THÈSE

En vue de l'obtention du

DOCTORAT DE L'UNIVERSITE DE TOULOUSE

Délivré par l'Université Toulouse Capitole

École doctorale : **Sciences Economiques-Toulouse School of Economics**

Présentée et soutenue par

GARCIA SANCHEZ Pablo

le 4 juin 2018

Essays on Macroeconomics and Financial Stability

Discipline : **Sciences Economiques**

Unité de recherche : **TSE-R (UMR CNRS 5314 – INRA 1415)**

Directeur de thèse : Monsieur Patrick FÈVE, Professeur, Université Toulouse-I Capitole

JURY

Rapporteurs Monsieur Fabrice COLLARD, Professeur, Université de Berne
Monsieur Franck PORTIER, Professeur, University College of London

Suffragants Monsieur Christian HELLWIG, Professeur, Université Toulouse-I Capitole
Monsieur Martial DUPAIGNE, Professeur, Université de Montpellier et Toulouse School of Economics

“Success is the ability to go from one failure to another with no loss of enthusiasm.”

Winston Churchill.

Abstract

The 2008 crisis and the ensuing Great Recession shook the consensus on how to run economic policy. They reminded us that financial imbalances could significantly derail economic activity. In addition, they showed that existing policy tools did not guarantee macro-financial stability; thereby leading to a rethink of monetary policy and financial regulation.

Such a reevaluation has prompted a call for macroprudential tools, i.e., those tools intended for limiting systemic risk and ensuring the resilience of the financial sector. Besides, it has raised new questions about monetary policy and its effects on the risk taking behavior of economic agents - the so-called *risk taking channel*.

A decade from the beginning of the crisis, the contours of a new policy framework for economic and financial stability are still very unclear. Knowledge on which regulatory instruments and how to employ them to curb the buildup of imbalances is limited. Neither is much known about the costs of those instruments. Regulatory intervention constraints some behaviors and distorts the allocation of resources. Consequently, the risk of imposing insidious costs on economic growth must not be underestimated.

Likewise, very little is known about the relationship between monetary policy and the perception and pricing of risk by market participants. Nonetheless, it is natural to think that the monetary policy stance may affect the risk taking behavior of economic units, by influencing the attitudes towards risk and the assessment of risks. If so, failure by monetary authorities to consider this phenomenon could exacerbate boom bust patterns.

The aim of this thesis is to explore the path towards macroeconomic and financial stability. I have based my work on the modern dynamic macroeconomic methods and techniques. Specifically, the first essay develops a canonical real business cycle model to assess the macroeconomic consequences of bank capital requirements, arguably the most used prudential tool. The second essay zooms in on the banking sector, and proposes a structural dynamic model with a large number of heterogeneous banks. The model is employed to study the effectiveness of interbank exposure limits. Having analyzed regulatory intervention, the last essay uses time series econometrics to shed some light on the risk taking channel of monetary policy.

It is my firm belief that macroeconomics models for financial stability analysis should consider nonlinear patterns such as state dependence, asymmetries and amplification effects. Under unusual conditions like financial booms or credit crunches, economic agents behave differently than during normal times. In other words, the inner workings of the macroeconomy become essentially nonlinear under abnormal circumstances.

Therefore, local behavior around the long run equilibrium of the economy is unlikely to contain relevant information about what may happen in exceptional events. In consequence, I study macroeconomic policy exclusively through the lens of nonlinear frameworks and techniques.

Regarding the main results, this thesis makes a strong case in favor of macroprudential regulation. I provide clear evidence suggesting that regulatory intervention can be a powerful tool to strengthen financial resilience, reduce economic volatility and smooth business cycles. In addition, this thesis shows that accommodative monetary policy can produce overconfidence among market participants; thereby increasing risk taking and contributing to the buildup of imbalances. In other words, it provides empirical evidence for the existence of a risk taking channel of monetary policy.

Résumé

La crise de 2008 et la recession qui l'a suivie ont modifié le consensus quant à la conduite de la politique économique (notamment monétaire). Elles nous ont rappelé que les déséquilibres financiers peuvent affecter durablement l'activité économique. De plus, elles nous ont montré que les instruments actuels de la politique économique ne garantissent pas toujours la stabilité financière. Ce constat nous invite à re-considérer la politique monétaire et la régulation financière.

Ainsi les politiques macro-prudentielles[1] sont au centre du debat sur la politique économique. De plus, de nouvelles questions emergent à propos de l'influence de la politique monétaire sur la prise de risque des agents économiques. Cette influence est appelée le canal de la prise de risque de la politique monétaire.

Dix ans après le début de la crise, les contours d'un nouveau cadre régulatoire visant à la stabilité du système économique et financier sont encore très ambigus. La connaissance quant aux instruments utiles et la manière de les mettre en place pour éviter l'accroissement des déséquilibres reste très limitée. De plus, les coûts économique de ces instruments sont encore mal connus. En effet, la régulation financière contraint les comportements du agents économiques. Par conséquent, le risque d'imposer des coûts sur l'activité économique liée à la regulation ne peut pas être sous-estimé.

De même, la relation entre la politique monétaire et le prix du risque financier est très incertaine. Pourtant, nous pouvons penser que les mesures prises par les banques centrales peuvent affecter les appréciations des risques, et ainsi avoir des conséquences sur la prise de risque des agents économiques. Si tel est le cas, ne pas tenir compte de ce phénomène peut exacerber les cycles d'expansion-récession.

L'objectif de cette thèse est d'explorer la stabilité macroéconomique et financière. Mon travail est fondé sur les méthodes et techniques de la macroéconomie dynamique moderne. Plus particulièrement, mon premier essai présente un modèle canonique des cycles réels pour étudier les consequences des exigences minimales de fonds propres dans le secteur bancaire, sans doute l'instrument prudentielle le plus utilisé. Le deuxième essai se concentre sur l'industrie bancaire, et propose une modèle structurel dynamique avec des agents hétérogènes. Le modèle est utilisé pour étudier l'efficacité des politiques visant à limiter l'exposition interbancaire. Ayant analysé la regulation financière, le troisième essai emploie l'économétrie des séries temporelles pour faire la lumière sur le canal de la prise de risque de la politique monétaire.

Les modèles macroéconomiques utilisés pour analyser la stabilité financière doivent prendre en con-

[1]Les politiques macro-prudentielles visent à éviter une désorganisation de grande ampleur du système financier, ce qui entrainerait de sérieuses conséquences pour l'économie réelle.

sidération des comportements non linéaires comme la dépendance du système économique aux conditions initiales, les asymétries ou les effets d'amplification. Dans certaines conditions inhabituelles, comme des "booms" économiques ou des périodes de resserrement de crédit, les comportements des agents économiques sont différents de leurs actions dans des situations normales. Autrement dit, le fonctionnement de l'économie devient essentiellement non linéaire dans des circonstances anormales. Par conséquent, les dynamiques locales autour de l'équilibre à long terme ne sont pas informatives de ce qu'il peut arriver dans des conditions extrêmes. J'étudie donc la politique économique en utilisant méthodes et techniques non linéaires.

Concernant les principaux résultats, cette thèse montre l'utilité potentielle des politiques macroprudentielles. Plus particulièrement, elle met en lumière le fait que la régulation financière peut renforcer la résilience financière, réduire la volatilité macro-financière et lisser les fluctuations économiques de façon significative. De plus, cette thèse dévoile qu'une politique monétaire expansionniste peut effectivement générer un excès de confiance parmi les agents économiques, et ainsi augmenter la prise de risque et les déséquilibres financiers. En d'autres termes, mes résultats confirment empiriquement l'existence du canal de prise de risque de la politique monétaire.

Acknowledgements

Foremost, I would like to express my sincere gratitude to my advisor Prof. Patrick Fève for his continuous support at my Ph.D study and research. His constant suggestion to work hard and aim for the best has helped me become a better researcher.

I would also take this opportity to thank all the researchers at Toulouse School of Economics and outside, who have helped me in refining and developing my ideas and techniques. I have gained inmensely through my discussions with Thomas Chaney, Ryan Chahrour, Alexander Guelbel and Robert Ulbrich. Likewise, I would like to thank the four members of the jury: Fabrice Collard, Franck Portier, Christian Hellwig and Martial Dupaigne, for carefully reading the manuscript and for giving such constructive comments. In addition, I will specially thank Jean-Guillaume Sahuc for his guidance and insightful comments.

A special thanks to my family who has been an inmense source of motivation and support. At the end, I would like to thank Camille for all her love and encouragement.

Contents

Chapter 1

The Macroeconomic Consequences of Bank Capital Requirements

Abstract

In the light of the recent crisis, there is now considerable concern about financial cycles and their implications for business fluctuations. Macroprudential policy has thus become part of the policy paradigm. In this work, a model of business cycles is developed which analyzes the macroeconomic consequences of a minimum bank capital standard. Numerical examples suggest that capital regulation can be useful in strengthening the resilience of the banking sector, and hence reduce macro-financial volatility.

1 Introduction

The 2008 financial crisis and the ensuing Great Recession have prompted a rethink of economic policy and financial regulation. At the core of this reconsideration is the growing awareness that financial disturbances can have long lasting adverse consequences on economic activity [Yellen (2013)]. The development of a policy framework responsible for financial stability is therefore at the forefront of the policy agenda. Says Bernanke (2012): *"Continuing to develop an effective set of macroprudential policy indicators and tools, while pursuing essential reforms to the financial system, is critical to preserving financial stability and supporting the U.S. economy"*.

This rethinking of financial regulation has recently led to substantial regulatory changes [De Nicolo et al. (2012)]. The new focus is on macroprudential tools, i.e., those policies intended for limiting systemic risk and ensuring the resilience of the financial sector as a whole. For instance, the new Basel III Accords raised minimum bank capital requirements, and introduced new instruments such as a leverage ratio and liquidity requirements. Alternative policies, such as caps on loan to value ratios and limits on credit growth, are also being implemented in various jurisdictions [Claessens (2015)].

While the need for macroprudential policies is now widely accepted, very little is known about their design, calibration and quantitative effects on the real economy [Claessens (2015)]. As noted by Blanchard et al. (2013), knowledge is still limited and much remains to be studied.

This paper examines the quantitative effects of bank capital requirements on the real economy. My analysis uses a nonlinear small open economy real business cycle model. I consider bank capital shocks (i.e. disruptions in the flow of resources between corporate borrowers and banks that take place in the event of default) and technology shocks. Bank capital shocks capture episodes of financial distress entailing the depletion of some assets on the balance sheet of the banking industry [Iacoviello (2015); Guerrieri et al. (2015)]. Technology shocks are a proxy for changes in the demand for loans.

I investigate three fundamental matters. First, the tradeoff between financial stability and the cost of financial intermediation associated with capital regulation. Second, what factors affect the likelihood of hitting the capital regulatory constraint. Third, the role of capital regulation in shaping business cycle fluctuations.

Recent events have made clear that nonlinearities are an essential component of contemporaneous macroeconomic analysis [see Richter et al. (2014)]. Successfully modeling extreme events, like credit booms and financial recessions, demands large and persistent deviations from the deterministic steady state. Furthermore, analyzing bank capital regulation requires to consider precautionary behavior [Brunnermeier and Sannikov (2014); Akinci and Queraltó (2014)], and the fact that, in reality, capital requirements bind only occasionally [Peura and Jokivuolle (2004); Jokipii and Milne (2008)]. Linear approximations around the long run equilibrium badly capture these equilibrium properties. Therefore, a nonlinear analysis is needed to avoid major biases, misleading advice and painful policy errors [Benes et al. (2014)]. Nonetheless, to circumvent technical complications, most quantitative general equilibrium models examining bank capital requirements rely on local perturbation methods [see e.g. Clerc et al. (2015); Begenau (2015); Mendicino et al. (2016)]. Thus, another contribution of this paper is to assess the macroeconomic consequences of capital regulation through the lens of a nonlinear framework.

Within my theoretical model, there is a key motive for capital regulation that encourages banks to hold larger equity buffers and discourages the use of external debt. I assume that banks' funding costs depend on the cross-sectional average level of bank equity capital. Individual banks, however, do not internalize this effect when deciding their balance sheet structure, and hence hold a sub-optimal low level of net worth in equilibrium. To put it differently, individual banks do not consider the fact that if they were to be better capitalized, they would make the financial sector more resilient; thereby lowering their funding costs and dampening macro-financial volatility.

My modeling approach captures a wide range of financial frictions. For example, models of default and incomplete markets [see e.g. Eaton and Gersovitz (1981); Arellano (2008); Lorenzoni et al. (2008)], borrowing constraints [see e.g. Uribe (2006); Mendoza (2010); Gertler et al. (2012)] or portfolio adjustment costs [see e.g. Schmitt-Grohé and Uribe (2003)] predict that funding costs react to aggregate debt and debt related measures. My approach is also consistent with the empirical literature documenting the inverse relationship between country risk premiums and financial resilience [see e.g. Ferrucci (2003); Dailami et al. (2008); Mody (2009); Petrova et al. (2010); Dell'Erba et al. (2013)]. In addition, it is consistent with studies showing that country spreads react to macroeconomic fundamentals; thereby exacerbating aggregate volatility [see e.g. Neumeyer and Perri (2005); Uribe and Yue (2006)].

To quantitatively assess the role of capital regulation in driving business cycles, I calibrate my model to Spain's economy. I choose Spain for two principal reasons. First, banks' activities, and hence banking regulation, are at the core of my model. In this regard, Spain is a fitting example, because traditional banks dominate the Spanish financial system.[1] Second, the 2008 crisis and its aftermath triggered a vicious cycle of soaring loans, failing bank equity, rising funding costs, tightening credit conditions, contracting output... This left a notable portion of the banking sector under-capitalized, which in turn further hurt economic performance. Increasing the resilience of the banking sector has thus become a key priority for

[1] In 2014, traditional banks (i.e. deposit taking institutions) accounted for 69% of total assets of financial institutions excluding the Spanish Central Bank [FSB (2015)]. This is quite a large value when compared, for instance, with the United States (26%), the United Kingdom (52%), Germany (59%) or France (62%).

policy makers [Linde (2016)]. As a result, banks are being forced to strengthen their capital positions. For instance, Spanish regulators implemented the new international regulatory frameworks Basel II.5 and III agreements in 2012Q1 and 2013Q1, respectively, notably increasing the strictness of bank capital regulation. Hence, Spain is a good laboratory to perform policy counterfactuals to gauge the effects of capital requirements.[2]

The single most remarkable result is that bank capital regulation can be a powerful tool to strengthen the resilience of the banking sector, and consequently dampen business cycle fluctuations. In all experiments considered, regulatory intervention increases the banks' level of net worth and decreases its volatility. As a result, regulated banks need less external finance and enjoy lower funding costs. This affects the real economy through the amount and volatility of lending, and therefore of employment and output. As a consequence, capital regulation leads to a considerable stabilization of the economy. A noteworthy feature of the equilibrium of my model is the power of precautionary behavior. Capital regulation affects banks' attitudes toward risk. Specifically, it encourages banks to build equity buffers in order to reduce the likelihood of hitting the minimum capital standard.[3] Consequently, the capital requirement constraint is usually either slack or not too tight. Hence, the potential costs associated with capital regulation are seldom materialized.

The remainder of the paper is organized as follows. Section 2 reviews the mechanisms for why bank capital regulation might matter for economic activity. Section 3 lays out the model and explores key analytical results. Section 4 presents the solution method, calibration, and numerical results. The final section concludes.

2 Why Might Bank Capital Regulation Matter?

Few issues in the policy debate are more contentious and elicited a wider range of firmly held views than the correct level of equity requirements. On the one hand, advocates of stricter regulation highlight the risks and inefficiencies associated with poorly capitalized institutions, and point to the high costs of the 2008 crisis [Admati et al. (2013)].

Bank capital has several benefits from a financial stability perspective. First, it improves banks' ability to absorb losses; thereby reducing the prospects of bank failure episodes [Dewatripont and Tirole (1994)]. Second, bank equity limits excessive risk taking and encourage sounder balance sheet management deci-

[2]Furthermore, as was mentioned previously my model assumes an inverse relationship between banks' funding costs and the health of the financial sector. Appendix A.5 shows that Spain is a nice illustration of such a link.

[3]In the real world, breaching the minimum equity threshold may be very costly for financial institutions. For instance, it can result in serious reputational costs, losses of charter value and adverse market reactions [Borio and Zhu (2012)].

sions. This occurs because thinly capitalized institutions may be tempted to take excessive risks due to limit liability. In other words, they do not fully internalized asset losses. Equity capital can contain these excesses by increasing shareholders' downside exposure [Rochet (1992)]. Thus, equity capital encourages banks to engage in more monitoring and invest in safer assets [Freixas and Rochet (2008)]. As a result, strict regulation can (i) protect creditors and taxpayers, (ii) reduce the risks of spillovers from the financial sector to the real economy, and (iii) foster sustainable economic growth.

On the other hand, opposers of more stringent regulation argue that the latter would notably raise the cost of financial intermediation, and hence impose insidious costs on economic activity. For instance, Kashyap et al. (2008) suggest that demanding financial institutions to maintain significantly higher equity buffers will raise their expected cost of funds; thereby impairing economic performance.

The main concern is the prospect that stricter capital regulation could restrict banks' ability to extend credit. This could actually happen whenever equity is *significantly* more expensive than debt [Borio and Zhu (2012)]. Therefore, equity requirements, while reducing the likelihood of financial crises, would also raise banks' overall funding costs, and hence hinder economic activity.

Although this sort of concern may sound intuitively reasonable, it differs substantially from the dominant paradigm in the academic literature: the Modigliani Miller Theorem. In their seminal paper, Modigliani and Miller affirmed that a firm value is independent of its capital structure. In the specific case of the banking sector, this theorem states that the debt-equity mix with which banks are funded affects neither their overall funding costs nor their lending activities. Consequently, increased capital requirements should not penalize economic growth.

Nonetheless, further theories provide a rationale for why the Modigliani Miller Theorem may not apply. Loosely speaking, the basic logic is that the existence of various market frictions breaks down the neutrality between the composition of banks' liabilities and credit supply. Frictions that are often referred to comprehend (i) the "debt overhang" problem [Myers (1977)], (ii) adverse selection in the equity market [Myers and Majluf (1984)], and (iii) tax shields and government guarantees that subsidize debt financing [Admati et al. (2013)].

As for the empirical literature, it suggests that higher bank capital is associated with a lower probability of failure [see e.g. Wheelock and Wilson (2000); Cole and White (2012); Beltratti and Stulz (2012); Fahlenbrach et al. (2012)]. It has also been well documented that more stringent regulation results in a more stable and robust credit supply in the long run [see e.g. Bernanke and Lown (1991); Kapan and Minoiu (2013)]. The intuition is straightforward. Equity capital improves banks' ability to resist both financial and real disturbances [Diamond and Rajan (2000)].

Another line of research has studied the effects of more stringent capital regulation on credit availability [see e.g. Francis and Osborne (2012); Brun et al. (2013); Aiyar et al. (2016)]. Overall, in the short run increases in equity requirements seem to put a brake on bank lending. A recent review of the literature on this topic [Martynova (2015)] found that raising the minimum capital standard by 1% is likely to reduce bank lending by 1.2%-4.5% in the short run.

Capital requirements are being increasingly used, despite the controversy and that little is known about their usefulness in reducing systemic vulnerabilities [De Nicolo et al. (2012)]. To see this point more clearly, Figure 1 presents information on the proportion of countries that have implemented the new bank capital regulation embedded in the Basel II.5 and III Accords.[4]

The new Basel Accords are designed to tackle the market failures brought to light by the global financial crisis. They consist of a number of fundamental reforms to the bank capital regulatory framework. The main objective is to boost the resilience of individual financial institutions by raising both the quantity and quality of the regulatory capital base. By doing so, the reforms also contain systemic risks that can build up across the financial industry over time. In other words, the Accords add a macroeconomic dimension to prudential regulation.

As shown in Figure 1, there has been a very significant tightening of capital requirements since the global financial crisis, as regulators have implemented the new international regulatory framework. Interestingly, instruments linked to capital buffers have been actively used both by advanced and emerging economies. Therefore, it appears that equity requirements will play a key role in the design of macroprudential regulation worldwide in years to come.

3 A Model of Business Cycles with Capital Requirements

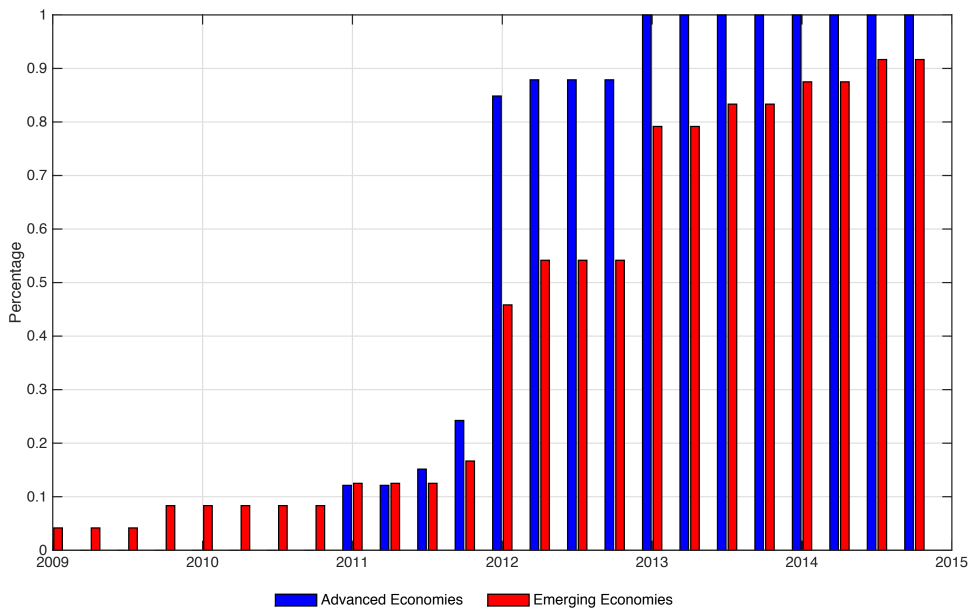
I begin this section by describing the structure of the model and the optimization problems of the economy's agents. I then analyze the key optimality conditions in order to provide the essential intuition regarding capital requirements.

3.1 Setup

Consider a discrete time economy populated by four types of agents: households, international investors, firms and banks. The representative household consumes, works and holds bank deposits. The representative firm operates a linear technology that requires labor to produce output. Following Mendoza (2010),

[4] The sample includes 33 advanced economies and 24 emerging economies. The data has been compiled by Cerutti et al. (2016).

Figure 1: Implementation of the Basel Accords



Note: Fraction of countries that have implemented the regulation embedded in the Basel II.5 and III Accords. The sample includes 55 countries and has been compiled by Cerutti et al. (2016).

Christiano et al. (2010), and others, input costs must be financed in advance of sales. Hence, the representative firm demands loans at the beginning of each period and repay them at the end.

In order to meet the demand for loans by local borrowers, a domestic representative bank borrows funds from both foreign lenders and domestic depositors. Note then the dual nature of the banking activity. The bank is a borrower vis-a-vis international investors and domestic households, whereas it is a lender when it comes to its relationship with local firms.

To make matters more interesting and realistic, in the model business fluctuations are partly driven by exogenous disruptions in the flow of resources between firms and banks. This type of shock is inspired in Iacoviello (2015) and Guerrieri et al. (2015). The shock can be viewed as losses for the banking industry stemming, for example, from a wave of non performing loans. More generally, it can simply be considered as a shock that depletes some assets on the balance sheet of the banking sector. Importantly, the shock is a pure financial shock, since real resources are not destroyed [Guerrieri et al. (2015)]. Therefore, its macroeconomic consequences can be interpreted as spillover effects from the financial sector to the real economy.

As was stated in the Introduction, my model features a pecuniary externality affecting banks' activities; which leads them to be undercapitalized. This market failure induces the need of some kind of regulatory intervention. I consider bank capital requirements; which set a lower bound on the bank capital to assets ratio.

Households

The representative household chooses sequences of consumption (C), hours worked (H) and bank deposits (D) in order to maximize its expected lifetime utility[5]:

$$E_t \sum_{t=0}^{\infty} \beta^t \frac{1}{1-\sigma} \left[C_t - \chi \frac{H_t^{1+\omega}}{1+\omega} \right]^{1-\sigma}, \tag{1}$$

where $\beta \in (0, 1)$ is the discount factor parameter and E_t is the conditional expectation operator. Its choices are constrained by:

$$C_t + D_t = w_t H_t + (1 + r^d_{t-1}) D_{t-1} + Q_t + \Xi_t, \tag{2}$$

where w is the wage rate, Q are wealth transfers between the bank and the household -to be specified below-, r^d is the interest rate of deposits, and Ξ are dividends from local firms.

[5]I follow Mendoza (2010), Gertler et al. (2012) and others, and define utility as in Greenwood et al. (1988). This functional form eliminates the wealth effect on labor supply. That is, the latter only depends on the real wage and not on consumption. This preference specification yields sensible fluctuations in hours worked in the absence of labor market frictions.

Firms

A representative firm produces the final good (Y) according to:

$$Y_t = A_t H_t, \tag{3}$$

where H_t is the amount of labor services used, and A_t is a technology shock. The latter evolves according to a 2-states Markov chain[6] with transition matrix Π.

As noted above, the wage bill must be paid in advance of sales. In consequence, each and every period the firm demands an amount of loans (L) equal to:

$$L_t = w_t H_t. \tag{4}$$

Therefore, the representative firm chooses labor inputs to maximize dividend payments to the household (Ξ):

$$\Xi_t = A_t H_t - (1 + r_t^l) w_t H_t + \epsilon_t, \tag{5}$$

taking as given input prices w as well as the interest rate of loans r^l. The term ϵ_t is a redistribution (or equivalently, bank capital) shock.[7] As noted above, it captures transfers of resources between banks and firms. Accordingly, the same shock appears in the law of motion for bank equity capital with opposite sign. I assume that the stochastic process for ϵ follows:

$$\epsilon_t = \delta \epsilon_{t-1} + u_t, \tag{6}$$

where $\delta \in [0, 1)$ and $u \sim i.i.d.N(0, \sigma_u^2)$.

Banks

Suppose a competitive environment in which each period a representative bank extends loans (L) to the representative firm. These loans are financed by combining borrowed funds from foreign investors (F), deposits from domestic households (D) and the bank's own net worth (N). Thus, the bank's balance sheet at period t is[8]:

$$L_t = N_t + F_t + D_t. \tag{7}$$

[6] Given that the model is solved employing a policy function iteration algorithm, the use of a continuous support for the stochastic shock is not feasible. I therefore discretize the stochastic variable according to a 2-states Markov chain.

[7] This modeling device can be found in Iacoviello (2015) and Guerrieri et al. (2015).

[8] It is important to stress that $[L, D, F]$ are control variables, whereas N is a state variable. Accordingly, N_t is predetermined at time t, and hence cannot jump.

The bank can also issue new equity (capital inflows) as well as pay dividends (capital outflows). Net external capital flows (Q) are thus positive whenever the overall amount of dividend payments exceeds the amount of new equity raised, and vice versa.

In order to restrict the bank's ability to accumulate enough equity capital to fund all loans internally, I assume that the bank faces quadratic adjustment costs when the current level of equity differs from its steady state value ($\bar{N}$). Formally, adjustment costs are represented as:

$$\Gamma(N_t) = \frac{\tau}{2}\left(\frac{N_t}{\bar{N}} - 1\right)^2, \tag{8}$$

where $\tau \geq 0$. These costs are needed to guarantee stationarity of the state variables.[9] The value of τ is chosen so that these costs are minimal and do not affect the dynamic properties of the model.

Equity capital therefore evolves by:

$$N_{t+1} = N_t + r_t^l L_t - r_t^f F_t - r_t^d D_t - Q_t - \Gamma(N_t) - \epsilon_t, \tag{9}$$

where r^f is the rate of return on international liabilities. The term ϵ is the bank capital shock, that when positive, transfers wealth from banks to firms. Hence, operating profits and new issues of equity feed to the total net worth of the bank, whereas dividend payments represent a leakage.

One point here deserves further comment. As noted above, banks are not usually able to recapitalize themselves immediately and costlessly. If this were true, capital regulation would be pointless. With this mind, two layers of imperfections relating to external capital flows are introduced. First, as in Bianchi and Bigio (2014) and Iacoviello (2015), the bank's preferences are designed in such a way that a stable path of net external capital flows is preferred[10]. Second, Eq.9 implies that when the bank raises new equity at time t, the collected funds are only available to make new loans at time $t + 1$. The bank is therefore prevented from increasing its equity stock at the very moment of being subject to capital regulation (i.e. just before undertaking new lending).

Regarding capital adequacy regulation, the bank faces an equity requirement constraint. The latter ensures that bank capital is at least a fraction κ of loans:

$$\frac{N_t}{L_t} \geq \kappa. \tag{10}$$

[9] See Schmitt-Grohé and Uribe (2003) for alternative ways of obtaining this.

[10] This formulation is equivalent to a formulation where the bank pays convex adjustment costs when it sheds or raises external capital.

I am now in a position to state the bank's optimization problem. The bank's preferences over dividend streams $\{Q_t\}_{t=0}^{\infty}$ are evaluated via and expected utility criterion:

$$E_t \sum_{t=0}^{\infty} \beta^t \Lambda_{t,t+1} \log(1 + Q_t), \tag{11}$$

where $\Lambda_{t,t+1}$ is the household's stochastic discount factor. As noted by Bianchi and Bigio (2014), introducing curvature into the objective function is essential. This assumption produces smooth dividends and slow-moving bank capital, as observed empirically.[11] Therefore, the bank's problem is to choose sequences $\{L_t, F_t, Q_t\}_{t=0}^{\infty}$ to maximize eq.11 subject to Eq.7, Eq.9 and Eq.10.

International Capital Markets

As stated above, the representative bank borrows funds from domestic households and international investors. More precisely, I assume that a large mass of foreign lenders is willing to lend to the local banking sector any amount at rate r_t^f. The existence of only one type of bank liability implies that the rate paid to domestic depositors equals the one paid to foreign lenders. That is, $r_t^f = r_t^d \ \forall t$. Furthermore, the small open economy assumption implies that this rate is determined by the foreign lenders.

A full model of the determination of country risk is beyond the scope of this paper. Nonetheless, a minimal framework of country risk is required in order to perform the quantitative analysis. To make matters interesting and realistic, I suppose that economic fundamentals drive risk premium. As noted by Neumeyer and Perri (2005), this notion can be grounded on models of default and incomplete markets [see e.g. Eaton and Gersovitz (1981); Arellano (2008); Lorenzoni et al. (2008)] in which the risk of default is high when economic fundamentals are weak and vice-versa. Also, theoretical frameworks with imperfect enforcement of contracts, occasionally binding borrowing constraints or portfolio adjustment costs predict that interest rate premiums increase with the level of total indebtedness [Schmitt-Grohe and Uribe (2015)].

Likewise, this idea is supported by the empirical literature examining the relationship between country spreads and various macro-financial indicators, such as debt and debt related variables, the fiscal balance or GDP growth [see e.g. Ferrucci (2003); Uribe and Yue (2006); Reinhart and Rogoff (2011); Petrova et al. (2010); Reinhart and Rogoff (2013); Fogli and Perri (2015)].

A related topic that has recently received considerable attention is the link between country spreads and financial fragility. Generally speaking, financial sector vulnerabilities have been shown to be strongly associated with higher risk premiums [see, for example, Mody (2009); Petrova et al. (2010)]. The basic

[11] This kind of preferences are usually found in the corporate finance literature. One way to rationalize these preferences is through agency frictions that might give rise to capital adjustment costs [Estrella (2004)].

logic is that financial sector stress projects a deterioration of growth prospects. In turn, the weaker economic outlook increases default probabilities; thereby exerting further pressure on the financial industry, and hence increasing risk country premiums. Put it differently, the health of the financial sector, economic activity and the country risk premium tend to be self-reinforcing forces.

All told, country spreads are broadly viewed as a comprehensive indicator of a country's overall risk premium, arising from market, credit, liquidity, and other risks [Petrova et al. (2010)]. Within my model, a parsimonious way to model this is to assume that the interest rate, r_t^f, is a decreasing function of the cross-sectional average level of equity capital ($\hat{N}$) across local banks. This modeling device is essentially the same as that used by Schmitt-Grohé and Uribe (2003), García-Cicco et al. (2010), Akinci and Queraltó (2014), among others. Formally, I opt for the logistic function:

$$r_t^f = \psi_0 \left[1 + e^{\psi_1 (\hat{N}_t - \bar{N})} \right]^{-1}. \tag{12}$$

Here $\bar{N}$, ψ_0 and ψ_1 are positive parameters. Specifically, $\bar{N}$ is the threshold around which the dynamics of r^f change. As $\hat{N}_t - \bar{N}$ approaches minus (plus) infinity, r^f approaches ψ_0 (zero). The parameter ψ_1 is the smoothness parameter. As ψ_1 increases, the dynamics of r^f change more abruptly depending on whether $\hat{N}$ is greater than or less than $\bar{N}$.[12]

The intuition behind Eq.12 is straightforward. Foreign lenders regard the cross-sectional average level of equity capital as an indicator of the strength of the domestic banking industry. As a consequence, a decreasing (increasing) level of average equity causes the premium to increase (decrease) as investors' perceived risk of investing in the domestic economy increases (decreases).

A point here deserves further comment. The fact that r_t^f depends on the cross-sectional average of equity gives rise to a pecuniary externality, which banks do not internalize when deciding their balance sheet structure. Specifically, individual banks do not take into consideration that their own net worth accumulation behavior affects r_t^f. Instead, they take it as exogenously given, and hence out of their control.[13] This assumption is not innocuous. Note that because all banks are identical, in equilibrium I have that $\hat{N}_t$ must equal N_t. The representative bank, ignoring the implications of its actions on r_t^f, holds a suboptimally low level of bank equity capital. As a consequence, it is exposed to higher interest rates than a social planner that internalizes Eq.12. Hence, this externality makes the competitive equilibrium inefficient and induces the need for regulatory intervention.

Of course, the purpose of Eq.12 is not to provide a satisfactory model of country risk, but only to capture the idea that a country's risk premium, economic performance and financial vulnerability tend to

[12]In the extreme case where ψ_1 approaches infinity, Eq.12 converges to the Heaviside function.
[13]Clerc et al. (2015) have coined the term *bank funding costs externality* to describe this effect.

go together. In addition, this reduced form approach predicts that banks' funding costs are associated with their risk profiles; which is consistent with conventional wisdom and has been stressed by a number of others [see e.g. Admati et al. (2013); Arnold et al. (2015)].

Competitive Equilibrium

A competitive equilibrium consists on sequences of prices

$$\{w_t, r_t^d, r_t^l, r_t^f\}_{t=0}^{\infty}$$

and allocations

$$\{C_t, H_t, D_t, L_t, F_t, Q_t, N_t, \epsilon_t\}_{t=0}^{\infty}$$

that satisfy households', firms' and banks' optimality conditions, the law of motion for net worth, the bank's balance sheet identity, labor market clearing, and the following market clearing condition:

$$Y_t = A_t H_t = C_t. \tag{13}$$

3.2 The Role of Capital Requirements

Equilibrium Conditions

Let me now look at the distortions introduced by the capital requirement constraint. First, it affects the bank's intertemporal decision rules. To see this point more clearly, the Euler equation for net worth is given by:

$$\eta_t = \beta_b E_t \left[\Lambda_{t,t+1} \left[\eta_{t+1}(1 + r_{t+1}^f - \frac{\tau}{\bar{N}} \left(\frac{N_t}{\bar{N}} - 1 \right) + \mu_{t+1} \right] \right], \tag{14}$$

where η is the Lagrange multiplier on the law of motion for net worth, which equals the marginal utility of payouts to the household, and μ is the Lagrange multiplier on the capital requirement constraint. As usual, the Euler equation balances the marginal cost of accumulating an extra unit of equity, given by η, with its marginal benefit. When the constraint is expected to bind next period (i.e. $E_t \Lambda_{t,t+1} \mu_{t+1} > 0$) the marginal benefit of an extra unit of equity is not just given by the present discounted value of the payments it generates (i.e. $E_t \Lambda_{t,t+1} \eta_{t+1}(1 + r_{t+1}^f - \frac{\tau}{\bar{N}}(\frac{N_t}{\bar{N}} - 1)))$, but by a larger value. This occurs because, in this case, this extra unit of equity eases the capital requirement constraint next period. Thus, it carries a shadow benefit equal to $E_t \Lambda_{t,t+1} \mu_{t+1}$. Capital regulation therefore encourages precautionary behavior, which in turn reinforces the resilience of the banking industry.

Second, the effects of the constraint on the lending rate can be derived from the bank's intratemporal optimality conditions. It can be shown that:

$$r_t^l = r_t^f + \kappa \frac{\mu_t}{\eta_t}. \tag{15}$$

This is a standard condition equating the marginal product of loans with their marginal cost. During periods in which the constraint binds (i.e. $\mu_t > 0$), the bank faces a higher effective marginal financing cost, capturing a shadow penalty for trying to expand lending when equity requirements are tight.

This result is fairly intuitive. Given that in the model equity is a predetermined variable[14], cutting back on lending is the only available channel of adjustment when the constraint binds. Therefore, the lending rate must adjust upwards in order to ensure market clearing in the domestic credit market.

A Key Trade-off

The analysis above suggests a trade-off between financial stability and the cost of financial intermediation. On the one hand, a minimum equity threshold generates a buffer that banks can use in case of distress. Hence, it reduces the probability of capital shortfalls and the credit crunches associated with them. Moreover, as will become clear, by limiting credit growth in the upturn of the cycle, capital requirements mitigate the build-up of vulnerabilities in the bank's portfolio.

On the other hand, the term $\frac{\kappa}{\eta_t}\mu_t$ in Eq.15 explicitly captures the notion that stricter capital regulation might be passed on to borrowers in the form of higher lending rates, and hence hinder economic activity.

4 The Quantitative Analysis

In the next section, I resort to numerical simulations to (i) investigate the quantitative properties of my model, as well as to (ii) perform policy counterfactuals in order to analyze the effectiveness of bank capital regulation.

I solve the model using the policy function iteration algorithm described in Richter et al. (2014); which is grounded on the work on monotone operators in Coleman (1991). Since this method allows me to solve the model fully nonlinearly, I can successfully deal with large and persistent deviations from the non-stochastic equilibrium. Also, I can easily handle the occasionally binding capital requirement constraint. Furthermore, I can capture precautionary behavior, as the technique fully accounts for shock uncertainty.

[14]The stickiness of bank equity has recently been documented by Adrian and Shin (2011).

Table 1: Baseline Parameter Calibration

Parameter	Symbol	Value	Source/Target
Non Financial Sector			
Discount Factor	β	0.995	Int. rate 2% an.
Risk Aversion	σ	1.000	Standard RBC value
Inverse Frisch Elast.	ω	3.000	Standard RBC value
Labor Disutility	χ	26.86	SS labor 30%
Financial Sector			
Equity Adjustment Cost	τ	4e-05	Stationary equilibrium
Long Run Level Bank Capital	$\bar{N}$	0.025	SS leverage 7.7%
Exogenous Processes			
Technology Persistence	ρ	0.956	Solow Residuals
Technology Shock Standard Deviation	σ_A	0.003	Solow Residuals
Persistence Defaults	δ	0.737	Net charge-offs
Standard Deviation Default Shock	σ_u	0.001	Net charge-offs
International Capital Markets			
Upper bound r^f	ψ_0	0.010	Int. rate 2% an.
Smoothness Parameter	ψ_1	16,329	SD Int. rate 1.8% an.

4.1 Calibration

The values assigned to the model's parameters are listed in Table 1. This calibration aims to explain the Spanish business and financial cycle. To do so, I use quarterly data for the period 1997Q3 to 2011Q4.[15] The reason why I only use data until 2011Q4 is because Spanish regulators implemented the Basel II.5 and III agreements in 2012Q1 and 2013Q1, respectively. In other words, capital requirements began to be significantly higher in 2012Q1. Since my main aim is to perform policy counterfactuals to assess the impact of more stringent regulation, it is convenient to calibrate the model using data before the tightening took place. To be consistent, in my baseline calibration, I then set the minimum capital standard, κ, at 0.

Regarding the non-financial sector, there are 3 standard parameters for which I choose conventional

[15] More details on the data are provided in appendix A.1.

values. First, I set $\beta = 0.995$ so that the household discounts the future at a 2% rate per annum. Second, the CRRA coefficient is set to $\sigma = 1$. Third, the Frisch labor supply elasticity, $1/\omega$, is set to 0.33, which is consistent with Chetty et al. (2012). In addition, I set the weight on leisure in the household utility function, χ, at 26.86, implying a share of active time spent working of one third in the deterministic steady state.

Turning now to the financial sector, the steady state level of bank capital, $\bar{N}$, is not uniquely pinned down by the parameter values, so I set it to match the average of the ratio between capital and total assets of Spanish Monetary Financial Institutions. During the sample period that value is equal to 7.7%. As for the equity adjustment cost parameter, τ, I set it to the minimum value that guarantees that the equilibrium solution is stationary.

Information on the Solow residuals is employed to calibrate the parameters associated with the 2-state Markov chain governing labor productivity. Specifically, the approach laid out in Tauchen and Hussey (1991) is used to discretize an AR(1) process with standard deviation and persistent parameters equal to 0.003 and 0.956, respectively. More details on this will be given in Appendix A.2.

To calibrate the parameters associated with the default shock, δ and σ_u, I use the net charge-offs to assets ratio of credit institutions.[16] More precisely, I estimate an AR(1) process, and let δ be the persistent parameter of such a regression and σ_u be the standard deviation of the residuals.

It remains to specify the values for the parameters linked to the international capital market (see Eq.12). Regarding ψ_0, in the non-stochastic steady state of the model, there is a linear mapping between the discount factor parameter, β, and ψ_0. This can be seen immediately from Eq.12 and Eq.14 evaluated at steady state. Specifically, $\psi_0 = 2(\beta^{-1} - 1)$; thereby imposing $\psi_0 = 0.01$.

As for ψ_1, the calibration strategy is to match a standard deviation of the (annualized) real interest rate[17] of 1.88%. This is a natural target as its theoretical counterpart is directly linked to ψ_1. The calibration procedure employs a grid search method. Specifically, I proceed as follows. First, I construct an equally space grid for ψ_1 on the region $[1, 22111]$ with 2,212 grid points. Second, I define the criterion function

$$\Omega = [SD(r_{\text{data}}) - SD(r_{\text{model}})]^2,$$

where $SD(r_{\text{data}})$ is the standard deviation of the real interest rate observed in the data and $SD(r_{\text{model}})$ its theoretical counterpart. Third, I solve the model, perform a 500,000 period time simulation and calculate the standard deviation of r^f at each grid point. Lastly, I evaluate the criterion function at each grid point,

[16] I use the 3-period backwards moving average to smooth fluctuations in the time series.

[17] The 10-year Spanish government bond is the instrument whose yield is used as the nominal interest rate. The real rate is obtained by subtracting the GDP deflator inflation from the nominal rate.

and select the one that yields the smallest value of the criterion. The resulting parameter estimate is $\psi_1 = 16,329$.[18, 19]

4.2 Business and Financial Cycle Statistics

This subsection aims to assess the ability of the model to account for Spanish business and financial cycle facts. I begin by simulating a 500,000 period time series, and then calculate key statistical moments. The results are reported in Table 2.[20] It is important to recall that the only moment used in the calibration exercise is the standard deviation of the interest rate, r^f.

Overall, the business cycle moments of the model are roughly in line with the data. In particular, the model does a fair job at matching the volatility of the Spanish economy. The model also captures the fact that interest rates are countercyclical (i.e. negative contemporaneous correlations with output). In addition, it does well at the dynamic correlations: the equity to assets ratio negatively leads interest rates at different time-horizons.

There are some discrepancies between the model and the data. For instance, the contemporaneous cross-correlations between output and the equity to assets ratio in the model is far from the one observed in the data. Another failure of the model is that the series for the equity to assets ratio and the interest rate are too persistent with first order autocorrelation coefficients in the neighborhood of 0.97.

As a last exercise to assess the quantitative properties of my theoretical framework, Figure 2 compares the density of the equity to asset ratio both in the data and in the 500,000 period simulation of the model. Remarkably, the model replicates reasonably well the observed distribution. For instance, both in the model and the data the distribution is leptokurtic (kurtosis of 5.6 in the data and of 4.3 in the model). That is, they have fatter tails than the normal distribution, and thus produce more outliers. Hence, the model approximates the density satisfactorily, mainly because it is able to capture the asymmetric behavior of the equity to assets ratio.

I therefore conclude that the quantitative properties of my model seem overall consistent with Spanish business cycle features.

---

[18] Appendix A.6 shows that the optimization problem is well defined; thus corroborating the validity of my methodology.

[19] Appendix A.7 presents the relationship between interest rates and bank capital once ψ_0, ψ_1 and $\bar{N}$ have been calibrated.

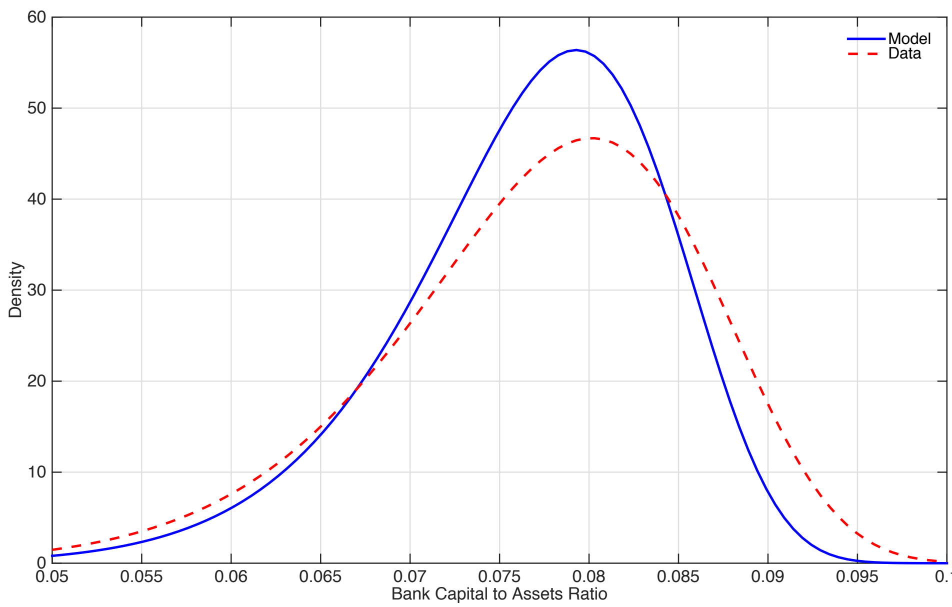
[20] Regarding the data, my measure of Spanish output is the real GDP in logs. To isolate the cyclical component of the series, I use the Hodrick-Prescott filter. My measure of bank capital to loans ratio is the capital and reserves to assets ratio of Spanish Monetary Financial Institutions. The real interest rate is measured as the 10-year government bond minus the GDP deflator inflation.

Table 2: Empirical and Simulated Business Cycle Statistics

	Data	Model ($\kappa = 0$)
Standard Deviation (%)		
Y_t	1.193	1.341
N_t/L_t	0.676	0.633
r_t^l	0.473	0.444
Contemporaneous Cross-Correlations		
Y_t, r_t^l	-0.107	-0.106
Y_t, N_t/L_t	-0.664	-0.082
Dynamic Cross-Correlations		
N_{t-8}/L_{t-8}, r_t^l	-0.611	-0.682
N_{t-12}/L_{t-12}, r_t^l	-0.817	-0.619
First Order Autocorrelation		
Y_t	0.928	0.745
N_t/L_t	0.800	0.966
r_t^l	0.733	0.993

Note: The variables Y, N/L, and r^l denote, respectively, output, equity to loans ratio and the lending rate. The variable Y is HP filtered in logs. The sample contains the period 1997-2011 at quarterly frequency.

Figure 2: The Unconditional Distribution of Bank Capital to Loans Ratio



Note: The figure shows the Weibull probability density function of the equity to assets ratio both in the data and in the model. The density for the model is computed via a 500,000 periods simulation.

4.3 Macroprudential Policy: Capital Requirements

Let me now consider bank capital requirements that work to offset banks' incentives to adjust their liability structure in favor of external debt. This is done by letting the minimum equity threshold, κ, be greater than 0. In what follows κ is set to 9%. That value equals the core capital-ratio target for Spanish banks imposed by the Spanish Central Bank since 2013.

As discussed in Section 2, there is extensive literature in corporate finance and banking that suggest that capital requirements involve a tradeoff between financial resilience and economic performance. The next exercise evaluates whether such a tradeoff is built into the policy functions of the calibrated version of my model. Specifically, I compare the policy functions of two alternative economies. The first economy features an active bank capital constraint (i.e. $\kappa = 9\%$) and is labeled the *Regulated* Economy. In the second model economy (my baseline) equity regulation is turned off (i.e. $\kappa = 0\%$). This economy is labeled the *Unregulated* Economy.

Figure 3 depicts the decision rules for bank net worth at $t + 1$, N_{t+1}, and output at t, Y_t, along the bank capital axis when $A_t = A_2$ and $\epsilon_t = 0$. The bank capital interval is centered on 0.0305 with a width of $\pm 13.5\%$, $[0.026, 0.035]$. In order to isolate the effects of regulation, Figure 3 plots the policy functions of the Regulated Economy in $\%$ deviations (output) and $\%$ differences (net worth) from the Unregulated Economy. The shaded areas represent the states of the economy where the constraint binds in the Regulated Economy.

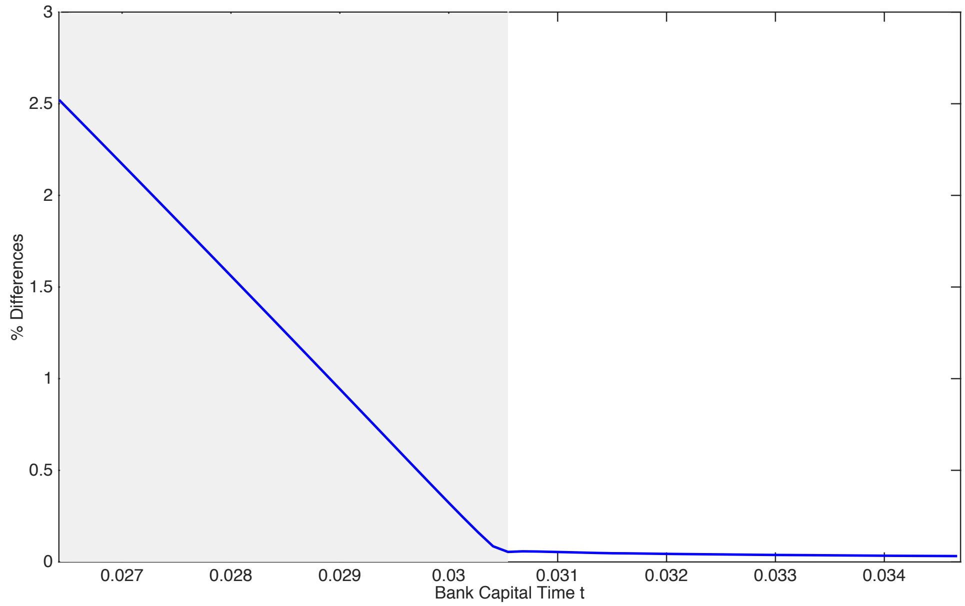
Remarkably the model captures the notion that capital requirements have clear benefits from a financial stability perspective, but may also hinder economic activity. To better understand this result, I begin by examining the region of the state space where the constraint binds. On the one hand, capital regulation strongly promotes the accumulation of equity. The top panel shows a significant difference in the bank's capital accumulation behavior in both economies. Specifically, the representative banks in the Regulated Economy consistently accumulates more equity capital than its counterpart in the Unregulated Economy. Moreover, this gap monotonically increases with the tightness of the constraint. It is in this sense that a minimum equity threshold acts as a buffer against losses; thus boosting financial stability.

On the other hand, capital regulation restricts the supply of credit, increases lending rates, and hence lowers output. For instance, the bottom panel reveals that when current bank capital is 0.027, output in the Regulated Economy is roughly 3% lower than in the Unregulated Economy. This difference is monotonically reduced as current bank capital increases (i.e. as the tightness of the constraint decreases).

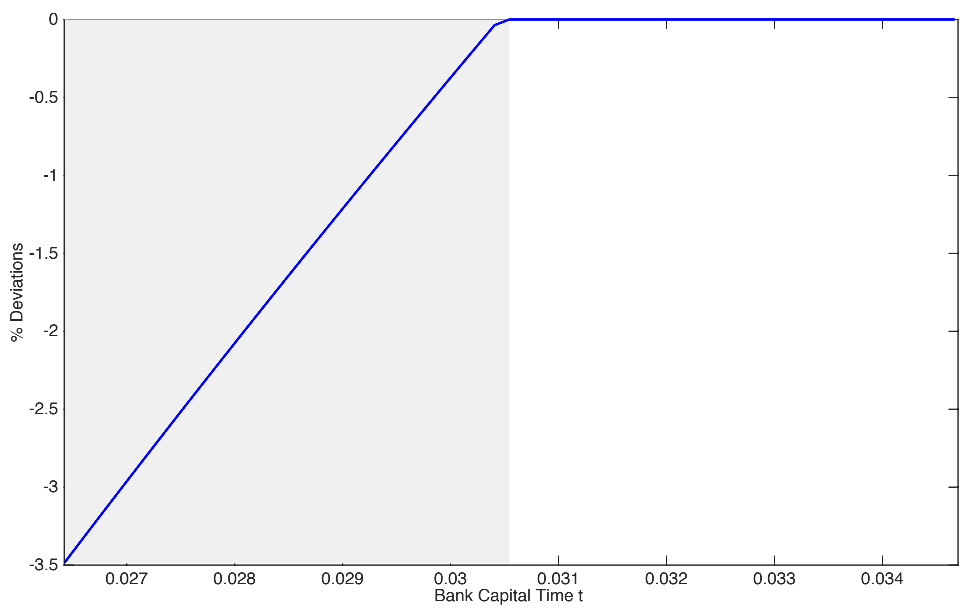
The last areas to consider are the states where the constraint does not bind. In those states, the policy functions for output are identical. This implies that capital regulation does not impose an insidious cost on

Figure 3: Policy Functions

(a) Bank Capital Time t+1



(b) Output Time t



Note: Policy functions of the Regulated Economy in % differences (bank capital) and % deviations (output) from the Unregulated Economy. The shaded areas represent the states of the economy where the constraint binds in the Regulated Economy.

economic activity as long as they are not actually binding. In terms of equity accumulation the differences in the policy functions are small but not insignificant. For instance, when current bank capital is 0.034, equity accumulation is 0.018 (in $\%$ terms) larger in the Regulated Economy, which represents a 0.7% of the steady state level of equity.

I therefore conclude that the quantitative solution of my model blends the two main views underlying the on-going discussion and research about the effects of capital requirements.

A subsequent, natural question that emerges is: under which conditions is the minimum capital standard more likely to be breached? In the model, binding events may be driven by changes in the condition of the borrowing sector, namely technology shocks. For example, a high level of productivity boosts the demand for capital working loans as the representative firm enlarges its production capacity. Bank capital, however, is sticky in the short run, and cannot adjust immediately to the new business environment. As a consequence, the equity to assets ratio declines ; thereby increasing the prospect of breaching the minimum capital standard. Likewise, banks may be brought up against the regulatory constraint due to unfavorable realizations of the bank capital shock. The intuition is straightforward. Adverse financial conditions impair banks' net worth, thereby triggering capital shortfalls. Lastly, binding events may be triggered by the (endogenous) banks' equity accumulation behavior.

Of course, these hypotheses are not mutually exclusive. The analysis that follows is designed to determine which among these factors are the most important sources of binding events. This is a quantitative question, which I settle by simulating a version of the model in which capital regulation is activated (i.e. $\kappa = 9\%$).

To be more precise, I first perform a 500,000 period simulation of the model. Second, I identify all the quarters in which the constraint binds. Then, I construct a dummy variable equal to 1 when the constraint binds and 0 otherwise. Third, I estimate a logistic regression. Specifically, I regress my dummy variable on the four period backward moving average of the productivity shock, the bank capital shock, and bank equity capital. The results are reported in Table 3.

I begin by considering the realizations of the exogenous disturbances separately (columns 1 and 2), and find that the fit is not extraordinary. Although both regressors are highly statistically significant, they account for no more than 13% of the variations in the probability of breaching the minimum capital standard. Next, I include the moving average of bank equity capital (column 3). Interestingly, in this case the pseudo-R^2 goes up to 31.5%; which highlights the endogenous nature of binding events in the model. To put it differently, a decline in the accumulation of bank capital over the previous four quarters is indicative of a heightened risk of breaching the minimum capital standard.

These findings lead to an interesting observation. As expected, the minimum equity threshold can be

Table 3: Prediction of Binding Events

Regressors	(1)	(2)	(3)
Mov. Aver. ϵ	669.9***	-	363.8***
Mov. Aver. A	-	114.5***	159.1***
Mov. Aver. N	-	-	-5361***
Pseudo-R^2	12.79	11.48	31.5

Note: Logit regression using a dummy equal to one when the capital requirement constraint binds (and zero otherwise) as dependent variable. All models include a constant term. The regression sample includes 498,996 observations and the bank is constrained in 17% of the periods. The variables Y, N/L, and r^l denote, respectively, output, equity to loans ratio and the lending rate. Mov. Aver. refers to the 4 periods backwards moving average of the indicated variable. Reported R^2 are the McFadden Pseudo-R^2. $^{***}p < 0.01$.

reached during periods of financial distress. However, it can also be breached during economic booms. In these instances, capital regulation can be seen as an automatic stabilizer that limit credit growth in the upturn of the cycle. This substantiates previous findings in the literature [see e.g. De Nicolo et al. (2012); Cerutti et al. (2015); Akinci and Olmstead-Rumsey (2015)] that instruments linked to capital buffers restrict risk taking and reduce the procyclicality of bank credit growth.

4.4 Counterfactuals

This subsection performs two policy counterfactuals to quantitatively gauge the impact of capital regulation on the Spanish economy. As will become clear, the main benefit from capital regulation is the reduction in macro-financial volatility.

Counterfactual A: Business Cycle Statistics

I now proceed to use my model to assess the effects of capital requirements on business cycle statistics. To this end, I conduct a 500,000 period stochastic time series simulation with no regulation in place. Then, I use the same shock sequence in the counterfactual scenario where capital requirements are active ($\kappa = 9\%$). Lastly, I calculate some key statistics of both economies. The results are reported in Table 4.

Table 4 is revealing in several ways. First, the level of output is largely unaffected by the minimum capital standard. Second, the bank holds, on average, an amount of equity that exceeds the minimum imposed by regulation. As was discussed in Section 3, regulatory intervention promotes precautionary behavior by encouraging banks to build up equity buffers in order to stay clear of the minimum capital standard. The intuition is straightforward. Within my framework, breaching the minimum capital standard is costly for banks, because it prevents them from smoothing exogenous disturbances.[21] As a result, regulated banks adjust their balance sheet structure to reduce the prospect of hitting the constraint. Third, equity requirements substantially reduce the lending rate. This occurs because capital regulation boosts financial resilience (i.e. leads to better capitalized banks). This, in turn, increases the confidence of foreign lenders, and hence results in lower banks' funding costs. Forth, capital requirements notably reduce macro-financial volatility. For example, the standard deviations of output and the equity to assets ratio are 1.5$\%$ and 67$\%$, respectively, lower in the Regulated Economy.

Counterfactual B: The Dynamic Effects of Bank Capital Shocks

As mentioned in Section 3, my model considers a specific form of bank equity shortfalls, namely a lump-sum transfer of resources from banks to firms. Iacoviello (2015) suggests that this shock can be seen as losses for the banking industry generated, for instance, by a wage of non performing loans. Furthermore, as noted by Guerrieri et al. (2015), this shock is purely financial, since it does not destruct real resources. As a result, its macroeconomic consequences can be interpreted as spillover effects from the financial sector to the real economy.

The next experiment performs a dynamic simulation for both the Regulated Economy and Unregulated Economy in response to a sequence of default shocks that impairs the balance sheet of the bank. More precisely, I feed into the model a sequence of unexpected shocks to u_t (see Eq.6), each quarter equal to 0.39$\%$ of annual outstanding loans, which lasts 16 quarters and causes the ratio loan losses to total loans to rise from 0$\%$ to 1.5$\%$. The shock here mimics the increase in the ratio non-performing loans to gross loans suffered by Spanish banks from 2007 to 2011. During this period, such a ratio rose from 0.8$\%$ to 6$\%$.

Figure 4 plots the generalized impulse response functions as in Koop et al. (1996) in order to take nonlinearities into account.[22] Let me begin by considering the responses of the Unregulated Economy (solid blue line). The shock damages the bank's balance sheet by impairing the value of its assets (i.e. loans minus non performing loans), relative to its liabilities. This strengthens the friction in the market for

[21] As was mentioned in the Introduction, in the real world when a bank fails to meet its capital requirement, both markets and regulators may restrict the bank's activities in several ways [Borio and Zhu (2012)]. For instance, regulators may limit the flow and size of dividend payments [Furfine (2001)]. Also, depositors might sanction under-capitalized banks by withdrawing deposits or demanding higher interest rates [Berger and Turk-Ariss (2015)].

[22] Please refer to Appendix A.4 for details about non linear impulse responses.

Table 4: Simulated Business Cycle Statistics

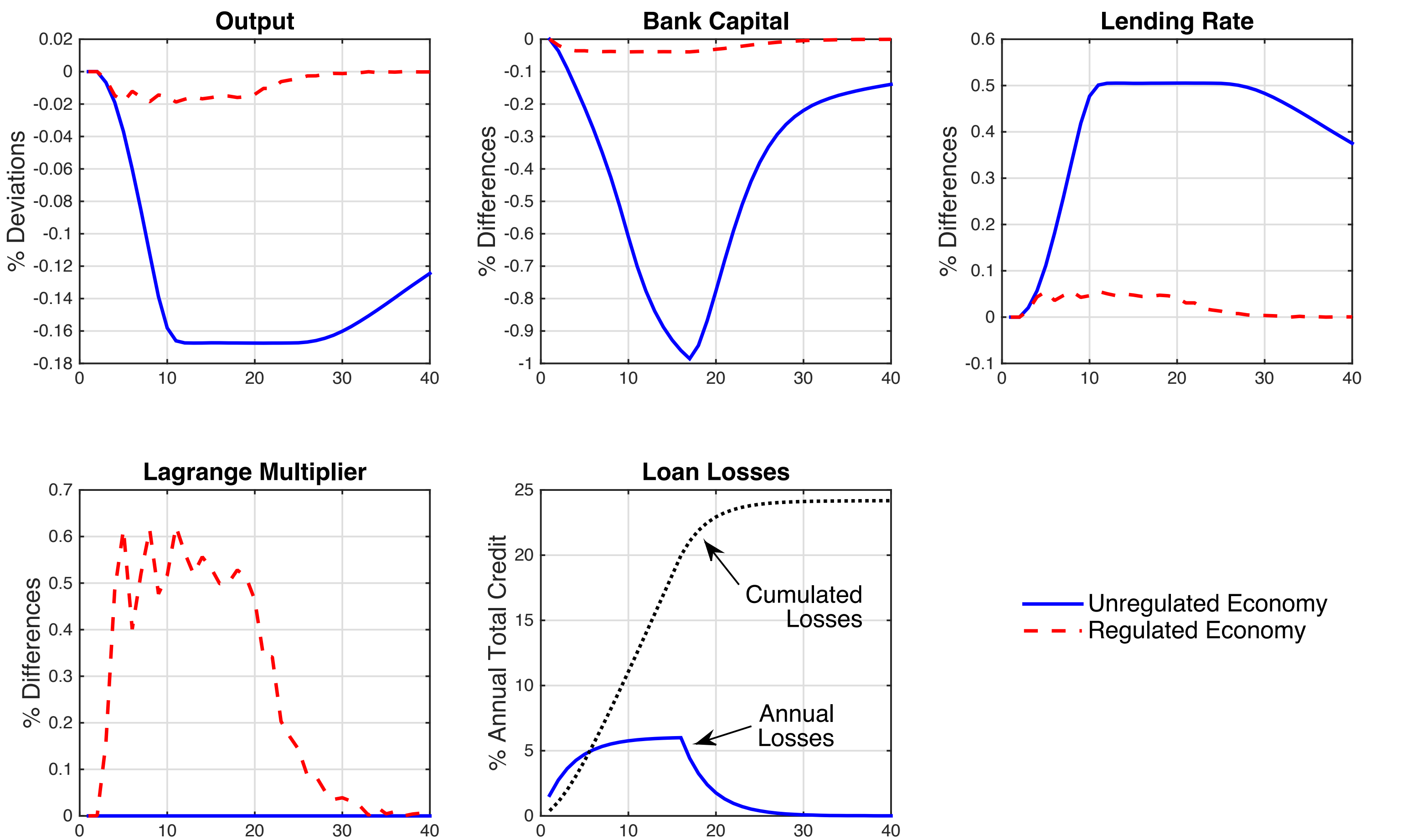
	Unregulated Economy	Regulated Economy	Dev. $\%$
Mean			
Y_t	0.333	0.334	0.300
N_t/L_t	0.077	0.092	19.48
r_t^l	0.005	0.001	-80.00
Standard Deviations $(\%)$			
Y_t	1.341	1.321	-1.565
N_t/L_t	0.633	0.208	-67.40
r_t^l	0.444	0.128	-71.17
Time at the constraint $(\%)$	-	17.15	-

Note: The variables Y, N/L, and r^l denote, respectively, output, equity to loans ratio and the lending rate. Business cycle statistics have been computed from a 500,000 period time series simulation of the model. The column Dev. $\%$ represents the percentage deviation of the outcome in the Regulated Economy with respect to the outcome in the Unregulated Economy.

external funds as foreign investors revise down their view of the domestic financial sector. As a result, the bank's funding costs increase. This is passed on to borrowers in the form of higher lending rates. Capital working loans therefore fall; dragging employment and output down.

In the aggregate, financial vulnerability strongly deteriorates economic performance. Note that the decline in output is not just large, but also very persistent. Ten years after the initial shock, output is still 0.12% below its long run average.

Figure 4: Dynamics After a Bank Capital Shock



Note: The figure depicts the responses of macro-financial aggregates to a shock that leads after 4 years to loan losses for banks equal to 6 percent (per annum) of total loans. Flow loan losses (solid blue line) are multiplied by 4 to express as a fraction of annual total credit.

Turning now to the responses of the Regulated Economy (dashed red line), Figure 4 shows that with capital requirements in place, the same sequence of shocks induce a milder decline in equity capital. Moreover, it is important to stress that the path of output is persistently lower in the Unregulated Economy compared to the case when a minimum capital standard is in place.

Two related mechanisms are at play. First, as I noted earlier, capital regulation encourages precautionary behavior. That is, it compels the bank to build up an equity buffer; thus strengthening its balance sheets and boosting its ability to absorb losses. By doing so, capital regulation leads to easier credit conditions during periods of financial distress, and hence contains the economic damage of loan losses.

Second, due to the country-risk premium, there exists a pecuniary externality which banks do not internalize when managing their balance sheets. Specifically, as was mentioned before, individual banks ignore the effect of their own level of net worth on the country-risk premium. Capital regulation partially corrects this market failure by forcing banks to maintain a minimum level of net worth. As a matter of fact, the right bottom panel reveals that the wave of loan losses brings the bank up against the minimum equity threshold (i.e. the Lagrange multiplier on the capital requirement constraint μ_t becomes positive). This in turn contains the decline of bank capital, improves banks' access to international capital markets, and lessens the contraction of output.

All told, these findings support the idea that capital requirements are indeed a powerful tool to strengthen financial resilience. By doing so, equity regulation reduces macro-financial volatility and smooths business cycle dynamics.

5 Concluding Remarks

This paper develops a business cycle model to assess the quantitative relevance of an occasionally binding bank capital requirement constraint. I focus on financial shocks, because they are now considered as the likely cause of many economic crisis. However, I also take into account technology shocks, since they are at the core of the vast majority of dynamic models.

I perform a non-linear analysis, which has two essential benefits. First, I am able to consider the kink that the occasionally binding constraint imposes on the policy functions of the model. Second, I am able to capture precautionary behavior linked to the possibility that the constraint may become binding in the future as a result of shocks yet unrealized.

I use my model to examine three fundamental matters. Firstly, the tradeoff between financial stability and the cost of financial intermediation associated with capital requirements. Secondly, what factors affect the likelihood of hitting the constraint. Thirdly, the role of capital regulation in shaping business cycle fluctuations.

Considered together, the results of this study suggest that bank capital requirements strengthen the resilience of the banking sector, and smooth business cycle fluctuations. In other words, bank capital requirements lead to a considerable stabilization of the macroeconomy.

In spite of the growing literature on macroprudential tools, particularly on capital requirements, many unknowns still exist, and a large research agenda remains. In order to justify policy intervention, further research on the choice and calibration of prudential regulation is essential. Also, it is crucial to gain evidence on the quantitatively effectiveness of macroprudential tools to make the policy design more transparent and accurate.

References

Admati, A. R., P. M. DeMarzo, M. F. Hellwig, and P. Pfleiderer (2013). The Leverage Ratchet Effect. Working Paper Series of the Max Planck Institute for Research on Collective Goods 2013_13, Max Planck Institute for Research on Collective Goods.

Adrian, T. and H. S. Shin (2011). Financial Intermediary Balance Sheet Management. *Annual Review of Financial Economics 3*(1), 289–307.

Aiyar, S., C. W. Calomiris, and T. Wieladek (2016). How does credit supply respond to monetary policy and bank minimum capital requirements? *European Economic Review 82*(C), 142–165.

Akinci, O. and J. Olmstead-Rumsey (2015). How Effective are Macroprudential Policies? An Empirical Investigation. International Finance Discussion Paper 1136, Board of Governors of the Federal Reserve System (U.S.).

Akinci, O. and A. Queraltó (2014). Banks, Capital Flows and Financial Crises. International Finance Discussion Paper 1121, Board of Governors of the Federal Reserve System (U.S.).

Arellano, C. (2008). Default Risk and Income Fluctuations in Emerging Economies. *American Economic Review 98*(3), 690–712.

Arnold, E. A., I. Größl, and P. Koziol (2015). Market Discipline Across Bank Governance Models. Empirical Evidence from German Depositors. Macroeconomics and Finance Series 201502, Hamburg University, Department Wirtschaft und Politik.

Begenau, J. (2015). Capital Requirements, Risk Choice, and Liquidity Provision in a Business Cycle Model. Technical Report 687, Society for Economic Dynamics.

Beltratti, A. and R. M. Stulz (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics 105*(1), 1–17.

Benes, J., M. Kumhof, and D. Laxton (2014). Financial Crises in DSGE Models: A Prototype Model. IMF Working Paper 14/57, International Monetary Fund.

Berger, A. N. and R. Turk-Ariss (2015). Do Depositors Discipline Banks and Did Government Actions During the Recent Crisis Reduce this Discipline? An International Perspective. *Journal of Financial Services Research 48*(2), 103–126.

Bernanke, B. and C. S. Lown (1991). The Credit Crunch. *Brookings Papers on Economic Activity 22*(2), 205–248.

Bernanke, B. S. (2012). Fostering financial stability. *Federal Reserve Bank of Atlanta Speeches, 9 April*.

Bianchi, J. and S. Bigio (2014). Banks, Liquidity Management and Monetary Policy. NBER Working Paper 20490, National Bureau of Economic Research, Inc.

Blanchard, O., G. Dell'Ariccia, and P. Mauro (2013). Rethinking macro policy ii. *Staff Discussion Notes No. 13/3*.

Borio, C. and H. Zhu (2012). Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism? *Journal of Financial Stability 8*(4), 236–251.

Brun, M., H. Fraisse, and D. Thesmar (2013). The Real Effects of Bank Capital Requirements. Les Cahiers de Recherche 988, HEC Paris.

Brunnermeier, M. K. and Y. Sannikov (2014). A Macroeconomic Model with a Financial Sector. *American Economic Review 104*(2), 379–421.

Cerutti, E., R. Correa, E. Fiorentino, and E. Segalla (2016). Changes in prudential policy instruments - a new cross-country database. International Finance Discussion Paper 1169, Board of Governors of the Federal Reserve System (U.S.).

Cerutti, E. M., S. Claessens, and L. Laeven (2015). The Use and Effectiveness of Macroprudential Policies; New Evidence. IMF Working Paper 15/61, International Monetary Fund.

Chetty, R., A. Guren, D. Manoli, and A. Weber (2012). Does Indivisible Labor Explain the Difference between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities. NBER Chapters, National Bureau of Economic Research, Inc.

Christiano, L. J., M. Trabandt, and K. Walentin (2010). DSGE Models for Monetary Policy Analysis. Handbook of Monetary Economics, Elsevier.

Claessens, S. (2015). An Overview of Macroprudential Policy Tools. *Annual Review of Financial Economics 7*(1), 397–422.

Clerc, L., A. Derviz, C. Mendicino, S. Moyen, K. Nikolov, L. Stracca, J. Suarez, and A. P. Vardoulakis (2015). Capital Regulation in a Macroeconomic Model with Three Layers of Default. *International Journal of Central Banking 11*(3), 9–63.

Cole, R. and L. White (2012). Deja Vu All Over Again: The Causes of U.S. Commercial Bank Failures This Time Around. *Journal of Financial Services Research 42*(1), 5–29.

Coleman, W. (1991). Equilibrium in a Production Economy with an Income Tax. *Econometrica 59*(4), 1091–1104.

Dailami, M., P. R. Masson, and J. J. Padou (2008). Global monetary conditions versus country-specific factors in the determination of emerging market debt spreads. *Journal of International Money and Finance 27*(8), 1325–1336.

De Nicolo, G., G. Favara, and L. Ratnovski (2012). Externalities and Macroprudential Policy. IMF Staff Discussion Notes 12/05, International Monetary Fund.

Dell'Erba, S., R. Hausmann, and U. Panizza (2013). Debt levels, debt composition, and sovereign spreads in emerging and advanced economies. *Oxford Review of Economic Policy 29*(3), 518–547.

Dewatripont, M. and J. Tirole (1994). A Theory of Debt and Equity: Diversity of Securities and Manager-Shareholder Congruence. *The Quarterly Journal of Economics 109*(4), 1027–54.

Diamond, D. W. and R. G. Rajan (2000). A Theory of Bank Capital. *Journal of Finance 55*(6), 2431–2465.

Eaton, J. and M. Gersovitz (1981). Debt with Potential Repudiation: Theoretical and Empirical Analysis. *The Review of Economic Studies 48*(2), 289–309.

Estrella, A. (2004). The cyclical behavior of optimal bank capital. *Journal of Banking & Finance 28*(6), 1469–1498.

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz (2012). This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent Financial Crisis. *The Journal of Finance 67*(6), 2139–2185.

Ferrucci, G. (2003). Empirical determinants of emerging market economies' sovereign bond spreads. Bank of England working paper 205, Bank of England.

Fogli, A. and F. Perri (2015). Macroeconomic volatility and external imbalances. *Journal of Monetary Economics 69*(C), 1–15.

Francis, W. B. and M. Osborne (2012). Capital requirements and bank behavior in the UK: Are there lessons for international capital standards? *Journal of Banking & Finance 36*(3), 803–816.

Freixas, X. and J.-C. Rochet (2008). Microeconomics of Banking, 2nd Edition. MIT Press Books, The MIT Press.

FSB (2015). Global shadow banking monitoring report. Technical report, Financial Stability Board.

Furfine, C. (2001). Bank Portfolio Allocation: The Impact of Capital Requirements, Regulatory Monitoring, and Economic Conditions. *Journal of Financial Services Research 20*(1), 33–56.

García-Cicco, J., R. Pancrazi, and M. Uribe (2010). Real Business Cycles in Emerging Countries? *American Economic Review 100*(5), 2510–2531.

Gavin, W. T., B. D. Keen, A. W. Richter, and N. A. Throckmorton (2015). The zero lower bound, the dual mandate, and unconventional dynamics. *Journal of Economic Dynamics and Control 55*(C), 14–38.

Gertler, M., N. Kiyotaki, and A. Queralto (2012). Financial crises, bank risk exposure and government financial policy. *Journal of Monetary Economics 59, Supplement*, S17–S34.

Greenwood, J., Z. Hercowitz, and G. W. Huffman (1988). Investment, Capacity Utilization, and the Real Business Cycle. *The American Economic Review 78*(3), 402–417.

Guerrieri, L., M. Iacoviello, F. Covas, J. Driscoll, M. Jahan-Parvar, M. Kiley, A. Queralto, and J. Sim (2015). Macroeconomic Effects of Banking Sector Losses across Structural Models. BIS Working Paper 507, Bank for International Settlements.

Iacoviello, M. (2015). Financial Business Cycles. *Review of Economic Dynamics 18*(1), 140–164.

Jokipii, T. and A. Milne (2008). The cyclical behaviour of European bank capital buffers. *Journal of Banking & Finance 32*(8), 1440–1451.

Kapan, T. and C. Minoiu (2013). Balance Sheet Strength and Bank Lending During the Global Financial Crisis. IMF Working Paper 13/102, International Monetary Fund.

Kashyap, A. K., R. G. Rajan, and J. C. Stein (2008). Rethinking capital regulation. *Proceedings - Economic Policy Symposium - Jackson Hole*, 431–471.

Koop, G., M. H. Pesaran, and S. M. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics 74*(1), 119–147.

Linde, L. (2016). Macro vulnerabilities, regulatory reforms and financial stability issues. *Spanish Central Bank Speeches, 25 May*.

Lorenzoni, G., F. Perri, and V. Guerrieri (2008). International Borrowing, Investment and Default. 2008 Meeting Paper 952, Society for Economic Dynamics.

Martynova, N. (2015). Effect of bank capital requirements on economic growth: a survey. DNB Working Paper 467, Netherlands Central Bank, Research Department.

Mendicino, C., K. Nikolov, J. Suarez, and D. Supera (2016). Optimal Dynamic Capital Requirements. Technical Report wp2016_1614, CEMFI.

Mendoza, E. G. (2010). Sudden Stops, Financial Crises, and Leverage. *American Economic Review 100*(5), 1941–66.

Mody, A. (2009). From Bear Stearns to Anglo Irish; How Eurozone Sovereign Spreads Related to Financial Sector Vulnerability. IMF Working Paper 09/108, International Monetary Fund.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics 5*(2), 147–175.

Myers, S. C. and N. S. Majluf (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics 13*(2), 187–221.

Neumeyer, P. A. and F. Perri (2005). Business cycles in emerging economies: the role of interest rates. *Journal of Monetary Economics 52*(2), 345–380.

Petrova, I., M. G. Papaioannou, and D. Bellas (2010). Determinants of Emerging Market Sovereign Bond Spreads; Fundamentals vs Financial Stress. IMF Working Paper 10/281, International Monetary Fund.

Peura, S. and E. Jokivuolle (2004). Simulation based stress tests of banks' regulatory capital adequacy. *Journal of Banking & Finance 28*(8), 1801–1824.

Reinhart, C. M. and K. S. Rogoff (2011). From Financial Crash to Debt Crisis. *American Economic Review 101*(5), 1676–1706.

Reinhart, C. M. and K. S. Rogoff (2013). Banking crises: An equal opportunity menace. *Journal of Banking & Finance 37*(11), 4557–4573.

Richter, A., N. Throckmorton, and T. Walker (2014). Accuracy, Speed and Robustness of Policy Function Iteration. *Computational Economics 44*(4), 445–476.

Rochet, J.-C. (1992). Capital requirements and the behaviour of commercial banks. *European Economic Review 36*(5), 1137–1170.

Schmitt-Grohe, S. and M. Uribe (2015). *Open Economy Macroeconomics*. Manuscript, Columbia University.

Schmitt-Grohé, S. and M. Uribe (2003). Closing small open economy models. *Journal of International Economics 61*(1), 163–185.

Tauchen, G. and R. Hussey (1991). Quadrature-Based Methods for Obtaining Approximate Solutions to Nonlinear Asset Pricing Models. *Econometrica 59*(2), 371–396.

Uribe, M. (2006). On Overborrowing. *American Economic Review 96*(2), 417–421.

Uribe, M. and V. Z. Yue (2006). Country spreads and emerging countries: Who drives whom? *Journal of International Economics 69*(1), 6–36.

Weise, C. L. (1999). The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autoregression Approach. *Journal of Money, Credit and Banking 31*(1), 85–108.

Wheelock, D. C. and P. W. Wilson (2000). Why Do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions. *The Review of Economics and Statistics 82*(1), 127–138.

Yellen, J. (2013). Interconnectedness and systemic risk: Lessons from the financial crisis and policy implications. *American Economic Association Speeches, 4 January*.

Appendix

A.1 Data Description

The dataset includes quarterly and annual data for Spain. The data come from four sources: (i) the European Central Bank (ECB), (ii) the Central Bank of Spain (BDE), (iii) the Organization for Economic Co-operation and Development (OECD), and (iv) the World Bank (WB). Information regarding individual time series is provided in table 5.

Table 5: Data Sources

Variable	Source	Period
Gross Domestic Product	OECD	97Q3-11Q4
Gross Domestic Product: Implicit Price Deflator	OECD	97Q3-11Q4
Total Employment	OECD	97Q3-11Q4
10-year Spanish Government Bond	OECD	97Q3-11Q4
10-year German Government Bond	OECD	97Q3-11Q4
Net Charge-offs to Assets Ratio of Banks and Credit Finance Establishments	BDE	97Q3-11Q4
Total Loans of Banks and Credit Finance Establishments	BDE	97Q3-11Q4
Equity of Banks and Credit Finance Establishments	BDE	97Q3-11Q4
Capital and Reserves of Monetary Financial Institutions	ECB	97Q3-11Q4
Total Assets of Monetary Financial Institutions	ECB	97Q3-11Q4
Banks' Non Performing Loans to Gross Loans	WB	07A-11A

A.2 Construction of Solow Residuals

Solow residuals are defined as

$$SR_t = log(Y_t) - log(H_t),$$

where Y_t denotes real gross domestic product and H_t total employment.

I begin by linearly detrending my empirical measure of labor productivity, SR_t. This is done by fitting a linear and quadratic time trend to the original series. Then I take the measured residuals, which can be

Table 6: Discretized State Space

State Variables	Lower Bound	Upper Bound	Grid Points
A	A_1	A_2	2
N	$0.6\bar{N}$	$1.4\bar{N}$	150
ϵ	$-0.3\bar{N}$	$0.3\bar{N}$	10

Note: Overbar variables refer to the deterministic steady state.

interpreted as the detrended TFP series, and estimate an AR(1) process:

$$a_t = \rho a_{t-1} + v_t,$$

where a is the detrended Solow residuals. I obtain the following estimates: $\rho = 0.956$ and the standard deviation of v_t of 0.0029. Lastly, I discretize such a process as a 2-state Markov chain using the approach laid out in Tauchen and Hussey (1991).

A.3 Solution Method

The model is solved using the policy function iteration with time iteration and linear interpolation algorithm described in Richter et al. (2014). Information regarding the construction of the discretized state space is provided in Table 6. The continuous state variables are N and ϵ. These are chosen from evenly spaced grids of 100 values of bank capital, $N = \{N_1 < N_2 < ... < N_{150}\}$, and 10 values of the default shock, $\epsilon = \{\epsilon_1 < \epsilon_2 < ... < \epsilon_{10}\}$. Hence, the state space of the model has $150 \times 10 \times 2$ nodes.

Under the AR(1) specification for the bank capital shock (see Eq.6), conditional expectations cannot be computed analytically. Calculation is therefore accomplished via quadrature methods. Specifically, I use Gauss Hermite quadrature to integrate across ϵ_{t+1}. In doing so I use 15 Gauss Hermite nodes for the exogenous disturbance u.

The following outline summarizes the policy function iteration algorithm I employ. The general procedure for implementing the algorithm is laid out in Richter et al. (2014).

1. Obtain an initial conjecture for Q_t on each grid point from the log-linear solution of the model. I use Chris Sims' *gensys.m* program to obtain this conjecture.

2. Using initial guesses and the equilibrium conditions of the model, solve for all time t variables.

3. Using linear interpolation, compute the time $t+1$ value for Q_{t+1}.

4. Calculate the time $t+1$ values of the variables appearing inside time t expectations.

5. Compute conditional expectations.
6. Minimize the Euler equations. To this end, I use Chris Sims' *csolve.m* optimization routine. The output of *csolve.m* is the updated decision rules.
7. If the distance between the updated and guessed policy values is smaller than a tolerance parameter, an approximation to the decision rules has been obtained. Otherwise, employ the updated policy function as the new initial conjecture and return to step 2.

A.4 Non-linear Impulse Response Functions

The general procedure for calculating non-linear or generalized impulse response functions (GIRFs) can be found in Koop et al. (1996). The reader is referred there for a formal statistical background.

As remarked by Weise (1999), there are four major differences between the impulse responses originated from a linear model and those generated from a nonlinear model. First, linear impulse responses are invariant to history, whereas nonlinear responses are state-dependent. In other words, nonlinear responses are sensitive to initial conditions. As a result, in the nonlinear case the history of shocks must be treated as a random variable.

Second, in the linear case future shocks can be set to their expected value -that is, to zero. This is not the case for nonlinear models: future shocks must be drawn from a particular distribution and their effects averaged out over a large number of draws.

Third, linear responses are invariant to the size of the shock. In contrast, in nonlinear model disturbances of different sizes give rise to different impulse responses.

Fourth, linear responses are symmetric. That is, the responses to positive and negative disturbances are mirror images of each other. This is not the case for nonlinear models.

For all of the foregoing reasons, impulse responses generated from nonlinear models should be calculated as the average of Monte Carlo simulations of the model [Gavin et al. (2015)]. The following algorithm is used to compute the generalized impulse response functions:

1. The model is simulated N times conditional on N random histories of shocks, $\Xi^A = \{A_t, u_t\}_{t=0}^T$. Let $\bar{x}_t^A = \frac{1}{N}\sum_{i=0}^N x_t^i(\Xi^A)$ be the average across these simulations.
2. The first τ, for $\tau = 1, ..., \tau^*$, elements of each history of shocks are replaced by the τ shocks of interest. A new collection of exogenous disturbances, Ξ^B, is therefore created.
3. The model is (re-)simulated conditional on Ξ^B. Let $\bar{x}_t^B = \frac{1}{N}\sum_{i=0}^N x_t^i(\Xi^B)$ be the average across the second set of simulations.

4. GIRFs may then be defined in percentage change as $(\bar{x}_t^B/\bar{x}_t^A - 1) * 100$ or in percentage difference as $(\bar{x}_t^B - \bar{x}_t^A) * 100$.

In this paper, I set T to 40 and N to 40,000.

A.5 Spain's Risk Premium and Financial Resilience

At the core of the model is the negative link between interest rates and financial vulnerability. Figure 5 offers historical evidence of how Spain's country spread relates to the health of the banking sector. Specifically, it plots Spain's risk premium[23] and the bank capital to loans ratio of Spanish banks from 1980 to 2015. As expected, the figure shows a clear inverse relationship between both magnitudes (there is a statistically significant cross-correlation of -0.34). To put it differently, sovereign bond spreads, and hence overall funding costs, have historically reacted to the leverage ratio of the Spanish banking industry (or equivalently, to their capability to pay back obligations). This historical evidence lends support to the idea that: as financial vulnerability increases, the market revises down its view of Spain's economic outlook, and hence sovereign spreads rise.

A.6 Grid Search Method

This subsection shows that the optimization problem to estimate ψ_1 is well defined. To this end, Figure 6 plots the value of the criterion function, Ω, in the neighborhood of the solution, $\psi_1 = 16,329$. The figure suggests that the existence of local minima can be excluded; thereby corroborating the validity of me methodology.

A.7 Interest Rates and Bank Capital

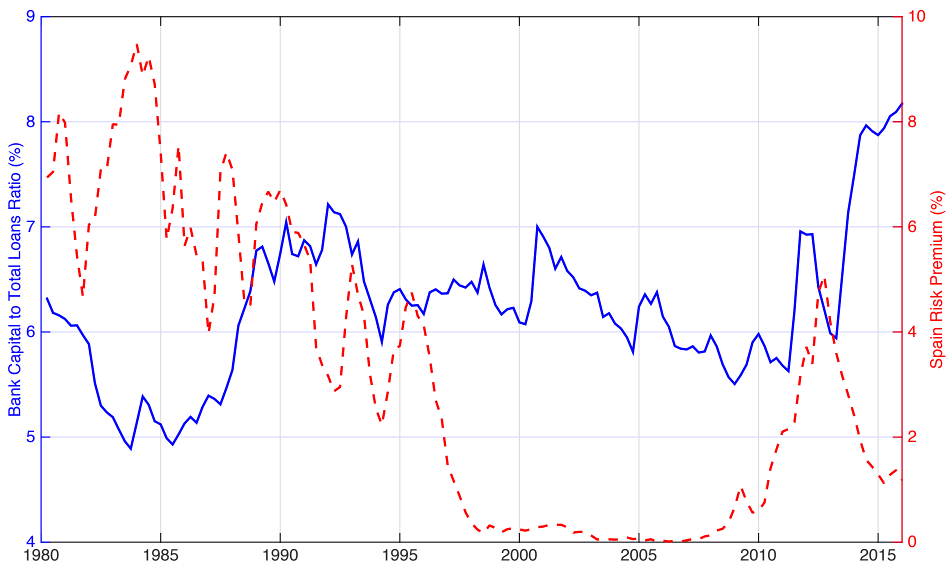
My model assumes that the interest rate, r_t^f, is a decreasing function of the cross-sectional average level of bank equity capital, $\hat{N}_t$. As was noted in Section 3, I opt for the logistic function (see eq.15). After the calibration exercise, the relationship between r_t^f and $\hat{N}_t$ is given by:

$$r_t^f = 0.01[1 + e^{16,329(\hat{N}_t - 0.025)}]^{-1},$$

which is depicted in Figure 7.

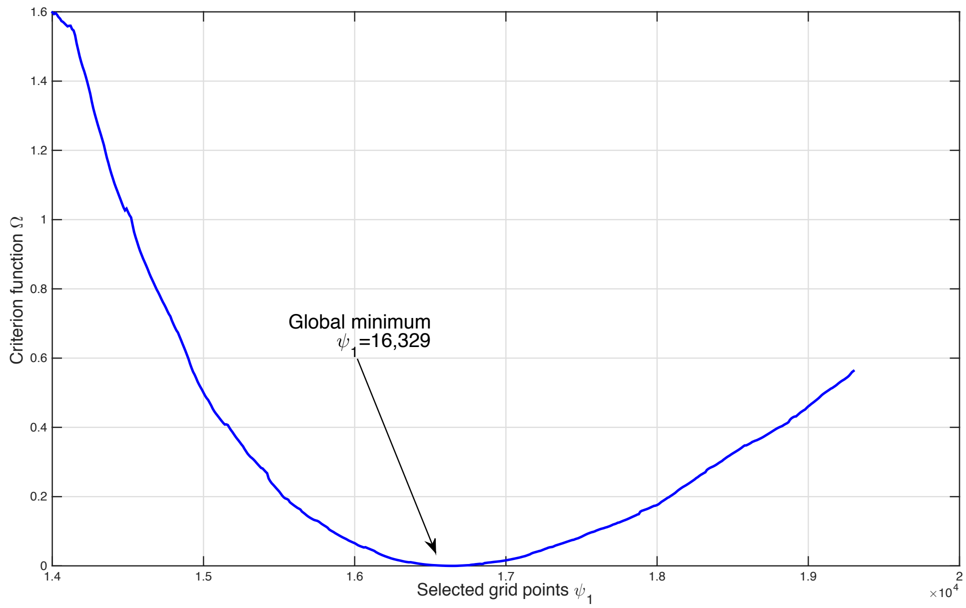
[23] Spain's risk premium is the spread between 10-year Spanish government bond, and the 10-year German bond. Given that the German bond is considered a risk-free asset, the spread is the premium paid for the risk of default.

Figure 5: Spain's Risk Premium and Financial Resilience



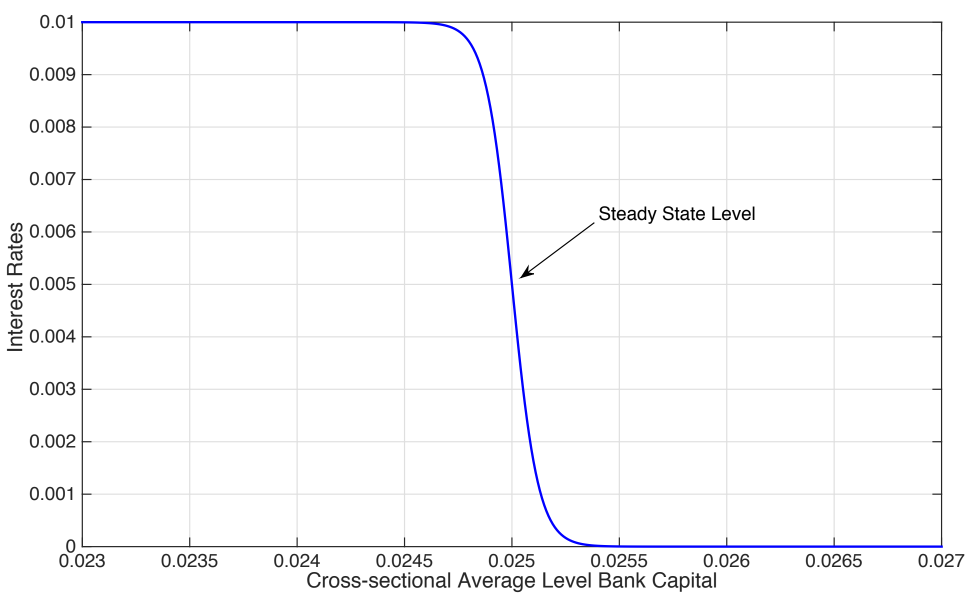
Note: Dynamics of Spain's risk premium and the bank capital to loans ratio of Spanish banks and credit finance establishments. Spain's risk premium is the spread between 10-year Spanish government bond, and the 10-year German bond. The sample contains the period 1980-2015. Data are at a quarterly frequency and are reported in % terms.

Figure 6: The Criterion Function in the neigborhood of the global minimum



Note: The figure exhibits the value of the criterion function, Ω, in the neighborhood of the global minimum, $\psi_1 = 16,329$.

Figure 7: Interest Rates and Bank Capital



Note: The figure shows the relationship between interest rates, r_t^f, and the cross-sectional level of bank capital, $\hat{N}_t$, when $\psi_0 = 0.01$, $\psi_1 = 16,329$ and $\bar{N} = 0.025$.

Chapter 2

Interbank Exposure Limits in a Dynamic Model of Banking

Abstract

The 2008 crisis and the ensuing Great Recession have prompted a reconsideration of economic policy and financial regulation. The development of a policy framework responsible for financial stability is at the forefront of the policy agenda. Motivated by this fact, I propose a stochastic dynamic model with heterogeneous banks. I then use the model to study the effectiveness of interbank exposure limits. My principal finding is that such a macroprudential instrument can be a powerful tool to promote financial resilience.

1 Introduction

Over the last decade, strengthening financial resilience has risen to the top of the policy agenda. Consequently, there is nowadays a renewed focus on macroprudential policies, i.e. those tools aiming to mitigate boom-bust patterns and systemic risk. Nonetheless, policymakers are still a long way from elaborating an efficient operational framework responsible for financial stability.

Knowledge on which instruments and how to employ them to address systemic risk is limited [Claessens (2015)]. Neither is much known about how macropudential tools should be adapted to economic and financial conditions. Questions also arise about the quantitative effects and potential costs on the real economy of those policies. For instance, says Yellen (2014): *"Experience with macroprudential tools remains limited, and we have much to learn to use these measures effectively"*.

The objective of this paper is to explore the effectiveness of interbank exposure limits. To this end, I propose a formal stochastic dynamic model of how banks with rational expectations optimally manage their balance sheets.

I require a set-up which can incorporate a large number of banks, each with a unique risk/return portfolio. Obviously, if banks were identical, there would be no interbank market by definition. In addition, bank heterogeneity captures the fact that the actual risk to which an individual bank is exposed strongly depends on its interactions with other banks [Goodhart et al. (2006)]. In this sense, aggregate risk is mainly endogenous risk steaming from the joint behavior of market participants, and not just the sum of individual risks [Nicolo et al. (2012)].

In reality episodes of financial distress often occur among the riskiest banks. Such episodes in turn produce interactions in the system that may threaten the health of other banks: a process of contagion. Despite this may have several channels[1], the interbank lending market is one the most important ones [Batiz-Zuk et al. (2016)]. As a result, interbank exposure limits are increasingly being used [Cerutti et al. (2017)]. However, very little is known about their design, calibration and quantitative effect. For example, BCBS (2010) states: " *there is no single correct approach to determine the adequate calibration, a single model may not provide the right answer, and results should be interpreted with care*".

My chief innovation is to study the macro-financial consequences of interbank exposure limits in a quantitative micro-founded model that considers the endogenous interactions among a large number of banks. In effect, most quantitative macroeconomic models view the banking sector as a single entity [see

[1]For example, contagion effects may occur via changes in asset market flows and prices [see e.g. Goodhart et al. (2005) and Allen et al. (2010)]

e.g. Gertler et al. (2012) and Iacoviello (2015)]; thereby (i) ignoring the interactions between financial institutions, and (ii) ruling out the existence of an interbank market. Therefore, they are not well suited to analyze the effectiveness of interbank exposure limits. As for the strand of literature using the tools of network analysis, the principal flaw is that they lack behavioral foundations [Upper (2011)]. That is, they assume that banks do not respond to changes in macro-financial conditions. Instead, banks sit tight as problems at their counterparts mount. Consequently, they cannot be used in stress testing exercises, in cost benefit analysis or in the analysis of policy options [Batiz-Zuk et al. (2016)].

Three main findings emerge from my analysis. First, interbank exposure limits reduce the risk of contagion. That is, they restrict the interdependence of the banking sector, and hence curbs the propagation of idiosyncratic shocks. Second, exposure limits promote precautionary behavior and thus leads to a better capitalized banking sector. In other words, they encourage banks to build equity buffers to minimize the likelihood of hitting the regulatory constraint. Third, exposure limits occasionally reduce the efficiency of the interbank market; thereby preventing the optimal allocation of resources. My model predicts that such distortions should not be overlooked.

The remainder of the paper is organized as follows. Section 2 lays out the model. Section 3 explains how the model is calibrated against US data and present numerical results. The final section concludes.

2 The Model

Time is discrete and the horizon is infinite. The economy is populated by I banks whose identity is denoted by i. Banks are heterogeneous with respect to wealth holdings, loan balances, deposit balances, productivity and the proportion of non performing loans.

The Balance Sheet

Each and every period, bank $i \in I$ invests in loans to the nonfinancial sector, l_t^i, lends or borrows in the interbank market, m_t^i, receives an amount of deposits, d_t^i, and manages a volume e_t^i of equity capital. Thus, the balance sheet identity is:

$$l_t^i = m_t^i + d_t^i + e_t^i, \tag{1}$$

which must hold at all times t. Importantly, equity capital is an endogenous state variable (i.e. it is predetermined at time t). The amount of deposits, d_t^i, is randomly determined[2] according to:

$$d_t^i = \bar{d^i} \left(d_{t-1}^i / \bar{d^i} \right)^{\rho_d} \exp(\varepsilon_{d,t}), \tag{2}$$

where $\varepsilon_{d,t} \sim$ i.i.d $\mathcal{N}(0, \sigma_d^2), |\rho_d| < 1$ and $\bar{d^i} > 0$.

The Evolution of Equity Capital

Similarly to Zhu (2008) and De Nicolo et al. (2014), banks differ in their ability to extract net revenue from loans. Formally, the net revenue is given by[3]:

$$f(A_t, a^i, l^i, \psi_t^i) = A_t a_t^i l_t^i - {l_t^i}^2/2 - \psi_t^i l_t^i. \tag{3}$$

Here, A_T is an aggregate productivity shock. It follows an AR(1) process:

$$A_t = (A_{t-1})^{\rho_A} \exp(\varepsilon_{A,t}), \tag{4}$$

where $\varepsilon_{A,t} \sim$ i.i.d $\mathcal{N}(0, \sigma_A^2)$ and $|\rho_A| < 1$. In addition, the term a^i is an idiosyncratic productivity shock, which evolves according to:

$$a_t^i = (a_{t-1}^i)^{\rho_a} \exp(\varepsilon_{a,t}), \tag{5}$$

where $\varepsilon_{a,t} \sim$ i.i.d $\mathcal{N}(0, \sigma_a^2)$ and $|\rho_a| < 1$. As for ψ_t^i, it represents the proportion of non performing loans. It follows an i.i.d. process:

$$\psi_t^i = \exp(\varepsilon_{\psi,t}), \tag{6}$$

where $\varepsilon_{\psi,t} \sim$ i.i.d $\mathcal{N}(\mu_\psi, \sigma_\psi^2)$. A point here deserves further comment. I assume that l_t^i is chosen before ψ_t^i is revealed.[4] Consequently, banks must form expectations about it. It can easily be shown that $\mathrm{E}(\psi_t^i) = e^{\mu_\psi + \sigma_\psi^2/2}$. This modeling device allows me to consider unexpected bank capital losses.

To restrict banks' ability to accumulate enough capital to fund all assets internally, I assume that they face quadratic adjustment costs when the current level of equity differs from its long run value, $\bar{e}$. Formally, adjustment costs are represented as:

$$c(e_t^i) = \tau (e_t^i - \bar{e})^2, \tag{7}$$

[2]This assumption is standard. See, for example, De Nicolo et al. (2014) and Covas and Driscoll (2014).

[3]The assumption of decreasing returns to scale is standard in the literature and empirically supported [see e.g. Cole et al. (2004); Berger et al. (2005); Carter and McNulty (2005)].

[4]Examples of analyses which make this type of information assumption can be found in Tirole (2006).

where $\tau \geq 0$. These costs are needed to guarantee stationarity of the state variables.[5]

Bank i either borrows ($m_t^i > 0$) or lends ($m_t^i < 0$) on the interbank market. Let ϕ_t be the average repayment rate on such a market.[6] If $m_t^i < 0$, equity capital evolves by:

$$e_{t+1}^i = l_t^i - \phi_t m_t^i - d_t^i + \underbrace{f(A_t, a^i, l^i, \psi_t^i) - c(e_t^i) - r^d d_t^i - \phi_t r_t^m m_t^i}_{\text{Operating Profits}} - q_t^i. \tag{8}$$

Here q_t^i represents dividend payments to shareholders. r^d is the interest rate of deposits, which for simplicity is assumed to be constant. r_t^m is the interest rate on the interbank market. Its value is determined so that the aggregate position of all banks on the interbank market is zero.

In contrast, if bank i borrow on the interbank market (i.e. $m_t^i > 0$), the evolution of equity capital is not affected by the overall repayment rate, ϕ_t:

$$e_{t+1}^i = l_t^i - m_t^i - d_t^i + \underbrace{f(A_t, a^i, l^i, \psi_t^i) - c(e_t^i) - r^d d_t^i - r_t^m m_t^i}_{\text{Operating Profits}} - q_t^i. \tag{9}$$

Interbank Exposure Limits

Interbank exposure limits aim to reduce the risk of contagion by restricting banks' actions on the interbank market [Cerutti et al. (2017)]. I model exposure limits as an occasionally binding borrowing constraint on the interbank market:

$$m_t^i \leq \gamma \Rightarrow l_t^i \leq d_t^i + e_t^i + \gamma, \tag{10}$$

where γ is a positive policy parameter. Note that the constraint can be viewed as an endogenous upper bound on banks' loans partly determined by the amount of equity capital. In other words, the prudential policy I propose has the flavor of a bank capital requirement constraint.

Banks' maximization problem

Banks' preferences over dividend streams $\{q_t^i\}_{t=0}^{\infty}$ are evaluated via and expected utility criterion:

$$E_t \sum_{t=0}^{\infty} \beta^t \log(1 + q_t^i), \tag{11}$$

[5]See Schmitt-Grohe and Uribe (2003) for alternative ways of obtaining this.

[6]The model considers a "complete" structure of claims on the interbank market. That is, every bank has symmetric exposures to all other banks. As a result, all lenders face the same proportion of defaulted claims.

As noted by Bianchi and Bigio (2014), introducing curvature into the objective function is essential. This assumption produces smooth dividends and slow-moving bank capital, as observed empirically.[7] Therefore, banks choose sequences $\{l_t^i, m_t^i, q_t^i\}_{t=0}^{\infty}$ to maximize eq.11 subject to eq.1, eq.8 (or eq.9), and eq.10.

Default

Banks are allowed to default. Specifically, bank i defaults if its end of period equity, e_{t+1}^i, drops below zero. In these instances, not all liabilities are repaid. I assume that deposit liabilities are senior to interbank liabilities.[8] Let J be the total number of banks that borrow on the interbank market. The repayment rate of bank $j \in J$ is then given by:

$$\phi_t^j = \frac{\tilde{m}_t^j}{m_t^j} \quad \text{with} \quad \tilde{m}_t^j = \begin{cases} m_t^j & \text{if} \quad e_{t+1}^j > 0 \\ \max[0, m_t^j + e_{t+1}^j] & \text{if} \quad e_{t+1}^j < 0 \end{cases} . \tag{12}$$

In words, if end of period equity, e_{t+1}^j, is positive, bank j repays its debts on the interbank market in full (i.e. $\tilde{m}_t^j = m_t^j$ and $\phi_t^j = 1$). However, if the bank fails (i.e. $e_{t+1}^j < 0$), shareholders exercise the limited liability option, and not all debts are repaid (i.e. $\tilde{m}_t^j < m_t^j$). The aggregate repayment rate is computed as the average across banks:

$$\phi_t = \frac{1}{J}\sum_{j=1}^{J} \phi_t^j \tag{13}$$

To keep the model simple, I follow De Nicolo et al. (2014), and assume that right after default, a new bank is formed with initial public capital $\hat{e}$, in order to conserve intermediation services.

Competitive Equilibrium

A competitive equilibrium consists on sequences of aggregates variables $\{r_t^m, \phi_t\}_{t=0}^{\infty}$ and individual variables $\{l_t^i, m_t^i, e_t^i, q_t^i\}_{t=0}^{\infty} \quad \forall i \in I$ such that:

1. Banks' policy functions solve their maximization problems (i.e. all banks optimize).
2. The interbank market clears:

$$\sum_i m_t^i = 0 \tag{14}$$

[7] This kind of preferences are usually found in the corporate finance literature. One way to rationalize these preferences is through agency frictions that might give rise to capital adjustment costs [Estrella (2004)]. Slow-moving equity can also be obtained by directly assuming capital adjustment costs.

[8] This assumption is widely used in the literature on contagion in financial markets [Upper (2011)].

3. ϕ_t satisfies eq.13.

3 The Quantitative Analysis

I now resort to numerical simulations to explore the effectiveness of interbank exposure limits. The computational strategy is laid out in Appendix 1. Accuracy checks are provided in Appendix 2.

In this section two economies are often compared. The first economy (my baseline) features an exposure limit and is labeled the Regulated Economy. The second economy is similar to the baseline except that it is not subject to financial regulation. This is done by setting the policy parameter, γ, to infinity. This economy is labeled the Unregulated Economy.

3.1 Calibration

The values assigned to the model's parameters are listed in Table 1. The model is calibrated against US annual data. Details on the data are provided in appending A.3.

The total number of banks[9] is 100. The discount factor is set to 0.96, a number often used in dynamic macroeconomic models. In terms of the parameters associated with the aggregate productivity shock, I set $\rho_A = 0.85$ and $\sigma_A = 0.03$. I have chosen these values to be consistent with the following outcomes. First, the model-implied standard deviation of total lending is roughly 0.03. Second, the model yields a first order serial autocorrelation coefficient of total lending close to 0.8. These values correspond to the moments of the total credit to the private non-financial sector from 1988 to 2016.

Regarding the parameters linked to the idiosyncratic productivity shock, I set $\rho_a = 0.9$ and $\sigma_a = 0.095$. These values are selected so that roughly 1% of banks fail each period. This number corresponds to the proportion of commercial banks and saving institutions that failed or required assistance transactions from 1984 to 2015. With respect to the parameters associated with the deposit shock, I set ρ_d to 0.8 and σ_d to 0.02. These values are obtained by fitting a first order autoregressive process to the total amount of deposits in the US economy from 1980 to 2016.

In terms of the parameters governing the proportion of non performing loans ψ_t^i, I set μ_ψ to -3.99 and σ_ψ to 0.61. These values are obtained by fitting a log normal distribution to the ratio non performing loans to total loans in the US economy from 1988 to 2016.

The steady state level of bank capital, $\bar{e}$, is not uniquely pinned down by the parameter values. Therefore, I set it to match the average of the ratio between equity capital and total assets of commercial banks.

[9]The results are robust to the choice of this parameter.

Table 1: Baseline Parameter Calibration

Parameter	Symbol	Value
Total number of banks	I	100
Discount factor	β	0.96
Interest rate deposits	r^d	0.04
Aggregate productivity persistence	ρ_A	0.85
Aggregate productivity standard deviation	σ_A	0.03
Idiosyncratic productivity persistence	ρ_a	0.90
Idiosyncratic productivity standard deviation	σ_a	0.09
Deposit persistence	ρ_d	0.80
Deposit standard deviation	σ_d	0.02
Mean default shock	μ_ψ	-3.99
Standard deviation default shock	σ_ψ	0.61
Steady state equity capital	$\bar{e}$	0.07
Interbank exposure limits	γ	1.03

From 1980 to 2016, this value was roughly 8%. As for the equity adjustment cost parameter, τ, I set it to the minimum value that guarantees that the equilibrium solution is stationary.

The parameter governing the tightness of exposure limits, γ, is chosen to be consistent with the following outcome: when in place, the instrument binds in roughly 20% of the periods.[10]

It remains to specify the long run equilibrium properties of the interbank market. I assume that the ratio total loans in the interbank market to total loans to the non financial sector equals 0.5. This value corresponds to the average ratio financial commercial paper outstanding to commercial and industrial loans from 2001 to 2016. In addition, I suppose that in steady state half of the banks borrow on the interbank market, while the other half lends.[11]

3.2 Evaluating the Quantitative Model

I first assess the ability of the model to account for US financial cycle facts. I begin by simulating a 50,000 period time series, and then calculate key statistical moments. Table 2 reports the results.

Generally, the financial cycle moments of the model are approximately in line with the data. More precisely, the model does a fair job at matching the volatility of the leverage ratio and of total lending. Also, the model captures the fact that roughly 1% of banks default each period. In addition, it does well at matching the serial autocorrelations. To be sure, there are some discrepancies between the model and the data. For example, the interest rate is slightly more volatile in the model than in the data. Another failure of the model is that the series for the interest rate is not persistent enough.

All told, the model seems to be consistent with US financial cycle features. I am of the opinion that this observation emphasizes its validity for analyzing the effectiveness interbank exposure limits.

3.3 Decision Rules

Let me now explore how the decision rules of the model are affected by interbank exposure limits. Figure 1 depicts the policy function for individual lending, l_t^i, as a function of idiosyncratic productivity, a_t^i when $\{e_t^i, d_t^i, \sum_i e_t^i, r_t^m, \psi_t^i\}$ are centered around their steady state values.

As idiosyncratic productivity increases from low levels, banks' ability to extract revenue from loans augments. Consequently, they invest more on loans. Given that deposits are an exogenous variable and

[10]The tightness of regulatory policy can be treated as an input given by the users of model. My choice is justified by the Senior Loan Officer Opinion Survey, which suggest that banks are constrained by capital regulation in roughly 20% of the periods [Covas and Driscoll (2014)].

[11]To this end, I assume that the steady state level of deposits, $\bar{d}^i$, is low for the first half of banks, and high for the second half.

Table 2: Empirical and Simulated Moments

	Data	Model
Standard Deviation(%)		
Leverage ratio	2.05	1.92
Total lending	3.79	2.91
Interest rate	2.70	4.41
Autocorrelation		
Leverage ratio	0.78	0.82
Total lending	0.83	0.85
Interest rate	0.88	0.72
Average (%)		
Bank failures	0.92	1.35

Note: The first column presents statistical moments of the US annual data. Theoretical moments are based on a 50,000 period time series simulation of the model.

equity is predetermined at time t, the extra lending is financed by borrowing in the interbank market. Exposure limits clearly affect these dynamics. Specifically, they restrict the amount that banks can borrow on the interbank market. As a result, they actually impose an upper bound on banks' loans.

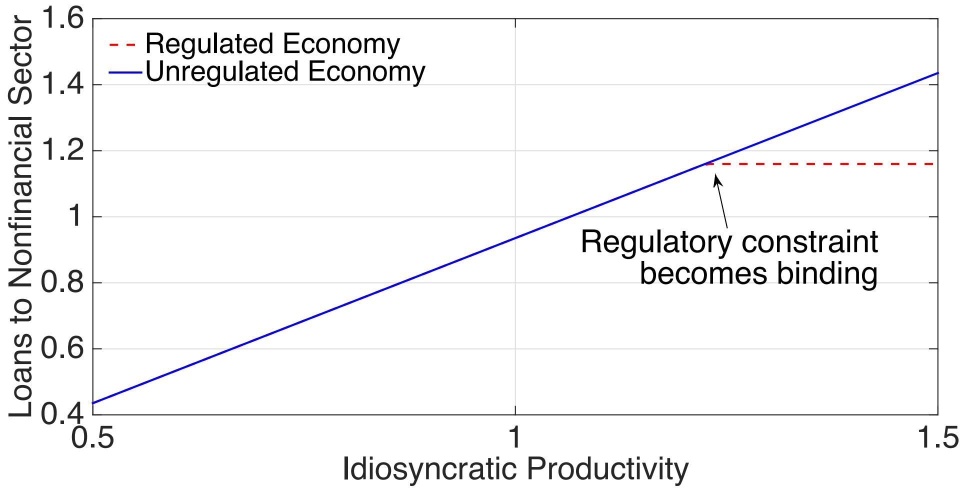
Thus, Figure 1 illustrates a clear tradeoff. On the one hand, exposure limits can have a negative impact on the efficiency of the interbank market in allocating banks' idiosyncratic shocks. On the other hand, they can reduce the interdependence of the banking sector, and hence lower the risk of contagion.

3.4 Stress Testing Analysis

In this subsection I perturb certain exogenous variables and trace out the dynamic responses of the model. The emphasis is on how the behavior of the banking industry is affected by interbank exposure limits. The results are based on Monte Carlo simulations of the model.[12]

[12] Please refer to Appendix 4 for more details about the methodology.

Figure 1: Policy Function for Loans



Note: Policy function for individual lending, l_t^i, as a function of idiosyncratic productivity, a_t^i when $\{e_t^i, d_t^i, \sum_i e_t^i, r_t^m, \psi_t^i\}$ are centered around their steady state values.

Idiosyncratic Bank Failures

I first analyze the role of exposure limits in reducing the risk of contagion. To this end, I conduct a simple experiment:

1. I first select a group of 5 banks who in steady state are borrowers on the interbank market.
2. I then feed them with a sequence of 4 positive productivity shocks. Formally, I set $\varepsilon_{a,t}^i = 0.15$ for $t = 1, 2, 3, 4$ and $i = 1, 2, 3, 4, 5$.
3. Lastly, I assume that at $t = 4$, a set of default shocks destroys 50% of their loans. That is, I suppose that $\psi_4^i = 0.5$ for $i = 1, 2, 3, 4, 5$.

Table 3 summarizes the percentage deviations from the steady state in total equity, $\sum_i e_t^i$, and in the average equity of the lenders on the interbank market, $\frac{1}{J}\sum_j e_t^j$, where J is the number of lenders, at the time of the default shocks and one period afterwards.

The sequence of positive productivity shocks encourage the group of 5 banks to expand their lending (see Figure 1). As noted above, deposits are exogenous and equity capital is a predetermined slow-moving variable. In consequence, banks turn to the interbank market to fund the new loans.[13] In this scenario, the

[13]This notion is supported by the corporate finance and banking literature showing that core liabilities (i.e. traditional deposits and equity capital) are sticky, and as a result, do not keep up with the expansion of balance sheets during booms [Harutyunyan et al.

Table 3: Idiosyncratic Bank Failures

	% Dev. from Steady State			
	Time T		Time $T+1$	
	Reg.Ec.	Unr. Ec.	Reg.Ec.	Unr. Ec.
Total Equity	-25.7	-36.4	-19.0	-22.0
Average Equity Lenders in Inter. Market	-14.6	-27.3	-8.66	-12.5

Note: Reg. Ec. and Unr. Ec. stand for Regulated Economy and Unregulated Economy respectively. The table summarizes the percentage deviations from the steady state in the value of total equity and the average equity of the lenders on the interbank market following a series of idiosyncratic bank failures.

interbank market allows for a better allocation of resources. However, it also increases the interdependence of the banking sector; thereby potentially undermining financial stability.

In effect, once the group of 5 banks is hit by the default shock and thus fail, the interbank market propagates the losses to the entire banking sector. Indeed, Table 3 reveals that aggregate equity falls more than 25%. The table also shows that the average equity of lenders in the interbank market significantly decreases. Remarkably, such a decline is solely due to contagion effects, since these banks have not been directly hit by any shock.

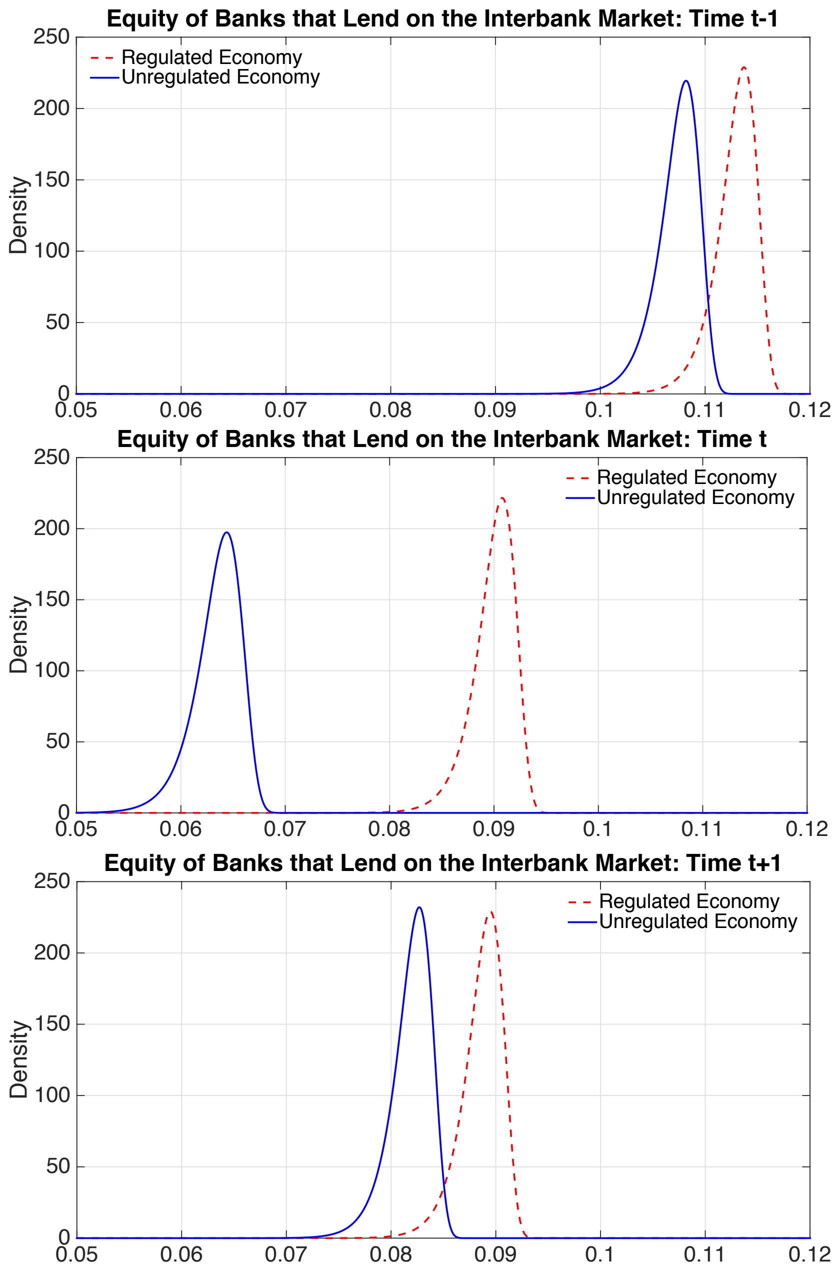
Regulatory intervention clearly alleviates the negative consequences of these dynamics. As can be seen from the table, the reduction in total equity and in the average equity of lenders is notable lower in the Regulated Economy. The intuition is straightforward. Exposure limits restrict the amount banks can borrow on the interbank market. By doing so, this policy reduces the transaction volume on such a market; thereby lessening the degree of interdependence in the banking sector. As a result, interbank exposure limits strengthen the resilience to contagion effects.

To see this point more clearly, Figure 2 depicts the densities of equity capital of the banks that lend on the interbank market.[14] The figure clearly illustrates the crucial role of interbank exposure limits in reducing the risk of contagion. In effect, it can be seen that the shift to the left of the density function at time t is much more pronounced in the Regulated Economy.

(2015)].

[14]Recall that these banks have not been hit by any exogenous shock. Therefore, the variations in their net worth is only due to interactive contagion effects.

Figure 2: Density Functions



Note: The figure shows the Weibull probability density function of equity capital of the banks that lend at on the interbank market at time t.

Idiosyncratic Productivity Shocks

I now proceed to analyze the potential costs associated with interbank exposure limits. To this end, I suppose that a groups of 5 banks experiences a positive shock, $\varepsilon_{a,t}^{i}$, so that idiosyncratic productivity increases by 20% at time t. Formally, I set $\varepsilon_{a,t}^{i} = 0.2$ for $i = 1, ..., 5$. Figure 3 plots the histograms of individual lending and interbank borrowing of these 5 banks.

As their ability to extract net revenue from loans augments, the 5 banks increase their borrowing in the interbank market, and use these additional funds to expand their lending to the nonfinancial sector. Therefore, there is a transfer of resources in the interbank market from less to more productive banks.

It is apparent from Figure 3 that exposure limits distort the workings of the interbank market. More precisely, regulatory intervention prevents the most productive banks from obtaining their desired level of funds; thereby forcing them to cut back on lending. For instance, note the significant differences between the dashed red line and the solid blue line in the right-middle panel of Figure 3. These differences are due to the fact that in the Regulated Economy the most productive banks hit the exposure limit constraint (see the left-middle panel), and are forced to reduce their credit supply.

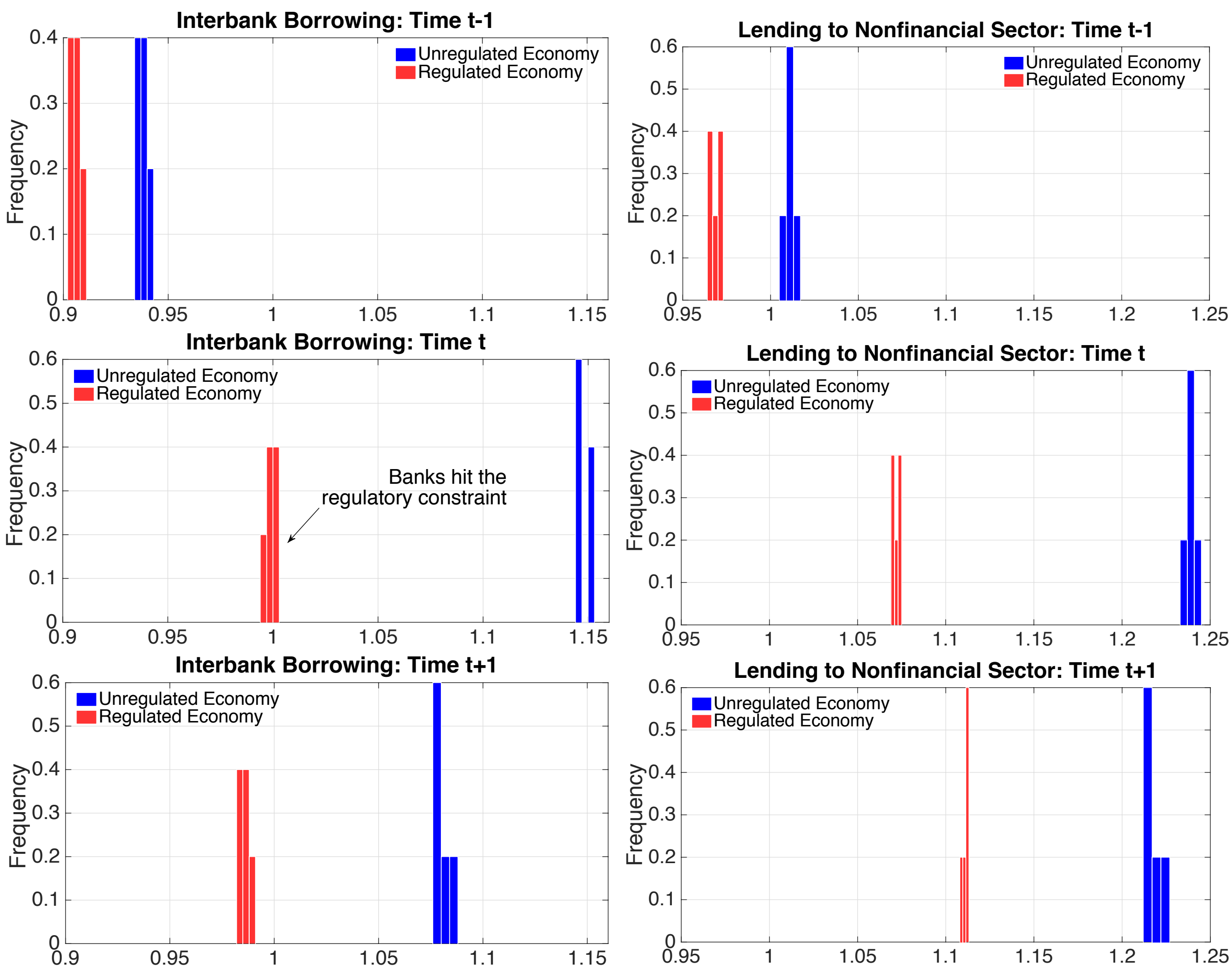
All told, the figure is a clear example of how exposure limits may reduce the efficiency of the interbank market and thus prevent the optimal allocation of resources.

3.5 The Long Run Equilibrium

A subsequent, natural question that emerges is: are the costs of exposure limits significant in the long run? Put differently, is there a steady state negative impact of exposure limits? To address this issue, I simulate a $100,000$ period time series and calculate some key statistical indicators. Table 4 presents the results.

The table is revealing in several ways. First, aggregate lending is slightly lower in the Regulated Economy. This confirms the notion that exposure limits occasionally prevent the optimal allocation of resources; thereby hindering the supply of credit. Second, regulated banks are on average better capitalized. The basic logic is as follows. As was discussed in Section 2, exposure limits can be viewed as an endogenous upper bound on banks' loans partly determined by the amount of equity capital. In consequence, regulated banks buildup equity buffers in order to stay clear of the regulatory constraint. In other words, exposure limits encourage precautionary behavior. Third, regulatory intervention reduces the risk of contagion; thus decreasing the frequency of episodes of financial distress and capital shortfalls. To see this point more clearly, note that the Regulated Economy features a notably lower proportion of bank failures each period. Fourth, exposure limits reduce financial volatility. For example, the standard deviation of total lending and the leverage ratio are 11.7% and 39%, respectively, lower in the Regulated Economy.

Figure 3: Histograms



Note: The figure shows the histograms of (i) interbank borrowing, and (ii) lending to the nonfinancial sector of the banks hit by a positive productivity shock at time t. Each bin value is the count of observations over the total number of observations. Therefore, the sum of the bar heights equals 1.

Table 4: Long Run Equilibrium

	Regulated Econ.	Unregulated Econ.	Dev. %
Average			
Total Lending	92.5	94.5	-2.11
Leverage Ratio	9.38	9.15	2.51
Interest Rate	0.06	0.06	0.00
Bank failures (%)	1.10	1.35	-18.5
Standard Deviation (%)			
Total Lending	2.57	2.91	-11.7
Leverage ratio	1.17	1.92	-39.0
Interest rate	4.51	4.41	2.26

Note: The column Dev. % represents the percentage deciation of the outcome in the Regulated Economy with respect to the Unregulated Economy. The leverage ratio is defined as the aggregate level of equity, $\sum_i e_t^i$, divided by the total lending to the nonfinancial sector, $\sum_i l_t^i$. Bank failures represent the percentage of banks that default each period.

To emphasize the effects of exposure limits on the capitalization of the banking sector, Fig 4 plots the density of the leverage ratio. Remarkably, the density in the Regulated Economy is tilted to the right (i.e. the left tails is thinner and the right tail is fatter) when compared with the density in the Unregulated Economy. To put it differently, the frequency of episodes in which the banking sector is in distress is lower in the Regulated Economy.

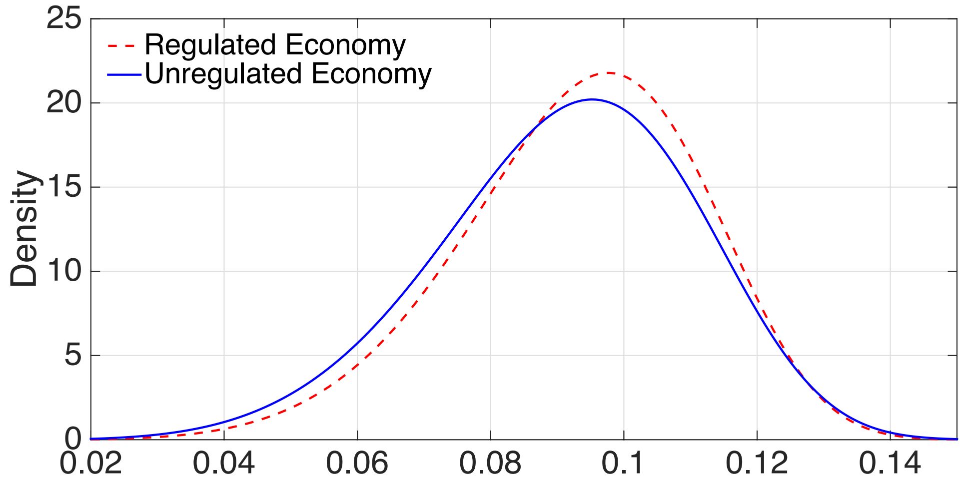
I conclude this section with the overall assessment that interbank exposure limits do boost financial resilience. However, their negative effects on the supply of credit ought not to be overlooked.

4 Concluding Remarks

The recent wave of financial and economic crises has prompted a rethink of financial regulation. Motivated by this, I propose a stochastic dynamic model with heterogeneous banks. I then use the model to assess the effectiveness of interbank exposure limits.

My findings suggest that interbank exposure limits can be a powerful tool to strengthen financial resilience. Two mechanisms are at play. First, exposure limits reduce the risk of contagion between financial institutions by restricting the interdependence of the banking sector. Second, exposure limits encourages

Figure 4: Leverage Ratio Density Function



Note: The figure shows the Weibull probability density function of the aggregate leverage ratio. The density is computed via a 100,000 periods simulation.

precautionary behavior by promoting the buildup of equity buffers. However, my results indicates that the negative impact of this policy tool on the supply of credit should not be underestimated.

In spite of the growing literature on macroprudential tools many unknowns still exist, and a large research agenda remains. In order to justify policy intervention, further research on the choice and calibration of prudential regulation is essential. Also, it is crucial to gain evidence on the quantitatively effectiveness of macroprudential tools to make the policy design more transparent and accurate. In addition, the incessant progress in the solution of quantitative macroeconomic models with micro heterogeneity makes this field a highly stimulating area for future research.

References

Allen, F., A. Babus, and E. Carletti (2010). Financial Connections and Systemic Risk. NBER Chapters, National Bureau of Economic Research, Inc.

Batiz-Zuk, E., F. Lopez-Gallo, S. Martinez-Jaramillo, and J. P. Solorzano-Margain (2016). Calibrating limits for large interbank exposures from a system-wide perspective. *Journal of Financial Stability 27*(Supplement C), 198–216.

BCBS (2010). Calibrating regulatory minimum capital requirements and capital buffers: a top-down approach. Technical report.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein (2005). Does function follow organizational form? evidence from the lending practices of large and small banks. *Journal of Financial Economics 76*(2), 237–269.

Bianchi, J. and S. Bigio (2014). Banks, Liquidity Management and Monetary Policy. NBER Working Paper 20490, National Bureau of Economic Research, Inc.

Carter, D. A. and J. E. McNulty (2005). Deregulation, technological change, and the business-lending performance of large and small banks. *Journal of Banking & Finance 29*(5), 1113–1130.

Cerutti, E., R. Correa, E. Fiorentino, and E. Segalla (2017). Changes in Prudential Policy Instruments - A New Cross-Country Database. *International Journal of Central Banking 13*(2), 477–503.

Claessens, S. (2015). An Overview of Macroprudential Policy Tools. *Annual Review of Financial Economics 7*(1), 397–422.

Cole, R. A., L. G. Goldberg, and L. J. White (2004). Cookie cutter vs. character: The micro structure of small business lending by large and small banks. *The Journal of Financial and Quantitative Analysis 39*(2), 227–251.

Covas, F. and J. C. Driscoll (2014). Bank Liquidity and Capital Regulation in General Equilibrium. SSRN Scholarly Paper ID 2520193, Social Science Research Network, Rochester, NY.

De Nicolo, G., A. Gamba, and M. Lucchetta (2014). Microprudential regulation in a dynamic model of banking. *The Review of Financial Studies 27*(7), 2097–2138.

Den Haan, W. J. (1996). Heterogeneity, Aggregate Uncertainty, and the Short-Term Interest Rate. *Journal of Business & Economic Statistics 14*(4), 399–411.

Estrella, A. (2004). The cyclical behavior of optimal bank capital. *Journal of Banking & Finance 28*(6), 1469–1498.

Gertler, M., N. Kiyotaki, and A. Queralto (2012). Financial crises, bank risk exposure and government financial policy. *Journal of Monetary Economics 59*(S), 17–34.

Goodhart, C. A. E., P. Sunirand, and D. P. Tsomocos (2005). A risk assessment model for banks. *Annals of Finance 1*(2), 197–224.

Goodhart, C. A. E., P. Sunirand, and D. P. Tsomocos (2006). A model to analyse financial fragility. *Economic Theory 27*(1), 107–142.

Harutyunyan, A., A. Massara, G. Ugazio, G. Amidzic, and R. Walton (2015). Shedding Light on Shadow Banking. Technical Report 15/1, International Monetary Fund.

Iacoviello, M. (2015). Financial Business Cycles. *Review of Economic Dynamics 18*(1), 140–164.

Krusell, P. and J. Smith, Anthony A. (1998). Income and Wealth Heterogeneity in the Macroeconomy. *Journal of Political Economy 106*(5), 867–896.

Nicolo, G. D., G. Favara, and L. Ratnovski (2012). Externalities and Macroprudential Policy. IMF Staff Discussion Notes 12/05, International Monetary Fund.

Schmitt-Grohe, S. and M. Uribe (2003). Closing small open economy models. *Journal of International Economics 61*(1), 163–185.

Tirole, J. (2006). *The Theory of Corporate Finance*. Princeton University Press.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability 7*(3), 111–125.

Yellen, J. L. (2014). Speech by Chair Yellen on monetary policy and financial stability. Technical report.

Zhu, H. (2008). Capital regulation and banks' financial decisions. *International Journal of Central Banking 4*(1), 165–211.

A.1 Computation Strategy

The model is solved using a parameterized expectation algorithm. It is important to notice that the policy functions of agent $i \in I$ depend on the cross-sectional wealth distribution. Then, if I is large, the dimension of the state space explodes. To overcome this problem, I follow Krusell and Smith (1998) and Den Haan (1996), and approximate the wealth distribution using moments. An outline of the algorithm will now be given.[15]

1. I first generate the exogenous stochastic processes $\{A_t, d_t^i, a_t^i, \psi_t^i\}_{t=0}^{T=8000}$ for $i = 1, ..., I$.
2. I then iterate to find the coefficients of the parameterized expectation. I begin by replacing the conditional expectations of the banks' inter-temporal optimality conditions with:

$$\Psi = \exp\left[\theta_0 + \theta_1 \log(a_t^i) + \theta_2 \log(1 + d_t^i) + \theta_3 \log(1 + e_t^i) + \theta_4 \log(\sum_i e_t^i) + \theta_5 \log(A_t)\right]$$

   The iterations begin with an initial value for $\{\theta_0, \theta_1, \theta_2, \theta_3, \theta_4\}$. The iteration procedure is as follows:

   (a) Using the exogenous driving processes and the function Ψ, I simulate the economy for $T = 8000$ periods. A golden-section search[16] is used to find the value of the interest rate on the interbank market, r_t^m, such that $\sum_i m_t^i = 0 \; \forall t$.

   (b) Update the coefficients of the approximating polynomial. As was discussed in the calibration exercise, I suppose that in steady state half of the banks borrow on the interbank market, while the other half lends. It is natural to think that the forecasting rules of banks belonging to these two groups might be slightly different. Therefore, I estimate two forecasting rules: one for banks that in steady state borrow in the interbank market and one for banks that lend.

   (c) I iterate until

$$\max\left[\frac{\theta_j^{n+1} - \theta_j^n}{1 + \left|\theta_j^n\right|}\right] < 0.0001$$

   where n refers to the number of the iteration, and $j = 0, ..., 4$.

A.2 Accuracy Checks

This section checks the accuracy of the numerical algorithm. I assess the intertemporal error banks make when they form expectations according to the approximate solution. This error is measured by the residual,

[15]The detailed procedure can be found in Den Haan (1996).
[16]More precisely, I use the Matlab function *fminbnd*.

u_t^i, of the Euler equation for equity capital. Let η_t^i be the Lagrange multiplier on the law of motion for net worth. In the absence of regulatory intervention, u_t^i is given by[17]:

$$u_t^i = \eta_t^i - \beta E_t \left[\eta_{t+1}^i \left[1 + r_{t+1}^m - \frac{dc(e_{t+1}^i)}{de_{t+1}^i} \right] \right].$$

For clarity, the Euler residual is normalized by the level of dividends. Thus, u_t^i / q_t^i captures the loss in terms of dividends banks experience by relying on the approximate solution rather than on the true one. I first compute u_t^i at each grid point. Then, I compute the following statistic:

$$\Upsilon = \log_{10} \left[E \left| \frac{u_t^i}{q_t^i} \right| \right] = -3.08$$

This means that a bank with \$1220 of dividends makes on average a one-dollar error in current dividends in each period relative to the next period's dividends. From an economic point of view, these errors can be seen as small enough to consider the approximation as accurate.

A.3 Data Description

The dataset includes annual data for the US. The data come from three sources: (i) the Federal Reserve Bank of ST. Louis (FRED), (ii) the Financial Accounts of the US (FA), and (iii) the Federal Depository Insurance Corporation (FDIC). Information regarding individual time series is provided in table 5.

A.4 Stress Testing Analysis

This section describes the procedure for performing the stress testing analysis. The results are computed as the average Monte Carlo simulations of the model. Specifically, the following algorithm is used:

1. Generate N random histories of exogenous shocks $\Xi^A = \{A_t, a_t^i, d_t^i, \psi^i\}_{t=0}^T$.
2. The first τ, for $\tau = 1, ..., \tau^*$, elements of each history of shocks are replaced by the τ shocks of interest. A new collection of exogenous disturbances, Ξ^B, is therefore created.
3. The model is simulated conditional on Ξ^B. Let $\bar{x}_t^B = \frac{1}{N} \sum_{i=0}^N x_t^i(\Xi^B)$ be the average across these simulations. Here $\bar{x}_t^B$ is a vector containing the endogenous variables of the model.
4. The stress testing exercise studies the statistical properties of $\bar{x}_t^B$.

In this paper, I set N to 10,000.

[17]The accuracy of the solution is not significantly modified by the introduction of exposure limits.

Table 5: Data Sources

Variable	Source	Period	Transformation
12-months London Interbank Offered Rate	FRED	88-16	N/A
Commercial & Industrial Loans	FRED	89-16	N/A
Financial Commercial Paper Outstanding	FRED	01-16	N/A
Nonperforming Total Loans to Total Loans	FRED	88-16	N/A
Total Deposits	FRED	88-16	HP
Total Credit to Private Nonfinancial Sector	FRED	88-16	HP
Total Failure and Assistance Transactions	FDIC	84-15	N/A
Total Equity of Domestic Financial Sectors	FA	88-16	N/A
Total Assets of Domestic Financial Sectors	FA	88-16	N/A

Note: HP: Hodrick Prescott filter. N/A: not applicable. Note that some variables are used to construct ratios and hence do not need to be transformed.

Chapter 3

State-dependent Risk Taking and the Transmission of Monetary Policy Shocks[1]

Abstract

Is risk taking an important channel by which monetary policy shocks affect economic activity? On the basis of a nonlinear structural VAR including a new measure of risk sensitivity by economic agents, we show that the role of the risk-taking channel depends on the state of the economy. While it is irrelevant during recession or normal times, it acts as an amplifier by boosting output during expansion. It means that, as long as monetary policy does not actively "lean against the wind", it may exacerbate boom-bust patterns.

[1]The content of this work is an extended version of the paper by Patrick Fève, Pablo Garcia and Jean-Guillaume Sahuc: *State-dependent risk taking and the transmission of monetary policy shocks*, Economics Letters, Volume 164, 2018, Pages 10-14.

1 Introduction

In the wake of the recent global financial crisis, the relationship between monetary policy and the risk appetite of economic agents has been pointed out. Market observers have claimed that the prolonged period of low interest rates under favorable economic and financial conditions in the early 2000s might have produced overconfidence by economic agents, (i) increasing dramatically their risk tolerance and (ii) contributing to financial imbalances. This mechanism, called the risk-taking channel of monetary policy, can have long lasting adverse consequences on economic activity if it is neglected (Borio and Zhu (2012) and Diamond and Rajan (2012), among others).

The aim of this paper is to investigate the importance of the risk-taking channel in the propagation of monetary policy shocks to the US economy. To this end, we build an indicator of risk sensitivity and introducing it together with output and a measure of the monetary policy stance in a logistic vector smooth transition autoregressive model (LVSTAR, Terasvirta et al. (2010)). Using a standard identification scheme for monetary policy shocks (Christiano et al. (1999)), we find that the role of the risk-taking channel depends on the state of the economy. During recession or normal times, it has a small effect on the transmission of monetary policy shocks to economic activity. However, during economic booms the risk-taking channel acts as an amplifier by boosting output. Excessive risk appetites may potentially lead to boom-bust patterns. Central banks should then account for this channel when adjusting their policy in order to mitigate the adverse consequence of their decisions on economic activity.

The rest of the paper proceeds as follows. Section 2 presents the risk sensitivity indicator. Sections 3 and 4 describe the empirical strategy. Section 5 presents the main results. Section 6 concludes.

2 Measuring Risk Taking

I aim to assess the resilience of the overall financial system, which crucially depends on the underlying health of all sectors of the economy (see e.g. Hatzius et al. (2010); Ampudia et al. (2016) and Bernstein et al. (2017)). To this end, I construct a coincidence risk sensitivity indicator.

2.1 Dynamic Factor Analysis

The index is basically a weighted average of a set of financial variables. Factor analysis is used to estimate the weight given to each indicator.[2] Formally, the index, F_t, is estimated using the following state space representation:

$$\Omega_t = \Gamma F_t + \eta_t, \tag{1}$$

$$F_t = \rho F_{t-1} + v_t, \tag{2}$$

where Ω_t is a vector of stationary variables that have been demeaned and standardized. η_t is an idiosyncratic error vector with $\eta_t \sim$ i.i.d $\mathcal{N}(0, \mathrm{H})$. The error term v_t is assumed to be i.i.d. $\mathcal{N}(0, \sigma^2)$. Γ is a matrix of factor loadings, capturing the sensitivity of each variable to F_t. The parameter ρ governs the evolution of the factor over time.

The model (1)-(2) is estimated using the EM algorithm outlined by Stock and Watson (2002) and Brave and Butters (2012). The EM algorithm demands one pass through the Kalman filter[3] and smoother, followed by re-estimation of the model parameters by linear regression. This technique guarantees that the resulting sequence of log-likelihood functions is non-decreasing.

2.2 What Is the Index Capturing?

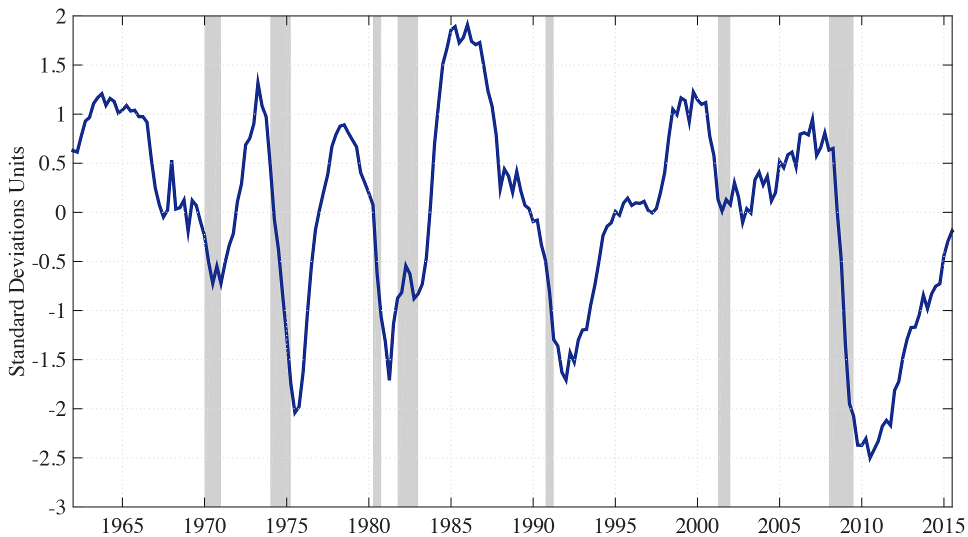
My goal is to assess the health and resilience of the US financial system. The variables in Ω_t must thus be chosen accordingly. In effect, usual market-based indicators of risk, such as interest rates and risk premia, are often low just before the peak of the financial cycle, when in retrospect, it transpires that risk was at its highest (Borio and Zhu (2012)). This is the reason why my index focus on the balance sheets and funding methods of the main US economic agents (households, non financial corporations and financial corporations). A detailed description of the underlying data used for the construction of the indicator is offered in the appendix.

Figure 1 plots the resulting risk sensitivity indicator, F_t. To establish a reference scale, the figure expresses the index relative to its sample mean and standard deviation. A zero value is, thus, equivalent to the sample mean, and deviations from zero are measured in standard deviation units. Positive (negative) values indicate higher (lower) levels of risk-tolerance, credit supply and indebtedness than on average.

[2]The benefit of this methodology is its capacity to determine the importance of each variable, so that the weight each receives is consistent with its historical importance to fluctuations in the health of the financial system.

[3]The Kalman filter is set up to cope with missing values as outlined by Durbin (2012).

Figure 1: Risk Sensitivity Indicator



Note: The shaded gray areas are recessions as defined by the NBER.

The series undergoes fairly large swings across time and is clearly procyclical. Known periods of economic expansion correspond closely with increasingly positive index values. Note also that the turning points of the index usually lead changes in economic conditions. This findings suggest that periods of economic stability during which funding constraints are slack, profits are high, and net worth is accumulating are fertile grounds for the growth of financial fragility. By contrast, financial fragility declines during economic recoveries as agents pay off their debts and save.[4]

3 Econometric Specification

3.1 The Theoretical Framework

I rely on a logistic vector smooth transition autoregressive (LVSTAR) model Terasvirta et al. (2010) in order to capture the nonlinear relationships between the financial and real sides of the economy. The specification is given by

$$X_t = A_0 + \sum_{j=1}^{q} [A_j + G(d_t)B_j]\, X_{t-j} + u_t, \tag{3}$$

[4]This finding matches well with Minsky (1980), Adrian and Song Shin (2010) and Borio (2014), among others.

where X_t is an m x 1 vector, A_0 is an m x 1 intercept vector, A_j and B_j, $j = 1, ..., q$, are m x m parameter matrices, u_t is a vector of canonical innovations with zero mean, and covariance matrix given by Σ_u, and

$$G(d_t) = \text{diag}\left[G_1(d_t), \cdots, G_m(d_t)\right], \tag{4}$$

is an m x m diagonal matrix of logistic transition functions

$$G_i(d_t) = [1 + exp\{-\frac{\gamma_i}{\sigma_d}(d_t - \bar{d})\}]^{-1}, \tag{5}$$

for $i = 1, ..., m.$ $\gamma_i > 0$, and $\bar{d}_t$ is the long run average of the transition variable d_t. By construction, the transition function $G_i(d_t)$ is bounded between 0 and 1. When $G(d_t) = 0$, the LVSTAR model becomes a linear vector autoregressive model (VAR) with parameters A_j. In contrast, when $G(d_t) = 1$, the LVSTAR model becomes a different VAR with parameters $A_j + B_j$. The smoothness of the transition from one extreme regime to the other is governed by the standardized parameter $\tilde{\gamma}_i = \gamma_i/\sigma_d$. The model is estimated by nonlinear least squares techniques.[5]

The vector X_t includes the detrended US real gross domestic product per capita[6], Y_t, my risk sensitivity indicator, F_t, and the shadow federal funds rate, R_t, of Wu and Xia (2016).[7] The data covers the period 1961Q1-2015Q3. Besides, the model includes two time lags of each variable.

I use the following usual strategy to identify monetary policy shocks. I denote ε_t the vector of structural shocks whose variance are normalized to unity and they are mutually uncorrelated. Let the mapping between canonical innovations and structural shocks $u_t = S\varepsilon_t$ where S is a 3×3 matrix. This matrix is obtained as the Cholesky decomposition of Σ_u. As in Christiano et al. (1999), I choose to position the variables in X_t in the following order $[Y_t, F_t, R_t]'$. Indeed, Christiano et al. (2005) argue that this identifying assumption reflects a long-standing view that many macroeconomic variables do not respond instantaneously to policy shocks. In addition, Ramey (2016) points out that results from Structural VARs are quite robust when this recursiveness assumption on aggregate output is maintained but lead to short-run depressive effects following an expansionary monetary policy when it is relaxed. When it comes to the position of the financial variable, I check the robustness of our findings when allowing the risk sensitivity indicator to respond in the same period (i.e when $X_t = [Y_t, F_t, R_t]'$). The key properties of the impulse

[5]Please refer to Terasvirta et al. (2010) for a detailed description of the estimation technique.

[6]The cyclical component of real GDP per capita is obtained by fitting a linear and quadratic time trends to the log of the original series.

[7]The shadow rate is a summary measure of total accommodation provided by conventional and unconventional monetary policies. When policy rates are positive, it is identical to the federal funds rate. When the zero lower bound is breached, it is the rate that observed long-term interest rates would imply if the policy rate could be negative.

Table 1: Evaluation Statistics

	Transition Variable		
	MA(Y_t)	MA(F_t)	MA(R_t)
Y Equation			
Mean square error	0.465	0.489	0.451
Sum of squares residuals	97.18	102.1	94.17
Theil's U-statistic	0.109	0.112	0.107
F Equation			
Mean square error	0.114	0.117	0.116
Sum of squares residuals	23.85	24.37	24.31
Theil's U-statistic	0.097	0.098	0.098
R Equation			
Mean square error	0.726	0.739	0.749
Sum of squares residuals	151.7	154.5	156.5
Theil's U-statistic	0.064	0.065	0.066
System as a Whole			
Sum of squares residuals	272.7	281.0	275.0

Note: The variables MA(Y_t), MA(F_t), and MA(R_t) denote, respectively, the backward-looking four quarters moving average of ouput, the risk sensitivity and the monetary policy rate.

responses are insensitive to this alternative identification scheme. More details on this will be given in Appendix A.6.

3.2 Determining the Transition Variable

The transmission variable d_t in (3)-(5) plays a key role in shaping the nonlinear dynamics of the model. Unfortunately, economic theory does not provide much guidance on the subject. Thus, I restrict attention to three candidates: the backward-looking 4 quarters moving averages of output, the risk sensitivity index and the monetary policy rate. After estimation, I evaluate key statistics for each of these models, and select the one that shows greater accuracy.

Table 2: Linearity Tests

	Standard Test	Robust Test
Y equation	12.5*	11.4*
F equation	18.2**	12.0*
R equation	8.40	6.94
All equations	42.8***	-

Note: The standard linearity test is based on Weise (1999). The robust version is based on Wooldridge (1990). Linearity is rejected if the test statistics is greater the critical value of the chi-square distribution for some desired false-rejection probability.

Table 1 displays the results. The moving average of output performs better in the F_t and R_t equations. In contrast, the moving average of the interest rate is preferred in the output equation. Finally, the sum of squares residuals of the whole system tilts the balance in favor of the moving average of Y_t. Therefore, in what follows, d_t is assumed to be the backward-looking 4 quarters moving average of Y_t

3.3 Lagrange Multiplier Tests for Linearity

Before assessing the (more complicated) nonlinear model, it is essential to test linearity. The basic logic is that if the true data generating process is linear and the nonlinear specification nests such a linear model, then the parameters of the nonlinear model cannot be estimated consistently [Terasvirta et al. (2010)].

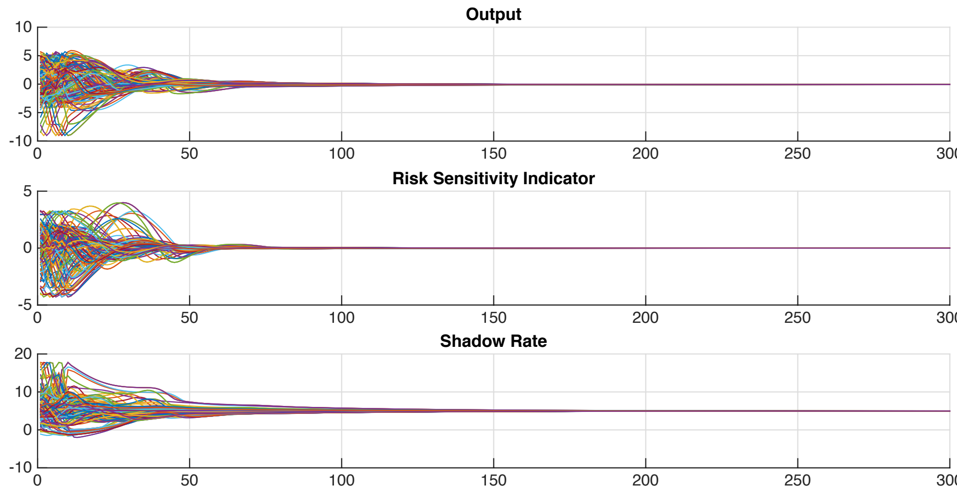
To this end, I use of the Lagrange multiplier test presented in Weise (1999). A test of linearity is a test of the null hypothesis $H_0 : \gamma_i = 0$ against $H_1 : \gamma_i \neq 0$ in (5). The test is a three step procedure based on a Taylor expansion of the transition function around the point $\gamma_i = 0$. The test can be performed equation by equation and for the system as a whole. Please refer to appendix 2 for more details on this. Furthermore, given that the standard test statistic is invalid in the presence of conditional or unconditional heteroskedasticity, I also consider the robust version presented in Wooldridge (1990).

Table 2 reports the results. Overall, the tests provide strong evidence against linearity and favor the use of our LVSTAR specification. To be more precise, linearity is rejected in the GDP and FCI equations. Besides, it is rejected for the system as a whole.

3.4 Evaluation of the Model

This subsection checks the stability of the model and conducts various misspecification tests.

Figure 2: Stability of the System



Note: Top panel: output equation. Middle panel: risk sensitivity index equation. Bottom panel: shadow rate equation. All paths converge to the same stable point; thus confirming the stability of the model.

Stability of the System

Stability is assessed numerically, by producing sequences of realizations from the model by turning off the noise, starting from a large number of initial conditions. Convergence to a single point is required for stability [Teräsvirta and Yang (2014)]. Figure 2 shows the results. All histories in the data set are considered as initial values. The paths always converge to the same stationary point; thereby confirming the stability of the model.

Misspecification tests

Table 3 shows some misspecification tests for measuring the quality of the model. The first row presents the Lilliefors test for normality. It shows the test statistic for the null hypothesis that the residuals are normally distributed. Normality cannot be rejected in the Y and F equations. It can, however, be rejected in the R equation; which suggests the presence of some outliers. The second row of Table 3 displays the Ljung-Box Q-test. This is a ”portmanteau” test that assesses the null hypothesis that the residuals exhibit no autocorrelation of order one. The results of the test do not suggest model misspecification. That is, the null hypothesis of no autocorrelation cannot be rejected in any equation. The third row presents the regression specification error test (RESET). A significant test statistic suggests some sort of model mis-

Table 3: Evaluating the Solution

	Equation		
	Y	F	R
Lilliefors test	0.05	0.04	0.13***
Ljung-Box Q-test	0.02	1.63	0.87
RESET test	0.04	2.52	3.61*
Parameter constancy test	2.30	0.18	0.29

Note: This table measures the quality of the model. The variables Y, F and R, denote, respectively, output, the risk sensitivity indicator, and the monetary policy rate.

specification, such as omitted variables or incorrect functional form [Ramsey (1969)]. The test never finds any evidence of misspecification in the Y and F equations. In the R equation, misspecification is rejected at the 5% significance level, but not at the 10% level. The fourth row checks parameter constancy.[8] A statistically significant test statistic indicates that the parameters of the model change smoothly over time. However in all equations, the test statistic is lower than the critical value at the 1% significant level. Thus, the hypothesis that the parameters are constant over time cannot be rejected.[9]

Taken together, these findings suggest that the modeling exercise has been quite successful.

4 Dynamic Responses to Monetary Policy Shocks

The main contribution of this paper is to assess the importance of the risk taking channel following a monetary policy shock. The procedure I use to isolate this channel in the transmission of monetary policy shocks is built on Bachmann and Sims (2012). In my setup, risk taking can operate as an amplifying mechanism for monetary policy shocks. In effect, if the systemic risk index reacts to monetary policy at any horizon, and if the coefficients of lagged systemic risk are significant in the output equation, then the dynamic response of systemic risk will influence the dynamic response of output to a monetary policy shock. My aim is to statistically isolate the direct effect of monetary policy shocks on output from the indirect effect operating through the risk taking behavior of economic agents. To this end, I construct hypothetical impulse responses to a policy shock keeping systemic risk fixed at all forecast horizons. A

[8] Please refer to Appendix 4 for more details on this.

[9] I also test the model against the alternative of a single structural break by using the Chow test. The model always passes it.

comparison of these hypothetical responses with the actual ones assesses the importance of risk taking as a transmission mechanism of policy shocks.[10]

In nonlinear models, impulse responses are sensitive to initial conditions. Consequently, I compute the the nonlinear impulse responses for three different cases: (i) a "normal" regime, in which the initial conditions of output are associated with the $[40\% - 60\%]$ percentiles of its empirical distribution, (ii) an "expansion" regime, in which the initial conditions of output are selected from the top 20% percentiles, and (iii) a "recession" regime, in which the initial conditions of output are selected from the bottom 20% percentiles.

Figure 3 displays the generalized impulse response functions of the model to a monetary policy shock, associated with the three above cases.[11] Solid lines represent the impulse responses to a one-standard deviation expansionary monetary policy shock in the LVSTAR model. Dotted lines show the hypothetical impulse responses holding the response of risk sensitivity fixed at zero. Dashed lines describe the results for the corresponding linear VAR model.

Two major findings emerge. First, in normal times the nonlinear impulse responses are very similar to those estimated in the linear model. However, this is no true in extreme states, particularly during expansions. The solid lines show that, while in recession output declines on impact before rising slightly a few quarters later, in an economic expansion it rises significantly and remains persistently well above zero. As for risk sensitivity, the impact of the shock is much stronger in the expansion regime.

Second, the behavior of output without the endogenous response of risk taking is lower than in the standard model across all regimes. This suggests a positive role of risk taking in the transmission of monetary policy. However, the impulse responses are strongly state-dependent. In the expansionary regime the difference between the hypothetical and actual output response is large. In contrast, in the low and normal growth regimes the difference is economically small and statistically insignificant. This corroborates the notion that the risk-taking channel is far from being the most important transmission channel of monetary policy. However, during booms when risk is underestimated, the buildup of risks can amplify significantly business fluctuations and increase macroeconomic volatility Borio and Zhu (2012).

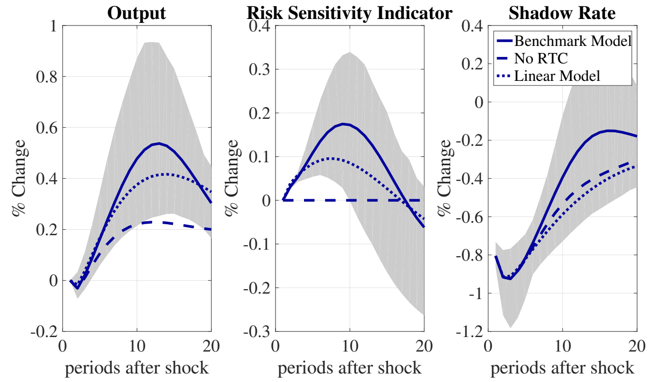
To quantify these findings, Table 4 presents two measures of the effect of monetary policy shocks on output : (i) the maximum response of output over a 20 quarter horizon, called max effect, and (ii) the sum over the same time horizon of the output response, called cumulative effect. As expected, the effect of the shock in a normal regime is very similar to that estimated in the linear model. By contrast, in expansion the effect is much larger. In particular, both the max and cumulative effects are almost three times as large

[10]See Appendix 5 for a formal exposition of the procedure.

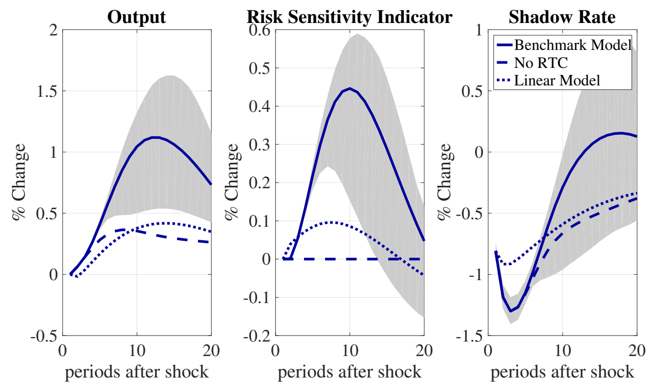
[11]The generalized impulse response functions are computed according to Koop et al. (1996).

Figure 3: Dynamic Effects of an Expansionary Policy Shock

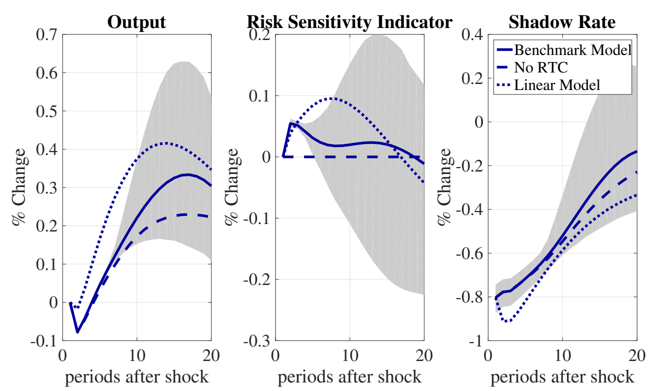
(a) Normal Times



(b) Expansion



(c) Recession



Note: Solid lines: benchmark model. Dotted lines: no risk taking channel. Dashed lines: linear VAR model. Gray shaded areas are the 90% confidence intervals of the benchmark model.

Table 4: The Effects of Monetary Policy Shocks on Output

	Lin. Mod.	Normal Times	Expansion	Recession
Benchmark Specification				
Max effect	0.41	0.50	1.18	0.33
Cumulative effect	5.75	6.14	15.6	3.79
Isolating risk sensitivity				
Max effect	-	0.22	0.36	0.23
Cumulative effect	-	3.13	5.36	2.66

Note: This table shows the effects of expansionary monetary policy shocks on output. The max effect is defined as the maximum response of output over a 20 quarter horizon. The cumulative effect is defined as the sum over the same time horizon of the output response.

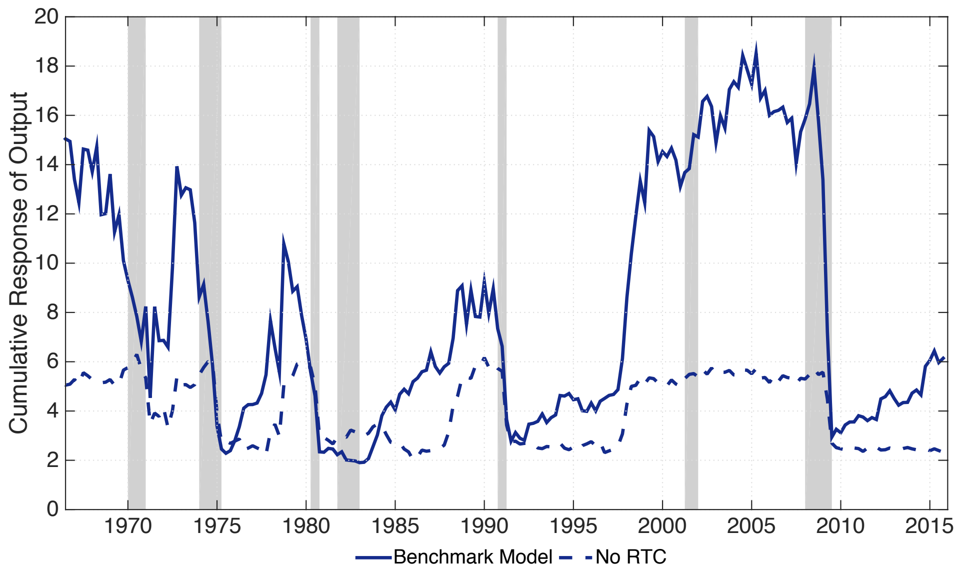
than in the linear specification. In recession, these effects are substantially smaller. The bottom panel of Table 1 summarizes the response of output when risk sensitivity is held fixed at zero. Both the max and cumulative responses of output are larger in the expansion regime. Nonetheless, the differences across regimes are much smaller than in the benchmark specification. This highlights, once again, the importance of a risk-taking behavior during economic booms.

The Historical Effects of Monetary Policy Shocks

The LVSTAR specification allows the effects of monetary policy to vary continuously with the state of the economy. To see this point more clearly, Figure 4 presents estimates for the historical effects of monetary policy shocks on output. For each period, I consider a one standard deviation negative (i.e. expansionary) policy shock, and report the cumulative response of output over a 20 quarter horizon. The figure plots the cumulative response in the solid line, with the hypothetical response where risk sensitivity is held constant as the dashed line.

Some notable features stand out. First of all, the cumulative response of output varies considerably over the business cycle. In particular, it tends to be elevated before NBER recessions. For instance, in 2007 it was around six times larger than in 2010. The correlation between the standard cumulative response and detrended GDP is significantly positive at 0.88. In the hypothetical case in which risk sensitivity is held fixed, in contrast, the response of output is much more stable; ranging from 2 to 6. Lastly, it is worth noting that the cumulative response was higher during the economic boom preceding the 2008 crisis. Unarguably,

Figure 4: The Cumulative Response of Output over Time



Note: Solid lines: benchmark model. Dotted lines: no risk taking channel. Shaded gray areas are recessions as defined by the NBER.

a period of rapid growth, coupled with lax lending standards, over-borrowing and excessive risk taking.

5 Concluding Remarks

In this paper, I provide evidence that the role of the risk-taking channel depends on the state of the economy. During economic booms, the risk-taking channel of monetary policy has an amplifying effect on output. It is therefore important for central banks to take this channel into account when adjusting their policy in order not to exacerbate boom-bust patterns and accommodate the buildup of financial imbalances.

Of course, my study, like all time series models, have limitations when it comes to structural inference and policy analysis. These weakness ought to encourage future theoretical work to develop non linear dynamic general equilibrium models to better understand the interrelationships among monetary policy, systemic risk and economic activity.

References

Adrian, T. and H. Song Shin (2010). Financial Intermediaries and Monetary Economics. Handbook of Monetary Economics, Elsevier.

Ampudia, M., H. van Vlokhoven, and D. Żochowski (2016). Financial fragility of euro area households. *Journal of Financial Stability 27*(Supplement C), 250–262.

Bachmann, R. and E. R. Sims (2012). Confidence and the transmission of government spending shocks. *Journal of Monetary Economics 59*(3), 235–249.

Bernstein, S., J. Lerner, and F. Mezzanotti (2017). Private Equity and Financial Fragility during the Crisis. Working Paper 23626, National Bureau of Economic Research. DOI: 10.3386/w23626.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance 45*(C), 182–198.

Borio, C. and H. Zhu (2012). Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism? *Journal of Financial Stability 8*(4), 236–251.

Brave, S. and R. A. Butters (2012). Diagnosing the Financial System: Financial Conditions and Financial Stress. *International Journal of Central Banking 8*(2), 191–239.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (1999). Monetary policy shocks: What have we learned and to what end? In *Handbook of Macroeconomics*, Volume 1, Part A, pp. 65–148. Elsevier.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (2005). Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy 113*(1), 1–45.

Diamond, D. W. and R. G. Rajan (2012). Illiquid Banks, Financial Stability, and Interest Rate Policy. *Journal of Political Economy 120*(3), 552–591.

Durbin, J. (2012). *Time Series Analysis by State Space Methods* (2nd Revised ed. edition ed.). Oxford: Oxford University Press, USA.

Hatzius, J., P. Hooper, F. S. Mishkin, K. L. Schoenholtz, and M. W. Watson (2010). Financial Conditions Indexes: A Fresh Look after the Financial Crisis. Working Paper 16150, National Bureau of Economic Research. DOI: 10.3386/w16150.

Koop, G., M. H. Pesaran, and S. M. Potter (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics 74*(1), 119–147.

Minsky, H. P. (1980). Money, Financial Markets, and the Coherence of a Market Economy. *Journal of Post Keynesian Economics 3*(1), 21–31.

Ramey, V. A. (2016). Chapter 2 - Macroeconomic Shocks and Their Propagation. In J. B. Taylor and H. Uhlig (Eds.), *Handbook of Macroeconomics*, Volume 2, pp. 71–162. Elsevier. DOI: 10.1016/bs.hesmac.2016.03.003.

Ramsey, J. B. (1969). Tests for Specification Errors in Classical Linear Least-Squares Regression Analysis. *Journal of the Royal Statistical Society. Series B (Methodological) 31*(2), 350–371.

Stock, J. H. and M. W. Watson (2002). Forecasting Using Principal Components from a Large Number of Predictors. *Journal of the American Statistical Association 97*(460), 1167–1179.

Terasvirta, T., D. Tjostheim, and C. W. J. Granger (2010). *Modelling Nonlinear Economic Time Series*. Oxford University Press.

Teräsvirta, T. and Y. Yang (2014). Specification, Estimation and Evaluation of Vector Smooth Transition Autoregressive Models with Applications. Technical Report 2014-08, Department of Economics and Business Economics, Aarhus University.

Weise, C. L. (1999). The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autoregression Approach. *Journal of Money, Credit and Banking 31*(1), 85–108.

Wooldridge, J. M. (1990). A Unified Approach to Robust, Regression-Based Specification Tests. *Econometric Theory 6*(1), 17–43.

Wu, J. C. and F. D. Xia (2016). Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. *Journal of Money, Credit and Banking 48*(2-3), 253–291.

Appendix

A.1 Information Underlying the Risk Sensitivity Indicator

Table 5: Description of Financial Variables by Economic Sector

Financial Indicator	Source	Period
Households		
Debt service payments to disposable personal income	BIS	1980Q1-2015Q3
Net worth	FA	1961Q1-2015Q3
Total liabilities	FA	1961Q1-2015Q3
Nonfinancial Corporate Business		
Net worth	FA	1961Q1-2015Q3
Total liabilities	FA	1961Q1-2015Q3
Short Term Liabilities to Total Liabilities	FA	1961Q1-2015Q3
Interest Service Ratio	FA	1961Q1-2015Q3
Financial Business		
Total Equity Capital	FA	1961Q1-2015Q3
Total liabilities	FA	1961Q1-2015Q3
Short Term Liabilities to Total Liabilities	FA	1961Q1-2015Q3
Total Financial Assets of Shadow Banks	FA	1961Q1-2015Q3
Additional Financial Indicators		
Total Credit to Private Non-Financial Sectors	BIS	1961Q1-2015Q3
Residential Property Prices	BIS	1975Q4-2015Q3

Note: I use the quarterly annual growth rate of each variable. BIS stands for Bank for International Settlements. FA denotes the Financial Accounts of the US. All variables are in real terms. Interest Service Ratio is equal to the net operating surplus plus interest received, divided by interest paid. These three variables are only available at annual frequency. I use cubic spline interpolation to disaggregate annual data to quarterly series. Shadow banks aggregates ABS issuers, finance companies and funding corporations.

A.2 Estimation Procedure

This subsection describes the numerical technique used to estimate my LVSTAR model. The model contains the parameters $\Xi = \{A_0, A_j, B_j, \gamma_i\}$ for $j = 1, 2$ and $i = 1, 2, 3$. The nonlinear least squares estimator of Ξ is obtained by solving the optimization problem:

$$\hat{\Xi}_{NLS} = \underset{\Xi}{\operatorname{argmin}} \sum_{t=1}^{T} u_t' u_t$$

A key to simplifying the optimization exercise is to note that when γ_i is known, the solution for $\{A_0, A_j, B_j\}$ is analytic. For this reason, I use a grid search over γ_i. Specifically, I proceed as follows:

1. I first construct an evenly spaced grid with 3000 nodes for γ_i.
2. Then I estimate $\{A_0, A_j, B_j\}$ by ordinary least squares conditionally on each value of γ_i in the grid.
3. Lastly, I select the set $\{\hat{A}_0, \hat{A}_j, \hat{B}_j, \hat{\gamma}_j\}$ that produces the smallest residuals sum of squares.

Of particular interest is the fact that this numerical optimization method does not require specific assumptions about the first and second partial derivatives of the objective function with respect to Ξ.

A.3 Lagrange Multiplier Tests for Linearity

Consider the model (3)-(5). A test of linearity is a test of the null hypothesis $H_0 : \gamma_i = 0$ against $H_1 : \gamma_i > 0$. Linearity can be tested equation by equation and in the system as a whole [Weise (1999)]. To test linearity equation by equation, I proceed as follows:

1. I first estimate the model under H_0. That is, I run the regression:

$$X_{m,t} = \sum_{j=0}^{q} \beta_j X_{t-j} + \varepsilon_t.$$

   I then collect the residuals $\hat{\varepsilon}_t$ and compute the residuals sum of squares, SSR_0.

2. Next, I run the auxiliary regression:

$$\hat{\varepsilon}_t = \sum_{j=0}^{q} \alpha_j X_{t-j} + \sum_{j=1}^{q} \delta_j d_t X_{t-j} + \upsilon_t,$$

   compute the residuals $\hat{\upsilon}_t$ and the residuals sum of squares SSR_1.

3. Finally, I calculate the test statistic:

$$LM = T\frac{SSR_0 - SSR_1}{SSR_0},$$

   where T is the number of observations. Under the null, LM is distributed $\chi^2(qm)$.

To test linearity in the system as a whole, I use the log-likelihood test outlined in Weise (1999). The null hypothesis is $H_0 : \gamma_i = 0$ in all equations. I define $\Gamma_0 = \frac{\hat{\epsilon}_t \hat{\epsilon}_t'}{T}$ and $\Gamma_1 = \frac{\hat{v}_t \hat{v}_t'}{T}$, where $\hat{\epsilon}$ and $\hat{v}$ are the residuals computed above. Then the statistic $LR = T\,[\log \mid \Gamma_0 \mid - \log \mid \Gamma_1 \mid]$ is asymptotically distributed $\chi^2(qm^2)$.

A.4 Parameter Constancy Test

To test parameter constancy equation by equation, I proceed as follows [see Terasvirta et al. (2010)]:

1. I estimate the benchmark model:

$$X_{m,t} = A_{m,0} + \sum_{j=1}^{2} \left[A_{m,j} + G(d_t)B_{m,j}\right] X_{t-j} + u_{m,t},$$

   and compute the residuals sum of squares, SSR_0.

2. I estimate the auxiliary model:

$$X_{m,t} = \delta_0 + \sum_{j=1}^{2} \left[\delta_j + G(d_t)\beta_j\right] X_{t-j} + \alpha_0 \sin(2k\pi\tau^*) + \alpha_1 \cos(2k\pi\tau^*) + \varepsilon_t.$$

   Here $k = 0.5T - 1$ is the frequency parameter and T is the number of observations. The variable $\tau^* = \frac{t}{T}$ with $t = 1, ..., T$ is the time trend. I compute the residuals sum of squares, SSR_1.

3. I compute the F test statistic:

$$F = \frac{\frac{SSR_0 - SSR_1}{2}}{\frac{SSR_1}{T-15}}$$

The null hypothesis, $H_0 : \alpha_0 = \alpha_1 = 0$, cannot be rejected if the F statistic is lower than the critical value of the F-distribution for some desired false-refection probability.

A.5 Isolating the Risk Taking Channel

For ease of exposition, I present the procedure in a linear VAR(1) model.[12] The method is conceptually identical in more complicated models. Consider the structural form:

$$\Psi_0 X_t = \Psi_1 X_{t-1} + \epsilon_t, \tag{6}$$

[12] See Bachmann and Sims (2012) for a more complete exposition.

where, $X_t = [Y_t \ F_t \ R_t]'$, Ψ_0 is an lower triangular parameter matrix, Ψ_1 is a 3×3 parameter matrix, $E(\epsilon_t) = 0$ and

$$E(\epsilon_t \epsilon_t') = \begin{pmatrix} \sigma_Y^2 & 0 & 0 \\ 0 & \sigma_F^2 & 0 \\ 0 & 0 & \sigma_R^2 \end{pmatrix}.$$

Suppose that the system has been in steady state for a while. Then a policy shock hits the economy at time 0:

$$\epsilon_0 = \begin{pmatrix} 0 \\ 0 \\ \sigma_R \end{pmatrix} \quad \text{and} \quad X_0 = \Psi_0^{-1} \epsilon_0.$$

The effect of the shock on variable $i = [Y, F, R]$ at horizon $h = 1, \cdots, H$ is:

$$\Phi_{i,h} = \underbrace{\Psi_0^{-1} \Psi_1}_{C} \Phi_{h-1}, \tag{7}$$

The though experiment of holding risk taking constant in response to a change in monetary policy demands setting $\Phi_{F,h} = 0$ at each forecast horizon. This is done by creating a hypothetical sequence of systemic risk shocks, $\tilde{\epsilon}_{F,t}$, so as to force this to hold at each relevant horizon. Formally, $\tilde{\epsilon}_{F,t}$ is given by:

$$\Phi_{F,h} = 0 \iff \tilde{\epsilon}_{F,t} = -c_{2,1} \Phi_{Y,h-1} - \underbrace{c_{2,2} \Phi_{F,h-1}}_{0} - c_{2,3} \Phi_{R,h-1}, \tag{8}$$

Given this sequence, the hypothetical impulse responses to the policy shock, $\hat{\Phi}_{i,h}$, are:

$$\hat{\Phi}_{i,h} = C \hat{\Phi}_{i-1,h} + \Psi_0^{-1} \begin{pmatrix} 0 \\ \tilde{u}_{F,t} \\ 0 \end{pmatrix}. \tag{9}$$

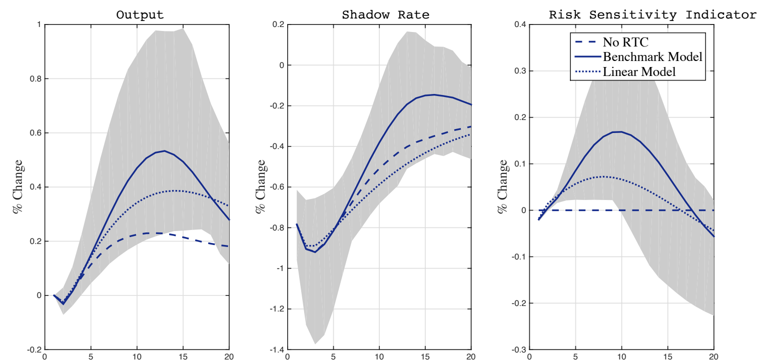
Comparing these hypothetical responses, $\hat{\Phi}_{i,h}$, with the actual responses, $\Phi_{i,h}$ provides a measure of how important the response of systemic risk is in transmission of the monetary policy shocks.

A.6 Robustness Check

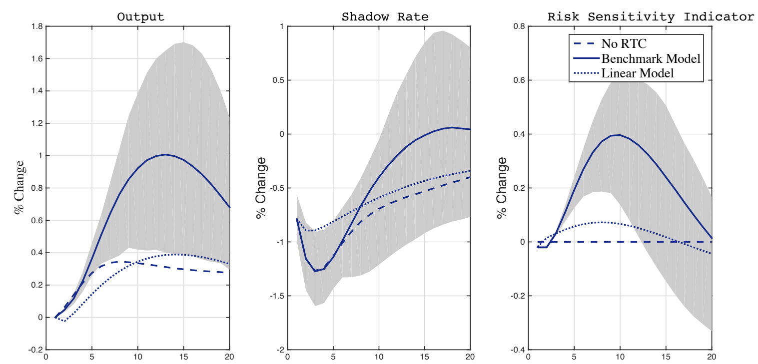
This section checks the robustness of my strategy to identify monetary policy shocks. To this end, I allow the risk sensitivity indicator to instantaneously respond to policy shocks. That is, I impose the following order of variables $X_t = [Y_t, F_t, R_t]'$. Figure 5 plots the generalized impulse response of the model to a monetary policy shock. It is apparent that the key properties of the impulse responses are insensitive to this alternative identification scheme.

Figure 5: Dynamic Effects of an Expansionary Policy Shock

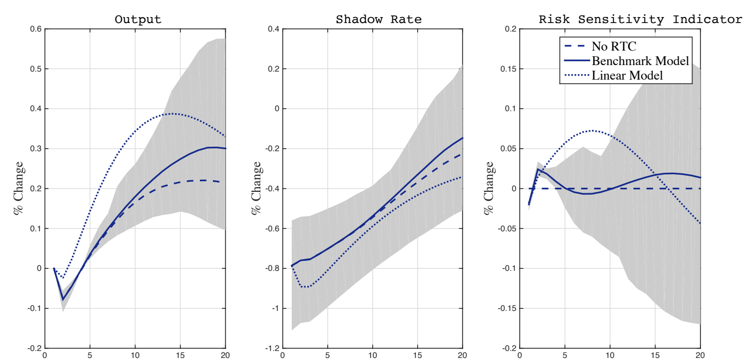
(a) Normal Times



(b) Expansion



(c) Recession



Note: Solid lines: benchmark model. Dotted lines: no risk taking channel. Dashed lines: linear VAR model. Gray shaded areas are the 90% confidence intervals of the benchmark model.