Contingent Convertible Bonds and Macroeconomic Stability in a Stock-Flow Consistent Agent-Based Model

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Abstract

In 2008, excessive risk-taking from banks led to large losses when households couldn't repay their debt. It resulted in bank bankruptcies and in costly bailouts borne by the taxpayers. To prevent this from happening again, regulators are demanding that banks be able to deal with this type of problem ex ante by setting aside larger and higher quality capital and by relying more on bail-in mechanisms. As a result, the banking sector has created a new type of asset: contingent convertible bonds (CoCos). When the banks' ratio of assets and liabilities exceed a threshold, these bonds either convert into shares or are written off, which boosts their capitalization. CoCos are intended to strengthen the stability of the banking system and to ensure that the government is not required to fully assume the bailout of banks. As no CoCo has yet been activated, their effectiveness remains hypothetical. Can they fulfil their mission of stabilising the banking sector ? How does this risk shifting translate for the whole economy? Can the costs of such bail-ins outweigh their benefits in some situations? Will CoCos play a stabilizing or destabilizing role in the event of another financial crisis?

This paper aims at assessing CoCos in a stock-flow consistent agent-based model. The JMAB model by Caiani et al. (2016) is extended by adding: 1. a new class of financial assets, 2. learning behaviours on the part of investors, 3. a variable opinion component (alternating between optimism and prudence on the part of issuing banks and investors) allowing to take into account possible financial contagion effects through information spillovers.

Keywords: stock-flow modelling, agent-based modelling, contingent convertible bonds, bail-in, bailout, financial instability

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1. INTRODUCTION

In 2008, excessive risk-taking and securitization opacity led to large losses for banks when households couldn't repay their debt. It resulted in bank failures and ultimately in costly bailouts borne by the taxpayers. Some banking regulation has been implemented since then to prevent this situation from happening again. Among others, the Dodd Frank Act in the United States and the Basel III agreements worldwide have encouraged so-called "second generation mechanisms" based on ex-ante resolution procedures with a focus on two pillars: first, priority given to bail ins over bailouts, and second, stricter Tier 1 capital requirements for banks. The focus on these two pillars has led banks to issue a new type of asset since 2008: contingent convertible bonds (CoCos).

A CoCo is a hybrid financial instrument that has characteristics of both debt and equity. In normal times, it works exactly like a standard bond. A bank issues some when it needs funds. Investors buy them and are entitled to interest payments and will get back the principal when the bond expires. In a crisis, when banks' capital crosses a certain threshold, these bonds convert into equity shares or are written off (principal write-down, PWD), which then boosts the capitalization of the issuers. These two possibilities (conversion vs. PWD) define the loss absorption mechanism (Avdjiev et al., 2013).

CoCos are intended to provide large financial companies with more stability at minimal costs. By being counted as Additional Tier 1 (AT1) in the overall Tier 1 capital calculation, they help banks complying with regulatory requirements just by simply issuing these bonds which are less expensive for them than equities. CoCos prevent banks from shifting their own risks and imbalances to the rest of the economy. They create a mechanism which modifies the composition of the right-hand side of the issuers' balance-sheet by substituting equity for the debt once the solvency ratio goes beyond a certain threshold. Such a device puts an explicit limit to the leverage effect that banks can take advantage of.

However, as no CoCo bond has yet been activated, their effectiveness remains hypothetical and subject of debates. Some authors argue that they should improve the solvency of the banking sector and reduce the likelihood of taxpayer-funded bailouts (Calomiris & Herring, 2013; Pennacchi, 2010). Other authors insist on the fact that CoCos reduce the need for fire-sells when banks' solvency worsen too much, which limits the risk of death spirals and financial contagion (Vallée, 2019). And finally, their advocates argue that they mitigate the hindering effects of regulation on banks' profitability, allowing them all things being equal to increase lending to the real economy (Duffie, 2009; Flannery, 2016; Squam Lake Working Group, 2009).

But CoCos also have detractors. On the disadvantage side, several research papers warn about a potential increase in risk-taking and moral hazard as banks know that they will be bailed-in by investors if not bailed-out by governments (Berg & Kaserer, 2015; Flannery, 2016; Hilscher & Raviv, 2014; Martynova & Perotti, 2018). Some authors show how sudden risk reassessments by investors due to CoCos' complexity could have destabilizing effects on the financial sector (Admati et al., 2013; M. Allen et al., 2002; Goodhart, 2010; Sundaresan & Wang, 2015). Others focus on how the loss-absorption mechanism triggered by CoCo activations may occur too late, hence limiting their usefulness (Delivorias, 2016; Pazarbasioglu et al., 2011). There are also concerns that CoCos might not reduce the actual risk the banking sector is facing, but simply displace it to other sectors in the economy (Avdjiev et al., 2013). And finally, a recent empirical paper by Bologna et al. (2020) shows the existence of a CoCo-specific financial contagion channel.

The existing literature is therefore particularly divided on the subject of CoCos. On the one hand, one can expect positive effects from CoCos issuances: individual banks should be more resilient in times of crises and there should be less need for bailouts. But on the other hand, these theoretical benefits are to be contrasted with expected (and even observed) negative effects such as an increase in moral hazard, sudden and destabilizing market adjustments and potential financial contagion effects.

This uncertainty is all the more problematic as the CoCo market has recently experienced increasingly frequent disruptions. In January 2016, Deutsche Bank announced expected negative results. Uncertainty followed as investors feared that Deutsche Bank's CoCos coupons would not be paid. A few months later, in September 2016, the press reported that Deutsche Bank had received a huge fine from the US Department of Justice. These two events pushed the yield to maturity on Deutsche Bank's CoCos to historic highs and created market-wide stress, affecting all major European banks. This incident highlighted that an isolated disruption in the financial system could cause investors to suddenly fear systemic risks and flee from CoCos, destabilising the market and exacerbating the original problem but Bologna et al. (2020) suggest that such a contagion effect could be attributed to the lack of experience with this new instrument. Early 2020, the economic downturn caused by the SARS-CoV-2 pandemic brought additional turmoil to the market. Just one month after its first successful CoCo issue in six years in February 2020, Deutsche Bank has again announced that it will delay the repayment of $1.25bn of 6.25% CoCo debt. The value of the recently sold CoCo bond fell to around 50% of its face value. At the same time, investors tried to protect themselves from risks by buying massive amounts of CDS on the debt of Deutsche Bank and other banks. As a result, the global investment management firm Pimco saw its $8bn capital securities fund – which had CoCos as its top five holdings at the end of 2019 – fall by almost 13% over the past year. In 2022, after years of very low interest rates, central banks are raising them to counter inflation. As long as rates were close to zero, CoCos provided investors with an opportunity for high returns and demand was strong. In order to continue to attract investors, banks have now to pay more and more interests on their CoCos. The question is whether this rise in interest rates will be sustainable for banks as maintaining their AT1 levels will become increasingly costly.

This leaves three sets of questions open. The first one is related to the effectiveness of CoCo bail-ins. Can CoCos fulfil their mission of stabilizing the banking sector in the event of a financial crisis. Can they prevent bankruptcies? How much capital would be necessary to bail-in banks after a crisis? To what extent do they reduce the need for bailouts?

The second one is related to potential hidden costs for the rest of the economy. Provided CoCos are effective for the banking sector, are they also for the economy as a whole? Could the costs of such bail-ins outweigh their benefits in some situations? Is the risk transfer from taxpayers to investors always a positive outcome? How does this risk shifting translate for the whole economy versus a system without CoCo bonds? How does CoCo bond issuances impact the systemic risk? Do they indeed reduce it, or simply shift it, or even worse, increase it? Will CoCos play a stabilizing or destabilizing role in the event of another financial crisis? In what situations could CoCos destabilize the economy?

And finally, given all these uncertainties, are regulators right to encourage such bail-in mechanisms?

This paper is based on a key assumption: the inability of the existing literature to settle these debates and answer these questions can be explained by the lack of research bridging the gap between microeconomics and macroeconomics. Indeed, as Charles Goodhart notes: "One of the weaknesses of some of the analysis of CoCos is that it concentrates on the effect on a particular troubled bank, rather than also exploring the effects on the market dynamics of the financial system as a whole, (one of the key inherent weaknesses of our prior regulatory system)." (Goodhart, 2010). Indeed, most of the existing theoretical literature focuses on the advantages and disadvantages of CoCos at a micro level. In doing so, these analyses do not allow to conclude whether CoCos are useful or dangerous for the economy as a whole. They only provide information on one particular aspect of CoCos at a time and only at the level of an individual bank.

However, what is valid for an isolated bank is not necessarily valid for the whole sector – as many aggregated repetitions of the same phenomenon. In a sector where the importance of its agents can be systemic and where each decision can have profound repercussions on a macroeconomic scale, as the 2008 crisis showed, banks are interdependent. They influence each other directly through their actions, but also indirectly by affecting their environment, which in turn affects the behaviour of other banks. As a result, well-documented simple and predictable local interactions may generate intricate and unexpected global patterns. For example, if two banks have invested in the same asset and one of them is in trouble due to a sudden drop in the value of its assets, it will react by triggering fire sales, accentuating the drop in price even more, which will affect the portfolio of the other bank that was until then solid.

Therefore, any comprehensive assessment of the effectiveness and potential hidden costs of contingent convertible bonds, should rely on a macroeconomic framework that takes into account the interactions between the agents that populate the economy. Since there have not yet been any regular CoCo activations, we cannot rely on empirical data so we need to simulate what would happen if CoCos were activated in an economy sufficiently close to what is actually observed in reality. This requires the use of a theoretical counterfactual model that is empirically anchored. The model must be able to draw macroeconomic conclusions based on microeconomic interactions.

This is precisely the purpose and main contribution of this paper: to propose a credible theoretical model, incorporating the contingent convertible bonds issued by the banking sector since the 2008 crisis, and seeking to answer the various questions posed above and so far, unanswered in the existing literature. More precisely, this work consists in extending the stock-flow consistent agent-based JMAB model developed by Caiani et al. (2016) by adding: 1. a new class of financial asset, 2. learning behaviours on the part of investors, 3. a variable opinion component (alternating between optimism and pessimism/prudence on the part of issuing banks and investors) allowing to take into account regime shifts and possible financial contagion effects through information spillovers. This results in the very first agent-based macroeconomic assessment of contingent convertible bonds.

Section 2 lists the arguments for using an SFC-AB model. Section 3 gives a presentation of the model used. Section 4 presents the results of three policy experiments. Section 5 provides a final discussion.

2. THE CASE FOR AN AGENT-BASED STOCK-FLOW CONSISTENT FRAMEWORK

2.1. THE MAIN FEATURES AND ADVANTAGES OF STOCK-FLOW CONSISTENT MODELS

The structure of stock-flow consistent (SFC) models is based on a combination of different blocks: balance sheet matrix, transaction matrix, behavioural equations, and sectors studied. SFC modelling provides a relevant framework for modelling chains of adjacent short periods (e Silva & Santos, 2011). In particular, the balance sheets of each period are driven by the payment flows and capital gains (or losses) of each previous period. These models are "intrinsically dynamic and path dependent" (Turnovsky, 1977). Compared to other types of models, they offer a number of advantages:

- They are based on accounting identities. Thus, the assets of some are the liabilities of others. This makes it possible to completely close the models, without forgetting any components and without introducing any from scratch. As Caiani et al. (2016) say: “it provides a fundamental check of the model logical consistency”. Any model that deviates from these accounting identities sees certain sectors or agents accumulate a stock of liabilities or assets without any counterpart. The transactions that are linked to these stocks can generate inconsistencies and repeatedly miscalculated balance sheets that possibly bias the conclusions of the model.
- They take into account the role that money, credit and the financial system can play. They thus allow to model explicitly the banking sector (not only indirectly as a mere friction on the real sphere) as well as endogenous and government money, and to better understand events such as financial crises.
- They capture interconnections between the real and the financial spheres (which we want to do since we want to explore how the stabilizing of the financial sector through CoCo bail-ins can be positive or negative for the rest of the economy).
- They can easily keep track of accounting ratios and imbalances between assets and liabilities for different sectors.
- They can easily feature multiple assets (as many as necessary).

- They account for path dependency. Persistence effects are not artificially produced. They come from the SFC structure of the model and the fact that the model never returns to the ex-ante status. Accumulation occurs in a differentiated and irreversible way.

Given these advantages and since the aim of this paper is to incorporate a financial asset into a macroeconomic model, to take into account the interactions between the financial and real spheres (in the context of bail-ins), to monitor accounting ratios for the triggering of CoCos and to observe the lasting consequences of their triggering throughout the economy, the choice of a SFC theoretical framework seems appropriate.

2.2. THE LIMITATIONS OF STOCK-FLOW CONSISTENT MODELS

The scope of purely aggregated stock-flow consistent models is limited by two sets of factors. First, they lack heterogeneity *per se* because all the sectors are fully aggregated. It means for instance that an SFC model cannot take into account the fact that not all CoCos activate simultaneously. Moreover, it cannot properly capture bank failures since the net worth of the aggregate banking sector never reaches zero. And yet, stability at the aggregate level does not necessarily mean that all agents are in equilibrium. There are no distributional effects (e.g., with some banks being stronger than others). The difficulties of some banks cannot be transmitted to others, and the effects of financial contagion are not captured.

Second, there are no microfoundations for behavioural rules, which are only specified at the aggregate sector level. This is equivalent to thinking in terms of one representative agent per sector. However, the properties of an aggregate function do not reflect those of individual functions (Gallegati & Kirman, 2019) and the aggregate behaviour of a heterogeneous set of agents cannot be interpreted as the decision of a representative agent as stated by Arrow's Weak Axiom of Revealed Preferences (WARP) (Arrow, 1959). Rather than allowing endogenous macroeconomic phenomena to emerge as a result of microeconomic interactions, they are imposed.

The adoption of the bottom-up perspective of agent-based models (ABM) helps to overcome these limitations.

2.3. THE MAIN FEATURES AND ADVANTAGES OF AGENT-BASED MODELS

Agent-based models are particularly appropriate when one is interested in global and emergent patterns that are more than the simple aggregation of individual behaviours, but that cannot be understood without starting from these individual behaviours in a microfounded bottom-up approach. They are used to describe how the combination of simple and predictable individual interactions can drive the behaviour of the overall systems and give rise to unexpected global patterns. Agent-based microfoundations rely on five key principles:

- Agents are autonomous. The overall system evolves as a result of local interactions rather than being organized by centralized authorities or institutions (even if they may exist in the model as environmental constraints). This principle is also known as "self-organization" (Kauffman, 1995).
- Agents are interdependent. This means that each individual's decisions depend at lead in part on the decisions of other. This may be the case directly, as they agents influence each other by imitation or persuasion in response to the influence they receive. But it can also be the case indirectly when their actions change the environment, which in turn affects the behaviour of other agents.
- Agents follow simple rules. They do not necessarily optimize and are characterized by bounded rationality (Simon, 1955, 1959). They follow rules taking the form of habits, protocols, conventions, norms and heuristics that appear to be robust tools for inference (Dosi et al., 2020; Gigerenzer & Brighton, 2009). This results in the update of a multitude of microeconomic variables for each agent.
- Agents are adaptive. They adapt to the information they receive based on feedback loops which can reinforce dynamics or create tipping points. This happens in two ways:
    - Through learning, which occurs during processes like reinforcement, the back-propagation of error in artificial neural networks or Bayesian updating. This affects the probability distribution of competing behaviours within the range available to each individual.
    - Through evolution, which occurs during processes like imitation, social influence and selection. This affects the frequency distribution of agent types and of behaviours across the population of agents.
- Agents are heterogeneous. They differ by income, preferences, productivity, size, etc. It allows to have a look at distributional effects.

2.4. LIMITATIONS OF AGENT-BASED MODELS

However, agent-based models are limited by three sets of factors in terms of behavioural assumptions, parametrisation, and their interpretation, although work is being done to overcome these obstacles (Turrell, 2016). The first one is related to the so-called "wilderness of bounded rationality" (Sims, 1980). Agent-based models are built by making a large number of choices and behavioural assumptions. Some of them are supported by research in behavioural economics but there are not always criteria for choosing which behaviour is the most realistic, and the results presented can vary greatly depending on these assumptions.

The second weakness of agent-based models is that they are subject to the Lucas Critique. Agents may not follow the same behaviours when policy interventions are made. Some of the heuristics used in AB models do not take that into account. However, it is possible to model such changes in behaviour, in particular through the introduction of learning agents.

Finally, ABMs can be hard to interpret. Changes in model inputs can greatly affect model outputs and it can be difficult to understand how exactly. This is inherent to complex systems. More analytically tractable models do not have this issue. A change of parameter has clearer effects. One way to remedy this issue is to carry out extensive robustness tests on the behavioural assumptions made and the parameter spaces.

2.5. COMPLEMENTARITIES BETWEEN STOCK-FLOW CONSISTENT AND AGENT-BASED APPROACHES

The combination of a stock-flow consistent framework and agent-based microfoundations generates complementarities between the two paradigms and addresses some limitations of each. Adding agent heterogeneity to SFC frameworks allows to take into account that not all CoCos activate simultaneously as well as the possibility of isolated bankruptcies. We can then study more precisely whether CoCo bail-ins are able to prevent these failures, whether some banks are more resistant than others and whether there are possible contagion effects without being blind to what happen within sectors. Adding agent-based microfoundations eliminates the need for ad hoc assumptions such as exogenous shocks. The macroeconomic accounting identities and constraints typical of the SFC accounting emerge from the interactions of single agents' balance sheets rather than being imposed. Furthermore, it allows us to observe how interactions at the micro level such as the supply, demand and activation of individual CoCos can generate unexpected global dynamics such as information diffusion and decreasing waves of adjustments following market disruptions, or non-linearities in macroeconomic effects of activations.

Conversely, while several ABMs are stock-flow consistent[2], not all are. This can lead to inconsistencies as pointed out by Caiani et al. (2016). For example, a situation may arise where banks can buy government bonds using a positive net worth but without the liquid assets needed to complete the transaction. This would happen if they have high loans but low reserves and if no attention is paid to accounting counterparts. Another problematic case comes from the entry-exit process of firms in some AB models which assume that a failed firm is replaced by another with a given stock of capital and liquid assets. If this stock appears ex-nihilo, it is similar to a positive exogenous shock. This is likely to skew consumption, savings, credit and investment upwards in the model.

Therefore, SFC models provide boundary macroconditions to AB models and AB models provide microfoundations to SFC models. Combining the two paradigms allow to model both the dynamic network of balance sheets which connect the real and the financial sphere, as well as agent interactions and heterogeneity (Godin, 2016). Given these advantages the choice of an SFC-AB theoretical framework seems suitable and results in the model presented in the next section.

3. PRESENTATION OF THE MODEL[3]

3.1. OVERALL STRUCTURE

The model presented in this section is an extension of the SFC-AB "JMAB" model, developed by Caiani et al (2016). Its overall structure is described by the flow chart in Figure 1. The modelled economy consists of:

- Two sets of firms: consumption firms and capital firms. Consumption firms produce consumption goods sold to households, using labour and capital goods produced by capital firms. Firms borrow from banks to finance their investment and production. Retained earnings are held as deposits.
- A set of banks that collect deposits from capital firms, consumption firms and households, purchase government-issued bonds, provide credit to both types of firms and issue contingent convertible bonds sold to households[4]. They are subject to liquidity and capital

[2] See e.g. Caiani et al. (2016); Riccetti et al. (2015); Salle & Seppecher (2015)
[3] A list of the mentioned parameters can be found in Appendix A
[4] The demand for CoCos is not limited to retail investors. It also concerns private banks, mutual funds, investment funds, pension funds, etc. Excluding these other sectors is therefore a simplifying assumption. However, two things should be noted.

adequacy constraints. Banks can request cash advances from the Central Bank when they lack the liquidity to meet these requirements. Issuing credit results in a contingent increase in the size of their balance sheets. As loans create deposits, the quantity of money in the model is determined endogenously.

- A set of households who work for capital and consumption firms and receive wages in return. They consume and make portfolio arbitrage between bank deposits and banks' contingent convertible bonds. Households pay taxes on their gross income and own shares in banks, consumption firms and capital firms from which they receive dividends. Finally, unemployed households receive unemployment benefits from the government.
- A public sector consisting of a central bank and a government. The central bank holds both banks' reserve accounts and the government's account. It supplies advances to banks at a fixed exogenous rate and buys residual government bonds that have not been purchased by banks. Its profits are transferred to the government. The government issues bonds to cover its deficit and collects taxes from banks, capital firms, consumption firms and households. It also pays unemployment benefits to unemployed households.

In consistency with Caiani et al. (2016) who themselves followed Riccetti et al. (2015), interactions between agents are modelled through a matching process. In each period, demanders compare the interest rates or prices charged by a random subset of suppliers. The size of this subset depends on a parameter reflecting the degree of information imperfection in the economy. Demanders switch from their old supplier to a new one with a probability defined by Delli Gatti et al. (2010) as a non-linear function (decreasing when the paid interest/price is a cash outflow for the demander or increasing when it is a cash inflow) of the difference between their old and their new interest/price. In some cases, suppliers may exhaust their selling stock, leaving demanders with an unsatisfied residual demand. Demanders then search for alternative suppliers among the initial random subset that was presented to them to satisfy this residual demand. Market interactions are closed when demand is completely satisfied, when demanders no longer have deposits to pay for the demanded stock, or when there are no suppliers able or willing to meet their demand.

First, it is not unrealistic in the light of existing empirical research. Retail investors are among the first group to purchase them, and households in general are exposed indirectly through the other sectors that purchase them. The demand-side results discussed below therefore remain relevant. Second, modelling these additional sectors, the agents that populate them, and their microeconomic behavioural rules is an indispensable research project for a better understanding of the CoCos market, but is outside the scope of this paper, which focuses more on what happens on the supply side than on the demand side. Extending the demand side, however, is part of future personal research projects.

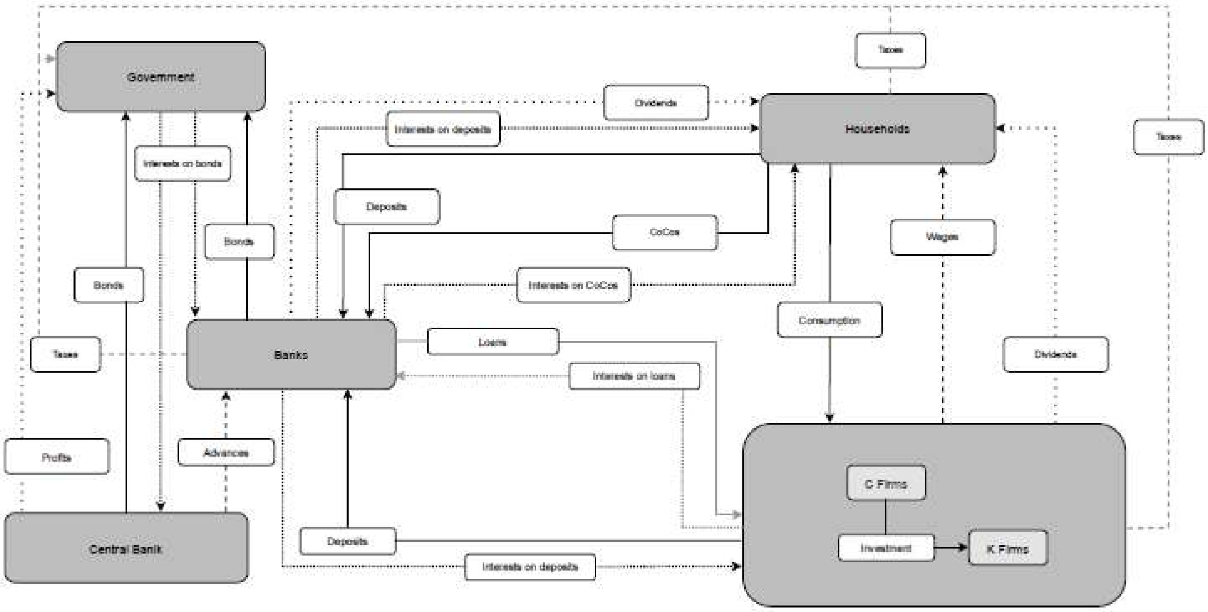

Figure 1: Flow diagram of the model. Arrows point from paying sector to receiving sector

The same calibration as Caiani et al. (2016) is used for the parameters and initial values of the variables not related to contingent convertible bonds. The variables and parameters related to CoCos cannot be empirically calibrated due to the lack of sufficient data. To overcome this limitation, robustness tests are performed to check the validity of the results regardless of the associated values.

3.2. AGENTS' BEHAVIOUR

This section presents the behaviour of each type of agent involved with CoCos (banks and households). The details on the firm and public sectors, important to understand the full functioning of the model but secondary to the CoCo problem, can be found in Appendix B. The reader can also refer to the online GitHub repository[5] for the full model code, as well as Caiani et al. (2016) for a detailed presentation of the initial version of the JMAB model.

In terms of notation, the variables relating to capital firms have a *k*-subscript, the ones relating to consumption firms have a *c*-subscript, the ones relating to households have an *h*-subscript and the one relating to banks have a *b*-subscript. As for expectations (associated with an *e*-superscript), all agents share the same adaptive way of forming them[6]:

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[5] https://github.com/elskr/sfc-abm_coco_contagion

[6] In a similar way to what can be found in other ABM models (Assenza et al., 2015; Dosi et al., 2010)

$$z_t^e = z_{t-1} + \lambda(z_{t-1} - z_{t-1}^e) \quad (1)$$

With $0 \leq \lambda \leq 1$

3.2.1. Bank behaviour

Credit supply

Firms interact with several banks on the credit market during each simulation period, selecting the best partner charging the lower interest rate (see the corresponding section below for the determination of the interest rate on loans) and eventually obtaining loans over several periods. The likelihood that firms obtain a loan depends on the credit rationing mechanism used by banks to assess loan demand (rather than a credit price rationing mechanism, following empirical evidence surveyed by Jakab and Kumhof (2014).

Consistent with Caiani et al. (2016), the model is based on a quantity rationing mechanism that takes into account both the risk and the bank's expected rate of return associated with each credit request. Therefore, the supply of credit for a given bank depends on its capital ratio targets, the probability of default and the creditworthiness of applicants based on collateral value and operating cash flows, as well as the expected rate of return of the loan for the bank. The probability of applicant default is computed in each of the next 20 periods ahead using a logistic function, based on the percentage difference between the borrowers' cash flows and the debt service on the given payment tranche associated with the hypothetical loans granted. The expected return on loans depends on the associated repayment amount as well as the probability of default of the borrower and the bank's risk aversion. It also takes into account the collateral of the firms (in case of a default by a consumption firm, a bank can temporarily size control of it and expect to recover a share of outstanding loans through the sale of capital goods).

Banks are willing to satisfy agents' demand for credit when the expected return is greater than or equal to zero. Otherwise, banks may still be willing to grant some credits, if there is an amount for which the expected return is non-negative.

Credit interest rate

Banks' interest rates on loans (see equation 2) depend on the difference between the banks' current capital ratio (equal to their net wealth divided by their total credit supply) and the target capital ratio (determined as the sector average for the past period). When banks are more capitalized than desired, they can afford to further expand their balance sheet by offering a lower interest rate than the average of their competitors, which has the effect of attracting more customers. When banks are less capitalized than desired, they reduce their exposure by offering a higher interest rate, which has the dual effect of making their loans less attractive while increasing their margin.

$$i_{b,t}^{l} = \begin{cases} \overline{\iota_{t-1}^{l}}\ (1 - FN) \text{ if } KR_{b,t} \geq KR_t^{\mathrm{T}} \\ \overline{\iota_{t-1}^{l}}\ (1 + FN) \text{ if } KR_{b,t} < KR_t^{\mathrm{T}} \end{cases} \tag{2}$$

With:

- $i_{b,t}^{l}$: the interest rate on loans of bank b in period t
- $\overline{\iota_{t-1}^{l}}$: the average interest rate on loans in period t-1
- FN : draw from a folded normal distribution $(\mu_{FN}, \sigma_{FN}^2)$
- $KR_{b,t}$: the capital ratio of bank b in period t
- KR_t^{T} : the target capital ratio

Deposits and bonds market

Banks hold the deposits of households, consumption firms and capital firms. They set their own deposit interest rate based on the difference between their actual liquidity ratio $LR_{b,t}$ and a target liquidity ratio LR_t^{T} defined as the sector average over the last period (see equation 3). When their liquidity ratio is above the target, banks set their interest rate on deposits with a positive mark-up over the average interest rate in order to attract customers. When their liquidity ratio is below the target, they set their deposit interest rate with a negative mark-up over the average interest rate to pay less deposit interests and restore this ratio. When the liquidity ratio falls below a mandatory lower bound decided by the regulator, banks request cash advances from the Central Bank. Finally, banks use their excess reserves to buy government bonds. The remaining bonds are purchased by the Central Bank.

$$i_{b,t}^{d} = \begin{cases} \overline{\iota_{t-1}^{d}} \,.\, (1 + FN) \text{ if } LR_{b,t} \geq LR_t^{\mathrm{T}} \\ \overline{\iota_{t-1}^{d}} \,.\, (1 - FN) \text{ if } LR_{b,t} < LR_t^{\mathrm{T}} \end{cases} \tag{3}$$

With:

- $i_{b,t}^{d}$: the interest rate on deposits of bank b in period t
- $\overline{\iota_{t-1}^{d}}$: the average interest rate on deposits in period t-1
- FN : draw from a folded normal distribution $(\mu_{FN}, \sigma_{FN}^2)$
- $LR_{b,t}$: the liquidity ratio of bank b in period t
- LR_t^{T} : the target liquidity ratio

Bank bankruptcies

Banks default when their net wealth turns negative. We assume that they are rescued by the government through bailouts financed entirely by depositors (households and firms). The number of banks in the model remains constant.

In order to restore positive net wealth, deposits from households and firms are reduced until the bank's net wealth becomes positive and its capital ratio equals the minimum required capital ratio. The loss borne by depositors is distributed in proportion to the size of their deposits.

Contingent convertible bond issuance

Econometric estimates are needed to verify the exact determinants of the issuance of CoCos by banks, but the available data do not yet allow for such work. A rule of thumb is proposed instead: banks issue no more and no less than the level of substitutability between Additional Tier 1 and Tier 1 allowed by the macroprudential rules laid down by the regulator. Basel III provides that Additional Tier 1 capital can substitute for Tier 1 capital up to 1.5% of the issuing bank's net wealth. It is therefore assumed that banks have no interest in issuing less than 1.5% of their net wealth in the form of CoCos, since this helps them complying with the Basel III solvency ratio requirements. It is also considered that it is not in the interest of banks to issue more than 1.5% of their net assets as CoCos. Beyond that, the benefit of issuing CoCos becomes limited. They are no longer counted as Additional Tier 1 capital. Banks can issue more of them but this does not contribute to improving their solvency ratio. They just pay more interest to investors and take the risk of dissatisfying their current shareholders who might fear too much dilution of their shareholder power in case of an activation (Bulow & Klemperer, 2013). The individual real supply and aggregate real supply of CoCos are therefore given by equation (4) and (5).

$$coco_{b,t} = \frac{AddT^{\ T}\ NW_{b,t-1}}{pbco^{T}} \tag{4}$$

$$coco_{t} = \frac{AddT1^{T}\ NWB_{t-1}}{pbc^{\ T}} \tag{5}$$

With:

- $coco_{b,t}$: the real supply of CoCos of bank b in period t
- $coco_{t}$: the aggregate real supply of CoCos in period t

- $AddT1^T$: the substitutability between Additional Tier 1 capital and Tier 1 capital decided by the regulator (1.5% here)
- $NW_{b,t-1}$: the net wealth of bank b in period t-1
- NWB_{t-1} : the net wealth of the banking sector in period t-1
- $pbco^T$: the announcement price of CoCos (exogenous and fixed)

Deferral of contingent convertible bond principal repayment

Consistent with empirical observations (Bologna et al., 2020), banks should be able to delay repayment of the principal of soon-to-be-matured CoCos when they fear for their solvency. This means that each bank *b* has a capital adequacy ratio threshold CAR_b^T below which it delays principal repayment. What capital adequacy ratio banks consider too low depends on whether they are optimistic or cautious about the economic situation and their liquidity capacity. For example, banks were much more cautious during the Covid-related economic crisis (hence the disruptions seen in the market) than before the crisis. Let $\overline{CAR^T}$ and $\underline{CAR^T}$ be respectively the optimistic and pessimistic exogenous capital adequacy thresholds under which banks decide to defer CoCo principal repayment, with $\overline{CAR^T} < \underline{CAR^T}$ (the criteria for deferral are more restrictive when banks are cautious).

Non-linear dynamic opinion are introduced, similar to what Salle & Seppecher (2015) did for households and firms in an agent-based model. Each bank's opinion, whether cautious or optimistic, depends on both its own situation and the prevailing majority sentiment among the banking sector:

- With a probability of 1-p, the bank relies on its own situation and looks at its liquidity ratio at the beginning of the period. If it is high enough (above a threshold LR^T), the bank is confident in its ability to repay CoCo principals ($CAR_b^T = \overline{CAR^T}$). If it's too low (below a threshold LR^T), the bank is more cautious ($CAR_b^T = \underline{CAR^T}$).
- With a probability p, the bank relies on the prevailing majority opinion among $b < size_B$ other banks. If most are confident, the bank is confident as well ($CAR_b^T = \overline{CAR^T}$). If most are cautious, the bank is cautious too ($CAR_b^T = \underline{CAR^T}$).

In practice, banks defer repayment as long as they feel they are in a critical solvency situation. And there will be activation of CoCos if they do not get out of this situation (delaying does not increase the net worth of the banks but prevents it from falling further).

Contingent convertible bond interest rate

Banks compete in the contingent convertible bond market by setting their own interest rate on CoCos (see equation 6). It depends on the difference between banks' current liquidity ratio and the target liquidity ratio (determined as the sector average for the past period). When their liquidity ratio is above the target, banks set their interest rate on contingent convertible bonds with a positive mark-up over the average CoCo interest rate to attract investors. When their liquidity ratio is below target, banks lower their interest rate on contingent convertible bonds to limit interest payments and thus restore their liquidity ratio.

Thus, it is the CoCos of the most stable banks that tend to attract the most investors (consistently with observations made by Avdjiev et al., 2020). A bank in an already fragile situation may issue CoCos but it will not be able to afford to pay high interest on them. Its CoCos will then be relatively less attractive to investors.

$$i_{b,t}^{BCO} = \begin{cases} \overline{\iota_{t-1}^{BCO}}\ (1+FN) \text{ if } LR_{b,t} \geq LR_t^{\mathrm{T}} \\ \overline{\iota_{t-1}^{BCO}}\ (1-FN) \text{ if } LR_{b,t} < LR_t^{\mathrm{T}} \end{cases} \tag{6}$$

With:

- $i_{b,t}^{BCO}$: the interest rate on CoCos of bank b in period t
- $\overline{\iota_{t-1}^{BCO}}$: the average interest rate on CoCos in period t-1
- FN : draw from a folded normal distribution $(\mu_{FN}, \sigma_{FN}^2)$
- $LR_{b,t}$: the liquidity ratio of bank b in period t
- LR_t^{T} : the target liquidity ratio

Contingent convertible bond pricing

The final price at which CoCos are traded is different from the announcement price $pbco^T$ set by the banks and shown in equations 4 and 5. This is a market clearing price which balances aggregate supply and demand. Households perform their portfolio arbitrage solely on the basis of the relative profitability of CoCos vs. deposits. Multiple prices based on the characteristics of the issuing banks could be implemented in a more sophisticated version of the model. However, the pricing of CoCos is not a central element of the analysis proposed here and we therefore opt for this simplifying choice. There is also no secondary market on which assets could be traded at different market prices. We have:

$$pbco_t = COCO_t / coco_t \tag{7}$$

With:

- $pbco_t$: the market clearing price for CoCos in period t

- $COCO_t$: the aggregate nominal demand for CoCos in period t
- $coco_t$: the aggregate real supply for CoCos in period t

Contingent convertible bond market matching mechanism

Following Riccetti et al. (2015), households are allowed to observe the interest rates charged by a random subset of banks (whose size depends on the degree of imperfect information investors face: they compare all interest rates if they have access to perfect information, or only a few otherwise). Following Delli Gatti et al. (2010), households switch from their previous partner to the best potential partner with a certain probability given by a non-linear function of the distance between the two compared interest rates. This means that households do not necessarily switch banks to buy their CoCos, even if they find a higher interest rate elsewhere. This inertia reflects their habits. Households may exhaust the stock of CoCos available at a given bank. In this case, they look for other suppliers in the randomly selected subset.

Contingent convertible bond activation mechanism

CoCos are activated when the banks' capital adequacy ratio falls below a given threshold value CAR^T. When this happens, all CoCos issued by the bank concerned are cancelled, regardless of their maturity. If the principal of some were to be repaid during this period, it is not and never will be. If CoCo interests were to be paid, they are not. The bank also does not issue new CoCos as long as its capital adequacy ratio is below this threshold. If the capital adequacy ratio continues to deteriorate and the bank's net worth reaches zero, then the bank goes bankrupt, triggering its bailout. This implementation therefore allows the bank to potentially recover between the time its CoCos are activated and the time it declares bankruptcy.

3.2.2. Household behaviour

Employed households set their reservation wage according to an adaptive heuristic rule: if over four periods (here, four quarters or one year) they have been unemployed for more than two, they reduce their reservation wage of the previous period by a stochastic amount. Otherwise, they increase their reservation wage only if the unemployment rate in the previous period is sufficiently low compared to a fixed threshold ν.

Households consume with fixed propensities out of expected real disposable income and expected real net wealth (following Godley and Lavoie, 2006) (see equation 8). They set their real demand based on expected prices of consumption goods before interacting with consumption firms.

$$c_{h,t} = \alpha_1 \frac{YD_{h,t}}{p_{h,t}^e} + \alpha_2 \frac{NW_{h,t}}{p_{h,t}^e} \tag{8}$$

With:

- $c_{h,t}$: the real consumption of household h in period t
- α_1 : propensity to consume out of expected real disposable income
- α_2 : propensity to consume out of real net wealth
- $YD_{h,t}$: nominal disposable income of household h in period t
- $NW_{h,t}$: nominal net wealth of household h in period t
- $p_{h,t}^e$: expectations on consumption good prices formulated in period t by household h

They hold deposit accounts at commercial banks $D_{h,t}$, earning a positive interest rate $i_{b,t}^d$ as well as contingent convertible bonds issued by commercial banks $COCO_{h,t}$, earning a positive interest rate $i_{b,t}^{COCO}$. At each period, households have to decide how to allocate their savings between these two types of financial assets. Following and extending Caiani et al. (2019), we implement a portfolio function inspired by Tobin's approach to household portfolio allocation (Brainard & Tobin, 1968). Households determine their desired allocation of financial wealth by comparing the expected rates of return on the assets they can purchase. While deposits are considered as a safe asset, contingent convertible bonds are weighted according to their perceived degree of risk, represented by their past activation rate indicated by $Pr_t^{activation}$. We define this past activation rate as the average number of banks involved in a CoCo activation over the last four periods (four quarters or one year) divided by the total number of banks. In this way, investors are able to react to past activations. If the market was disrupted in previous periods, this is factored into their calculation of the profitability of CoCos and all else being equal they reduce their demand for them. However, one may suspect the existence of non-linearities. An isolated activation is likely to cause some turmoil that is quickly forgotten by investors. But what could be expected in the case of a generalised activation? What would happen to the demand for CoCos if banks reissued them afterwards? It is unlikely that investors would move past the event as quickly as they would after an isolated activation. Would investors avoid CoCos altogether? If so, it would be much harder for banks to raise AT1 capital. This version of the model only partially explores this possibility. There are periods in the model where there are more or less activations at the same time. If there are many, $Pr_t^{activation}$ will be higher and the demand for CoCos lower.

With lp_t the share of wealth households wish to hold as deposits, we obtain equation (9) which summarizes the portfolio arbitrage. We derive equation (11) for the aggregate nominal demand for CoCos, as well as equations (12) and (13) which correspond respectively to the nominal individual demand for CoCos and the individual demand for deposits, expressed as a share of the net wealth of the household concerned.

$$lp_{h;t} = \begin{cases} \left[1 + \xi_{h;t} \cdot ||_{delay;t}\right] \cdot \sigma_1 . exp\left(-\sigma_2 \left[\overline{\iota_t^{BCO}}\left(1 - Pr_t^{activation}\right) - \overline{\iota_t^d}\right]\right) \text{if } \overline{\iota_t^{BCO}} \geq \overline{\iota_t^d} \\ \left[1 + \xi_{h;t} \cdot ||_{delay;t}\right] \cdot \sigma_1 \ \text{ if } \overline{\iota_t^{BCO}} < \overline{\iota_t^d} \end{cases} \tag{9}$$

$$||_{delay;t} = \begin{cases} 1 \text{ if some principal repayment got delayed in period t} \\ 0 \text{ if no principal repayment got delayed in period t} \end{cases} \tag{10}$$

$$COCO_t = (1 - lp_t)\, NWH_t \tag{11}$$

$$COCO_{h,t} = (1 - lp_t)\, NW_{h,t} \tag{12}$$

$$D_{h,t} = lp_t\, NW_{h,t} \tag{13}$$

With:

- σ_1 such as $0 < \sigma_1 < 1$, an exogenous upper bound to the share of wealth that households want to hold in the form of deposits.
- σ_2 such as $0 < \sigma_2 < 1$, a fixed parameter acting as a proxy for how sensitive households' portfolio arbitrage is to changes in expected rate of return and perceived risk of CoCos.
- $\overline{\iota_t^{BCO}}$: the average interest rate on CoCos in period t
- $\overline{\iota_t^d}$: the average interest rate on deposits in period t
- $\left(1 - Pr_t^{activation}\right)$: the probability CoCos won't activate in period t
- $\xi_{h;t}$ such as $0 < \xi_{h;t} < 1$, the size of households' reaction to a repayment delay announcement from banks
- $COCO_t$: the nominal aggregate demand for CoCos in period t
- $COCO_{h,t}$: the nominal demand for CoCos of household h in period t
- NWH_t : the net wealth of the household sector in period t
- $NW_{h,t}$: the net wealth of household h in period t
- $D_{h,t}$: the demand for deposits of household h in period t

The share of deposits in household portfolio arbitrage (conversely the share of CoCos) depends negatively (positively) on the spread between the activation risk-weighted rate of return on CoCos and the interest rate on deposits. The higher the rate of return on CoCos, the higher the share of CoCos in household net wealth. The higher the probability of activation of

CoCos, the riskier they will be perceived to be and the lower the share of CoCos in household net worth.

There are no individual reputations effect following an isolated activation. There is a general effect on the whole market in the sense that the overall demand for CoCos decreases afterwards. But investors do not treat the troubled bank differently when it is able to issue CoCos again. However, in the absence of activations that would provide more information but based on recent market disruptions, it can be concluded that such a reputation effect is not necessarily evident. When Deutsche Bank reissued CoCos in 2020, 6 years after a wave of uncertainty about its ability to repay the previous issue, investors welcomed the news as a sign that DB was strong enough to afford to issue CoCos again. The reissue in this case sent a positive information signal.

If a bank announces a delay in repayment of CoCos, then the indicator function $||_{delay;t}$ (equation 10) takes the value 1 and the nominal demand of household h in period t for deposits is adjusted according to the parameter $\xi_{h;t}$. Since households' savings are allocated between deposits and CoCos, this adjustment $\xi_{h;t}$ affects the demand for CoCo in the opposite direction. This means that if any bank announces a delay in the repayment of its CoCos, this will trigger an information spillover process. Investor households will do the same thing they did in 2016 following the Deutsche Bank announcement: they will turn away from the CoCos market and suddenly readjust their portfolio allocation.

We now need to specify the size of this adjustment $\xi_{h;t}$. We could consider it as a fixed exogenous parameter. But the existing literature would contradict such a decision. Consistent with the findings of Bologna et al. (2020), the information-based financial contagion channel appears to fade over time as investors learn about what is happening on the market. Hence another addition to the model: learning behaviours from investors. It is not realistic that investors always react naively in the same way to the announcement of a deferral of repayment. Rather, it appears that they initially overreact and then adjust their portfolio reallocation.

Formally, we introduce stochastic reactive reinforcement learning into the model with a modified Roth-Erev algorithm.[7] We allow households to explore 7 possible reactions to the announcement of delayed repayment: a 60%, 50%, 40%, 30%, 20%, 10% decrease in the proportion of their savings devoted to CoCos, as well as no decrease at all[8]. Each reaction j

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[7] For full details, see Nicolaisen et al. (2001) who proposed this modified version of the Roth-Erev algorithm for the first time.
[8] $\xi_{h;t}$ can take the values 0.7, 0.6, 0.5, 0.4, 0.3, 0.2, 0.1 and 0.0

(with j an integer between 0 and 6) is associated with a propensity q_j to choose it. After being set exogenously to initialize the model, they are updated according to the following endogenous process:

$$q_{j;t+1} = \begin{cases} [1-r] \, . \, q_{j;t} + Interests_{j;t}^{TOT} \, . \, [1-e] & \text{if action j has been chosen} \\ [1-r] \, . \, q_{j;t} + q_{j;t} \, . \, \frac{e}{N} & \text{if another action has been chosen} \end{cases} \tag{14}$$

With:

- r such as $0 < r < 1$, the so-called recency parameter.
- e such as $0 < e < 1$, the so-called experimentation parameter $\overline{\iota_t^{BCO}}$: the average interest rate on CoCos in period t
- N the number of possible actions (here, $N = 7$)
- $Interests_{j;t}^{TOT}$: the payoff associated with the choice of action j (i.e., the total interests earned in period t by the investor making this decision, equal to the sum of CoCo interests and deposit interests)

A number of things need to be clarified at this point:

- First, the propensities to choose a stock in period t depend on the value of these propensities in period t-1. The initialization of the parameters thus makes it possible to guide the initial choices made by the investors. If we want to model an over-reaction in portfolio allocation following a delay announcement, we have to calibrate the initial propensities in favour of the higher intensity adjustment.
- Second, once the model is initialized, the propensity to choose action j is updated according to what that choice yields ($Interests_{j;t}^{TOT}$). The exploration parameter e encourages investors to explore different options. If e tends towards zero, then choosing action k over action j has no positive effect on the propensity to choose j. Only the propensity of action k is updated. Once an action begins to be preferred, it remains so. As e increases, there are more spillovers of reward and the other actions still have a greater chance of being explored.
- Investors are likely to forget what they learn. This is the role of the recency parameter r. If r tends towards 1, more weight is given to recent payoffs (in the extreme case where $r = 1$, investors no longer take into account what has happened so far). If r tends towards zero, equal weight is given to all payoffs received to date.

In the model, these propensities are updated each time the CoCos market is disrupted by a repayment delay. Once they are all calculated, probabilities of choosing each action are deduced. The probability of choosing action j thus depends on the relative propensity of action j compared to the total sum of propensities. It is given by the following formula:

$$p_{j;t} = \frac{q_{j;t}}{\sum_{n=0}^{N-1} q_{n;t}} \tag{15}$$

This is done for each household, resulting in completely heterogeneous behaviours when faced with a refund announcement. No reaction is imposed in an *ad hoc* manner. Households explore on their own the option that brings them the most benefit. This exploration is done stochastically. There is no guarantee that they will all arrive at the same "optimal" reaction. But we will be able to observe trends in the section devoted to simulations.

The gross nominal income of employed households (see equation 16) is equal to the sum of their wages, interest earned on deposits, interest earned on CoCos and dividends received. They pay a tax on this gross income (a fixed lump sum). Unemployed households receive tax-free unemployment benefits from the government, defined as a fixed share of the average wage.

$$YP_{h,t} = W_{h,t} + i_{b,t-1}^{d}\, D_{h,t-1} + i_{b,t-1}^{COCO}\, COCO_{h,t-1} + Div_{h,t} \tag{16}$$

With:

- $YP_{h,t}$: the gross nominal income of household h in period t
- $W_{h,t}$: the wage earned by household h in period t
- $i_{b,t-1}^{d}$: the interest rate on deposits of bank b in period t-1
- $D_{h,t-1}$: deposits held by household h in period t-1
- $i_{b,t-1}^{COCO}$: the interest rate on CoCos of bank b in period t-1
- $COCO_{h,t-1}$: CoCos held by household h in period t-1
- $Div_{h,t}$: dividends received by household h in period t

4. NUMERICAL SIMULATIONS

To begin with, an aggregate version of the model associated with a real stationary state and a balanced nominal growth path is derived. It is solved numerically by setting reasonable exogenous values for the parameters for which empirical data are available. The initial aggregate stock and flows values of each sector are uniformly distributed among the individual agents. Only then do the microeconomic interactions begin. Initially, the agents that make up each sector are all identical. Their decentralized interactions and the adaptive revision of their strategies over time gradually bring out heterogeneity in the model. After a few periods, the balance sheets of each agent differ. They face different prices and interest rates. Some households are fired and others hired, some firms and banks go bankrupt while others continue to operate.

A Hodrick-Prescott filter is applied on each time series to separate their cyclical component from their trend component. As a result, the statistical tests and econometric analyses conducted in the following sub-sections are performed on stationary time series. Otherwise, the tests would be invalid and the estimates spurious.

4.1. EMPIRICAL VALIDATION

We first conduct an empirical validation of the model by verifying that our extension is able to reproduce the stylized facts initially reproduced by the original JMAB model of Caiani et al. (2016). The introduction of CoCos into the JMAB framework should not unduly disrupt its ability to capture mechanisms relevant to real-world economic dynamics. The parameters used to reproduce these stylized facts correspond to the calibration used for the baseline scenario.

The baseline scenario consists in 100 Monte Carlo Simulations of 400 periods each. We use the results of these simulations to check whether the model is able to reproduce the same stylized facts as the original JMAB model. This is done by comparing the properties of our artificially produced time series with those of real time series, following the same method as Caiani et al. (2016). The simulations yield similar results suggesting that our extension fits several key macro and microeconomic stylized facts. At the macro level, the model reproduces important properties of business cycles such as the pro-cyclicality of employment, consumption and investment (Stock & Watson, 1999). Inflation is pro-cyclical and lagging and mark-ups are counter-cyclical and lagging (Rotemberg & Woodford, 1999) (see Figure 2). Firms' total debt and leverage are pro-cyclical (Lown & Morgan, 2006; Leary, 2009) (see Figure 3, top and bottom left, and bottom right). Banks' leverage is pro-cyclical (Nuño & Thomas, 2017) (see Figure 3, top right).

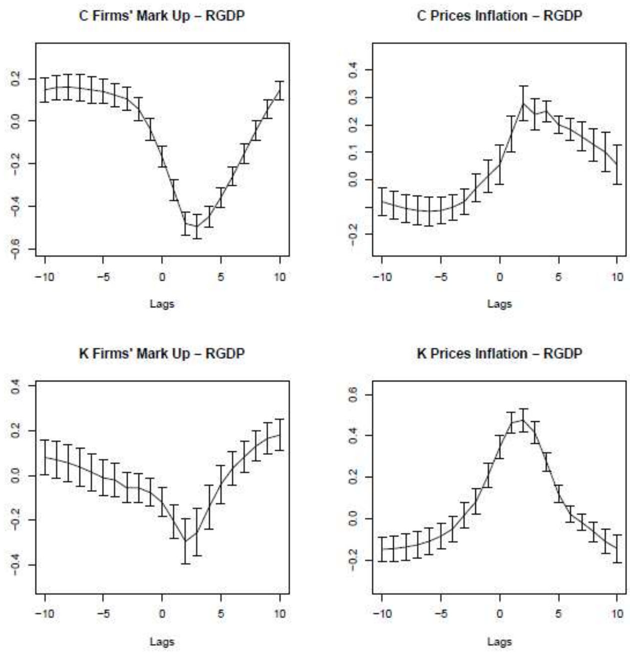

Figure 2: Average artificial cross-correlations of the markup and price de-trended series up to the 10th lag. Segments show the standard deviations of Monte Carlo average cross-correlations.

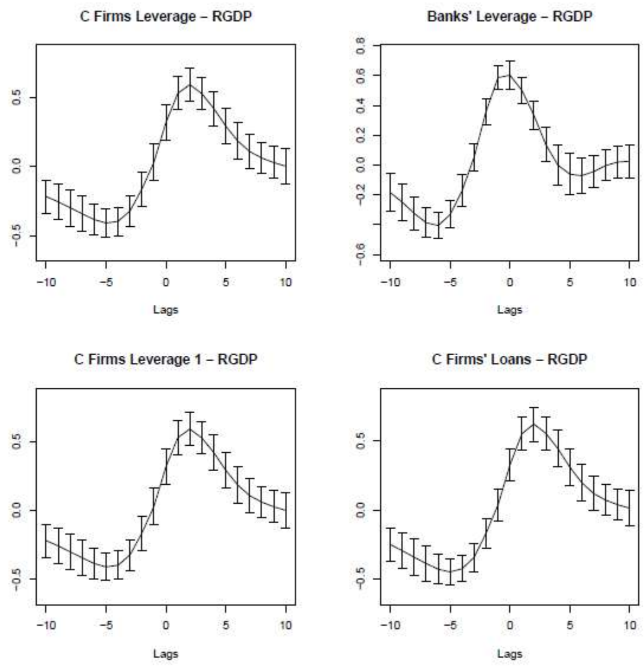

Figure 3: Average artificial cross-correlations of the markup and price-detrended series up to the 10th lag. Segments show the standard deviations of the Monte Carlo average cross-correlations.

At the micro level, the model generates hump-shaped investment, in accordance with the observations reported by Doms & Dunne (1998) who show thanks to US longitudinal data that investment is not smoothed over time, but alternates between high-intensity spikes and periods of lower intensity or even high intensity and periods of low intensity (with sometimes no investment at all). This lumpiness is illustrated by Figure 4.

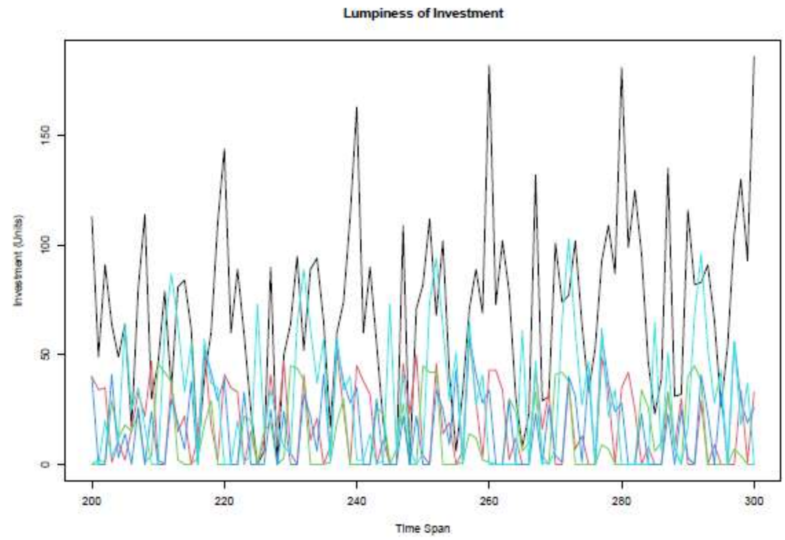

Figure 4: Hump-shaped investment. Lines show 5 consumption firms between periods 200 and 300 of a single simulation run.

The model is also able to reproduce both high path dependency and strong heterogeneity for firms, consistent with empirical observations reported by Dosi et al. (1997). The high path dependency is illustrated by Figures 5 and 6, which show the market shares of 20 capital and consumption firms, between periods 200 and 400 of one typical simulation run. One can observe that firms that succeed in establishing a dominant position on the market tend to maintain this dominant position over time (and vice versa), even if disruptions are occasionally possible.

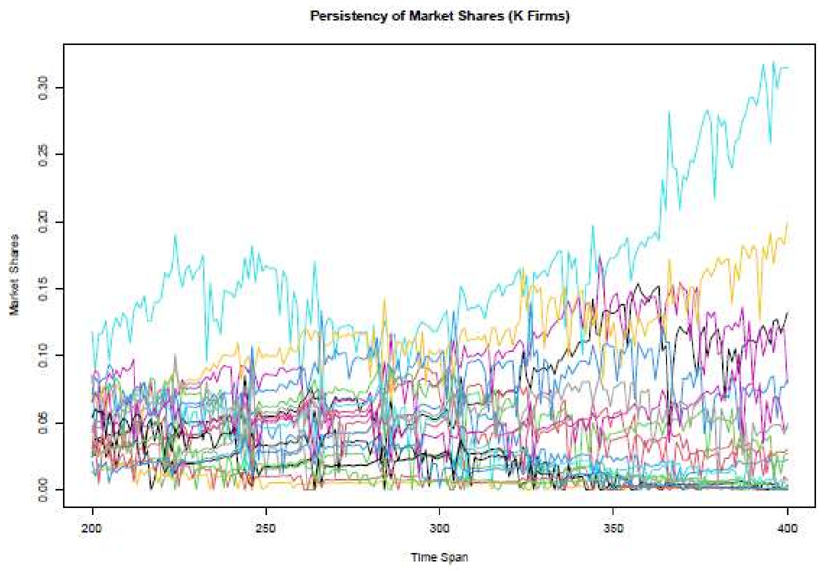

Figure 5: Market shares persistency for capital firms. Lines show 20 capital firms between periods 200 and 400 of a single simulation run.

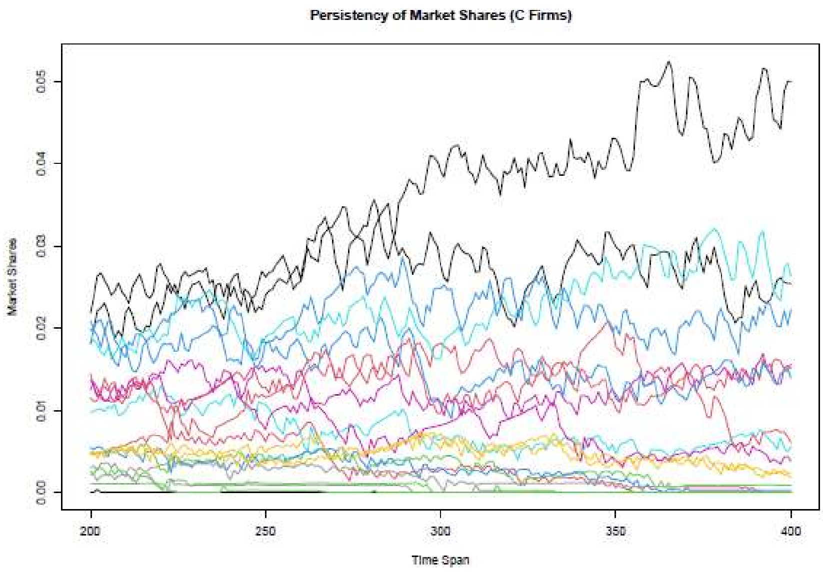

Figure 6: Market shares persistency for consumption firm. Lines show 20 consumption firms between periods 200 and 400 of a single simulation run.

Firm heterogeneity is analysed by different means: shape parameters, Jarque-Bera tests, graphic analysis, and comparisons with log-normal and power-law fits through Vuong's likelihood tests. When it comes to shape parameters. Capital firm size measured by their sales has a skewness equal to 2.79 and an excess kurtosis equal to 10.22, suggesting a strongly right-skewed distribution (Bulmer, 1979). The same applies to consumption firms with a skewness equal to 1.02 and an excess kurtosis equal to 1.13. Jarque-Bera statistical tests (which are used to test the null hypothesis that these skewnesses and kurtoses match a normal distribution[9]) yield p-values equal to 0 for both capital and consumption firms, and χ^2 respectively equal to 9629.7 and 1697.2. Thus, the normal distribution hypothesis is unquestionably rejected for both types of firms. This is illustrated by Figures 7 and 8, which show a photography of the degree distribution of capital and consumption firms in period 400 of the 100 baseline Monte Carlo simulations. These log-log plots display the actual distribution of firm sizes (dots), the theoretical power law fit (in red) and the theoretical log-normal fit (in green). Even if the model is initialized with identical firms, they eventually vary in size with, with a concentration of

[9] See Verbeek (2017) for more details on Jarque-Bera statistical tests

small ones (displayed at the top left of both graphs) and some very large ones (displayed at the bottom right of both graphs).

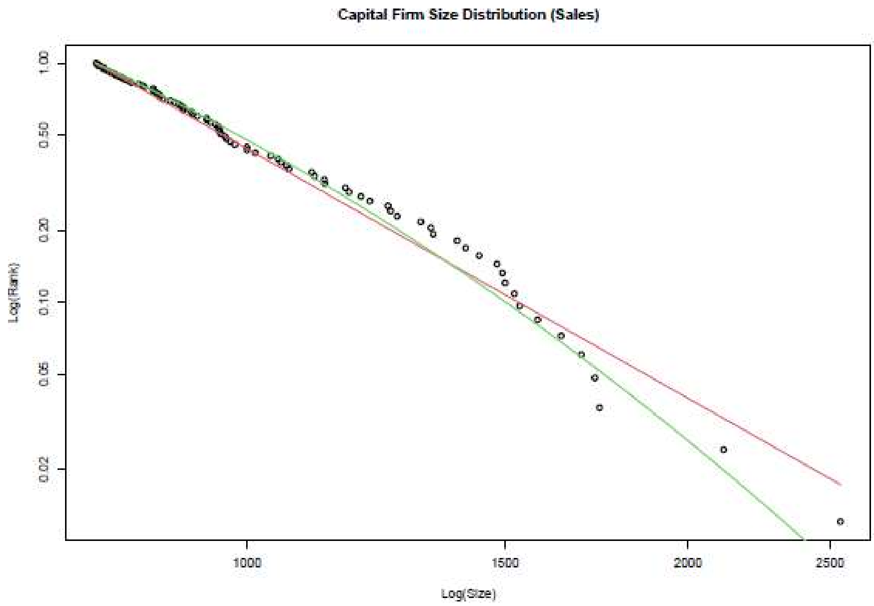

Figure 7: Capital firms upper tail size distribution (dots), log-normal fit (green line) and power-law fit (red)

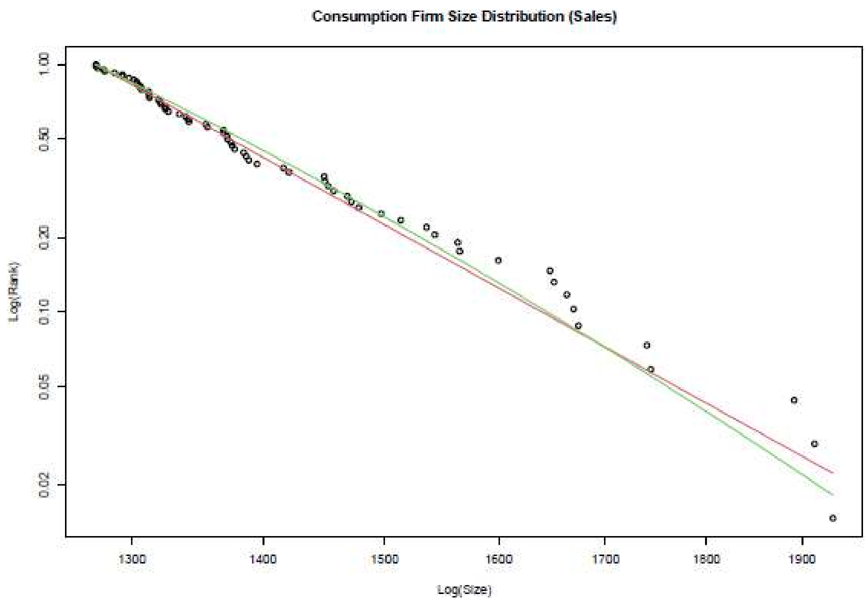

Figure 8: Consumption firms upper tail size distribution (dots), log-normal fit (green line) and power-law fit (red)

This version of the model is also able to reproduce an important financial stylized fact: large changes in asset prices occur more often than would be expected with a normal distribution and rationally behaving investors. More precisely, fat tails are observable in the distribution of asset price variation (Cont, 2001). Such fat tails can be observed for the price change of CoCos as shown in Figure 9. A Jarque-Bera statistical test yields a p-value equal to 0 and a χ^2 respectively equal to 101551. Thus, the normal distribution hypothesis is unquestionably rejected for CoCo price changes.

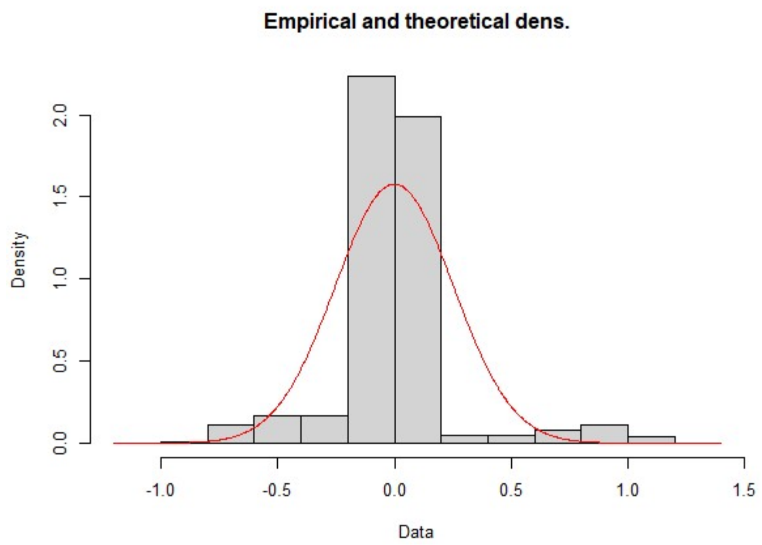

Figure 9: Empirical distribution of CoCo price changes (bars) and theoretical normal distribution (solid curve)

4.2. POLICY EXPERIMENT 1: TESTING THE EFFECTS OF INTRODUCING COCOS FOR DIFFERENT VALUES OF THE ACTIVATION THRESHOLD

The empirical validation of the model discussed in the previous section shows that the model generates cycles. These cycles are sufficient to lead to bank failures, requiring costly bailouts borne by the taxpayer. The introduction of automatic bail-in mechanisms through the issuance and activation of CoCos should improve bank balance sheets in time of crisis without government intervention. Thus, we should observe a decrease in the total cost of bailouts with the introduction of CoCos in the model.

To verify this, we run two sets of 25 simulations[10]: one without CoCos (this is simply the original JMAB model), the other with CoCos activated when the bank's capital ratio falls below 60 percent (this threshold corresponds to our baseline scenario, other threshold values

[10] Following the method used by Caiani et al. (2016) for their own sensitivity analyses.

are tested later). We then perform Mann-Whitney tests[11] to check for statistical differences for several variables of interest: the number of bank bankruptcies and the bailout costs, but also their liquidity and capital adequacy ratios, consumption, investment and GDP. The results from these tests are presented in Table 1 below.

Table 1: Mann-Whitney nonparametric tests (25 Monte Carlo runs of 400 periods) with and without CoCos - (***): p-value < 0.001; (**): p-value < 0.01; (*): p-value < 0.05

Effects of the introduction of CoCos on …	
... bank bankruptcies	< (***)
... bank bailout costs	< (***)
... bank average capital ratio	> (***)
... average consumption	-
... average investment	> (***)
... average GDP	> (***)

The introduction of CoCos into the economy has significant effects. For the banking sector, we observe fewer bankruptcies, lower bailouts costs[12] and higher capital ratios. These positive effects are due to the fact that the crises that banks face over the cycles generated by the model are relatively less fatal for them when they issue CoCos. Not only do CoCos help with shifting the direct burden of bank rescues from all taxpayers to banks' creditors, but they also limit losses as their automatic activation occurs earlier and faster than bailouts operated by the government (thus leading to fewer bank failures, lower total bailout costs and higher capital ratios). This must be put into perspective with the theoretical debates presented in the literature review in the introduction. While Delivorias (2016) and Pazarbasioglu et al. (2011) raised concerns about the ability of CoCos to be an effective loss-absorbing mechanism when banks really need them, it appears that they do make a difference, even if they do not completely prevent bank failures and bailouts at the expense of the taxpayer. The results are in line with Helberg and Lindset's claim that "CoCos can take up the role as the first line of defence and public bail-in may be a complementary tool for banks that will likely remain distressed after the conversion" (Helberg & Lindset, 2014), as well as the literature that states that CoCos improves the solvability of the banking sector (Calomiris & Herring, 2013; Pennacchi, 2010).

[11] We implement Mann-Whitney nonparametric tests since we have unpaired samples and the time series change between runs of simulations, partly due to the random path of the model and partly due to our parameter sweep.

[12] Nevertheless, we continue to see bankruptcies and therefore bailouts. CoCos make it possible to reduce them but not to prevent them entirely.

This stabilization of the banking sector during crises has second-order effects on the real economy. Indeed, there is a significant positive effect of the introduction of CoCos on investment and GDP. This effect can be explained by a positive financial accelerator (Bernanke et al., 1999). The fact that banks are relatively less likely to go bankrupt means that they can continue their activities, notably lending to firms to finance their investments and thus GDP. These results are robust to different values of the activation threshold as shown in Figure 10. We perform Mann-Whitney tests for several activation threshold values between 0.60 and 0.70 with a 0.01 increment between each set of 25 Monte Carlo simulations, as well as for a scenario without CoCos. Investment and GDP values are and significantly higher in an economy with CoCos than in an economy without, whatever the value of the activation threshold tested. This is in line with the academic literature that sees CoCos as an advantage for the real sphere (Duffie, 2009; Flannery, 2016; Squam Lake Working Group, 2009; Vallée, 2019).

It should be noted that the effects on consumption are ambiguous and not significant.[13] We know that households benefit from the positive second-order effects of stabilizing the banking sector in a crisis scenario. They are less likely to bear bailouts, and the relative increase in investment and GDP positively affects their wages. The ambiguous and non-significant results for consumption reported by the Mann-Whitney tests can therefore be explained by a counterbalancing negative effect. As the activation of CoCos leads to a transfer of net wealth from investors (households) to banks, the banks' creditors see part of their asset portfolio melting away. They will never get their principal back. And they will not receive the interests they should have received on the CoCos they held. All this negatively affects their consumption, which depends on both their income and their net wealth, as we saw in the presentation of the model.

[13] Exact p-values for the Mann-Whitney baseline and robustness checks can be found in the corresponding section of the online appendix: https://github.com/elskr/sfc-abm_cocos/tree/main/paper)

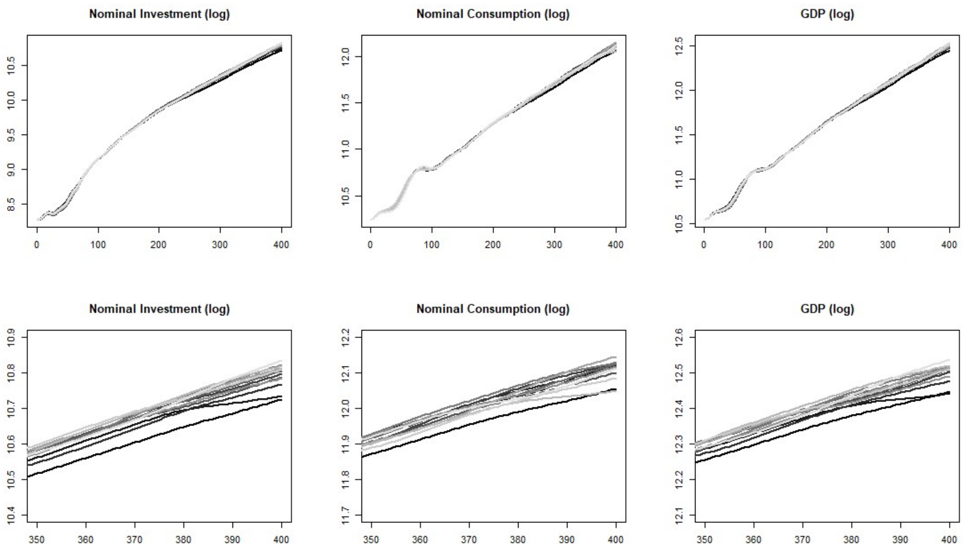

Figure 10: Different threshold of activation: lighter grey corresponds to higher threshold. Black (the lowest line in the bottom three graphs) corresponds to the scenario without CoCos. Top and bottom left: log of nominal investment. Top and bottom centre: log of nominal consumption. Top and bottom right: log of nominal GDP.

4.3. POLICY EXPERIMENT 2: TESTING THE EFFECTS OF THE QUANTITY OF COCOS IN CIRCULATION FOR DIFFERENT VALUES OF THE ACTIVATION THRESHOLD

We have shown in the previous section that the increased stabilization of the banking sector following the activation of CoCos in the event of a crisis generates positive second-order effects for the rest of the economy. However, we have also shown that these bail-ins do not have only positive effects. By shifting the burden of debt rescue, they introduce destabilizing mechanisms that can counteract these positive second-order effects, making the net effect for the economy as a whole ambiguous. In this section, we examine one of the determinants of this net effect: the quantity CoCos in circulation at the time of activation.

For bail-ins to be effective, the quantity of CoCos in circulation at the time of activation must be sufficiently large. Not enough and the contingent inflow of capital does not allow banks to sufficiently absorb the shocks they face. Fewer bankruptcies are avoided. The interruption of banking activity then has negative repercussions on the real sphere (consumption, investment and GDP) and the government has to deploy bailouts that weigh even more on the real sphere insofar as these have to be financed by the taxpayer. We can therefore put forward a first hypothesis. One can expect, at least up to a certain point, a positive relationship between the outstanding quantity of CoCos at the time of activation and the macroeconomic aggregates: the larger the outstanding volume, the greater the magnitude of the positive effects highlighted in section 4.2.

However, the larger the volume of CoCos in circulation, the more investors (in this case households) are harmed in the event of an activation, which is likely to weigh on consumption as also highlighted in section 4.2. We can therefore put forward a second hypothesis. One can expect, at least from a certain point, a negative relationship between the outstanding quantity of CoCos at the time of activation and the macroeconomic aggregates. The economy can end up in a situation where the volume of CoCos is too high and the net effects of an activation become negative for the real sphere.

These two hypotheses taken together suggest nonlinear effects of the amount of CoCos in circulation. To test these hypotheses, we estimate two nonlinear penalized spline regression models (for the method, see Kauermann et al., 2009 ; for another application to ABM models, see, e.g. Dawid et al., 2014): one for consumption (17) and one for GDP (18). We set the time dimension to t=300 to get panel data of dimension 2 (threshold of activation p[14]; Monte Carlo run i). η designates random effects and ε designates error terms. s designates the spline function (it is no longer a fixed parameter as in linear regressions but a third-order polynomial depending on the amount of CoCos in circulation). The results of the nonlinear penalized spline regressions are shown in Table 2.

$$C_{p,i} = \alpha_0 + s(COCO_{p,i}) + \sum_{p=1}^{11} \eta_{p,i} + \varepsilon_{p,i} \tag{17}$$

$$Y_{p,i} = \alpha_0 + s(COCO_{p,i}) + \sum_{p=1}^{11} \eta_{p,i} + \varepsilon_{p,i} \tag{18}$$

The quantified parameters estimated in this penalized spline regression cannot be interpreted directly. However, two things can be noted. First, both smooth terms are significant (i.e., there is indeed a significant non-linear effect of the amount of CoCos in circulation on consumption and GDP). Secondly, the adjusted R^2s are higher than with the linear models with quadratic terms (which also weighs in favour of a nonlinear interpretation of the relationship between the quantity of CoCos in circulation in the economy and the macroeconomic aggregates). Figure 11 shows the graphical representation of these nonlinearities.

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[14] For robustness's sake, we perform 11 Monte Carlo experiments for 11 values of threshold of activation between 0.59 and 0.70 with a 0.01 increment between each experiment. Each experiment is run 25 times over 400 periods.

Table 2: Nonlinear penalized spline models

Penalized spline model – Consumption (17)

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept)	121533.9	1317.9	92.221	< 0.0001
B. smooth terms	edf	Ref.df	F-value	p-value
S(COCO)	5.101	5.101	9.249	<0.0001
Adjusted R²: 0,155				

Penalized spline model – GDP (18)

A. parametric coefficients	Estimate	Std. Error	t-value	p-value
(Intercept)	177861.7	1765.3	100.752	< 0,0001
B. smooth terms	edf	Ref.df	F-value	p-value
S(COCO)	3.82	3.82	5.045	<0.0001
Adjusted R²: 0,0876				

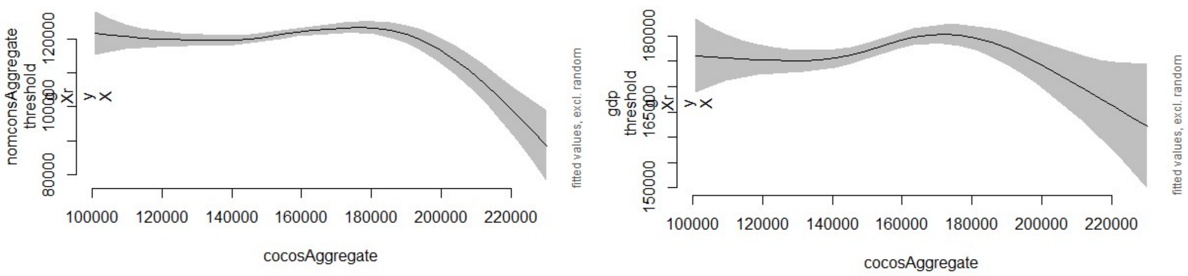

Figure 11: Graphical representation of the estimated non-linear penalized spline models. Left: effect of the quantity of CoCos on aggregate consumption. Right: effect of the quantity of CoCos on GDP. In light grey: confidence bands.

The issuance of CoCos and their activation allow banks to be more resilient in the event of a crisis and to maintain their activities. They can continue to lend to firms, which has a positive second-order effect on investment. This fuels GDP and consumption growth up to a certain point (as shown by the initial rise of consumption and GDP as the quantity of CoCos increases). However, the more CoCos in circulation, the greater the net wealth transfer when bail-ins occur. Beyond a certain amount (reached at the top of the two curves), the negative effect on consumption start to outweigh the positive second-order effects and this eventually affects GDP as well (hence the final decline in both curves).

4.4. POLICY EXPERIMENT 3: TESTING THE IMPACT OF CONTINGENT CONVERTIBLE BONDS ON FINANCIAL CONTAGION

4.4.1. How information spillovers and learning behaviours work in the model

Before analysing the possible role of CoCos in financial contagion, it is important to describe how the spillover information system and learning behaviours work in the model, and how they are sensitive to parameter changes.

The model is able to reproduce information spillovers on the CoCo market and the resulting learning behaviour. Banks occasionally announce postponements of repayments (see Figure 12, left). With each announcement, there is an information spillover and investors abruptly adjust the share of CoCos they hold in their portfolio arbitrage. The baseline scenario gives a higher initial propensity to the extreme choice of reducing the share of CoCos in one's asset portfolio by 60% (see the baseline calibration in Appendix A). In a typical simulation (shown in Figure 12, right), investors reduce this share by an average of about 38.7% when the first deferral is announced around period 150. But we observe that the size of this adjustment decreases over time. First rapidly, then more slowly, until it converges towards an adjustment of around 21%. This suggests that investors are overreacting in a way that is detrimental to them and their financial income. This is consistent with the existing literature that warns of the temporal inconsistency and irrationality of CoCos buyers (Admati et al., 2013; H. Allen, 2012; Goodhart, 2010; Sundaresan & Wang, 2015). They behave as if the asset were a simple debt instrument with too little chance of being activated and panic when clauses explicitly provided for in the contracts are activated. By withdrawing abruptly from the market, this leads to a loss of income for them. As they realise this, they adapt their behaviour to maximise the interests they receive. This leads to a strategy that is optimal on average across the sector when convergence is achieved, but still involves a downward adjustment in demand for CoCos following market disruptions.

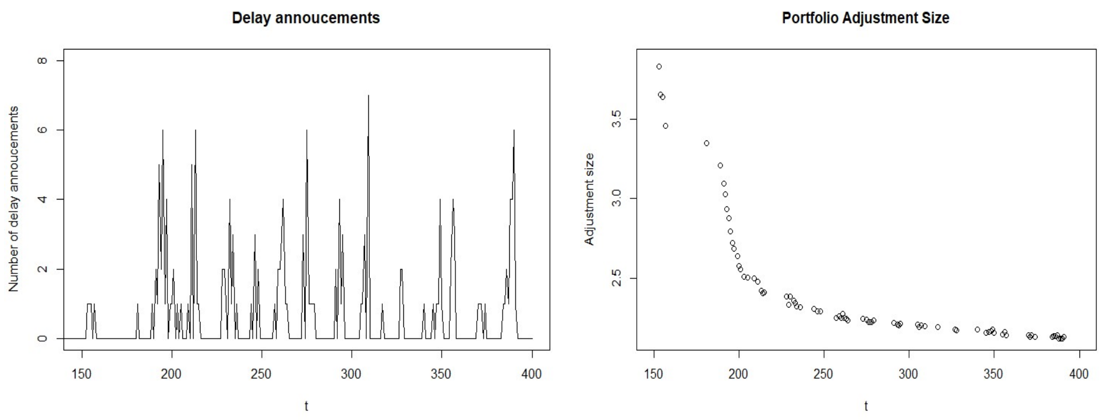

Figure 12: Number of repayment deferrals announced by banks (left) and portfolio size adjustment following a CoCo repayment deferral (right) between periods 100 and 400 for a typical single simulation

Table 3 shows the different parameter sweeps performed for robustness checks. The learning phenomenon is present in the model, regardless of the parameter sweeps performed on the initial propensity assigned to the extreme choice of reducing the share of CoCos in one's financial asset portfolio to 60% (q_6), the recency parameter (r) and the exploration parameter (e).

Table 3: Parameter sweeps

Parameter	Description	Baseline	Increment	Sweep
q_6	Initial propensity of adjustment size = -60%	8	2	[2 ; 10]
e	Exploration parameter	0.1	0.2	[0 ; 1]
r	Recency parameter	0.2	0.2	[0 ; 1]

Each of these parameters affects the dynamics of learning behaviour in a specific way. Adjusting q_6 changes the magnitude of the investors' initial reaction. The higher the value, the more they will react to a deferral announcement (see Figure 13). Adjusting r changes the time it takes for investors to adapt to disruptions in the market. The higher r is, the less inertia there is in their adjustments and the faster they converge to an optimal reaction after an announcement of a repayment delay (see Figure 14). Finally, adjusting e changes the size of the portfolio adjustment towards which average investor reactions converge. The higher the value of the parameter, the less likely they are to abandon solutions that consist in heavily adjusting their asset portfolio, resulting in a higher convergence value (see Figure 15).

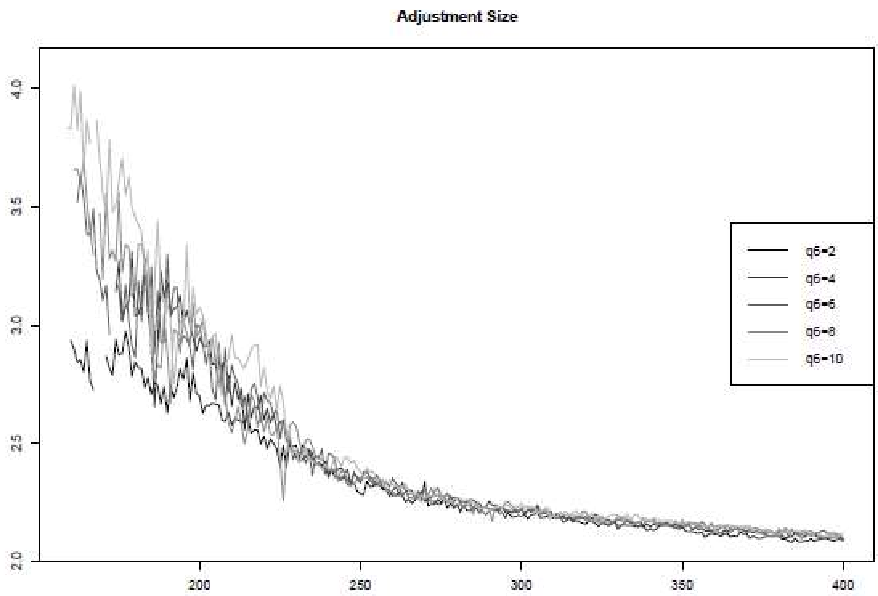

Figure 13 : Portfolio size adjustment following a CoCo repayment deferral (right) between periods 150 and 400 for different values of q6 (25 Monte Carlo simulations per parameter value)

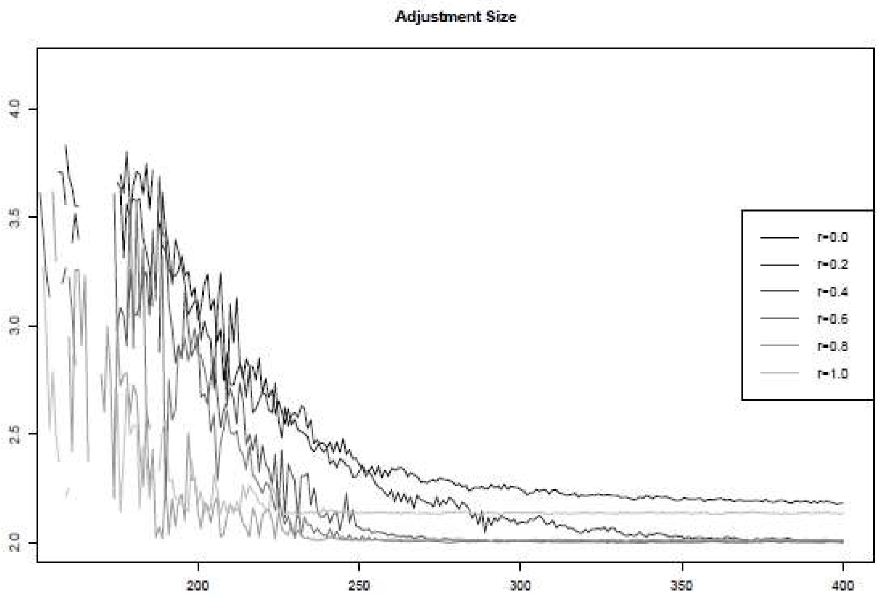

Figure 14: Portfolio size adjustment following a CoCo repayment deferral (right) between periods 150 and 400 for different values of r (25 Monte Carlo simulations per parameter value)

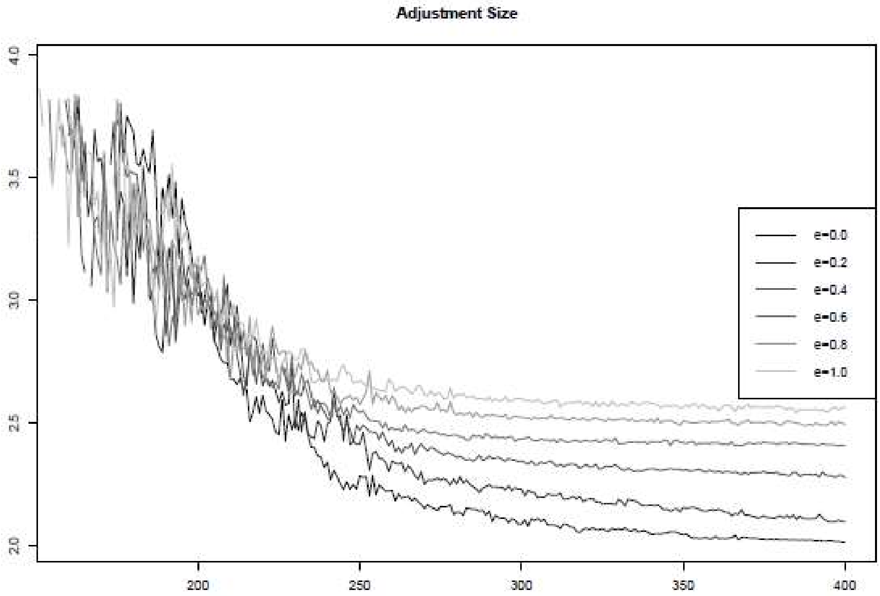

Figure 15: Portfolio size adjustment following a CoCo repayment deferral (right) between periods 150 and 400 for different values of e (25 Monte Carlo simulations per parameter value)

4.4.2. Contingent convertible bonds and information-based financial contagion

The model is able to reproduce what is observed by Bologna et al. (2020). A non-refund announcement induces a sharp drop in the aggregate demand for CoCos. But as the situation is repeated, the adjustment decreases, suggesting that investors are learning. The question is whether these information spillovers are likely to generate financial contagion in the model. To answer it, we need to rely on a measure of financial contagion. Several are used in the literature and are listed by Acharya & Yorulmazer (2008): intertemporal correlation of bank events, risk premiums of bank debt, deposit flows and stock price reaction.

The selection of the financial contagion measure is dictated by the limitations of JMAB. There is no interbank market, so we cannot look at risk premiums on bank debt. There are no deposit runs (households decide which bank to give their deposits to, solely on the basis of the interest rate they offer), so we cannot look at deposit flows. Bank shares are not priced on a secondary market, so we cannot watch their price evolution. But we can look at intertemporal correlation of bank events such as CoCo activations.

I check in the Baseline scenario if the activation of CoCos in period t can be explained by the activation of CoCos in previous periods (which captures a potential domino effect), announcements of delayed repayment (which capture a potential financial contagion through information spillovers), real GDP, loans, capital good inflation and consumption good inflation (to control for the macroeconomic situation). Since we are trying to explain the number of occurrences of an event (CoCos activations) based on panel data (two dimensions: simulation run i, and period t), we need to use a Poisson autoregressive model. A similar approach can be found in Schoenmaker (1996). The R package used is *pglm.*

The first step is to ensure that the time series of the variables selected do not have a unit root, and if so, to transform them so that they do not. Using an augmented Dickey-Fuller (similar to what can be found in Levin et al., 2002), the unit root hypothesis cannot be rejected for GDP and both price levels. But it can be rejected in the changes of these variables. The period-to-period changes in logarithms are therefore used to ensure the absence of unit roots. Formally, the following models are estimated:

$$Y_{t;i} = \alpha_0 + \alpha_1 \Delta GDP_{t;i} + \alpha_2 \Delta P^C_{t;i} + \alpha_3 \Delta P^K_{t;i} + \alpha_4 \Delta DELAY_{t;i} + \alpha_5 \Delta DELAY_{t-1;i} + \alpha_6 \Delta DELAY_{t-2;i} + \alpha_7 \Delta DELAY_{t-3;i} + \alpha_8 \Delta DELAY_{t-4;i} + \alpha_9 Y_{t-1;i} + \alpha_{10} Y_{t-2;i} + \alpha_{11} Y_{t-3;i} + \alpha_{12} Y_{t-4;i} + \eta_{t;i} + \varepsilon_{t,i} \quad (19)$$

$$Y_{t;i} = \beta_0 + \beta_1 \Delta LOANS_{t;i} + \beta_2 \Delta P^C_{t;i} + \beta_3 \Delta P^K_{t;i} + \beta_4 \Delta DELAY_{t;i} + \beta_5 \Delta DELAY_{t-1;i} + \beta_6 \Delta DELAY_{t-2;i} + \beta_7 \Delta DELAY_{t-3;i} + \beta_8 \Delta DELAY_{t-4;i} + \beta_9 Y_{t-1;i} + \beta_{10} Y_{t-2;i} + \beta_{11} Y_{t-3;i} + \beta_{12} Y_{t-4;i} + \eta_{t;i} + \varepsilon_{t,i} \quad (20)$$

$$Y_{t;i} = \gamma_0 + \gamma_1 \Delta GDP_{t;i} + \gamma_2 \Delta LOANS_{t;i} + \gamma_3 \Delta P^C_{t;i} + \gamma_4 \Delta P^K_{t;i} + \gamma_5 \Delta DELAY_{t;i} + \gamma_6 \Delta DELAY_{t-1;i} + \gamma_7 \Delta DELAY_{t-2;i} + \gamma_8 \Delta DELAY_{t-3;i} + \gamma_9 \Delta DELAY_{t-4;i} + \gamma_{10} Y_{t-1;i} + \gamma_{11} Y_{t-2;i} + \gamma_{12} Y_{t-3;i} + \gamma_{13} Y_{t-4;i} + \eta_{t;i} + \varepsilon_{t,i} \quad (21)$$

With:

- $Y_{t;i}$: the number of activated CoCos in period t, run i
- $\Delta GDP_{t;i}$: difference of the real GDP in period t, run i
- $\Delta LOANS_{t;i}$: difference of loans in period t, run i
- $\Delta P^C_{t;i}$: difference of consumption good inflation in period t, run i
- $\Delta P^K_{t;i}$: difference of capital good inflation in period t, run i
- $\Delta DELAY_{t-j;i}$: difference lagged j times of delay announcements in period t, run i
- $Y_{t-j;i}$: the number of activated CoCos, lagged j times, run i
- $\eta_{t;i}$: random effects
- $\varepsilon_{t,i}$: residuals

The null hypothesis is that the CoCo activations are unrelated to each other. If this is the case, one should find associated estimated coefficients that are not significantly different from zero. Conversely, if these estimated coefficients are significantly different from zero and positive, then a CoCo activation in period t causes a domino effect and is likely to lead to additional activations (controlled for the macroeconomic environment).

When analysing results from Poisson autoregressive models, an indicator equivalent to R-squared is not directly available. McFadden's Pseudo R-squared is used as an alternative. The log likelihood of the null modem (the model with only an intercept and no covariates) is treated as a total sum of squares while the log likelihood of the full model is treated as the sum of squared errors. By taking the ratio of the full-model likelihood over the null-model likelihood, one can check the level of improvement over the intercept model offered by the full model.

The summaries of each regression are presented in Table 4. Two key results should be noted. The first relates to the CoCo activations in the previous periods. Controlling for macroeconomic conditions and no matter which model specification is chosen, the estimated coefficient for the first lag is always positive and significant at the 1% level. This means that activations have domino effects from one period to the next. However, these persistent effects do not seem to extend beyond one quarter in the model as the estimated coefficients for the second, third and fourth lags are not significantly different from zero.

The second important result relates to the postponement of CoCo repayments. Controlling for macroeconomic conditions and regardless of the model specification chosen, the estimated coefficients for lags 1 to 4 are always positive and significant at the 1% level. This means that an increase in postponements of CoCos repayment have persistent effects from one period to another (four quarters in the model).

The comparison of the pseudo R-squared indicates better performance by the third model. It is therefore chosen to complete the analysis of the results and in particular to discuss the residuals. The *pglm* package is relatively underdeveloped and does not allow for direct extraction of residuals or for testing serial correlation in them. It is therefore necessary to proceed indirectly. The package allows to obtain the fitted values. This makes it possible to calculate the residuals by subtracting these fitted values from the observed values. The residuals can then be regressed on their lag of one period to verify the presence of an AR(1) process. The p-value of the coefficient found is equal to 0.51 so there is insufficient evidence in the sample to conclude that a serial correlation in the residuals exists. This is confirmed by inspection of the autocorrelation plot of the residuals (Figure 16). This further ensures the robustness of the results presented.

Table 4: Results for the Poisson autoregressive models

	(1)	*(2)*	*(3)*
Intercept	**-4.67***** (44.23)	**-3.71***** (38.60)	**-4.06***** (38.95)
Y_{t-1}	**0.25***** (5.70)	**0.22***** (5.00)	**0.20***** (4.67)
Y_{t-2}	**0.01** (0.08)	**-0.33** (1.59)	**-0.06** (0.50)
Y_{t-3}	**0.24** (1.45)	**-0.06** (0.47)	**0.07** (0.45)
Y_{t-4}	**0.04** (0.23)	**-0.20** (1.01)	**-0.21** (1.08)
$\Delta DELAY_t$	**0.71***** (41.12)	**0.70***** (41.87)	**0.61***** (34.26)
$\Delta DELAY_{t-1}$	**0.54***** (15.40)	**0.46***** (12.73)	**0.45***** (12.54)
$\Delta DELAY_{t-2}$	**0.56***** (15.26)	**0.45***** (12.33)	**0.46***** (12.69)
$\Delta DELAY_{t-3}$	**0.67***** (15.31)	**0.57***** (13.59)	**0.55***** (13.15)
$\Delta DELAY_{t-4}$	**0.59***** (14.6)	**0.45***** (11.75)	**0.46***** (12.19)
ΔP_t^C	**51.72**** (2.88)	**72.21*** (3.73)	**98.91***** (5.13)
ΔP_t^K	**12.95** (0.95)	**-20.41** (1.53)	**-4.63** (0.36)
ΔGDP	**18.03***** (13.24)	-	**15.83***** (12.12)
$\Delta LOANS$	-	**-5.37**** (2.72)	**-5.15**** (2.68)
Log-likelihood	**-1770.57**	**-1635.89**	**-1562.756**
Pseudo R^2	**0.54**	**0.58**	**0.60**

*Notes: *p-value<0,05; **p-value<0,01; ***p-value<0,001 ; t-stats in parentheses (absolute values)*

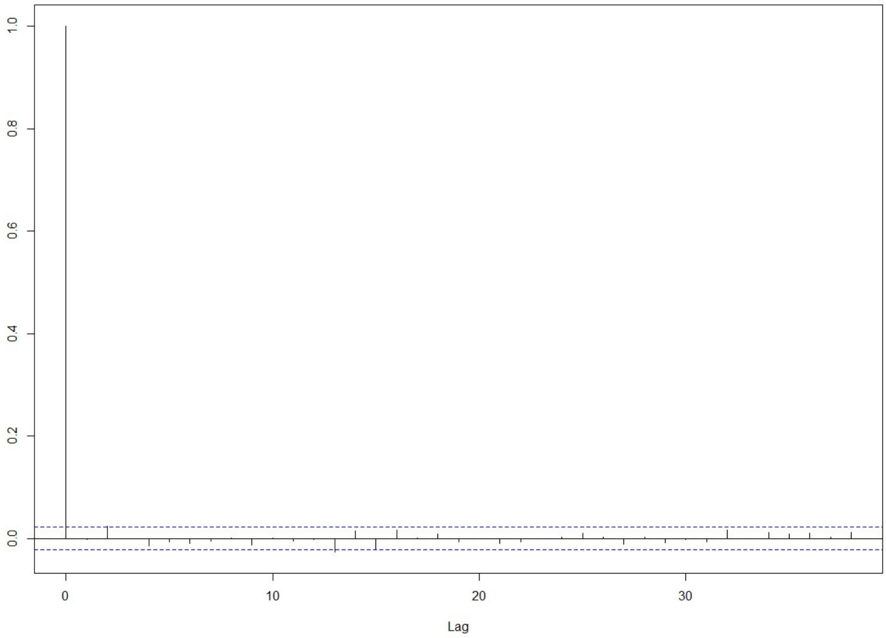

Figure 16: Autocorrelation plot of the residuals of the third regression

5. CONCLUSION

This paper explicitly introduces contingent convertible bonds in a stock-flow consistent agent-based model. CoCo demand depends on a trade-off between the rate of return on a safe asset (bank deposits) and the rate of return on a risky asset (CoCos) weighted by the share of activations in previous periods. CoCo supply is such that banks take advantage of macroprudential rules on Additional Tier 1. The price equalises supply and demand. The interest rate is flexible and specific to the liquidity ratio of each bank (the more liquidities banks have, the more they can afford to raise their rates to attract investors, and vice versa). Market matching is done by connecting banks with investors. The latter compare the interest rates offered and choose the most advantageous. The activation of CoCos takes place when the capital adequacy ratio of banks falls below a given threshold value. In this case, principal repayments and interest payments for outstanding issues are cancelled. In addition, a dynamic opinion mechanism similar to Salle & Seppecher (2015) is introduced for banks and investors. Banks become cautious when a principal repayment would threaten their solvency. In this case, they put it off until their situation improves (or deteriorates further until activation). Investing households become pessimistic when they feel the market is at risk. In this case, they reconsider their portfolio arbitrage. To further extend the model, stochastic reactive reinforcement learning is implemented with a modified Roth-Erev algorithm similar to Nicolaisen et al. (2001). Households are allowed to explore different possible reactions to the announcements of delayed repayments, including no reaction at all. Each reaction is associated with a propensity to choose it and is updated according to an endogenous reward process based on earned financial interests. These propensities are modified each time the CoCo market is disrupted. Households explore on their own the better option that brings them the most benefits. This exploration is done stochastically.

Three policy experiments are conducted based on Monte Carlo simulations. The first one focuses on the effects of the introduction of CoCos in the economy and of different activation threshold values. Comparing an economy where banks issue non-convertible bonds with an economy where they issue CoCos, it is found thanks to Mann-Whitney non-parametric tests that the existence of an Additional Tier 1 buffer strengthen the capital ratios of banks. The risk of bank failures is lower, which means fewer bailouts and therefore lower costs for taxpayers. These findings are consistent with the existing literature (Calomiris & Herring, 2013; Pennacchi, 2010). The greater resilience of banks allows them to maintain their operations in times of crisis. They can therefore continue to lend to the real economy, which generates positive second-order effects for the major macroeconomic aggregates of investment and output, as predicted by some authors (Duffie, 2009; Flannery, 2016; Squam Lake Working Group, 2009). These effects rely on a positive financial accelerator (Bernanke et al., 1999). The effects on consumption are ambiguous. This ambiguity is explored in a second policy experiment. A penalized spline regression shows that the volume of CoCos in circulation in the economy has non-linear effects on consumption and incidentally on GDP. The larger the volume of outstanding CoCos, the greater the adverse effects on investors' net wealth. Above a certain volume, their activation negatively affects consumption and ultimately GDP.

The third policy experiment investigates the consequences of disruptive announcements in the CoCo market. The results from a Poisson autoregressive model show that each repayment delay has perverse effects for banks, even though they are set up to preserve their balance sheet and not to have to repay costly principals. They create a wave of pessimism among investors who suddenly turn away from the market. This decision is time inconsistent as evidenced by the reduction in portfolio adjustment. This is supported by the existing literature which focuses on the irrationality of CoCos buyers (Admati et al., 2013; H. Allen, 2012; Goodhart, 2010; Sundaresan & Wang, 2015). They behave as if this asset were a simple debt instrument with negligible chance of being activated and panic when clauses explicitly provided for in the contracts are activated. This causes them an unnecessary loss of financial income. As they realise this, they adapt their behaviour to maximise the interests they receive. The size of the overadjustment therefore decreases over time until it converges. In other words, it is beneficial for investors to partly withdraw from the market when it experiences disruptions but not as much as they initially do. This portfolio reallocation has negative consequences for the banking sector, as highlighted by some theoretical papers on CoCos (Admati et al., 2013; M. Allen et al., 2002; Goodhart, 2010; Sundaresan & Wang, 2015). It is becoming more difficult for banks, including those that did not cause the isolated disruption, to set aside Additional Tier 1. As demand for CoCos falls, so does their price. Each repayment delay generates information spillovers that are likely to trigger activations of contingent convertible bonds, which in turn may cause domino activations. This complements the empirical observations of Bologna et al. (2020) by showing that the difficulties of one bank can spread to others through a financial contagion channel.

Based on these findings, one can say that CoCos are indeed fulfilling their initial mission of intermittently strengthening the solvency of the banking sector and reducing the costs of bailouts by soliciting investors. In this respect, they are positive for the macroeconomic aggregates, which benefits from positive second-order spillovers. But by relying on this instrument, regulators are playing a risky game. Their activation could take a heavy toll on the whole economy: the real sphere which could be too badly affected if the volume of CoCos in circulation is too high and the financial sphere which would suffer from possible financial contagion effects by information.

Given these risks, it is necessary to further develop the counterfactual analysis of CoCos in order to better understand them. The model proposed in this paper have limitations that need to be overcome. Micro data on CoCos - such as investor preferences and bank activation thresholds - is needed to estimate the optimal size of the CoCo market, the optimal level of substitutability between AT1 and T1 and the optimal issuance ceiling. The demand side of CoCos could be fleshed out with institutional investors introduced as a new sector. In a way like what happened with the securitization of ABS, CoCos could be bought by other actors of the financial sector. Systemic risk might not be reduced but simply shifted to other parts of the financial sector. Further work is also needed to verify all the factors that are likely to mitigate or exacerbate the CoCo-specific contagion channel. The macroeconomic consequences of the CoCo-specific contagion channel remain to be explored. A negative financial accelerator can be expected, making the final assessment of CoCos more cautious. Finally, the ex-ante role of CoCos is missing. Activation risks can be expected to limit banks' risk-taking behaviour, or conversely, the moral hazard associated with the possibility of being bail-in if they are not bail-out could exacerbate it.

Until such improvements are made, I propose a set of policy recommendations that are likely to guide the actions of regulators. Adjusting the degree of substitutability between Tier 1 and Additional Tier 1 could be a way to control the lower bound of the volume of CoCos in circulation, thus ensuring that enough are issued to limit the need for bailouts in the event of a crisis. Banks have an interest in taking advantage of this opportunity to meet the Basel III solvency criteria, which they often denounce as too restrictive. Since CoCos are also used to send a strong positive signal to investors, as illustrated by Deutsche Bank in 2020, and since the demand for them is high given their attractive interest rates, banks may have an incentive to issue more than what is accounted as Additional Tier 1. Setting a maximum issuance ceiling and discouraging banks from using them as a screening device could be a way to control the upper bound of the volume of outstanding CoCos, thereby ensuring that potential bail-ins would not be too destabilizing for the economy when a crisis occurs. Moreover, regulators should consider more carefully the role of CoCos in Tier 1 capital. While the Additional Tier 1 capital cushion can, all other things being equal, absorb some shocks and limit the use of bailouts, it can also create opportunities for the difficulties of individual banks to spread to the rest of the sector. To mitigate the financial contagion risks, every effort should be made to ensure that the way in which CoCos operate is as clear as possible to investors who buy them. This would prevent over-adjustments in the market in case of disruptions.

Disruptions on the CoCo market have become increasingly frequent in recent years and doubts about the ability of some banks to sustain repayment of their maturing AT1s are growing. The increase in interest rates decided by central banks to fight inflation will increase the cost for banks to keep their CoCos and weigh on their solvency. Ensuring the best possible scenario after a CoCo activation is becoming a pressing issue but is within the reach of regulators.

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APPENDIX A: LIST OF PARAMETERS

Parameter	Description	Baseline
$size_H$	Number of households	8000
$size_C$	Number of consumption firms	100
$size_K$	Number of capital firms	20
$size_B$	Number of banks	10
λ	Adaptive expectations parameter	0.25
υ	Firms' inventories target share	0.1
μ^N	Productivity of labour in K sector	2
l^K	Capital/labour ratio in K sector	6.4
μ_c^K	Productivity of capital	1
γ_1	Profit rate weight (investment function)	0.01
γ_2	Capacity utilization rate weight (investment function)	0.02
$\bar{r}$	Target profit rate (investment function)	0.04345
$\bar{u}$	Target capacity utilization rate (investment function)	0.8
ν	Unemployment threshold in wage revision function	0.08
α_1	Propensity to consume out of income	0.38581
α_2	Propensity to consume out of wealth	0.25
σ_1	Deposit share upper bound	0.6
σ_2	Portfolio arbitrage sensitivity parameter	0.2
$(\mu_{FN}, \sigma_{FN}^2)$	Folded normal distribution parameters	(0,0.0094)
$pbco^T$	Announcement price of CoCos	500
$AddT1^T$	Targeted additional tier 1	0.015
CAR^T	CoCo activation threshold	0.6
$i_{b,0}^l$	Initial interest rate on loans	0.0075
$i_{b,0}^d$	Initial interest rate on deposits	0.0025
$i_{b,0}^{BCO}$	Initial interest rate on CoCos	0.0025
q_0	Initial propensity of adjustment size = -0%	2
q_1	Initial propensity of adjustment size = -10%	2
q_2	Initial propensity of adjustment size = -20%	2
q_3	Initial propensity of adjustment size = -30%	2
q_4	Initial propensity of adjustment size = -40%	2
q_5	Initial propensity of adjustment size = -50%	2
q_6	Initial propensity of adjustment size = -60%	8
e	Exploration parameter	0.1
r	Recency parameter	0.2
$\overline{CAR^T}$	Optimistic capital adequacy threshold	0.75
$\underline{CAR^T}$	Cautious capital adequacy threshold	0.95
LR^T	Liquidity threshold for opinion formation	0.60
b	Number of banks observed to form an opinion	6
p	Herding probability	0.6

APPENDIX B: PRESENTATION OF THE FIRM AND PUBLIC SECTORS

Firm behaviour

Production planning and labour demand

The desired output of capital and consumption firms in period t (y_t^D) depends on their expected sales for the same period. It is assumed that firms want to accumulate a certain amount of real inventories inv_t, expressed as a fixed share υ of expected sales s_t^e, as a hedge against unexpected changes in demand (Steindl, 1976) and to avoid frustrating customers with an insufficient supply (Lavoie, 1992).

$$y_{kt}^D = s_{kt}^e(1+\upsilon) - inv_{kt-1} \quad (22)$$

$$y_{ct}^D = s_{ct}^e(1+\upsilon) - inv_{ct-1} \quad (23)$$

Capital firms produce their output solely out of labour. Their demand for labour N_{kt}^D depends on their desired output y_t^D and labor productivity μ^N which is assumed to be exogenous and fixed.

$$N_{kt}^D = y_{kt}^D/\mu^N \quad (24)$$

Consumption firms produce their output out of labour and capital goods. Their demand for labour N_{ct}^D depends on their real capital stock k_{ct}, the constant capital-labor ratio l^K and the rate of capacity utilization u_{ct}^D required to produce the desired level of output.

$$N_{ct}^D = u_{ct}^D \frac{k_{ct}}{l^K} \quad (25)$$

With u_{ct}^D such as:

$$u_{ct}^D = Min\left(\frac{y_{ct}^D}{k_{ct}\,\mu_c^K}, 1\right) \quad (26)$$

Where μ_c^K indicates the capital productivity.

Excess workers are randomly selected from the pool of employees and are laid off. A positive turnover rate is assumed, expressed as a fixed share ϑ of firms' employees.

Pricing

Prices of consumption and capital firms, p_{ct} and p_{kt}, are set as a mark-up ($\varphi_{ct} > 0$ and $\varphi_{kt} > 0$) over their expected unit labor costs.

$$p_{ct} = (1+\varphi_{ct})\frac{W_{ct}^e\,N_{ct}^D}{y_{ct}^D} \quad (27)$$

$$p_{kt} = (1 + \varphi_{kt}) \frac{W_{kt}^{e} N_{kt}^{D}}{y_{kt}^{D}} \tag{28}$$

With W_{ct}^{e} and W_{kt}^{e} the expected average wage in both sectors.

The mark-up rate is endogenously readjusted every period according to a heuristic adaptive rule. When firms had more inventories than desired in the previous period, they lower their mark-up rate in order to make themselves more attractive to customers (and conversely increase their mark-up rate when they had fewer inventories than desired).

Investment

Firms invest in order to achieve a desired production capacity growth rate g_{ct}^{D} based on the difference between, on the one hand, the past period's rate of return r_{ct-1} and a fixed target $\bar{r}$[15] and, on the other hand, the desired capacity utilization rate u_{ct}^{D} and a fixed target $\bar{u}$ corresponding to the "normal" utilization rate.[16]

$$g_{ct}^{D} = \gamma_1 \frac{r_{ct-1} - \bar{r}}{\bar{r}} + \gamma_2 \frac{u_{ct}^{D} - \bar{u}}{\bar{u}} \tag{29}$$

$$r_{ct} = \frac{OCF_{ct}}{K_{ct-1}} \tag{30}$$

With:

- OCF_{ct} : the operating cash flow of consumption firm c in period t[17]
- K_{ct-1}: the previous period value of consumption firm c's stock of capital discounted by the age of capital goods of which this stock is made up

The real demand for capital goods is equal to the number of units of capital needed to replace obsolete capital and close the gap between the current and the desired level of production capacity. Once consumption firms have chosen their supplier of capital goods, the desired nominal investment is calculated by multiplying the real demand for capital goods by the price charged by the selected supplier.

Demand for credit

Consumption firms' demand for credit corresponds to what they need to pay for their expenses (investment, wage payments, dividend payments) after using the surplus cash flow of the period

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[15] We assume here that firms do not necessarily seek to maximize their profit but rather to achieve at least some target. See, e.g., Rothschild (1947); Gordon (1948); Simon (1955) on the subject of profit satisficing.
[16] See Eichner (1976), for empirical evidence on firms aiming for normal rates of utilization ranging in the 80-90%
[17] See Gilchrist and Himmelberg (1995) for empirical evidence on the role of cash flow for firm investment

(which corresponds to what is left after firms set aside a fixed part of their profits as a security deposit). The credit demand of capital firms is the same minus investment expenditure since they are considered in the model as not investing.

Labour, goods and deposit markets

After banks and firms have interacted on the credit market, firms interact on the labour market with unemployed households and production begins. If there are not enough workers available, the production of firms may be constrained. Households and consumer firms then interact on the consumption goods market and households consume what they buy. Consumption firms purchase capital goods that will be used in subsequent periods. Finally, taxes are paid on gross profits and dividends are distributed to households.

Firm bankruptcies

Firms default when their net wealth becomes negative or when they run out of liquidity. We assume that they are rescued through bail-ins supported by households (who own the firms and receive dividends). Their deposits are sufficiently depleted so that the net wealth of bankrupted firms becomes positive again. Thus, the number of firms in the model remains constant. [18]

Public sector behaviour

The central bank makes a profit equal to the interest it earns on the residual bonds it purchases and on the cash advances it makes to banks. These cash advances are repaid after a period with a fixed interest rate that acts as an upper bound to the interest rate set by banks on deposits.[19]

The government pays benefits to unemployed households. It also collects taxes on income and profits from households, firms, and banks (a lump sum). It issues bonds that last one period (for simplicity's sake). Their interest rate and price are set exogenously. The amount of bonds issued is such that it covers what is needed to pay for public expenditures (unemployment benefits and interest payments on bonds) minus taxes and the profit redistributed by the central bank.

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[18] For more details on the firm bail-in mechanism, see Caiani et al. (2016)

[19] In the original JMAB model, the public sector is not very developed. In particular, there is no monetary policy as such. The central bank rate is fixed. This part of the model could be improved in future work.