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THE SYSTEMIC RISK OF CORPORATE CREDIT SECURITIZATION REVISITED

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ABSTRACT

We develop a stock-flow-consistent macroeconomic model with an agent-based focus on corporate credit markets, including a securitization process. Against the background of increased corporate indebtedness, our interest is in quantifying contagion effects that endogenously arise from corporate defaults in a securitized credit portfolio. We calibrate the model to the U.S., where corporate credit securitization has been re-intensified in recent years. Simulations deliver adverse medium- to long-term effects as soon as the share of securitized loans in total new loans economy-wide approaches 10%. Securitization activities above this threshold lead to significant welfare losses from the medium-term onwards. Two transmission channels are conceivable. A collapsing special purpose vehicle (SPV) either causes distortions in the banking sector or increases liquidity constraints that ultimately dampen households' consumption due to their financial investment in the securitized tranches. A more concentrated banking sector reinforces the adverse shock of a liquidation of the SPV. In contrast, a faster and better-equipped bank rescue mechanism in the form of levies within the banking sector helps to contain the consequences of a SPV collapse.

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May 27, 2020

Abstract

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Keywords: securitization, systemic risk, agent-based, stock-flow consistent

JEL Classifications: E03, G21, G23

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1 Introduction

In the upswing since the financial crisis of 2007, corporate debt has increased noticeably in several economies, particularly in the U.S. Along with increased leverage ratios of firms, securitization of corporate loans has regained importance. Because of its possible systemic relevance, regulatory authorities, responsible for market supervision, have begun to re-intensify their monitoring, while the issue had receded into the background for many years (FED, 2019; FSB, 2019). In the meantime, policymakers in the European Union have proposed a new standardized type of securitization to increase the volume of cross-border lending. This standardized type is supposed to minimize negative feedback effects of troubled securitization vehicles on the banking sector (Commission, 2015; Véron and Wolff, 2016). In view of these developments, the paper at hand deals with the following research questions: What level of securitization activity induces systemic risks? What is the medium- to the long-term consequence for the real economy? Can these risks be mitigated by preventing banks from keeping the equity tranche in the banking book? What institutional structure of the banking sector in terms of bank size and the design of bank rescue mechanisms can minimize these risks?

The literature on the systemic risks of securitization partly follows an empirical approach and partly a more theory-guided model-based strand. While the former concentrates on the mechanisms before and during the financial crisis, the latter attempts to capture the balance sheet changes that pooling of credit claims and its subsequent sale to capital market investors brings about. Empirical studies conclude that securitization has played an essential role in the deepening of the crisis. Keys et al. (2010) find that a laxer credit screening takes place after loans have been securitized. Maddaloni and Peydró (2011) disclose that securitization amplifies the effects of low interest rates on bank risk-taking. Besides, securitized loans unfold systemic effects as an underlying of repurchase transactions (Gorton and Metrick, 2012). Securitization can cause trouble in the banking sector, because the risk transfer from banks to capital market investors does not work efficiently (Acharya et al., 2013). Also, a freeze of the securitization market tightens credit supply conditions after banks start to run their business based on the related accounting exchanges on the asset and liability side (di Patti and Sette, 2016).

Among the modeling approaches, macroeconomic agent-based models deserve particular reference. This approach generates aggregated dynamics that allow for more than a strict replication of microeconomic optimization in equilibrium but instead result from the interaction of economic agents with heterogeneous behavior and beliefs (Deissenberg et al., 2008; Lengnick, 2013; Dawid et al., 2014). Therefore, these models are well suited for analyzing how the failure of a single entity within the financial system causes cascade failure (Battiston et al., 2007; Delli Gatti et al., 2010; Fischer and Riedler, 2014). Such cascades also relate to the question about an optimal degree of diversification, as diversification can decrease the idiosyncratic risk for a single entity, but increase the (neglected) systemic risk through stronger connectivity (Wagner, 2010; Gennaioli et al., 2013). In recent years, agent-based modelers started to pay attention to sectoral completeness at the macroeconomic level. They also took their models closer to the data in terms of both calibration and validation (Caiani et al., 2016; Mazzocchetti et al., 2018). Besides, balance sheets from specific financial market institutions, including shadow banks, were incorporated in macro models (Bhaduri et al., 2015; Moreira and Savov, 2017; Botta et al., 2018). We follow this strand of literature and build a stock-flow-consistent macroeconomic model with an agent-based focus on corporate credit markets, including securitization.

Several model-based studies conclude that high volumes of loan securitization increase the vulnerability of the financial system (Gennaioli et al., 2013; Brunnermeier and Sannikov, 2014; Bhaduri et al., 2015; Moreira and Savov, 2017; Botta et al., 2018). However, except for the paper by Mazzocchetti et al. (2018), few efforts have been made to carefully quantify the securitization intensity from which risks in the medium to long run are highly likely to become systemic and to produce harmful effects on the real economy. To the best of our knowledge, our study is the second to estimate this threshold of systemic securitization propensity. We measure it by the volume of securitized loans as percentage of total new loans in the period of SPV origination. Moreover, we go beyond the analysis of Mazzocchetti et al. (2018) and investigate the consequences of different securitization intensities under alternative conditions. Our scenarios attempt to cover the institutional design of the banking sector and its connection to the special purpose vehicle (SPV), which represents less regulated shadow banking activity in our model. In particular, we investigate whether high securitization intensities remain without systemic effects if there is no direct connection between banks and SPV through equity tranches or guarantees, unlike in the years before the financial crisis (Acharya et al., 2013). Finally, we analyze the resilience of the banking sector, depending on the size of individual banks and depending on the design of a bank rescue mechanism.

Our results can be summarized as follows. In our model, significant adverse medium- to long-term effects become apparent as soon as the economy-wide securitization intensity reaches about 10%. Under such conditions, we find welfare losses irrespective of whether the collapse of the special purpose vehicle leads to distortions in the banking sector or whether increasing liquidity constraints dampen households' consumption due to their financial investment in the securitized tranches. A more concentrated banking sector reinforces the adverse shock of a liquidation of the SPV. In contrast, a faster and better-equipped bank rescue mechanism in the form of levies within the banking sector helps to mitigate the consequences of a possible SPV collapse.

This article is organized as follows. Section 2 summarizes selected literature on securitization. Section 3 presents the main building blocks of the model. Section 4 explains its calibration to US data. Section 5 presents a variety of simulation results depending on the institutional design of the financial sector. Section 6 validates the model based on a Monte Carlo simulation depending on the stochastic terms of the model. Section 7 concludes. Additional material is provided in an Appendix.[1]

[1] Matlab functions are available at https://github.com/thomastheotheobald/monty.

2 Related Literature

2.1 A brief history of securitization

The first securitization activities date back to the early 1970s when the U.S. Government National Mortgage Association ('Ginnie Mae') participated in the granting of mortgages to first-time homeowners and refinanced this mortgage pool by issuing securities.[2] In the course of the 1990s, privately issued securitizations gained in importance. The instruments, sometimes called 'traditional' securitization (Chernenko et al., 2014), were mostly residential and commercial backed mortgage securities (RMBS, CMBS), and consumer asset-backed securities (ABS). The latter bundle credit card debt as well as car and student loans into tranches to sell them to capital market investors. The tranches are usually called senior, mezzanine, and junior or equity according to their increasing liability in the event of default. These financial instruments started to be issued and traded in the United Kingdom from the mid-1980s onwards; some years later, the legal basis for such transactions was also established in continental Europe.

From the end of the 1990s to 2007, the boom in securitization was mainly based on new types of securitization: i. Sub-prime RMBS, where part of the underlying loans had a non-investment grade credit rating. ii. Collateralized debt or loan obligations (CDO/CLO), which structured corporate loans and bonds. iii. Short-term asset-backed commercial papers (ABCP), which were based on different types of long-term assets as in the case of CDO and ABS, but additionally contained guarantees.[3] With the first defaults in securitized asset portfolios in 2007, the market lost investors' interest and the special purpose vehicles (SPVs) got into trouble. In the case of ABCPs, the SPVs were no longer able to service the debt from expiring securities due to the short-term refinancing structure of long-term assets. Sponsoring financial institutes had to step in (Acharya et al., 2013).

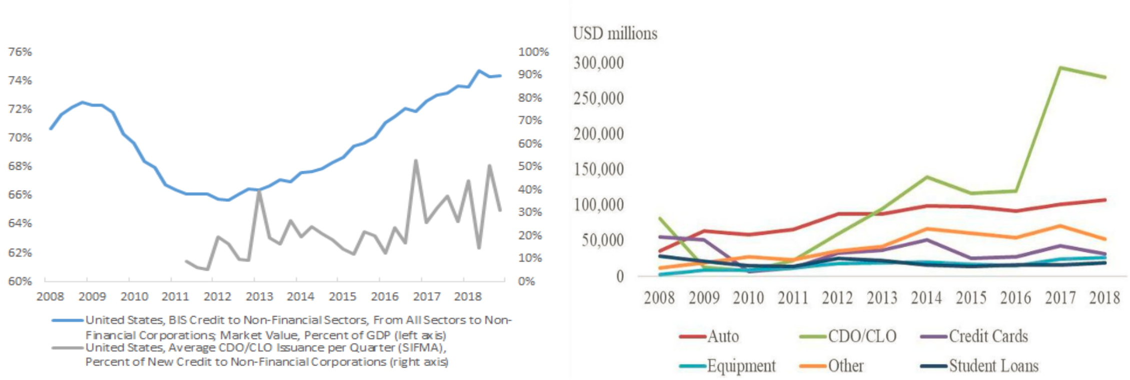
Against this background, this paper attempts to carefully quantify the volumes above which securitization gives rise to systemic risks that materialize in the medium to long term. It is insightful to recall the quantities that characterize the rise and fall of securitizations before and after the financial crisis of 2007. Pozsar et al. (2010) report that assets of U.S. shadow banks grew from almost zero in the early 1980s to as much as USD 20 trillion in 2007. From the mid-1990s, these assets started to exceed those of the traditional banking sector. In 2007, the ratio was almost 2:1. Segoviano et al. (2013) refer to global issuance of private-sector securitizations increasing from around USD 1.4 trillion to just under USD 2.9 trillion between 2000 and 2007. In Europe, the annual issuance rose from around EUR 100 billion in 2000 to about EUR 750 billion in 2007. By 2013, it had declined back to just under EUR 200 billion. For the U.S., Acharya et al. (2013) document that ABCPs alone had reached a considerable volume in macroeconomic terms in the run-up to the financial crisis of 2007:

[2] 'Freddie Mac' followed in 1971 and 'Fannie Mae' in 1981. All these corporations received special government benefits to achieve the goal of strengthening homeownership.

[3] Originating banks guarantee to repurchase maturing ABCPs, if the SPV is unable to service the debt.

"ABCP outstanding grew from USD 650 billion in January 2004 to USD 1300 billion in July 2007. At that time, ABCP was the largest money market instrument in the U.S... For comparison, the second-largest instrument was Treasury bills with about USD 940 billion outstanding ... [Furthermore in] July 2007, medium-term notes and capital notes of [related investment vehicles] accounted for about USD 400 billion" (Acharya et al., 2013).

Figure 1: US corporate credit and private issuance of securitization between 2008-2018



Source: The figure on the left-hand side is based on data from the Bank for International Settlements (BIS). The figure on the right-hand side stems from Valladares (2019) based on data from the Securities Industry and Financial Markets Association (SIFMA).

Although parts of our analysis are transferable to other types of credit, we primarily deal with corporate credit markets. The relevant type of securitization in this context is CDO / CLO. Segoviano et al. (2013) report that the global CDO issuance increased fivefold from around USD 200 billion in 2000 to about USD 1 trillion in 2007. Consequently, at this time, the ratio between CDO issuance and new credit to the non-financial corporate sector in the U.S. was above 50%.[4] Figure 1 illustrates the evolution of U.S. corporate credit (relative to GDP) as well as the private sector securitization issuance since 2008. As indicated in the introduction, the CDO/CLO issuance volume has significantly recovered in recent years.

2.2 Empirical literature on securitization

The variety of reasons for the expansion and collapse of the securitization market can be roughly summarized as follows: In the expansion phase, banks' general incentive to pack and sell loans has been to free up regulatory capital to meet the dynamic demand for new loans (Acharya et al., 2013). Investors, in general, have been searching for high yields, while relying on risk-reducing benefits of

[4] According to BIS data, new credit from all creditors to non-financial corporations grew from 2006 to 2007 by roughly USD 1.1 trillion. The issuance of CDOs in the U.S. accounted at least for half of the global total.

diversification concerning the assets in the credit pool (Segoviano et al., 2013). This motivates our modeling approach.

Segoviano et al. (2013) provide a more refined list of adverse developments linked to the securitization market in the run-up to the crisis of 2007. These range from macroeconomic developments, such as continuously rising real estate prices and low interest rates,[5] to institutional characteristics such as a lack of control over lending standards,[6] misaligned incentives and principal-agent problems between the institutions involved.[7] Similarly, Chernenko et al. (2014) examine securitized holdings of insurance companies, and mutual funds. They find the behavior of (inexperienced) mutual funds managers to be more consistent with risk-neglecting beliefs than with performance-based disincentives. Gennaioli et al. (2012) propose a similar transmission. For insurance companies, in contrast, Chernenko et al. (2014) identify higher investments in non-traditional securitization among poorly capitalized insurers. This points towards risk-shifting as a result of agency problems (Eisdorfer, 2008). In our model, we do not explicitly implement these characteristics. Instead, we induce the size and the timing of the SPV origination exogenously. However, these findings help understand how the securitization market could grow to gigantic volumes.

Concerning the bust of the securitization market, Chernenko et al. (2014) find little evidence of widespread fire sales, as discussed by Brunnermeier and Oehmke (2013) in the context of financial networks. Instead, they conclude from weak transaction data that a self-reinforcing buyer strike and, therefore, price adjustments took place. For the endogenous mechanism in our model, which can end up with the liquidation of the SPV, it is only relevant that a significant share of the companies, whose loans are securitized, are subject to noticeable default risk. The data set exploited by Chernenko et al. (2014) shows a percentage of CDO holdings with AAA rating amounting only to 40 %. Even this share was probably still too high against the background of the rating process at that time. Models used by credit rating agencies poorly accounted for parameter and model uncertainty, and ratings were often tailored to the needs of their clients (Coval et al., 2009).

In a seminal paper, Acharya et al. (2013) analyze the role of ABCPs in the creation of the financial crisis. Among other things, they estimate the loss of investors in conduits and of financial institutions that provided guarantees to these conduits. The authors find that, after including the events of 2007-onwards, conduit exposure significantly reduced bank equity, while the guarantees repaid the majority of investors. There was little risk transfer from banks to outside investors. In this context, Gorton and Metrick (2012) describe securitization of loans as the asset part of a new type of banking called securitized banking. On the liabilities side, they identify repurchase operations (repo) as an essential component of funding under this new regime. While the 2007 events around the sub-prime housing

[5] Based on firm loan data from the Euro Area bank lending survey, Maddaloni and Peydró (2011) find that a one percentage point increase in the securitization intensity decreases the net percentage of banks reporting a tightening of credit standards by 19 points.

[6] Based on panel data of securitized sub-prime mortgage loans in the U.S., Keys et al. (2010) find a doubling of securitization volumes being on average associated with about a 10%–25% increase in firm defaults.

[7] This includes banks, special purpose vehicles, mutual funds as investors, credit rating agencies, regulators.

market in the USA initially led to swings in counterparty risk as measured by the spread between the LIBOR and OIS rate, it was finally the subsequent reaction of repo haircuts that drove U.S. banks into solvency problems. Similar to the finding by Acharya et al. (2013), Gorton and Metrick (2012) conclude that the banks kept significant parts of the securitized loans in their portfolios. The analysis by di Patti and Sette (2016) is pointing into the same direction: Employing difference-in-difference estimates, they show that the extent to which Italian banks tightened lending standards was positively related to the share of loans banks securitized before the crisis.

The lack of risk transfer is crucial for the systemic impact of increased securitization volumes. Some observers, pointing at the European Capital Market Union, argue to contain risks out of securitization by standardizing the products (Commission, 2015; Véron and Wolff, 2016). The standardization shall ensure that capital market investors buy all the tranche securities involved in a securitization. Here, the aim is to eliminate the deficit in risk transfer from the banking sector to capital market investors. However, as our model simulations show, such a structure does not prevent systemic risks for the real economy as soon as the economy-wide securitization intensity exceeds a certain threshold.

2.3 Models including bankruptcies in credit networks

An essential building block for our model is corporate insolvency, in particular, if it affects debtor companies whose loans have been securitized. In this case, write-offs of assets reduce the SPV's profitability, which may trigger a bankruptcy cascade. For this reason, the literature on the effects of insolvencies in credit networks forms a cornerstone for our modeling approach. Battiston et al. (2007) develop a model of a production network in which retailer firms connect to supplier firms and finance their capital goods demand by trade credit. Given a constant number of suppliers and customers, the authors evaluate the propagation of firm insolvencies under different strategies. If firms adapt their orders when a supplier goes bankrupt instead of bearing the costs of a production loss, insolvency avalanches will be weaker. At the same time, such a strategy results in a single supplier for each firm, a process of concentration. Similarly, in our model, a firm is only affiliated with one bank, while a bank has several corporate clients. Moreover, Battiston et al. (2007) analyze a scenario of endogenous interest rates, where an increase in default risk implies an increase in borrowing and hence production costs. Under such conditions, insolvency propagation is fiercer (Duffee, 1999). Delli Gatti et al. (2010) also use a dynamic-interest specification in a production network that additionally includes a banking sector. The interest rate is a decreasing function of the net worth of debitor firms, which pay less with lower leverage, and creditor banks, which demand less, if well-capitalized, to attract more business. We comprehensively calibrate this functional form to U.S. data.

Another result of Delli Gatti et al. (2010) is relevant for us, namely the conditions under which firm insolvencies propagate to bank insolvencies. The authors find that contagion crucially depends on the feedback of a single agent's net worth on the net worth of her neighbor agents. In other words, systemic consequences are imminent from a negative shock on the individual agent (idiosyncratic risk), if the agent is subject to an environment of bad debt. The stronger the feedback or the more agents (with low net worth) are involved, the higher the systemic risks. We expand the financial market modeling in Delli Gatti et al. (2010), including securitization, so that corporate insolvencies may hit the SPV, whose equity tranche is held by the banks. If a bank just fulfills the regulatory capital requirements, the shock from the SPV may lead to bank solvency problems. In turn, bank insolvencies create bottlenecks in financing. Thus adverse effect s on aggregate demand may arise.

2.4 Models including shadow banking activity

The effects of shadow banking, especially securitization, are summarized similarly in model-based studies of different economic schools, irrespective of whether these studies employ utility-maximizing (macro-)financial models (Gennaioli et al., 2012, 2013; Moreira and Savov, 2017), postkeynesian stock-flow consistent models (Bhaduri et al., 2015; Botta et al., 2018) or an agent-based macro-model (Mazzocchetti et al., 2018). All these studies mention a possible welfare-increasing effect from credit expansion in the short-run, but in the medium- to long-run an increase in financial market fragility.

Gennaioli et al. (2012) develop a model for financial innovation, in which intermediaries create supposedly safe securities out of existing cash flows. Their incentive comes from additional investor demand from that cannot be met by traditional securities.[8] In this spirit, the authors modify a standard model for financial innovation (Allen and Gale, 1994) so that investors (and possibly intermediaries) neglect certain tail-risks. Compared to the result under rational expectations, securitization activity is then excessive. A news update, such in 2007 the first house price decline in years, makes investors aware of the neglected risks and leads them to flee into the quality of traditional securities. Gennaioli et al. (2013) elaborate on this approach by modeling not only aggregate but also idiosyncratic risks. Insurance against idiosyncratic risks - diversification - here interacts with the neglect of aggregate risk. This interplay increases financial market instability. Moreira and Savov (2017) emphasize the liquidity side of securitization—the authors model uncertainty depending on a learning process. Investors are willing to rely on shadow money instruments, including securitized assets, as long as these are likely to remain liquid. An asset price and economic activity boom follow, but fragility increases over time as investors focus on riskier assets. The corresponding “rise in uncertainty raises shadow banking spreads, forcing financial institutions to switch to collateral-intensive financing.“ The subsequent collapse of the shadow banking sector, which has become too big, creates a Minsky moment so that economic activity declines (Minsky, 1986).

Bhaduri et al. (2015) develop a framework that includes shadow banks in addition to regulated financial institutions and non-financial sectors. Such an economic system has self-reinforcing credit

[8] In the second half of the 1990s, the volume of U.S. treasury bonds in circulation remained roughly constant, while foreign demand increased, especially from Asia. Other possible causes encompass the aging of the population and increasing wealth inequality (Jones, 2015).

expansion capabilities but is also fragile depending on a gradually narrowing reserve and real capital base. The authors analytically identify different adverse regimes whose characterization ranges from stagnation to abrupt crashes. Botta et al. (2018) explore a short-run macro model with a shadow bank sector. They show that the latter increases the profitability of the financial industry while at the same time, banks meet their capital requirements. The authors simulate a variety of shadow bank-driven regimes stimulating economic activity in the short-term, while productive capital formation declines, and income distribution becomes more skewed.

The paper that comes closest to our analysis is the one by Mazzocchetti et al. (2018), as the authors, like us, study the macroeconomic effects of different securitization intensities in an agent-based macro framework. However, the model design differs in essential details. At first glance, the structure by Mazzocchetti et al. (2018) seems more comprehensive, including a continuous process of different types of securitization (ABS pooling corporate loans, MBS pooling household mortgages). However, our approach of concentrating on corporate loan securitization with a single credit pooling per simulation run allows a more in-depth analysis of the SPV's liquidation effects on aggregate demand. This approach enables scenarios changing the institutional design of the financial sector and of a bank resolution mechanism.

3 An Agent-based Model of Corporate Credit Securitization

3.1 Framework

In this section, we outline the basic features and some limitations of our model. We consider a closed economy that evolves in a sequential manner with discrete-time index t and model life span $[0, T] = \{t \in \mathbb{N} | 0 \leq t \leq T\}$. Due to the complexity of the overall framework, which arises through the interaction and mutual feedback of heterogeneous market participants - firms, banks, and shadow bank - we keep some parts of the model as simple as possible, in particular the household sector. For the sake of simplicity, we also abstract from an active government sector and an endogenous reaction of monetary policy set by the central bank. Labor market dynamics are only implicit. By all these simplifications, we aim to prioritize the transmissions that are essential to describe the effects of securitization on the business cycle. More specifically, we aim at elaborating the financial accelerator approach in an evolving credit network with a special focus on corporate loan securitization (Bernanke and Gertler, 1989; Greenwald and Stiglitz, 1993; Kiyotaki and Moore, 1997; Delli Gatti et al., 2010).

In the model, the private sector consists of households and firms. The former acts as a single aggregate at the macroeconomic level, while the firm sector is micro-founded and divided into a (non-financial) corporate, (financial) banking and shadow banking sectors.[9] Firms and banks are supposed

[9]We henceforth refer to non-financial businesses with "firms" and to financial businesses with "banks". The SPV stands for shadow banking activity.

to interact at the microeconomic level. Through this interaction, the financial sector provides the external funding of firms' real economic investment projects. Investment in capital goods drives economic growth in the model. There is no distinction between firm layers representing producers of capital and consumption goods. Firms act exclusively at the demand side for credit and do not fund each other.[10] Similarly, the banks appear only as credit suppliers for the corporate sector, i.e., the model abstracts from interbank transactions. In the model, loans generate deposits as long as banks fulfill the capital requirements (endogenous money creation). In the following, we consistently use $i \in \{1, \ldots, N_C\}$ for the index of firms and $k \in \{1, \ldots, N_B\}$ for the one of banks.

A firm can finance its business investment by issuing new shares, by retaining earnings or by borrowing money from the bank. Firm-bank credit relations evolve by a randomized partner selection mechanism similar to the one proposed by Delli Gatti et al. (2010) and Caiani et al. (2016). In particular, in each period t, each firm i picks a subset $M = \{1, \ldots, n << N_B\}$ of banks and requests a loan from the one which offers the best conditions, i.e., the loan with the lowest interest rate. As long as all banks in the subset M are solvent, we assume the transaction costs for the loan matching to be small enough to neglect them.

In the case of firm insolvency, the firm can no longer participate in economic activity. Assets and liabilities do not grow any longer. At the same time, solvent firms take over the investment capacities and customers of the insolvent firm so that the desired level of investment at the macro level remains the same in the production planning of the next period. These proceedings imply that solvent firms are assumed to grow bigger and bigger - a concentration process that prevents individual firm insolvencies from directly having an impact on the real economic outcome. In contrast, this may happen through the financial sector. The reason why we follow this approach is that it allows for a transparent and endogenous way firm insolvencies affecting the banking sector and the securitized loan portfolio of the SPV. The alternative would be a firm market entry mechanism that needs to be calibrated to the data. However, there should be no obvious bias from the selected modeling design concerning the research questions.

In contrast, one simplification may suggest a bias which points in the direction of underestimating the risks from securitization. That may be true because we model only interest and not also redemption payments explicitly. Fischer and Riedler (2014) emphasize that the maturity structure of debt may serve as credit friction. As a consequence, leverage tends to develop procyclically (Adrian and Shin, 2010). Since we do not consider repayment structures explicitly but apply a perpetual bond concept, this finding by Fischer and Riedler (2014) may suggest a potential underestimation of systemic risks.

A distinctive feature of our model is the connection of the banking sector to the SPV responsible

[10] This is one reason why the resulting dynamics do not induce a pure power-law distribution of (solvent) firm size in contrast to Delli Gatti et al. (2010) and Caiani et al. (2016). Instead, our density function for the firm size distribution shows discontinuities. Even more relevant for this potential shortcoming of our model is the firm concentration process, which we model in the spirit of Rosen (1981). However, our modeling design is on purpose as it allows for an endogenous firm insolvency process without market entries.

for securitization. Banks have the opportunity to sell parts of their corporate loan portfolio to enhance their lending capacity. The SPV carves up the cash flows related to the underlying pool of corporate debt into different tranches and sells the senior tranche securities as diversified credit bundles to capital market investors, i.e., the household sector.

3.2 Stock-Flow Consistency

To illustrate the overall structure and coherence of the model, Tables 1 and Table 2 present the balance sheet and the transaction flow matrix, as is common in the so-called stock-flow consistent literature (Godley and Lavoie, 2006; Bhaduri et al., 2015; Caiani et al., 2016; Botta et al., 2018; Mazzocchetti et al., 2018). Double-entry balance sheets record the stocks held by economic agents, which contains both real and monetary assets and liabilities.

Table 1: Balance sheet matrix (before SPV liquidation)

	Households	Firms	Banks	SPV	$\sum$
Capital		$+K$			$+K$
Deposits	$+M$		$-M$		0
CDO/CLO (Securities)	$+S_A$		$+S_B$	$-S$	0
Loans		$-L_b$	$+L_b$		0
Securitized Loans		$-L_s$		$+L_s$	0
Equities	$+E_f + E_b$	$-E_f$	$-E_b$		0
Net Worth	$-NW_h$	$-NW_f$	$-NW_b$		$-K$
$\sum$	0	0	0	0	0

The rows of Table 1 show assets and liabilities among sectors, which sum up to 0. An exception is given by the capital stock, whose counterpart is the sum of the sectoral net wealth positions. The components of household net wealth - deposits, equities, and tranche securities - result from a portfolio choice. The composition can also be influenced by insolvencies, in particular the bankruptcy of the SPV. In our model, firms' and banks' net wealth position are small relative to household sector wealth. In Table 1, firms' and banks' net wealth corresponds to changes in the equity price. The SPV does not have a net asset position, i.e., its profits arising from the interest rate spread between loans and tranche securities are instantaneously passed on to the owner banks.

The upper part of Table 2 describes the agents' flows of revenues (+) and payments (-). The bottom displays the balance sheet changes. Take the household sector column as an example. In the upper part of this column, the components of disposable household income - wages and capital income consisting of dividends and interest income - are the counterpart of consumption expenditures.

Table 2: Transaction flow matrix (before SPV liquidation)

	Households	Firms		Banks		SPV	$\sum$
Cash receipts / outlays		Current	Capital	Current	Capital		
Consumption	$-C$	$+C$					0
Wages	$+WB$	$-WB$					0
Investment		$+I$	$-I$				0
Profits	$+FD_f + FD_b + F_s$	$-F_f$	$+FU_f$	$-F_b$	$+F_b$	$-F_s$	0
Deposit Interest	$+r_M M(-1)$			$-r_M M(-1)$			0
Securitization Interest	$+r_B S_A(-1)$					$-r_B S_A(-1)$	0
Loan Interest		$-r_L L(-1)$		$+r_L L_b(-1)$		$+r_L L_s(-1)$	0
Change in Deposits	$-\Delta M$				$+\Delta M$		0
Change in CDO/CLO	$-\Delta S_A$				$-\Delta S_B$	$+\Delta S$	0
Change in Loans			$+\Delta L$		$-\Delta L_b$	$-\Delta L_s$	0
Change in Equities	$-\Delta p_f E_f - \Delta p_b E_b$		$+\Delta p_f E_f$		$+\Delta p_b E_b$		0
$\sum$	0	0	0	0	0	0	0

The transaction flow matrix displays all cash flows in the economy, which can either stem from cash receipts or outlays from the income and expenditure matrix (top part) or from changes in assets and liabilities (bottom part).

The resulting net position, household net savings, can then be used to change asset positions in the form of deposits, bank or firm shares, or senior tranche securities (A-tranche) resulting from the securitization of the corporate loans (CLO). Finally, all inputs and outputs of the household sector add up to 0. In this respect, most entries in Table 2 are self-explanatory. What might be worth mentioning is that we assume no interest payments on the equity tranche (B-tranche) and that the banking sector passes on the profits made by the SPV directly to the household sector. These profits strengthen capital income in addition to the distributed profits of the corporate and the banking sector. There are several ways to test and guarantee the stock-flow consistency of the model. First, consistency of assets and liabilities at the micro-level in (solvent) firms and banks can be established explicitly, i.e., by allowing for new share issues at the end of each period (see Equation 9). Second, some parameters can be calibrated to a 'missing equation' representing an identity not explicitly part of the model equations. If this equation holds, the model is consistent and stable (quasi-steady-state solution). In our case, this particular equation describes the identity of capital (savings) and current account (investment) at the macro level. For the consistency check, households' savings, computed as the change in household net (financial) wealth, must be in line with corporate investment. Besides, we check the identity of assets and liabilities in all balance sheets involved.

3.3 The Sequence of Events

The following sequence of events characterize the economic activity in each period:

1. *Production Planning and Credit Demand:* Firms estimate their sales opportunities in a growing economy and adjust the desired investment demand. Credit demand is determined accordingly, taking into account internal financing options.

2. *Partner Selection Mechanism:* The firm chooses a subset of potential credit suppliers. Each bank in the subset offers a customized credit contract. The firm chooses the one with the "best" credit conditions, i.e., the lowest interest rate.

3. *Credit Market Clearing:* Banks grant loans, if they meet the capital requirements.

4. *Employment and Production:* Labor supply is only implicit in the model and assumed to follow demand. Each firm produces its output based on its available resources.

5. *Goods Market Clearing:* The (aggregate) household sector receives wages, interest, and dividend payments from financial assets and determines consumption as a function of income and wealth.

6. *Bank Asset Management:* In period t_{SPV}, parts of banks' assets, i.e., the corporate loans, are pooled into two tranches and securitized by a special purpose vehicle (SPV). Banks keep the B-tranche in their books, while the SPV sells the A-tranche to capital investors, i.e., the household sector.

7. *Firm Failure:* A firm will go bankrupt if its leverage ratio exceeds a threshold ratio close to 1. Firm insolvency is an endogenous outcome of the model as firms randomly enter into unfavorable credit conditions (high yield), while path dependency reinforces this process.

8. *Bank Failure:* A bank will go bankrupt if its equity ratio falls short of the minimum regulatory capital requirement. For firms, bank insolvency represents transaction costs implying that realized investments fall below the desired level (credit friction).

9. *Bank Rescue Mechanism:* A bankrupt bank is recapitalized after a certain time and up to a certain extent by a bank levy organized within the banking sector (resolution process).

10. *Shadow Bank Failure:* The SPV's revenues are the loan interest payments of those firms whose loans have been securitized. If this cash flow is suffering from firm insolvencies, this may induce negative profits for the banks involved (the B-tranche owners), as the SPV still has to pay full interest to capital market investors (the A-tranche owners). In this case, the banks decide to liquidate the SPV. Loans are then transferred back into the balance sheets of the respective banks, while the investor households receive deposits or equities in return. As a result, banks' equity ratios can decline.

3.4 Production planning

We are guided by the production planning of companies as proposed by Caiani et al. (2016). Firm's sales expectations are assumed to follow an adaptive form (Equation 1).[11] Accordingly, each firm i computes its planned capital accumulation rate necessary for production (Equation 2). The accumulation rate is a function of the return on capital and the expected demand (Amadeo, 1986; Palley, 2017). To be precise, it positively varies with firm i's planned capacity utilization rate $u^D_{i,t}$, which, according to Caiani et al. (2016), is defined by the income-to-capital ratio adjusted for a firm-specific capital productivity disturbance $\mu^K_{i,t}$ (Equation 3).[12] From the accumulation rate it is straightforward to derive the desired level of real investment (Equation 4). By construction, these investments represent the first difference of the desired capital stock.[13]

[11] Notice that superscript D indicates the desired or expected value of a variable, while realized variables are without a superscript. For instance, realized consumption c will be discussed in Equation (9).

[12] $\mu^K_{i,t} = \mu^K_{i,t-1} + \epsilon^\mu_{i,t}$ with $\epsilon^\mu_{i,t} \sim \mathcal{N}(0, \sigma_\mu)$ is supposed to follow a random walk.

[13] For the sake of simplicity, capital depreciation is ruled out. Taking into account the depreciation requires a recalibration of the model.

$$c_{i,t}^{D} = c_{i,t-1}^{D} + \lambda\left(c_{t-1} - c_{i,t-1}^{D}\right) + \epsilon_{i,t}^{c} \quad \text{with} \quad \epsilon_{i,t}^{c} \sim \mathcal{N}(0,\sigma_c) \tag{1}$$

$$g_{i,t}^{D} = \gamma_1 u_{i,t-1}^{D} + \gamma_2 \left(\frac{\pi_{t-1}}{K_{t-1}}\right) \tag{2}$$

$$u_{i,t}^{D} = \frac{y_{i,t}^{D}}{K_{i,t}^{D}(1+\mu_{i,t}^{K})} = \frac{c_{i,t}^{D} + i_{i,t}^{D}}{K_{i,t}^{D}(1+\mu_{i,t}^{K})} \tag{3}$$

$$i_{i,t}^{D} = g_{i,t}^{D} K_{t-1} \qquad K_{i,t}^{D} = K_{t-1} + i_{i,t}^{D} \tag{4}$$

Whether the realized capital stock is identical to the desired one depends on whether credit market constraints become binding.

3.5 Partner Selection Mechanism

To finance the planned investment projects, each firm i supplements its internal funds by applying for a loan from a bank k. A selection mechanism is therefore needed to match the demand and supply of credit. This so-called partner selection includes some coordination steps (Delli Gatti et al., 2010). In each period, each firm i chooses a random subset $M \in \mathbb{N}^{n\times 1}$ of potential credit suppliers. This set may also contain banks that had to file for insolvency, which is motivated by the fact that in the event of insolvency, ongoing credit agreements are affected. Each of the banks $k \in M$ offers firm i an individual and customized credit contract. The corresponding loan interest rate offer refers to

$$r_{i,t}^{k} = \tilde{r} + \rho_{LR}(LR_{i,t} - \overline{LR}) - \rho_{ER} ER_t^{k} + \epsilon_{i,t}^{r} \qquad \text{with} \qquad \epsilon_{i,t}^{r} \sim \mathcal{N}(0,\sigma_r). \tag{5}$$

The loan interest rate depends on the long-term average lending rate ($\tilde{r}$). This average appears as the intercept of the lending rate function. Additionally, three factors influence the individual lending rates: *First*, the firm-specific leverage ratio is taken into account relative to a sector-wide reference level $\overline{LR}$.[14] Accordingly, if the firm i's leverage ratio exceeds the reference measure, bank k perceives the firm as risky and charges a lending rate with a higher risk-premium. A low leveraged firm is supposed to be a favorite customer because its loans have a low probability of default. It receives a customized credit contract with a low interest rate, which may even fall short of the market rate $\tilde{r}$ for $LR_{i,t}$ being sufficiently low. The responsiveness to the firms' leverage ratio is measured with $\rho_{LR} > 0$.

The *second* factor, the bank takes into account when determining the lending rate, is bank-specific,

[14] The reference ratio $\overline{LR}$ can be interpreted as the leverage ratio a firm faces to maintain stable profits, on average. As it turns out, the economy responds sensitively to it as it has an impact on the share of firms that may fail on their debt. In this sense, $\overline{LR}$ is a 'deep' parameter as it splits the firm sector into two territories depending on the uniform initial distribution of firms' funding structure. One territory consists of enterprises that eventually fail because they are subject to a higher initial leverage ratio. Once a firm operates at $LR_{i,t} - \overline{LR} > 0$, it remains there since it faces permanently higher risk premia, which gradually impairs its financial position. The lucky firms are those who operate at $LR_{i,t} - \overline{LR} < 0$. This configuration is on purpose to allow for a certain degree of firm insolvencies in the economy. Firm insolvency builds the starting point for analyzing systemic risk that endogenously arises from shadow banking activity.

namely the bank's equity ratio. It enters the lending rate function negatively, which implies that well-capitalized banks can offer lower loan interest rates to expand their business. Banks offer loans whether they are approaching the regulatory capacity requirements or not. It follows that less capitalized banks are assumed to charge a higher lending rate as they have to strengthen their equity base. The sensitivity of the bank's equity ratio is the parameter $\rho_{ER} > 0$. *Third*, the lending rate is also influenced by a stochastic term $\epsilon_t^r \sim \mathcal{N}(0, \sigma_r)$ reflecting the impact of residual factors on the banks' lending rate offer. These factors may include costs from information asymmetries, banking competition pressure, and other reasons.

Once the firm received individual offers, it sorts the interest rate offers related to the banks in subset M in ascending order and agrees to the "best" one, i.e., the contract with the lowest loan interest rate. In each period, this process repeats without any memory effects. There is no autocorrelation in the credit agreement. The stochastic process $\{M_t\}_{t \in T}$ is independent.[15]

3.6 Firm and Bank Insolvencies

The interaction of banks and firms in the credit market determines the financing options of firms' investment projects and hence the accumulation of capital. The durability of each agent's economic life varies according to the evolution of its funding structure. As common in agent-based models, firms and banks may go bankrupt when they run out of liquidity or do not meet regulatory requirements.

In the present framework, firm i is insolvent if its leverage ratio $LR_{i,t}$ exceeds a high threshold value, $\overline{LR}^{MAX}$, close to 1. The firm has not necessarily stopped servicing its debt. The condition just reflects the fact that banks no longer consider the company creditworthy. The banks do not accept it as a customer for another loan agreement, and the firm has to terminate its business. In reality, under such conditions, the firm might be able to continue (for some time) and to finance a small part of investment projects from internal sources. But such a subtle distinction goes beyond the scope of this paper. We do not aim to replicate the exact share of the firm and bank insolvencies in the economy, but rather to estimate the new fragility that may result from different intensities of securitization.

Similar to the firm sector, banks are active economic agents as long as they are well-capitalized, i.e., they fulfill the regulatory minimum capital requirements. Formally, a bank k is insolvent if its equity ratio $ER_{k,t}$ falls short of the minimum requirement ratio $\underline{ER}^{MIN}$ in line with the BASEL III threshold.[16] It can be argued that the selected value, although close to the average of U.S. banks, is not legally binding in all jurisdictions. However, in such a situation, a bank would probably not pass a stress test. Hence, there would be no permission to continue banking operations since the bank is no longer safeguarded against financial turmoils.

[15] If memory effects are taken into account, the calibration becomes more complicated to avoid a too highly concentrated banking sector consisting only of too-big-to-fail institutions. Such a credit network may arise from the high probability of the firms remaining at the house bank. See Battiston et al. (2007) for an extreme case of such a concentration process.

[16] Note that this does not correspond to the risk-adjusted, but the absolute capital requirements.

3.7 Credit Market Frictions and Welfare Implications

Bank insolvencies correspond to credit market frictions, which may compromise macroeconomic outcomes. In the process of partner selection, financial costs become relevant, if not all potential credit suppliers in the subset $\tilde{M}$ are still solvent. In this case, firms need to spend extra efforts in sorting out the insolvent creditor and in searching for a suitable one. The transaction costs reduce the available loan amount for business investments. The height of the costs is determined as follows. Before the firm signs the contract with the "best" bank, it monitors the bank's financial position in previous periods as a proxy for the current solvency. Correspondingly, if a bank was already bankrupt in the previous period, the firm moves to the "second-best" bank. If this bank has no solvency issue in the period $t-1$, both parties will sign the loan agreement. Otherwise, the firm moves one step ahead. This process continues until the firm meets a solvent bank in the subset $\tilde{M}$. Hence, the search costs strictly depend upon the number of the firm's attempts to find the next lender,

$$S_{i,t} = \#\{k \text{ insolvent} | k \in M\}_{i,t} \cdot \bar{\mu}^S, \tag{6}$$

where $\bar{\mu}^S$ stands for a constant cost scaling parameter and # for the number of banks in the subsequent set to which the insolvency characteristics apply.

Solvent firms invest the same amount in their production capacity and generate sales, except those subject to credit frictions. Here, search costs reduce the firms' loan availability. As a consequence, realized investment may fall short of the planned level, i.e. $i_{i,t} - i^D_{i,t} < 0$. If a firm is exclusively matched to insolvent banks, i.e. all members in $\tilde{M}$ face solvency problems, it can only invest up to its internal financing capacity. Summarizing,

$$\Delta l_{i,t} = \begin{cases} i^D_{i,t} - \pi^{\text{retained}}_{i,t-1} & \text{if} \quad \#\{k \text{ insolvent} | k \in M\}_{i,t} = 0 \\ (1 - S_{i,t})(i^D_{i,t} - \pi^{\text{retained}}_{i,t-1}) & \text{if} \quad 0 < \#\{k \text{ insolvent} | k \in M\}_{i,t} < n \\ 0 & \text{else.} \end{cases} \tag{7}$$

Realized investment at the individual firm and at the macro level can then be derived by

$$i_{i,t} = \Delta l_{i,t} + \pi^{\text{retained}}_{i,t-1}, \qquad i_t = \sum_{i=0}^{N_C} i_{i,t}, \tag{8}$$

where the joint effect of the randomized credit network and the credit market frictions may cause a mismatch of planned and realized investment magnitudes. This deepens the heterogeneity in the firm sector.

In the model, aggregate demand consists of investment and consumption, i.e. $y_t = i_t + c_t$, where consumption is essentially a function of disposable household income and wealth:

$$c_t = \alpha_1 y^d_{t-1} + \alpha_2 m^d_{t-1} + \alpha_3 \left[(p^f_t e^f_t) + spvA_{t-1}\right] + \alpha_4(p^b_t e^b_t) \tag{9}$$

Disposable income y^d consists of wages, ωy_t, and various forms of capital income.[17] Household wealth consists of deposits m^d, tranche securities $spvA$, firm e^f and bank equities e^b where the associated price functions are described in the Equations (B.6) and (B.12) in the appendix.[18] Apart from the sensitivity of the consumption function to its parametrization, objections could be raised against its backward-looking nature. From appropriate preferences over wealth, however, one can derive a similar functional form under forward-looking rational expectations (Michaillat and Saez, 2018). So far, we have developed a model in sections 3.4 - 3.7, in which a higher number of bank insolvencies arising from corporate credit default at the micro level has a higher probability of resulting in lower aggregate demand at the macro level due to credit market frictions. To measure welfare in different simulation runs, we will simply refer to cumulative output, i.e. the welfare measure used is $U = \sum_{t=0}^{T} y_t$.

Before turning to the simulation results, we will elaborate on the financial sector of the model in two ways. First, we add a bank rescue mechanism to recapitalize insolvent banks. Second, we add a special purpose vehicle (SPV) that allows banks to securitize part of their loan portfolio. As a consequence, we have to specify how the banks deal with potential losses of the SPV.

3.8 Bank Rescue Mechanism

In contrast to the firm sector, the model comprises a market re-entry mechanism for banks. The mechanism helps to stabilize the economy after bank crashes. This allows us to examine its efficiency based on its parametrization. Since we do not explicitly model the government sector, the rescue mechanism is assumed to be organized within the banking sector. It works as follows:

All banks are sorted in descending order according to their equity ratios $ER_{k,t}$. This ordering makes it possible not only to identify the insolvent banks but also to memorize the duration of the insolvency. Banks are assumed to be at least ζ periods out of business. This duration reflects the minimal sluggishness of insolvency proceedings. In this way, banks are identified that are eligible for resolution. Recapitalization of such bad banks is assumed to be carried out entity by entity. The best-capitalized bank allocates part of its equity to the worst one. The second best bank does the same with the second-worst and so on. This procedure implements a resolution fund to which banks contribute depending on their profitability proxied by their equity ratio. Banks contribute to this fund because of their interest in ensuring that the financial system does not collapse completely. The

[17] These are interest and dividend payments specified in Equation (B.31), (B.32) and (B.34) in the appendix. Also note that it is sufficient for a quasi steady state solution, if consumption is not a function of contemporaneous, but previous period's income multiplied by the capital accumulation rate.

[18] Their functional form (GARCH process and pricing by sector average) is generally supported by the literature. The parametrization is selected so that price dynamics only show small volatility (Appendix Section A). A more comprehensive analysis, including higher volatility, goes beyond the scope of this paper.

capacity of a resolution fund is nevertheless limited. Hence, the procedure only allows a maximum number, η, of banks that can be recapitalized per period. If the number of eligible banks is higher than η, only η of them are chosen randomly. The remaining banks have to wait for recapitalization in the subsequent periods. The recapitalization costs amount to a fixed fraction, κ, of the rescuers' equity capital. If this 'financial injection' suffices, the bank carries on operating on the market. If it is not sufficient, it waits for further help in the subsequent period. In this way, the bank-specific rescue mechanism has a parsimonious design while avoiding arbitrary inflows into the economy. In related and not necessarily consistent approaches, bankrupt companies are often just replaced by new market entrants with fixed asset structure (Delli Gatti et al., 2010).

3.9 Securitization and Shadow Bank Failure

This section discusses the implications of balance sheet changes related to securitization activities. Our model follows the principle of effective demand. Hence, the mere outsourcing of corporate loans from the bank balance sheet to the SPV and thus the increase in lending capacity does not necessarily stimulate real economic activity. A welfare-enhancing effect only emerges, if there is a simultaneous increase in credit demand and real investment. In any case, there is a small impulse on household capital income and thus consumption, which results from the fact that the interest rate on tranche securities is higher than the deposit rate, i.e., $r_M < r_S < r_L$. Altunbas et al. (2009) and Botta et al. (2018) find significant effects on real production, at least in the short term. To robustify our results, we add a scenario with intense credit frictions from the beginning. After that the securitization process starts (Section 5.7). As it turns out, there are indeed welfare-enhancing effects under such conditions.

If the number of defaults in the securitized corporate loan portfolio rises sharply, the owner banks decide to liquidate the SPV. Investors holding the A-tranche securities for the return purposes are not prepared to waive their claims from the outset. In the event of SPV liquidation, two possible balance sheet changes are conceivable depending on the contractual arrangements: In the first case, the banks have to bear the impairment costs. In the model, this corresponds to the banks taking back the corporate loans at nominal value against deposits, i.e., at the expense of their equity ratio. In the second case, capital market investor households bear the costs. Here, the banks merely have a kind of trustee function for the securitized loan portfolio. In the model, this corresponds to banks exchanging the loans for newly issued bank shares, i.e., not at the expense of the bank equity ratio.

4 Model Calibration

Complex models, including different layers of economic activity (micro, mezzo, macro), may suffer from overparameterization. In the following, however, we do our best to motivate the parameter selection sufficiently. Also note that Section 6 presents the results of a Monte Carlo simulation and

Appendix E those of sensitivity analyses for selected parameters.[19]

Table 4 in the appendix contains the complete list of parameters. Apart from the initialization, one can classify the parameters into two categories: First, those directly set to data or values taken from other studies. Second, those calibrated to meet target ratios or inequalities. As a special case, the second category applies to the marginal propensity to consume out of disposable income, α_1, which is calibrated to guarantee stock-flow consistency of the model (see Section 3.2).

4.1 Initialization

Fischer and Riedler (2014) introduce an agent-based model of financial markets with heterogeneous agents trading a risky asset, while prices evolve endogenously under chartists' and fundamentalists' price expectations. We build on their results about an emerging log-normal distribution of bank size and select the initial value distribution of banks' assets correspondingly. We then allocate an identical amount of equity for all banks to guarantee that no bank is insolvent right from the start, i.e., $\theta_B > \underline{ER}^{MIN}$. This inequality also implies a log-normal distribution for the equity ratios. Other initial values, in particular firm leverage ratios with $\theta_C < \overline{LR}^{MAX}$, are uniformly distributed as is common in the literature. During the initialization process, we make sure that identities in the model hold.

4.2 Parameters taken from the literature

Concerning the propensity to consume out of deposits α_2, we refer to Carroll et al. (2011). The wage share and the share of distributed profits in total profits correspond to U.S. average values since the 1980s (Belabed et al., 2017). The selected threshold of 5% for $\underline{ER}^{MIN}$ is between the rather low requirements of Basel III (3 %) and the average capitalization of large U.S. banks (7%) as reported by Hoenig (2018). Based on this value, the evolving distribution of capital-to-asset ratios is in line with the range of U.S. commercial banks as described by Karmakar and Mok (2015). See the validation in Appendix D. For the maximum firm leverage ratio, we roughly refer to Hovakimian et al. (2001) and Graham et al. (2015). We are guided by the authors' data summaries, which propose that observable capital ratios of non-financial corporates $1 - \overline{LR}^{MAX}$ are at least twice as high as those of banks.

4.3 Targeted Parameters

For the calibration of the wealth components' propensities to consume other than α_2, we assume the following ordering $\alpha_4 < \alpha_3 < \alpha_2$ with respect to the liquidity of the respective assets. Bank shares are supposed to be the least liquid, as they are subject to specific sector risks, unlike the firm shares as the non-financial sector consists of different industries. For the tranche securities, the higher propensity

[19] The source code of our model allows to extend these analyses. Results are available upon request.

to consume seems also plausible, if the investors believe in the diversification benefits neglecting the default risk of the SPV (Gennaioli et al., 2012, 2013). Finally, the marginal propensities to invest in the capital stock, γ_1 and γ_2, are calibrated so that the (private sector) investment ratio of the economy is within a realistic range between 15% and 20%.

There are also two scaling parameters to ensure that the yield on assets and liabilities follows the ordering $r_M < r_S < r_L$. This order states that the deposit rate is lower than the corporate loan rate. Between these two parameters is the interest rate of the tranche securities. This relation motivates households to invest in the tranche securities instead of deposits. Hence, the SPV makes an average profit equal to the spread between the lending rate and the interest rates on the tranche securities.

5 Results

5.1 Model Dynamics

Figure 2 presents model dynamics from a simulated path with a securitization intensity of 1%, and re-scaled U.S. data for the period 1969 to 2008. Except for minor shortcomings, the model replicates the U.S. trends. One reason why we cannot expect a perfect fit is that we are modeling a closed economy without foreign trade and payments. With this caveat in mind, the following issues are striking.

Due to the concentration process in the firm sector of the model, the remaining solvent firms, after about 20 years, have such market power and internal financing capacities that they can mainly finance their investment from these resources. Correspondingly, credits, and deposits fall short of the data from the middle of the simulation period (Figures 2a and 2d). The simulated path also underestimates the proportion of insolvent banks[20]. This discrepancy gets smaller if securitization activity increases. Otherwise, the securitized loan portfolio is hardly affected by corporate insolvencies (Figure 2b & 2c). Over the simulation period, the capital stock develops more weakly in the model than in the data (Figure 2e). But towards the end of the simulation period, weak real economic investment activities in the 2000s have led the observable capital stock to move back towards the simulated path. By definition, the same applies to net investments as the first difference of the capital stock (Figure 2f). Since aggregate demand in the model only corresponds to domestic private sector demand in national account data, the trend growth of consumption and GDP in the model is also somewhat weaker than in reality (Figures 2g - 2i).

Note that the underestimated trend growth in some series still allows us to evaluate the effects of systemic risks as changes from baseline. Apart from the trend, the cyclical properties of variables at the macro-level are relevant for the model validation. Additionally, the model should also conform to

[20] As no bank-specific data are publicly available, we refer here to the commercial and industrial U.S. delinquency rates from the Federal Reserve.

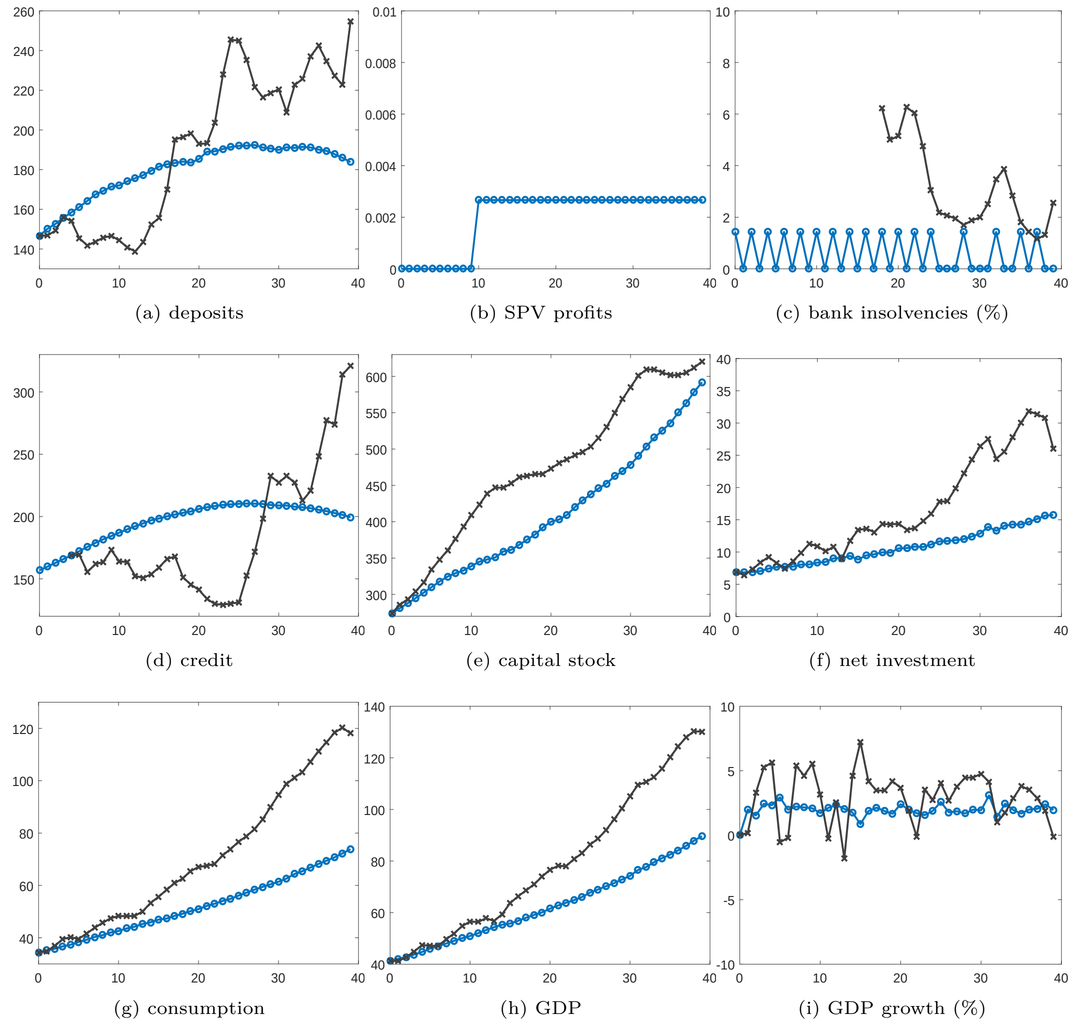
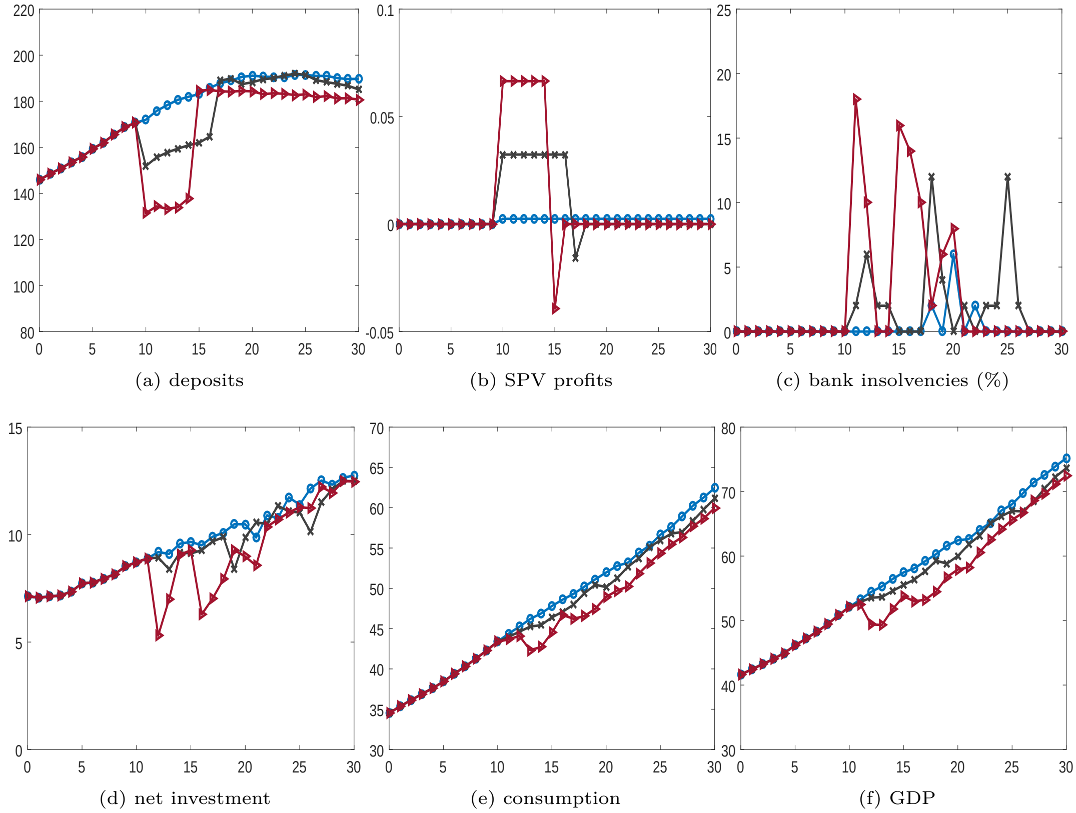


Figure 2: A benchmark scenario: The blue line (o) shows the model dynamics at a securitization intensity of 1%, the black (x) re-scaled US data for the period 1969 to 2008. Bank insolvency indicates the share of insolvent banks in the total banking sector. Data source: Macrobond.

data at the micro-level. Appendix D, in this regard, compares the model outcome and the observed data concerning the distribution of banks' equity ratios as well as auto- and cross-correlations of detrended GDP components. Overall, the validation delivers satisfactory results.

5.2 A scenario in which the banks bear the risk: What happened in the financial crisis?

This section examines a path-dependent scenario in which most of the risks associated with corporate loan securitization remain in the bank books (Acharya et al., 2013). We distinguish between three securitization intensities ($\nu_{SPV} = 1\%$, $\nu_{SPV} = 10\%$ and $\nu_{SPV} = 20$ %). Securitization starts after 10 periods.



(a) deposits (b) SPV profits (c) bank insolvencies (%)

(d) net investment (e) consumption (f) GDP

Figure 3: A scenario where banks bear the risk: Model dynamics at a securitization intensity of ν_{SPV} =1% (blue o-line), $\nu_{SPV} = 10\%$ (black x-line) and $\nu_{SPV} = 20\%$ (red triangle-line).

With the transfer of loans from the bank balance sheets to the special purpose vehicle, the amount of deposits in the economy decreases. The investor households exchange their deposits for the A-tranche securities issued by the SPV (Figure 3a). The higher the securitized volume, the higher the profits the SPV generates from the interest margin (Figure 3b). As long as securitization does not lead to bank insolvencies (Figure 3c), no adverse effects hit the real economy due to financing constraints. The investment, consumption, and aggregate income paths are stable (Figure 3d - 3f), if the securitization intensity is low.

Due to the presumed firm concentration process, defaults in the securitized portfolio are likely at some point. The higher the securitization volume, the faster these defaults occur (Figure 3b). Under these circumstances, the SPV suffers profit declines and even losses, as interest income declines for identical expenses. Due to the profit losses, the owner banks decide to liquidate the SPV. Since this scenario assumes that the banks are contractually obliged to bear the default risk, they compensate the investors in the form of bank deposits. In the model, the re-transfer of corporate loans weakens the equity ratios of the banks involved. Depending on the securitized volume, this can lead to an increase in bank insolvency (Figure 3c).

As a consequence, real economic investment activity is affected by financing constraints. Production suffers and, in the wake of income losses, so does consumption (Figure 3d - 3f). Figure 3 illustrates how strongly the systemic risks along this transmission channel take effect given a securitization intensity of 20%. But even at a securitization intensity of 10%, welfare losses seem significant compared with the benchmark intensity of 1%. The black GDP line steadily moves below the blue GDP line (Figure 3f).

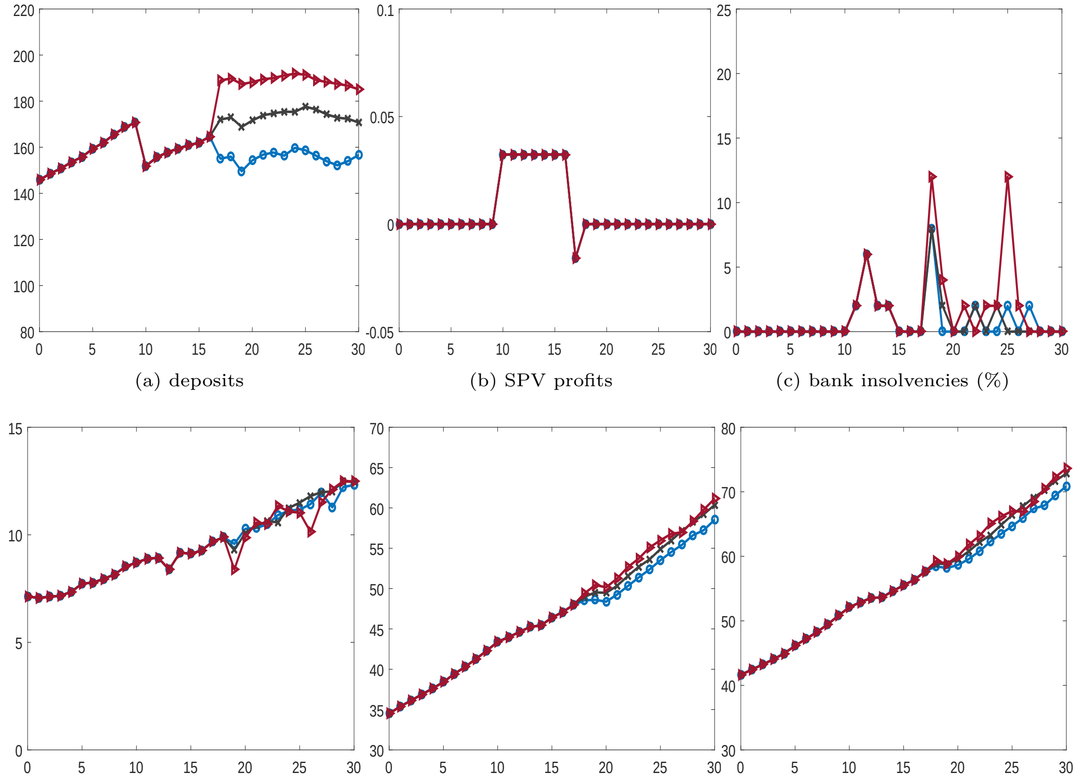
5.3 A scenario in which investors bear the risk: Does standardization reduce systemic risks?

This section explores a scenario in which capital market investors bear the risk of liquidation of the SPV. Some observers argue that standardized products on the securitization market achieve a more efficient risk transfer from banks to capital market investors and thereby lower the systemic risks (Commission, 2015; Véron and Wolff, 2016). We, therefore, test whether this design avoids harmful real economic effects of increased securitization activities in the medium to long run. Based on the previous findings, we leave the securitization intensity at 10% for three different simulation paths under consideration (Figure 4b).

In contrast to the previous scenario, in which the equity tranche obliged banks to bear 100% of the losses, we now consider different degrees to which investors participate in potential losses. In other words, this scenario assumes that also the equity tranche securities are partially sold on capital markets. We distinguish between a B-tranche share remaining in the bank book of 70% (Figure 4 blue o-line), 85% (black x-line) and 100% (red triangle-line).[21] The last value characterizes the already known scenario, which now serves as a benchmark: The black line in Figure 3 corresponds to the red line in Figure 4.

Overall, the result show that an increased risk participation of the investors does not improve welfare at the macro-level (Figure 4f). The opposite is the case, at least if one compares the 70% risk absorption of banks with the 100% scenario. The blue line of aggregate demand moves steadily below the red one. How to explain this result? Two counterbalancing effects are at work.

[21] A 100 % sale of the equity tranche seems unlikely, as the rating of the tranche securities could deteriorate noticeably.



(a) deposits (b) SPV profits (c) bank insolvencies (%)

(d) net investment (e) consumption (f) GDP

Figure 4: A scenario where the capital market investors bear the risk: The securitization intensity is always 10%. Model dynamics at bank risk participation of $\delta = 70\%$ (blue o-line), $\delta = 85\%$ (black x-line) and $\delta = 100\%$ (red triangle-line).

On the one hand, as expected, the increased investor risk participation leads to fewer bank insolvencies in case of liquidation of the SPV (Figure 4c). As a result, there are fewer frictions on the credit supply side in financing real economic investments (Figure 4d). On the other hand, the increased investor risk participation dampens consumption (Figure 4e). The model delivers this result endogenously because the re-transfer of corporate loans to bank balance sheets is no longer exclusively at the expense of the bank equity ratios. Instead, investors now partly receive bank shares in return. These are less liquid assets, which implies lower consumption. Therefore, the systemic risks of increased securitization activity continue to materialize.

5.4 Interaction effects of securitization and investors' loss absorption

The previous scenarios can now be combined by simultaneously changing both the securitization intensity and the investor risk absorption. Such an analysis takes into account possible nonlinearities in the form of interaction effects. Figure 5 shows the results, which are on a qualitative base as expected from the previous scenarios. In quantitative terms, the interaction effect is striking.

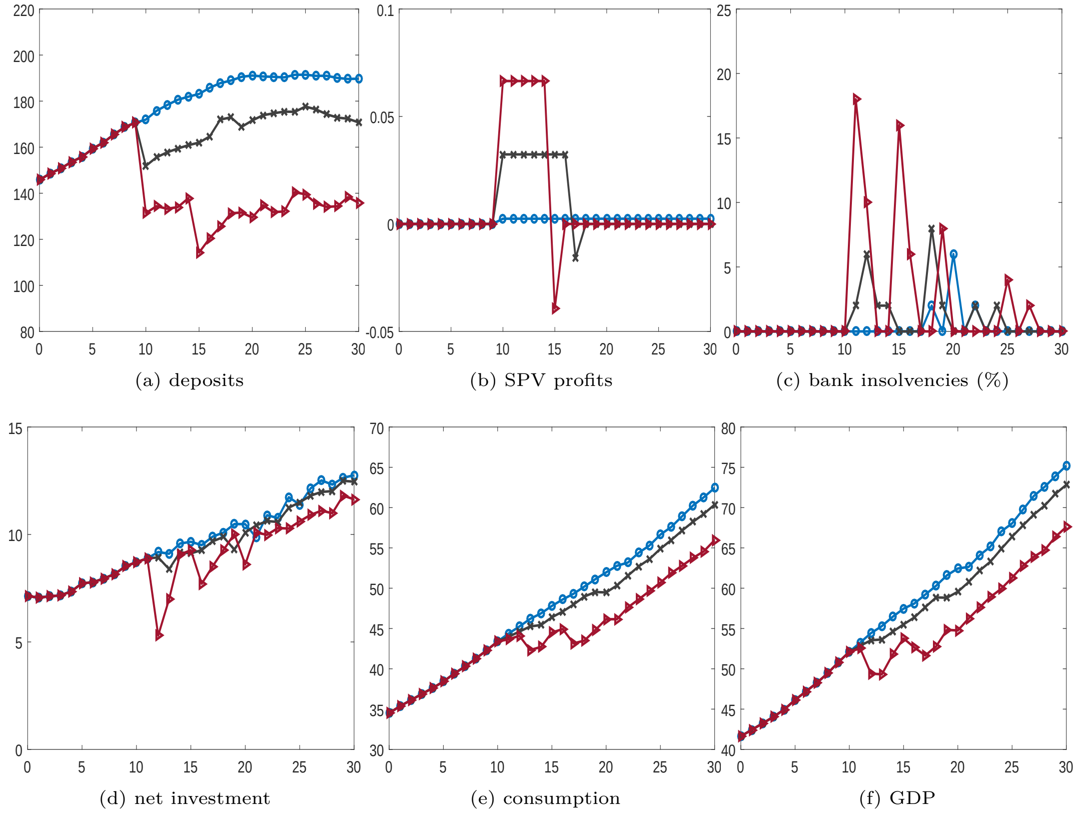


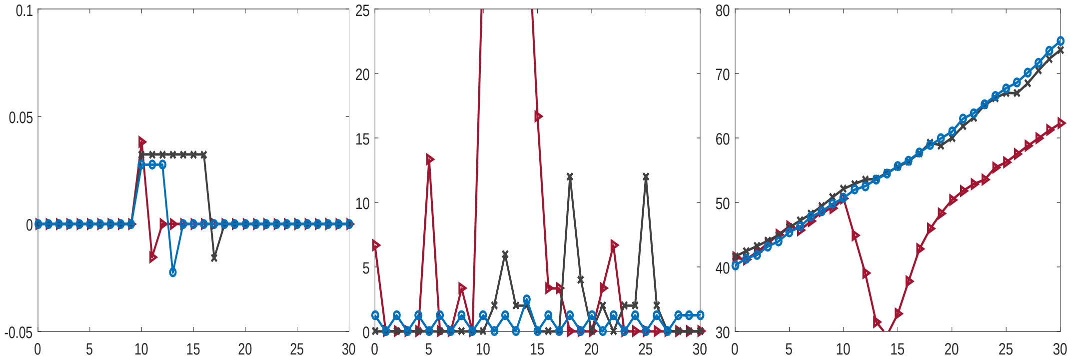
Figure 5: A scenario including interaction effects: Model dynamics for the securitization intensity and bank risk participation $\nu_{SPV} = 1\%$, $\delta = 100\%$ (blue o-line); $\nu_{SPV} = 10\%$, $\delta = 85\%$ (black x-line) and $\nu_{SPV} = 20\%$, $\delta = 70\%$ (red triangle-line).

A comparison of the total welfare reductions from the scenarios in which the securitization intensity and the loss absorption of the investors increases individually (Figures 3 and 4) with the welfare reduction in the combined scenario (Figure 5) shows that the latter is significantly larger.

5.5 Effects of the banking sector structure

Usually, in agent-based models, different quantities for the types of agents, in our case firms and banks, play a role. To investigate this, we keep the securitization intensity, the bank loss absorption, and the number of firms constant while the number of banks in the model changes. The more banks in the model, the smaller the average bank tends to be.

Figure 6 shows the results of such an exercise. There are nonlinearities concerning the lifetime of the SPV, which do not follow a straightforward explanation (Figure 6a). As might not be expected, not the least concentrated banking sector implies the longest life span of the SPV, but a medium



(a) SPV profits (b) bank insolvencies (%) (c) GDP

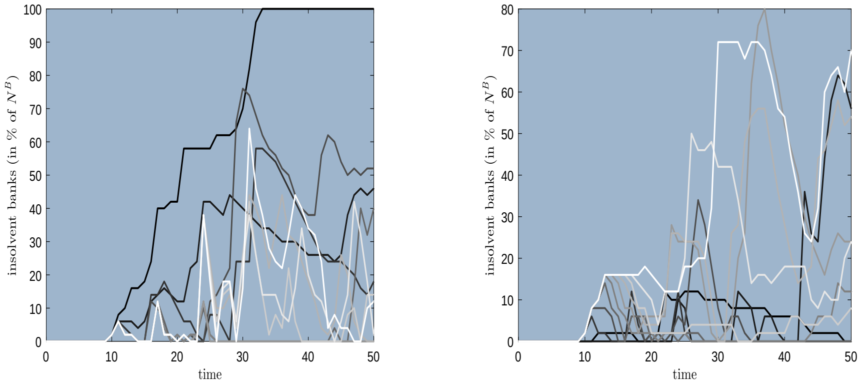
Figure 6: A scenario for different banking sector concentrations at $\nu_{SPV} = 10\%$ and $\delta = 100\%$: Total number of banks $N^b = 80$ (blue o-line); $N^b = 50$ (black x-line) and $N^b = 30$ (red triangle-line).

concentrated one.[22] In the case of the highest concentration of the banking sector, however, the SPV can stay the shortest time in the market. The bulk of bank insolvencies (Figure 6b) arises as a result of the securitization activities. The more concentrated the banking sector, the higher the number of bank insolvencies because more loans per bank are re-transferred. Hence, the effect on the individual bank equity ratio tends to be more severe. While the consequences for the real economy hardly differ between a low and a medium-concentration banking sector scenario, the welfare-reduction is massive when the banking sector is highly concentrated (Figure 6c).

5.6 Effects of the bank rescue mechanism

To analyze the efficiency of the bank resolution, we study the sensitivity of bank insolvencies (and thus indirectly of credit frictions) to two parameters of the rescue mechanism. The first parameter corresponds to the maximum number of bank recapitalization per period (η). The second stands for the duration until recapitalization (the length of insolvency proceedings ζ). For the sensitivity analysis, both parameters are incremented by 1 in the range [0, 10]. Figure 14 shows the results for each parametrization whereby the following applies: The higher the parameter, the brighter the line. Results are clear-cut and as expected. The higher the number of banks admitted to recapitalization, the fewer banks fail over the entire simulation period (Figure 14a). The longer the duration of the insolvency proceedings, the more bank failures are observed (Figure 14b). In other words, if adequately equipped, a levy organized within the banking sector can be effective in mitigating the consequences of excessive securitization.

[22] Note that everything else equal, bank insolvencies can randomly occur before the liquidation of the SPV. Subsequently, more firms go bankrupt increasing the probability of loan defaults in the securitized portfolio.



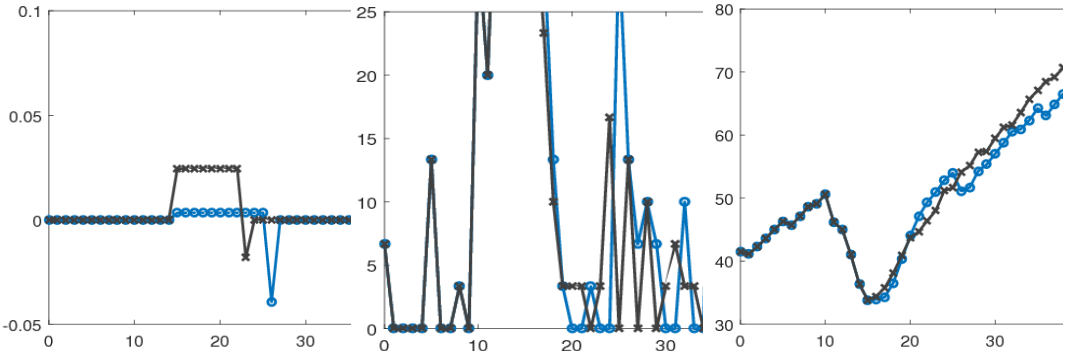
(a) Bank insolvencies subject to changes in η (b) Bank insolvencies subject to changes in ζ

Figure 7: Robustness of the banking sector depending on the bank rescue mechanism.

5.7 Under which conditions can securitization be beneficial for an economy ?

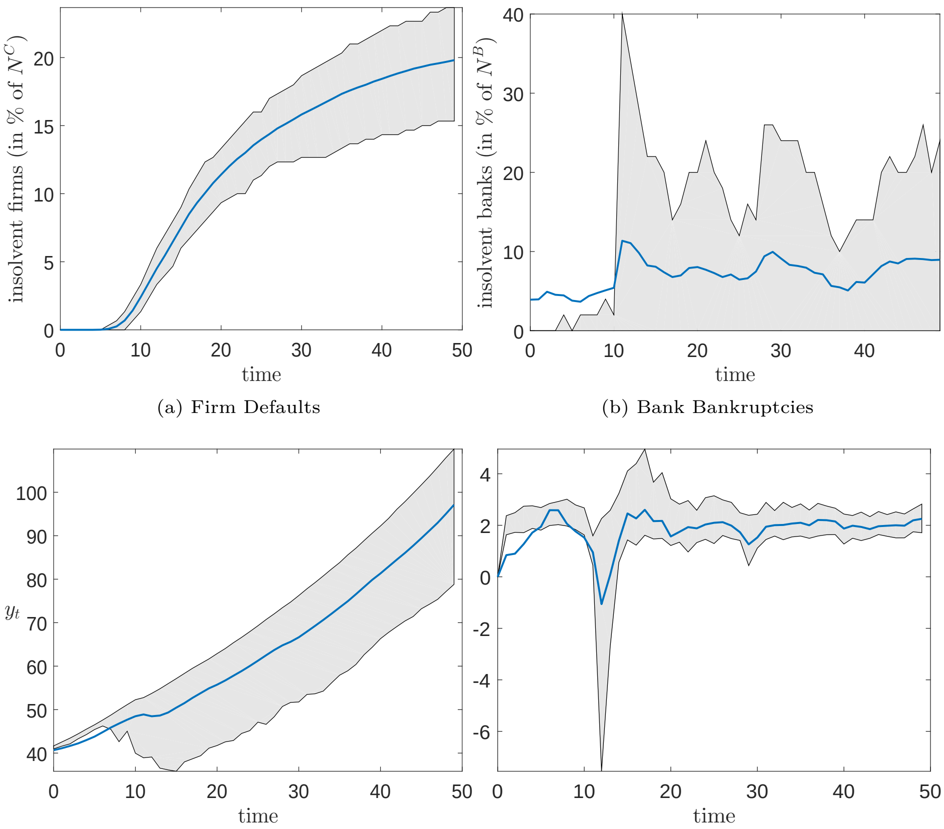
Some studies, e.g., Altunbas et al. (2009) and Botta et al. (2018), mention a stimulating effect of securitization on real economic production, at least in the short term. In this section, we investigate if the presented model also allows for such effects. Since the model is primarily demand-driven, it is necessary to create starting conditions where significant credit supply-side frictions already exist before securitization. Under such conditions, the SPV origination can dissolve some of these frictions as the equity ratios of the banks increase in the wake of the corporate loan outsourcing. Figure 8 summarizes the results of such an exercise. Figure 8a shows that the SPV lifetime is only slightly shorter at the higher securitization intensity of 10% than at the lower one of 1%. The joint effect of the higher securitization volume and the bank rescue mechanism succeeds in stabilizing the banks' balance sheets more efficiently than in the scenario with lower securitization intensity (Figure 8b). Accordingly, aggregate demand develops more vibrantly in the simulation with the higher securitization intensity than with the lower (Figure 8c).

Overall, the analysis confirms previous studies. Securitization can, under certain conditions, stimulate the economy. These conditions, however, are obvious: First, the economy cannot be in a demand-driven regime, when securitization starts. Instead, there must be restrictions on the supply side of credit. Irrespective of real economic consequences, financial intermediaries can have an incentive to securitize loans because of improving capital ratios or satisfying investor demand for new types of assets (financial innovation). Second, we only find that a temporary-elevated securitization intensity can help to remove credit frictions similar to a one-time starter. We cannot draw any conclusions about the effects of continuous operation, which probably implies a higher probability of bank insolvency and hence threatens to produce the same adverse effects that we find in the demand-driven regime from the medium-term onwards.



(a) SPV profits (b) bank insolvencies (%) (c) GDP

Figure 8: A scenario where securitization yields welfare gains with parametrization $\nu_{SPV} = 1\%$ (blue o-line) and $\theta_{SPV} = 10\%$ (black x-line). For the sake of exposition, we further re-calibrated the experiment to pronounce the effects. We chose $\rho_{LR} = 0.1$ (instead of $\rho_{LR} = 0.06$) and $\overline{LR} = 0.65$ (instead of 0.5). We further postponed the securitization timing (instead of the 10th period).



(a) Firm Defaults (b) Bank Bankruptcies

(c) GDP (d) GDP Growth Rate

Figure 9: The plot displays results for 1000 paths starting securitization after 10 periods with a securitization intensity of 10%. The blue line shows the mean. The confidence band contains 90% of the realizations.

6 Robustification

The different scenario results so far are subject to path dependency. We, therefore, conduct a Monte Carlo analysis with 1000 replications to ensure that the findings hold under the variation of the stochastic terms in the model equations. Figure 9 shows the results for a securitization intensity of 10%. Regarding the average simulation path, this level of securitization activity implies a higher number of bank insolvencies and significant output losses as could be expected from the transmissions described before. The fact that one can observe this pattern for the majority of the simulation paths suggests that the findings also hold under uncertainty. Further robustifications are conducted in Appendix E using sensitivity analysis for the parametrization of the partner selection mechanism, the investment, and the consumption function.

7 Conclusion

This paper deals with the systemic risk of the securitization market. For this purpose, we develop a stock-flow consistent macroeconomic model with an agent-based focus on corporate credit markets, and a special purpose vehicle (SPV) connected to multiple banks. Although such vehicles are often originated by only one bank, there are many interlinkages to other financial intermediaries through credit and derivatives. The securitization intensity plays a crucial role for the systemic character of securitization. We measure this intensity as the share of securitized loans in total new loans in the period in which the SPV starts its business.

Our results suggest that the securitization intensity should be lower than previously reported in the literature. The only estimate we know from the study by Mazzocchetti et al. (2018) finds an optimal value of 15 %. Instead, our model reveals a significant medium to long-term welfare loss as soon as the securitization intensity approaches 10% of the economy's total new loan volume. Welfare losses become evident irrespective of whether a collapsing SPV leads to distortions in the banking sector or increases liquidity constraints that ultimately dampen household consumption. The optimal level of the securitization intensity will depend on whether the economy is in a credit supply-constrained regime or not. If not, the optimum should be far cbelow 10%. Our findings are, therefore, intended as a warning that the revitalization of corporate credit securitization in recent years does not promise to be sustainable for future macro and financial stability.

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Appendix

A Variables and Parameters

Variable	Description	Equation(s)
	Macro Level	
c_t	household's consumption	(B.20)
e_t^f	corporate equities	(B.26)
e_t^b	bank equities	(B.27)
g_t	(realized) capital accumulation rate	(B.24)
i_t	(realized) investment	(B.25)
K_t	(realized) physical stock of capital	(B.22)
l_t	actual volume of corporate loans	(B.23)
m_t^d	deposits	(B.33)
p_t^f	corporate equity price	(B.28)
p_t^b	banks' equity price	(B.29)
y_t	output	(B.19)
y_t^d	disposable income	(B.18)
u_t	capacity utilization	(B.21)
$\tilde{\Pi}_t$	corporate retained earnings	(B.4)
Π_t^d, Π_t^T	distributed and total corporate profits	(B.35), (B.34)
r_t	average loan rate	(B.30)
r_t^m	deposit rate	(B.31)
r_t^{spvA}	return on the SPV-A security	(B.32)
$spvA_t$	SPV A-tranche security	(B.16)
$\Pi_{SPV,t}$	SPV profits	(B.17)
	Micro Level	
$e_{i,t}$	firm i's equities	(B.7)
$e_{k,t}$	bank k's equities	(B.11)
$ER_{k,t}$	banks' equity ratio	(B.14)
$i_{i,t}^D$	firm specific desired investment	(4)
$i_{i,t}$	firm specific investment	(8), (B.1)
$g_{i,t}^D$	firms' planned capital accumulation rate	(2)
$g_{i,t}$	firms' actual capital accumulation rate	(B.3)
$K_{i,t}^D$	firm i's planned level of assets	(4)
$K_{i,t}$	firm i's assets	(B.2)
$l_{i,t}$	firms' external funds	(7)

$l_{k,t}$	banks' assets	(B.10)
$LR_{i,t}$	firms' leverage ratio	(B.8)
$m^d_{k,t}$	banks' deposits	(B.13)
$p^f_{i,t}$	equity price of each firm i	(B.6)
$p^b_{k,t}$	equity price of each bank k	(B.12)
Φ_t	firm market share	(B.9)
$\tilde{\Pi}_{i,t}$ ($\Pi_{i,t}$)	firms' retained earnings (total profits)	(B.5), (B.4)
$r^k_{i,t}$	firms' loan interest rate	(5)

Description	Parameter	Value	Source and Motivation
		Values taken from the literature	
Marginal propensity to consume out of deposits (liquidity)	α_2	0.055	Carroll et al. (2011, Table 5)
Wage share and share of distributed profits	ω, χ	$0.7, 0.2$	Belabed et al. (2017, Appendix A)
Threshold equity ratio	$\bar{ER}^{MIN}$	0.05	Hoenig (2018, Column 4)
Threshold leverage ratio	$\bar{LR}^{MAX}$	0.90	Graham et al. (2015, Table 1): $1 - \bar{ER}^{MIN} > \bar{LR}^{MAX}$
		Targeted Parameters	
Initial bank equity ratio	θ_B	0.07	motivated by $\theta_B > \bar{ER}^{MIN}$
Initial firm leverage ratio	θ_C	0.80	motivated by $\theta_C < \bar{LR}^{MAX}$
Marginal propensity to consume out of disposable income	α_1	0.60	calibrated to ensure stock flow consistency
Marginal propensity to consume out of corporate share holding	α_3	0.045	motivated by $\alpha_4 < \alpha_3 < \alpha_2$
Marginal propensity to consume out of bank share holding	α_4	0.03	motivated by $\alpha_4 < \alpha_3 < \alpha_2$
Marginal propensity to invest out of capacity utilization	γ_1	0.03	motivated by $0.15 < I/Y < 0.20$
Marginal propensity to invest out of profit rate	γ_2	0.025	motivated by $0.15 < I/Y < 0.20$
Scaling parameter linking deposit and loan rates	θ_r	0.85	motivated by $r_M < r_S < r_L$
Scaling parameter linking tranche and loan rates	θ_{spvA}	0.95	motivated by $r_M < r_S < r_L$
		Partner Selection Mechanism	
Number of firms	N_C	300	see X for the sensitivity to a modified N_B/N_C ratio
Number of banks	N_B	50	see X for the sensitivity a modified N_B/N_C ratio
Loan rate intercept	$\tilde{r}$	0.04	average US prime rate charged by banks since 2001 (FED)
Benchmark firm leverage ratio	$\overline{LR}$	0.50	motivated by $\overline{LR} < \bar{LR}^{MAX}$
Loan rate sensitivity to firm leverage ratio	ρ_{LR}	0.01	see X for the sensitivity to a modified value
Loan rate sensitivity to bank equity ratio	ρ_{ER}	0.06	sensitivity analysis available on request
Scaling paremeter for firms' matching costs	$\bar{\mu}^S$	0.05	see X for the sensitivity to a modified value
Number of firms' potential credit supplier	M	5	see X for the sensitivity to a modified value

Bank Rescue Mechanism			
Maximum number of recapitalized banks per period	η	5	see X for the sensitivity to a modified value
Duration of the insolvency proceedings	ζ	2	see X for the sensitivity to a modified value
Size of recapitalization	κ	0.2	sensitivity analysis available on request
Shock Processes (joint effect analyzed by MC)			
Firms' sensitivity to sale prediction errors	λ	0.01	assumed to maintain persistence
Standard deviation of the price expectation error term	σ_c	1.00	assumed to be standard normally distributed
Standard deviation of the capital productivity error term	σ_μ	0.1	assumed to have a low volatility (Caiani et al., 2016, p. 39)
Standard deviation of the loan rate error term	σ_r	0.007	assumed to have a low volatility (Caiani et al., 2016, p. 39)
Intercept in the GARCH firm equity price process	σ_0^P	0.05	assumed to induce a low volatility
Return sensitivity in the GARCH firm equity price process	σ_1^P	0.05	assumed to induce a low volatility
Persistence in GARCH firm equity price process	σ_2^P	0.05	assumed to induce a low volatility

B Model Equations

B.1 Production planning

$$c^D_{i,t} = c^D_{i,t-1} + \lambda \left(c_{t-1} - c^D_{i,t-1} \right) + \epsilon^c_{i,t} \quad \text{with} \quad \epsilon^c_{i,t} \sim \mathcal{N}(0, \sigma_c) \tag{1}$$

$$g^D_{i,t} = \gamma_1 u^D_{i,t-1} + \gamma_2 \left(\frac{\pi_{t-1}}{K_{t-1}} \right) \tag{2}$$

$$u^D_{i,t} = \frac{y^D_{i,t}}{K^D_{i,t}(1+\mu^K_{i,t})} = \frac{c^e_{i,t} + i^D_{i,t}}{K^D_{i,t}(1+\mu^K_{i,t})} \tag{3}$$

$$i^D_{i,t} = g^D_{i,t} K_{t-1} \qquad K^D_{i,t} = K_{t-1} + i^D_{i,t} \tag{4}$$

B.2 Corporate sector

$$\Delta l_{i,t} = \begin{cases} i^D_{i,t} - \tilde{\Pi}^{\text{retained}}_{i,t} & \text{if} \quad \#_{\{i,t\}} = 0 \\ (1 - S_{i,t})(i^D_{i,t} - \tilde{\Pi}_{i,t}) & \text{if} \quad 0 < \#_{\{i,t\}} < n \\ 0 & \text{else} \end{cases} \tag{7}$$

$$i_{i,t} = \begin{cases} \Phi_t \cdot i^D_{i,t} & \text{if} \quad \#_{\{i,t\}} = 0 \\ \Delta l_{i,t} + \tilde{\Pi}^{\text{retained}}_{i,t} & \text{if} \quad 0 < \#_{\{i,t\}} < n \\ \tilde{\Pi}_{i,t} & \text{else} \end{cases} \tag{B.1}$$

$$\Delta K_{i,t} = i_{i,t} \tag{B.2}$$

$$g_{i,t} = i_{i,t} / K_{i,t-1} \tag{B.3}$$

$$\Pi_{i,t} = \Phi_t \Pi^T_t \tag{B.4}$$

$$\tilde{\Pi}^{\text{retained}}_{i,t} = (1 - \chi) \Pi^T_t \tag{B.5}$$

$$p^f_{i,t} = \exp \left\{ ln(p^f_{i,t-1}) + \epsilon^p_{i,t} \right\} \quad \text{with} \quad \epsilon^p_{i,t} \sim N(0, \sigma^p_{i,t})$$
$$(\sigma^p_{i,t})^2 = \sigma^p_0 + \sigma^p_1 \cdot ln \left(\frac{p^f_{i,t}}{p^f_{i,t-1}} \right)^2 + \sigma^p_2 \cdot (\sigma^p_{i,t-1})^2 \tag{B.6}$$

$$e_{i,t} = (K_{i,t} - l_{i,t}) / p^f_{i,t} \tag{B.7}$$

$$LR_{i,t} = \frac{l_{i,t-1}}{p^f_{i,t-1} \cdot e_{i,t-1} + l_{i,t-1}} \tag{B.8}$$

$$\Phi_t = 1/N^C \tag{B.9}$$

B.3 Banking sector

$$\Delta l_{k,t} = \begin{cases} \sum_{i \in \Theta_k} l_{i,t} & \text{if no SPV is involved} \\ \sum_{i \in \Theta_k} l_{i,t} - \sum_{i \in \Theta_k \cup \Theta_{SPV}} l_{i,t} & \text{otherwise} \end{cases} \tag{B.10}$$

$$e_{k,t} = e_{k,t-1} \tag{B.11}$$

$$p^b_{k,t} = \begin{cases} p^b_{k,t-1} \cdot \left(1 + \frac{\sum_{k=1}^{N^B} \Delta l_{k,t}}{\sum_{k=1}^{N^B} l_{k,t-1}}\right) & \text{if} \quad ER_{k,t} \geq \overline{ER}^T \\ (l_{k,t} - m^d_{k,t})/e_{k,t} \quad \text{else} \end{cases} \tag{B.12}$$

$$m^d_{k,t} = l_{k,t} - p^b_{k,t} e_{k,t} \tag{B.13}$$

$$ER_{k,t} = \frac{p^b_{k,t} \cdot e_{k,t}}{l_{k,t}} \tag{B.14}$$

where Θ_k is the set of bank k's customers and Θ_{SPV} incorporates the respective firms behind the securitized debt obligations.

B.4 Special purpose vehicle

$$\theta_{SPV} = \frac{\sum_{i \in \Theta_{SPV}} l_{i,t}}{\sum_{k=1}^{N^B} l_{k,t}} \tag{B.15}$$

$$spvA_t = \sum_{i \in \Theta_{SPV}} l_{i,t} \tag{B.16}$$

$$\Pi_{SPV,t} = \sum_{i \in \Theta_{SPV}} r_{i,t} \cdot l_{i,t-1} - r^{spvA}_t \cdot spvA_{t-1} \tag{B.17}$$

where Θ_{SPV} refers to the set of firms whose obligations are pooled in the A-tranche.

B.5 The macroeconomic level - Household sector and aggregation

The household sector acts as an aggregate in the model[23]:

[23] Notice that the macro variables from the production planning are not listed here. They are simply obtained by summing up the correspondig micro variables

$$y_t^d = \omega \cdot y_t + \Pi_t^d + r_t \cdot m_{t-1}^d + r_t^{spvA} \cdot spvA_{t-1} \tag{B.18}$$

$$y_t = c_t + i_t \tag{B.19}$$

$$c_t = \alpha_1 y_{t-1}^d + \alpha_2 m_{t-1}^d + \alpha_3 \left[\Delta(p_t^f e_t^f) + spvA_{t-1}\right] + \alpha_4 \Delta(p_t^b e_t^b) \tag{B.20}$$

$$u_t = y_t / K_t \tag{B.21}$$

$$K_t = \sum_{i=1}^{N^C} K_{i,t} \tag{B.22}$$

$$l_t = \sum_{i=1}^{N^C} l_{i,t} \tag{B.23}$$

$$g_t = \Delta K_t / K_{t-1} \tag{B.24}$$

$$i_t = \sum_{i=1}^{N^C} i_{i,t} \tag{B.25}$$

$$e_t^f = \sum_{i=1}^{N^C} e_{i,t} \tag{B.26}$$

$$e_t^b = \sum_{k=1}^{N^B} e_{k,t} \tag{B.27}$$

$$p_t^f = \frac{\sum_{i=1}^{N^C} p_{i,t}^f \cdot e_{i,t}}{\sum_{i=1}^{N^C} e_{i,t}} \tag{B.28}$$

$$p_t^b = \frac{\sum_{k=1}^{N^B} l_{k,t} - \sum_{k=1}^{N^B} m_{k,t}^d}{\sum_{k=1}^{N^B} e_{k,t}} \tag{B.29}$$

$$r_t = \frac{\sum_{i=1}^{N^C} r_{i,t} \cdot l_{i,t}}{\sum_{i=1}^{N^C} l_{i,t}} \tag{B.30}$$

$$r_t^m = \theta_r \cdot \frac{\sum_{i=1}^{N^C} r_{i,t} \cdot l_{i,t}}{\sum_{i=1}^{N^C} l_{i,t}} \tag{B.31}$$

$$r_t^{spvA} = \theta_r \cdot \frac{\sum_{i=1}^{\Theta_{SPV}} r_{i,t} \cdot l_{i,t}}{\sum_{i=1}^{\Theta_{SPV}} l_{i,t}} \tag{B.32}$$

$$m_t^d = \sum_{k=1}^{N^B} m_{k,t}^d \tag{B.33}$$

$$\Pi_t^{\text{distributed}} = \chi \Pi_t^T \tag{B.34}$$

$$\Pi_t^T = (1-\omega) y_t \tag{B.35}$$

$$\tilde{\Pi}_t^{\text{retained}} = \Pi_t^T - \Pi_t^D - \sum_{i=1 | i \notin \Theta_{SPV}}^{N^C} r_{i,t-1} l_{i,t-1} \tag{B.36}$$

C Initialization

C.1 Initial Values

Variable	Description	Value
	Macro Level	
c_0	consumption	$0.7 \cdot y_0$
e_0^f	corporate equities	$\sum_{i=1}^{N^C} e_{i,0}$
e_0^b	bank equities	$\theta^b \cdot l_0^f$
g_0	capital accumulation rate	$i_0/K_0 = \delta$
i_0	investment	$\delta \cdot K_0$
K_0	physical stock of capital	200
l_0^f	volume of loans (macro level)	$\sum_{i=1}^{N^C}$
m_0^d	deposits	$l_0^f - e_0^b p_0^{e,b}$
u_0	utilization rate	y_0/K_0
y_0	output	$0.5 \cdot K_0$
$\tilde{\Pi}_0$	corporate retained earnings	$\Pi_0^T - \Pi_0^d$
Π_0^d	distributed corporate profits	$\chi \cdot \Pi_0^T$
Π_0^T	total corporate profits	$(1-\omega) \cdot y_0$
V_0	Household's financial wealth	$m_0^d + p_0^f e_0^f + p_0^{e,b} e_0^b$
	Micro Level	
$e_{i,0}$	endowment of firm i's equity	$(K_0/N^C - l_{i,0})/p_{i,0}^f$
$e_{k,0}$	endowment of bank k's equity	e_0^b/N^B
$ER_{k,0}$	bank k's equity ratio	$(p_{k,0}^b \cdot e_{k,0})/l_{i,0}^k$
$i_{i,0}$	investment	$\delta \cdot K_{i,0}$
$g_{i,0}^D$	planned investment of firm i	$g_0 = \delta$
$K_{i,0}$	endowment of firm i	K_0/N^C
$l_{i,0}$	volume of firm i's loans	$LR_{i,0} \cdot K_0/N^C$
$l_{k,0}$	bank assets	see appendix C.2
$LR_{i,0}$	firms' leverage ratio	see appendix C.2
$m_{k,0}^d$	banks' deposits	$l_{i,0}^k - p_{k,0}^b \cdot e_{k,0}$
$p_{i,0}^f$	equity price of each firm i	1
$p_{k,0}^b$	equity price of each bank k	1
Φ_0	market share firm	$1/N^C$
$\tilde{\Pi}_{i,0}$	retained earnings of individual firm i	$(1-\chi)\Pi_{i,0}$
$\Pi_{i,0}$	total profits of individual firm i	$\Phi_0 \cdot \Pi_0^T - \tilde{r} \cdot l_{i,0}$

C.2 Initialization Process

In this section, we highlight the initialization process of the model. We pay special attention to this process since we do not aim to violate the stock-flow consistency at any stage. Furthermore, the model aims at the greatest possible proximity to data.

Note that firms are identically endowed on their asset side since we identically distribute the initial economic-wide capital stock among all firms $K_{i,0} = K_0/N^C$. The heterogeneity, however, arises due to randomly chosen financing structure LR_i among all firms. In particular, we assume that the firms' initial leverage ratios are drawn from a uniform distribution, formally $LR_{i,0} \sim \mathcal{U}(\underline{lr}, \overline{lr})$, where the support $(\underline{lr}, \overline{lr})$ is configured to cover a range of leverage ratios excluding insolvencies $(LR_{i,0} < LR^{MAX})$. Then, we derive the respective firm equity position residually, i.e. $e_{i,0} = (K_{i,0} - l_{i,0})/p^f_{i,0}$ with the initial equity price normalized to one.

At the next stage, the initial credit network between firms and banks is randomly selected. In detail, we construct an array that contains a flag for each firm, $C = \{1, \cdots, N^C\}$, with N^C being the number of firms in the economy. We permute the array to obtain $\tilde{C}$. Next, we allocate the firms to the banks and formulate the initial credit contract. Accordingly, the set $\tilde{C}$ is divided into N^B equally sized subsets. If the ratio N^C/N^B is not an integer, each bank signs an initial credit contract with $\lfloor N^C/N^B \rfloor$ number of firms while the remaining firms, if there are any, are allocated to randomly chosen banks. Hence, each bank k initially funds approximately the same number of firms. From the initial credit network, we compute the banks' assets by simply summing up the granted loans in bank k's portfolio. We obtain $l_{k,0}$. Using the initial values depicted in Table 5, we compute the banks' equity ratios. Even though the initial leverage ratios are uniformly distributed, and the initial number of firms that get funded by each bank is roughly the same for all, the initial distribution of bank equity ratios is bell-shaped. Its kurtosis is about 3, which usually indicates a normal distribution. But note that the distribution cannot be symmetric because of minimum capital requirements.

D Validation

Caiani et al. (2016) propose a procedure for the validation of stock-flow consistent agent-based models with comprehensive sector mapping. We follow their approach and present a comparison of synthetic model data with observable data taking both cross-sectional properties at the micro-level as well as time series properties at the macro level into account.

D.1 Validation at the micro level: The distribution of bank equity ratios

Figure 10 shows the model distribution of banks' capital ratios after 30 periods. The left-hand graph is based on the outcome of a randomly selected path with a securitisation intensity of 1% and the right-hand graph based on one with an intensity of 10%. Figure 11 shows the corresponding descriptive density distribution of US commercial banks according to the data set exploited by Karmakar and Mok (2015).

Figure 10: Model Bank Equity Ratio

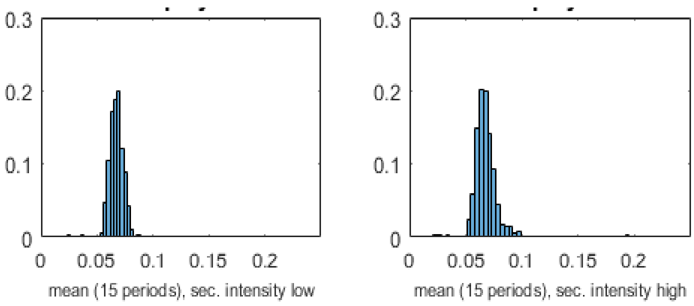
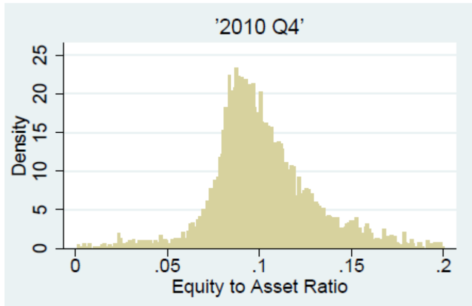


Figure 11: Karmakar and Mok (2015)



Three main similarities between the model data and the observed data are striking: i. most banks have an equity-to-asset ratio of about 7 %, ii. the distribution is skewed to the right, iii. only a few banks have an equity ratio of less than 5 %. The most important difference is that, unlike in the model, the observable data include more banks with capital ratios above 10%, i.e., the model distribution is not complete in this sense. However, note that the data set by Karmakar and Mok (2015) does not contain non-commercial banks. The model also roughly matches the average leverage ratio of global systemically important banks in the U.S. (US-GSIB) mentioned by Hoenig (2018).

D.2 Validation at the macro level: Auto- and cross-correlation

Figure 12 and 13 compare the observable (left hand) and model data (right hand) in terms of the auto- and cross-correlations of GDP components, after trend filtering the data.[24] Given that the model is subject to simplifications at the macro level, all in all, the comparison provides promising conformity.[25]

[24] As the standard for yearly data, we apply the Hodrick-Prescott filter with $\lambda = 100$.

[25] A lack of conformity in the form of different signs only emerges with the first-order auto-correlation of investment and the cross-correlation between GDP and the second lag of consumption.

Figure 12: Auto-correlations of real ouptput, investment and consumption

Autocorrelation Data: Real GDP — Sample: 1969 2008

	AC	PAC	Q-Stat	Prob
1	0.505	0.505	10.986	0.001
2	-0.043	-0.400	11.067	0.004
3	-0.355	-0.196	16.800	0.001
4	-0.357	-0.076	22.756	0.000

Autocorrelation Real GDP — Included observations: 40

	AC	PAC	Q-Stat	Prob
1	0.248	0.248	2.6500	0.104
2	-0.158	-0.234	3.7503	0.153
3	-0.348	-0.273	9.2610	0.026
4	-0.174	-0.056	10.676	0.030

Autcorrelation Data: Investment — Sample: 1969 2008

	AC	PAC	Q-Stat	Prob
1	0.341	0.341	5.0018	0.025
2	-0.118	-0.265	5.6181	0.060
3	-0.397	-0.311	12.762	0.005
4	-0.283	-0.073	16.504	0.002

Autocorrelation Model: Net Investment — Included observations 40

	AC	PAC	Q-Stat	Prob
1	-0.162	-0.162	1.1366	0.286
2	-0.047	-0.075	1.2328	0.540
3	-0.323	-0.355	5.9695	0.113
4	0.009	-0.142	5.9731	0.201

Autocorrelation Data: Consumption — Sample: 1969 2008

	AC	PAC	Q-Stat	Prob
1	0.460	0.460	9.1317	0.003
2	0.019	-0.245	9.1474	0.010
3	-0.175	-0.098	10.536	0.015
4	-0.230	-0.116	12.997	0.011

Autocorrelation Model: Consumption — Included observations: 40

	AC	PAC	Q-Stat	Prob
1	0.107	0.107	0.4966	0.481
2	0.162	0.152	1.6532	0.438
3	-0.362	-0.407	7.5921	0.055
4	0.021	0.111	7.6129	0.107

Figure 13: Cross-correlations of real ouptput-investment and real output-consumption

Cross Correlation Data: GDP - Investment — Sample: 1969 2008
Correlations are asymptotically consistent approximations

i	lag	lead
0	0.7432	0.7432
1	0.5913	-0.0247
2	0.2287	-0.4443
3	-0.1116	-0.4929
4	-0.2086	-0.2344

Cross Correlation Model: GDP - Investment — Included observations: 40
Correlations are asymptotically consistent approximations

i	lag	lead
0	0.7306	0.7306
1	0.2891	-0.2665
2	0.0085	-0.2987
3	-0.2074	-0.2688
4	-0.1800	0.0056

Cross Correlation Data: GDP - Consumption — Sample: 1969 2008
Correlations are asymptotically consistent approximations

i	lag	lead
0	0.8111	0.8111
1	0.6060	0.2473
2	0.1767	-0.1289
3	-0.1905	-0.2630
4	-0.3088	-0.1667

Cross Correlation Model: GDP - Consumption — Included observations: 40
Correlations are asymptotically consistent approximations

i	lag	lead
0	0.3522	0.3522
1	-0.0605	0.7011
2	-0.2252	0.1959
3	-0.1873	-0.1032
4	0.0110	-0.2434

E Sensitivity Analysis

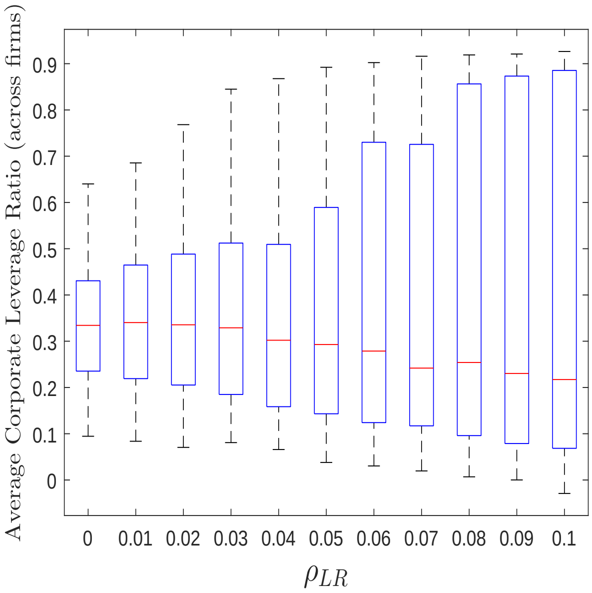
This section presents the results of sensitivity analysis for the parameters of the partner selection mechanism (Figure 14), the investment (Figure 15), and the consumption function (Figure 16). The general rule in the graphs is: The brighter the line, the higher the value of the parameter.[26]

Figure 14a shows the resulting distribution of firms' leverage ratios for different values of the loan rate coefficient ρ_{LR}, in particular their average (red) and their dispersion across firms. The blue box characterizes the area between the bottom and top quartiles. The Figure 14b plots the share of insolvent firms in total firms and the lifetime of the SPV as a function of ρ_{LR}. As expected, the higher the lending rates that firms have to pay according to their leverage ratio, the more self-reinforcing and faster the process of firm concentration is. With an increasing ρ_{LR}, the model results in a higher proportion of insolvent firms in the economy. Hence, the probability rises that the securitized loan portfolio is also affected. Accordingly, the lifetime of the SPV is shorter. Figure 14c shows the effects of increasing search costs after a firm matches an insolvent bank. Nonlinearities occur, but in general, one can conclude that higher search costs lead to lower credit demand. As a result, the probability of future bank failures is reduced in the further course of the simulation run. Figure14d plots the effects of the bank subset size, which determines the opportunities of firm-bank matching. The larger this subset, the higher the probability that a firm will be able to switch to a solvent bank, which stabilizes the banking sector in the long-run.

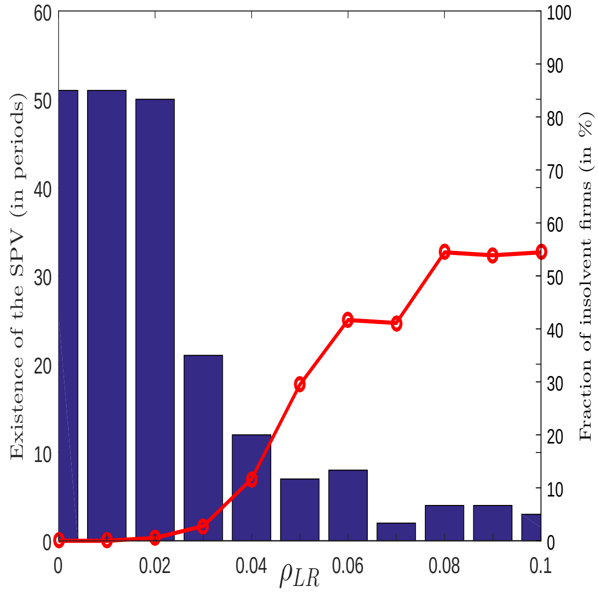
Concerning the coefficients of the investment and consumption function, it is worth to study the incurred costs of credit market frictions in terms of realized investment falling short of the desired level. Figure 15 shows that the higher the propensities to invest, the higher the credit demand, which in turn increases the risk of excessive lending and, in the long term, of bank insolvencies and credit frictions.

The Figures 16a and 16c are striking as they show negative values for high values of the consumption function parameters. Negative values correspond to realized investment exceeding the desired level. These dynamics are not plausible, which illustrates that huge parameter changes endanger the model stability and, as can be verified, the stock-flow consistency of the model. Figure 16b shows that stronger consumption out of deposits stimulates growth, which limits bank insolvencies and thus credit frictions in the further course of the simulation run. The effects are similar for Figure 16d, which shows the results for consumption out of bank shares.

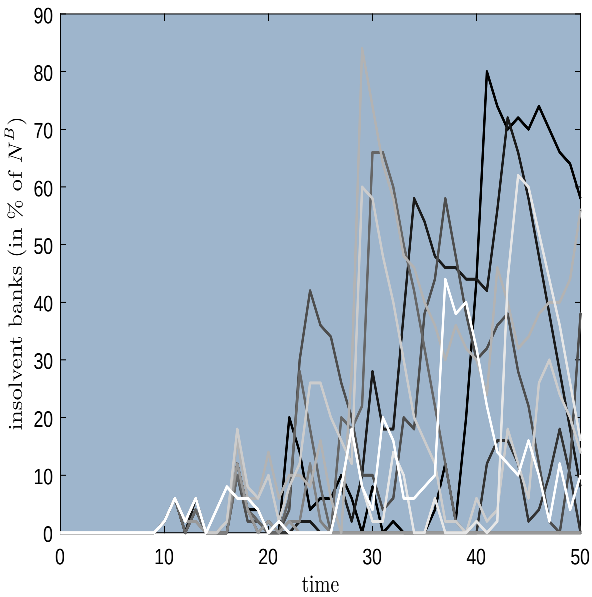
[26] The respective parameter ranges and incremental steps are available on request.



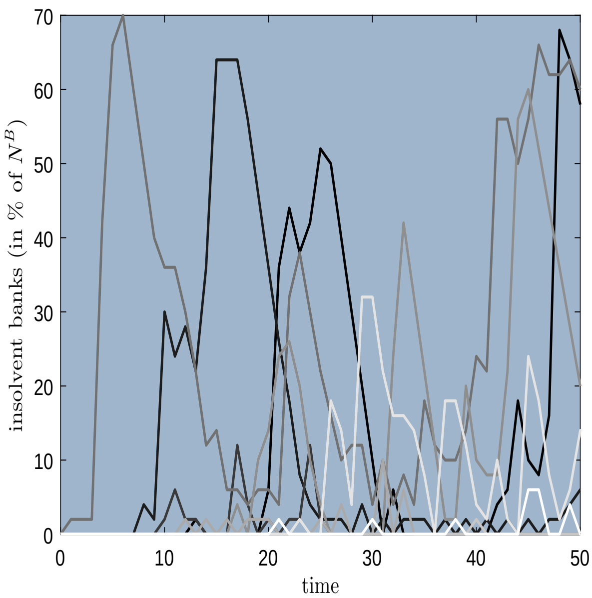
(a) Corporate leverage ratio depending on ρ_{LR}



(b) SPV lifetime depending on ρ_{LR}.

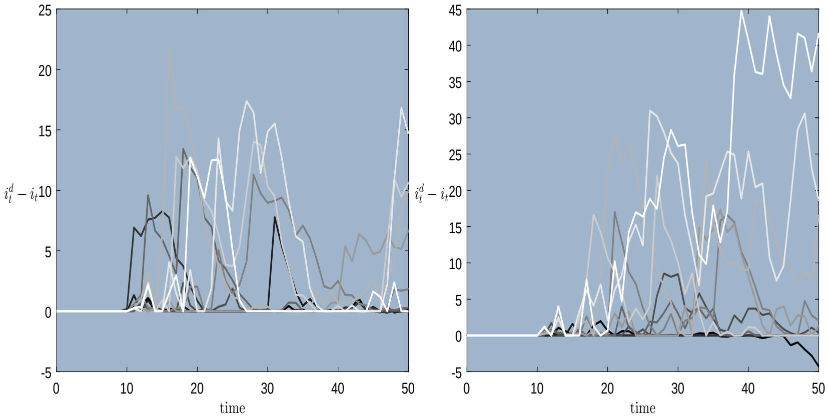


(c) Bank insolvencies subject to changes in $\bar{\mu}^S$



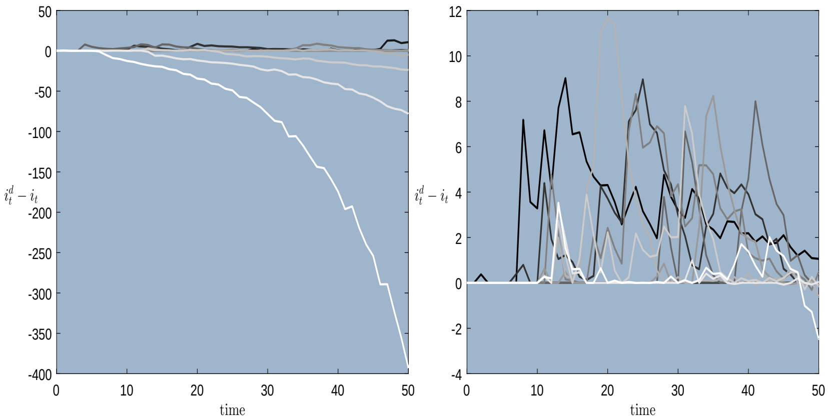
(d) Bank insolvencies subject to changes in M.

Figure 14: Effects of parameter changes in the partner selection mechanism.

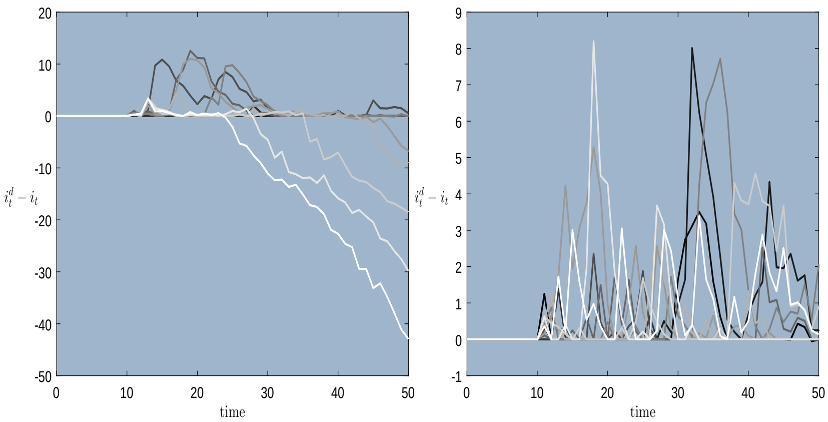


(a) γ_1 (b) γ_2

Figure 15: Credit market frictions with respect to the investment function parametrization.



(a) α_1 (b) α_2



(c) α_3 (d) α_4

Figure 16: Credit market frictions with respect to the consumption function parametrization.

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