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## Interbank loans, collateral and modern monetary policy

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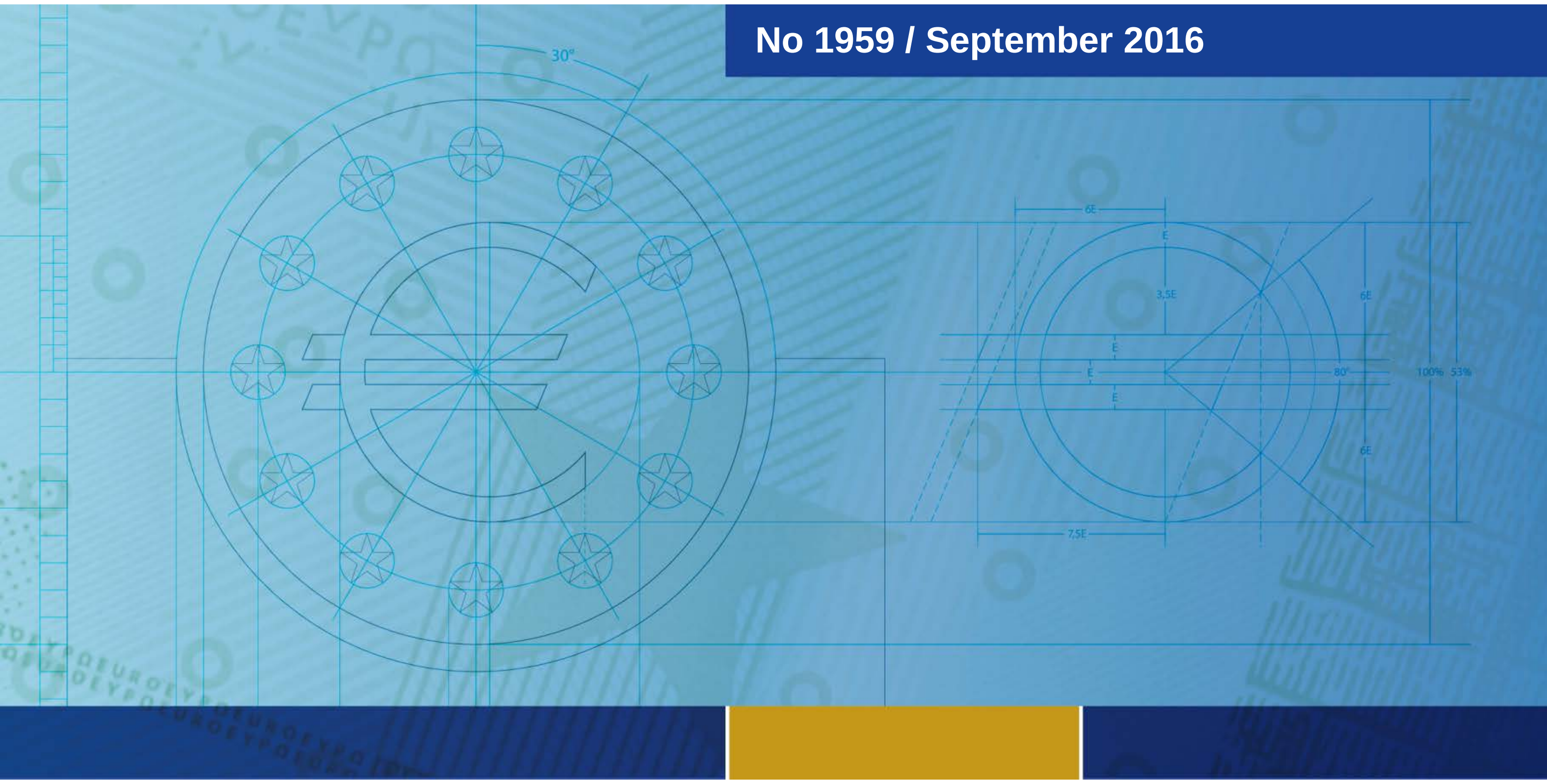

**Abstract**

This study develops a novel agent-based model of the interbank market with endogenous credit risk formation mechanisms. We allow banks to exchange funds through unsecured and secured transactions in order to facilitate the flow of funds to the most profitable investment projects. Our model confirms basic stylized facts on (i) bank balance sheet distributions, (ii) interbank interest rates and (iii) interbank lending volumes, for both the secured and the unsecured market segments. We also find that network structures within the secured market segment are characterized by the presence of dealer banks, while we do not observe similar patterns in the unsecured market. Finally, we illustrate the usefulness of our model for analysing a number of policy scenarios.

*Keywords:* Interbank lending, Agent-based models, Collateral, Repo, Networks
*JEL Codes:* C63, E17, E47, E58

## 1. Non-technical Summary

Interbank markets have attracted a lot of attention in the years following the financial crisis as they played a central role in propagating the distress at that time (Mehrling, 2011). In the aftermath of the collapse of Lehman Brothers both unsecured and secured interbank markets proved to be vulnerable to different types of risk and revealed different shock transmission channels. For secured transactions, debt is guaranteed by an asset whereas unsecured transactions are settled without collateral. While unsecured lending determines clear links between creditors and debtors, secured lending is less susceptible to counterparty risk but heavily depends on the quality of the securities pledged as collateral. Consequently, the malaise in the unsecured market spreads through contagion or the domino channel, while the repo market distress can be perceived as a result of a common-factor shock or the so-called popcorn effect. In recent years, mainly as a result of lack of market confidence and due to the growth of shadow banking, increased volumes of funds are traded in the secured market at the cost of decreased interest in the unsecured market (European Central Bank, 2013).

Consequently, the secured lending market has become one of the focal points of macro-prudential regulators and financial authorities. Due to the complexity of the interbank environment, however, there is no clear-cut analytical framework which allows policy makers to track developments in the interbank lending patterns and evaluate various policy scenarios. This paper aims to contribute to the ongoing discussion on the nature of interbank markets, by proposing a generic methodology to analyse this topic. We develop a novel agent-based model with endogenous network and credit risk formation mechanisms. We consider a set of banks who have to decide in every period how much of their portfolio to allocate into different asset classes and how to fund their positions. Each bank can invest in either bonds, investment projects, or can decide to lend money in the unsecured or secured interbank market. The portfolio allocation decision is made by optimizing the expected risk-return trade-offs across all the asset classes. Apart from equity capital, banks in this model finance their positions through deposits, interbank debt or by receiving liquidity from a central bank at discouragingly high costs. Banks that enter the interbank market are repeatedly matched based on their offered rate, such that the banks with the best offers transact together, until no further trades are possible. Each bank faces leverage and liquidity constraints imposed by a regulator. If the equity capital becomes negative, or if a bank fails to pay back its debt, the bank is declared bankrupt.

The baseline model confirms some stylized facts, such as a large number of small and medium-sized banks in the market as well as lower secured lending rates and higher secured lending volumes compared to their unsecured equivalents.

The policy analysis predicts that the deterioration of the collateral quality is associated with higher interbank rates, both in the unsecured and repo market segments. An exogenous shock to the production sector is associated with a higher number of bank bankruptcies and a sentiment shift towards safer classes of assets. The model illustrates that a central bank forward guidance policy restores confidence in the markets by reducing interbank market volatility. Additionally, the model suggests that if supervisory authorities reduce capital requirements, banks boost their leverage, which translates into more bank failures. On the other side, limited availability of collateral reduces banks debt dependence and consequently decreases the number of banks failures in the system.

Interestingly, the model also generates non-trivial network structures of interbank lending. We observe a natural emergence of dealer banks in the repo segment, whereas the unsecured market is characterized by a number of connections with lower clustering patterns.

The proposed framework can be applied in a variety of policy experiments. For instance, the model provides a potential foundation for stress testing and for studying the propagation of bank-specific shocks.

## 2. Introduction

Interbank markets played a crucial role in propagating the distress during the recent financial crisis (Brunnermeier, 2009). Unsecured lending determines clear links between creditors and debtors, explicitly stating the risk relation. If a debtor defaults, the lender's risk materializes and she has to bear the losses. Once the losses cannot be absorbed anymore, a shock in one institution translates into a shock in the other, leading to a domino effect or contagion.

Secured lending is less susceptible to bank shocks. Once a debtor defaults, the creditor receives the collateral, hampering possible spillover effects. However, secured lending depends heavily on the quality of collateral. In fact, Gorton and Metrick (2012) argue that the recent crisis was ignited by a collateral shock, leading to the so-called "pop-corn" effect in the entire financial system. Importantly, both interbank lending segments are heavily interdependent as, because of the equilibrium condition, there should be no arbitrage opportunities between them.

At the same time, because repo lending is usually backed by securities similar to those used in Open Market Operations (OMO), secured lending serves as a key channel of the monetary policy transmission mechanism (Heider and Hoerova, 2009). Since the unprecedented policy measures taken by the Federal Reserve, the Bank of Japan and the European Central Bank (i.e. collateral policies, asset purchase programs and forward guidance; often referred to as the Modern Monetary Policy (MMP)), the amount of collateral and its valuation have been heavily affected. This indeed raises questions on the management of interbank lending, on the quality of collateral and on the effectiveness of the monetary policy transmission.

This study develops a novel Agent-Based Model (ABM) with endogenous network and credit risk formation mechanisms. By doing so, this paper contributes to the existing literature which assumes exogenous credit risk premiums (Heider and Hoerova, 2009) or exogenous network structures (Gai et al., 2011). In our model the risk premiums in the unsecured and secured market result from the banks' forecasting rules and therefore depend on the past performance of benchmark risk factors and interest rates. Consequently, because credit risk forecasts affect the demand and supply of interbank liquidity, the interbank network can form non-trivial structures, which we confirm in our stylized experiments.

We consider a set of banks who have to decide on the optimal allocation of their assets across asset classes. Banks can choose to invest in bonds, investment projects or can decide to lend out money in the secured or unsecured interbank market. This allocation is made based on the expected returns in each market and the covariance between market returns, in line with the Markowitz (1952) portfolio theory. The expected returns on the bond and interbank markets are predicted with either a trend-following or an adaptive rule. A requirement threshold is invoked on the amount that is kept in reserve and there are restrictions on going long and short. Banks that enter the interbank market are repeatedly matched based on their offered rate, such that the banks with the best offers transact together, until no further trades are possible. At the start of a new period the bond portfolios mature, investment projects end and banks pay back their debt in the interbank market. If at any point the equity of a bank becomes negative, or if a bank fails to pay back its debt, the bank is declared bankrupt.

The baseline results capture the empirically observed dynamics of interbank markets. In particular, we observe that the unsecured market segment is characterized by higher interest rates and lower lending volumes than the secured segment. Additionally, we replicate stylized facts about the distribution of a number of bank balance sheet characteristics. We invoke different scenarios, either exogenous or policy-driven, to the model and analyze their effects on the system dynamics and interbank network structures.

Furthermore, our results confirm basic stylized facts about interbank market dynamics. The model reveals non-trivial interbank network structures, such as clustering patterns and the emergence of dealer banks in the repo market segment. Our model shows that banks might take advantage of deteriorating macroprudential regulations, like higher target leverage ratios, exacerbating financial risks and increasing the number of bank failures.

The model suggests that MMP can significantly change interbank market structures. For instance, an exogenous repo shock, which decreases the quality of collateral securities, can be contained by a central bank asset purchase program both through price and quantity channels. Additionally, forward guidance makes banks more precise in the forecasts, which restores market confidence and shifts asset allocation towards more risky classes, while at the same time reducing bankruptcies.

The organization of this paper is the following. The motivation and a review of the related literature are discussed in Section 3. The model and the trading mechanism are described in Section 4, together with the timing of the markets. Section 5 shows the resulting behavior of the baseline model and Section 6 presents the scenario analyses. Finally Section 7 concludes.

## 3. Motivation and literature review

Interbank markets have attracted a lot of attention in the years following the financial crisis as they proved to exacerbate the financial malaise at that time (Mehrling, 2011). De Andoain et al. (2014) analyze the degree of fragmentation in the euro overnight unsecured money market for a sample of individual loans from the TARGET2 settlement system. They document significant market fragmentation between June 2008 and August 2013. Although the ECB's non-standard policy actions have alleviated market tensions, they report that the fragmentation remains considerable in the European unsecured money market. Bech et al. (2015) focus on changes in lending patterns between fed funds market participants around the time of the Lehman Brothers failure. They confirm the emergence of significant lending patterns in the aftermath of the implementation of the "Interest on Reserves" policy by the Federal Reserve on October 9, 2008. In particular, they find that around the Lehman failure the banks formed separate lending clusters with each other, confirming market fragmentation.

Hatzopoulos et al. (2015) confirm preferential trading patterns in the e-MID market, which is the only electronic interbank market in the euro area and US, between 1999 and 2009. They show that, although preferential trading can be found over the whole period, there is no trend in the number of trading links. Interestingly, Hatzopoulos et al. (2015) also report that in the crisis period the preferential-connection transactions were settled at a higher rate than their non-preferential equivalents.

Filipovic and Trolle (2013) document that unsecured market risk can differ with the term structure of the contracts. Their results suggest that counterparty default risk elevates the interest rates at longer maturities, while liquidity risk plays a major role for short-term maturities.

Because of lack of market confidence, an increased amount of funds has been traded in the secured market at the cost of decreased volumes in unsecured markets, increasing the difference in trading volumes. In 2013 the total amount of unsecured transactions decreased by 34%, while the repo market grew by 17% (European Central Bank, 2013). After the slowdown following the onset of the financial crisis, the value of interbank repos has increased and reached around EUR 5,499 billion by the end of 2013 (European Central Bank, 2014).[1] The crisis revealed that although the repo rates are less susceptible to market distress, the haircuts can be significantly exacerbated (Mancini et al., 2014). This can be the result of either a run on repo (Gorton and Metrick, 2012) or a credit crunch spiral (Krishnamurthy et al., 2014).

In practice, collateralized lending can occur against any type of collateral pledged, as long as both parties (and sometimes the regulator) agree to that. In this study we consider the safest type of collateral, i.e. the General Collateral (GC). GC represents a basket of non-specific government securities with negligible risk (Hördahl and King, 2008).

It is worth to mention that in Europe the repo transactions are legal transfers of titles to collateral, from the seller to the buyer, through outright sales. This makes it easier to book and track on the agent level. On the other side, in the US the transfer of title is more complex as it does not rely on the explicit transfer of ownership rights (Mancini et al.,

[1]Compared to EUR 4,633 billion in 2008 at the time when the financial crisis erupted.

2014). In our model we book the repo transactions as the outright sales of collateral and allow banks to trade freely in the interbank market, being in line with those characteristics.

Because of its increased importance as a source of interbank liquidity, the secured market attracted a lot of attention in the professional literature. Analyzing a large data set of repo transactions, Mancini et al. (2014) find that the central counterparty-based segment of the repo market (where the majority of interbank repos are traded) can act as a shock absorber during a period of distress. They argue that this characteristic is driven by anonymous trading via a central counterparty and reliance on safe collateral. For practical reasons our model assumes a kind of repo market maker, or a central counterparty which allows for a complete exchange of trading information. Nevertheless, our findings suggest a natural emergence of a type of dealer banks, i.e. few banks which are more central in the secured-market network (the unsecured market does not exhibit such strong evidence in favor of dealer banks). Additionally, we pay close attention to the quality of collateral.[2] The haircut values are determined randomly on the interval specified by the policy maker.[3]

Hördahl and King (2008) report that during the financial malaise from mid-2007 until February 2008, the repo market activity became highly concentrated in the shortest maturities and against the highest-quality collateral, compared to the unsecured market in which a shift occurred from longer to shorter term maturity loans. Interestingly, they discover discrepancies between the US and euro-zone repo markets: while the rates in the US declined, they rose in the euro zone. Hördahl and King (2008) attribute this phenomenon to the differences in magnitude of the financial shock in both areas as well as to the availability of sovereign collateral during times of distress.

Interestingly, Gerlach (2011) documents that the behavior of the European repo rate during the last financial crisis reflected not only a sharp worsening of the macroeconomic fundamentals, but was also driven by a change in the ECB's policy reaction function. This underpins the role the repo market played in the monetary policy transmission mechanism at the zero-lower bound. In addition, Greenwood et al. (2015) study the propagation of an exogenous shock in the presence of common banking exposure. They show that if a bank faces a negative equity shock it will sell the assets at any cost, dampening the prices and igniting fire sales at other banks. Fire sales are found to be a substantial shock-amplifying channel, which can put the whole financial system at risk even if the initial shock magnitude

[2] In this study we abstract from triparty repos as it brings an unnecessary complication and amounts to only around 10% of the whole European repo market (European Central Bank, 2012; Mancini et al., 2014). Although the dynamics of the triparty repo was relatively stable in 2007-2009 in the US, the liquidity in the market declined in the mid-2008, signaling similar short-term shock responsiveness to the bilateral market (Copeland et al., 2014).

[3] This is in fact parallel to the eligibility rules prescribed to the Eurex Repo market by the ECB.

is limited (Bluhm et al., 2013; Bluhm and Krahnen, 2014). Aymanns and Georg (2015) additionally argue that the vulnerability of the financial sector to common shocks is stronger if banks pursue similar investment strategies.

As the interconnections between financial institutions are a dominant source of systemic risk (Bluhm and Krahnen, 2014), a lot of attention has recently been paid to the nature and vulnerabilities of interbank networks explicitly. Through the prism of an endogenous network model, Bluhm et al. (2013) find that increased financial stability can come at the cost of lower provision of financial services to the real economy as there is a trade-off between limiting the effects of potential sequential cascades and fostering banks to invest in non-liquid assets. Iori et al. (2006) show that the unsecured interbank network can be unambiguously system-stabilizing if banks are homogeneous in their liquidity or size. They also argue that heterogeneity across banks leads to larger direct and indirect contagion effects, making the whole network structure more fragile. Georg (2013) studies the influence of various network structures on the shock-resilience in a multi-agent interbank market. He documents that central bank policies are only stabilizing in the short term and he argues that, in case of unsecured transactions, random networks are less stable than their money-center equivalents. Interestingly, Nier et al. (2007) show that more concentrated networks can be more prone to systemic risk. For example, with a limited number of banks the default of one bank can more easily trigger knock on defaults.

In addition to unsecured interbank lending, Gai et al. (2011) develop a network model which includes the repo segment as well. They show how a liquidity crisis can occur through contagion in a web of interlinkages. They also document that increased complexity and concentration can amplify interbank network fragility. In addition to Gai et al. (2011), our paper contributes to the discussion on the theoretical nature of the interbank market in two ways. Firstly, by modeling a time-dependent structure of the bank balance sheets it allows tracking the dynamics of the system over time. Secondly, the proposed framework allows simulating a variety of policy scenarios, which we aim at exploring in detail in Section 6.

Due to high complexity of the setting, which incorporates the dynamics of the unsecured and secured interbank transactions, we rely on agent-based techniques. They allow for tracking the micro behavior of atomistic agents through a prism of simple heuristic rules that banks apply in their decision-making processes. In such a setting, the macro dynamics emerges from the aggregation of micro realizations. The biggest advantage of applying agent-based techniques to interbank models lies in the agents' explicit ability to interact. In other words, we can model and track the trading patterns of banks in a more complex environment than it was allowed by standard techniques (see for instance Ashraf et al., 2011).

Agent-Based Models (ABMs) attracted a lot of attention in the years following the crisis due to their success in describing the bubble-like dynamics and interactions among individuals (Delli Gatti et al., 2011). Consequently, the ABMs are being more heavily applied in modeling financial markets and financial interconnectedness.

As an example of an ABM, Thurner (2011) shows how excessive levels of leverage in financial markets can lead to systemic events. Fischer and Riedler (2014) build a banking ABM and reproduce many empirical stylized facts from the financial markets, like a log-normal distribution of bank balance sheets, a positive and convex relation between leverage and size-inequality, and a positive relation between leverage and systemic risk. Caccioli et al. (2014) develop an agent-based network model and show that amplification of financial contagion can occur due to the combination of overlapping portfolios and excessive leverage. In this respect, they argue that too much portfolio diversification can induce significant systemic risk. Hałaj and Kok (2015) propose an endogenous network-formation ABM and study the implications for stress testing and macroprudential policies. They show that properly designed policies make a significant difference through their impact on the network formation and ultimately on the risk of interbank contagion.

Lengnick et al. (2013) develop a monetary ABM and confirm that the interbank market improves macroeconomic stability in normal times but serves as a shock amplifier in times of financial malaise. Bertella et al. (2014) find that with high investor heterogeneity their stylized financial ABM shows excess volatility and kurtosis, similar to real market fluctuations. Bargigli et al. (2014) analyze the effects of leverage- and network-accelerators in the macro ABM of Riccetti et al. (2013), and find that improved economic activity implies a denser network at the cost of increased leverage and increased concentration in the banking sector. They also document feedback loops between financial and firm networks. Financial defaults lead to a more fractioned banking network, forcing companies to concentrate their funding on bigger banks. This, however, increases the default risk of bigger banks, potentially causing more financial fragmentation.

In this paper we apply a modified version of the Hałaj-Kok bank optimization and interbank trading algorithms to secured and unsecured market segments. We allow banks to include the overall riskiness of the interbank market in their decision-making processes (Hałaj and Kok (2015) consider the size of the interbank market). Additionally, we also put different liquidity weights on short- and long-term investments. This makes our model setup more flexible and allows for a more granular analysis of the decision-making processes of banks. Similarly, although our framework draws upon the model proposed by Fischer and Riedler (2014), we introduce several substantial novelties and improvements compared to this model. Firstly, as advertised above, we focus on two money-market lending segments. This induces a more comprehensive structure of bank balance sheets, including bonds, interbank

| Assets | Liabilities |
| --- | --- |
| $L_{I,t}$ | $Dep_t$ |
| $L_{IB,t}$ | $Eq_t$ |
| $B_t$ | $D_{IB,t}$ |
| $Re_t$ | $D_t$ |

Table 1: Stylized balance sheet of an individual bank in period $t$. On the asset side $L_{I,t}$ are the investment loans, $L_{IB,t}$ are the interbank loans, $B_t$ are the bond holdings and $Re_t$ are the reserves. On the liability side $Dep_t$ are the deposits, $Eq_t$ is the equity capital, $D_{IB,t}$ is the interbank debt and $D_t$ are other debt obligations.

exposures and short-term deposits. Secondly, we allow for endogenous network formation through forecasting strategies and consequently estimated demand or supply of interbank liquidity. Thirdly, banks trade with each other using the search-and-match algorithm, which also determines the price of interbank lending explicitly. Fourthly, in our setting the banks' optimization problem distinguishes between short- and long-term investments through liquidity preferences (as suggested by for instance Baltensperger, 1980). Last but not least, we extend the scope of the analysis to cover various shock and policy scenarios, which brings novel results on interbank networks and their shock-susceptibility.

## 4. Methodology

We consider a set of $N$ banks which are endowed with balance sheets consisting of assets and liabilities. On the asset side they hold investment loans, interbank loans, bonds and reserves. Those are funded by deposits, equity, interbank debt and other outside capital debt owed to a central financier.[4] For simplicity, we assume that there is an economy-wide deposit insurance scheme. The balance sheet of an individual bank can be represented in the stylized form of a T-table as shown in Table 1.

In each of the $T$ periods, which in our setting represent quarters, banks have to decide how much of their assets to allocate to different markets. These markets are the bond market, investments, the unsecured interbank market and the secured interbank market. This allocation is based on the expected returns in each market, while keeping the reserves above a requirement threshold. For the bond and interbank markets traders predict the expected

[4]The outside capital debt plays a similar role as in Fischer and Riedler (2014), however, it does not enter the banks' decision-making processes. As a central financier, we assume a central bank which serves as a liquidity backstop.

returns either with a trend-following or an adaptive rule. Moreover, restrictions on going short and long are invoked. In the interbank and bond market the banks with the highest bid and lowest ask price trade together, resulting in a rate that equals the midpoint of the rates of both banks. The demand of one of the two banks is fulfilled and this bank 'leaves' the interbank market. This procedure is repeated until the lowest ask exceeds the highest bid and no further transactions are possible. At the start of the period the bond portfolios are sold, part of the investment projects end and banks pay back the debt in the interbank market that is due that period. If at any point the equity becomes negative, or if a bank fails to pay back their debt, the bank is declared bankrupt. To maintain the number of banks a new bank is revived in the place of the bankrupt bank. With this assumption we do not study the evolution of the number of new banks, but solely the bankruptcy process.

**Deposits**

Banks roll-over short-term deposits at the beginning of each period. To avoid potential complexities resulting from the deposits' dynamics and sudden deposit withdrawals, we assume that there exists an economy-wide deposit insurance scheme. Also, in each period maturing deposits are paid back to the depositors at the risk-free interest rate and new deposits are collected. To make the model consistent with empirically observed characteristics, we assume that the portion of deposits is a *dep* multiple of the equity base at that time plus stochastic noise which follows $N(0, \sigma_{dep})$. The deposits last for a period and are then updated again.

**Bond market**

In the baseline setting, banks can buy an unlimited number of bonds for both investment and collateral purposes. Importantly, the bond market is assumed to be not fully free of risk. We model the bond rate with an initial value $r_{b_0}$ and increments that are normally distributed with mean zero and a minimal standard deviation of $\sigma_b$. This allows capturing the quality of collateral securities and therefore to study its implications for the system dynamics. Each bank predicts the future developments in the bond market based on the heuristics she uses.

**Investments**

In each period banks can do long-term investments, which last for $\tau$ periods. At the beginning of each period a continuum of projects is drawn exogenously, with the average return drawn from a uniform distribution on the support from 0 to $\mu_i$. Projects with above-average expected rates of returns are assumed to be riskier and their risk parameter is drawn from a uniform distribution of $[0, \delta_i]$. Projects with below-average returns are assumed to have on average lower riskiness drawn on $[0, \delta_i/2]$. Each bank $i$ is assigned an investment project, with a yearly expected rate of return and riskiness given above. The riskiness parameter reflects the standard deviation of an investment return, as if it was following a normally distributed process. Before allocating funds the banks are informed about the exact distribution of the rate of return, but the precise realization is not known yet. At the start of the next period $t$ the investment project of period $t - \tau$ ends and the return is added to the reserves. The realized rate of return on these investments is drawn from a normal distribution with the previously known mean and standard deviation.

**Interbank market**

Banks are allowed to trade in the secured and unsecured interbank markets, where in secured trades bonds are used as a collateral security and loans have a duration of $\tau$ periods.[5] The fact that interbank loans are multi-period allows for non-trivial network formation in the model. The per period rate that banks offer or ask equals the bond rate plus a risk premium that equals the expected risk for a given market.

Once the expectations are formed, we adjust the forecasts of the unsecured risk premium by the discounted number of fails in the previous periods to make sure that bankruptcies (i.e. non-repaid loans, and not only market volatility) are reflected in the risk estimates. Nevertheless, to avoid spurious distortions we keep this adjustment small so that the adjusted and non-adjusted forecasts are not statistically different from each other for a low number of fails. This guarantees that the number of bankruptcies enters the bank's decision-making process, however, it does not shut down the unsecured market when the number of fails is of minor concern. The correction for fails takes the form of the change in the discounted number of fails divided by the number of banks, where the number of fails is discounted by the factor $q$. [6]

The expected risk is determined by using either a trend-following or an adaptive rule, taking into account the past performance of the rules. In both markets the interbank rates are then equal to the weighted averages of all the rates at which transactions were closed, where the weights are determined by the size of the transactions. In the initial $\tau$ periods, where no transactions happen yet, the rates are drawn from a uniform distribution on the interval $[r_{b_0}, r_{b_0} + 2\sigma_b]$.

[5] We keep the duration of the interbank loans similar to investment loans as it clearly distinguishes between short- and long-term assets. It is however possible to introduce a variety of loan maturities which we intend to explore in detail in future studies.

[6] At this stage we keep this sensitivity constant, however, it can be endogenized to meet the market sentiment of banks' forecasts.

**Allocation strategy**

Each bank determines how much to allocate into each market segment using the optimal portfolio selection strategy (Markowitz, 1952). In each period banks form their expectations about the returns in each market segment, i.e. bonds and interbank trading. Moreover, the distribution of returns on investment is known to all banks. They keep a portion of reserves on their balance sheet equal to the amount of the minimum reserve requirements $re_{min}$ and they invest the remainder to maximize their Constant Relative Risk Aversion (CRRA) next-period utility function, where the risk is represented by the variance-covariance matrix between all the markets (Bodie et al., 2008).[7] Since in this setting we have two types of classes, i.e. short- and long-term, we exploit the courtesy of the CRRA function and allow for different risk-aversion weights, depending on maturity (see for instance Baltensperger (1980). The maximization problem of each bank becomes

$$\max_{w} w^T E_t r_{t+1} - (\gamma \circ w)^T \Sigma_t w, \tag{1}$$

where $w = (w_b, w_i, w_{IB}^U, w_{IB}^S)^T$ are the weights for each market segment, $r_t = (r_{b,t}, r_{i,t}, r_{IB,t}^U, r_{IB,t}^S)^T$ is the vector of expected returns in each segment, $\gamma = (\gamma_s, \gamma_l, \gamma_l, \gamma_l)^T$ is a vector of risk aversion levels and $\circ$ denotes the Hadamard product. Risk aversion is divided into two groups, depending on investments' maturity: $\gamma_s$ reflect the risk aversion towards short-term assets and $\gamma_l$ towards long-term assets. Following Georg (2013), the former is uniformly drawn from $[\gamma_{min}, \gamma_{max}]$ and the latter is the maturity-dependent multiple of the former and takes the form $\gamma_l = \tau\gamma_s/2$. Accordingly, $\Sigma$ is the variance-covariance matrix between the returns. In line with with Fischer and Riedler (2014) we let each element of the $\Sigma$ matrix evolve as

$$\sigma_{i,j,t} = \theta_{FE}(E_{t-1}r_{i,t} - r_{i,t})(E_{t-1}r_{j,t} - r_{j,t}) + (1 - \theta_{FE})\sigma_{i,j,t-1}, \tag{2}$$

where $\theta_{FE}$ is the memory parameter and the indices $i$ and $j$ run over all the market segments. We additionally restrict the weights to be in the region $[0,\lambda]$ except for interbank weights which are allowed to fall within $[-\lambda,\ \lambda]$, with $\lambda$ being the target leverage ratio set by a policy maker. In fact, allowing banks to go short means that they borrow in a particular market, which is a driving force of the trading algorithm described below. In general, leverage constraint can be rather applied to the overall size of the balance sheet. Nevertheless, due to sequential trading banks need to know how much of the funds they are allowed to trade before entering the market. Applying the leverage constraint at more granular level does not violate the aggregate leverage constraint but contains the volatility of particular asset markets and

[7]For simplicity the reserves are assumed to bear no interest, but this does not have any qualitative effect on the results.

makes banks' decision-making processes consistent with macroprudential regulations.

The rationale behind the trading mechanisms is the following. In each period a bank forecasts the interest rates in the secured and unsecured interbank market and the bond market. If the forecasts for a given market are relatively low it means that the bank will be better off borrowing in this market and lending out in markets which offer higher rates of return, taking into account the relative riskiness of both markets.

Technically, if the bank decides to go long in a given market, it reallocates the reserves. If it goes short, it increases its liabilities. The weights are then translated into absolute exposure with respect to available liquidity a bank collected from a given period's revenues. We calculate the optimal weights by non-linear programming using the Nelder-Mead algorithm (see Nelder and Mead, 1965).

**Trading mechanism**

After banks have entered the interbank market, trades are determined by selecting banks with the most favorable rate first. The bank that offers the highest rate and the bank that asks the lowest rate are matched, and they trade at a price equal to the midprice of bid and ask, following the principle of a market maker. The amount traded equals the minimum demand of both banks. The bank with the lowest demand leaves the market and this mechanism is repeated until no further trades are possible. At that moment, the lowest remaining ask price exceeds the highest offer and the market is cleared. In the unsecured market the borrower expands his reserves and debt by the borrowed amount and the lender shifts the reserves to loans (see Table 2). In the secured market the borrower expands his reserves by the borrowed amount, but has to return bonds to the lender that equal the value of the borrowed amount multiplied by a haircut $h$ (see Table 3). The trade cannot exceed the available collateral, denoted by $coll$. The minimal haircut level is drawn from the right tail of the normal distribution that is truncated at 1 and has a mean of one plus the rate of the lender, and a standard deviation of $h_s$. We assume that banks behave non-strategically when it comes to required haircut levels and they are only concerned about the expected profits on a given loan. This allows to treat haircuts as insurance against foregone profits, and therefore relate the haircut levels to the level of interest rates. In equilibrium the profits from repaid loans should be equal the collateral value on non-repaid loans, so that the haircut value should represent the interest rate paid back on the loan upon maturity. We allow for a degree of deviation in the haircut to better correspond to the market dynamics and individual preferences. Subsequently the average interbank rate is calculated for both markets, where the weights equal to the size of the transactions.

We assume that banks do not exhibit any strategic behavior on the interbank market and thus their rates equal their forecasts. Chatterjee and Samuelson (1983) show that, in a two-player setting with incomplete information about the expected risk of the counterparty, the Nash-equilibrium consists of offering a linear transformation of the own expected risk. For example, when expected risks are uniform on [0,1], the optimal offer equals a proportion of the own expected risk, and opposite for the asking price. Under some constraints, the same holds for multi-agent settings, which are studied in Cervone et al. (2009). This result holds for traders that are homogeneous in the sense of the distribution of their expectations and knowledge of other market participants. This implies that adding strategic behavior would slightly decrease the magnitude of trading, but not the remainder of the trading mechanism. In fact our trading algorithm is similar to the one proposed by Hałaj and Kok (2015).

In the booking procedure we closely rely on the money market description in Stigum and Crescenzi (2007) and Mehrling (2011). Both trading mechanisms are summarized as T-accounts in Tables 2 and 3. Since the interbank transactions have maturity of $\tau$, we present the repayment procedure at the period $t+\tau$. It can be readily observed that in the unsecured market of our model, the bank who lends out money to the production sector (see the debtor description in part (a) of Table 2) expands its balance sheet, whereas the interbank lender reshuffles its assets (Mehrling, 2011).[8] On the other side, we book the repo transaction as a sale of securities with a promise to repurchase in the next period. Therefore, it does not result in an immediate expansion of the balance sheet, but serves rather as a shift of debt from one period to another (Stigum and Crescenzi, 2007).

For clarity reasons in the booking diagrams we abstract from any swap procedures, like for instance reserves being swapped into cash or *vice versa*, and therefore assume that all the model transactions are within the banking clearing system. This assumption does not need to be problematic as it does not alter any of the model parameters and allows for better tractability of bank balance sheets.

Due to the sequential trading procedure, it is possible that at the end of trading the bank's total demand for interbank funds will not be satisfied or that the supply of interbank liquidity will not be fully absorbed. This is possible because a bank can be a borrower in one market segment and a lender in the other, depending on its perceived market characteristics. When a bank has a funding gap it has to compensate for this by borrowing from a central bank. This increases its other debt obligations (variable $D_t$ from Table 1). For simplicity, we assume that this liquidity backstop is always granted by a central bank at a discouragingly high interest rate $r_{LB}$.[9] The Markowitz allocation strategy function does not allow banks to

[8] The increased amount of reserves are supposedly allocated into interest-bearing instruments, of which a bank expects to bring a higher return than $r^U_{IB,t}$.

[9] Alternatively one can assume a quantity constraint for this type of financing. Our simulations suggest

a) Granting the naked loan in period $t$ at a $\tau$-period rate $r^U_{IB,t}$.

| Debtor | | Creditor | |
|---|---|---|---|
| Assets | Liabilities | Assets | Liabilities |
| $L_{I,t}$ | $Dep_t$ | $L_{I,t}$ | $Dep_t$ |
| $L_{IB,t}$ | $Eq_t$ | $L_{IB,t}[+\mathrm{X}]$ | $Eq_t$ |
| $B_t$ | $D_{IB,t}[+\mathrm{X}]$ | $B_t$ | $D_{IB,t}$ |
| $Re_t[+\mathrm{X}]$ | $D_t$ | $Re_t[-\mathrm{X}]$ | $D_t$ |

b) Paying back the loan in period $t + \tau$ at a $\tau$-period rate $r^U_{IB,t}$.

| Debtor | | Creditor | |
|---|---|---|---|
| Assets | Liabilities | Assets | Liabilities |
| $L_{I,t+\tau}$ | $Dep_{t+\tau}$ | $L_{I,t+\tau}$ | $Dep_{t+\tau}$ |
| $L_{IB,t+\tau}$ | $Eq_{t+\tau}[-r^U_{IB,t}\mathrm{X}]$ | $L_{IB,t+\tau}[-\mathrm{X}]$ | $Eq_{t+\tau}[+r^U_{IB,t}\mathrm{X}]$ |
| $B_{t+\tau}$ | $D_{IB,t+\tau}[-\mathrm{X}]$ | $B_{t+\tau}$ | $D_{IB,t+\tau}$ |
| $Re_{t+\tau}$ $[-(1 + r^U_{IB,t})\mathrm{X}]$ | $D_{t+\tau}$ | $Re_{t+\tau}$ $[+(1 + r^U_{IB,t})\mathrm{X}]$ | $D_{t+\tau}$ |

Table 2: Booking procedure for the unsecured transactions in the interbank market. The nominal value of the granted loan is X. The adjustment terms are put in squared brackets. The unsecured rate is a $\tau$-period rate.

a) Granting the secured loan in period $t$ at a $\tau$-period rate $r^S_{IB,t}$ and haircut $h$ †.

| Debtor | | Creditor | |
|---|---|---|---|
| Assets | Liabilities | Assets | Liabilities |
| $L_{I,t}$ | $Dep_t$ | $L_{I,t}$ | $Dep_t$ |
| $L_{IB,t}$ | $Eq_t[-h\text{X}]$ | $L_{IB,t}$ | $Eq_t[+h\text{X}]$ |
| $B_t[-(1+h)\text{X}]$ | $D_{IB,t}$ | $B_t[+(1+h)\text{X}]$ | $D_{IB,t}$ |
| $Re_t[+\text{X}]$ | $D_t$ | $Re_t[-\text{X}]$ | $D_t$ |

b) Paying back the loan in period $t+\tau$ at a $\tau$-period rate $r^S_{IB,t}$ and haircut $h$.

| Debtor | | Creditor | |
|---|---|---|---|
| Assets | Liabilities | Assets | Liabilities |
| $L_{I,t+\tau}$ | $Dep_{t+\tau}$ | $L_{I,t+\tau}$ | $Dep_{t+\tau}$ |
| $L_{IB,t+\tau}$ | $Eq_{t+\tau}$ $[+(1+h)\text{X}^* - (1+r^S_{IB,t})\text{X}]$ | $L_{IB,t+\tau}$ | $Eq_{t+\tau}$ $[+(1+r^S_{IB,t})\text{X} - (1+h)\text{X}^*]$ |
| $B_{t+\tau}[+(1+h)\text{X}^*]$ | $D_{IB,t+\tau}$ | $B_{t+\tau}[-(1+h)\text{X}^*]$ | $D_{IB,t+\tau}$ |
| $Re_{t+\tau}$ $[-(1+r^S_{IB,t})\text{X}]$ | $D_{t+\tau}$ | $Re_{t+\tau}$ $[+(1+r^S_{IB,t})\text{X}]$ | $D_{t+\tau}$ |

Table 3: Booking procedure for the secured transactions in the interbank market. The nominal value of the granted loan is X, the current value of the granted loan includes changes in the value of the bond rate and is denoted as X$^*$, and $h$ represents the haircut level. The adjustment terms are put in squared brackets. The secured rate is a $\tau$-period rate.

breach the leverage constraint $\lambda$. If a bank borrows more money than it lent in the interbank market, the liquidity surplus is invested in the production loans and bonds, in proportion to their direct exposure in that period.

**Expectations**

We include two types of forecasting strategies in the model to all the risk variables: a trend-following ($E^T$) and an adaptive ($E^A$) rule. The risk variables are predicted separately for the unsecured and secured transactions. Banks also form forecasts on the future development of the bond interest rate, reflecting the concerns about possible policy actions and economic performance. We allow agents to predict the risk premiums of the interbank markets rather than interest rates per se, as this allows capturing the risk patterns explicitly. It also makes the banks behave more like risk traders as observed in modern financial literature (Stigum and Crescenzi, 2007). Since the bond rate is a benchmark for the calculation of the risk premiums, in the bond market banks forecast the development of interest rate movements explicitly. In the first period the continuum of agents is split into two equal parts and from the second period on the agents are allowed to switch between their forecasting rules.

Since the trading happens in the same period, we keep the contemporary notation, however, we treat the forecasts as forward-looking variables taken in expectations $E$. The adaptive agents follow a simple adaptive rule of the form

$$E^A_{i,t} v_t = \omega \bar{v}_{t-1} + (1-\omega) E_{i,t-2} v_{t-1} + \varepsilon_{1,t}, \tag{3}$$

where $v_t$ is the variable corresponding to either the secured, unsecured or the bond market, $\omega$ is the memory parameter and $\varepsilon_{1,t}$ is the noise term that follows $N(0, d_1)$. More specifically, for the interbank markets the risk premium $v_t$ is calculated as the difference between the realized interbank rate (secured or unsecured) and the benchmark rate, and hence $v_t$ is generally positive. In the bond market $v_t$ corresponds to the realized interest rate on bonds. The rule states that the next period's forecast equals the average realization augmented by the scaled forecasting error. If a forecast was too large, it will be updated downwards, whereas if it was too small the opposite will happen. This is a version similar to the rule in Fischer and Riedler (2014).

that such liquidity constraints increase bankruptcies, but they are dependent on the exact specification of the banks' responses to such policies. We therefore consider this an interesting topic for investigation and leave it for further research.

On the other hand, trend-followers apply a simple trend-extrapolation rule of the form

$$E^{T}_{i,t}v_t = v_{t-1} + g(v_{t-1} - v_{t-2}) + \varepsilon_{2,t}, \tag{4}$$

where $v_t$ has a similar description as above, $g$ is the strength of the trend-following behavior and $\varepsilon_{2,t}$ follows $N(0, d_2)$. According to this rule, the change in rate over the previous period will partly proceed. Similar types of adaptive and trend-following rules are advocated in Hommes (2011, 2013).

At the start of a period banks can switch between forecasting rules, based on the squared forecasting error. The error for both the adaptive (A) and the trend-following (T) rule is calculated as

$$\mathrm{Er}^{*}_{i,t} = -(v_{t-1} - E^{*}_{i,t-1}v_{t-1})^2, \tag{5}$$

where $* \in \{A, T\}$. An agent sticks to its current forecasting rule $* \in \{A, T\}$ with probability

$$\frac{\exp\left(\beta \mathrm{Er}^{*}_{i,t}\right)}{\exp\left(\beta \mathrm{Er}^{A}_{i,t}\right) + \exp\left(\beta \mathrm{Er}^{T}_{i,t}\right)}, \tag{6}$$

where $\beta$ is the intensity of choice parameter that determines how fast agents select the better performing rule. Low values of $\beta$ in this discrete choice model indicate that the performance of the rule has a low impact on the probability of being selected.

**Interbank network formation**

Both the secured and the unsecured interbank market constitute an endogenous network. A priori banks do not prioritize counterparties, but are only concerned with the eventual transaction price, i.e. rate. However, this still leads to non-arbitrary network formation, firstly because of a difference in size of banks and therefore a difference in demand on the interbank market, and secondly because of expectations of the risk premiums. In subsequent periods banks tend to use the same expectational rule, and hence banks that posted a favorable offer on the interbank market tend to do so again in the next period. We also considered a version of the model in which, in the unsecured interbank market, lending banks prioritize counterparties that are less risky in terms of their leverage. In the current model this has been left out because, even though this induces a higher clustering, it is preferred to leave the network formation to be expectation-endogenous in terms of counterparties.

**Timing**

The timing of the model is the following. At the beginning of each period agents observe the market's interest rates from the previous period and they update their forecasting type, depending on the heuristics' performance. In the next stage the profits from the maturing investments are realized and deposits are updated. The realized returns on the investment loans are drawn from a normal distribution with the mean and standard deviation that were known to the bank at the moment of investing. The returns are then added to the reserves, together with the returns on bonds. Equity is adjusted accordingly. At this stage, if the equity falls below zero a bank does not declare bankruptcy yet as it is possible that profits from the interbank market could save a troubled bank.

In the next step banks realize profits and losses from the interbank transactions. Because banks do not fail until their liabilities exceed their assets, and to account for possible cascade effects, we model the clearing algorithm as an iterated process. Banks use their reserves to pay (part of) their debt. When the bank has borrowed funds from multiple counterparties, the repayment is proportionally distributed over them. This ensures that when a bank ultimately fails, it has paid back its debt proportionally over the counterparties. At the moment that all banks with outstanding debt have ran out of reserves, these banks are declared bankrupt. If a bank cannot pay a part of its debt, it will have adverse effects on its creditors which will only recover part of the funds. In the secured market the creditor will keep the remaining fraction of collateral with effectively limited effects. In the unsecured market those unpaid obligations are calculated as creditors' losses and put directly on their balance sheets. If because of this a creditor does not have sufficient funds to cover its own obligations, it will go bankrupt as well, creating a possible domino effect in the market.

The profits from unsecured transactions are booked as the returns, i.e. the interest rate at which the transaction took place, on direct exposure to the debtor. The returns on the collateralized loans are booked as the returns on loans, and not collateral. If the secured-market transaction is paid, the collateral returns to the debtor bank, which then receives the returns on these bonds. Since there is a maturity mismatch between the interbank and bond markets, we assume that collateral securities are rolled by the creditor bank over $\tau$ periods and pay the discounted interest for the debtor upon the return of collateral.[10] At this time any bank with negative equity is declared bankrupt.

In the next stage, banks form forecasts on the expected risk and returns in all the markets. Given the expectations the bank chooses their optimal portfolio allocation and enters the interbank market. In the baseline scenario, we assume that the investment projects and

[10]Otherwise the creditor bank could take a strategic advantage of higher-interest securities and keep the collateral. It would limit the incentives to trade in the secured market so that we keep the setting simple and assume that for repo contracts the returns on pledged collateral are frozen until the maturity date. If a bank does not repay the secured loan, the securities together with their discounted interests belong to the creditor bank.

bonds are exogenous and come in ample amount. The interbank transactions are then realized by the search-and-matching algorithm described above.

At the end of each period the interbank rates are calculated as the weighted average of all transactions and all the balance sheet variables are stored. A simple timeline can represent the model's behavior:

1. update forecasting strategies,
2. update deposits,
3. realize profits from maturing investment loans and bonds,
4. realize profits from maturing interbank loans and declare bankruptcies,
5. form risk and return expectations,
6. calculate the optimal portfolio allocation,
7. trade in the interbank market,
8. store the variables and proceed to the next period.

## 5. Baseline results

We calibrate the model based on the international standards, German aggregates and in accordance with the literature on the topic. The exact calibration values together with their description can be found in Table 4.

The minimum reserve requirement, or the required rate of reserves, is set in accordance with the statutory minimum of the Federal Reserve Board (FRB).[11] The target leverage ratio corresponds to the 6% leverage ratio also advertised by the FRB.[12] Nevertheless, we monitor the system's dynamics under an increased and decreased leverage target in our policy scenarios. The interest rate on bonds is equal to the average yield on German general government bonds, averaged over quarterly intervals from January 2000 until April 2015. The standard deviation of increments in the bond rate is chosen to be marginal, to provide some dynamics with little effects on portfolio allocation. The liquidity backstop is chosen at a relatively high level to prevent arbitrage opportunities. The deposit-to-equity ratio is

[11]We also experimented with lower reserve requirements to correspond, for instance, to the minimum reserve ratio in the euro area. Besides a moderately more rapid growth of the bank balance sheets, all the results were preserved.

[12]In fact the 6% leverage ratio in our setting is consistent with the proposed Basel III framework under which the leverage ratio should be above 3% plus additional capital buffers, which depending on the bank's systemic importance, can range from 2.5% to 3.5% (statutory 2.5% plus additional 1% surcharge of loss-absorbing capacity). This number is also consistent with the debt-to-equity ratio of German banks, which in 2007 was approximated at around 16.2 according to the sample of 1549 German banks from the Bankscope database.

| Variable | Description | Value |
|---|---|---|
| | Central bank and policy variables | |
| $re_{min}$ | minimum reserve requirement | 0.08 |
| $\lambda$ | target leverage level | 16.7 |
| $r_{LB}$ | liquidity backstop interest rate | 0.1 |
| $r_{b_0}$ | initial interest rate on bonds | 0.033 |
| $\sigma_b$ | standard deviation of the bond rate | 10bp |
| $coll$ | amount of available collateral (bonds) | $\infty$ |
| | Portfolio choice | |
| $\gamma_{min}$ | minimal risk aversion | 1.76 |
| $\gamma_{max}$ | maximal risk aversion | 2 |
| $\theta_{FE}$ | memory parameter in variance-covariance matrix | 0.5 |
| $\mu_i$ | max. expected return from the investment projects | 0.067 |
| $\delta_i$ | max. standard deviation of the investment returns | 0.256 |
| $q$ | discount factor of fails in the unsecured market | 0.5 |
| $h_s$ | haircut standard deviation | 0.01 |
| $dep$ | mean deposits to equity ratio | 10.55 |
| $\sigma_{dep}$ | standard deviation deposits | 0.05 |
| | Expectations | |
| $\omega$ | memory parameter in fundamental forecasting rule | 0.5 |
| $g$ | strength of trend-following behavior | 0.25 |
| $d_1$ | st. deviation of the noise term in fundamental rule | 50bp |
| $d_2$ | st. deviation of the noise term in chartists' rule | 50bp |
| $\beta$ | intensity of choice parameter | 1 |
| | Initial values randomization | |
| $c_1$ | lower bound of the initial secured and unsecured rates | 0.033 |
| $c_2$ | upper bound of the initial secured and unsecured rates | 0.035 |
| $k_1$ | st. deviation of the initial variance-covariance matrix | 0.5 |
| | General model parameters | |
| $N$ | number of banks | 100 |
| $T$ | number of periods | 500 |
| $S$ | number of simulations | 200 |
| $T_{init}$ | initial periods | 100 |
| $T_s$ | shock period | 300 |
| $T_{year}$ | periods per year | 4 |
| $\tau$ | length of investment and interbank loans | 4 |

Table 4: Calibration parameters. Rates are given on a yearly basis.

calibrated on a sample of 1549 German banks in 2013, with low dispersion values to limit possible distortions.

Risk aversion for the short-term assets is set according to Georg (2013). The scaling transformation of the risk-aversion on the long-term assets is chosen simple, but it has no effect on the aggregate dynamics of the results. The memory parameter equally balances the old with the new dependence structures in the variance-covariance matrix. The expected returns and the volatility of investment projects are chosen in line with the average annual values of the DAX index over the years 2000 to 2014. This guarantees incentives for banks to invest in all the asset classes. Consequently, we calibrate the model to match the quarterly dynamics, i.e. long-term investments correspond to the annual returns and short-term to quarterly payments (or for each long-term investment there are four short-term ones). The discount factor on fails is set at one half and the haircut levels are chosen to meet the haircut patterns from the pre-crisis period (Stigum and Crescenzi, 2007).

The expectation parameters are set to make both forecasting rules similar so that the dynamics of the system is not driven entirely by one type of beliefs. Similarly, the errors and the intensity of switching are chosen to make possible biases marginal. The initial values are set to kick-start the algorithm and their influence quickly disappears.

In the first period we assume that the size of each bank's balance sheet equals 1. Half of the agents are using the chartist strategy whereas the others are adaptive. The initial expectations on production loans are drawn from the uniform distribution parameterized with $\mu_i$ for the expected returns and $\delta_i$ for the expected risk. The initial period's allocation of production loans is calculated based on the expected returns and risk using the optimal portfolio methodology, since there is no interbank trading in the initial $\tau$ periods. Until period $\tau$ the investment projects yield returns which are randomized and averaged over their expectations in the previous periods. The reserves are set to the minimum requirement level $re_{min}$ and the rest of the assets are allocated to bonds. On the side of the liabilities, each bank starts with the target leverage level $\lambda$ so that the initial period equity is equal to $1/\lambda$ times the sum of debt and deposits. There is no interbank debt in the first $\tau$ periods.

Also in the first $\tau$ periods we allow for some random dynamics in the interbank rates and correlation between different market rates in the variance-covariance matrix. In particular, the risk components in the unsecured and secured interbank market are drawn from the uniform distribution on the interval $[c_1, c_2]$. Each entry of the initial variance-covariance matrix is drawn from the normal distribution with a mean of 0 and a standard deviation of $k_1$, truncated between -1 and 1.

We burn-in the first $T_{init} = 100$ periods and let the model run until period $T = 500$. To make sure that the results are not an effect of random events, we run the model $S = 200$

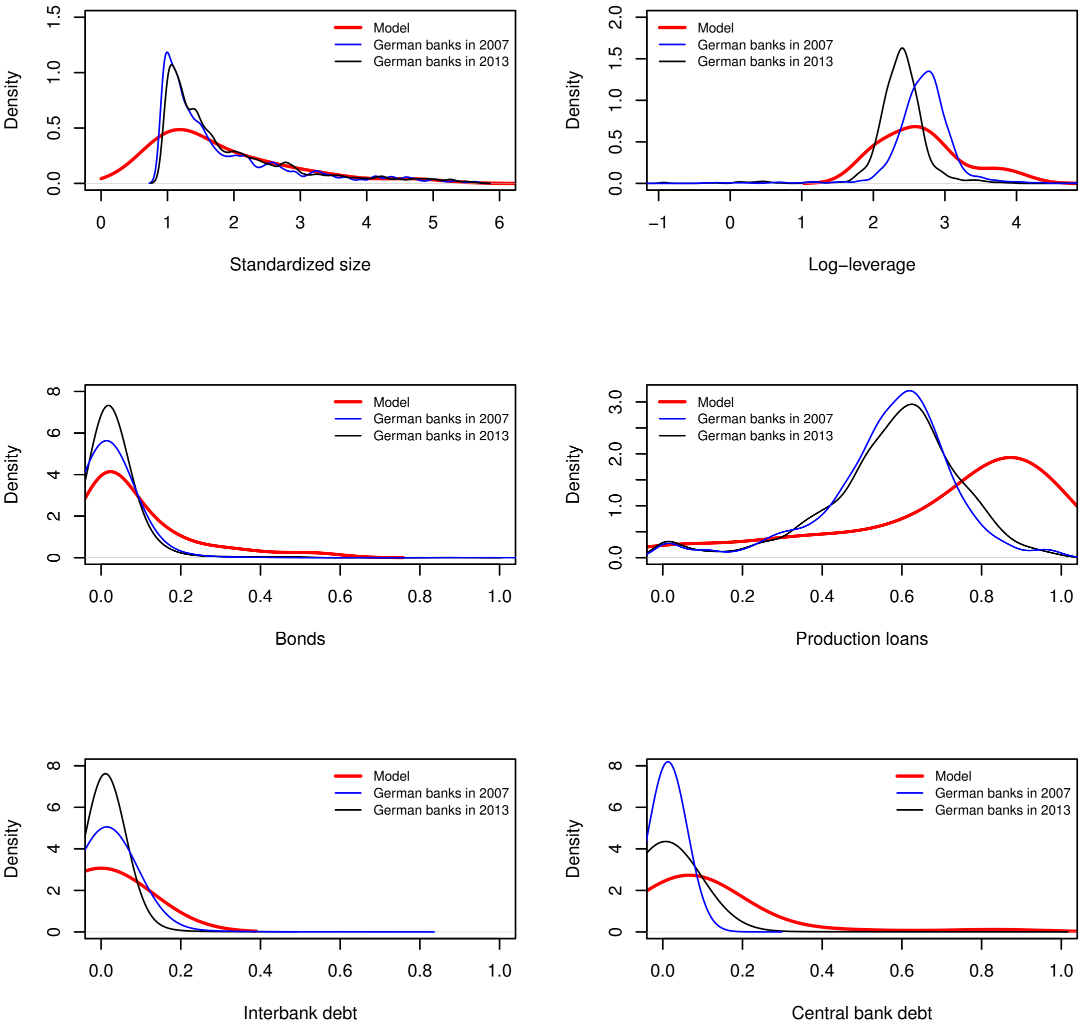


Figure 1: The distribution of the standardized bank balance sheets, log-leverage ratios, the fractions of bond holdings and production loans to total assets and the fractions of interbank debt and central bank debt to total liabilities after 500 periods under the baseline scenario and the empirical distribution of German banks' equivalents in 2007 and 2013. For the empirical representations we respectively consider banks' total assets, liabilities-to-equity ratio, fractions of government bond holdings and net loans to total assets, and fractions of 3- to 12-month unsecured interbank debt and exposure to central bank to total liabilities. Source: Bankscope.

times and calculate the averages.

Fig. 1 shows the distribution of bank balance sheets, log-leverage levels, bond holdings, investment loans, interbank debt and central bank debt from a random simulation after 500 periods (100 burn-in and 400 model periods). We compare the distributions with empirically observed data, obtained from a sample of German banks in 2007 and 2013. The data include total assets, liabilities-to-equity ratio, holdings of general government securities relative to total assets, the fraction of net loans to total assets, the share of unsecured medium-term (3- to 12-month) interbank debt in total liabilities and the share of central bank exposure to total liabilities.[13] For transparency, in the plots we smooth the densities by the optimal biased cross-validated bandwidth, but due to data irregularities we apply larger bandwidth values for the interbank and central bank debts. The data comes from Bankscope and covers a sample of 1549 banks in each year.

It can be readily observed that the model reproduces the highly skewed distribution of bank balance sheets observed in reality. This finding is indeed consistent with the results on the log-normal distribution of bank balance sheets from an ABM developed by Fischer and Riedler (2014). The model-implied distributions are also relatively flatter than the empirical equivalents. However, this is a direct consequence of the lower number of banks used in the simulations and the bank-recovery procedure after a bank is declared bankrupt. Furthermore, the model seems to capture the distribution of the leverage ratio (here calculated as a liabilities-to-equity ratio), although again due to the lower number of banks it is relatively flatter. On the asset side, the distribution of bond holdings is well represented in the model. The proportion of model-implied production loans is modestly larger than the empirically observed data. This can be a consequence of scarcity of asset classes in the model or the loan origination fees and operating expenses which build the difference between the net and gross loan amounts and are not captured in the model explicitly. On the side of the liabilities, the model represents the distribution of the medium-term interbank exposure, although it slightly overshoots the funding from the central bank.

To get a more comprehensive view on the dynamics of the model, we present the evolution of the interbank market and bank balance sheets over time.[14] As a complement, we present basic network statistics of the interbank linkages, including the average Kleinberg hub centrality, the total number of interbank connections (the degree of a bank in the network), the clustering coefficient and the number of non-connected banks, i.e. so-called islands. Hub centrality is an application of the eigenvector centrality to directed networks.[15] It therefore measures the relative importance of a node in the network, where importance is defined as receiving many links from other important vertices (Kleinberg, 1999). The degree of a node measures the number of incoming and outgoing connections. The clustering coefficient measures the probability that two vertices which are both connected to a given node are also

[13]To be able to compare the model and empirical observations we standardize the size of the bank balance sheets by the normal transformation.

[14]Since we use $T_{init} = 100$ burn-in periods, the timing in the charts goes from 100 to 500.

[15]With eigenvector centrality nodes outside strongly connected components or their out-components have zero centrality, exactly what hub centrality aims to correct for.

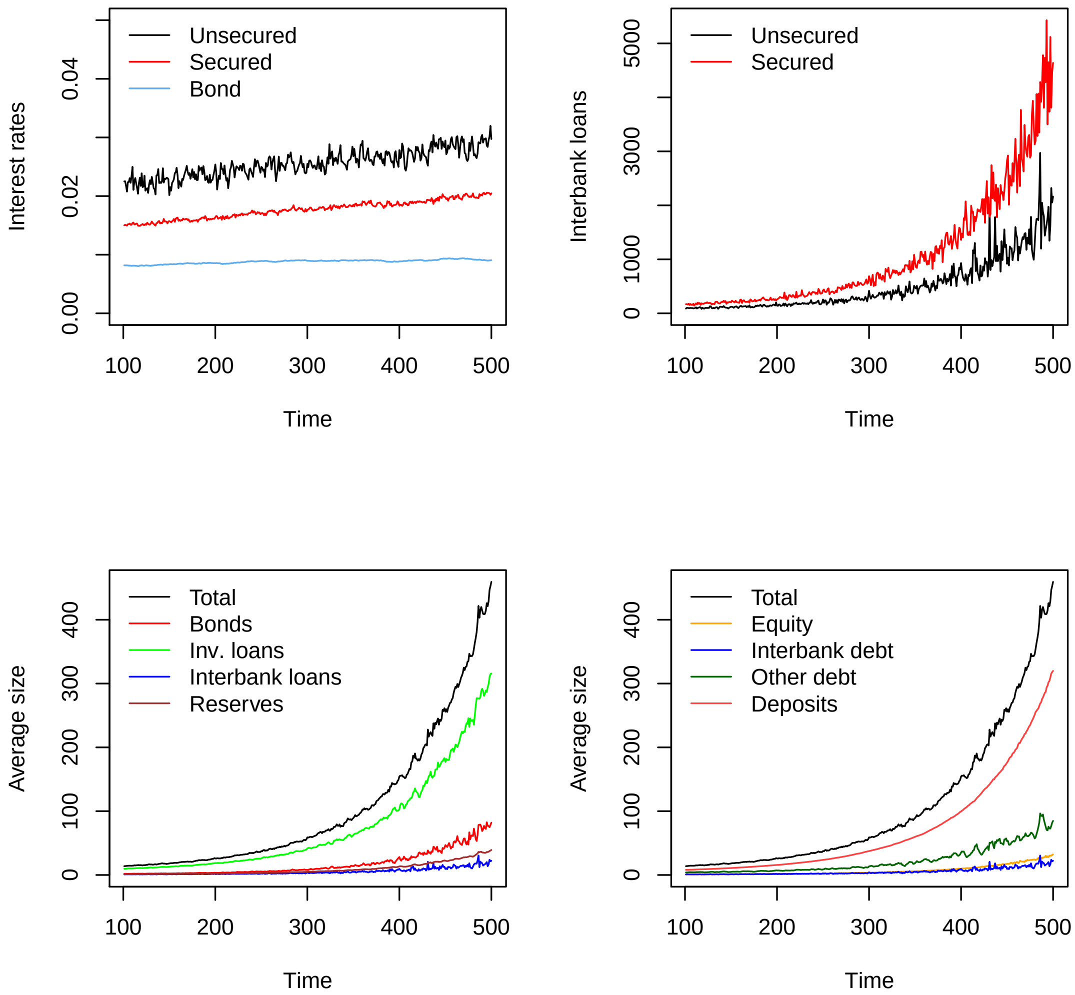


Figure 2: The dynamics of the interbank interest rates, volumes and bank balance sheets under the baseline scenario. For all the variables the averages are taken over 200 simulations. Interest rates are denoted per period.

connected to each other (Jackson, 2008). We also report the number of islands to observe the behavior of the entire network, including the banks which do not have any trading relations in a particular period. The results for the market and balance-sheet dynamics of the baseline model are presented in Fig. 2 and corresponding network statistics are depicted in Fig. 3.

The baseline model shows that the rate in the unsecured interbank market is higher and more volatile than in the secured segment, confirming the observations made by Stigum and Crescenzi (2007). We find that the mean difference between the two rates is statistically significant at a 1% significance level. The higher volatility of the unsecured rate represents its risk well, compared to collateralized transactions. Consequently, the model confirms that

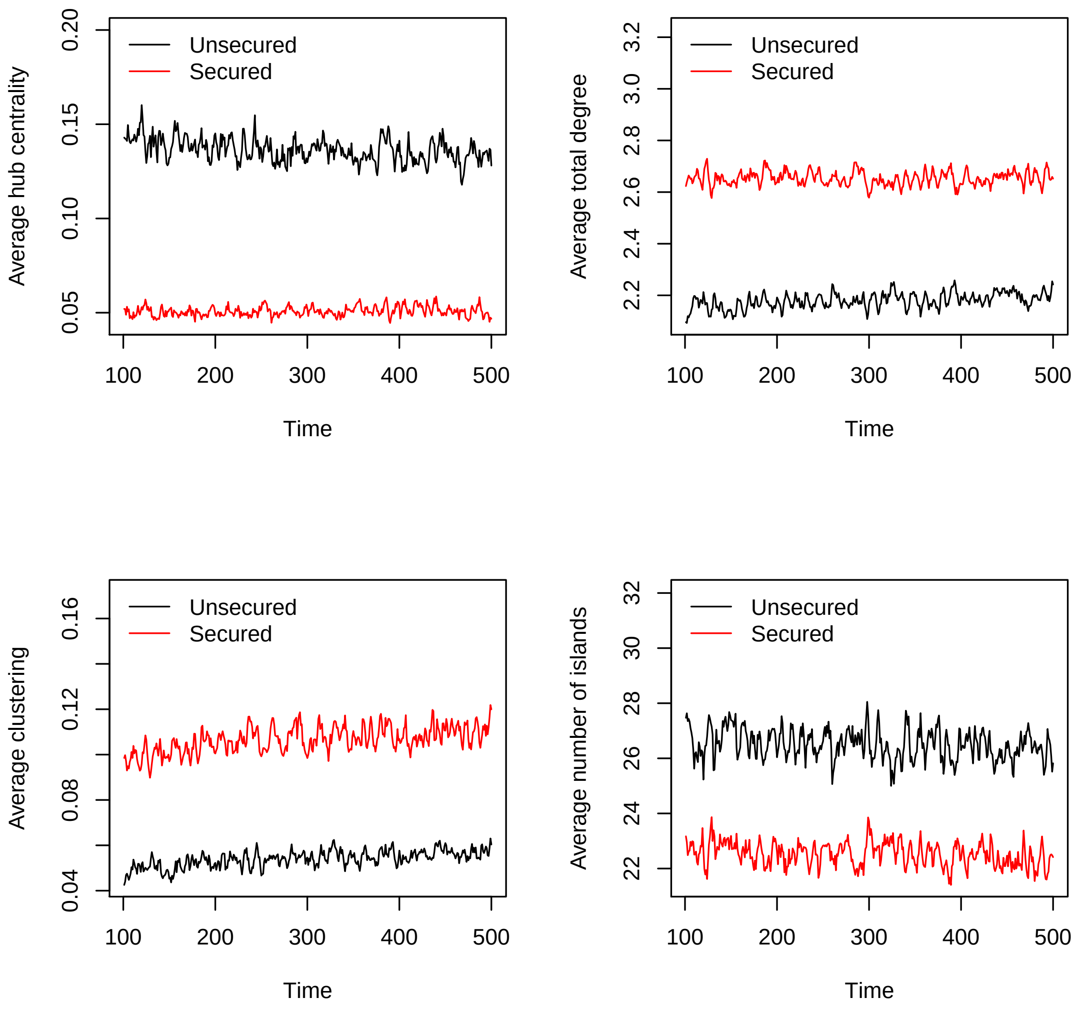


Figure 3: The dynamics of the interbank network statistics under the baseline scenario. For all the variables the averages are taken over 200 simulations.

the size of the secured market is larger than the size of the unsecured equivalent (European Central Bank, 2013). The rates are modestly increasing, but they seem to level off towards the last periods. We also find an interesting feature of the role of interbank interconnectedness on system's stability. When banks go bankrupt, because of non-repaid debt, they sometimes tend to drive other banks into bankruptcy as well so that the bankruptcies are clustered in a specific period. This finding is in line with the so-called "domino effect", where the failure of one institution translates into troubles of the other.

Consistent with Fig. 1, the asset side of bank balance sheets is dominated by production loans, before bonds, reserves and unsecured interbank loans. It is worth pointing out that due to our booking procedure of repo transactions, which we treat as outright sales of collateral, the figures do not plot the secured lending in the interbank debt. The actual total interbank exposure is therefore more than double what is presented in the plots. The liabilities are dominated by deposits, followed by central bank debt, equity and unsecured interbank funding.

The network statistics (Fig. 3) point to interesting characteristics of the secured and unsecured interbank network formations. Firstly, the hub centrality for the unsecured network is higher and more volatile than for the secured market segment. On the contrary, the clustering within the unsecured market is weaker, and the total degree is lower, than in the secured segment. Those features can suggest that (i) the unsecured network consists of many star-like communities with the hubs being connected between each other and (ii) the secured network is more interconnected but has a small fraction of central hubs. Those features are consistent with the structure of the empirically observed markets. The small fraction of central hubs in the secured segment can represent the natural emergence of dealer banks which, due to their market perceptions, serve as market makers in the repo transactions (Stigum and Crescenzi, 2007). The unsecured market is also found to be less clustered in the Italian interbank market in short- and long-term transactions (see Bargigli et al., 2015).

As an additional robustness check, we confirm that the clustering coefficients in both market segments are statistically significant, since the probability that two vertices which are connected to a given node are also connected to each other significantly exceeds the general probability of a connection, where the latter equals the degree divided by the total possible trading partners.

Due to the scarcity of data, it is difficult to compare the exact statistics. Nevertheless, Bargigli et al. (2015) carry out an experiment on the Italian interbank network, analyzing short- and long-term interbank contracts in the unsecured and secured markets. For instance they report that the clustering coefficient in the long-term (longer than 12 months) unsecured and secured markets were respectively 0.056 and 0.135 in 2008. The model-implied equivalents are respectively 0.056 and 0.109. Similarly, we find that that both networks exhibit negative assortativity (or disassortativity), confirming the findings of Bargigli et al. (2015).[16] The model-implied average assortativity equals -0.55 for the unsecured and -0.48 for the secured market, being modestly lower than what has been confirmed empirically for both market segments.

Our findings can suggest that the secured market is indeed less risky to trade in, as

[16] A network is said to be assortative if the degree of a node is positively correlated with the degree of its neighbors.

predicted by theory (Stigum and Crescenzi, 2007). It has lower volatility of rates and hub centrality figures are visibly more stable. In the further exercises we investigate the dynamics of the model under two types of scenarios. In the first one we test the responsiveness of the model to exogenous shocks, and in the second we test the implications of various policy responses, which cover the scope of the MMP.

## 6. Scenario analysis

The results of the baseline model are compared with models in which we alter model parameters after period $T_s$. These shock models are divided based on the shock specification, which is either exogenous (or driven by external market fluctuations) or caused by a deliberate policy action. The description of particular scenarios is given in Table 5.

For transparency reasons, the exact evolution of the market and balance-sheet dynamics of the scenario models and the corresponding network statistics are presented in the Appendix. The general results are presented in Tables 6 and 7. We compare averages from the baseline model before and after the shock moment $T_s$, to the post-shock dynamics of the models that involve a shock. Moreover, we report the statistical significance of the post-shock difference between the scenarios and the baseline model. For this we use a two-sample t-test, where we consider the post-shock period in which the difference between the baseline model and the scenario is closest to the mean difference.[17] This results in less data being used, which makes significance tests slightly more conservative, but allows for a truthful representation of the true difference between the scenario and the baseline model.

### *6.1. The effects of exogenous shocks*

We consider two exogenous shocks: (i) deterioration of the quality of the collateral security and (ii) a negative production shock. In Scenario 1 the quality of collateral is reduced through a higher standard deviation of the collateral rate, which doubles to 20bp per year.[18] The production shock (Scenario 2) results in 50 percent lower profits from production loans.

The shock in Scenario 1, in which the quality of collateral is decreased, solely significantly affects the interbank rates. At the moment of the shock the forecasts of the bond rate are

[17] This is done because the period-to-period samples are not purely random, as there is $\tau$-period dependency between them. As a robustness check, we confirm the main results by testing the significance levels for the other periods.

[18] We also carried out extra robustness checks on the effects of haircut policies on interbank lending. Since the haircut levels do not directly enter the bank's decision-making process, they do not significantly change the dynamics of the system if the change in haircut levels is small. If the shock to the haircut levels is large, banks recognize this over time and it results in the same dynamics as implied by the price-volatility shock to collateral.

| | Description | Par./Var. | Value before $T_s$ | Value after $T_s$ |
|---|---|---|---|---|
| | | Exogenous shocks | | |
| Scenario 1 | decrease of collateral quality | $\sigma_b$ | 10bp | 20bp |
| Scenario 2 | negative production shock | $\mu_i$ | 0.067 | 0.034 |
| | | Policy actions | | |
| Scenario 3 | forward guidance | $d_1, d_2, \sigma_b$ | 50bp, 50bp, 10bp | 25bp, 25bp, 5bp |
| Scenario 4 | decrease of the bond rate to the negative territory | $r_b$ | $r_{b_0} = 0.033$ | -0.01 |
| Scenario 5 | decrease of the bond rate | $r_b$ | $r_{b_0} = 0.033$ | 0.01 |
| Scenario 6 | improved collateral quality | $\sigma_b$ | 10bp | 5bp |
| Scenario 7 | increase in the target leverage ratio | $\lambda$ | 16.7 | 33 |
| Scenario 8 | decrease in the target leverage ratio | $\lambda$ | 16.7 | 10 |
| Scenario 9 | capped availability of collateral securities | $coll$ | $\infty$ | $\overline{coll}_{[t<T_s]}/2$ |

Table 5: Description of scenarios together with the parameters or variables which are adjusted after the period $T_s$. Interest rate values are denoted yearly.

already crystallized and hence an increase of its standard deviation does not affect the mean dynamics. The repo market however relies on the collateral quality and hence the secured interbank rate increases significantly. Because of arbitrage conditions between the interbank market segments, banks' liquidity demand is shifting towards the unsecured market which results in higher unsecured interest rates. The GC volatility shock is transmitted to the interbank market volatility. The trades and overall interest rates are characterized by more irregular behavior. In order to compensate for this, banks demand higher returns from interbank lending, ultimately leading to higher interest rates in both segments. Besides, the overall market characteristics remain largely untouched.

In Scenario 2 the production loan returns are lowered, which decreases the overall size of the banking sector. As expected, due to lower profitability of production loans, the composition of the assets shifts towards safer securities, i.e. bonds. Also, the interbank rates diverge from each other. It can be driven by the fact that bonds gained on attractiveness as interest-bearing assets and banks are more reluctant to borrow against them. It results in decreased attractiveness of the repo market, with more fragmented network structures as for instance lower hub centrality. To the contrary, since the unsecured market does not involve collateral, banks are shifting towards this source of financing which is reflected in higher clustering.

### *6.2. The effects of policy actions*

Besides the exogenous shocks illustrated in the previous section, we study models in which we simulate a specific policy action after period $T_s$. Forward guidance is invoked in Scenario 3 by decreasing the standard deviation of the forecasting rules from 50bp to 25bp, and the standard deviation of the bond rate decreases from 10bp to 5bp. This setting is consistent with the goal of forward guidance, i.e. coordinating the evolution of private sector's expectations about the monetary policy and asset prices (see for instance Gavin et al., 2014). In practice forward guidance is implemented by clear communication channels of a monetary authority. If a central bank can convince the markets about its future intentions, market expectations will be on average more accurate and less volatile. To sterilize the effects of the forward guidance, we assume that the interest rates are kept at a given level and a policy maker can achieve lower volatility of forecasts through a more efficient communication strategy.

In Scenarios 4 and 5 we simulate gradual decreases in the short-term interest rates. In particular, Scenario 4 reflects lowering the interest rates below the zero bound, as observed in the euro area, for instance with respect the Quantitative Easing (QE) program. We simulate it by lowering the bond rate in four periods to -0.01. Scenario 5 reflects a more standard

| | Baseline | Baseline | Scenario 1 | Scenario 2 |
|---|---|---|---|---|
| **General information** | | | | |
| Period | 101-300 | 301-500 | 301-500 | 301-500 |
| Bankrupt | 0.37% | 0.38% | 0.40% | 0.49% |
| Balance sheet size | 28.79 | 184.46 | 318.80 | 139.69* |
| **Assets** | | | | |
| Production loans | 72.04% | 72.45% | 71.55% | 64.93%*** |
| Unsecured loans | 5.26% | 4.48% | 4.64% | 4.48% |
| Secured loans† | 11.66% | 10.67% | 10.25% | 12.07% |
| Bonds | 13.93% | 14.45% | 15.16% | 21.95%*** |
| Reserves | 8.78% | 8.62% | 8.65% | 8.64% |
| **Liabilities** | | | | |
| Deposits | 63.84% | 67.75% | 67.15% | 67.49% |
| Equity | 6.32% | 6.71% | 6.65% | 6.69% |
| Other debt | 24.58% | 21.06% | 21.56% | 21.34% |
| **Market rates** | | | | |
| Bond rate | 0.86% | 0.91% | 0.86% | 0.77% |
| Unsecured rate | 2.38% | 2.72% | 3.09%** | 3.27% |
| Secured rate | 1.64% | 1.89% | 2.14%** | 1.80% |
| **Network statistics unsecured market** | | | | |
| Hub centrality | 13.82% | 13.82% | 13.01% | 12.55% |
| Total degree | 2.17 | 2.17 | 2.25 | 2.21 |
| Clustering | 5.21% | 5.21% | 5.98% | 6.40%* |
| Number of islands | 26.65 | 26.65 | 25.63 | 26.43 |
| **Network statistics secured market** | | | | |
| Hub centrality | 5.03% | 5.03% | 4.87% | 4.42%* |
| Total degree | 2.66 | 2.66 | 2.64 | 2.58 |
| Clustering | 10.41% | 10.41% | 11.06% | 10.79% |
| Number of islands | 22.59 | 22.59 | 22.62 | 23.27 |

Table 6: Averages of the basic model variables and network statistics in the baseline model pre- and post-shock, as well as the exogenous shock models post-shock. Interest rates are denoted per period. Interbank transactions are reported on the asset side but they have respective liability equivalents. † due to booking procedures secured transactions are off-balance. Statistical significance of the difference between the scenarios' outcome and baseline model is denoted by *, ** and correspond to 5% and 1% significance levels, respectively. A detailed description of the scenarios can be found in Table 5.

monetary policy action where in two periods the annualized bond rate decreases to 0.01.

Scenario 6 is a mirror-reflection of Scenario 2. We assume that markets restore their confidence in collateral security due to policy actions such that the quality of collateral improves. We simulate this by decreasing the volatility of collateral, i.e. by reducing the standard deviation of the bond rate to 5bp. This scenario is also in line with the quantitative side of the QE as, once a monetary authority decides to pursue an asset-purchase program, markets consider a wider variety of assets as being safe. This could have been observed in yield compression among the euro-area government securities in the months after the QE begun.

In Scenarios 7 and 8 we focus on the explicit financial stability and supervisory roles a central bank can play in the banking system. Those are often mentioned as being part of the MMP, as after the recent crisis there is a prevailing view that central banks should assume greater responsibility in controlling potential financial imbalances (Billi and Vredin, 2014). Therefore, in our study we investigate the effects of target leverage ratios on system's performance and risk. In Scenario 7 we increase the regulatory leverage ratio to 33, corresponding to the 3% basic leverage target under Basel III. In Scenario 8 we lower this ratio to 10.

Finally, we investigate the potential quantity effects of the asset-purchase programs. Since the central bank purchases decrease the availability of collateral on the market, it can affect banks' portfolio strategies and consequently the interbank market. For instance, even though the quotas of the euro-zone asset-purchase programs were set to bring little market distortions, the ECB monitors the situation of GC. Also, to avoid potential collateral scarcity, the ECB decided that securities would be available for lending in a harmonized manner across National Central Banks and the ECB (International Monetary Fund, 2015). To observe what happens if the amount of GC is reduced, in Scenario 9 the available collateral is capped at half the average value of the pre-shock periods.

Our model confirms that forward guidance restores confidence in the markets. It is reflected in reduced unsecured market interest rates and an overall shift in the balance sheet composition. On the asset side there is an overall shift from safer assets, like bonds and reserves to production loans, which can be viewed as having a positive effect on the real economy. Also banks seem to be more deposit- and equity-funded, with reduced dependence on central bank financing. As a result of improved market confidence the number of bankruptcies decreases. In the unsecured network we observe an increase in the number of islands, and the degree decreases. This can suggest that increased precision of forecasts somehow reduces the number of banks which are matched on the unsecured market. As a result banks seek more secured market financing, which is reflected in a more dense and complete secured market network.

As a result of decreased profitability of bonds, in Scenarios 4 and 5 banks shift from this asset class to higher-return production loans. It is indeed consistent with the portfolio reallocation channel, manifested by the ECB in 2015's asset-purchase programs. We confirm that the effects of the interest rates' decreases are transmitted to the interbank market. Also, as a result of lower returns banks tend to expand slower on average. On the funding side, banks tend to be more reliant on central bank financing and decrease their deposit and equity bases. This can be a sign of potential fragility of the system as banks are willing to supply more liquidity in the interbank transactions when the unsecured market rate is lowered. It is indeed confirmed by more dense network statistics in the unsecured segment in Scenario 4, since the supply of interbank funding is lowered and, in order to satisfy their demand, banks set up credit lines with a larger number of counterparties. It indeed results in a more dense and interconnected network, with larger centrality, degree and clustering measures and a lower number of non-connected counterparties.

The policy action in Scenario 6 corresponds to increased quality of collateral security. It can be verified that this scenario does not result in any significant changes to the system's dynamics nor does it influence the interbank network formation. Interestingly, this finding suggests that effects of collateral on interbank lending are asymmetric. It can result from the fact that, once deteriorating collateral quality makes trades more volatile, banks demand higher returns on the interbank market. In principle, there is no upper limit to this extra compensation. Nevertheless, in case of improved quality of collateral and therefore lower volatility of the market, banks demand lower returns. But due to arbitrage opportunities in our setting the rates in those markets should not fall below the bond rate, as otherwise banks would always be better off by investing in bonds than in the interbank market.

As expected, the majority of the dynamics is influenced by altering the leverage constraint in Scenarios 7 and 8. The observed figures and patterns are largely in line with Thurner (2011) and Caccioli et al. (2014). An increased allowed leverage in Scenario 7 provides opportunity for increased balance sheets, at the expense of an increased number of bankruptcies as a result of higher risk. On the asset side of the balance sheet production loans are replaced by secured loans and bonds as lower capital requirements make those investments more appealing. The liability side does not change significantly to a large extent. It seems that banks tend to hold more of the central bank credit. Moreover, the unsecured interbank rate increases as a result of increased bank-specific demand for interbank unsecured funds. It is the reason why the unsecured market network becomes denser and more connected. The clustering coefficient reaches nearly 10% and the number of islands decreases substantially, signaling that more banks engage in the interbank transactions. The secured market becomes even more dealer-based, with lower hub centrality and higher clustering.

Scenario 8 generates balance sheet results that are opposite to Scenario 7, as expected. Nevertheless, due to higher capital requirements both interbank market segments seem to dry out. A lower unsecured market rate is again driven by the demand side. In the interbank network more banks become isolated and the overall interconnectedness of the interbank network deteriorates.

Our model suggests that decreased availability of collateral (Scenario 9) shifts the structure of assets towards production loans. Again, this is consistent with the portfolio reallocation channel stimulated by the QE. Banks also tend to be more deposit- and equity based, with lower dependence on central bank funds. On average this results in higher net profits with less debt-dependence and consequently a lower number of bankruptcies. Since collateral is limited, the interbank market changes its structure. Interestingly, it seems that banks decrease their dependence on interbank funds but they also shift to relatively more unsecured transactions, driving its interest rates down. This indeed results in an unsecured rate that is closer to the secured rate, and the network characteristics of the secured market look more like the pre-shock unsecured market with a higher hub centrality and lower clustering. The unsecured market network becomes less dense and interconnected. Also more banks are not participating in interbank transactions, presumably because they either do not have enough collateral or because the unsecured lending lost attractiveness. It seems that the interbank transactions are narrowed to banks which accumulated higher portions of bonds before the $T_s$ period and therefore are able to pledge them as collateral in repo transactions.

The shocks described above sketch interesting guidelines for central banks and macroprudential regulators. Since the interbank market is a source of liquidity, policy makers can use it as a transmission channel to affect macroeconomic performance. Our scenario analyses point to possible aggregate consequences of combined effects, which result from different policy measures. The model predicts that cheap lending induces higher leverage ratios and more volatile balance sheets and banks' investments. Therefore, consistent with theory, lower capital standards induce higher risk in the financial system which can lead to some forms of credit rationing to the private sector. In Scenario 7 we show that lower leverage constraints lead to a faster credit growth in absolute terms, but the composition of banks' assets does not shift towards production loans.

To some extent those risks can be compensated by restoring market confidence through forward guidance policies, tighter prudential oversight and asset-purchase programs, implemented by both price and quantity channels. For instance, a repo shock resulting in decreased quality of collateral, or increased price volatility of GC, can be contained by central bank asset repurchases (Scenarios 4 and 9).

The presented model shows that the performance of the interbank market and the in-

| | Baseline | Baseline | Scenario 3 | Scenario 4 | Scenario 5 | Scenario 6 | Scenario 7 | Scenario 8 | Scenario 9 |
|---|---|---|---|---|---|---|---|---|---|
| **General information** | | | | | | | | | |
| Period | 101-300 | 301-500 | 301-500 | 301-500 | 301-500 | 301-500 | 301-500 | 301-500 | 301-500 |
| Bankrupt | 0.37% | 0.38% | 0.27%* | 0.48% | 0.42% | 0.38% | 0.63%*** | 0.15%*** | 0.27%* |
| Balance sheet size | 28.79 | 184.46 | 147.58* | 118.36*** | 97.37*** | 175.21 | 285.08* | 123.60*** | 168.72 |
| **Assets** | | | | | | | | | |
| Production loans | 72.04% | 72.45% | 75.05%** | 74.06%* | 73.66% | 72.80% | 70.47%** | 75.35%*** | 80.30%*** |
| Unsecured loans | 5.26% | 4.48% | 3.56%* | 5.17% | 5.08% | 4.54% | 4.65% | 4.91% | 3.03%*** |
| Secured loans† | 11.66% | 10.67% | 12.73% | 12.30% | 12.12% | 10.65% | 11.75% | 8.23%** | 3.47%*** |
| Bonds | 13.93% | 14.45% | 12.97%* | 12.00%*** | 12.52%** | 14.03% | 16.23%* | 11.03%*** | 8.42%*** |
| Reserves | 8.78% | 8.62% | 8.42%** | 8.77%* | 8.74% | 8.63% | 8.65% | 8.70% | 8.25%*** |
| **Liabilities** | | | | | | | | | |
| Deposits | 63.84% | 67.75% | 72.18%*** | 63.93%*** | 64.44%** | 67.49% | 65.52% | 67.58% | 78.96%*** |
| Equity | 6.32% | 6.71% | 7.16%** | 6.33%** | 6.37%* | 6.68% | 6.48% | 6.69% | 7.80%*** |
| Other debt | 24.58% | 21.06% | 17.10%*** | 24.58%*** | 24.11% ** | 21.29% | 23.34%* | 20.82% | 10.21%*** |
| **Market rates** | | | | | | | | | |
| Bond rate | 0.86% | 0.91% | 0.78% | -0.29%*** | 0.27%*** | 0.81% | 0.77% | 0.85% | 0.80% |
| Unsecured rate | 2.38% | 2.72% | 2.39%** | 1.47%*** | 1.83%*** | 2.71% | 3.91%*** | 2.09%*** | 2.41%** |
| Secured rate | 1.64% | 1.89% | 1.80% | 0.51%*** | 1.00%*** | 1.89% | 1.89% | 1.84% | 1.82% |
| **Network statistics unsecured market** | | | | | | | | | |
| Hub centrality | 13.82% | 13.46% | 14.18% | 15.21%* | 14.83% | 13.42% | 16.15%*** | 11.77%** | 6.47%*** |
| Total degree | 2.17 | 2.19 | 2.00*** | 2.31** | 2.23 | 2.19 | 2.71*** | 1.97*** | 2.10*** |
| Clustering | 5.21% | 5.58% | 4.97% | 6.41%* | 5.84% | 5.63% | 9.81%*** | 3.72%*** | 4.49%*** |
| Number of islands | 26.65 | 26.36 | 30.43*** | 24.04*** | 25.46 | 26.41 | 19.37*** | 29.60*** | 27.61* |
| **Network statistics secured market** | | | | | | | | | |
| Hub centrality | 5.03% | 5.12% | 5.53% | 5.79% | 5.67% | 5.07% | 4.38%** | 6.37%*** | 13.93%*** |
| Total degree | 2.66 | 2.65 | 2.91*** | 2.69 | 2.66 | 2.66 | 2.89*** | 2.35*** | 2.51*** |
| Clustering | 10.41% | 10.90% | 13.25%*** | 10.48% | 10.60% | 11.03% | 13.40%*** | 8.38%*** | 6.89%*** |
| Number of islands | 22.59 | 22.46 | 19.10*** | 22.12 | 22.43 | 22.32 | 19.17*** | 27.44*** | 24.21*** |

Table 7: Averages of the basic model variables and network statistics in the baseline model pre- and post-shock, as well as the exogenous shock models post-shock. Interest rates are denoted per period. Interbank transactions are reported on the asset side but they have respective liability equivalents. † due to booking procedures secured transactions are off-balance. Statistical significance of the difference between the scenarios' outcome and baseline model is denoted by *, **, *** and correspond to 10%, 5% and 1% significance levels, respectively. A detailed description of the scenarios can be found in Table 5.

terbank network formations seem to be heavily dependent on the non-standard policies (or MMP) which, if well exploited, can guarantee financial and macroeconomic stability. MMP can also provide guidelines for tackling real shocks, however, our model setting does not allow investigating this phenomenon in detail. Given an exogenous production shock (see Scenario 2), banks shift away from production loans towards safer assets. This can be counteracted by improved market confidence or lower interest-rates. Nevertheless, only the revival of the production sector would guarantee sustainable growth. We consider that endogenizing the production sector therefore serves as a natural continuation of this line of research in order to provide a more comprehensive overview of the relation between the real and financial sector.

## 7. Conclusions

The goal of this paper is to develop an agent-based model of the interbank money market and to study the effectiveness of different policy measures on aggregate dynamics and financial stability. The proposed framework allows capturing complex structures of the real interbank market, including the interdependence of its unsecured and secured segments. Due to the flexibility of agent-based techniques and the possibility to track and shock the exact components of bank balance sheets as well as their risk-taking behavior, we are able to evaluate the effectiveness of a number of policy actions.

A big advantage of the model is that, to a large extent, it reflects the dynamics of empirically observed financial patterns. Firstly, we confirm basic stylized facts about the distribution of bank balance sheets as well as about the relationship between interest rates and volumes in the unsecured and repo markets. The model generates a highly skewed distribution of the total size of bank balance sheets in favor of small and medium-sized banks which is consistent with the distribution in many European countries. Similarly, under the baseline scenario the repo rates are in between the bond rate and the unsecured rate, and the volumes of the repo transaction are larger than in the unsecured segment (Stigum and Crescenzi, 2007; European Central Bank, 2013). The endogenous networks of the interbank markets exhibit significant clustering. Moreover, we observe an emergence of dealer banks in the secured market network, contrary to the unsecured segment, where the network is characterized by a number of connections with lower clustering patterns. This is again consistent with empirically observed structures (Stigum and Crescenzi, 2007). The model also provides evidence for the "domino effect" in the interbank market. This is revealed through bankruptcy-clustering patterns, where collapsing banks tend to cause solvency problems for their counterparties.

In the analysis we simulate two types of disturbances to the model: either exogenous or policy-driven. Deteriorating quality of general collateral is reflected in the interbank rates as well as in the overall risk in the banking sector since the number of bankruptcies increases. This is consistent with the so-called "pop-corn" effect or the common-exposure effect. We also observe that the effects of improved collateral quality are negligible, suggesting that changes in collateral quality work asymmetrically. We confirm that a negative production shock results in a shift of banks' preferences towards safer assets.

We find that under forward guidance policies the number of bankruptcies is reduced and market confidence is restored. A decrease in bond interest rates is well transmitted to the interbank market and urges banks to invest in higher-yield instruments. Shifts in the leverage constraint influence the entire dynamics: a higher allowance increases average profits but also increases the bankruptcy rate. Moreover, banks pose more demand for unsecured funds so that the unsecured rate increases. Decreasing the leverage targets results in the opposite dynamics.

We also study the impact of limited availability of collateral securities. Our results suggest that since the general collateral is less common, banks cannot use it as a cheap source of liquidity and therefore engage less in interbank transactions and keep higher capital buffers and deposit bases. As a result, the number of bankruptcies decreases. Moreover, the interbank market is dominated by banks which have sufficient stocks of collateral. This finding can reflect a kind of preferential trading pattern (Hatzopoulos et al., 2015).

Our model also shows that banks will clearly take advantage of higher allowed leverage ratios, which exacerbates financial risks and increases the number of banks' failures.

The policy scenarios described above may sketch interesting guidelines for central banks and macroprudential regulators. Our findings suggest that policy rates are transmitted to the interbank market but the effectiveness of this transmission can depend on exogenous factors. For example, it can depend on the situation in the production sector or on the overall quality of debt obligations, but also on market confidence.

Although the model replicates many of the stylized facts observed in real markets, a few of its caveats have to be pointed out. Firstly, the model replicates approximately the shape of the distribution of banks' leverage. The exact size of the leverage ratio in individual banks is nevertheless too small to correspond to the real leverage characteristics when interbank lending is too costly. Secondly, the model assumes that the rate of returns on investment projects is exogenous and independent of bank funding. A clear-cut extension of the model is therefore to endogenize the profitability of investments to fully understand the relation between the financial and the real sector.

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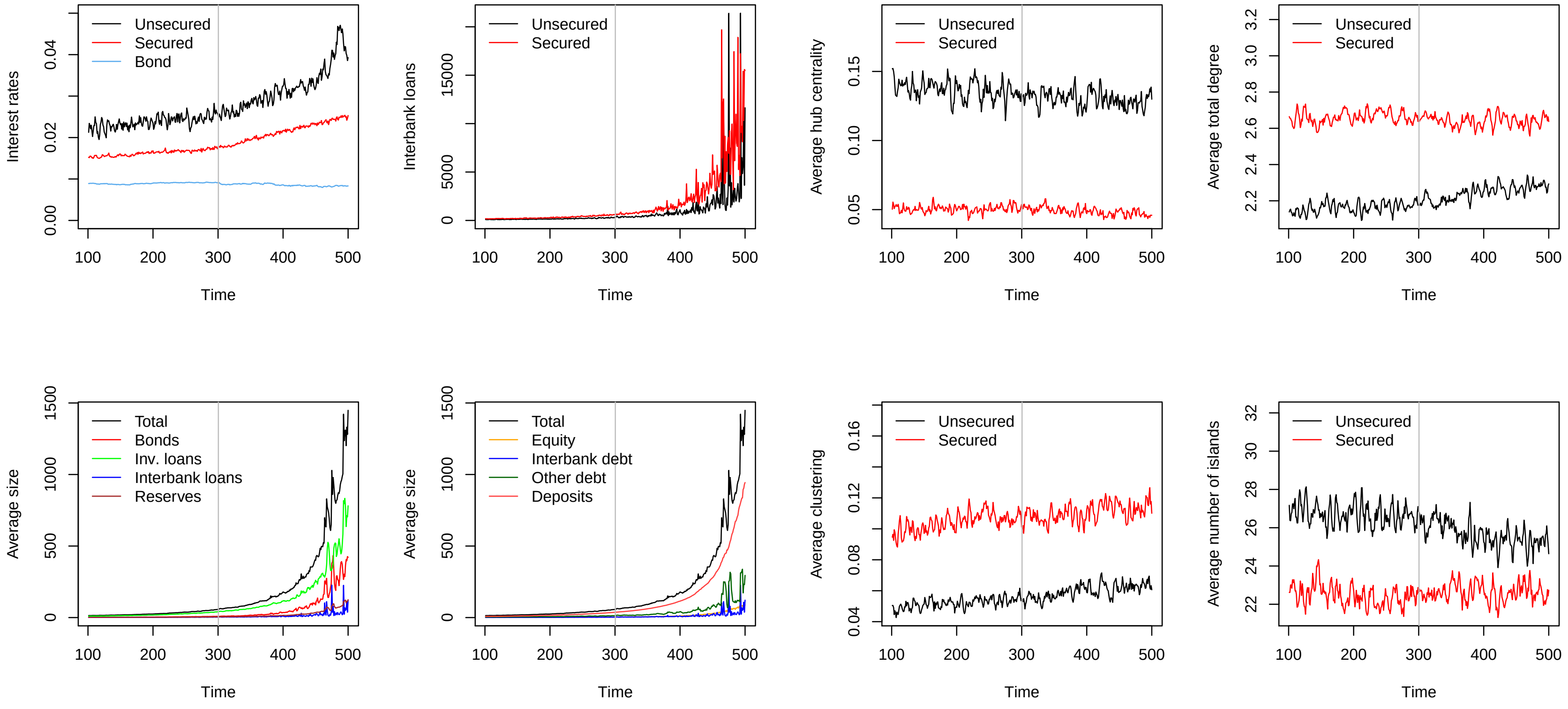
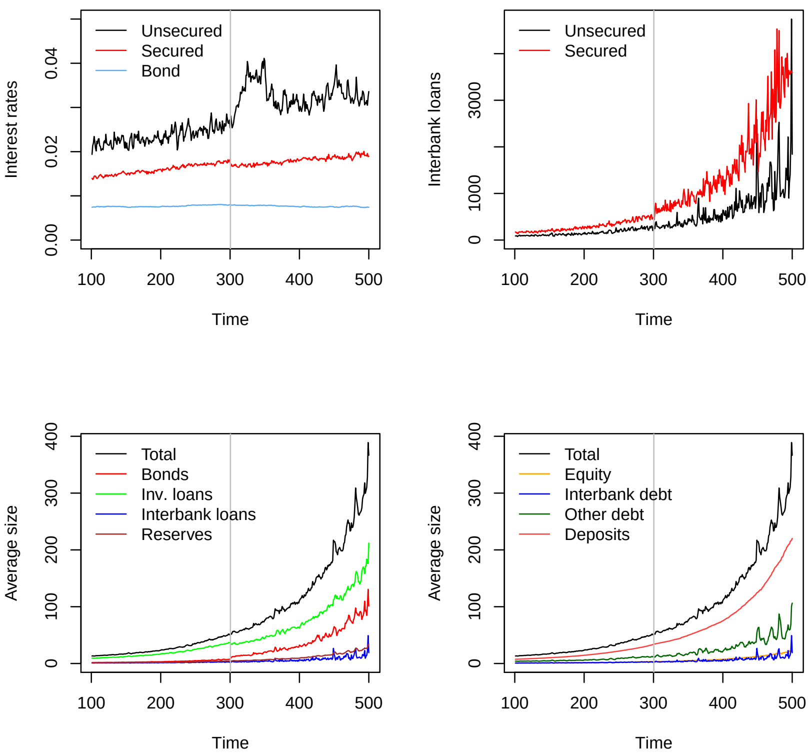


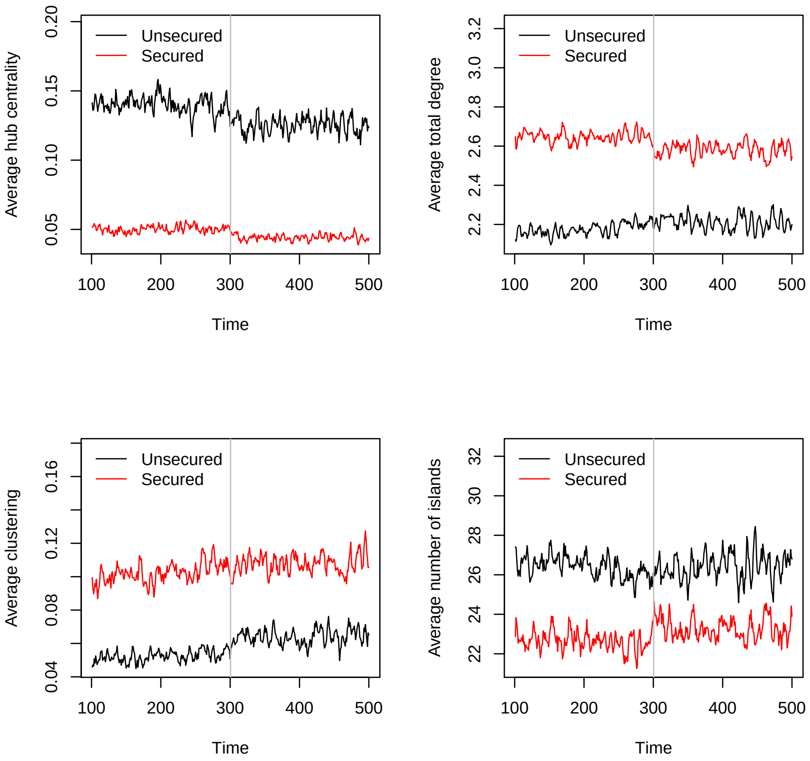

(a) Interbank and balance sheet dynamics

(b) Network statistics

Figure A.1: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 1 (deterioration in quality of collateral security). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.

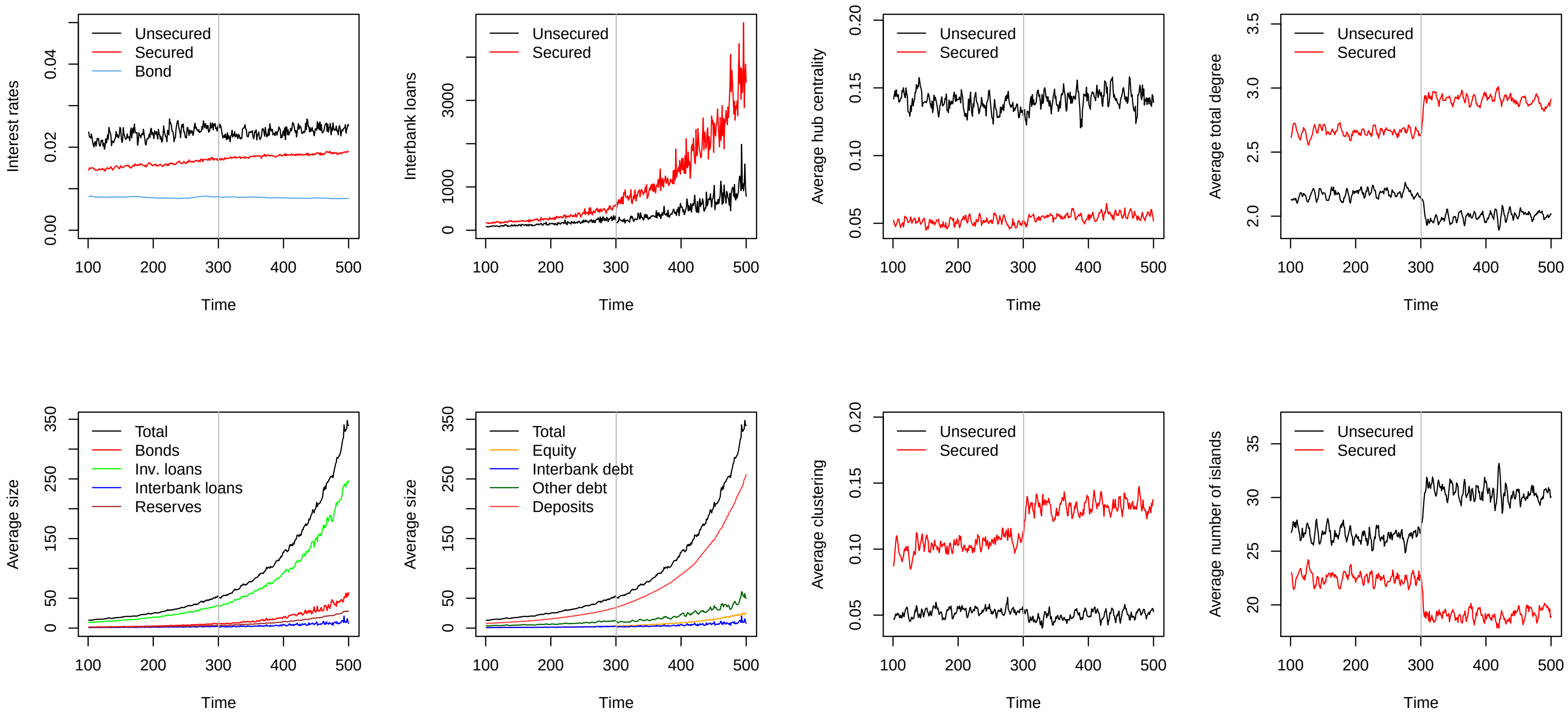



(a) Interbank and balance sheet dynamics




(b) Network statistics

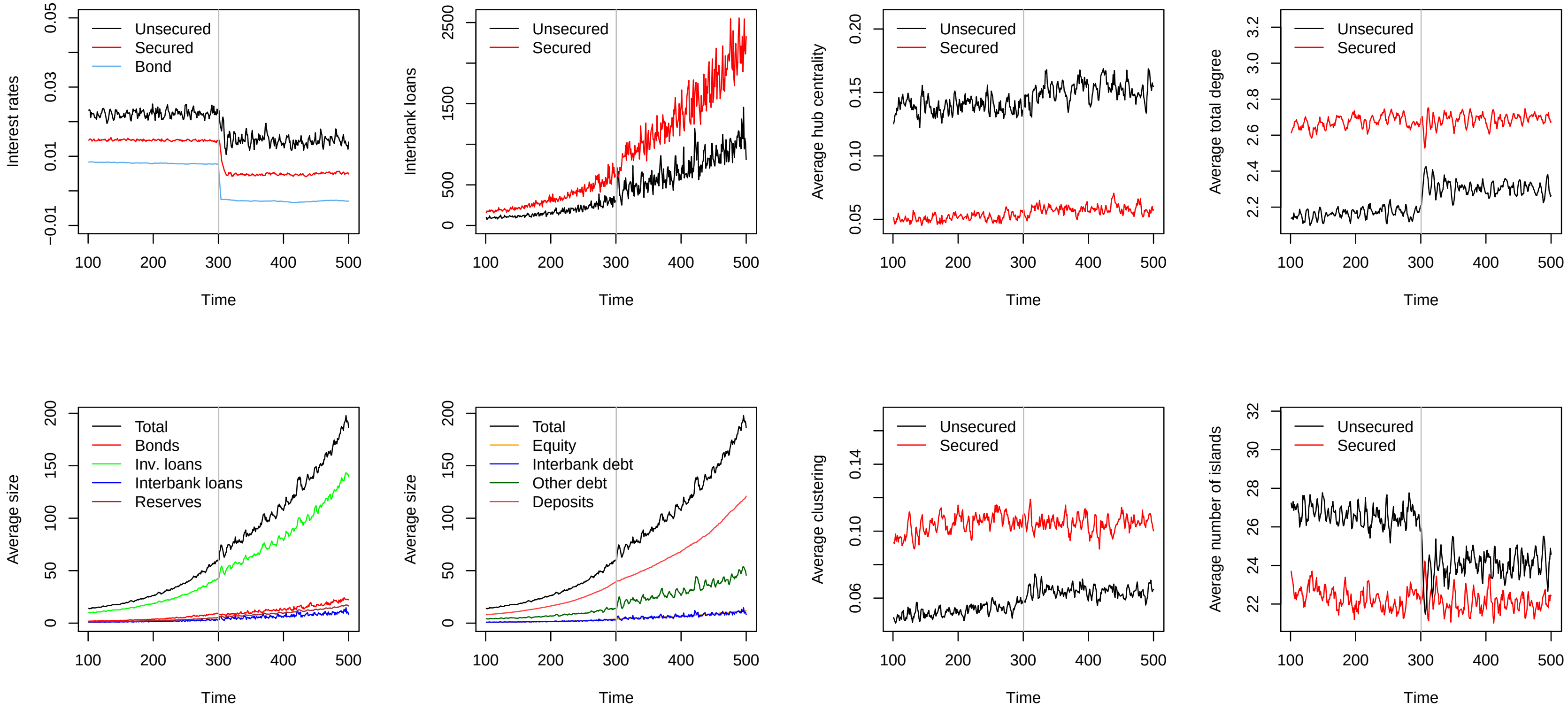
Figure A.2: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 2 (negative production shock). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.




(a) Interbank and balance sheet dynamics

(b) Network statistics

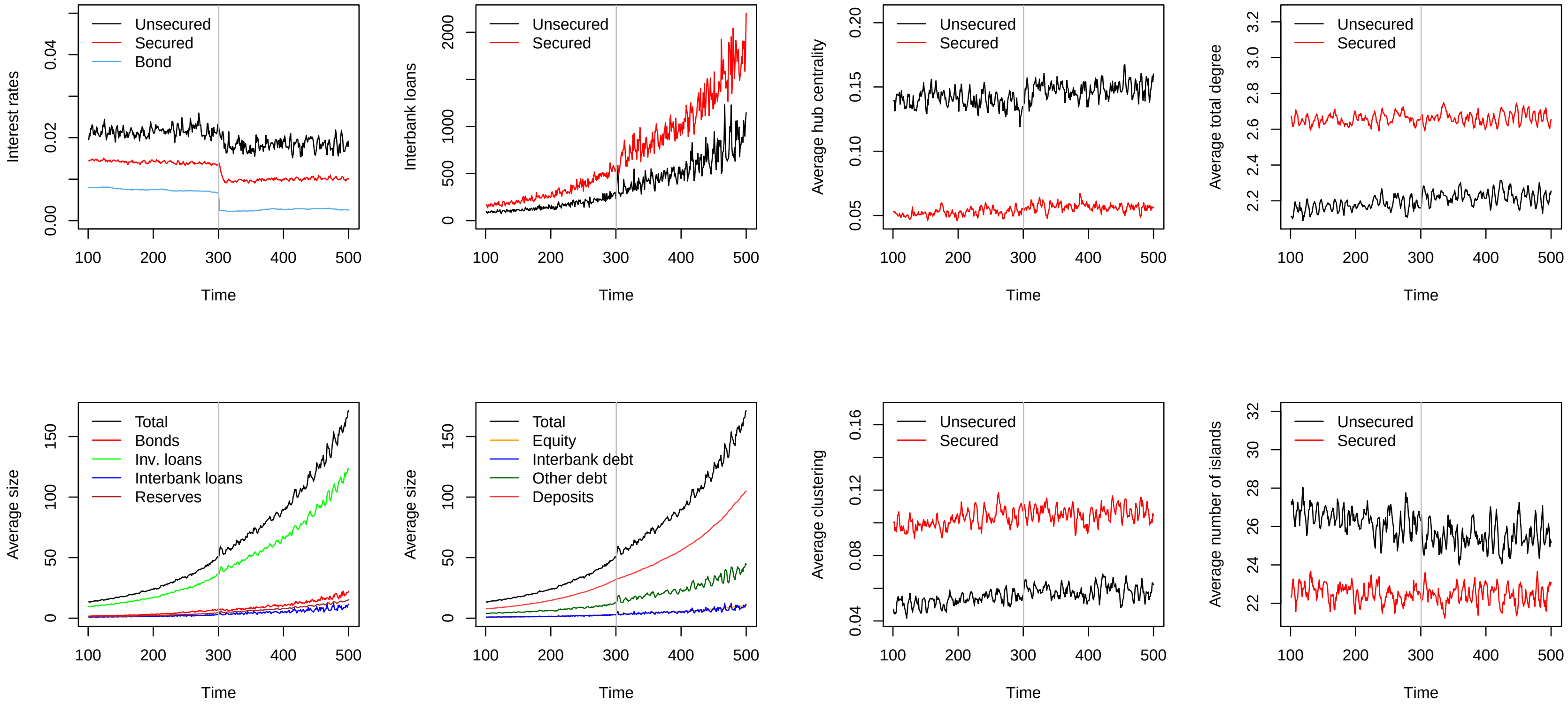
Figure A.3: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 3 (forward guidance policy). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.




(a) Interbank and balance sheet dynamics

(b) Network statistics

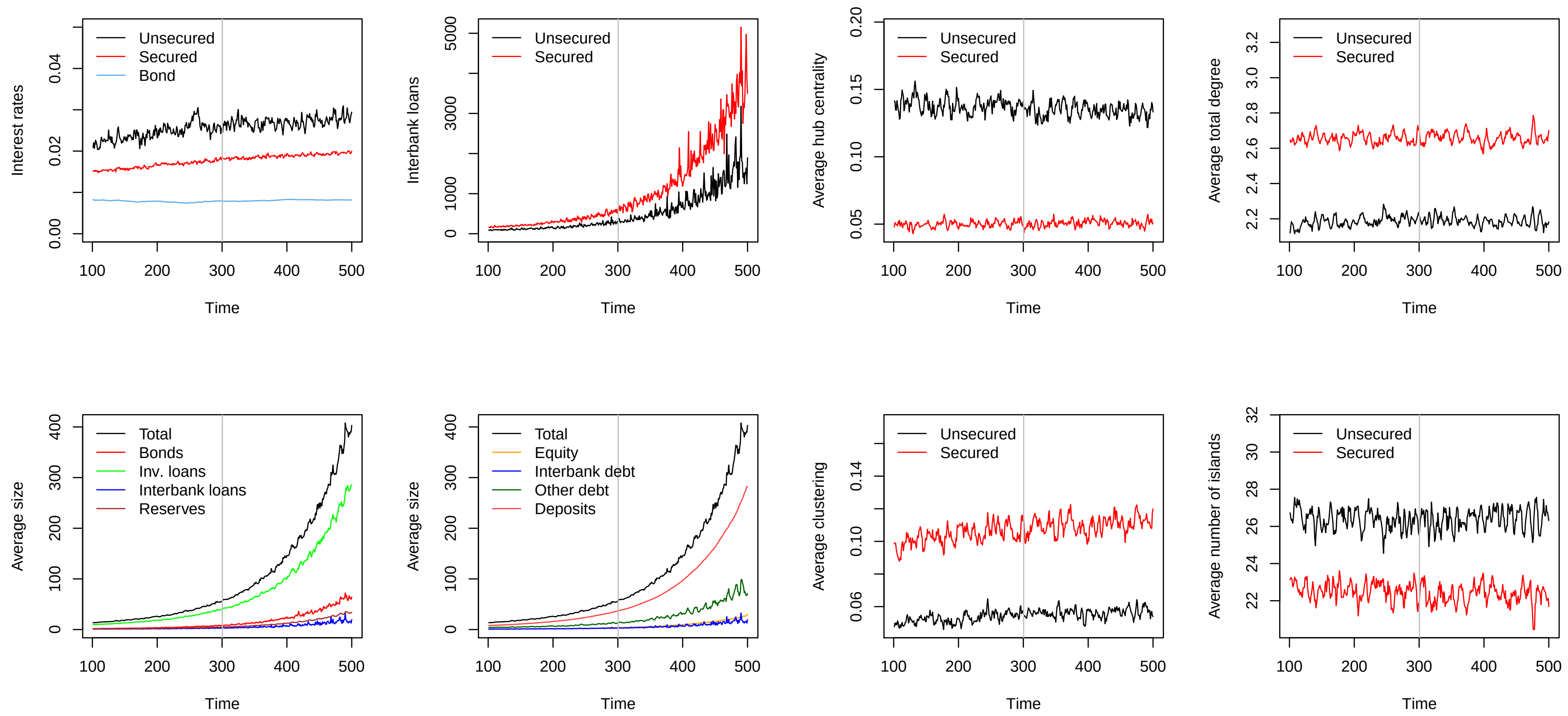
Figure A.4: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 4 (decrease of the interest rates to the negative territory). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.




(a) Interbank and balance sheet dynamics

(b) Network statistics

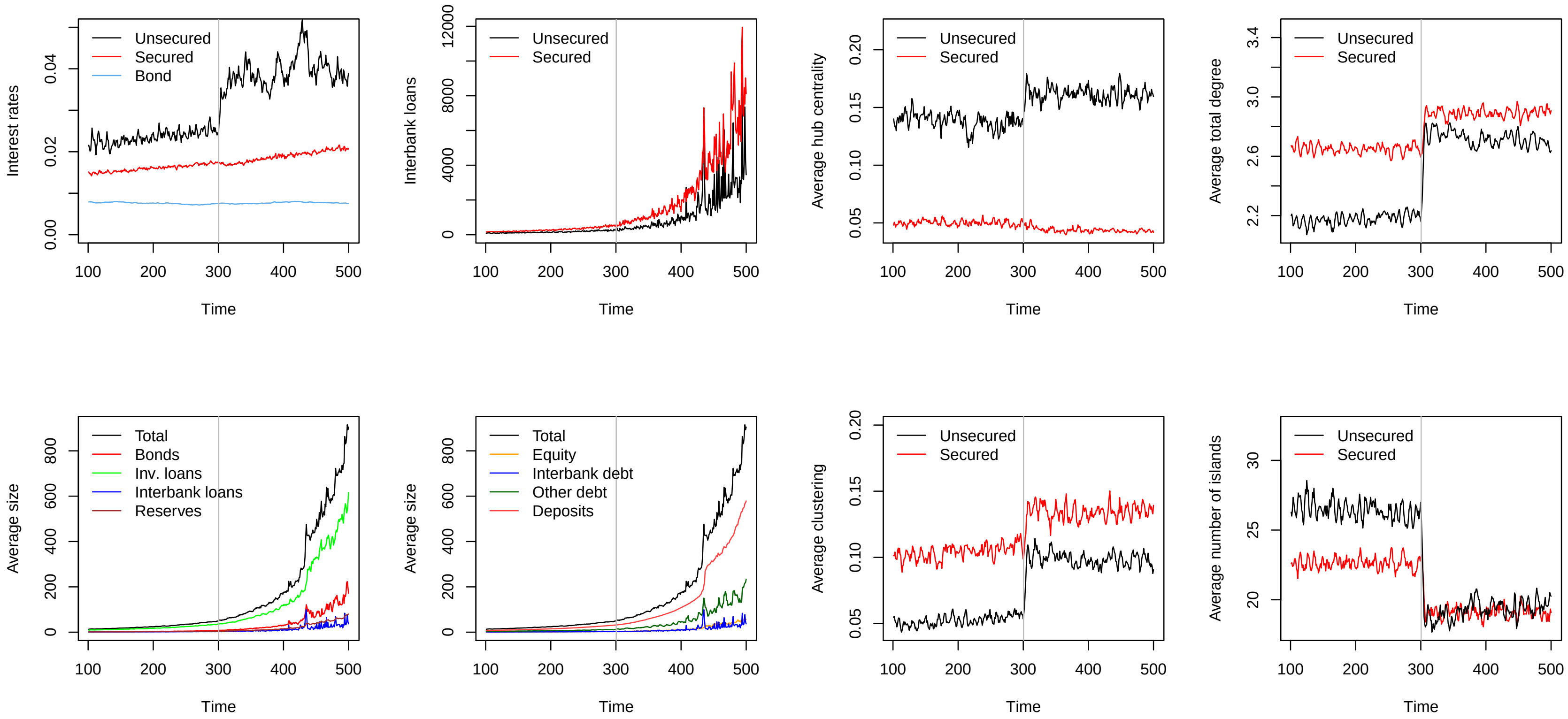
Figure A.5: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 5 (decrease of the interest rates). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.




(a) Interbank and balance sheet dynamics

(b) Network statistics

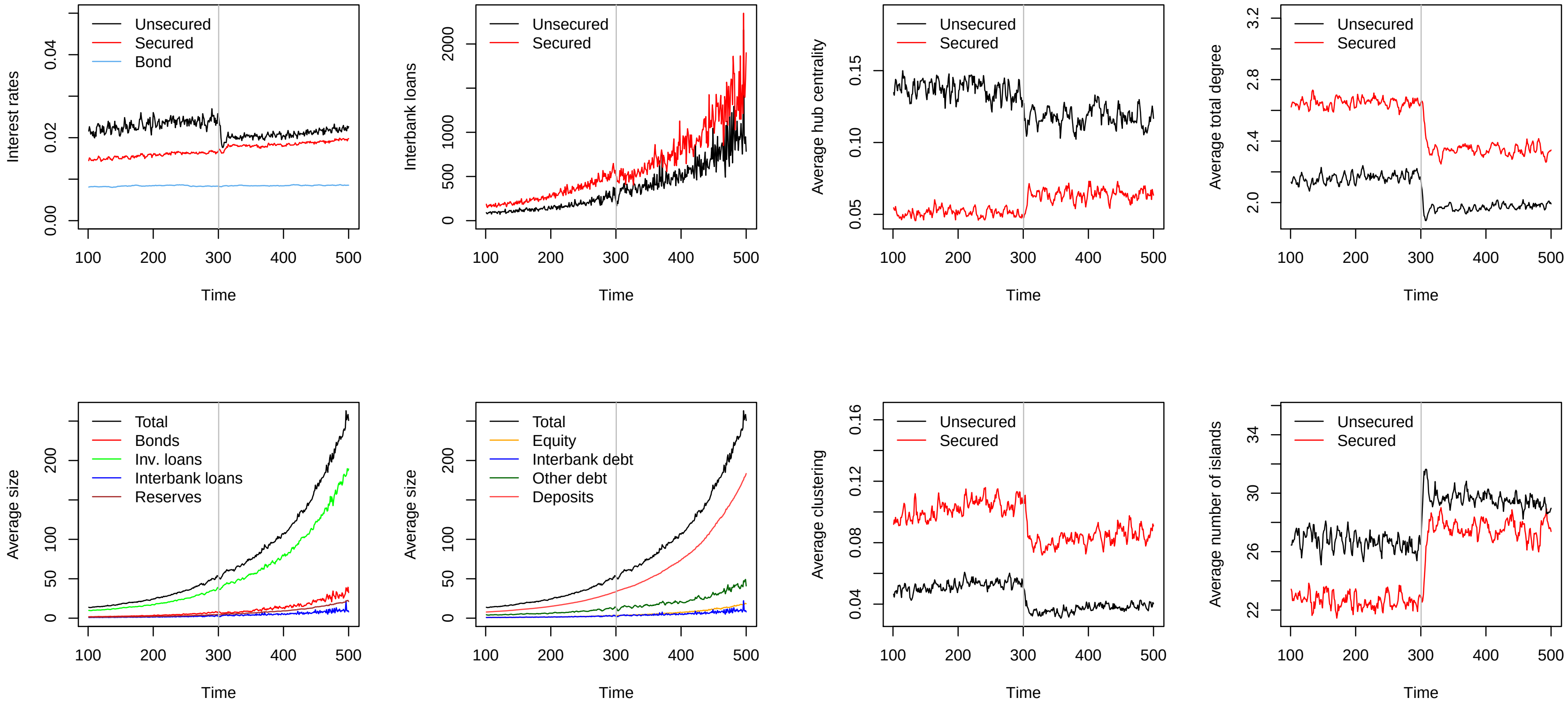
Figure A.6: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 6 (improved quality of collateral security). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.




(a) Interbank and balance sheet dynamics

(b) Network statistics

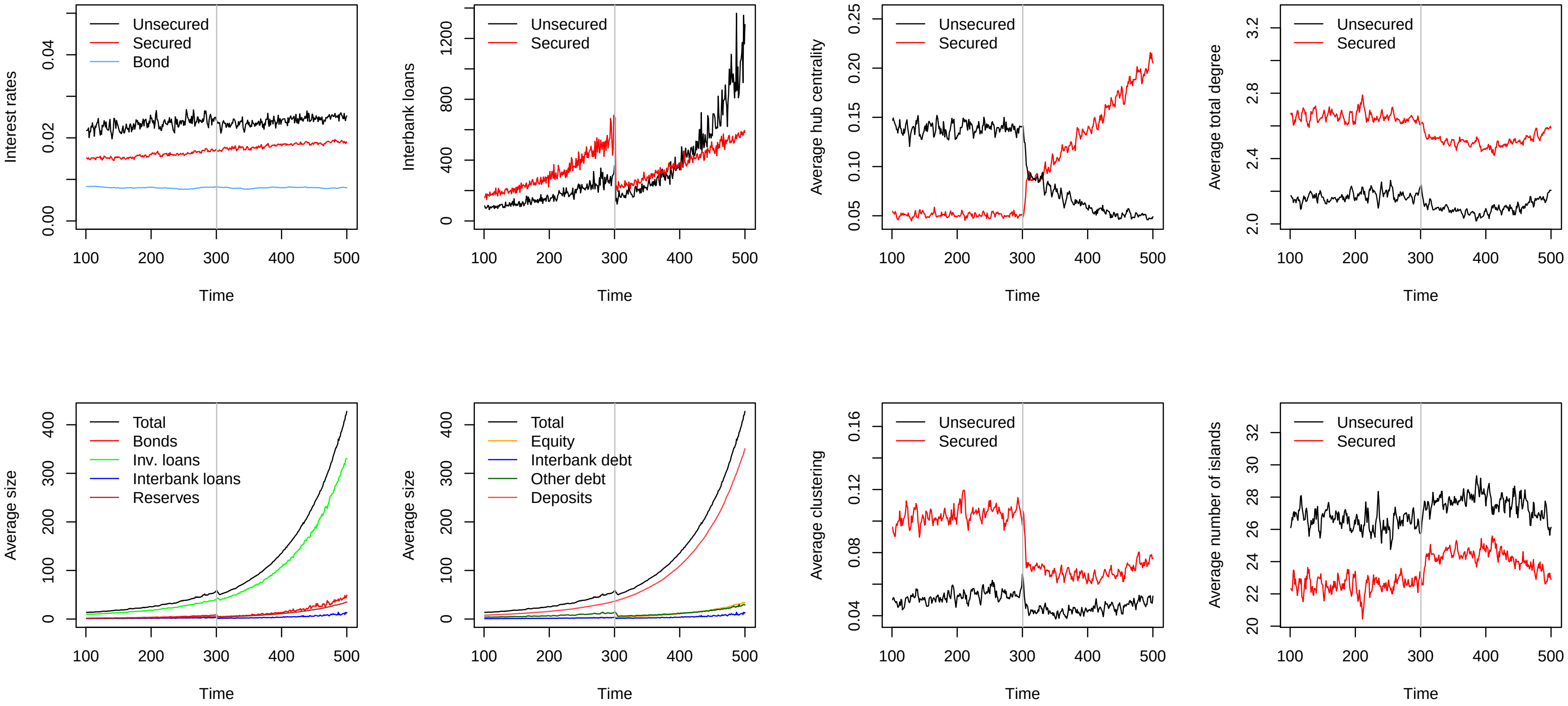
Figure A.7: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 7 (increase of target leverage ratio). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.




(a) Interbank and balance sheet dynamics

(b) Network statistics

Figure A.8: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 8 (decrease of target leverage ratio). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.




(a) Interbank and balance sheet dynamics

(b) Network statistics

Figure A.9: The dynamics of the interbank interest rates, volumes and bank balance sheets (panel a) and basic network statistics (panel b) under Scenario 9 (limited availability of collateral security). The averages for all variables are taken over 200 simulations. The vertical line indicates the shock period $T_s$ and interest rates are denoted per period.

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