How does Financial Vulnerability amplify Housing and Credit Shocks?

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Abstract

In this paper we study the how financial vulnerability affects the propagation of housing and credit shocks. First, we estimate a non-linear model generating impulse responses that depend on the level of households' Debt to Service Ratio, i.e. the fraction of income that households use to pay back their debt. Second, we use sign restrictions to jointly identify a wide set of financial and economic shocks. We find that financial vulnerability: i) amplifies the response to housing, ii) makes the response to credit supply shocks stronger on impact but less persistent. Finally, during the first year since the arrival of the shock, recessionary shocks have larger effects with respect to expansionary ones of the same size.

Keywords: Financial vulnerability, macroprudential policy, non-linear models, Housing.

JEL Codes: : C32, E51, E58, G01.

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1 Introduction

Households' financial vulnerability can help to explain the unusual magnitude of the economic downturn observed during the Great Recession (Jordà et al. (2013); Mian et al. (2017)). When agents' debt burden is high, shocks having a direct impact on financial conditions are expected to have a larger impact with respect to the case where the debt burden is low (Kiyotaki and Moore (1997)).

In this paper we ask how financial vulnerability affects financial shocks, studying the propagation of exogenous variations in: i) collateral prices (housing shocks), ii) lending conditions (credit shocks), iii) and cost of debt (monetary policy shocks). To answer this question, we estimate a non-linear econometric model on US data by using Local Projections (LP, Jordà (2005)) with state effects. To track financial vulnerability, we use the Debt Service Ratio, i.e. the fraction of income that is used to pay interest and amortize the principal (thereafter DSR). This choice allows to obtain impulse responses that depend on households' financial vulnerability. As endogenous variables we use output, investments, inflation, short term interest rate equity growth and the ratio between stocks of credit and the market value of real estate. Through sign restrictions, we jointly identify a wide set of structural shocks: financial shocks (housing, credit shocks), monetary shocks and real shocks (aggregate demand, aggregate supply, investment shocks). In line with the sign restrictions strategy by Furlanetto et al. (2017), the ratio between debt stock and house prices is used to to disentangle housing from credit shocks, in that an expansionary credit (housing) shock has a positive (negative) impact on this ratio. We find the following set of results. First, under high vulnerability the effect on output to a housing shock is overall twice as large as the effect obtained in a linear model featuring the same specification. Instead, under low vulnerability, the response to an housing shock of a similar size is not statistically significant. Second, under high financial vulnerability a positive credit shock is amplified only during the first year since the arrival of the shock, whereas its effect turns negative for the rest of the projection.

The choice of DSR features different positive aspects. First, the DSR is a measure of financial fragility that takes into account three different components of financial vulnerability: i) the cost of debt, related to the effective interest rate payed by the average household; ii) the aggregate stock of debt issued by households, iii) the evolution of households' income. For this reason, the DSR is one of the main indicators used in banking, to assess households' risk in the mortgage sector. Second, the DSR can ex-ante inform about the build-up of financial risks in households' sector, as opposed to variables which signal only current financial distress (e.g. financial stress indicators) or ex-post signalling indicators (e.g. NBER recessionary periods, industrial production evolution). In this respect, the DSR in 3 years difference is widely used in risk analysis to detect the build-up of financial risk in the economy given its good signalling properties as an early warning indicator of financial crisis. Together with its good early warning performance, expressing the DSR in its 3 years difference helps getting rid of the low-frequency structural change of the variable and focusing on its signalling property. Our results are robust to using 2 years and 5 years difference.

The paper delivers two key results. First, financial vulnerability generally amplifies the response of financial shocks. The role of financial vulnerability in amplification can be read in light of the theoretical works that study the presence of financial accelerators in the economy (Kiyotaki and Moore (1997)). In these models, agents are subject to borrowing constraints and can borrow only up to fraction of their collateral. If their collateral decreases because of an incoming shock, so does the debt limit: agents will be forced to reduce their leverage and spend less, amplifying the initial fluctuation. Second, the propagation of the shock depends on its origin, since the positive effect of credit shocks are overturned under high vulnerability, whereas the expansion is more persistent for housing shocks. The overshooting of credit shocks under high vulnerability is consistent with the presence of debt overhang, which induces financially vulnerable agents to deleverage after a period of debt expansion. This type of overshooting is not found for housing shocks, whose effects are more persistent. The more persistent effect of the housing shock is in line with the findings of Justiniano et al. (2015), who show that, in their model, only housing shocks are able to induce a collateral effect strong enough to explain the credit cycle observed over the financial crisis.

In an extension of our model, we allow for the possibility to obtain sign effects by complementing the benchmark model with interaction terms between the standard regressors and indicator functions, assuming value equal to 1 when the variables are below their historical median value, and zero otherwise. The presence of these terms generates impulse responses that vary according to the sign of the shock. In the first part of the projection, recessionary housing and credit shocks have an effect on output that is at least two times larger under high vulnerability with respect to the expansionary shocks in absolute terms. Interestingly, our results are in line with the findings of Guerrieri and Iacoviello (2017); Jensen et al. (2020). In their models, since the borrowing constraints are only occasionally binding, recessionary shocks have a stronger and more concentrated effect with respect to the expansionary ones, given the asymmetric role played by the collateral channel in shocks transmission.

In another extension of the model, we further disentangle credit demand shocks from credit supply shocks, by restricting the response on impact of the mortgage rate, in that an expansionary demand (supply) shock has a positive (negative) effect on the mortgage rate. This extension allows to establish that financial vulnerability amplifies the effects of the shocks during the first year and makes them less persistent for the rest of the projection, in line with the interpretation that such expansions are hampered by possible debt overhang. However, this amplification is substantially stronger for credit supply shocks.

The remainder of the paper is as follows. Section 2 frames the paper in the literature. Section 3 presents the empirical model. In Section 4, data and the identification strategy are presented. Section 5 presents the results and robustness analysis. Section 6 discusses our empirical results in light of macroeconomic theory. Section 7 concludes.

2 Literature

This work contributes to three streams of literature.

A first stream of literature investigates how the impact of financial shocks vary according to the state of the economy. Cheng and Chiu (2017) study the impact of mortgage rate shocks across the business cycle while Barnichon and Brownlees (2018); Carriero et al. (2018) and Colombo and Paccagnini (2019) analyze whether credit shocks are subject to state and sign effects.[1] Through different identification techniques, these papers identify how financial shocks are amplified under a certain state of the economy (respectively credit distress and recession). In our paper, we disentangle financial shock according to their origin (housing and credit shocks) and find that this distinction is key to detect non-linear effects in that: i) both housing and credit shocks determine a stronger effect when financial vulnerability is high in the first year of the projection, but ii) only housing shocks are persistent. Differently from these papers, our state variable is a measure of the build-up in financial vulnerability (the DSR) which has good ex-ante signalling properties in risk assessment (Lang et al. (2019)). Besides, Barnichon et al. (2016); Carriero et al. (2018) detect important sign effects in that credit recessionary shocks have a stronger impact than expansionary shocks. We find the same type of evidence for the first year since the arrival of the shock.[2].

A second stream of literature focuses on the identification of credit and housing shocks (Furlanetto et al. (2017); Gambetti and Musso (2017); Musso et al. (2011); Walentin (2014))These works have been conducted in a linear framework. In particular Furlanetto et al. (2017) provide a series of set-ups to jointly identify different types of financial shocks (housing, credit demand and credit supply shocks). We expand their analysis, by applying their type of identification strategy in a non-linear framework so to obtain impulse responses depending on the evolution of the DSR. Finally, financial frictions

[1]Carriero et al. (2018) estimate a Smooth Transition- Multivariate Autoregressive Index model (ST-MAI model) to analyze how positive and negative structural shocks are amplified in periods of credit distress. Through Gaussian Mixed Average approaches Barnichon and Brownlees (2018) assess how expansionary and recessionary credit supply shocks in the economy propagate according to the state of the business cycle.

[2]Other works study these type of non-linear effects but focus on the propagation of monetary shocks (Aikman et al. (2016, 2017); Alpanda and Zubairy (2017); Barnichon and Matthes (2016); Bauer and Granziera (2016); Franz (2017); Harding and Klein (2018); Hofmann and Peersman (2017))

generating amplification mechanisms became central in theoretical models with financial accelerators, agents' financial conditions affect the propagation of financial shocks (Bernanke et al. (1996); Christiano et al. (2015); Kiyotaki and Moore (1997); Liu et al. (2013)). Our paper contributes to this literature by looking for empirical evidence of shocks' amplification, related to financial vulnerability. Our results are in line with the types of non-linearities produced by Guerrieri and Iacoviello (2016) and Jensen et al. (2020).

3 Empirical model

3.1 Econometric model

We estimate a smooth regime switching model by using Local Projections (thereafter LP, Jordà (2005)). The local projections consist in a series of regressions, one for each forecast period: $h = 1, ..., H$. The impulse responses for the horizon h are directly recovered from the coefficients estimated for that particular horizon, without computing the Moving Average representation of the model. We use LP, since they are particularly suited to estimate models that incorporate different types of non-linearities.[3] The smooth transition regime delivers impulse responses depending on the regime of the economy (in our case the 3-year change in the DSR).[4]

For each period $t = 0, ..., T$, horizon $h = 0, ..., H$, with n the number of endogenous variables, p the number of lags, our econometric setting is:

$$\begin{aligned} Y_{t+h} = \; & F(z_{t-1})(\alpha_h^D + \beta_h^D Y_{t-1} + \Sigma_{\ell=2}^{p} L_{h,\ell}^D Y_{t-\ell}) \\ & + (1 - F(z_{t-1}))(\alpha_h^U + \beta_h^U Y_{t-1} + \Sigma_{\ell=2}^{p} L_{h,\ell}^U Y_{t-\ell}) \\ & + u_{h,t}, \end{aligned} \tag{1}$$

[3]In recent years, this method has been extensively used to assess the effect of structural shocks on the economy Among others, Alessandri and Mumtaz (2019); Tenreyro and Thwaites (2016) for monetary shocks, Auerbach and Gorodnichenko (2013) for fiscal shocks, Fieldhouse et al. (2018) for public asset purchase shocks.

[4]In a extension of the model, the impulses will be also affected by the position of the explanatory variables relative to certain cutoff value (e.g. their median historical value) allowing the model to have sign dependent effects.

where Y_t is the $(n, 1)$ matrix of endogenous variables at time t, z_{t-1} is the scalar state variable at time $t-1$ and $u_{h,t}$ is the $(n, 1)$ vector of errors at horizon h at time t. The scalar function $F(z_t)$ governs the transition between high and low regime. As standard, the transition function is the logistic transformation of the original z_t:

$$F(z_t) = \frac{1}{1 + exp\left(-\theta\left(\frac{z_t - c}{\sigma_z^2}\right)\right)} \tag{2}$$

This transformation normalizes z_t into the interval $[0, 1]$ and facilitates the interpretation of the state variable. The parameter c controls the fraction of the sample spent in either state.[5] The parameter θ determines the smoothness of the transitions between both states.[6] Both parameters are generally calibrated (Auerbach and Gorodnichenko (2013)). First, we set c at the historical median of the original state variable, so that the resulting state spends half of the time in both regimes. Second, we calibrate $\theta = 3$ in line with Franz (2017); Tenreyro and Thwaites (2016). Our results are robust to a large range of other calibrations.

We construct confidence intervals using the block-of-blocks bootstrap approach, suggested for LP by Kilian and Kim (2011) to account for the autocorrelation in time series.[7] For robustness check, we compute confidence intervals through alternative methods. First, we use the bootstrap-after-bootstrap method, which corrects for bias in bootstrap estimates (see Kilian (1998); Kilian and Kim (2011)). Second, we use the covariance matrix approach.[8]

[5] $z_t > c$ is equivalent to $F(z_t) > 0.5$. Defining c as the $p - th$ quantile of the historical time series of z_t forces $F(z_t)$ to spend $p\%$ of the time below 0.5, i.e. in the low regime.

[6] The higher θ, the faster $F(z_t)$ goes toward 0 and 1, i.e. converging to a dummy-regime switching.

[7] This method consists in constructing all possible overlapping tuples of m consecutive dates in the matrix Y of endogenous variables, along with the corresponding block of regressors for each selected dates, at each horizon of regression (hence the blocks-of-block denomination). We then draw in this family of blocks to construct the bootstrapped time series. We follow Horowitz (2018) recommendation of $m \propto T^{1/3}$, resulting in $m = 5$ following. We thus select blocks of five consecutive dates to build the bootstrap time series.

[8] In particular, we use the so-called Spacial Correlation Consistent (SCC) covariance

3.2 Shocks identification

Our strategy for structural shock identification relies on sign restrictions (Canova and De Nicolo (2002); Rubio-Ramirez et al. (2010); Uhlig (2005)). Our restrictions are theoretically founded and mostly based on the dynamics predicted by standard empirical DSGE models. As in the literature of VAR models, the reduced-form error for horizon h, $u_{t,h} \sim N(0, \Omega_h)$, can be written as a linear combination of structural shocks $\epsilon_{t,h} \sim N(0, I)$:

$$u_{t,h} = \Gamma \epsilon_{t,h}, \tag{3}$$

with $\Gamma\Gamma' = \Sigma$. To identify Γ, a set of restrictions is needed. In this paper, we use the algorithm proposed by Rubio-Ramirez et al. (2010). In a first step, we recover the variance covariance matrix of the reduced form error $\hat{\Omega_h}$ from the main equation 1 at horizon 1. Second, we compute the diagonal matrix D of eigenvalues and a matrix of eigenvectors Υ define $\Omega = \Upsilon D^{1/2}$ so that $\Gamma\Gamma' = \hat{\Omega}$. Then for each round, we draw a matrix of independent normal vectors $W \sim MN(0, I_{N^2})$, we take Q from its QR decomposition and we generate the impulse response ΓQ. If the generated impact matrix verifies the sign conditions, the proposed impulse is accepted and stored, otherwise it is rejected. This process is repeated until a sufficiently large number of draws has been accepted [9]. To compute the median response from the set of accepted draws we use "Median-Target" strategy proposed in (Fry and Pagan (2011)).[10] We use this method for each of the bootstraped time series.

matrix proposed by Driscoll and Kraay (1998). This approach allows to compute cumulative IRF, when the coefficients for different horizons are mechanically correlated. In fact, this method is a panel data generalization of Newey and West (1987) and accounts for autocorrelation, heteroskedascity and also cross-serial correlation between different individuals in different times. By treating horizons as individuals, we control for their correlation (Falck et al. (2018)).

[9] We take 500 accepted draws for the point estimate and 100 for the bootstraps. Increasing the latter to 10,000 provides no substantial improvement, while considerably increasing the computational burden

[10] As there are multiple accepted draws for the same $\hat{\Gamma}$, each draw implicitly corresponds to a specific *model*, and it is necessary to summarize the information. The Median Target Strategy consists in selecting a single shock among all acceptable shocks, the one that has minimal euclidean distance to the median impact matrix. The selected shock is then as close as possible to this median impact matrix, which is the most suited to correctly

4 Data

Our database includes US macro and financial data from 1983Q1 to 2019Q1. As starting date, we select the beginning of the Great Moderation (Cheng and Chiu (2017)). Depending on the specifications, our set of endogenous data includes quarterly growth in real output (GDP), inflation (CPI), the short term rate, stock prices (S&P500), all in quarterly log-difference, 30-year fixed rate mortgage rates, the ratio between investments (real gross private domestic investments) and output, the ratio between households' debt (loans and debt securities) and the total value of real estate held by households. The series of output, inflation, mortgage rate, investment and total value of households' real estate come from Federal Reserve Bank of St. Louis Database (FRED®), stock prices come from Yahoo®. In order to overcome the non-linearity introduced by the Zero Lower Bound and take into account the expansionary non-conventional monetary policy, the short term rate is the shadow rate computed by Wu and Xia (2016).

4.1 The choice of the interaction variable

The state variable is the Debt Service Ratio of households as computed by Drehmann et al. (2015a):

$$\frac{D_t}{Y_t}\frac{i_t}{1-(1+i_t)^{-m}}, \tag{4}$$

where Y_t is income, D_t is debt, i_t is the lending interest rate, m is the maturity. The DSR is the fraction of revenue that households have to pay in the current period in order to repay a debt of m maturity in equal portion. The use of Debt Service Ratio allows directly capturing the effects of financial vulnerability on the impulse responses. In our benchmark estimation the DSR is expressed in 3 years difference for two reasons. First, in this way we

represent the variety of acceptable shocks. Another common practice consists in taking the matrix of the median impulse response. However, as pointed in Fry and Pagan (2011), this method is not suited for summarizing information of the models, as this might select structural shocks identified from different draws (i.e. different models).

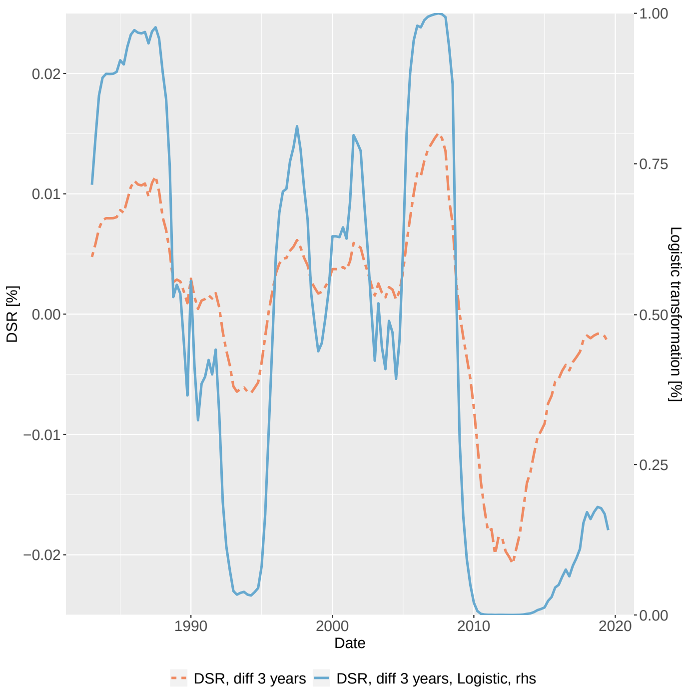


Figure 1: Debt to Service Ratio (DSR) in 3 years difference. Note. The red dashed line presents the DSR ratios computed by the BIS. The blue solid line is the transition function from high to low state regimes, obtained in our benchmark estimation with $c = 0.5$ and $\theta = 3$.

get rid of the low frequency structural change. Second, the 3 years difference is widely used in macroprudential analysis to assess the evolution of risks and has been showed to be a performing early warning indicator in the prediction of crisis (Drehmann et al. (2015a); Lang and Welz (2017)). We use the DSR computed by the Bank of International Settlements (Drehmann et al. (2015b)) while in the robustness check we use an alternative DSR computed by the US Federal Reserve.[11]

As shown in figure 1, the DSR in 3 years difference has the two highest peaks in the second half of the 1980's, in the pre-crisis period, whereas its troughs can be found at the beginning in the first half of the 1990's and in the aftermath of the crisis.

[11] An alternative measure providing information on the position of households is the Loan-to-Value ratio (the ratio between total loans and the collateral value). However, the LTV features a poor performance in signalling the build-up of financial vulnerability, mostly due to the higher level of pro-cyclicality of collateral prices.

5 Results

In our benchmark exercise we assess how financial vulnerability affects the propagation of housing and credit shocks. The benchmark specification features 2 lags, but results are robust to other lags choices (1 and 3). We estimate the response of the economy for 16 quarters.

This specification includes the following set of endogenous variables: real output quarterly growth, quarterly inflation, the ratio between investments and output, the shadow policy rate, stock prices quarterly growth and the ratio between households' total credit (loans and debt securities) and real estate at market value (flow of funds).

Sign restrictions are built on the identification strategy used by Furlanetto et al. (2017) as reported in Table 1[12]. Aggregate Demand and Aggregate Supply shocks are in line with standard economic theory: output and inflation have a positive co-movement with respect to an Aggregate Demand shock, while the comovement is negative for Aggregate Supply shocks. To disentangle aggregate demand shocks from the investment shocks we put another restriction on the ratio between investments and output. If the impact of the shock is positive (negative), we identify an investment shock (Aggregate Demand). This restriction is in line with Smets and Wouters (2007) and Justiniano et al. (2010), for which investments shocks have a stronger impact on investment growth than on output, opposite to the aggregate demand shocks. In order to disentangle investment shocks from financial shocks, we assume that the former have a negative impact on stock prices while the latter have a positive effect. This restriction derives from Christiano et al. (2010), in which investment shocks, by increasing the efficiency in the accumulation law of capital, increase capital supply and decrease its price (i.e. stocks prices). Finally, to disentangle financial shocks in housing and credit shocks we use the ratio between total credit and housing value, assuming

[12] In our benchmark application, we jointly identify housing, credit and monetary policy shocks, while Furlanetto et al. (2017) follow a two step procedure. In a first exercise, they identify monetary policy and financial shocks, without disentangling credit form housing shocks. In a second exercise, they disentangle housing and credit shocks but exclude the monetary policy shock to ease the computational burden associated with a too large number of structural shocks to identify.

	Output	Inflation	Policy rate	Inv/Out ratio	Stock prices	Credit/RE ratio
Agg.Demand	+	+	+	-		
Agg.Supply	+	-			+	
Mon.Policy	+	+	-			
Investment	+	+	+	+	-	
Housing	+	+	+	+	+	-
Credit	+	+	+	+	+	+

Table 1: The table presents the sign restrictions assumed on the reaction on impact of endogenous variables (column) to identify the structural shocks shocks (row). When the space is empty, the response is left unrestricted.

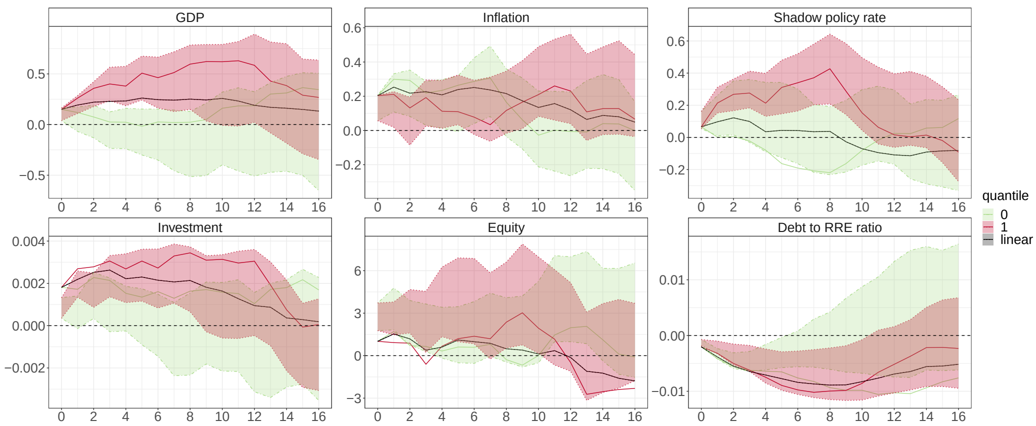


Figure 2: Impulse responses of a selection of the endogenous variables to a housing shock. Note. The responses of output growth and equity growth are cumulated, while the responses for the ratio of investment/output are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% confidence intervals.

that credit (housing) shocks have a positive (negative) impact on this ratio.

In figure 2 we report the responses of our endogenous variables to a housing shock. The lines in red are the responses when vulnerability is high ($F(z_t) = 1$), while the line in green are the responses when vulnerability is low ($F(z_t) = 0$). In order to assess the role of state effects we report the response of the linear model (black line), estimated using the same variables used in the non-linear specification, but with no state effect. To ease the comparison, for the linear model we use the same impact matrix used in the non-linear specification. From the comparison of the impulse responses across the different regimes, we find that higher vulnerability substantially amplifies housing shocks. Under high vulnerability, the response of output to an housing shock is statistically significant for the first two years and

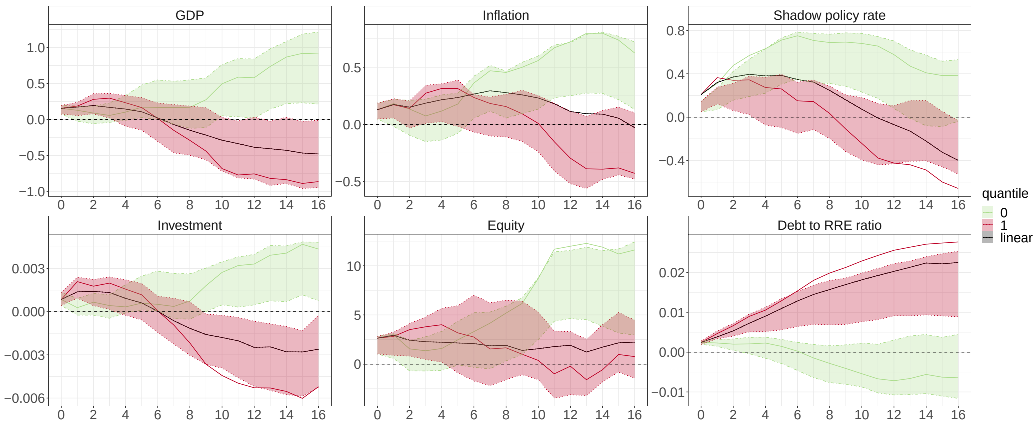


Figure 3: Impulse responses of a of output growth to a credit shock.
Note. The responses of output growth and equity growth are cumulated, while the responses for the ratio of investment/output are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% confidence intervals.

is at least twice larger with respect to the response obtained in the linear model. Conversely, under low vulnerability, the response of output is not significantly different from zero for all the projection horizon. Similar non-linear dynamics are found for the other variables: under high vulnerability the responses of investments over output ratio and equity are overall twice as large as the response under low vulnerability. Finally, the drop in the ratio between debt and house prices remains statistically significant across the horizon under high vulnerability, in line with a stronger and more persistent increase in house prices. These results show an important amplification of the housing shocks under high vulnerability and are in line with the findings of the theoretical models featuring a financial accelerator (Kiyotaki and Moore (1997)), where borrowing constraints amplify collateral fluctuations: when collateral prices decrease, agents have to reduce their debt, spending less and further amplifying the negative fluctuations of house prices.

In figure 3 we report the responses of output growth to a credit shock. As already found by Furlanetto et al. (2017), in the linear case, the response of output to credit shock is positive at the beginning of the projection (e.g. the first six quarters) and then turns negative for the rest of the projection. The use of the non-linear specification allows us to shed light on this result. In the non-linear case, this overshooting in the response of output is found only under high vulnerability. Until the sixth quarter, the response of output is twice as large as the response under the linear case. Moreover, with respect to the linear model, the negative effects are twice as large after the sixth quarters under high vulnerability. Vice-versa, under low vulnerability, the response of output is smaller with respect to the linear case in the first part of the projection. After the first ten quarters since the arrival of the shock, the response become strongly positive and statistically significant along all the projection horizon. The other endogenous variables feature a similar dynamics: investments and equity go through a stronger expansion under high vulnerability in the first part of the projection, while their response turn negative after two years since the arrival of the shocks. Finally, the observed Loan-to-Value shows an important non-linearity: when vulnerability is high, the response is strongly positive and significant across all the horizon, whereas under low vulnerability, the effect on the debt/houses ratio is not significantly different from zero. This result can be rationalised by the fact that households under high vulnerability cn be more subject to debt overhang, forcing indebted households to deleverage and overturning the initial positive effect of the shocks. This interpretation is consistent with the strong positive reaction found for LTV under high vulnerability. Finally, under low vulnerability the more persistent reaction of output and the more stable response of LTV could be explained by the fact that, under those conditions, the expansion of credit is sustainable.

The asymmetric result in the amplification of housing and credit shocks is one of the key result of the paper. This finding recalls the result by Justiniano et al. (2015). In this paper, a structural model is used to determine which shock, between housing and credit, is more likely to be at the origin of the credit expansion and deleveraging observed in the US financial cycles over the Great Recession. According to their results, only the housing shock has the property to generate a persistent debt expansion as the one observed in the pre-crisis period.[13]

[13]Their model features savers and borrowers, with the latter ones can borrow up to a fraction of their collateral. Their result is related to the fact that the housing shock pushes

5.1 State and sign effects

In this extension, we assess how the amplification effects found in previous section vary according to the sign of the shock. To do so, we complement the original model with additional interaction terms between the standard regressors and indicator functions. These indicators take value equal to 1 when the regressor is below its historical median value and 0 otherwise. Thanks to this additional terms, the impulse responses will not only depend on the regime of the economy (i.e. the level of financial vulnerability) but also on the position of the explanatory variables.

We modify Equation 1 the following way:

$$\begin{aligned} Y_{t+h} = \; & F(z_{t-1})(\alpha_h^D + \beta_h^D Y_{t-1} + \beta_h^{D,<} Y_{t-1}^{\mathbb{1},\bar{Y}} + \Sigma_{\ell=2}^{p} L_{h,\ell}^{D} Y_{t-\ell}) \\ & + (1 - F(z_{t-1}))(\alpha_h^U + \beta_h^U Y_{t-1} + \beta_h^{U,<} Y_{t-1}^{\mathbb{1},\bar{Y}} + \Sigma_{\ell=2}^{p} L_{h,\ell}^{U} Y_{t-\ell}) \\ & + u_{h,t}, \end{aligned} \tag{5}$$

where the term $Y_{t-1}^{\mathbb{1},\bar{Y}}$, delivering the sign effect, is equal to:

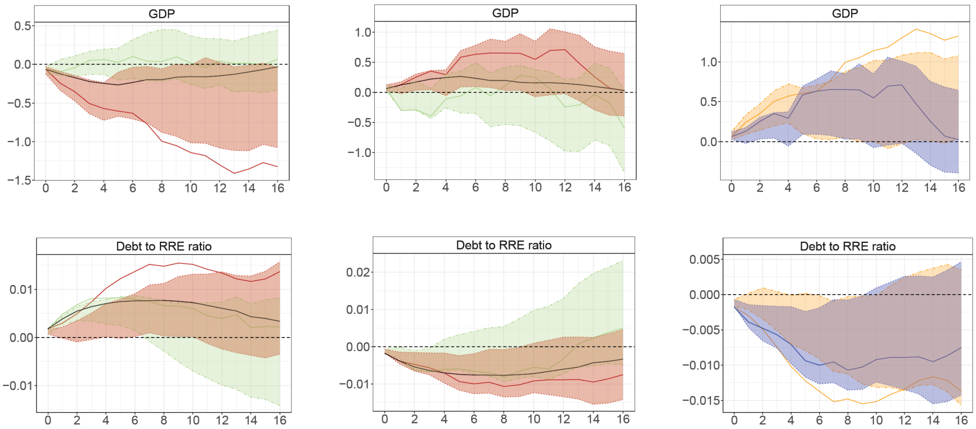
$$Y_{t-1}^{\mathbb{1},\bar{Y}} = \begin{pmatrix} Y_{1,t-1}\mathbb{1}_{Y_{1,t-1}<\bar{Y_1}} \\ ... \\ Y_{n,t-1}\mathbb{1}_{Y_{n,t-1}<\bar{Y_n}} \end{pmatrix}, \tag{6}$$

where the $i-th$ element is the product between the $i-th$ element in Y_{t-1} and the indicator function $\mathbb{1}$, assuming value 1 (0) when the $i-th$ variable $Y_{i,t-1}$ is below (above) its cutoff value $\bar{Y_i}$. In order to obtain sign dependent impulse responses, we set the initial state of our endogenous variables to the cutoff value used in the estimation, so that the sign of the shock will determine which set of coefficients is activated.

savers and borrowers to increase their spending in housing, producing a persistent positive effect on house prices. This substantial increase in house prices will allow borrowers to expand their debt, generating an important collateral channel. Conversely, the credit shock pushes only borrowers to increase their spending in housing, while the increase in house prices will bring savers to reduce their housing consumption: overall the different reactions between savers and borrowers will producing a milder increase in house prices, triggering a smaller collateral channel.

Recessionary shock | Expansionary shock | Sign effect

(a) (b) (c)



(d) (e) (f)

Figure 4: Impulse responses of output growth and debt/house price ratio to a housing shock.
Note. The responses of output growth and equity growth are cumulated, while the responses for the ratio of investment/output are in levels. The red (green) lines are the impulses when state is high (low). On the left hand graph (central graph) we report the responses to a recessionary (expansionary) shock. On the right hand graph, we report the responses under the high state to an expansionary (recessionary) in blue (orange). Impulses to recessionary shocks are multiplied by -1 for the sake of comparison. Shaded areas represent the 67% confidence intervals.

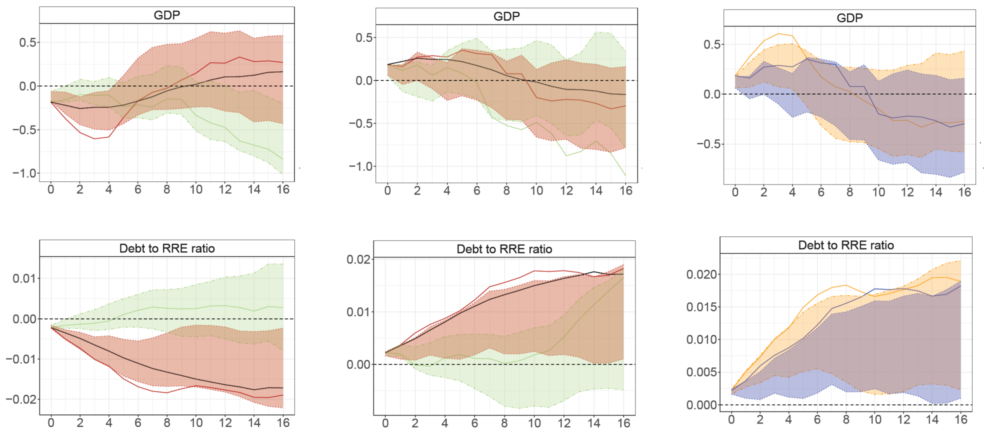
Thanks to this specification, we can jointly assess the state and the sign effects of housing and credit shocks. Except for those additional terms, we use the same variables and the identification strategy of the baseline model.

In Figure 4 we report the response of output and of the ratio of debt over house prices to housing shocks. In the top row of the figure, we report the responses to a recessionary shock, whereas below we report the responses to an expansionary one of the same size. When the state is high (red lines), the response of output to a recessionary shock is strongly negative and significant along all the projection horizon. Compared to the response obtained from the linear model, under high vulnerabilities impulse responses are: i) more persistent: the effect is significant across the whole projection horizon ii) from two to ten times larger in the first part of the projection. Conversely, under low vulnerability, the response to a recessionary shock is not statistically significant across all the projection horizon. Besides, equity growth, short term interest rates and investments/output show similar dynamics. Expansionary shocks (bottom row) feature similar state-effect, being qmplified by financial vulnerbility. In the third graph, we report the responses to expansionary and to recessionary shock, by multiplying by -1 the responses to the recessionary shock, for the sake of comparison. In the first part of the projection, the response of output to a recessionary shock is twice as large as the one obtained from an expansionary shock, while in the second part of the projection, the confidence intervals of the two shocks overlap. This result recalls the finding of Guerrieri and Iacoviello (2017) that find that recessionary shocks are stronger than expansionary in absolute terms. The intuition comes from the fact that when collateral prices drop, so does debt limits and constrained households can be forced to reduce their spending, amplifying the initial negative fluctuation. Instead, after expansionary shocks, households can decide to inter-temporally postpone their spending and not to expand their debt up to the new limit, with more limited effect on economic activity.

In figure 5 we report the responses of output growth to recessionary credit shock (left graph) and to an expansionary credit shock (right graph). In this specification, for recessionary shocks, high vulnerability: i) amplifies the response of output at the beginning of the projection; ii) reduces the persistence of the shock across the projection horizon. Moreover, under high vulnerability, the recessionary shock has a stronger negative reaction of the debt to houses ratio. On the opposite side, expansionary shocks determine similar responses to the one produced in the benchmark specification: output reacts more positively in the first part of the projection and becomes more negative in the second part of the projection (though here responses are not statistically significant). Besides, expansionary shocks determine a significant increase in the observed debt to houses ratio under high vulnerability, while under low vulnerability no significant effects are found. This result supports the interpretation according to which debt overhang, that follows debt expansion under high vulnerability, hampering the initial positive effects of the shocks. In the third graph, we report the impulse responses to expansionary and recessionary shocks (the latter one multiplied by -1) under high vulnera-

Recessionary shock | Expansionary shock | Sign effect

(a) (b) (c)



(d) (e) (f)

Figure 5: Impulse responses of a selection of the endogenous variables to a credit shock. Note. The responses of output growth and equity growth are cumulated, while the responses for the ratio of investment/output are in levels. The red (green) lines are the impulses when state is high (low). On the left hand graph (central graph) we report the responses to a recessionary (expansionary) shock. On the right hand graph, we report the responses under the high state to an expansionary (recessionary) in blue (orange). Impulses to recessionary shocks are multiplied by -1 for the sake of comparison. Shaded areas represent the 67% confidence intervals.

	GDP	Inflation	Inv/Out ratio	Stock prices	Credit/RE ratio	Mortgage rate
AD	+	+	-			
AS	+	-		+		
Investment	+	+	+	-		
Housing	+	+	+	+	-	+
Cred supply	+	+	+	+	+	-
Cred demand	+	+	+	+	+	+

Table 2: The table presents the sign restrictions assumed on the reaction on impact of endogenous variables (column) to identify the structural shocks shocks (row). When the space is empty, the response is left unrestricted.

bility: in the first part of the projection, recessionary shocks have a stronger effect in absolute terms whereas confidence intervals strongly overlap after the first year since the arrival of the shock. The asymmetric response of output with respect to credit shocks recalls the findings by Jensen et al. (2020), where a DSGE model with occasionally binding borrowing constraints is used to explain the observed asymmetry of the business cycle. According to their result, recessionary credit shocks have a stronger negative effect on impact whereas expansionary shocks have a smaller but more persistent effect on the economy.

5.2 Credit demand and credit supply

In our benchmark specification a clear result emerged: whereas under high financial vulnerability the response of output to housing shocks is amplified, the response to credit shocks overshoots. In this extension, we detect non-linear effects disentangling credit demand from credit supply shocks.

To do that, we modify the previous specifications in two ways. First, we add the mortgage rate to the set of endogenous variables and use it to disentangle credit demand shocks -for which the response of the mortgage rate has the same sign of the response of output- from credit supply shock -for which the sign of the two responses is different (Table 2). Second, for the sake of parsimony, we follow Furlanetto et al. (2017) and exclude of the policy rate from this specification.

In Figure 6 we report the responses of the economy to a credit demand shock. Under high vulnerability, the response of output growth to a credit demand shock is positive and statistically significant on impact, whereas it

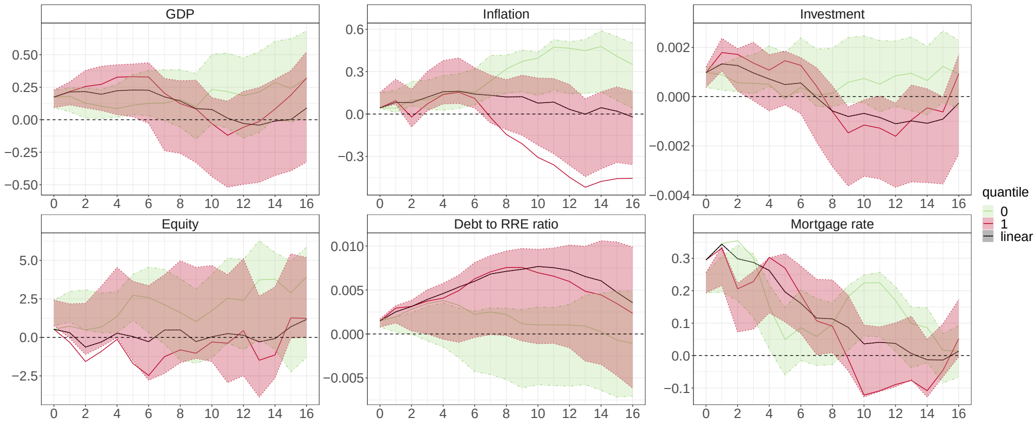


Figure 6: Impulse responses to a credit demand shock.
Note. The responses of output growth and equity growth are cumulated, while the responses for the ratio of investment/output are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% confidence intervals.

becomes not statistically significant after six quarters since the arrival of the shock. Similarly, investments over output react positively during the first two years, whereas in the second part of the projection, their response turn negative. Instead, under low vulnerability, the effect of credit demand shock in the economy is not statistically significant across the projection horizon, made exception for the first two quarters since the arrival of the shock.

In Fig/. 7, we report the responses to credit supply shocks. Overall, these shocks deliver similar non-linear dynamics as the ones found in the benchmark specification for the credit shock. First, under high vulnerability the expansionary effect on output is limited to the beginning of the projection under high vulnerability. Second, the shock is more persistent under low vulnerability. Third, the debt to house ratio reacts positively under high vulnerability, while it significantly decreases under low vulnerability. As explained discussing the results of the benchmark specification, this important state effects of the debt to house ratio and of output are consistent with the role of debt overhang being triggered under high financial vulnerability.

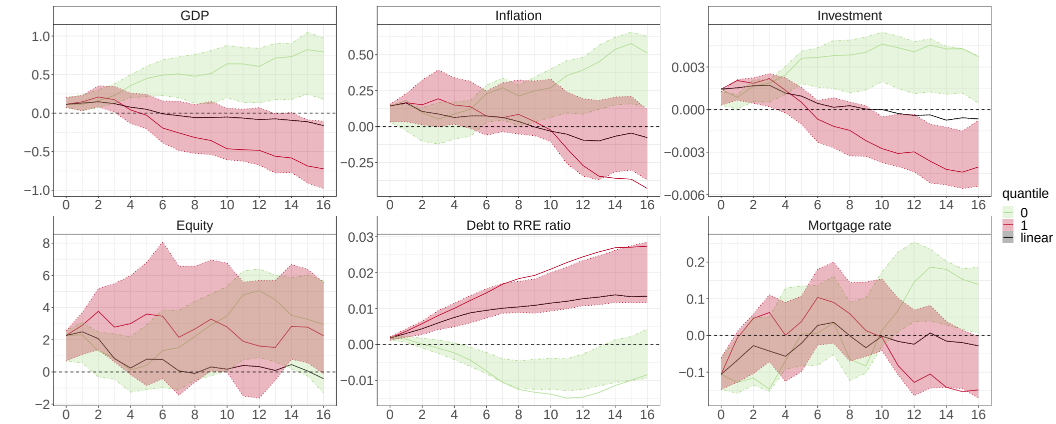


Figure 7: Impulse responses to a credit supply shock.
Note. The responses of output growth and equity growth are cumulated, while the responses for the ratio of investment/output are in levels. The red (green) lines are the impulses when leverage is high (low). Shaded areas represent the 67% confidence intervals.

5.3 Sensitivity analysis

Results are robust to different specifications. First we used two alternative econometric methods. We run the Smooth local projections developed by Barnichon and Brownlees (2018) to efficiently estimate local projections coefficients by using B-spline and ridge regressions. Using this method, we found very similar quantitative and qualitative results. We also implement the bootstrap-after-bootstrap bias-correction method, which only marginally affect results. Second, we run the regressions with one and three lags, instead of the two lags used in the baseline. Third, we use other calibrations for smoothing transition parameter $\theta = 1.5, 5$. Fourth, in order to test the results to different transformations of our state variable, we use different transformations of the DSR. We use the 2 and 5-year difference instead of the 3-year one, and also use as an alternative source the DSR provided by the Federal Reserve. Fifth, we use the mortgage debt, instead of total debt, to compute the debt to house ratio. Sixth, we use alternative inflation measures (Core CPI quarterly variation, GDP deflator quarterly variation). Seventh, we use as alternative measures for the policy rate the Fed Fund Rate and the one-year government bond rate[14]. In all these robustness checks, results remain qualitatively and quantitatively similar to what found for the benchmark specification.

6 Discussion

In this section we resume our main results and discuss them in light of the findings of macroeconomic theoretical works studying the propagation of financial shocks.

Housing shocks are amplified under vulnerability This result can be interpreted in light of the models building on Kiyotaki and Moore (1997) and studying the role of financial accelerator. As in Liu et al. (2013, 2016), households can borrow up to a fraction of their collateral. Housing shocks affecting collateral prices can directly modify borrowers' agents capacity, potentially amplifying the initial fluctuations. Given the presence of these borrowing constraints, the financial condition of households affect the response. The larger is the fraction of borrowers and of debt in the economy, the stronger will be this financial acceleration.

When recessionary, amplification of housing shocks is even stronger. To this extent, Guerrieri and Iacoviello (2017) build a DSGE model where the presence of occasionally binding constraint causes a strong sign effect in the propagation of the housing shock. Drops in collateral prices forces agents to deleverage, while increases of the same size allow them to intertemporally optimize and not to expand their debt as much as they could.

Under high vulnerability, expansionary credit shocks determine a positive effect at the beginning but are less persistent. This overshooting featuring the response of output to credit shock is also found in

[14]The last one is supposed to include also information on the forward guidance cite and is less affected by the materialization of the Zero Lower Bound, see Gertler and Karadi (2015)

Furlanetto et al. (2017). Our non-linear specification seems to suggest that debt overhang, originated under high vulnerability, can be responsible for the overturn of the effect after the first year since the arrival of the shock.

Vulnerability makes recessionary credit shocks stronger on impact but less persistent. Jensen et al. (2020) find this same type of results thanks to the role of occasionally binding constraints: expansionary shocks allow agents (in their case entrepreneurs) to inter-temporally postpone their spending, making the effects of the shocks less strong on impact but smoother with respect to recessionary shocks, which force agents to deleverage amplifying the initial negative fluctuation.

Not all financial shocks propagate in the same way: housing shocks are more persistent. This finding is in contrast with Jensen et al. (2020) where credit shocks and land shocks feature similar non-linear effects, but somehow recalls the finding of Justiniano et al. (2015). Their work studies whether the observed credit boom bust cycle over the Great Recession is related to a a credit shock or to housing shocks. In their model, only housing shocks can produce a sensible variation in collateral prices and, consequently, trigger the financial accelerator.[15] This difference between the two shocks in triggering the collateral channel could rationalize our result.

[15] Justiniano et al. (2015) use a macroeconomic model featuring an asymmetric collateral constraint on households: when collateral decreases, agents are forced to reduce the new debt flows but not the outstanding debt. This modelling choice is key to match an observed feature of the data in that after crisis, the ratio between credit/real estate does not decrease and actually spikes. First, they identify the housing shock as the main driver of the fluctuations, since in their model housing shock deliver an increase in the credit/house prices ratio as observed during the crisis. Second, they find that a shock on the credit side generates a variation in house prices value that is not strong enough to generate a big amplification spiral. In fact, credit shocks trigger an increase in willingness to buy houses for borrowers but not for savers. Since these two effects partially offset each other, the positive effect on houses is smaller, triggering a smaller collateral channel. Instead, housing shocks affect both savers and borrowers willingness to buy houses, triggering a stronger increase in house prices and triggering a stronger effect on debt. Third, they do not find significantly strong effects on output growth. This can also be related to the fact that the financial friction is applied only to the households and not to other agents (as banks or firms).

...bur overall recessionary shocks are stronger than expansionary ones. In line with the most theoretical results (Guerrieri and Iacoviello (2017); Jensen et al. (2020); Maffezzoli and Monacelli (2015)) recessionary shocks have overall stronger effects in absolute terms. According to their findings, a weaker role of the collateral channel after expansionary shocks is at the origin of this asymmetry detected in the business cycle.

7 Conclusion

In this paper we detect important non-linear effects featuring financial shocks. First, we find that financial vulnerability: i) amplifies and makes more persistent housing shocks, ii) amplifies credit shocks only on impact and makes them less persistent for the rest of the projection. At the origin of this difference lies the possible presence of debt overhang or a weaker collateral channel concerning the transmission of the credit shocks. Second, recessionary shocks are overall stronger on impact.

If overall we find results in line with the findings of models with occasionally binding constraints, the asymmetric propagation between housing and credit is in contrast to what usually found in this literature, where housing and credit shocks usually feature very similar amplification mechanisms. This result suggests to better take into account the asymmetries related to the propagation of housing and credit shocks, in the spirit of what done by Justiniano et al. (2015).

Finally, our results have key implications for policy makers. On the positive side, they call for the monitoring of macrofinancial indicators of households balance-sheet fragility. From a normative perspective, they suggest the development of macroprudential tools to prevent the excessive build-up of such vulnerability.

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