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Abstract

The paper presents a version of the Eurace macro-agent-based model which reproduces a credit economy in which the securitisation process and a bailout mechanism for banks bankruptcies are implemented. Within this model framework, we study five systemic risk indicators which have the aim to assess financial imbalances within the financial system. Two of them are the well-known mortgage-to-GDP ratio and the Capital Adequacy Ratio which are constructed to detect only the in-balance sheet changes in credit exposure. We consider two additional indicators, similar to the previous ones with the only difference is that they are able to account also for the off-balance sheet items. Moreover, we introduce a novel indicator, so-called VUC indicator, which also targets the off-balance assets. Results confirm that higher securitisation propensities weaken the financial stability of banks with relevant effects on different sectors of the economy. Most important, the analysis of the systemic financial indicator reveals the important issue of designing suitable systemic risk indicators for predicting incoming financial crises, finding that an essential feature of these indicators should be to integrate off-balance banks assets.

Keywords: systemic financial risk indicators, securitisation, housing market, agent-based models

Introduction

The paper contributes to the literature of macro-financial agent-based models, financial innovation and systemic risk. The study aims to answer the question of why financial risk indicators, with a particular focus on those detecting financial instabilities, remain only partially able to identify in time and quantify the actual financial system risk exposure. The models applied so far for detecting financial imbalances (e.g. see Borio and Lowe (2002); Misina and Tkacz (2009); Barrell et al. (2010) among others) still present large errors in their predicting power (ECB (2011) and Deghi et al. (2018)).

We analyse five systemic risk indicators which have the aim to assess financial imbalances within the financial system. Two of them are the well-known mortgage-to-GDP ratio and the Capital Adequacy Ratio[1](e.g. see Borio and Lowe (2002) and Barrell et al. (2010)), which are constructed to detect only the in-balance sheet (in-BS) changes in credit exposure of the single bank (CAR) and the financial system as a whole (credit-to-GDP). We consider two additional indicators, similar to the previous ones with the only difference that they are able to account also for the off-BS items. We call them adjusted CAR and adjusted mortgages-to-GDP . Moreover, we introduce a last indicator, so-called VUC indicator (see Lauretta et al. (2016)), which also targets the off-balance sheet (off-BS) assets.

Usually, banks decide to forward the off-BS items to the securitisation process to reduce the level of risk exposure of their credit portfolio. We analyse these indicators and compare the in-BS and off-BS dimensions in the context of the agent-based macroeconomic simulator Eurace (Cincotti et al. (2010), Cincotti et al. (2012a), Raberto et al. (2012) and Teglio et al. (2017)). To the best of our knowledge, this is the first time that in-BS and off-BS measures to detect financial imbalances are analysed and implemented in an agent-based economy.

Eurace reproduces an artificial macroeconomy integrating different sectors and markets characterised by heterogeneous and bounded rational agents. Each agent is characterised by a double-entry balance sheet(i.e. the "balance sheet approach" described in Teglio et al. (2010)) which enables us to observe the debts-credits dynamics in- and off-balance sheet and, thus to take account of those dynamics in the assessment of the systemic financial risk. We use this model for its peculiarity to reproduce real-world economic dynamics in a simplified but still rich way. In fact, it presents the ideal environment for the study of the out-of-equilibrium and non-linear dynamics of the economy.

The version of Eurace presented here includes a housing market in the style of Ozel et al. (2016), and implements a securitisation mechanism on the footprints of Mazzocchetti et al. (2018) and Lauretta (2018) that allows banks to free up their balance sheets from risk-weighted assets and circumvent the prudential capital requirements. A behavioural rule governs the model: the securitisation propensity. It is introduced as an exogenous parameter and determines the level of banks resort on the securitisation. To higher values of the

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[1]Actually we use the leverage of the bank as risk indicator, defined as $1/CAR$. In this way, the indicator should increase with systemic risk, coherently with the other indicators.

securitisation propensity corresponds a higher resort to securitisation. Moreover, the model shows a bailout resolution mechanism for banks' bankruptcies, which foresees the banks' rescue by means of government spending if banks' equity becomes negative (see Section 3.2 for more details).

In the aftermath of the crisis, the management of banks breakdowns has been a major concern for the public institutions of most developed countries around the globe. In the last decade, sovereign States and international organisations coped with the burden of the threat of banks' failures and employed several policy tools to bring back the economic system to a certain level of stability. Moreover, some financial institutions turned out to be "too big to fail", therefore government interventions became vital. To give an example, the US government intervened in 2008 with the TARP[2] (Troubled Asset Relief Program) allowing the Treasury to purchase illiquid, difficult-to-value assets from banks, up to 475 billion dollars, de facto introducing the first financial system bailout. Accordingly, the Federal Reserve responded to the financial crisis by implementing unconventional monetary policies (e.g. quantitative easing among others), that involved the purchase of mortgage-backed securities, bank debt and Treasury notes, reaching 2.1 trillion dollars in June 2010[3]. During the banking crises, also several European governments organised rescue packages to support banks, which involved 114 financial institutions during the period 2007-2013 (Gerhardt and Vennet (2017)).

We run simulations for a time span of 35 years. The results show that increasing the value of securitisation propensity enhances the amount of off-BS mortgages transferred to the securitisation process, while reducing the amount hold in-BS and, thus increasing, once the boom and bust occurs, the intensity of a recession, given a higher credit exposure of the whole financial system. The securitisation mechanism allows banks to exploit regulatory capital arbitrage and impact dramatically on their CAR. Consequentially, they can avoid issuing new equity and remain able to continue to meet the capital requirements while their overall systemic risk grows.

The bailout mechanism introduced in the model reproduces well what we witnessed in the last decade after the Global Financial Crisis (GFC). It shows the effect of the securitisations process on government accounting and how the costs of a bailout fall on the taxpayers. Also, we can observe the negative effects of the increased risk exposure of the credit market on the housing market and business cycle dynamics (see Section 5 for more details on this particular point).

Moreover, we compute the systemic risk indicators mentioned at the beginning of this introduction, and the outcomes show that banks can satisfy the capital requirement while they keep building-up gradually a higher risk exposure. The mortgages-to-GPD and capital adequacy ratios in their original version do not detect the development of the increasing exposure because they monitor only the in-BS dynamic and they do not consider the off-BS items. Therefore, this two indicators can become misleading. However, the adjusted version of mortgages-to-GDP and CAR together with the VUC indicator seem more adequate to monitor

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[2]see https://www.treasury.gov/initiatives/financial-stability/TARP-Programs/Pages/default.aspx
[3]see https://www.federalreserve.gov/monetarypolicy/bst_recenttrends.htm

and anticipate this risk exposure (see Section 5).

The discussion on the effectiveness and reliability of the systemic risk indicators has been particularly lively so far, both for what concerns timing and impact on the real economy (see Section 1). Certainly, the costs of banks' bailout have been high for the entire economy and mostly burdened on taxpayers. Therefore, it is of the utmost importance to develop and study better indicators which could time and prevent the increase of the systemic risk in the economy.

The remainder of the paper is organised as follows. Section 1 presents a brief review of the systemic risk indicators and explains how they are used in this study. Section 2 and 3 review the main elements of the EURACE model and describe in details the novel modelling features. Sections 4 and 5 shows the results of computational experiments and discuss them. Section 6 concludes the paper with final remarks.

1. Literature review

It is extremely important to have timely and effective measures of systemic financial risk assessment because they are central to macro-prudential supervisory and regulatory policies. This means that there is the need for tools and models able to monitor, capture and evaluate potential risks that can build up financial instabilities within the financial system. Usually, the notion of systemic financial risk is associated with assessing the total size of the risk present at a certain point in time within the financial system (Schwaab et al. (2011)), namely the time-varying probability of a systemic event. It is characterised by both cross-sectional (how risks are correlated across financial institutions) and time-related dimensions (how systemic risk evolves over time given a change in certain business and market conditions) (Hartmann et al. (2009); Adrian and Brunnermeier (2016a)).

In the past, the Value at Risk (VaR) was the most common measure of risk used by financial institutions and authorities, and it was able to analyse the single institution's level of risk. However, this measure was unable to capture the single institution's contribution to the overall systemic risk and the ensuing cross-sectional dimension of the systemic risk (Adrian and Brunnermeier (2016b)). In the aftermath of the global financial crisis (GFC) the Governments, Central Banks, and other Financial Authorities have been dealing with the cumbersome process to bring back the financial system to certain degrees of stability and recover the damaged economies of the countries involved. The debate, in both academic and non-academic level, started questioning systemic risk methodologies (e.g. see Acharya et al. (2017); Adrian and Brunnermeier (2016b); Banulescu and Dumitrescu (2015); Diebold and Yilmaz (2014); Billio et al. (2012); Goodhart and Segoviano (2009); Huang et al. (2009)). For example, the European Central Bank (ECB (2011)) in its Financial Stability Review of June 2011 contributed to this open discussion and introduced three models, each focusing on different aspects of systemic risk. The first aimed to apply a multivariate regression quantiles to assess the contribution of each financial institution to systemic risk. The second used macro and credit risk data in order to detect financial institutions shared exposure to common observed and unobserved drivers of financial distress. Finally, the third one provided a coincident indicator of systemic risk by aggregating information from different segments of the overall financial system. More recently, in the Financial Stability Review of the ECB 2018, Deghi et al. (2018) propose a financial stability risk index (FSRI) for the Euro area, which forecasts the near-term risk for the economy to fall into a deep recessions. The index power is derived from the extraction of the co-movement information of a combination of a large set of macro-financial indicators and taking into account also the role of spillovers and contagion risk.

A relevant section of the literature in systemic risk focuses on identifying those systemically important institutions that can trigger systemic instability in the financial system. A branch of the literature has used contingent claims analysis in order to assess systemic risk (e.g. Lehar (2005); Gray et al. (2008)). However, this approach presents a downside given the strong assumptions imposed concerning the banks' liability structure. Other scholars have relied instead on market data (Huang et al. (2012); Adrian and

Brunnermeier (2016b) and Billio et al. (2012) among others). An important contribution to mention is that of Acharya et al. (2017) who assume that undercapitalization of the financial sector as a whole produces negative externalities which can impact on the real economy. They measure the single bank's contribution to systemic risk as its propensity to be undercapitalised when the system is undercapitalised, i.e. systemic expected shortfall (SES). SES increases in the institution's leverage and its marginal expected shortfall (MES). Adrian and Brunnermeier (2016b) introduced *CoVar*, which they define as "the difference between the Conditional Value at Risk (*CoVaR*) of the financial system conditional on an institution being in distress and the *CoVAR* conditional on the median state of the institution." Huang et al. (2009, 2012) developed a systemic risk indicator measured by the price of insurance against systemic financial distress. It assesses the single bank's (or group of banks) marginal contribution and identifies the systemic importance of each bank to the systemic risk. The authors refer to this indicator as distress insurance premium or DIP. Moreover, the post-crisis literature on systemic financial risk (e.g. Trichet (2009); ECB (2009, 2011) and Bandt et al. (2012)) distinguished three main (but linked to each other) sources of financial instability: contagion, shared exposure to financial markets or macroeconomic risks, and financial imbalances. Contagion risk is defined as an initially idiosyncratic market disturbance which become widespread in the cross-section over time and is led by price co-movement on the downside. Shared exposure to financial market or macroeconomic risks is the situation where adverse conditions of the financial markets or the macroeconomy may impact on financial intermediaries and markets and cause simultaneous negative effects. Finally, financial imbalances occur in presence of boom and bust of credit or other asset prices. For the purpose of this study, we will focus our attention on the financial imbalances in particular. They are not easy to detect and quantify, given that they can arise and develop gradually over time without producing any relevant change in inflation.

Among the most common measures, the literature often refers to the Credit-to-GDP ratio and the Capital Adequacy (e.g. see Borio and Lowe (2002), Barrell et al. (2010)) to assess systemic risk. The first measure detects the credit exposure of the entire financial system with respect to GDP, while the second, also known as the capital to risk-weighted assets (RWA) ratio, measures the single bank's credit exposure with respect to its available capital. However, all the systemic measures discussed above rely mostly on in-BS data and asset prices and do not take into account the role played by other variables, such as the off-BS assets. The latter permits banks to hedge their idiosyncratic risk and presents the peculiarity, through the securitization process, of amplifying financial imbalances within the financial system while keeping volatility low (i.e. what Brunnermeier and Sannikov (2014) define the "volatility paradox") by impacting on the Capital Adequacy Ratio and favouring the creation of endogenous multi-leverages (Lauretta (2018)). As a consequence, the financial system, as a whole, results in a higher risk exposure which is only partially detected by the available systemic risk measures.

2. Model

The model presented used in this paper to conduct our investigation is the agent-based macroeconomic model Eurace (see Cincotti et al. (2012a); Raberto et al. (2012) and Teglio et al. (2017)).

In general, agent-based models (ABM) have been widely used in the last decade in many economic fields, including macroeconomics (see e.g. Caiani et al. (2016) and Fagiolo and Roventini (2017) for a survey and a comparison with DSGE models). The main advantage of the ABM approach relies on the opportunity to study the emergent aggregate statistical regularities in the economy, which are not originated by the behavior of an average and rational individual, but are the result of agents behavior and interactions.[4]

Eurace model represents a fully integrated macroeconomy composed by several agents that act following behavioral rules and interact through various markets. Each agent is characterised by a double-entry balance sheet that includes the details of all assets and liabilities (Table 8). The dynamical change of agents' balance sheet entries depends on agents plans and on the result of agents interaction within the different market settings. Figure 1 provide an overview of the model, showing the main agents and their interactions through markets. Arrows directions indicate the role that agents take in the markets, i.e. demand or supply.
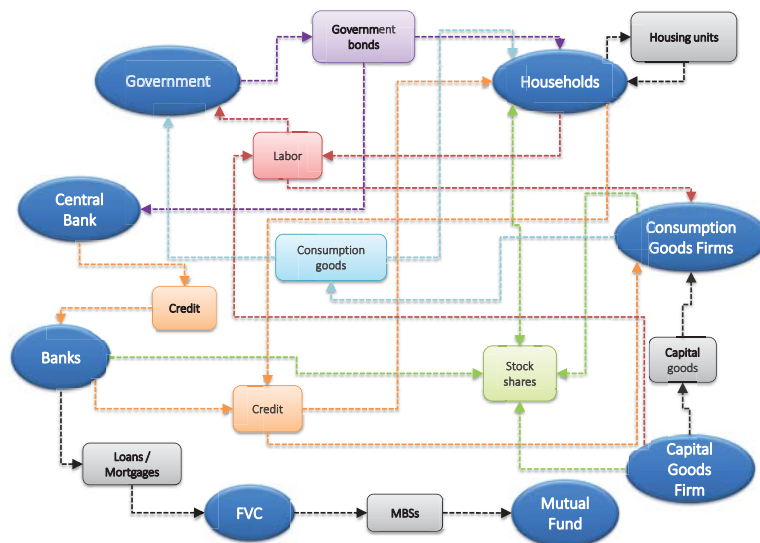

Figure 1: Eurace model overview. Round box include agents, while rectangular boxes include markets. The outgoing arrows represent the supply and incoming arrows represents the demand

In the model agents' decision processes are characterized by bounded rationality and limited capabilities of computation and information gathering; thus, agents' behavior follows adaptive rules derived from the management literature about firms and banks, and from experimental economics literature about the behavior of consumers and financial investors (Teglio et al. (2010); Raberto et al. (2012); Cincotti et al. (2012b); Teglio

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[4]For instance, in Eurace small idiosyncratic shocks at the firm level may generate single firm bankruptcies, which cause credit rationing by banks and so waves of bankruptcies among firms, and then entailing large aggregate fluctuations in the economy.

et al. (2017)). In general, agents interact in different types of markets, i.e. market for consumption goods and capital good, housing market, labor market, credit market, securitization market and financial market for stocks and government bonds (figure 1). Most markets are based on a decentralized exchange with pairwise trading, thus allowing us to capture some realistic features of goods, labour and credit markets, like price dispersion, exchange out of equilibrium and rationing.

Furthermore, the balance sheet approach (Teglio et al. (2010)) allows us to ensure the consistency at any time step between stocks and flows in the model, both at the level of the single agent and at the aggregate one, in line with the post-Keynesian stock-flow-consistent modeling approach (Godley and Lavoie (2012)). Macroeconomic agent-based stock-flow constistent models have been developed up to date only in few works (Kinsella et al. (2011), Riccetti et al. (2015), Caiani et al. (2016)). In particular, Caiani et al. (2016) build a general and flexible benchmark macroeconomic AB-SFC model, where the economy is fully decentralized and all transactions between private agents occur through local interactions based on matching protocols. The stock-flow consistency of a model allows to check that all monetary and real flows are accounted for, and that all changes to stock variables are consistent with these flows[5].

3. Novel modelling features

In this study, we aim to assess the systemic risk arising from the securitisation practise. For this purpose, we enriched Eurace model with an improved securitisation process and a bank resolution mechanism, which allows us to evaluate the risks for the whole economy entailed by banks' bankruptcies. In the following, we provide a description of the core modelling features related to this work, highlighting the new developments.

3.1. Securitisation process

The securitisation mechanism used in this paper is an enhancement of the one proposed in Mazzocchetti et al. (2018). In particular, we have introduced an engogenous demand for mutual fund (MF) equity shares, enabling the MF to finance its activity by issuing new shares, that can be purchased by households using part of their monthly disposable income. This demand side specification plays a crucial role in the securitisation functioning, since a restraint in MF liquidity hampers its capacity to purchase MBSs, thus forcing the banks to retain unwanted credit in its balance sheet.

We recall here the main characteristics of the securitisation process, focusing on the mortgage case, and then introduce the new features. The choice to securitise only mortgages relies on the opportunity to take into account the prepayment risk, i.e. the risk that households pay off their mortgages through housing units' fire sales when financially distressed (a description of the housing market is recalled in the appendix, for further details and related computational experiments with the housing market, see Ozel et al. (2016)). The prepayment of mortgages plays a crucial role in the securitisation market, mainly for two reasons:

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[5]A detailed description of Eurace balance sheet matrices is provided in the appendix

- Prepayments reduce the amount of mortgages in banks' balance sheet; thus, a wave of mortgage prepayments triggered by housing units' fire sales may hamper banks' possibilities to sell the desired amount of mortgages to the FVC.

- Prepayments reduce the profits of banks and, if securitisation is active, also of the mutual fund. In fact, whenever a mortgage is payed off the payments of its interest stops.

Securitisation mechanism allows banks to free up their balance sheet from mortgages and their related risk by selling them to a Financial Vehicle Corporation (FVC), which finances its activity by creating mortgage-backed securities (MBs) and selling them to a MF. Since Eurace includes a capital requirement provision that mimics Basel II regulations, banks can exploit the securitisation process to reduce the risk weighted assets in their balance sheet, thus complying with capital requirements without increasing their equity.

In the following, we describe the mortgage lending process and the securitisation framework. Let us consider a bank b with equity E_b and risk-weighted portfolio W_b, consisting of risk weighted loans $W_{b,\mathcal{L}}$ and mortgages $W_{b,U}$, such that:

$$W_b = W_{b,\mathcal{L}} + W_{b,U}. \tag{1}$$

A household h can send a credit requests to banks. Whenever it enters in the housing market, it can buy house units and, in case its liquidity is lower than the offered price, it asks for a mortgage. Let us assume that $\widehat{U}_{bh}$ is the mortgage asked by the potential borrower (household h) to the bank b. Bank b can grant the mortgage amount $\widehat{U}_{bh}$ to household h only if is endowed with an amount of equity which is higher than a fraction of the risk-weighted assets in its balance sheet, i.e. it satisfies the capital requirement:

$$E_b \geqslant k(W_b + \omega_{\widehat{U}_h}\widehat{U}_{bh}) \tag{2}$$

where k is fixed and equal to 0.1[6]. Moreover, risk weight of household mortgages $\omega_{\widehat{U}_h}$ is assumed constant and equal to 70%[7].

As stated in equation 2, bank's lending activity is limited by the ratio of its risk-weighted assets and equity. The ceiling of risk-weighted assets for the bank is given by α times its equity capital, i.e. αE_b, where $\alpha = \frac{1}{k}$. Thus, from a regulatory perspective, bank is constrained by the following rule: $W_b \leq \alpha E_b$. With the introduction of the securitisation mechanism, the bank can put off its balance sheet the amount of risk-weighted assets that exceed the ceiling; thus it could keep lending whenever W_b exceeds αE_b. However, we want to consider a behavioral specification that allows the bank to sell credit when it approaches the ceiling, thus considering different thresholds, computed quarterly as a fraction of the ceiling. For this purpose, we introduce an exogenous securitisation propensity parameter $\mu \leq 1$. According to μ, the bank's threshold is

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[6]For a study of the effects of different capital requirements in Eurace see Raberto et al. (2012)

[7]We refer to the standardised approach to credit risk outlined in Basell III reform, where residential real estate exposures only adjust on Loan to Value ratio(LTV), which we assume constant and equal to 100% (see BIS (2017)).

given by $(1 - \mu)\alpha E_b$. The higher the value of μ, the lower will be the threshold of the bank, resulting in more securitisation. In fact, whenever bank's risk-weighted assets exceed the threshold, the bank computes the amount S_b of risk weighted assets that it want to sell to the FVC as:

$$S_b = W_b - (1 - \mu)\alpha E_b \tag{3}$$

Conversely, S_b is set to zero (no securitisation), if bank's risk-weighted assets do not exceed the threshold.

We define U_b as the amount mortgages in bank b balance sheet. It is worth remarking that W_b is the sum of risk weighted loans ($W_{b,\mathcal{L}}$) and risk weighted mortgages ($W_{b,U}$); thus S_b is computed including also the risk-weighted loans. However, we securitise only mortgages, which in extreme cases may be not enough to fully satisfy the bank's planned sales.

The amount of mortgages (U_{S_b}) that the bank sell to the FVC is computed as the ratio between S_b and the bank's risk-weighted mortgages and is uniformly distributed among bank's mortgages. In particular:

$$\begin{cases} U_{S_b} = \left(\dfrac{S_b}{W_{b,U}}\right) U_b & \text{if} \quad W_{b,U} > S_b \\ U_{S_b} = U_b & \text{if} \quad W_{b,U} \leq S_b \end{cases} \tag{4}$$

FVC funds the purchase of loans and mortgages by issuing mortgage-backed securities (MBSs), that are sold to the MF. In the same fashion of Mazzocchetti et al. (2018), the MF is endowed with an initial provision of liquidity that allows it to purchase an amount of securitised products for two quarters, given a μ equal to 100%. Furthermore, the fund aims at maintaining its liquidity at the target level (M_D^*), which represents the amount of "operating liquidity" that is needed to carry out the securisation process for a quarter with μ equal to 100%.

Each quarter, mutual fund computes its liquidity needs L_D as:

$$\begin{cases} L_D = M_D^* - M_D & \text{if} \quad M_D^* > M_D \\ L_D = 0 & \text{if} \quad M_D^* \leq M_D \end{cases} \tag{5}$$

where M_D is the current liquidity of the fund. Therefore, L_D represents the amount of liquidity that the fund should rise. To do so the mututal fund can issue new equity shares, that generally are purchased by households.

The rationale behind the use of a liquidity target relies on the choice to avoid a direct relation between quarterly securitisation and the issuing of new shares, which would give rise to frequent shocks on households disposable income. On the contrary, a liquidity target let the fund to periodically adjust the liquidity level in order to have always enough resources to purchase ABSs and MBSs. Therefore, the fund uses the liquidity simply as a buffer for its securitisation activity, but relies on share issuing for financing new purchases.

The mutual fund computes quarterly the liquidity needed to reach its target, and, accordingly, issues new

shares that are bought by the households at the face value [8]. Moreover, the mutual fund remunerates the owners of the issued shares paying a monthly interest, given by the central bank policy rate plus a spread $s_{D,t}$. To some extent the mutual fund may be considered as a fund whose benchmark is the policy rate, which is outperformed by the spread $s_{D,t}$. A minimum spread value ϖ is fixed, so that the mutual fund always pays an interest that is higher than the policy rate. However, when new shares are to be issued, the spread is increased by the mutual fund until it fulfills its liquidity needs. Accordingly, the spread is reduced when the fund has enough liquid resources.

In order to link the spread to the fraction of disposable income that households are willing to invest in equity shares, we enriched the behavioral specification of the demand side of mutual fund's shares by including the following relation:

$$b_t = min(\eta \, s_{D,t}, \varrho) \tag{6}$$

where b_t is the fraction of disposable income that households use to purchase new shares,[9] ϱ is the maximum income percentage that households can invest and η is a parameter which represent the marginal propensity of households' investments in new shares with respect to the spread. In this setting, η is equal to 15; thus for each yearly percentage point offered by the mutual fund as a spread on the policy rate, households spend the 15% percent of their monthly disposable income to purchase the shares. Although the securitisation is active on a quarterly base and the liquidity needs L_D are updated accordingly with the same timing, the issues of new shares occur monthly, in order to smooth the purchases across the quarters. The shares bought by households give them the right to receive the earnings of the mutual fund, which are given by the interest payments on the mortgages associated with securitised products.

It is worth remarking that the purchase of ABSs and MBSs by the mutual fund in the model is not 100% guaranteed. In particular, households are available to buy mutual fund's shares only within a certain proportion of their disposable income (ϱ); otherwise, mutual fund may not be able to finance the purchase of ABSs and MBSs and securitisation stops until new funds are raised by the mutual fund.

3.2. Bailout

In order to tackle banks' bankruptcies, we introduce a bailout mechanism which is activated whenever the banks' equity becomes negative.

It is worth remarking that, whenever credit rationing occur, banks increase their equity by retaining their earnings, with the aim to comply with the capital requirement ($W_b \leq \alpha E_b$) and grant more credit. However, bank's equity may be reduced by loans and/or mortgages write-offs, which can occur in case of GCPs bankruptcies or severe financial distress of households. If write-offs are high enough to make banks'

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[8]The face value is computed as the ratio between the nominal value of the mutual fund assets divided by the number of outstanding shares.

[9]Thus the shares are distributed among households proportionally to their disposable income.

equity fall down below zero, the government intervenes by recapitalising the banks for an amount that allows the credit institutions to re-comply with capital requirements.

Therefore, in this setting the cost of banks' bankruptcies is supported by government and finally burden the tax payers. In fact, the fiscal policy pursued by government is the stability and growth pact (SGP), which targets a deficit to GDP of 3%. The bailout costs increase government spending and most likely its deficit to GDP ratio, bringing it to override the target compelling the government to increase tax rates.

4. Computational experiments

Results are obtained by performing Monte Carlo computational experiments, i.e., simulations are run using different seeds of the pseudorandom number generator for each scenario. Following Lauretta (2018) and Mazzocchetti et al. (2018), we set five values of the securitization propensity μ (0%, 5%, 10%, 20%, 30%). Simulations have a duration of 35 years and are replicated using 50 different seeds per scenario, for a total of 200 simulation runs. The computational experiments have been performed with the following settings: 3000 households, 50 Consumption Goods Producers, 3 Banks, 1 Capital Good Producer, 1 Financial Vehicle Corporation, 1 Mutual Fund, 1 Government and 1 Central Bank.

Even though simulations run for a time span of 35 years, for the first five years banks are not allowed to sell credit to the Financial Vehicle Corporation, thus there are five common years of transition phase, which we do not consider in the analysis. Trajectories can diverge at the beginning of year 6, when banks can sell mortgages to the FVC and the distinction among securitisation scenarios is enabled.

We present results using the median of yearly averages (computed across different time windows) over the seeds for each one of the considered scenarios. In particular we show, for each of the five values of μ (0%, 5%, 10%, 20%, 30%), the median of economic and financial variables over the 50 seeds, along with the first and the third quartile. In the description of results, in-BS mortgages represent the mortgages accounted in banks' balance sheet, while off-BS mortgages are the mortgages securitised and put off banks' balance sheet. Total mortgages represent the sum of in-BS mortgages and off-BS mortgages. Furthermore, in order to better distinguish between monetary and non-monetary variables, in the figures we use the symbol "E€" (Eurace Euro) to refer to the currency unit in the model (see Ponta et al. (2018)).

Moreover, to the aim of our investigation, we analyse a set of five indicators: banks' leverage, i.e the ratio between banks' weighted assets and equity, computed using only in-BS weighted assets and total weighted assets; mortgage to GDP ratio, computed using only in-BS mortgages and total mortgages; a fifth indicator, the so-called VUC indicator (see Lauretta et al. (2016) and Eq. 7):

$$VUC = \frac{\frac{\sum_{b=1}^{N} TC_T}{Eq^b}}{GDP} \tag{7}$$

This indicator can be seen as a transformation of the credit-to-GDP indicator in which the numerator expresses the ratio between the sum of the portion of banks credits TC_T forwarded to the securitisation process (off-BS assets) and the total banks equity Eq^b. Following the common practice in the literature (e.g. see Borio and Lowe (2002); Borio and Lowe (2004); Drehmann and Juselius (2014)), the GDP is used to scale the indicator. The credit-to-GDP takes into account the leverage applied at the commercial bank level, but ignores the role played by other leverages operating within the financial system at different levels. The VUC indicator symply detects a second order of leverage, representative of the multi-leveraging effect Lauretta (2018) operating within the financial sector, which can trigger systemic financial risk. This indicator has a relevant obsevartory power and improves recognition of systemic-risk-building-up dynamics in particular

for what concerns the off-BS flows. For policy purposes, the VUC indicator used together with the most common credit-to-GDP ratio can improve the early-warning detection of financial imbalancies in the financial system. It is worth remarking that the indicators, differently from the other variables, are presented using the median, the first and the third quartile of yearly values (computed only in certain years, i.e. year 1, 5, 10, 15, 20, 25, 30 after securitisation starts) over the seeds for each one of the five values of μ (0%, 5%, 10%, 20%, 30%). The reason is given by the need to consider the yearly values of the indicators in order to compute the cross-correlations. In fact, we present a cross-correlation analysis between the indicators and the yearly number of bankruptcies. Moreover, we add a cross-correlation measure between mortgages-to-GDP indicators and the yearly number of firesales. Therefore, in order to correctly perform the cross-correlations analysis, we consider the yearly time series of the indicators.

5. Results

Results of the computational experiments show the economic impact of the securitisation process across time, focusing on the effect on the housing market and, more in general, on a selection of relevant economic variables. In the specific context of securitization, we also introduce and test a set of systemic risk indicators, that should be used as early warning for incoming financial crises.

In the next sections, we describe first the main economic implications of the securitisation process, analyzing the specific effect of different securitisation propensity (μ), and finally we examine the effectiveness of the proposed risk indicators.

5.1. The securitisation mechanism

As outlined in section 3.1, the securitisation process involves banks, a financial vehicle corporation (FVC) and a mututal fund (MF). The latter is provided with an intial amount of liquidity which covers two quarters of securitisation with μ equal to 100%. Moreover, the MF targets a liquidity threshold, under which new equity shares are issued and sold to households.

Figures 2 and 3 show the effects of the different scenarios on the MF. Scenarios with a higher value of μ show higher purchases of mortgage-backed securities (panel (b)) which are financed by means of both internal resources and by issuing of new equity shares (panels (a) and (c)). However, households' monthly income percentage that can be invested in shares' purchase is limited, thus an excess supply of MBSs may not be sustained by the fund, and banks could be rationed, i.e. not able to fulfill their planned credit sales (panel (d)).

Some details of the mutual fund equity shares are shown in figure 3. In particular, the mutual fund pays an interest rate to reward shareholders (panel (a) shows the yearly interest rate paid by the fund), and increases the spread whenever it needs to collect more liquidity, in order to attract more investors. This happens more frequently in the case of high securitization scenarios, as the liquidity needed by the fund to buy new MBS is higher. The higher MF spread induce households to invest a more substantial fraction of

14

their income in fund shares (panel (b)). It is worth remarking the interest rate of the MF shares is composed by the CB policy rate (panel (c)) and a spread. According to the MF interest rate, the mutual fund pays monthly dividends to the shareholders.

Figure 4 reports the main effects of the securitisation propensity on bank's balance sheet. For higher propensity μ, banks sell more mortgages, thus reducing the amount of mortgages accounted in banks' balance sheet (panel (b)) and enlarging the off-balance sheet volume (panel (a)). Consequently, the proportion of off-BS mortgages over the total amount of credit enhances.

Securitisation allows banks to free up their balance sheet from risky assets, thus in the short run their capital adequacy ratio increases and more credit can be granted by the bank. Therefore, the growth rate[10] of mortgages (which are securitized) is higher than the growth rate of firm's loans (which are not securitized), as shown in figure 6.

Those findings are in line with the securitisation mechanism explained in section 3.1. In particular, according to equation 3, when securitisation is active banks de facto refer to their internal capital adequacy ratio (CAR), avoiding the regulatory constraints[11]. In particular, the securitision instrument allows banks to escape the capital requirement obligation, by selling risk-weighted mortgages to the FVC in exchange of liquidity. This aspect is highlighted in figure 10b, showing that bank leverage [12] is much higher in the case of securitisation.

5.2. Securitisation effects on credit and housing market

In order to assess the impact of securitisation on lending activity and on the housing market, we analyse the total credit growth rate considering two different time horizons after the activation of the securitization mechanism: a short one presenting the first five years and a long one, where we report all the 30 years.

Panels (a), (b) and (c) of figure 5 show an increase in the volume of total credit in the first five years. In fact, at the beginning of year 6 banks start to free up their balance sheets by selling risky assets, enabling the issuing of additional credit. After one year, mortgages growth rates are higher in the scenarios with positive μ, showing that securitisation accelerates credit growth. As the paper focuses on the securitisation of mortgage loans, which means being able to expand the supply of mortgages, we set up a parametrization of the housing market where the demand by households is also sustained[13]. This is the main reason why the mortgage loans growth rate is more affected by securitisation propensity with respect to the firms loans growth rate.

The effect of securitisation in the medium and long run is shown in figure 6, and strictly depends on securitisation propensity (μ). In fact, the higher the value of μ, the lower are credit growth rates in the long

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[10]Growth rates are computed as the percentage increase of the selected indicator I with respect to its value in year 5, when securitization is enabled, i.e., $g(t) = (I(t) - I(5))/I(5)$

[11]in the current setting the capital requirement is fixed at 10%;

[12]Bank leverage is the inverse of CAR, i.e., assets over equity. Here we refer to both in-BS and off-BS assets

[13]In particular, the value of the stock T_{ETA} and flow T_{DSTI} constraints is equal to 0.5, while probability to enter in the housing market (Φ_H) is 50%. For details on the effects of different parameterizations in the housing market see Ozel et al. (2016)
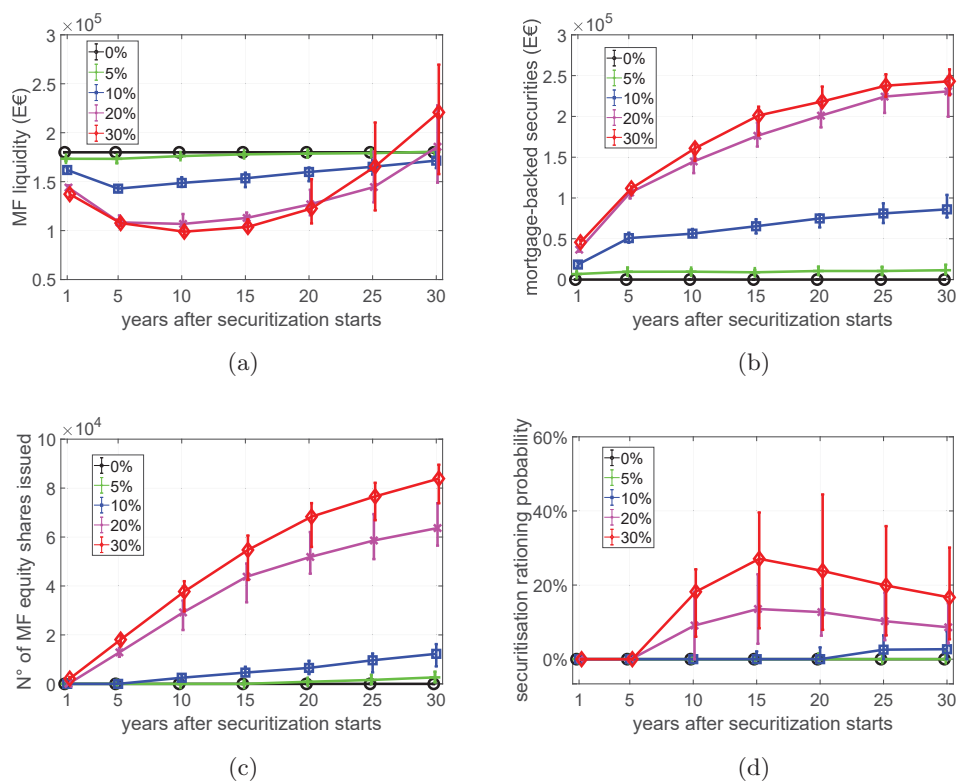
Mututal Fund data

Figure 2: Yearly mean's median, first quartile and third quartile over 50 seeds of a set of mutual fund's data. Yearly means are computed across different time windows, each of them reported in the x-axis. Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)

Mutual fund shares issuing
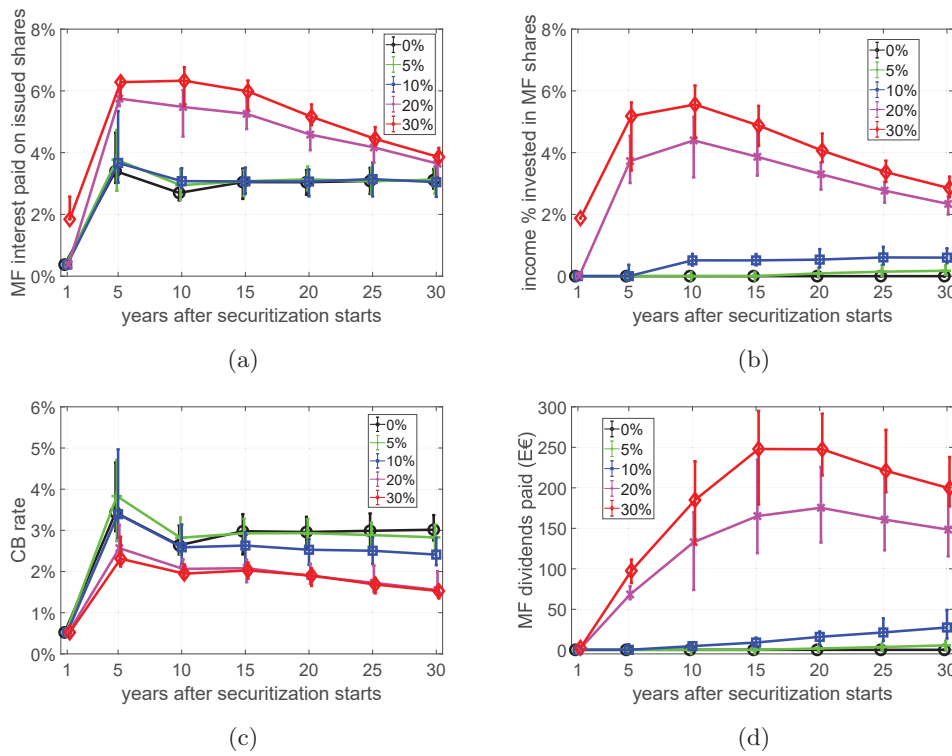
Figure 3: Yearly mean's median, first quartile and third quartile over 50 seeds of a set of mutual fund's shares issuing data. Yearly means are computed across different time windows, each of them reported in the x-axis. Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)

17

Banks' balance sheet data

Figure 4: Yearly mean's median, first quartile and third quartile over 50 seeds of a set of banks' balance sheet data. Yearly means are computed across different time windows, each of them reported in the x-axis. Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)

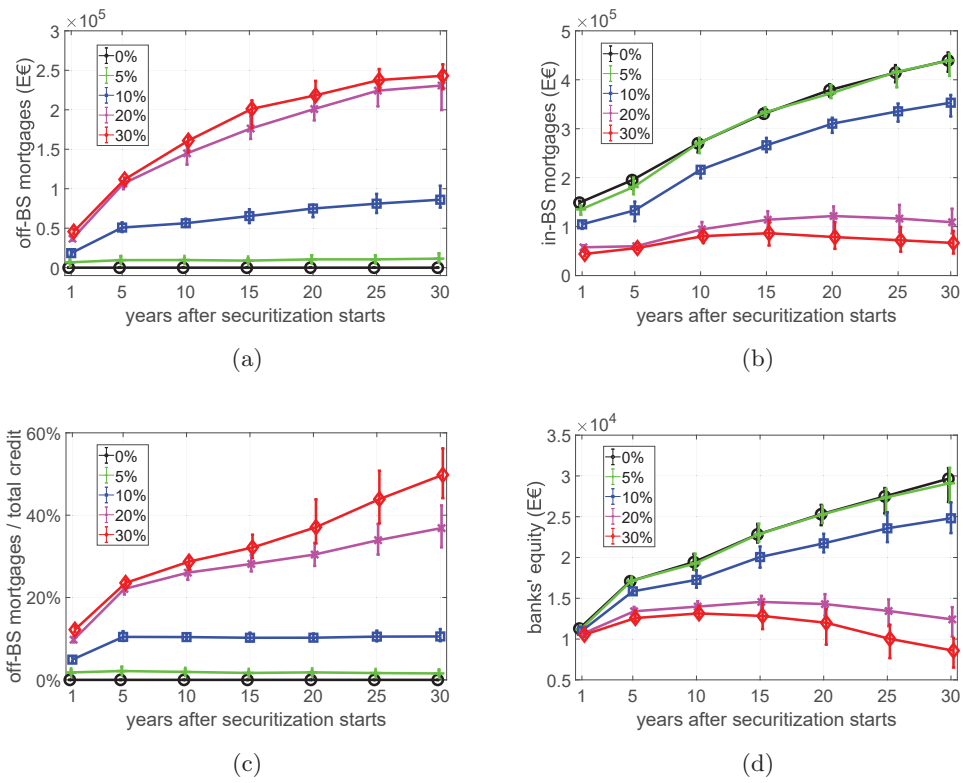run. This is mainly due to the higher instability triggered by the short-term boost of lending activity, not supported by an adeguate equity base increase, but built only on mortgages sales. In fact, securitisation may be impaired because the mutual fund does not have enough funds (panel (d) of figure 2) and when μ is high banks may find it difficult to increase their equity base by retaining earnings, since most of them flow out to off-BS mortgages. The results can be an increase in credit rationing (panel (a) of figure 7) and a decrease of loans and mortgages growth rate. Moreover, in the long run a low equity level increases the risk of banks bankruptcies due to credit write-offs.

The dynamics of the housing market is strictly linked with the mortgage volumes. In fact, the easier access to mortgage loans enhances the demand for housing units by households, triggering a boost in the housing price (panel (b) of figures 5 and 6). Following the dynamics of the mortgages, the housing unit price growth rate is larger in the short run (after securitisation has been enabled) and for higher values of securitisation propensity. However, in the medium and long run results may be reversed, with scenarios characterized by greater μ showing a slow down of the housing market activity, culminating in higher fire-sales volumes (figure 6e).

It is worth noting that both in the credit and housing markets a low value of securitisation propensity ($\mu = 5\%$) achieves the best results, boosting credit activity in the short run without suffering growth rate decreases in the long run with respect to the baseline scenario ($\mu = 0\%$).

5.3. Securitisation impact on firms

The effects of securitisation process affect also the financing activity of firms. In particular, following the pecking order theory, Consumption Goods Producers (CGPs) first finance their production plan by means of internal resources, then they resort to bank credit, and finally, if rationed in the credit market, they issue new shares and sell them to households.

Thus, a boost or a restraint in banks' lending activity changes the financial structure of GCPs. In fact, as the securitisation process starts and banks are able to free up their balance sheet from risky assets, thus improving their capability to grant new loans to firms, CGPs face lower rationing in the credit market. Panel (a) of figure 7 illustrated this aspect, showing a reduction of credit rationing in the very first year after securitisation starts. However, in scenarios where the propensity μ is high, the lower bank equity level and the increase of fire-sales (figure 6e) that reduces the amount of mortgages in banks' balance sheet, may impair the securitisation process (see section 3.1) and increase the number of credit rationing in the medium and long run.

The higher frequency of firms rationed in the credit market leads to a higher number of illiquidity bankruptcies, where firms are no more able to roll over debt and finance their production plan (figure 7b).

5.4. Securitisation effects on government accounting

Figure 8 shows the impact that banks' defaults have on the government accounting. As stated in section 2, a resolution mechanism for banks bankruptcies has been introduced in Eurace: if banks' equity becomes

19

Growth rates

(a)

(b)

(c)

(d)

Figure 5: Growth rate's median, first quartile and third quartile over 50 seeds of credit and housing price. Growth rates are computed as the percentage increase of the selected variable in certain years (each of them reported in the x-axis) with respect to its value in year 5. Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)
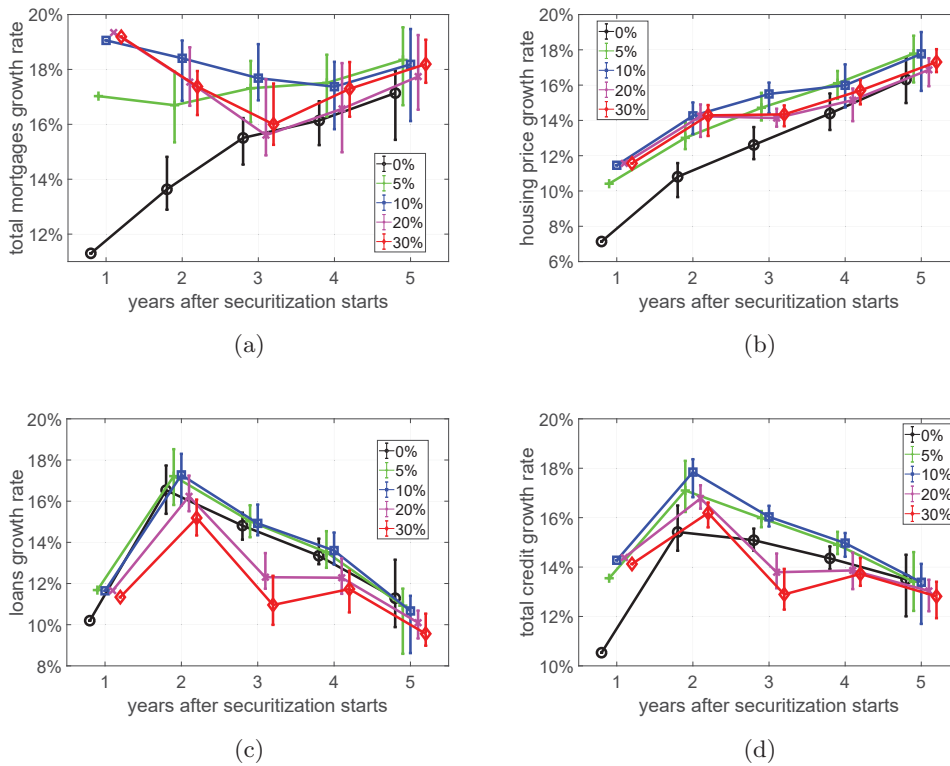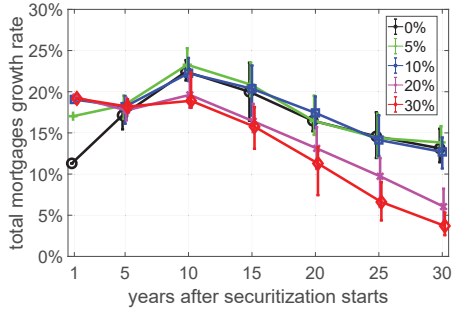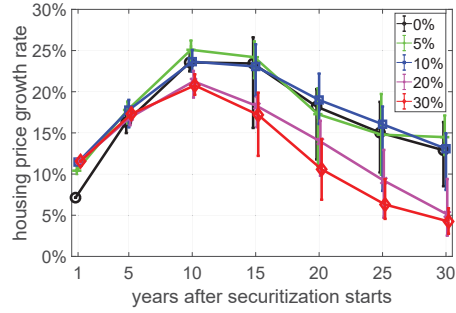
Growth rates

Figure 6: Growth rate's median, first quartile and third quartile over 50 seeds of credit and housing price. Growth rates are computed as the percentage increase of the selected variable in certain years (each of them reported in the x-axis) with respect to its value in year 5. Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)
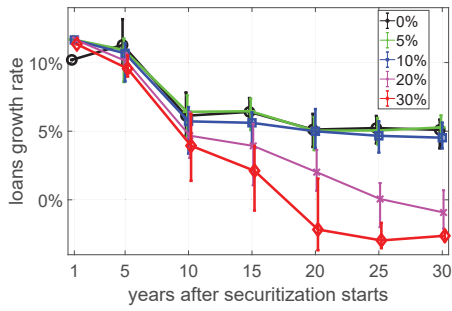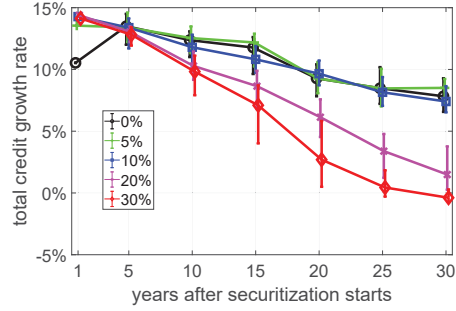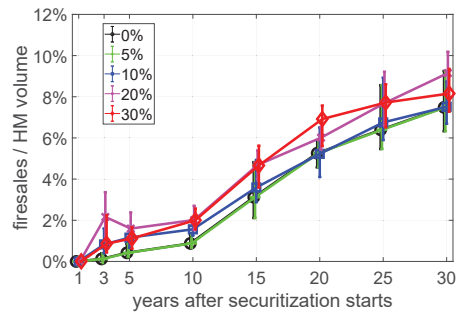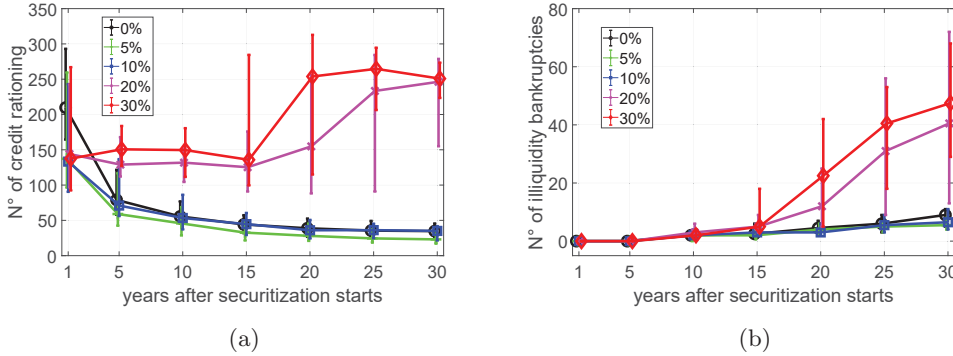
Firms' data

Figure 7: Yearly mean's median, first quartile and third quartile over 50 seeds of a set of firms' data. Yearly means are computed across different time windows, each of them reported in the x-axis. Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)

negative, the government provides the banks with the liquidity necessary to exceed the regulatory capital requirement and carry on lending activity. However, bailout costs are paid by the government (panel (c) in figure 8), increasing its expenses (panel (a) in figure 8) and deficit to GDP ratio (panel (b) in figure 8). In a Stability and growth pact scenario[14], this leads to an increase of taxes, de facto offloading the costs of bailout on taxpayers (panel (d) in figure 8).

5.5. Securitisation and macroeconomic variables

By affecting the credit and the housing market, securitisation also impacts the main macroeconomic indicators. Figure 9 shows real consumption (panel (a)) and unemployment rate (panel (b)). In the short and medium run the securitisation process allows banks to grant more credit (figures 5), triggering also an expansionary effect on consumption (in relative terms, comparing the different values of μ) and a consequent reduction of the unemployment rate. However, in the longer run, expecially for scenarios with $\mu = 20\%$ and 30%, the higher instability of the banking system, subsidized by taxpayers by means of recessive fiscal policies, leads to higher levels of unemployment.

5.6. Systemic risks indicators

Figure 10 presents the time evolution of five systemic risk indicators, which are potential candidates to be used as early warnings for incoming financial crises. As the focus of the paper is on the banking system and credit market, we examined indicators that mainly target banks' assets. In particular, we distinguish two types of indicators, a first one, reported in figures 10a and 10c, which considers only assets in the balance sheet of the bank, and a second one, reported in figures 10b, 10d and 10e, which includes also off-balance sheet assets.

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[14]In the current framework, the fiscal policy is ruled by a Stability and Growth Pact scenario (SGP), where government target a deficit to GDP ratio of 3 %, by adjusting the tax rates (see Teglio et al. (2017) for details)

Government data

(a)

(b)

(c)

(d)

Figure 8: Yearly mean's median, first quartile and third quartile over 50 seeds of a set of government data. Yearly means are computed across different time windows, each of them reported in the x-axis. Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)
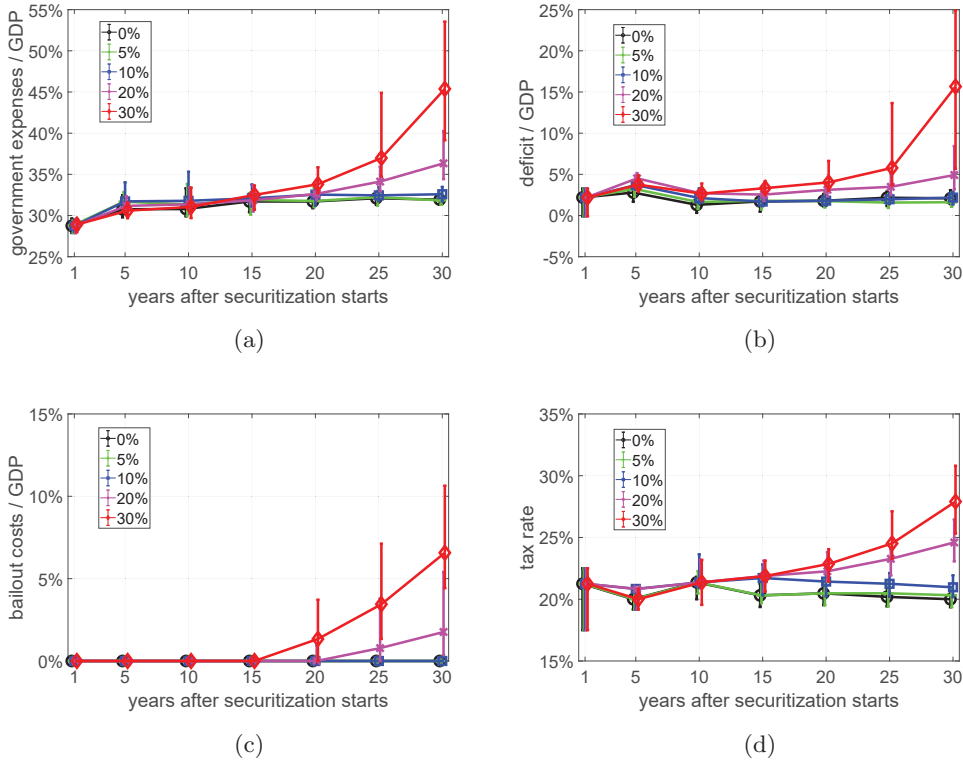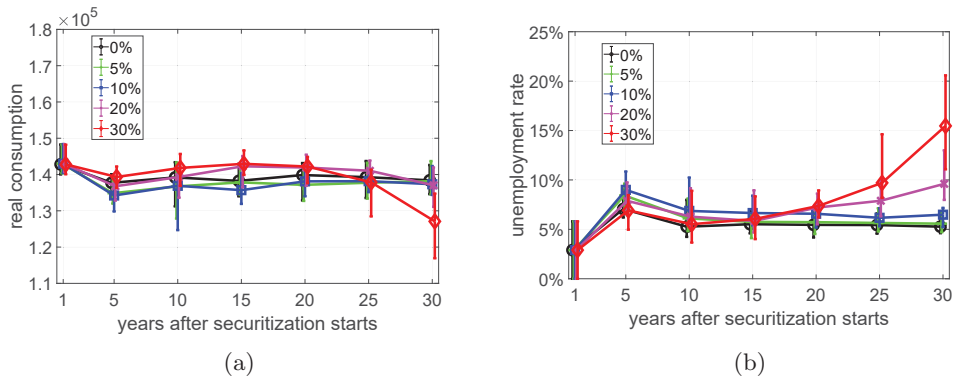
Macroeconomic data

(a)

(b)

Figure 9: Yearly mean's median, first quartile and third quartile over 50 seeds of a set of macroeconomic output. Yearly means are computed across different time windows, each of them reported in the x-axis. Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)

The indicators in the upper row (figures 10a and 10b) represent bank leverage, computed as the ratio between bank's weighted assets and equity. The indicators in the middle row (figures 10c and 10d) focus on the ratio between mortgages and GDP, while the last indicator (figure 10e) focuses specifically on the off-balance sheet assets, as explained in section 4.

We remind here that the capital requirements for banks are set to 10%, therefore allowing for a maximum leverage of 10. Indeed, banks are able to comply with a leverage value under 10 until year 15, as figure 10a shows, while afterwards the leverage tends to increase in the case of higher securitization propensity, as banks are not stockpiling enough capital buffer. The leverage measure increases when also off-balance assets are considered, as in figure 10b, supposedly revealing a higher systemic risk in the economy.

In a similar way, figure 10d shows the mortages to GDP ratio when also off-balance mortgages are considered. However, in this case, differently from the previous one, the risk indicator in the high securitisation scenarios are lower. Therefore this indicator does not warn about a higher risk when securitisation is active.

The last indicator, in figure 10e, which targets directly the off-balance sheets assets, weighted by the economic activity (GDP), reveals, on the other hand, a strong risk in the case of high securitization scenarios.

We assess the effectiveness of the different risk indicators in predicting economic and financial crises by examining the cross-correlation of the indicators with the number of total bankruptcies, used as a proxy for the crisis. Tables from 1 to 5 report these cross-correlations, considered with negative lags up to four years, even if we are mainly interested to examine the minus one lag, i.e., the correlation of total bankruptcies with the risk indicator one year before.

In principle, a good indicator should have a high correlation value for all the different scenarios, as the securisation propensity is not directly observable in the real world. In general, indicators including off-BS assets have a better performance, while the ones excluding them could be completely misleading as in the case of table 3, where the cross-correlation at $t-1$ is even negative. In particular, the total mortgage to GDP indicator and the VUC indicator show both a positive and consistent correlation between the number of bankruptcies and the value of the indicators in the previous years. However, the values of the correlation coefficients are not extremely high and it is not easy to identify a clear "alarm" threshold, beyond which the economy should be considered at danger.

In tables 6 and 7 we use fire-sales in the housing market as an alternative indicator for measuring the magnitude of the crisis. Results show again that it is essential to consider indicators with off-BS assets in the high securitization scenarios. Moreover the correlation between the mortgage to GDP indicator with successive crises (measured as fire-sales amount) is stronger. This can be explained by the fact that borrowers of mortgage loans are the first "victims" of an extra leveraged credit market, and therefore the effect on fire-sales is stronger. The effect on firms' bankruptcies is still there, but it is attenuated by a longer economic transmission chain of the credit shock.

Crosscorrelations

Systemic risk indicators

(a)

(b)

(c)

(d)

(e)
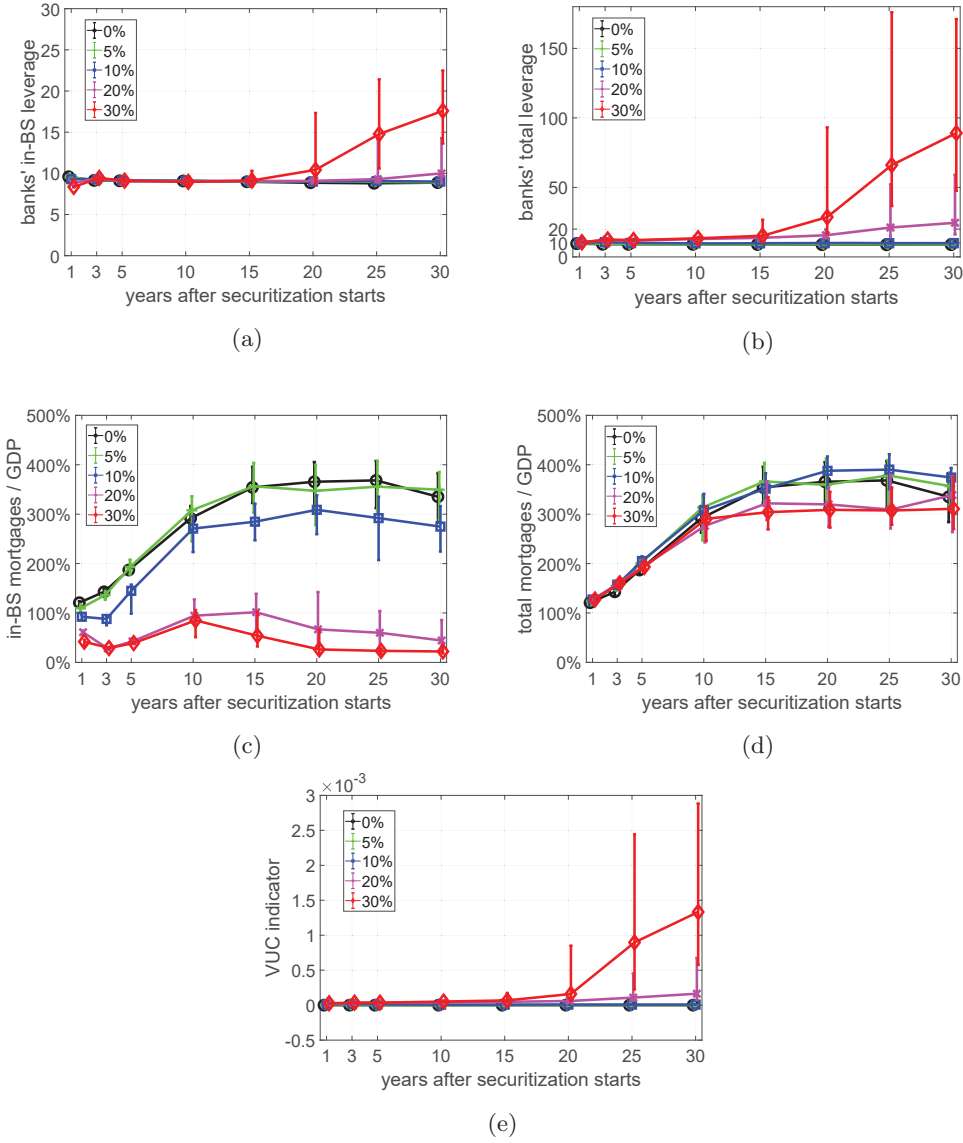
Figure 10: Yearly value's median, first quartile and third quartile over 50 seeds of systemic risk indicators. Yearly values are computed by considering each indicator in certain years (each of them reported in the x-axis). Five securitisation propensity values (μ) are considered (0%,5%,10%,20%,30%)

μ	t-4	t-3	t-2	t-1	t
0%	-0.07(0.01)	-0.20(0.02)	-0.31(0.02)	-0.06(0.02)	0.28(0.01)
10%	-0.04(0.01)	-0.08(0.01)	-0.10(0.01)	0.01(0.01)	0.26(0.01)
20%	0.13(0.03)	0.14(0.04)	0.12(0.04)	0.19(0.03)	0.28(0.03)
30%	0.23(0.04)	0.25(0.04)	0.22(0.04)	0.22(0.04)	0.19(0.03)

Table 1: Cross-correlation of regulatory leverage (banks' equity to in-BS weighted assets ratio) and total bankruptcies. Standard errors in parentheses

μ	t-4	t-3	t-2	t-1	t
0%	-0.07(0.01)	-0.20(0.02)	-0.31(0.02)	-0.06(0.02)	0.28(0.01)
10%	-0.05(0.01)	-0.08(0.01)	-0.05(0.01)	0.21(0.01)	0.40(0.02)
20%	0.23(0.03)	0.26(0.03)	0.27(0.04)	0.34(0.03)	0.35(0.03)
30%	0.33(0.03)	0.36(0.04)	0.31(0.03)	0.29(0.03)	0.18(0.03)

Table 2: Cross-correlation of total leverage (banks' equity to total weighted assets ratio) and total bankruptcies. Standard errors in parentheses

μ	t-4	t-3	t-2	t-1	t
0%	0.19(0.02)	0.18(0.02)	0.21(0.02)	0.23(0.02)	0.28(0.02)
10%	0.19(0.02)	0.21(0.02)	0.18(0.02)	0.05(0.02)	0.04(0.02)
20%	0.01(0.03)	0.02(0.03)	-0.02(0.03)	-0.20(0.03)	-0.27(0.02)
30%	-0.09(0.02)	-0.11(0.03)	-0.14(0.02)	-0.24(0.02)	-0.26(0.02)

Table 3: Cross-correlation of in-BS mortgages to GDP ratio and total bankruptcies. Standard errors in parentheses

μ	t-4	t-3	t-2	t-1	t
0%	0.19(0.02)	0.18(0.02)	0.21(0.02)	0.23(0.02)	0.28(0.02)
10%	0.14(0.01)	0.17(0.02)	0.17(0.02)	0.19(0.02)	0.24(0.02)
20%	0.15(0.02)	0.18(0.02)	0.19(0.02)	0.23(0.02)	0.25(0.02)
30%	0.16(0.01)	0.18(0.01)	0.18(0.02)	0.24(0.02)	0.27(0.02)

Table 4: Cross-correlation of total mortgages to GDP ratio and total bankruptcies. Standard errors in parentheses

μ	t-4	t-3	t-2	t-1	t
0%					
10%	-0.08(0.02)	-0.07(0.02)	0.03(0.02)	0.43(0.02)	0.48(0.02)
20%	0.24(0.03)	0.26(0.03)	0.26(0.03)	0.35(0.03)	0.30(0.03)
30%	0.27(0.03)	0.28(0.03)	0.22(0.03)	0.22(0.03)	0.12(0.03)

Table 5: Cross-correlation of VUC indicator and total bankruptcies. Standard errors in parentheses

μ	t-4	t-3	t-2	t-1	t
0%	0.23(0.02)	0.27(0.01)	0.41(0.01)	0.47(0.01)	0.60(0.01)
10%	0.23(0.02)	0.25(0.02)	0.34(0.02)	0.36(0.01)	0.51(0.01)
20%	0.07(0.03)	0.07(0.03)	0.13(0.03)	0.05(0.03)	0.09(0.03)
30%	-0.06(0.02)	-0.07(0.02)	-0.03(0.02)	-0.08(0.02)	0.01(0.03)

Table 6: Cross-correlation of in-BS mortgages to GDP and firesales. Standard errors in parentheses

μ	t-4	t-3	t-2	t-1	t
0%	0.23(0.01)	0.27(0.01)	0.41(0.01)	0.47(0.01)	0.60(0.01)
10%	0.26(0.01)	0.30(0.01)	0.42(0.01)	0.43(0.01)	0.59(0.01)
20%	0.24(0.01)	0.24(0.01)	0.38(0.01)	0.27(0.01)	0.51(0.01)
30%	0.24(0.01)	0.23(0.01)	0.37(0.01)	0.26(0.01)	0.47(0.01)

Table 7: Cross-correlation of total mortgages to GDP and firesales. Standard errors in parentheses

6. Conclusions

The paper studies the effects of the securitisation process in the assessment of the systemic financial risk indicators, using the agent-based model Eurace, which includes a housing market in the style of Ozel et al. (2016), and implements a securitisation mechanism on the footprints of Mazzocchetti et al. (2018) and Lauretta (2018) that allows banks to free up their balance sheets from risk-weighted assets and circumvent the prudential capital requirements. The model has been enriched with an endogenous demand specification of mutual fund equity shares and with a bailout resolution mechanism, which foresees the banks' rescue by means of government spending if banks' equity becomes negative.

We analyse the impact of securitisation on credit market and on real economy, finding that scenarions with higher securitisation propensities weaken the financial stability of banks with relevant effects on different sectors of the economy. Moreover, a set of five systemic financial risk indicators is considered: banks' leverage, i.e the ratio between banks' weighted assets and equity, computed using only in-BS weighted assets and total weighted assets; mortgage to GDP ratio, computed using only in-BS mortgages and total mortgages; a fifth indicator, the so-called VUC indicator, which is given by the ratio between off-balance sheet credit and banks' equity, normalized with the GDP.

The results presented in the paper brings clear evidence of the role played by the securitisation process, above certain levels of securitisation propensity, in paving the way toward booms and busts and ensuing economic recessions. Furthermore, the analysis shows how banks can satisfy their capital requirements while contributing to gradually building up higher risk exposure of the whole financial system.

The outcome of the computational experiments show that while the mortgage-to-GDP and banks' leverage can be misleading when considering only in-BS assets, thus not detecting correctly the financial imbalances, the adjusted version of those indicators together with the VUC indicator instead seem more adequate to monitor and anticipate this risk exposure.

Therefore, the paper highlights the importance of considering off-BS items when assessing for systemic risk. However, we remain of the opinion that this does not mean to downgrade the systemic risk indicators based on in-BS items, but their analysis and interpretation for regulatory reasons should be integrated the off-BS items, which play a relevant role in detecting systemic risk, as our results shows. The ABM framework allows to analyse, through numerical simulations, the relevance of off-balance assets in assessing systemic financial risk. Otherwise, this would be more complicated to verify empirically, given the lack of data availability on banks' off-BS assets. Only recently, the European Central Bank has started to gather from the Special Purpose Vehicle/Entity (SPV/SPE) these kind of data for the Euro area.

The data are available from 2012 annually and only from 2014 are they provided quarterly. Future work needs to be done in this direction, and our analysis contributes to highlight as a priority for regulation the access to the off-BS assets data. Of course, other variables can play an important role in developing systemic risk, such as, among others, the size of financial institutions and the exposure in interbank lending. Future research may consider the extension of the present work by developing indicators which compute not only the

in-BS and off-BS dimensions, but incorporate also other possible relevant variables for monitoirng systemic financial risk.

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7. Appendix

7.1. Balance sheet matrices

In order to provide an exhaustive description of agents' balance sheets and the stock-flow relations among sectors in Eurace, we present a set of four tables. Table 8 shows the asset and liability entries of each particular agent type. Table 9 represents the balance sheet matrix, describing all assets and liabilities for each sector (here a sector has to be seen as a class of agents). In this matrix a plus (minus) sign corresponds to agents assets (liabilities), and each column can be read as the aggregated balance sheet of a specific sector. Rows show assets and claims of assets among sectors, thus generally adding up to 0. Exceptions are capital and inventories, which are accumulated by CGPs, and households equity shares of CGPs and banks that do not add up to 0 because market price and book value can be different. However, being the equity shares of capital good producer (KGP), financial vehicle corporation (FVC), and mutual fund (MF) not traded in the financial market, their market price and book value coincide. Table 10, called transaction flow matrix, shows all the stock and monetary flows among agent classes. The top part, i.e. cash receipts/outlays, describes the flows of revenues (plus sign) and payments (minus sign) that agents get and make. Agents are reported in the columns, and monetary flows are reported in the rows. The result of agents sector transactions is the net cash flow (NCF). The bottom part of Table 10 describes the changes in financial/monetary assets/liabilities among periods. Finally, table 11, called equity capital change matrix, reports the variation of agents' equity capital between two periods, due to net cash flows, price changes in assets and liabilities, stock changes in real assets, and issues of equity shares.

Table 8: Agent class balance sheets

Agent class	Assets	Liabilities
Household *abbrev.*: HH *index*: $h = 1, \ldots, N_{Hous}$	Liquidity: M_h Stock portfolio: $\Sigma_b n_{E_{h,b}} p_{E_b} +$ $\Sigma_f n_{E_{h,f}} p_{E_f} +$ $n_{E_{h,K}} p_{E_K} +$ $n_{E_{h,D}} p_{E_D}$ Gov Bonds: $n_{h,G}\, p_G$ Housing units: X_h	Mortgages: U_h Equity: E_h
Consumption Goods Producer *abbrev.*: CGP *index*: $f = 1, \ldots, N_{Firm}$	Liquidity: M_f Capital goods: K_f Inventories: I_f	Debt: $D_f = \sum_b \ell_{f,b}$ Equity: E_f
Capital Goods Producer *abbrev.*: KGP	Liquidity: M_K	Equity: E_K
Financial Vehicle Corporation *abbrev.*: V	Liquidity: M_V Loans: $\mathcal{L}_V$ Mortgages: U_V	Asset backed securities (ABSs): ABS_V Mortgage backed securities (MBSs): MBS_V Equity: E_V
Mutual Fund *abbrev.*: D	Liquidity: M_D Asset backed securities (ABSs): ABS_D Mortgage backed securities (MBSs): MBS_D	Equity: E_D
Bank *abbrev.*: B *index*: $b = 1, \ldots, N_{Bank}$	Liquidity: M_b Loans: $\mathcal{L}_b = \sum_f \ell_{b,f}$ Mortgages: $U_b = \sum_h U_{b,h}$ Stock portfolio: $n_{E_{b,V}} p_{E_V}$	Deposits : $\mathcal{D}_b = \sum_h M_{b,h} + \sum_f M_{b,f} + M_{b,K}$ CB standing facility: $D_b = \ell_{b,CB}$ Equity: E_b
Government *abbrev.*: G	Liquidity: M_G	Outstanding government bonds value: $D_G = n_G\, p_G$ Equity: E_G
Central Bank *abbrev.*: CB	Liquidity: M_{CB} Loans to banks: $\mathcal{L}_{CB} = \sum_b \ell_{CB,b}$ Gov Bonds: $n_{CB,G}\, p_G$	Outstanding fiat money: Fiat_{CB} Deposits: $\mathcal{D}_{CB} = \sum_b M_b + M_G$ Equity: E_{CB}

Balance sheets of any agent class characterizing the Eurace economy. Balance sheet entries in the table have a subscript character, that is the index of an agent in the class to which the variable refers. In some cases, we can find two subscript characters, where the second one refers to the index of an agent in another class where there is the balance-sheet counterpart. For instance, D_f refers to the total debt of firm f, i.e. a liability, and $\mathcal{L}_b$ refers to the aggregate loans of bank b, i.e. an asset. $\ell_{f,b}$ (or $\ell_{b,f}$) refer to the loans granted by banks b to firms f. Of course, $\sum_b \mathcal{L}_b = \sum_f \ell_{b,f}$ represents an aggregate balance sheet identity, that is verified along the entire simulation. $n_{E_{h,x}}$ represent the number of outstanding equity shares of agents x held by households h. The market price of the equity shares is given by p_{E_x}. The stock portfolio's value of household h is then computed as: $\sum_x n_{E_{h,x}} p_{E_x}$. Government bonds' number and market price are given by n_G and p_G, respectively.

Table 9: Sectorial balance sheet matrix.

| | Non-Financial Private Agents | | | Financial Private Agents | | Banks | Policy Makers | | |
	HHs	CGPs	KGP	V	D	Bs	G	CB	Σ
Housing units	$+X_H\,p_X$								$+X_H\,p_X$
Capital		$+K_F\,p_K$							$+K_F\,p_K$
Inventories		$+I_F\,p_c$							$+I_F\,p_c$
Government Bonds	$+n_G^H\,p_G$						$-n_G\,p_G$		0
Debt / Credit	$-\text{Mortgages}$	$-\text{Loans}$		$+\text{Loans}_V$ $+\text{Mortgages}_V$		$+\text{Loans}$ $+\text{Mortgages}$ $-\text{Loans}_{CB}$		$+\text{Loans}_{CB}$	0
Securitised Loans						$-\text{Loans}_V$ $-\text{Mortgages}_V$			0
ABSs , MBSs				$-\text{ABS}_V$ $-\text{MBS}_V$	$+\text{ABS}_D$ $+\text{MBS}_D$				0
Private Liquidity	$+M_H$	$+M_F$	$+M_K$	$+M_V$	$+M_D$	$-D_B$		$-D_{CB}$	0
Banks, Government Liquidity						$+M_B$	$+M_G$		0
CB Liquidity / Fiat Money								$+M_{CB}$ $-\text{Fiat}_{CB}$	$+M_{CB,0}$
Traded Equity	$+\Sigma_f n_{E_f} pE_f$ $+n_{E_K} pE_K$ $+n_{E_D} pE_D$ $+\Sigma_b n_{E_b} pE_b$	$-E_F$	$-E_K$	$-E_V$	$-E_D$	$-E_B$ $+n_{E_V} pE_V$			$+\Sigma_f n_{E_f} pE_f - E_F$ 0 0 $+\Sigma_b n_{E_b} pE_b - E_B$ 0
Equity	$-E_H$						$-E_G$	$-E_{CB}$	$-E_H - E_G - E_{CB}$
Σ	0	0	0	0	0	0	0	0	

Table 9: Sectorial balance sheet matrix. Subscripts represent the index of the agent to which the stock refers. Uppercase subscripts are used when the stock refers to a whole sector, whereas lowercase subscripts are used when it refers to a single agent (for instance in the case of sums). Finally, superscript characters are introduced when the balance sheet counterpart is more than one single sector.

Table 10 (rotated landscape table):

	HHs	CGPs	KGP	V	D	Bs	G	CB	CB money creation	Σ
Cash receipts/outlays										
Consumption	−	+								0
Wages	+	−	−							0
Transfers	+	−	−				−			0
Investment		−	+							0
Taxes	−	−	−			−	+			0
Dividends	+	−	−	−	−	−/+				0
Securitisation Interest				+		−				0
ABSs/MBSs coupons				−	+	−				0
Bond coupons	+						−	+		0
CB coupons payback							+	−		0
Banks interests	−	−				+				0
CB loans interests						−		+		0
CB interests payback						+		−		0
	$=$ NCF	$=$ NCF	$=$ NCF	$=$ NCF	$=$ NCF	$=$ NCF	$=$ NCF	$=$ NCF		NCF
	$+$NCF	$+$NCF	$+$NCF	$+$NCF	$+$NCF	$+$NCF	$+$NCF	$+$NCF		0
Change in financial/monetary assets/liabilities										
Δ Loans / Mortgages	$+\Delta$ Mortgages	$+\Delta$ Loans				$-\Delta$ Loans $-\Delta$ Mortgages $+\Delta$ Loans$_{CB}$			$-\Delta$ Loans$_{CB}$	0
Δ Issue of new shares / bonds	$-\Sigma_f pE_f \Delta n_{E_f}$ $-pE_D \Delta n_{E_D}$ $-pE_G \Delta n_{E_G}$	$+\Sigma_f pE_f \Delta n_{E_f}$			$+pE_D \Delta n_{E_D}$		$+pE_G \Delta n_{E_G}$			0
Δ Securitized loans / mortgages				$+\Delta$ Loans$_V$ $+\Delta$ Mortgages$_V$		$-\Delta$ Loans$_V$ $-\Delta$ Mortgages$_V$				0
Δ Issue of ABSs/MBSs				$+\Delta$ ABS$_V$ $+\Delta$ MBS$_V$	$-\Delta$ ABS$_D$ $-\Delta$ MBS$_D$					0
Δ Private Liquidity & Δ Banks' deposits	$-\Delta M_H$	$-\Delta M_F$	$-\Delta M_K$	$-\Delta M_V$	$-\Delta M_D$	$+\Delta D_B$				0
Δ Banks/Pub. Liq. & Δ CB deposits						$-\Delta M_B$	$-\Delta M_G$	$+\Delta D_{CB}$		0
Δ CB Liq. / Δ Fiat Money								$-\Delta M_{CB}$	$+\Delta$ Fiat$_{CB}$	0
Σ	0	0	0	0	0	0	0	0	0	

Table 10: Sectorial transaction flow matrix of agents populating the EURACE economy

	HHs	CGPs	KGP	V	D	Bs	G	CB	Σ
Equity$_{t-1}$	$E_{H,t-1}$	$E_{F,t-1}$	$E_{K,t-1}$	$E_{V,t-1}$	$E_{D,t-1}$	$E_{B,t-1}$	$E_{G,t-1}$	$E_{CB,t-1}$	$E_{TOT,t-1}$
	+NCF	+NCF	+NCF	+NCF	+NCF	+NCF	+NCF	+NCF	0
Price change in assets/liabilities									
Housing units	$+\Sigma_h \Delta p_X X_h$								$+\Sigma_h \Delta p_X X_h$
Tangible Capital		$+\Sigma_f \Delta p_K K_f$							$+\Sigma_f \Delta p_K K_f$
Inventories		$+\Sigma_f \Delta p_c I_f$							$+\Sigma_f \Delta p_c I_f$
Equity shares	$+\Sigma_f \Delta pE_f\,{}^nE_f$ $+\Sigma_b \Delta pE_b\,{}^nE_b$								$+\Sigma_f \Delta pE_f\,{}^nE_f$ $+\Sigma_b \Delta pE_b\,{}^nE_b$
Bonds	$+\Delta p_G\,{}^nG$						$-\Delta p_G\,{}^nG$		0
Stock change in real assets									
Tangible Capital		$+\Sigma_f p_K \Delta K_f$							$+\Sigma_f p_K \Delta K_f$
Inventories		$+\Sigma_f p_c \Delta I_f$							$+\Sigma_f p_c \Delta I_f$
Issues of equity shares		$+\Sigma_f pE_f \Delta^nE_f$			$+p E_D \Delta^nE_D$				$+\Sigma_f pE_f \Delta^nE_f$ $+p E_D \Delta^nE_D$
Equity$_t$	= $E_{H,t}$	= $E_{F,t}$	= $E_{K,t}$	= $E_{V,t}$	= $E_{D,t}$	= $E_{B,t}$	= $E_{G,t}$	= $E_{CB,t}$	= $E_{TOT,t}$

Table 11: Equity capital change matrix. ΔK_f represents the net investment, i.e. the difference between gross investment and capital depreciation. NCF stands for Net Cash Flow. Bank's b equity shares are traded in stock market but banks do not issue equity shares. However, mutual fund's D equity shares are not traded in the financial market but the mutual fund can issue new equity shares.

7.2. Stylized facts and validation

Since in the explanations of computational experiments' results we often refer to the synchronization among different variables during the business cycle, we have performed a cross-correlation analysis, in order to objectively assess the correlation of those variables for different time lags. Figure 11 shows some cross-correlation figures. We condider monthly HP detrended time series' averages of 50 simultation runs, one for each seed used for the pseudo-random number generator. In figure 11, we show the cross-correlations for 20 positive and negative lags, as well as the upper and lower confidence bounds. We observe that real GDP is positively correlated with consumption and investments, and it is anti-correlated with the unemployment rate. GDP also shows a positive correlation with loans to firms, which are leading the business cycle expansion, while stock and bond prices are anti-correlated. This results are in line with main stylized facts on credit and business cycle (see for instance Watson and Stock (1999), Napoletano et al. (2006), Cappiello et al. (2010) and Uribe and Schmitt-Grohé (2017)).
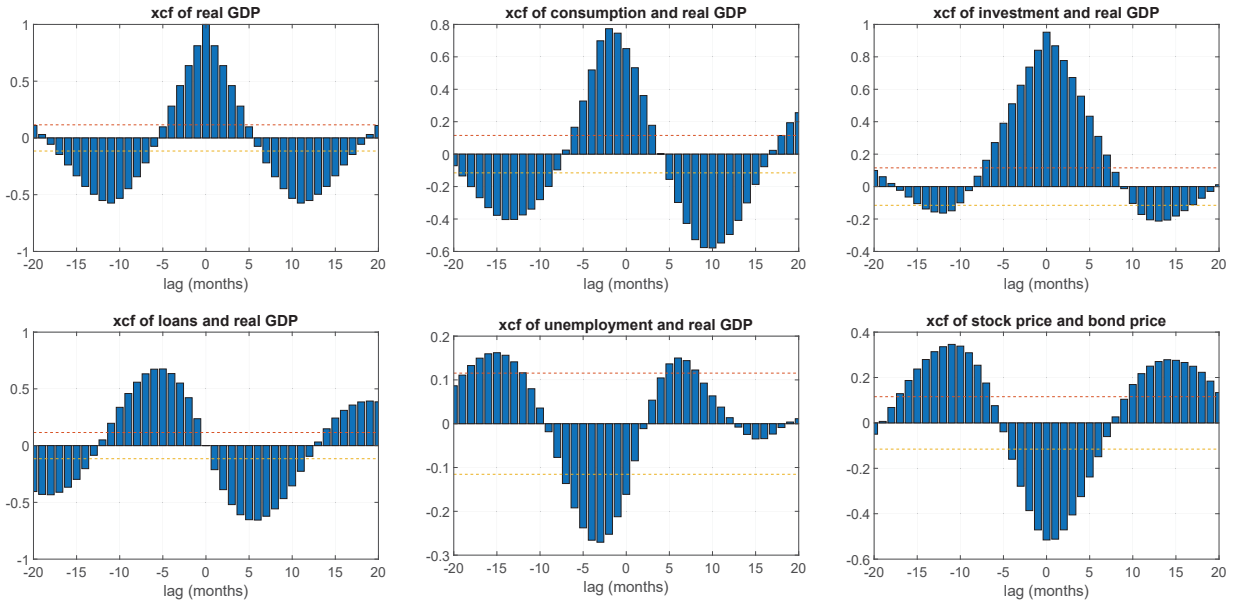

Figure 11: Cross-correlations. Time series considered are monthly and hp filtered.

Concerning the validation of the model, it is worth remarking that Eurace initialization complies with two main requirements: stock-flow consistency and input validation. In particular, we use a specific model's software that is able to initialize the model in an automatic way. We define in this software all the cross-relations between the balance sheet items of the economic agents and we control for the consistency of the process. The initialization starts by setting at 1 the initial value of the nominal monthly wage, and from this reference variable we keep on computing all the others.

In this way we are able to provide an "input validation", where models fitness is ensured by setting

parameter values and variables ratios according to empirical analysis of actual data[16].

7.3. Housing market

We use the housing market setting described in Ozel et al. (2016). In this framework, the access to the housing market by the households is driven by an exogenous probability Φ_H; once in the housing market, households may randomly take the role of buyer or seller, except in the case of fire sale, where households enter in the housing market because are forced to sale their housing units due to financial distress, which is defined as:

$$\frac{R_{U_h}}{Z_l + Z_e} \geq \Psi_S \tag{8}$$

where R_{U_h} is the quarterly payments (principal and interests) related to mortgages U_h of household h, $Z_l + Z_e$ is the sum of quarterly labor and capital income after taxes, and Ψ_S is a given threshold. If the financial distress is critically high and steps over a threshold ι_S, the household undergoes a mortgage restructuring with a consequent loss on the equity of the credit bank.

It is worth noting that in the eventuality of fire sales, the selling price set by the household is lower than the last average market price (p_{X_t}), in order to increase the probability to sell the housing unit and obtain liquidity. In particular, we distinguish between sell orders and fire sell orders. In the first case, the price set by the household is:

$$p_{X_t} = p_X(1 + \xi\varphi_H) \tag{9}$$

where ξ is a random component draw from uniform distribution between 0 and 1 and φ_H is the maximum percentage price increase of monthly housing price[17].

In the second case, fire seller households post one of their housing unit for sale at price p_{X_t}, given by:

$$p_{X_t} = p_X(1 - \xi\varphi_S) \tag{10}$$

where φ_S is the maximum fire sale price reduction.

Households with the buyer role are randomly queued and each buyer in the queue in turn select the cheapest available housing unit to buy and a transaction takes place at the posted sale price. When all buyers had their turn in the housing market or there are no more housing units for sale, the housing market closes and a new housing price p_H is computed as the average of the realized transaction prices. This process takes place each month.

Households may buy a housing unit by means of their liquidity resources or, if they are not sufficient,

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[16]For a detailed decription of model validation see Teglio et al. (2017)

[17]It is straightforward that households try to sell their housing unit at a price that is higher than market price when they are not facing financial distress

throught a mortgage from a bank. All mortgages last 20 years, and each month the borrowers repay mortgages installments, which are made up of a constant principal component and an variable interest component on remaining installments, computed as central bank interest plus a fixed spread of 1%. The rationale behind this choice is to mimic variable rate mortgages, whose interests are mostly tied to reference rates or indices that are linked with the central bank policy rate (e.g., EURIBOR in Europe). The spread represents the bank's margin. Although we consider a fixed bank's margin that is not linked with households' creditworthiness, it is important to remark that banks check upstream that the applicant borrowers comply with two constrains. In particular, a stock and flow thresholds are included, namely equity to assets ratio (ETA) and debt-service-to-income ratio (DSTI). Therefore, bank checks that:

- household's net wealth (Equity E_h) to her total wealth (Assets A_h) ratio is higher than a threshold T_{ETA}:

$$\frac{E_h}{A_h} \quad T_{ETA} \tag{11}$$

- household's debt payments for the upcoming quarter to income is lower than a threshold T_{DSTI}:

$$\frac{R_{U_h} + R_{U_h}}{(Z_l + Z_e)} \leqslant T_{DSTI} \tag{12}$$