Finland	90 – 95%	..	..
France	..	33%	..
Hungary	80%	25 – 60%	..
Iceland	85 – 90%	..	..
Ireland	80 – 90%	..	3.5
Latvia	95%	40%	6
Lithuania	85%	40 – 60%	..
Malta	85%	40%	..
Netherlands	100%	..	..
Norway	60 – 85%	..	5
Poland	85 – 90%	40 – 50%	..
Portugal	80 – 90%	50%	..
Romania	60 – 85%	40%	..
Slovakia	80 – 90%	60%	8 – 9
Slovenia	80%	50 – 76%	..
Sweden	85%	..	..
United Kingdom	..	..	4.5

Table A.1: Borrower-based measures active in European countries

B Risky and conservative credit: Full matrices

Risky credit: Proportion of loans with **LTV ratio** > **90%**:

year	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
2000	0,38	0,38	0,29	0,39	0,38	0,47	0,35	0,14	0,35	0,41	0,31	0,33	0,51	0,57	0,29	0,51	0,28	0,54
2001	0,29	0,49	0,19	0,40	0,47	0,43	0,39	0,14	0,37	0,32	0,25	0,38	0,52	0,60	0,26	0,53	0,28	0,28
2002	0,26	0,39	0,37	0,35	0,51	0,49	0,49	0,14	0,41	0,37	0,39	0,38	0,51	0,59	0,26	0,51	0,30	0,30
2003	0,41	0,35	0,12	0,19	0,43	0,47	0,49	0,14	0,50	0,35	0,32	0,43	0,51	0,50	0,33	0,41	0,28	0,22
2004	0,28	0,37	0,23	0,30	0,49	0,42	0,45	0,14	0,40	0,36	0,45	0,31	0,52	0,50	0,20	0,44	0,26	0,30
2005	0,13	0,39	0,33	0,30	0,46	0,46	0,39	0,14	0,53	0,37	0,32	0,30	0,50	0,69	0,25	0,51	0,36	0,36
2006	0,26	0,49	0,26	0,32	0,51	0,47	0,41	0,14	0,50	0,36	0,46	0,28	0,51	0,39	0,39	0,53	0,20	0,38
2007	0,24	0,46	0,32	0,24	0,50	0,43	0,34	0,14	0,52	0,38	0,38	0,36	0,56	0,49	0,60	0,55	0,22	0,35
2008	0,19	0,37	0,29	0,32	0,51	0,32	0,38	0,08	0,44	0,35	0,27	0,38	0,44	0,66	0,45	0,59	0,22	0,38
2009	0,20	0,43	0,20	0,31	0,52	0,32	0,43	0,02	0,50	0,51	0,26	0,54	0,54	0,51	0,43	0,62	0,15	0,35
2010	0,20	0,40	0,16	0,22	0,49	0,32	0,37	0,02	0,38	0,42	0,32	0,44	0,55	0,54	0,56	0,57	0,27	0,34
2011	0,20	0,29	0,26	0,27	0,51	0,41	0,38	0,02	0,44	0,44	0,33	0,45	0,47	0,71	0,31	0,55	0,31	0,36
2012	0,21	0,37	0,11	0,22	0,41	0,21	0,33	0,02	0,41	0,34	0,10	0,36	0,38	0,46	0,48	0,52	0,24	0,44
2013	0,18	0,21	0,22	0,25	0,38	0,56	0,31	0,02	0,42	0,43	0,23	0,37	0,30	0,66	0,44	0,43	0,25	0,53
2014	0,41	0,25	0,22	0,24	0,40	0,26	0,38	0,04	0,41	0,22	0,36	0,38	0,36	0,52	0,40	0,17	0,22	0,58
2015	0,38	0,24	0,30	0,17	0,30	0,41	0,40	0,04	0,42	0,25	0,24	0,43	0,33	0,54	0,41	0,38	0,24	0,42
2016	0,33	0,32	0,44	0,19	0,25	0,34	0,46	0,04	0,42	0,11	0,20	0,40	0,35	0,49	0,27	0,35	0,23	0,33
2017	0,35	0,33	0,37	0,17	0,32	0,37	0,45	0,04	0,42	0,16	0,22	0,30	0,34	0,52	0,34	0,38	0,23	0,25
2018	0,35	0,33	0,37	0,17	0,32	0,37	0,45	0,04	0,42	0,16	0,22	0,30	0,34	0,52	0,34	0,38	0,23	0,25
2019	0,35	0,33	0,37	0,17	0,32	0,37	0,45	0,05	0,42	0,16	0,22	0,30	0,34	0,52	0,34	0,38	0,23	0,25

Risky credit: Proportion of loans with **DSTI ratio** > **40%**:

year	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
2000	0,05	0,05	0,26	0,05	0,10	0,14	0,04	0,14	0,07	0,09	0,10	0,10	0,09	0,08	0,21	0,11	0,17	0,16
2001	0,08	0,08	0,17	0,02	0,15	0,17	0,08	0,14	0,15	0,12	0,04	0,10	0,09	0,10	0,07	0,11	0,19	0,21
2002	0,02	0,03	0,38	0,05	0,18	0,13	0,10	0,14	0,12	0,07	0,05	0,09	0,09	0,05	0,09	0,09	0,17	0,17
2003	0,04	0,07	0,36	0,07	0,13	0,16	0,08	0,14	0,16	0,10	0,08	0,03	0,09	0,08	0,06	0,07	0,17	0,04
2004	0,03	0,05	0,33	0,05	0,15	0,12	0,10	0,14	0,19	0,09	0,11	0,04	0,08	0,10	0,04	0,08	0,24	0,18
2005	0,01	0,10	0,40	0,03	0,19	0,19	0,08	0,14	0,14	0,13	0,07	0,11	0,10	0,08	0,05	0,11	0,20	0,17
2006	0,06	0,07	0,37	0,07	0,11	0,18	0,09	0,14	0,12	0,12	0,09	0,15	0,07	0,07	0,05	0,11	0,17	0,11
2007	0,14	0,09	0,39	0,07	0,09	0,15	0,10	0,14	0,14	0,10	0,10	0,06	0,08	0,07	0,11	0,09	0,13	0,07
2008	0,06	0,07	0,42	0,07	0,14	0,15	0,10	0,08	0,21	0,12	0,14	0,13	0,08	0,11	0,11	0,11	0,09	0,14
2009	0,05	0,08	0,47	0,05	0,13	0,08	0,08	0,02	0,18	0,12	0,09	0,03	0,11	0,13	0,12	0,07	0,09	0,07
2010	0,13	0,05	0,36	0,04	0,05	0,16	0,09	0,02	0,19	0,10	0,11	0,08	0,14	0,10	0,07	0,11	0,20	0,04
2011	0,18	0,07	0,45	0,05	0,05	0,12	0,08	0,02	0,30	0,07	0,09	0,10	0,07	0,08	0,10	0,12	0,17	0,09
2012	0,02	0,09	0,50	0,04	0,02	0,26	0,11	0,02	0,15	0,05	0,07	0,16	0,07	0,11	0,12	0,12	0,13	0,05
2013	0,03	0,04	0,47	0,07	0,02	0,35	0,10	0,02	0,17	0,13	0,07	0,07	0,07	0,10	0,14	0,09	0,17	0,08
2014	0,03	0,06	0,45	0,04	0,05	0,04	0,09	0,04	0,17	0,09	0,03	0,11	0,09	0,09	0,16	0,09	0,18	0,06
2015	0,06	0,06	0,33	0,05	0,03	0,20	0,10	0,04	0,17	0,03	0,12	0,08	0,09	0,10	0,06	0,09	0,17	0,09
2016	0,09	0,05	0,48	0,07	0,04	0,12	0,10	0,04	0,17	0,07	0,22	0,12	0,09	0,15	0,13	0,08	0,18	0,04
2017	0,07	0,05	0,41	0,10	0,04	0,16	0,09	0,04	0,17	0,07	0,17	0,12	0,08	0,31	0,10	0,08	0,18	0,04
2018	0,07	0,05	0,41	0,10	0,04	0,16	0,09	0,04	0,17	0,07	0,17	0,12	0,08	0,31	0,10	0,08	0,18	0,04
2019	0,07	0,05	0,41	0,10	0,04	0,16	0,09	0,05	0,17	0,07	0,17	0,12	0,08	0,31	0,10	0,08	0,18	0,04

Risky credit: Proportion of loans with **LTI ratio** > **3**:

year	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
2000	0,17	0,05	0,33	0,08	0,12	0,19	0,07	0,14	0,16	0,17	0,09	0,15	0,19	0,41	0,14	0,29	0,15	0,32
2001	0,17	0,09	0,20	0,12	0,21	0,23	0,09	0,14	0,22	0,15	0,08	0,15	0,19	0,43	0,07	0,34	0,14	0,14
2002	0,11	0,08	0,47	0,21	0,32	0,31	0,09	0,14	0,14	0,13	0,10	0,16	0,19	0,34	0,04	0,33	0,17	0,06
2003	0,08	0,07	0,49	0,21	0,27	0,35	0,10	0,14	0,26	0,14	0,15	0,08	0,19	0,39	0,06	0,34	0,14	0,12
2004	0,19	0,12	0,46	0,17	0,28	0,38	0,17	0,14	0,26	0,26	0,11	0,18	0,19	0,44	0,07	0,44	0,12	0,30
2005	0,20	0,18	0,48	0,13	0,31	0,55	0,20	0,14	0,39	0,31	0,16	0,30	0,19	0,45	0,09	0,49	0,19	0,17
2006	0,21	0,20	0,52	0,19	0,32	0,53	0,23	0,14	0,41	0,39	0,35	0,35	0,11	0,48	0,11	0,56	0,14	0,19
2007	0,23	0,19	0,54	0,23	0,28	0,51	0,27	0,14	0,45	0,40	0,23	0,32	0,16	0,42	0,24	0,51	0,13	0,22
2008	0,23	0,20	0,63	0,20	0,29	0,50	0,27	0,08	0,50	0,39	0,27	0,37	0,21	0,56	0,21	0,55	0,13	0,32
2009	0,24	0,23	0,61	0,17	0,21	0,52	0,31	0,02	0,50	0,44	0,37	0,45	0,22	0,59	0,18	0,60	0,15	0,20
2010	0,33	0,21	0,57	0,14	0,18	0,61	0,27	0,02	0,31	0,38	0,34	0,46	0,14	0,44	0,16	0,58	0,20	0,21
2011	0,39	0,19	0,61	0,12	0,08	0,56	0,32	0,02	0,20	0,32	0,27	0,56	0,13	0,53	0,18	0,56	0,24	0,23
2012	0,38	0,23	0,57	0,17	0,08	0,60	0,32	0,02	0,38	0,23	0,25	0,55	0,03	0,48	0,21	0,51	0,21	0,16
2013	0,30	0,26	0,74	0,21	0,06	0,50	0,29	0,02	0,17	0,25	0,27	0,51	0,04	0,42	0,21	0,51	0,25	0,35
2014	0,49	0,28	0,79	0,20	0,07	0,40	0,32	0,04	0,20	0,19	0,27	0,48	0,14	0,47	0,15	0,39	0,23	0,23
2015	0,19	0,28	0,43	0,24	0,08	0,45	0,28	0,04	0,18	0,19	0,16	0,54	0,10	0,42	0,19	0,42	0,24	0,25
2016	0,35	0,35	0,60	0,21	0,15	0,43	0,33	0,04	0,19	0,26	0,49	0,52	0,06	0,62	0,17	0,46	0,23	0,34
2017	0,27	0,28	0,51	0,25	0,24	0,44	0,42	0,04	0,19	0,27	0,32	0,56	0,17	0,66	0,18	0,50	0,24	0,40
2018	0,27	0,28	0,51	0,25	0,24	0,44	0,42	0,04	0,19	0,27	0,32	0,56	0,17	0,66	0,18	0,50	0,24	0,40
2019	0,27	0,28	0,51	0,25	0,24	0,44	0,42	0,05	0,19	0,27	0,32	0,56	0,17	0,66	0,18	0,50	0,24	0,40

C GVAR Weight matrices

Figure C.1 shows the weight matrices used in the construction of the GVAR foreign variables: the baseline and alternative for credit variables, and the trade-based one for GDP weighting.

Weight matrix: Based on FSC (2020)

	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
AT		0,00	0,06	0,06	0,00	0,02	0,02	0,01	0,03	0,02	0,01	0,01	0,05	0,03	0,04	0,00	0,33	0,46
BE	0,02		0,00	0,06	0,00	0,06	0,13	0,05	0,03	0,12	0,06	0,03	0,06	0,13	0,01	0,04	0,02	0,15
CY	0,00	0,00		0,01	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DE	0,27	0,06	0,14		0,32	0,23	0,33	0,17	0,24	0,21	0,16	0,21	0,33	0,33	0,24	0,07	0,05	0,04
EE	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,13	0,00	0,00	0,00	0,00	0,00
ES	0,02	0,01	0,00	0,08	0,03		0,16	0,40	0,05	0,05	0,09	0,03	0,00	0,07	0,21	0,74	0,00	0,00
FR	0,06	0,53	0,07	0,25	0,15	0,28		0,17	0,30	0,19	0,61	0,58	0,01	0,29	0,22	0,11	0,23	0,03
GB	0,00	0,00	0,00	0,00	0,00	0,00	0,06		0,00	0,31	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
GR	0,00	0,00	0,47	0,00	0,00	0,00	0,00	0,01		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IE	0,01	0,01	0,01	0,02	0,00	0,02	0,04	0,07	0,05		0,00	0,01	0,00	0,05	0,00	0,00	0,03	0,01
IT	0,54	0,02	0,10	0,25	0,12	0,18	0,09	0,04	0,16	0,03		0,05	0,29	0,07	0,02	0,01	0,34	0,29
LU	0,01	0,01	0,01	0,01	0,03	0,01	0,02	0,01	0,00	0,01	0,00		0,01	0,02	0,01	0,00	0,00	0,00
LV	0,00	0,00	0,01	0,00	0,32	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00
NL	0,07	0,36	0,12	0,25	0,03	0,15	0,13	0,07	0,08	0,07	0,06	0,09	0,08		0,16	0,02	0,00	0,02
PL	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00	0,00
PT	0,00	0,00	0,00	0,00	0,00	0,05	0,01	0,00	0,03	0,00	0,01	0,00	0,01	0,01	0,09		0,00	0,00
SI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04	0,00	0,00	0,00		0,00
SK	0,00	0,00	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	

Weight matrix: Alternative based on Cantone, Wildmann and Rancoita (2020)

	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
AT		0,02	0,08	0,09	0,00	0,02	0,02	0,01	0,00	0,02	0,02	0,01	0,06	0,03	0,06	0,01	0,56	0,10
BE	0,05		0,00	0,08	0,00	0,08	0,06	0,06	0,03	0,01	0,06	0,04	0,05	0,14	0,06	0,11	0,05	0,04
CY	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DE	0,55	0,20	0,19		0,21	0,17	0,33	0,25	0,24	0,22	0,21	0,18	0,32	0,32	0,28	0,18	0,15	0,16
EE	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,13	0,00	0,00	0,00	0,00	0,00
ES	0,02	0,02	0,00	0,05	0,03		0,13	0,24	0,03	0,04	0,13	0,02	0,00	0,05	0,11	0,37	0,00	0,02
FR	0,14	0,38	0,09	0,38	0,21	0,28		0,17	0,32	0,25	0,45	0,61	0,02	0,32	0,14	0,20	0,04	0,13
GB	0,05	0,10	0,00	0,16	0,00	0,00	0,16		0,00	0,35	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00
GR	0,00	0,00	0,34	0,00	0,00	0,00	0,00	0,01		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IE	0,02	0,03	0,01	0,04	0,03	0,03	0,04	0,10	0,08		0,01	0,01	0,00	0,05	0,00	0,01	0,10	0,02
IT	0,03	0,04	0,11	0,07	0,16	0,20	0,09	0,05	0,16	0,02		0,05	0,28	0,06	0,13	0,04	0,08	0,43
LU	0,01	0,03	0,01	0,01	0,00	0,01	0,03	0,01	0,00	0,01	0,00		0,01	0,02	0,00	0,01	0,01	0,02
LV	0,00	0,00	0,01	0,00	0,32	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00
NL	0,13	0,18	0,14	0,11	0,05	0,18	0,13	0,09	0,08	0,08	0,10	0,07	0,07		0,16	0,06	0,01	0,07
PL	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00	0,00
PT	0,00	0,01	0,00	0,00	0,00	0,04	0,01	0,01	0,05	0,00	0,02	0,00	0,02	0,01	0,06		0,00	0,00
SI	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04	0,00	0,00	0,00		0,01
SK	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	

Weight matrix: Traditional using IMF DOTS trade weights

	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
AT		0,01	0,01	0,09	0,02	0,01	0,02	0,02	0,02	0,01	0,05	0,02	0,02	0,02	0,04	0,01	0,15	0,13
BE	0,03		0,04	0,10	0,05	0,06	0,14	0,10	0,05	0,15	0,08	0,27	0,04	0,18	0,05	0,04	0,03	0,03
CY	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DE	0,56	0,24	0,10		0,22	0,22	0,27	0,26	0,22	0,19	0,28	0,31	0,21	0,39	0,46	0,19	0,31	0,38
EE	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,22	0,00	0,00	0,00	0,00	0,00
ES	0,02	0,04	0,06	0,06	0,03		0,13	0,07	0,10	0,04	0,10	0,03	0,03	0,04	0,05	0,37	0,04	0,03
FR	0,05	0,20	0,04	0,15	0,07	0,23		0,13	0,10	0,08	0,19	0,16	0,05	0,10	0,08	0,15	0,08	0,09
GB	0,03	0,09	0,10	0,10	0,05	0,09	0,09		0,06	0,32	0,08	0,03	0,10	0,12	0,07	0,06	0,02	0,05
GR	0,00	0,00	0,33	0,01	0,00	0,01	0,01	0,01		0,01	0,02	0,00	0,00	0,01	0,00	0,00	0,02	0,00
IE	0,00	0,04	0,01	0,02	0,00	0,01	0,03	0,09	0,02		0,01	0,01	0,01	0,02	0,01	0,01	0,00	0,00
IT	0,10	0,07	0,16	0,11	0,05	0,13	0,13	0,08	0,20	0,05		0,04	0,05	0,06	0,08	0,07	0,20	0,07
LU	0,00	0,02	0,00	0,01	0,00	0,00	0,01	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00
LV	0,00	0,00	0,01	0,00	0,25	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,01	0,00	0,00	0,00
NL	0,06	0,24	0,08	0,19	0,11	0,08	0,11	0,17	0,10	0,12	0,08	0,09	0,09		0,09	0,07	0,05	0,04
PL	0,05	0,03	0,03	0,11	0,12	0,03	0,04	0,04	0,04	0,02	0,05	0,03	0,15	0,04		0,02	0,06	0,14
PT	0,00	0,01	0,01	0,01	0,01	0,11	0,02	0,01	0,01	0,01	0,02	0,01	0,01	0,01	0,01		0,01	0,01
SI	0,03	0,00	0,01	0,01	0,01	0,00	0,00	0,00	0,01	0,00	0,02	0,00	0,00	0,00	0,01	0,00		0,02
SK	0,06	0,00	0,01	0,03	0,01	0,01	0,01	0,01	0,01	0,00	0,01	0,01	0,02	0,01	0,04	0,01	0,04	

Figure C.1: Weight matrices for the GVAR foreign variables.

In order to verify the consistency between the baseline and alternative weighting for credit variables and to illustrate the considerable divergence with respect to the traditional trade-based matrix, we provide country (i.e. row) correlations in Figure C.2.

	AT	BE	CY	DE	EE	ES	FR	GB	GR
r (TFSE,Cantone et al.)	0,421	0,893	0,963	0,666	0,944	0,981	0,933	0,908	0,989
r (TFSE,Trade)	0,515	0,743	0,908	0,778	0,858	0,914	0,962	0,513	0,777
r (Cantone et al.,Trade)	0,956	0,872	0,859	0,672	0,782	0,855	0,921	0,800	0,721

	IE	IT	LU	LV	NL	PL	PT	SI	SK
r (TFSE,Cantone et al.)	0,954	0,969	0,998	0,999	0,995	0,861	0,873	0,669	0,586
r (TFSE,Trade)	0,937	0,676	0,519	0,547	0,821	0,630	0,887	0,579	0,230
r (Cantone et al.,Trade)	0,841	0,802	0,495	0,548	0,781	0,848	0,967	0,495	0,397

Figure C.2: Weight matrices: Correlation coefficients for countries.

D Data sources

The time series for GDP and total credit are originally extracted from the IMF's International Financial Statistics and the BIS's Credit Statistics, respectively, as shown in Table D.1:

Country	**GDP**	**Total credit to households**
AT	IMF/IFS/Q.AT.NGDP_R_K_SA_IX	BIS/total_credit/Q.AT.H.A.M.USD.A
BE	IMF/IFS/Q.BE.NGDP_R_K_SA_IX	BIS/total_credit/Q.BE.H.A.M.USD.A
CY	IMF/IFS/Q.CY.NGDP_R_K_SA_IX	Directly from National Bank of Cyprus
DE	IMF/IFS/Q.DE.NGDP_R_K_SA_IX	BIS/total_credit/Q.DE.H.A.M.USD.A
EE	IMF/IFS/Q.EE.NGDP_R_K_SA_IX	Directly from Eesti Pank
ES	IMF/IFS/Q.ES.NGDP_R_K_SA_IX	BIS/total_credit/Q.ES.H.A.M.USD.A
FR	IMF/IFS/Q.FR.NGDP_R_K_SA_IX	BIS/total_credit/Q.FR.H.A.M.USD.A
GB	Directly from ONS: YBEZ	BIS/total_credit/Q.GB.H.A.M.USD.A
GR	IMF/IFS/Q.GR.NGDP_R_K_SA_IX	BIS/total_credit/Q.GR.H.A.M.USD.A
IE	IMF/IFS/Q.IE.NGDP_R_K_SA_IX	BIS/total_credit/Q.IE.H.A.M.USD.A
IT	IMF/IFS/Q.IT.NGDP_R_K_SA_IX	BIS/total_credit/Q.IT.H.A.M.USD.A
LU	IMF/IFS/Q.LU.NGDP_R_K_SA_IX	BIS/total_credit/Q.LU.H.A.M.USD.A
LV	IMF/IFS/Q.LV.NGDP_R_K_SA_IX	Directly from Latvijas Bankas
NL	IMF/IFS/Q.NL.NGDP_R_K_SA_IX	BIS/total_credit/Q.NL.H.A.M.USD.A
PL	IMF/IFS/Q.PL.NGDP_R_K_SA_IX	BIS/total_credit/Q.PL.H.A.M.USD.A
PT	IMF/IFS/Q.PT.NGDP_R_K_SA_IX	BIS/total_credit/Q.PT.H.A.M.USD.A
SI	IMF/IFS/Q.SI.NGDP_R_K_SA_IX	Directly from Banka Slovenije
SK	IMF/IFS/Q.SK.NGDP_R_K_NSA_IX	Directly from Narodna Banka Slovensko

Note: Values for IE until 2001Q4 are extrapolated using the BIS series for bank credit to non-financial private sector.

Table D.1: GDP and credit time series mnemonics.

As detailed in Section 3, We extract LTV data from the HFCS at loan level and use the information to create shares of ”risky” and ”conservative” credit by country and year. However, given that we use *mortgage* data from a *household* survey, we multiply aggregate household credit values from the BIS to account by the ratio of mortgage loans to total household loans. For that purpose, we resort to the ECB's CBD2 dataset, available through the Statistical Data Warehouse; we compute the average ratios for the period 2018Q1-2019Q3.

Country	**Mortgage loans to Households**
AT	CBD2.Q.AT.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
BE	CBD2.Q.BE.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
CY	CBD2.Q.CY.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
DE	CBD2.Q.DE.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
EE	CBD2.Q.EE.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
ES*	CBD2.Q.ES.W0.67._Z._Z.A.F.A1135._X.ALL.CA._Z.LE._T.EUR
FR	CBD2.Q.FR.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
GB*	CBD2.Q.GB.W0.67._Z._Z.A.F.A1135._X.ALL.CA._Z.LE._T.EUR
GR	CBD2.Q.GR.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
IE*	CBD2.Q.IE.W0.67._Z._Z.A.F.A1135._X.ALL.CA._Z.LE._T.EUR
IT	CBD2.Q.IT.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
LU	CBD2.Q.LU.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
LV	CBD2.Q.LV.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
NL	CBD2.Q.NL.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
PL	CBD2.Q.PL.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
PT	CBD2.Q.PT.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
SI	CBD2.Q.SI.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
SK	CBD2.Q.SK.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR

Note: For countries marked with (*), loans for house purchase were used due to data availability.

Table D.2: Mortgage-to-total loans ratios: Numerator.

Country	**Total loans to Households**
AT	CBD2.Q.AT.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
BE	CBD2.Q.BE.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
CY	CBD2.Q.CY.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
DE	CBD2.Q.DE.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
EE	CBD2.Q.EE.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
ES	CBD2.Q.ES.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
FR	CBD2.Q.FR.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
GB	CBD2.Q.GB.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
GR	CBD2.Q.GR.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
IE	CBD2.Q.IE.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
IT	CBD2.Q.IT.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
LU	CBD2.Q.LU.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
LV	CBD2.Q.LV.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
NL	CBD2.Q.NL.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
PL	CBD2.Q.PL.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
PT	CBD2.Q.PT.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
SI	CBD2.Q.SI.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
SK	CBD2.Q.SK.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR

Table D.3: Mortgage-to-total loans ratios: Denominator.

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