Inaugural-Dissertation

Essays on Bounded Rationality in Financial Macroeconomics

vorgelegt von

Naira Kotb

Bamberg, 2023

Essays on Bounded Rationality in Financial Macroeconomics

Inaugural-Dissertation

zur Erlangung des akademischen Grades eines Doktors der Wirtschaftswissenschaften (Dr. rer. pol.)

Fakultät Sozial- und Wirtschaftswissenschaften der Otto-Friedrich-Universität Bamberg

vorgelegt von

Naira Kotb

Bamberg, August 2022

URN: urn:nbn:de:bvb:473-irb-586705
DOI: https://doi.org/10.20378/irb-58670

Datum der Abschlussprüfung: 06. Februar 2023

Erstgutachter:
Prof. Dr. Christian R. Proaño
Professur für Volkswirtschaftslehre, insb. Angewandte Wirtschaftsforschung
Otto-Friedrich-Universität Bamberg

Zweitgutachter:
Prof. Dr. Frank Westerhoff
Lehrstuhl für Volkswirtschaftslehre, insb. Wirtschaftspolitik
Otto-Friedrich-Universität Bamberg

Drittgutachter:
Prof. Mishael Milaković, Ph.D.
Lehrstuhl für Volkswirtschaftslehre, insb. Internationale Wirtschaft
Otto-Friedrich-Universität Bamberg

Dedication

I dedicate this work to my father, the self educated economic journalist who was forced by his illness to quit school at the age of 12, but managed to create his own very unique art of schooling: a lifetime of self-discipline, reading, learning and wondering–every single day.

To the most passionate, most intellectually faithful man I have ever known, to ***Mesbah Kotb****.*

Your Naira

Bamberg, August 2022

Words of Gratitude

The dissertation at hand is the result of my doctoral studies, which I pursued as a member of the graduate research program *Bamberg Research Group on Behavioural Macroeconomics (BaGBeM)*, financed by the *University of Bamberg* and the *Hans-Böckler Foundation (HBS)*. Throughout my journey to that end, I have received numerous support and encouragement from people who were very humane and very professional, and from institutions that put the interest of research and researchers as a top priority. In the next few lines, I will try, as much as my words will aid me, to express my gratitude towards them.

First and foremost, I am grateful to my supervisor, Prof. Dr. **Christian R. Proaño**, for his endless efforts towards the success and prosperity of our *BaGBeM* and for he has been a great source of support and motivation for me personally throughout the years: I have learnt a lot from you, whether in research, teaching or team- and networking. You have practically taught me that being a compassionate boss does not have to be at conflict with being a motivating and forward-pushing one.

Second, I would like to thank Prof. Dr. **Frank Westerhoff**, and Prof. **Mishael Milaković**, Ph.D.: you have been a source of encouragement to me as well as to the entire group. I am thankful for every time you attended a presentation for me or gave me a constructive feedback to my work.

I gratefully acknowledge the financial support by the *Hans Böckler Foundation*: the support I received as a mother in Academia has been both assuring and securing. I am especially thankful for the decision to extend my funding due to the consequences of the Covid-19 pandemic. That decision alone was very critical for the well-being of myself, my research and my family.

I am greatly thankful to the *Welcome Center for internationally mobile scholars* at the *University of Bamberg*: your effort makes all the difference for the international researchers and their families. Your positive impact is noticed and appreciated. Thank you and please keep this up.

Thanks is also due to our amazing secretary **Claudia Bauersachs**: thank you for always being there when I needed your help.

I am also thankful to Dr. **Matthias Lengnick** at the *University of Kiel*, for he has taught me a lot of coding skills at the beginning of my PhD journey: thank you for your willingness to share your knowledge and expertise (and your code) without waiting for something in return.

I would like to thank my colleagues at the *University of Bamberg* (especially the lovely and wonderful **Ivonne Schwartz**): your friendly, approaching and warm personalties made me feel that Bamberg was truly my home. You made hard situations feel easier and tough missions feel accomplishable (also thank you for always telling me that my German was good, even though we all know it was not).

To my sweet brother, **Yousef Kotb**, and my twin sister, my first and eternal love, **Ranim Kotb**: you have always been, and will always be, my support system, and here I am, the least smart sibling among the three of us, getting a PhD.

Last but not least, I would like to tell my mother, **Salwa Zaki**, the one person I owe every good thing in life to, and my husband, **Alaa Hussein**, who loves and believes in his wife so much, he never hesitates to sacrifice everything for her: thank you. I did this by you, and through you. I hope I could make you proud (not that this is enough to pay you back or anything).

Collectively, all the above mentioned people have made it possible for me to accomplish this success. I feel very grateful, but also guiltily privileged. I can only wish such an empowering environment for every mother(slash)researcher in the world.

Bamberg, August 2022 Naira Kotb

Coauthorship and Contributions

This dissertation is composed of three chapters. While chapter 3 is based on a single-authored paper, chapters 1 and 2 are based on joint work with Prof. Dr. Christian R. Proaño (Professorship of Economics, especially Empirical Economics at the University of Bamberg). Below, I detail the contributions of my coauthor and myself.

The idea of the paper described in chapter 1, *Capital-Constrained loan creation, households' stock market participation and monetary policy in a behavioural New Keynesian model*, was originated by me. My coauthor, Christian R. Proaño, helped me develop and enhance it, on both the core and the appearance levels. I took the job of deriving and simulating the model, also with guidance from Prof. Proaño. We collectively wrote the text of the paper.

The idea of the paper discussed in chapter 2, *Monetary policy, stock prices and temporal aggregation in a New Keynesian model with behavioural expectations*, was originated by my coauthor, Christian R. Proaño. Together, we developed it further. We both derived the model. I took the job of coding and simulation. We both wrote the text of the paper.

Contents

List of Abbreviations

DCP	Data Collection Process
DGP	Data Generation Process
FWC	Financial Wealth Channel
GFC	Global Financial Crisis
IRFs	Impulse Response Functions
LAW	leaning against the wind

List of Figures

List of Tables

Summary

The fast, interwind, and overwhelming aspects of the economic, political and social challenges to humanity since the outbreak of the Covid-19 crisis certainly opened for new research questions, and motivated us to reinvestigate conceivably settled ones. What role do constraints on cognitive abilities and bounded rational behaviour play in calm times as well as in crisis-ridden ones? How do failures in one sector of the economy transmit to another? How critical is the need for novel data and fast analysis? How system wide panics (i.e. loss of trust) can arise? To what extent are they destructive? And how can they be avoided? These are all presently valid and greatly relevant economic questions.

Klaes and Sent (2005) trace the timeline of the evolution of the concept of bounded rationality back to as far as the year 1840. Since its most coherent introduction by Herbert A. Simon, bounded rationality succeeded in serving as a *realistic* alternative to models of rational decision making which "treat the mind as a Laplacean superintelligence equipped with unlimited resources of time, information, and computational might" (Gigerenzer, 2002, p. 37). That being stated, Harstad and Selten (2013, p.497) stress how bounded rationality is yet to "develop a coherent approach to a range of topics as wide as that addressed by neoclassical" models. The world of finance, as described by Gigerenzer (2018), is a prime candidate for studying the role of bounded rationality and heuristics.

Heuristic, is a Greek originated word which means "serving to find out or discover". In an uncertain world (e.g. the financial world), heuristics are tools to deal with uncertainty: a tactic to deliberately ignore information, use fewer resources and thus simplify the process of decision making (Gilli et al., 2008; Anufriev and Hommes, 2012; Mousavi and Gigerenzer, 2014, 2017). To dismiss the idea that *heuristics* should be associated with complete irrationality or lack of informativity, Gigerenzer (2018) reminds us that the term appears in the title of Einstein's 1905 Nobel Prize winning paper on quantum physics.

The outbreak of the Global Financial Crisis (GFC) and the lengthy, deep and global REAL economic downturn that followed, have confounded macroeconomics and undoubtedly embedded the relevance of financial sector conditions for the macroeconomy. For instance, Dou et al. (2020) highlight how the GFC and the Great Recession that followed revealed serious gaps in commonly used approaches to define, measure, and manage financial sector activities that pose risks to the macroeconomy as a whole (see also Brunnermeier and Sannikov, 2014). Similarly, Ingrao and Sardoni (2019) look at how the treatment of banks and finance from the macroeconomic perspective evolved during the 20th century to the present, and show how the urge generated by the GFC favoured the flourishing of many works concerned with the macroeconomic interactions between the financial and real sectors of the economy, to the extent that it is hard to find mainstream macroeconomic models that do not incorporate, in one way or another, some form of financial intermediation (see also Gorton and Winton, 2017).

Against this background, the thesis at hand pursues better understanding of the role of boundedly rational expectations, agents' heterogeneity and heuristics-based decision making in the macro-financial context. Financial-macro linkages and spill over channels are especially important for policy (e.g. monetary policy) considerations (see, for instance, Adrian and Liang, 2018). This thesis, particularly through chapters 1 and 2, is concerned with analysing channels through which monetary policy impacts the real activity, in models where the financial sector is– quoting Gorton and Winton (2003)– "not a veil" but rather a critical and interactive aspect of the macroeconomy.

More particularly, in the first chapter of this thesis, *Capital-constrained loan creation, households' stock market participation and monetary policy in a behavioural New Keynesian model*, my coauthor and I incorporate a stock market and a banking sector in a behavioural macro-finance model with heterogeneous and boundedly rational expectations. Households' savings in this model are diversified among bank deposits and stock purchases, and banks' lending to firms is subject to capital-related deviation costs. We demonstrate that households' participation in the stock market, coupled to the existence of a capital-constrained banking sector, affects the transmission of monetary policy to the economy significantly, and that households' deposits act as a critical spill-over channel between the real and the financial sectors. Further, we relate the deviation costs in the banking sector with the degree of pass-through of monetary policy shocks. Last but not least, we investigate the performance of a leaning against the wind (LAW) monetary policy, which targets asset prices, concerning macroeconomic and financial stability and show that a moderate policy reaction to stock market disturbances can achieve the stability of the stock market at a fairly low level of instability in the real activity. However, a strong policy reaction to stock prices may largely destabilize the real sector.

In chapter 2, *Monetary policy, stock prices and temporal aggregation in a New Keynesian model with behavioural expectations*, my coauthor and I focus on the time, more accurately the frequency, dimension of the problem. More specifically, we investigate the implications of temporal aggregation, i.e. the discrepancy between the Data Generating Process (DGP) and the Data Collection Process (DCP), for the design of monetary policy in a New Keynesian macroeconomic framework with boundedly rational agents, and manage to show that responding to the stock price is justified when real data is only available at a delay due to temporal aggregation. Under these conditions, moderately reacting to high frequency stock price movements can stabilize both the financial and the real sectors. We stress in this paper the *cost of waiting*, i.e. waiting for the official collection and publication of the real data as opposed to reacting to the second best indicator for the performance of the (real) economy: the stock price, which acts as a proxy for the unobserved real updates.

One can argue for the relevance of this rationale for the policy design during the Covid-19 pandemic. The *statistical darkness* (Tissot and de Beer, 2020) brought by the harsh and sudden disruption of economic activities on the one hand, and the urgent need for timely and solid policy response on the other hand, strongly highlighted the call for high-speed (even real time) statistics and supplementary data. Tissot and de Beer (2020) describe how the traditional macro statistics, which is usually available on annually, quarterly, or at best monthly basis was not sufficient for the policy makers, as the massively fast dynamics of the crisis called for having information on what was going on more frequently, (i.e. on a weekly or even daily basis). In a crisis time, they explain, there exists the need to go beyond the standard offering of official statistics and reach for more timely, frequent and well-documented indicators to guide policy. This would offer the benefit of mixing different types of data (e.g. daily financial prices, weekly indicators, monthly industrial output and quarterly GDP) (see also Irving-Fisher-Committee, 2021).

Chapter 3, *Optimism, pessimism and panics in a macroeconomic model with a banking sector*, aims at modelling bank runs in a behavioural macroeconomic context. Specifically, it extends Gertler et al. (2020*a*) by assuming boundedly rational expectations, allowing for optimistic and pessimistic attitudes to play a role in the asset pricing mechanism, and modifying the bankers' maximization problem, such that they have to make decisions (i.e. set the leverage multiple) while taking the prevailing optimistic and pessimistic expectations into consideration. I show that the behavioural aspects in the model, coupled with the possibility of an economy-wide panic, can produce results that are comparable to GFC witnessed events: when a bank run equilibrium is feasible, even a small-sized exogenous shock (e.g. a negative shock to capital quality) can induce bank panics which force banks to fire-sell their assets, leading to a sharp contract in the capital price, investment and the real activity; news-driven booms can lead to subsequent financial and real busts, even in the absence of any capital shocks.

Gorton (1988) lists two possible views of bank panics. In the first view, bank panics are *mysterious* random events, possibly a self-confirming equilibrium in settings with multiple equilibria, caused by shifts in the beliefs of agents which are unrelated to the real economy. In the second view, agents cannot discriminate between the riskiness of various banks because they lack bank-specific information. They rely on aggregate information to asses risk in which case it can occur that banks may be perceived to be riskier. Consumers then withdraw enough to cause a panic. In the paper discussed in chapter 3, as we will see, panics are a mixture of those two views. I manage to show, in this final chapter, how as long as there exists an optimism-pessimism balance in the economy, banks are disabled from massively expanding their balance sheets. The banking sector is thus moderately leveraged and the economy as a whole can fairly survive mildly negative real shocks. When such an optimism-pessimism balance is disrupted by means of some overoptimistic news, banks are able to enormously increase their leverage and panics can follow.

Collectively, the papers presented in this dissertation aim at studying macroeconomic dynamics when financial activities, whether banking, or stock markets, or both, greatly influence the outcome of the macroeconomy. Further, the backward looking, heterogeneous, boundedly rational expectations assumed in the models are not of a trivial effect. Such expectations intensify the dynamics, and enable us to present and discuss features that would have otherwise been disregarded, had forward looking, homogeneous, rational expectations been assumed. Future work can possibly cover more sophisticated financial sector frameworks, for example heterogeneous banks and interbank networks, as well as information based financial-macro dynamics.

Chapter 1

Capital-Constrained Loan Creation, Households' Stock Market Participation and Monetary Policy in a Behavioural New Keynesian Model [1]

[1]This Chapter is based on joint work with Prof. Dr. Christian R. Proaño. The paper has been published under Creative Commons Attribution 4.0 License: Kotb, N. and Proaño, C. R. (2022), 'Capital-constrained loan creation, household stock market participation and monetary policy in a behavioural New Keynesian model', *International Journal of Finance & Economics*, 1–19. https://doi.org/10.1002/ijfe.2619.

1.1 Introduction

As pointed out e.g. by Woodford (2010), the incorporation of financial intermediation in macroeconomic models in a way that conforms with existing institutional frameworks is a necessary step for a better understanding of the transmission of monetary policy. Further, as argued by Milani (2017), abstracting from a key financial market, such as the stock market, in macro-financial models may lead to serious misspecification issues which may in turn lead to a biased understanding of the interaction between the financial and the real sectors.

So far, the literature on financial frictions and monetary policy transmission has outlined two main channels: the *balance sheet channel* (Bernanke and Gertler, 1989) which stresses the impact of monetary policy on the borrowers' (firms' and households') balance sheets, and hence on the external finance premium they are confronted with, and the *bank lending channel* (Bernanke and Blinder, 1988) which focuses on the effects of monetary policy on the supply of credit (i.e. loans) by banks. The bank lending channel has traditionally been dependent on bank reserves as the main mechanism behind its transmission: a contractionary monetary policy that drains bank reserves reduces the extent to which banks can take reservable deposits; if banks cannot substitute these with non-reservable forms of finance, banks would be forced to issue less loans or liquidate existing ones. However, as financial innovations and deregulations have massively enabled banks to raise non-reservable deposits, bank reserves have become unfit as an explanation to the transmission of monetary policy to the real economy through banking, as discussed e.g. by Romer and Romer (1990) and Bernanke and Gertler (1995).

Researchers attempting to find a more convincing explanation for the bank lending channel have turned their attention to the role of bank capital. Van den Heuvel (2002), Kopecky and VanHoose (2004*a*,*b*), Borio and Zhu (2012) and Gambacorta and Shin (2018) show that it is the inadequate level of bank capital, rather than reserves, what leads to sluggish lending. Peek and Rosengren (1995) stress that capital-constrained banks and non-constrained banks respond very differently to monetary policy shocks: a change in monetary policy that drains bank deposits leads capital-constrained banks to cut their loan supply to firms which, not having an adequate replacement to loans, would be in turn forced to reduce their economic activity. The bank lending channel requires thus two conditions to be effectively present. First, bank deposits are vital to banks and cannot be costlessly or frictionlessly replaced by other sources of funding. And second, firms are largely bank dependent in the sense that any disruption in the supply of loans by banks would strongly impact their economic activities (Bernanke and Gertler, 1995; Kashyap and Stein, 1994; Lin, 2019). Bank capital requirements then establish the link between these two conditions: when deposit levels fall, capital constrained banks have to cut loan supply, which in turn triggers a downward pressure on the real activity. Indeed, Van den Heuvel (2006) argues that even in the presence of a "perfect" market for non-reservable liabilities for banks, capital constraints generate a mechanism through which monetary policy shifts the bank loan supply.

Further, as pointed out by Caballero (2010), factors like boundedly rational behaviour, expectations formation and complex dynamics should not be ignored, as they play a key role in the interaction between the financial and the real sectors, and in the emergence of macro-financial instability. Against this background, the present paper seeks to contribute, from a behavioural perspective, to our understanding of the mechanisms through which the financial system and the real sector of the economy interact, and how the interaction between the banking sector and the stock market may affect the transmission mechanism of monetary policy. Our model builds on the previous work by Branch and McGough (2010), De Grauwe (2011); De Grauwe (2012), Proaño (2011, 2013) and in particular, De Grauwe and Macchiarelli (2015). We do so by nesting a heterogeneous agents stock market and a capital-constrained banking sector in a behavioural New Keynesian model with boundedly rational expectations.

Regarding the banking sector, we follow Gerali et al. (2010) in assuming that banks aim at keeping their capital-to-assets ratio as close as possible to an exogenous target level. They face quadratic costs when they divert from such a target. According to this setting, banks set the spread of the loan rate over the deposit rate in a way that maximizes their profits given the costs of deviating from the capital-to-assets target ratio. As we will see, such a setting generates a feedback loop between the real and the financial sides of the economy, affecting the shape of the business cycle.

our specification for the stock market is based on decisively more behavioural grounds. More specifically, we follow Lengnick and Wohltmann (2016) by differentiating between speculative and non-speculative motives for stock demand. These two types of stock demand follow different rules and have different determinants. By adopting this stock market specification we aim at shedding some light on the macroeconomic implications of households' stock market participation when it is driven by bounded rationality and heterogeneous behavioural expectations. As we will show below, the mechanism through which households switch between stocks and deposits, and the determinants for these economic decisions, are central to the model. These do not only directly affect the stock price, but also the banking sector and the level of the loan interest spread, and hence the entire economic activity.

Our model, though quite stylized, features a variety of important and innovative aspects. First and foremost, our model features an economy where both market-based and bank-based financial sectors are represented and can be easily analysed. Each of these two sectors is governed by different sets of rules, transmits shocks to the real sector differently and reacts itself differently to exogenous shocks. Moreover, and as illustrated and stressed in the following sections, the interaction between these two sectors leads to significantly important transmission channels that are otherwise neglected when we study each of them separately. Further, rather than adopting the benchmark rational expectations assumption, the boundedly rational expectation formation assumed for both the real sector and the stock market recognizes the limited cognitive abilities of agents in the real world. Lastly, our setup highlights the role of the deviation costs in the banking sector in the degree of pass-throughness of monetary policy shocks.

This latter issue has been recently investigated by Darracq Paries et al. (2020) who examine the way macroprudential policy (i.e. capital requirements) affects the monetary transmission mechanism (and vice versa) in different medium scale DSGE models and find that high levels of capital requirements make the economy less responsive to both conventional and unconventional monetary policy. We arrive at similar results using our framework. At the empirical level, Lambertini and Uysal (2014) and Eickmeier et al. (2018) assess the macroeconomic effects of changes in regulatory capital requirements in the U.S., paying a special attention to the role of monetary policy in cushioning real and credit market effects of such requirements, and Garcia Revelo et al. (2020) analyse the interdependence between the effectiveness of macroprudential policies and the monetary policy stance.

The remainder of the chapter is organised as follows. Section 1.2 explains the structure of the model. Section 1.3 discusses calibration. Section 1.4 discusses the main results. Section 1.5 evaluates the effectiveness of a leaning against the wind (LAW) monetary policy in such a behavioural macro-financial framework. Section 1.6 concludes.

1.2 The Model

1.2.1 The Real Sector

In the following, we assume that the economy's potential output level is constant and that the actual aggregate output is not restrained by any supply factors, and is thus purely demand-driven. The economy's output gap y_t represents the log deviation of the current demand-driven output from its constant potential level. Similar to De Grauwe and Macchiarelli (2015), we assume that the two components of aggregate demand, aggregate consumption (c_t) and aggregate investment (i_t) (expressed as log-linearised deviations from their respective steady states), are given by

$$c_t = d_1 y_t + d_2 \tilde{E}_t[y_{t+1}] + d_3(r_t - \tilde{E}_t[\pi_{t+1}]) + d_4 \tilde{E}_t[\Delta s_{t+1} - \pi_{t+1}] + \epsilon_t^c \tag{1.2.1}$$

and

$$i_t = e_1\tilde{E}_t[y_{t+1}] + e_2(\rho_t - \tilde{E}_t[\pi_{t+1}]) + \epsilon_t^i \tag{1.2.2}$$

where π_t is the inflation rate, r_t is the nominal risk-free short-term interest rate (i.e. the policy rate, defined below in equation 1.2.19); ρ_t is the loan interest rate charged by banks consisting of r_t plus a spread term χ_t (see equation 1.2.17), s_t is the stock price and ϵ_t^c and ϵ_t^i are stochastic disturbances following an AR(1) process. Equation (1.2.1) differs from De Grauwe and Macchiarelli (2015) in that the expected real stock price also influences (positively) private consumption. The tilde above the expectation operator (i.e. $\tilde{E}_t$) indicates boundedly rational, backward-looking expectations, as will be later explained.

Further, we assume that the aggregate price inflation is determined by a standard expectations-augmented Phillips Curve equation given by

$$\pi_t = b_1\tilde{E}_t[\pi_{t+1}] + b_2 y_t + \epsilon_t^\pi \tag{1.2.3}$$

where b_1 determines the impact of future expected inflation on current inflation, b_2 is the slope of the Phillips Curve and ϵ_t^π is a stochastic cost-push term following an AR(1) process.

Analogously to Lengnick and Wohltmann (2016), but in the absence of taxes and stock dividend payments, the households' budget constraint is

$$c_t + d_t + (s_{t-1} - p_{t-1})\Lambda_t = (w_t - p_t)n_t + (r_{t-1} - \pi_t)d_{t-1} + (s_{t-1} - p_{t-1})\Lambda_{t-1} + \zeta_t$$

where p_t is the price level, $(w_t - p_t)n_t$ is the households' wage income in real terms, d_t is the households' deposits, Λ_t is the households' net stock demand and ζ_t represents the firms' profits which are assumed to be fully distributed to the households.[2] The firms' budget constraint is

$$(w_t - p_t)n_t + i_t + (\rho_{t-1} - \pi_t)l_{t-1} + \zeta_t = y_t + l_t$$

where l_t represents the firms' new loans. Under the assumption that firms finance their investments thoroughly through loans, so that $i_t = l_t$, as for example in Chiarella et al. (2012), the firms constraint reduces to

$$(w_t - p_t)n_t + (\rho_{t-1} - \pi_t)l_{t-1} + \zeta_t = y_t.$$

The consolidation of the two budget constraints yields then

$$y_t + (r_{t-1} - \pi_t)d_{t-1} + (s_{t-1} - p_{t-1})\Lambda_{t-1} = c_t + d_t + (s_{t-1} - p_{t-1})\Lambda_t + (\rho_{t-1} - \pi_t)l_{t-1}. \tag{1.2.4}$$

[2]In order to avoid a quite complicated nonlinearity which would arise if Λ_t would be multiplied by s_t or p_t (see equation 1.2.10), we replaced s_t and p_t with the past values in this budget constraint.

1.2.2 Expectations

Expectations are formed in a boundedly rational way according to the discrete choice learning approach by Brock and Hommes (1998). We follow De Grauwe and Macchiarelli (2015) in assuming two types of expectation rules: chartist (represented by the letter c) and fundamentalist (represented by the letter f), defined respectively as:

$$\tilde{E}_t^c[z_{t+1}] = z_{t-1} \qquad z \in (y, \pi, s) \tag{1.2.5}$$

$$\tilde{E}_t^f[z_{t+1}] = z^* \qquad z^* \in (y^*, \pi^*, s^*) \tag{1.2.6}$$

where z^* represents the fundamental value of $z \in (y, \pi, s)$, assumed equal to zero (i.e. no deviation from the steady state).

As it is standard in the discrete choice learning approach, agents switch between the two rules, and the aggregate market expectations are the weighted average of both rules:

$$\tilde{E}_t[z_{t+1}] = \omega_t^{z,c}\tilde{E}_t^c[z_{t+1}] + \omega_t^{z,f}\tilde{E}_t^f[z_{t+1}] \tag{1.2.7}$$

where the weights of agents and the utility function associated with each rule (ω_t and U_t, respectively) are determined as follows:

$$\begin{aligned} \omega_t^{z,c} &= \frac{\exp(\gamma U_t^{z,c})}{\exp(\gamma U_t^{z,c}) + \exp(\gamma U_t^{z,f})} \\ \omega_t^{z,f} &= \frac{\exp(\gamma U_t^{z,f})}{\exp(\gamma U_t^{z,c}) + \exp(\gamma U_t^{z,f})} = 1 - \omega_t^{z,c} \end{aligned} \tag{1.2.8}$$

and

$$U_t^{z,j} = mU_{t-1}^{z,j} - (\tilde{E}_{t-2}^j[z_{t-1}] - z_{t-1})^2 \tag{1.2.9}$$

where m is a memory parameter, $j \in (c, f)$, and γ reflects the reaction of ω_t to U_t.

1.2.3 The Stock Market

Following Lengnick and Wohltmann (2016), two types of stock demand are assumed: speculative and non-speculative. In contrast to Lengnick and Wohltmann (2016), where households demand stock only non-speculatively, while speculative demand is left for financial agents who do not play any other role in the model (e.g. in the real sector), we assume that households demand stock both for non-speculative and speculative motives.[3] The households' net stock demand is thus represented by:

$$\Lambda_t = \underbrace{[c_{\Lambda,y} y_t - c_{\Lambda,r}(r_t) - c_{\Lambda,s}(s_t - p_t)]}_{\text{non-speculative demand}} + \underbrace{[\omega_t^{s,f} D_t^f + \omega_t^{s,c} D_t]}_{\text{speculative demand}} \tag{1.2.10}$$

where D_t^c and D_t^f are the net stock demand of chartists and fundamentalists respectively, defined in turn by:

$$D_t^j = \tilde{E}_t^j[s_{t+1}] - s_{t-1} \qquad j \in (c, f). \tag{1.2.11}$$

Equation (1.2.10) shows that households have two types of stock demand: a speculative demand which depends on households' expectation (speculation) for s_{t+1} and a non-speculative demand. According to the former, households demand more stock when they expect an increase in the stock price, and vice versa. According to the latter, households demand more stocks when their income increases, and less stocks when the deposit (policy) rate or the stock price increase.

More specifically, the households' non-speculative demand for stocks (i) increases if an agent can afford buying more stocks (as a result of a higher output gap y_t), (ii) decreases if the real price of stocks $(s_t - p_t)$ increases, and (iii) decreases when the yield on deposits (r_t) increases.[4] Further, the non-speculative stock demand does not (directly) depend on the expected stock price (i.e. non-speculative motive).

Finally, following Westerhoff (2008) and Lengnick and Wohltmann (2016), we assume that the evolution of the log stock price s_t is determined by the following impact function:

$$s_t = s_{t-1} + \Lambda_t + \epsilon_t^s \tag{1.2.12}$$

which relates stock price changes positively to excess households' stock demand, where ϵ_t^s is an AR(1) disturbance term.

1.2.4 The Banking Sector

The aggregate balance sheet of the banking sector is illustrated in Table 1.1. While both aggregate deposits d_t and the interest rate paid on them r_t (assumed to be equal to the policy rate to be discussed

[3]Indeed, assuming that financial agents remain "model outsiders" in the real sector creates a leakage problem which may affect the dynamics of the model. By merging these types of demands together, we solve such a problem while still keeping the key idea of Lengnick and Wohltmann (2016).

[4]For more details on the derivation and the explanation of the non-speculative households' stock demand, refer to Lengnick and Wohltmann (2016).

below) are determined outside the banking sector, banks determine the loan-deposit spread rate (χ_t) and consequently the aggregate loan supply level (l_t), as e.g. in Samitas et al. (2018). They respond to shocks; cyclical conditions in the real sector, and indirectly, stock market conditions by adjusting the spread rate, while obeying a balance sheet identity (Assets=Liabilities + Net worth).

Table 1.1: The aggregate balance sheet of the banking sector

Assets	Liabilities
Loans (l_t)	Household deposits (d_t)
	Net worth

Banks make loans (l_t) to firms earning a revenue of $\rho_t l_t$, and accept deposits (d_t) from households that cost interest payment of $r_t d_t$.

The banks' net worth (bank capital) is defined as the difference between the banks' assets and the banks' liabilities, the banks' capital-to-asset ratio (ν_t) is thus defined as follows:

$$\nu_t = \frac{\text{bank net worth}}{\text{bank assets}} = \frac{l_t - d_t}{l_t}. \tag{1.2.13}$$

Following Gerali et al. (2010), banks are assumed to pay a quadratic cost (parametrized by a coefficient κ) whenever the capital-to-asset ratio ν_t deviates (either way) from the target value ν^*. To keep our calculations linear, however, we rearrange the previous equation to express it in terms of a fraction of loan supply, i.e.

$$l_t - d_t = \nu_t l_t. \tag{1.2.14}$$

Using this modified expression, the banks' profit maximization problem can be expressed as:

$$\max_{l_t} \quad \chi_t l_t - \frac{\kappa}{2}(l_t - d_t - \nu^* l_t)^2. \tag{1.2.15}$$

As explained in Gerali et al. (2010), the first term in the maximization problem (1.2.15) is the banks' total profits from loans, the second term is the total cost of deviating from the target ν^*. Banks take the aggregate deposit level d_t as given. Maximizing the previous expression with respect to l_t leads to the following first-order condition:[5]

$$l_t = \eta(\chi_t + \kappa(1 - \nu^*)d_t) \tag{1.2.16}$$

[5]For the full derivation refer to equation (1.7.22) in the appendix .

with $\eta = \frac{1}{\kappa(1-\nu^*)^2}$. Accordingly, banks' loan supply depends positively on the banks' marginal profits from loans (i.e. the spread rate χ_t), and the households' deposits d_t, and negatively on the target for the capital-to-asset ratio ν^*.

Under the assumption that banks know the loan demand function expressed by equation (1.2.2) (the firms' investment function), they set the spread rate such that the level of loan demanded by firms is equal to the profit maximizing loan level that banks wish to supply.[6] Rearranging equation (1.2.16) yields:

$$\chi_t = \kappa(1-\nu^*)((1-\nu^*)l_t - d_t) \tag{1.2.17}$$

where $l_t = i_t$. The left-hand side of the equation represents the marginal benefit from increasing lending (an increase in profits equal to the spread); the right-hand side is the marginal cost from doing so (an increase in the costs of deviation from ν^*). Banks choose the level of loan supply that equalizes the marginal benefit with the marginal cost (leading to a marginal profit of zero). For $\kappa \to 0$,[7] the profit maximizing spread rate is approximately zero.

1.2.5 Monetary Policy

We assume in our baseline model that the policy rate is determined by the following standard Taylor rule:

$$r_t = \phi_\pi(\pi_t - \pi^*) + \phi_y(y_t - y^*) + \phi_r r_{t-1} + \epsilon_t^r. \tag{1.2.18}$$

Accordingly, the central bank's policy interest rate is a function of the past policy rate (pursuing therefore an interest rate smoothing policy), the deviations of current output and inflation from their respective targets (which are assumed to be equal to their fundamental levels y^* and π^*, respectively), and ϵ_t^r, a stochastic disturbance term.

In section 1.5, we will also consider the following specification

$$r_t = \phi_\pi(\pi_t - \pi^*) + \phi_y(y_t - y^*) + \phi_r r_{t-1} + \phi_s(s_t - s^*) + \epsilon_t^r \tag{1.2.19}$$

where the additional term $\phi_s(s_t - s^*)$ represents, for $\phi_s > 0$, a LAW policy by the central bank with respect to stock price deviation from its fundamental value.

[6] If banks choose a lower interest rate than this rate, loan (investment) demand will be higher than the level of loans desired by banks to be supplied. On the other hand, if they choose a higher interest rate, loan demand will be lower than the level desired to be supplied.

[7] We do not set $\kappa = 0$ to avoid a division by zero in equation (1.2.16).

1.3 Calibration

Table 1.2: Baseline parametrization

Parameter	Description	Value
Real Sector, Stock Market and Expectations		
d_1	marginal propensity of consumption out of income	0.5
d_2	coefficient on expected y in consumption equation	$(1 - d_1)(0.5) - e_1{}^{\star}$
d_3	coefficient on real rate in consumption equation	-0.01
d_4	coefficient on expected real stock price in consumption equation	0.1
e_1	coefficient on expected y in investment equation	0.1
e_2	coefficient on real rate in investment equation	$(-0.5)(1 - d_1) - d_3{}^{\star}$
b_1	coefficient of expected inflation in inflation equation	0.99
b_2	coefficient of output gap in inflation equation	0.05
σ_{ϵ^y}	standard deviation shocks output gap equation	0.08
σ_{ϵ^π}	standard deviation shocks inflation equation	0.08
$\rho^{\pi/y/s}$	shock persistence	0.15
$c_{\Lambda,r}$	coefficient of interest rate in households' demand for stock equation	1
$c_{\Lambda,y}$	coefficient of output gap in households' demand for stock equation	1
$c_{\Lambda,s}$	coefficient of stock price in households' demand for stock equation	0.5
γ	switching parameter in Brock Hommes mechanism	10
m	speed of declining weights in mean squares errors (memory)	0.5
σ_{ϵ^s}	standard deviation shocks stock price function	0.08
Monetary Policy		
ϕ_π	coefficient of inflation in Taylor equation	1.5
ϕ_y	coefficient of output gap in Taylor equation	0.5
ϕ_r	interest smoothing parameter in Taylor equation	0.5
ϕ_s	coefficient of stock price in Taylor equation	0
π^*	the central bank's inflation target	0
y^*	the central bank's output gap target	0
σ_{ϵ^r}	standard deviation shocks Taylor equation	0.08
ρ^r	shock persistence	0.15
Banking Sector		
ν^*	target capital-to-loans ratio	0.09
κ	deviation cost parameter	1

* The derivation of the parameters of the investment and consumption functions can be found in De Grauwe and Macchiarelli (2015).

The baseline calibration of our model (summarized in Table 1.2) follows Lengnick and Wohltmann (2016) (for the stock market and households' stock demand), De Grauwe and Macchiarelli (2015) (for the real sector) and Gerali et al. (2010) (for the banking sector), with some minor adjustments from our side, being the most important one the way κ is calibrated. In Gerali et al. (2010), the cost of divergence is calculated as follows: the quadratic divergence from the targeted capital-to-asset ratio (i.e. $(\nu_t - \nu^*)^2$) is measured proportional to the outstanding bank capital, then multiplied by the cost factor. In our model we sought linearity in calculating the divergence cost (see equation 1.2.14), and thus the interpretation of κ is slightly different.

1.4 Scenario Analysis

In the following we describe the dynamic adjustment paths of our model to different kinds of shocks by means of impulse responses obtained via Monte Carlo simulations.[8]

Figure 1.1 describes how our model economy reacts to a contractionary monetary policy shock in three different scenarios: when households do not participate directly in the stock market (dotted line), when their stock demand is purely non-speculative (dashed line), and when their demand is both non-speculative and speculative (continuous line). We will consider this latter case as our baseline scenario in the following simulations. In all three cases, we assume that loan creation is capital-constrained (with $\kappa = 1$), and that monetary policy is conducted in a traditional manner (with $\phi_y > 0$, $\phi_\pi > 0$ and $\phi_s = 0$). All other coefficients follow the baseline values reported in Table 1.2.

As it can be observed, an increase in the policy rate leads to a rise in the loan interest rate which in turn leads to a decrease in aggregate investment, output, consumption and price inflation.[9] On impact, the spread between the loan and the deposit rates shows nearly no reaction to the shock in all three depicted cases due to the presence of two opposite effects that cancel one another: on the one hand, the fall in inflation rate, output gap, deposits as well as the stock price has an upward pressure on the spread rate (see equation 1.7.25 in the appendix), on the other hand the positive monetary shock itself has a downward pressure on the spread rate.

Through the budget constraint and the stock net demand equations (1.2.4 and 1.2.10, respectively), a drop in income (output gap) lowers the households' deposits and their non-speculative net stock demand. The decrease of the latter leads to an immediate drop in the stock price. This is inline with the explanation illustrated in (Lengnick and Wohltmann, 2016, p. 156). Manifestly, these effects are absent when households do not participate in the stock market neither non-speculatively nor speculatively. Indeed, in this case, the stock market does not react at all to the increase in the policy rate, and therefore there is no feedback mechanism affecting the households' deposits (and thus the banks' net worth) in the following periods.

The importance of the households' stock market participation, and the behavioural stock market specification along the lines of Lengnick and Wohltmann (2016) is clearly illustrated by the dashed (only non-speculative stock demand) and continuous (both non-speculative and speculative stock demand) lines in Figure 1.1. Following the drop in the stock price, households increase their deposits in the banking sector, what leads to a deterioration of the banks' net worth. This effect is larger under

[8]See Appendix 1.7 for a description of how we computed these impulse-responses.

[9]As described in Appendix 1.7, we always consider a shock of size 0.5.

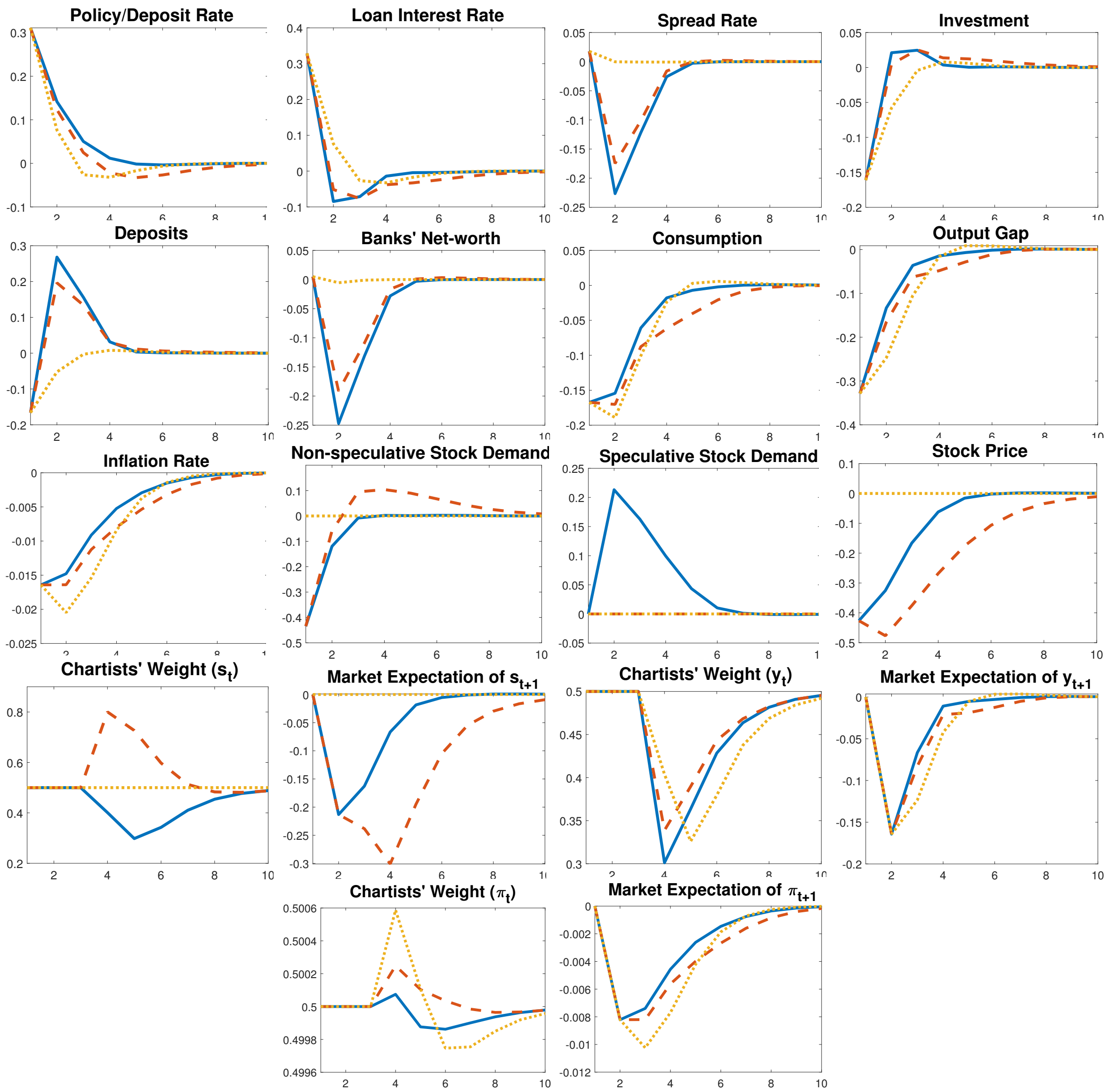

Figure 1.1: Impulse responses to a monetary policy shock under no households' stock market participation (dotted line), under only non-speculative stock demand (dashed line) and under both households' non-speculative and speculative stock demand (continuous line) for $\kappa = 1$ and $\phi_s = 0$.

full stock market participation (that is, under households' both non-speculative and speculative stock demand). This leads to a drop in the spread between the loan and the policy (deposit) rate which effectively lowers the loan interest rate, boosting aggregate investment in the following periods.

Regarding the dynamics in the stock market, when households demand stock speculatively as well as non-speculatively, a drop of the stock price below its steady state causes a spike in fundamentalists' demand as they expect the stock price to rise and go back to the steady state. This has a positive effect on the stock price which is clearly observable relative to the case where there is no households' speculative stock demand and therefore where the impact of the fundamentalists' net stock demand is not present. The presence of speculative stock demand based on boundedly rational expectations has thus an impact on the actual development of the stock price and by extension, through the mechanisms previously outlined, on the evolution of the banks' net worth and aggregate investment.

Figure 1.2 illustrates the impact of a positive stock price shock under two scenarios: only non-speculative households' stock demand and both speculative and non-speculative demand.[10] In the presence of non-speculative stock demand, the stock price rises on impact by less than the value of the shock because part of the rise is offset due to an immediate drop in the non-speculative demand. Note that while the non-speculative stock demand reacts on impact, the speculative demand reacts with a delay. Therefore both models react similarly on impact.

In the following periods, chartists' expectations lead to a rise in expected stock price, pushing aggregate private consumption up. As a result, the output gap and aggregate investment also increase. When speculative demand is present (continuous line), a stock price above the steady state means that fundamentalists are demanding less stocks, and are diverting more of their funds towards bank deposits instead. Accordingly, deposits slightly rise and as a consequence, the spread rate decreases, which enhances investment, consumption and output gap even further. Finally, we can observe that, in the presence of speculative demand, the stock price returns quicker to the steady state (due to the fall in fundamentalists' demand). Therefore we can conclude that the presence of fundamentalists' demand aids the stability of the stock market following a stock price shock.

We can also observe that while the effect of the expected stock price on consumption and the effect of the stock price itself on the non-speculative stock demand are existent in both model scenarios, the presence of fundamentalists' stock demand adds another mechanism through which the stock market spills over to the real sector, mainly through the effect of such demand on deposits, and thus on the spread rate. Such a channel can only exist in the presence of a capital-constrained banking sector through a positive κ.

To further investigate the role played by different kinds of stock demand on the model dynamics, Table 1.3 reports the variances of key macro-financial variables under two scenarios: only non-speculative stock demand and both speculative and non-speculative stock demand. We can observe that under the presence of all real, monetary as well as financial shocks, the fundamentalists' demand slightly enhances the stability of the model (i.e. slightly lower variances for all variables). The reason behind

[10] The case with no households' net stock demand is obviously irrelevant in the case of a stock price shock, and is therefore not included in the analysis.

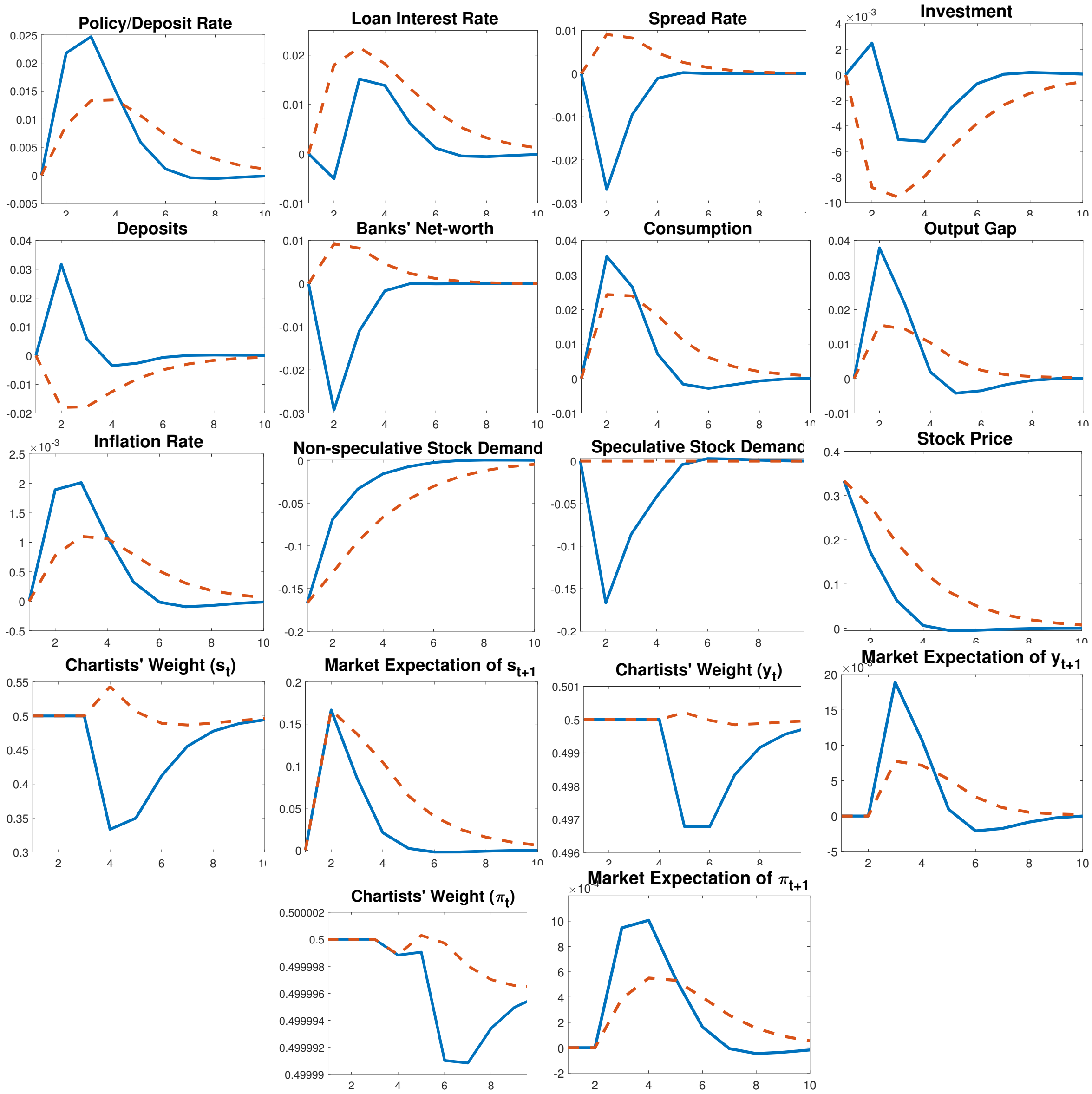

Figure 1.2: Impulse responses to a stock price shock under only households' non-speculative stock demand (dashed line) and with both households' non-speculative and speculative stock demand (continuous line) for $\kappa = 1$ and $\phi_s = 0$.

this, as discussed in the results of Figure 1.2, is that fundamentalists demand stock in a manner that pushes the stock price to the steady state faster, bringing the variability of the entire model down.

Our next exercise is aimed at exploring the role of the capital requirements (represented by different values of κ) in the dynamics of the economy. Figure 1.3 investigates the model dynamics following a contractionary monetary policy shock based on the model parameters reported in Table 1.2. On

Table 1.3: Monte-Carlo-based variances of key macrofinancial variables

Output	**Inflation**	**Consumption**	**Investment**	**Bank's Net Worth**	**Stock Price**
Only Non-Speculative Households' Stock Market Participation					
0.0194	0.0058	0.011	0.003	0.016	0.035
Non-Speculative and Speculative Households' Stock Market Participation					
0.0143	0.0057	0.0074	0.0026	0.006	0.027

Variances based on a Monte-Carlo simulation of 10000 runs

impact, the loan interest rate rises by the same amount as r_t, and consumption, investment, output gap, inflation as well as non-speculative stock demand and the stock price fall. In the following period, at a non-zero value for κ, the spread rate reacts negatively, bringing the loan interest rate down. At higher values of κ, the fall in the spread rate is more prominent, and as a result, the contractionary effect of the policy shock on inflation, consumption, investment and output gap is "diluted". In other words, a contractionary monetary policy shock is only partially transmitted to the economy when the capital requirements are particularly tight (high κ). By contrast, when capital requirements are loose ($\kappa \to 0$), a contractionary monetary policy is fully transmitted to the economy.[11]

In Figure 1.4, the effect of a positive stock price shock is analyzed. The continuous line is the baseline case discussed in Figure 1.2. The dashed line represents the reaction of the model to the shock under no deviation costs (i.e. $\kappa \to 0$). We can observe that consumption in both scenarios increases due to the rise in expected stock price (brought by chartists' expectations). This raises output gap and inflation slightly. Since the spread rate does not decrease in case of a zero κ, the dashed lines show less boost in the real activity (i.e. consumption, inflation an output gap) than the baseline scenario represented by the continuous line.

Analogously to Table 1.3, Table 1.4 reports the variances of key macro-financial variables for different values of the deviation costs parameter κ. It can be observed that when all the relevant macro-financial shocks are considered, higher values for κ translate into higher instability (i.e. slightly higher variances). There are various factors behind this result: first and foremost, although the model does not feature a direct link between the stock market and the banking sector, the coexistence of the banks' balance sheet constraints, households' net demand for stocks and banks' setting power over the loan spread rate creates an indirect link between the two sectors which in turn strengthens the spill over effects between these sectors and the real sector.

[11] For an overview on the empirical evidence for the incomplete interest rate pass-through from policy to loan rates see de Bondt et al. (2005).

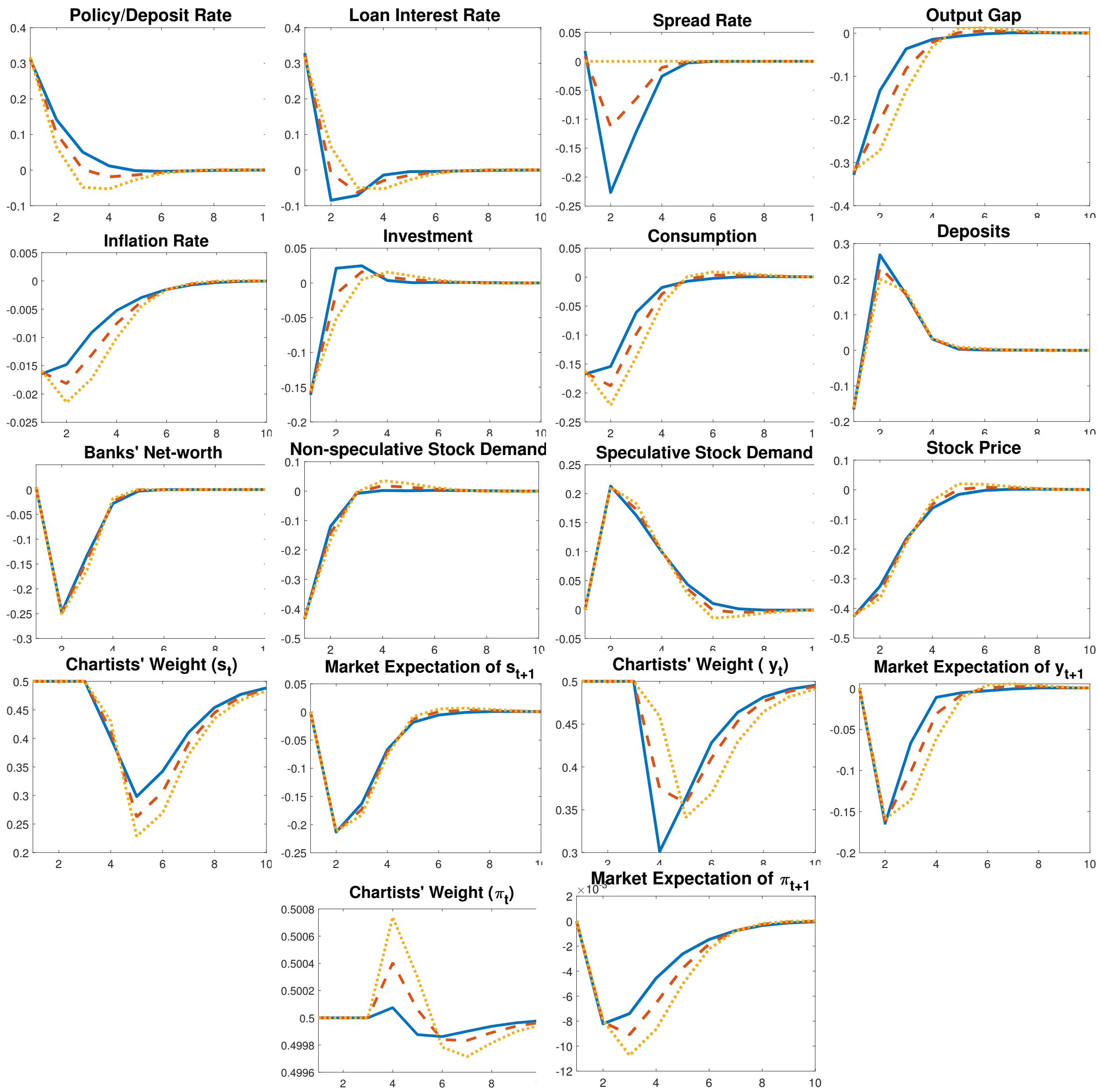

Figure 1.3: Impulse responses to a monetary policy shock for different values of the deviation cost parameter: $\kappa = 0.001$ (dotted line), 0.5 (dashed line), and 1 (continuous line) under households' non-speculative and speculative stock market participation and $\phi_s = 0$.

The fact that in our model the deposit level falls outside the frame of the banks' market power and is rather decided at the households' level, creates and additional "channel variable" through which changes in the real sector and the stock market affect the banking sector. The latter sector then spills over to the first two sectors through the process through which the spread rate is adjusted. This is in line with Drechsler et al. (2017), which singles out deposits as being: (1) a uniquely stable funding source for banks, (2) the main source of liquid assets for households, and consequently, (3) an

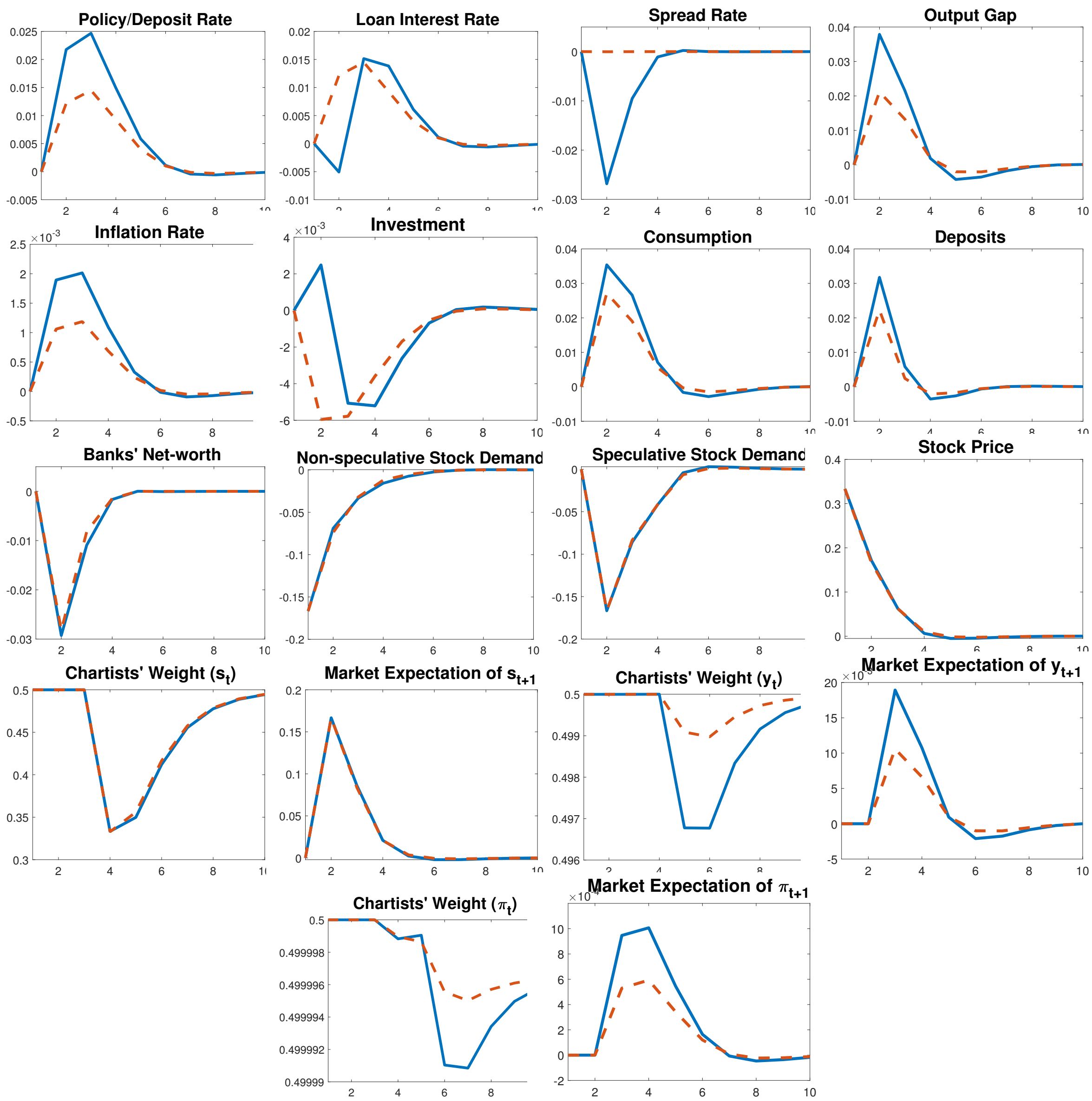

Figure 1.4: Impulse responses to stock price shock for $\kappa = 0.001$ (dashed line) and $\kappa = 1$ (continuous line) under households' non-speculative and speculative stock market participation (with $\phi_s = 0$).

important channel through which monetary policy is transmitted. Similarly, in our model households can sell (withdraw) deposits to consume, buy stocks, or pay interest on their debts (i.e. deposits are liquid assets for households). Banks have to cut their lending (raise the loan spread) when the deposit level falls and vice versa (i.e. deposits are a critical source of funding to banks). And finally, as seen above, deposits respond strongly to monetary policy shocks and transmit these to the banking sector and consequently to the rest of the economy.

Table 1.4: Monte-Carlo-based variances of key macrofinancial variables

Output	**Inflation**	**Consumption**	**Investment**	**Bank's Net Worth**	**Stock Price**
			$\kappa = 0.001$		
0.011	0.0057	0.0055	0.0021	0.0044	0.026
			$\kappa = 0.5$		
0.012	0.0057	0.0059	0.0023	0.0045	0.0261
			$\kappa = 1$		
0.014	0.0057	0.0074	0.0026	0.0059	0.0266

Variances based on a Monte-Carlo simulation of 10000 runs

Further, similar to e.g. Lin (2019), when households change their assets allocation between stocks and deposits, banks' lending to firms is altered, and by extension, aggregate investment and aggregate demand. The process through which households' deposits, responding to different shocks (e.g. monetary policy shocks), affect the real economic activity is only made possible through the presence of capital constraints on the banking sector. This is in line with the literature on the role of banks' capital constraints in monetary policy transmission discussed above.

1.5 Monetary Policy and Stock Prices

We now turn our focus on the conduct of monetary policy in our framework. In particular, we allow the parameter ϕ_s in equation (1.2.19) to be positive in order to investigate in more detail the effectiveness of a LAW monetary policy (see e.g. Bernanke and Gertler, 1999, Gilchrist and Leahy, 2002) in stabilizing the stock market and whether this comes at the cost of output and inflation stability. We evaluate the effectiveness of a LAW policy in two different ways. First, we study impulse responses of the model variables to a one-time stock price shock under different values of ϕ_s in order to assess the ability of a LAW monetary policy to stabilize the stock market following a stock market shock. Then, we analyse the effect of varying the value of ϕ_s on the variances of y_t, π_t and s_t for various constellations of real and financial shocks.

Figure 1.5 illustrates the model dynamics following a stock price shock under different values for ϕ_s. We can observe that the on impact rise in the stock price is negatively related to the value of ϕ_s. This is because the higher the value of ϕ_s, the larger is the reaction of the policy rate r_t to the shock, therefore the larger is the rise in deposits as well as the fall in the non-speculative stock demand. Such an immediate fall in the stock demand partially offsets the initial shock effect. For $\phi_s = 0$, the real and banking variables do not react on impact to the shock (continuous line). By contrast, for a

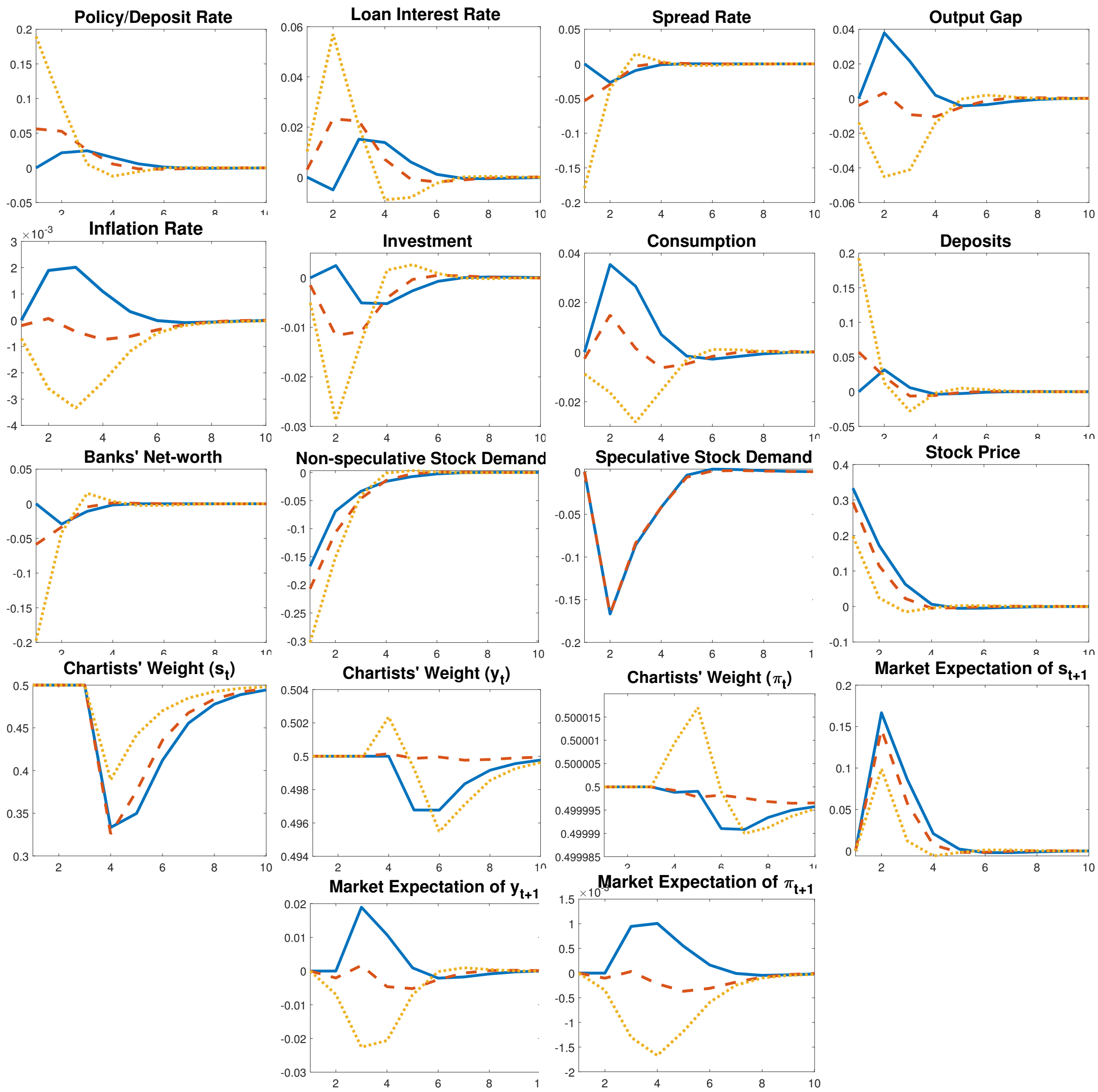

Figure 1.5: Impulse responses to a stock price shock at $\phi_s = 0$ (continuous line), $\phi_s = 0.2$ (dashed line) and $\phi_s = 1$ (dotted line) with $\kappa = 1$ (high deviation costs).

slightly positive value of ϕ_s (dotted line), the rise in the policy rate has a contractionary effect on the real economy on impact; output gap, investment, consumption and inflation fall. Further, when ϕ_s has a non-zero value, the rise of the policy rate induces a rise in deposits, leading to a reduction in the banks' net worth and thus to a fall in the loan spread rate.

The development of the variables in the following periods depends on the value of ϕ_s. For $\phi_s = 0$, the rise in the expected stock price induces a rise in consumption which in turn has an expansionary effect on the real economy. At a high value for ϕ_s, the negative effect of the higher policy rate outweighs the positive effect of the stock shock, being the final effect contractionary, leading consumption, investment, output gap and inflation to fall below their respective long-run steady state levels. For a relatively moderate value for ϕ_s, the expansionary effect of the shock and the contractionary effect of the policy reaction offset one another, leaving the model variables fairly stable around the steady state.

While a LAW monetary policy seems thus to be highly effective in stabilizing the stock market following a stock price shock, its effect on the real sector depends on the value of ϕ_s. A moderate value can stabilize the real sector together with the stock market, but a high value would stabilize the stock market at the expenses of the real stability (see also Filardo and Rungcharoenkitkul, 2016).

To examine further the interplay of the banking regulatory stance (represented by κ) and the performance of a LAW monetary policy with respect to macroeconomic and financial stabilization we simulate our theoretical model for 10000 runs, and compute the (average) variances of the output gap, price inflation and the stock price for various values of ϕ_s and κ in the presence of all real and financial shocks.

Figure 1.6: Variances of y_t, π_t and s_t at different combinations of ϕ_s and κ. Variances are based on a Monte-Carlo simulation of 10000 runs with $\sigma_{\epsilon^\pi} = \sigma_{\epsilon^r} = \sigma_{\epsilon^s} = \sigma_{\epsilon^y} = 0.08$.

Figure 1.6 illustrates the results of this simulation exercise. As it can be observed, the stock price is always better stabilized at higher values for ϕ_s regardless the value of κ, and the output gap is more stable at a combination of high ϕ_s and low κ. Thus, when all real, financial and monetary shocks are accounted for, there seems to be no trade-off between output and stock price stability. This is because, through households' stock demand, the real activity is highly connected to the stock price, stabilizing one would stabilize the other. These results are similar to the ones obtained in Lengnick and Wohltmann (2016).

Finally, we repeat this simulation exercise considering only stock price shocks and abstracting from all other real and monetary disturbances ($\sigma_{\epsilon^\pi} = \sigma_{\epsilon^r} = \sigma_{\epsilon^y} = 0$), and report again the variances of the output gap, price inflation and the stock price for different values of ϕ_s and κ.

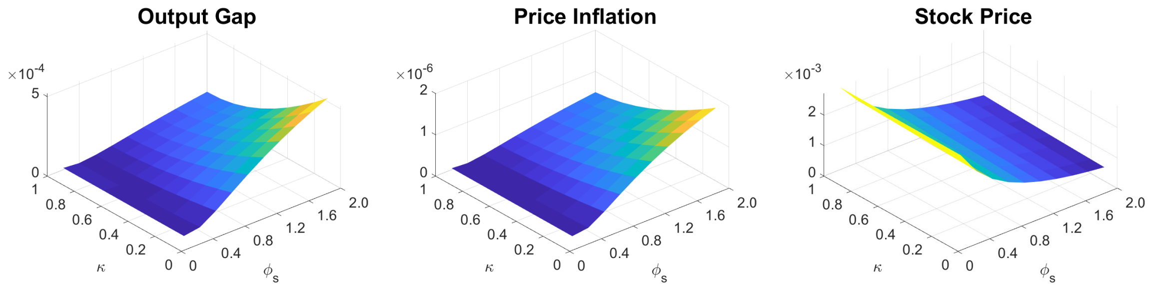

Figure 1.7: Variances of y_t, π_t and s_t at different combinations of ϕ_s and κ based on a Monte-Carlo simulation of 10000 runs with $\sigma_{\epsilon^s} = 0.05$ and $\sigma_{\epsilon^\pi} = \sigma_{\epsilon^r} = \sigma_{\epsilon^y} = 0$.

Figure 1.7 illustrates the results of this final exercise. As it can be observed, when only stock price shocks are considered, beyond a certain value for ϕ_s (=0.2), a trade-off between output and price inflation volatility on the one hand and the stock price volatility on the other hand becomes evident. A more aggressive LAW policy, represented by higher values of ϕ_s, reduces indeed the variance of the stock price, but at the same time increases the variance of output and inflation (see Figure 1.5).

The finding that the performance of a LAW monetary policy is dependent on the nature of the shocks hitting the economy is also discussed in Gourio et al. (2018). In their model, when only real shocks (i.e. productivity and demand shocks) are considered, the central bank achieves both inflation stability AND simultaneously limits the risk of financial crises by targeting inflation stability. On the other hand, when financial shocks are present, the failure to respond to such shocks exposes the economy to larger crises risks. In this case, it is optimal for the central bank to consider a LAW policy to reduce financial risks against the costs of larger fluctuations in aggregate demand and inflation.

1.6 Concluding Remarks

While the need for a better regulation of the financial system has been widely acknowledged in the economics profession since the global financial crisis, there are still many open questions concerning the aggregate effects of the individual regulatory and macroprudential policies which have been implemented around the world, and how and under which circumstances may such policies interact with the more traditional monetary and fiscal policies. Against this background, this paper extends the literature on macro-financial linkages by analysing the interaction between the stock market, the banking sector and the real sector in a behavioural macroeconomic model along the lines of De Grauwe and Macchiarelli (2015).

Our paper highlights households' participation in the stock market as well as constraints on the banking sector as two critical channels through which developments in the financial sector spill over to the real sector and the monetary policy's effect on the real sector is altered. Further, we consider the effectiveness of a LAW monetary policy in stabilising the stock market and whether this comes at cost of the real stability. We find that a moderate policy reaction to stock market disturbances can achieve the stability of the stock market at a fairly low level of instability in the real activity. However, a strong policy reaction to stock prices may largely destabilize the real sector.

1.7 Appendix to Chapter 1

Model Derivation

The aggregate supply equation (Phillips Curve) is defined as:

$$\pi_t = b_1 \tilde{E}_t \pi_{t+1} + b_2 y_t + \epsilon_t^{\pi}. \tag{1.7.1}$$

Market expectations for π_{t+1} and y_{t+1} are given by:

$$\tilde{E}_t \pi_{t+1} = \omega_t^{\pi,c} \tilde{E}_t^c \pi_{t+1} + (1 - \omega_t^{\pi,c}) \tilde{E}_t^f \pi_{t+1} \tag{1.7.2}$$

$$\tilde{E}_t y_{t+1} = \omega_t^{y,c} \tilde{E}_t^c y_{t+1} + (1 - \omega_t^{y,c}) \tilde{E}_t^f y_{t+1} \tag{1.7.3}$$

where ω_t^c is the weight of chartists and $1 - \omega_t^c = \omega_t^f$ is the weight of fundamentalists.

Fundamentalists' and chartists' expectations are given by:

$$\tilde{E}_t^c z_{t+1} = z_{t-1} \qquad z \in (y, \pi)$$

$$\tilde{E}_t^f z_{t+1} = z^* \qquad z^* \in (y^*, \pi^*) \tag{1.7.4}$$

where y^*, π^* are assumed equal 0. Equations 1.7.2 and 1.7.3 could thus be simplified respectively to:

$$\tilde{E}_t \pi_{t+1} = \omega_t^{\pi,c} \pi_{t-1} \tag{1.7.5}$$

$$\tilde{E}_t y_{t+1} = \omega_t^{y,c} y_{t-1}. \tag{1.7.6}$$

Plug equation 1.7.5 in equation 1.7.1 to reach the first state equation:

$$\pi_t = b_1 * \omega_t^{\pi,c} \pi_{t-1} + b_2 y_t + \epsilon_t^{\pi}. \tag{1.7.7}$$

Taylor rule is defined by:

$$r_t = \phi_\pi (\pi_t - \pi^*) + \phi_y (y_t - y^*) + \phi_r r_{t-1} + \phi_s s_t + \epsilon_t^r \tag{1.7.8}$$

where s_t is the real stock price.

Aggregate demand is decomposed into consumption and investment:

$$y_t = c_t + i_t. \tag{1.7.9}$$

Consumption is defined by:

$$c_t = d_1 y_t + d_2 \tilde{E}_t y_{t+1} + d_3 (r_t - \tilde{E}_t \pi_{t+1}) + d_4 \tilde{E}_t (\Delta s_{t+1} - \pi_{t+1}). \tag{1.7.10}$$

Market expectations of s are given by:

$$\tilde{E}_t s_{t+1} = \omega_t^{s,c} \tilde{E}_t^c s_{t+1} + (1 - \omega_t^{s,c}) \tilde{E}_t^f s_{t+1} \tag{1.7.11}$$

where

$$\tilde{E}_t^c[s_{t+1}] = s_{t-1} \tag{1.7.12}$$

$$\tilde{E}_t^f[s_{t+1}] = s^* \tag{1.7.13}$$

where $\tilde{E}_t^f[s_{t+1}]$ and $\tilde{E}_t^c[s_{t+1}]$ denote the expectations of fundamentalists and chartists with respect to the future real stock price, respectively, and s_t^* is the fundamental value of s_t according to the fundamentalists. It is assumed equal to 0 (i.e. no deviation from the steady state).

Equation 1.7.11 could thus be simplified to:

$$\tilde{E}_t s_{t+1} \quad = \quad \omega_t^{s,c} s_{t-1}. \tag{1.7.14}$$

Investment is defined by:

$$\begin{aligned} i_t &= e_1 \tilde{E}_t y_{t+1} + e_2(\rho_t - \tilde{E}_t \pi_{t+1}) \\ &= e_1 \tilde{E}_t y_{t+1} + e_2(r_t + \chi_t - \tilde{E}_t \pi_{t+1}) \end{aligned} \tag{1.7.15}$$

where χ_t is the interest rate spread.

Plug Taylor rule and market expectations of π_t and y_t in 1.7.10 and 1.7.15 then plug these in 1.7.9 and rearrange to reach the <u>second state equation</u>:

$$\begin{aligned} (1 - d_1 - \phi_y d_3 - \phi_y e_2) y_t =& (d_3 + e_2)\phi_\pi \pi_t + e_2 \chi_t + (d_2 \omega_t^{y,c} + e_1 \omega_t^{y,c}) y_{t-1} \\ & - (d_3 \omega_t^{\pi,c} + e_2 \omega_t^{\pi,c} + d_4 \omega_t^{\pi,c}) \pi_{t-1} + \\ & (d_3 + e_2)\phi_r r_{t-1} + (d_3 + e_2)\epsilon_t^r + (d_3 \phi_s + e_2 \phi_s) s_t + d_4 \omega_t^{s,c} s_{t-1}. \end{aligned} \tag{1.7.16}$$

The consolidated budget constraint of households is defined by:

$$y_t + (r_{t-1} - \pi_t) d_{t-1} + (s_{t-1} - p_{t-1}) \Lambda_{t-1} = c_t + d_t + (s_{t-1} - p_{t-1}) \Lambda_t + (\rho_{t-1} - \pi_t) l_{t-1}. \tag{1.7.17}$$

Households' demand for stock is defined by:

$$\Lambda_t = [c_{\Lambda,y} y_t - c_{\Lambda,r} r_t - c_{\Lambda,s}(s_t - p_t)] + [\omega_t^{s,c} D_t^c + (1 - \omega_t^{s,c}) D_t^f] \tag{1.7.18}$$

where D_t^c is the net demand of chartists and is given by:

$$\begin{aligned}D_t^c &= E_t^c s_{t+1} - s_{t-1} \\ &= s_{t-1} - s_{t-1} \\ &= 0\end{aligned} \tag{1.7.19}$$

and D_t^f is the net demand of fundamentalists and is given by:

$$\begin{aligned}D_t^f &= E_t^f s_{t+1} - s_{t-1} \\ &= 0 - s_{t-1} \\ &= -s_{t-1}.\end{aligned} \tag{1.7.20}$$

Substitute c_t and Λ_t in equation 1.7.17 with equations 1.7.10 and 1.7.18 respectively, then plug in the Taylor rule, the market expectations as well as the net demand of chartists and fundamentalists to reach the third state equation:

$$\begin{aligned}d_t = [-d_{t-1} + c_{\Lambda,r}s_{t-1}\phi_\pi - \sum \pi_{t-1}c_{\Lambda,r}\phi_\pi + c_{\Lambda,s}\sum \pi_{t-1} - c_\Lambda, ss_{t-1} + l_{t-1} - d_3\phi_\pi]\pi_t \\ -[-1 + s_{t-1}c_{\Lambda,s} - c_{\Lambda,r}s_{t-1}\phi_y - \sum \pi_{t-1}c_{\Lambda,y} + \phi_y \sum \pi_{t-1}c_{\Lambda,r} + d_1 + \phi_y d_3]y_t \\ -[-c_{\Lambda,r}\phi_s - c_{\Lambda,s}s_{t-1} + \sum \pi_{t-1}c_{\Lambda,r}\phi_s + c_{\Lambda,s}\sum \pi_{t-1} + d_3\phi_s]s_t \\ +[d_3\omega_t^{\pi,c} + d_4\omega_t^{\pi,c}]\pi_{t-1} - d_2\omega_t^{c,y}y_{t-1} + r_{t-1}d_{t-1} \\ +[\Lambda_{t-1} - c_{\Lambda,s}\sum \pi_{t-1} + s_{t-1}\omega_t^{f,s} - \omega_t^{f,s}\sum \pi_{t-1} - d_4\omega_t^{c,s} + c_{\Lambda,r}\phi_r r_{t-1} + c_{\Lambda,r}\epsilon_t^r]s_{t-1} \\ -\sum \pi_{t-1}\Lambda_{t-1} - \sum \pi_{t-1}c_{\Lambda,r}\epsilon_t^r - \sum \pi_{t-1}c_{\Lambda,r}r_{t-1}\phi_r + c_{\Lambda,s}[\sum \pi_{t-1}]^2 - \rho_{t-1}l_{t-1} - d_3\phi_r r_{t-1} - d_3\epsilon_t^r.\end{aligned} \tag{1.7.21}$$

Banking

The banking sector faces the following maximization problem:

$$\max_{l_t} \quad \chi_t l_t - \frac{\kappa}{2}(l_t - d_t - \nu^* l_t)^2.$$

Take derivative with respect to l_t:

$$\begin{aligned}&\chi_t - \kappa(1-\nu^*)((1-\nu^*)l_t - d_t) = 0 \\ &\chi_t - \kappa(1-\nu^*)^2 l_t + \kappa(1-\nu^*)d_t = 0 \\ &\kappa(1-\nu^*)^2 l_t = \chi_t + \kappa(1-\nu^*)d_t \\ &l_t = \frac{1}{\kappa(1-\nu^*)^2}\chi_t + \frac{1}{1-\nu^*}d_t.\end{aligned} \tag{1.7.22}$$

Assume $\frac{1}{\kappa(1-\nu^*)^2} = \eta$. Equation 1.7.22 becomes:

$$l_t = \eta\chi_t + \kappa\eta(1-\nu^*)d_t. \tag{1.7.23}$$

Banks are assumed to set the spread rate such that the quantity of loans demanded by firms is equal to the profit maximizing loan level they wish to supply. In other words, the spread rate takes the value that clears the credit market:

$$\begin{aligned} i_t &= l_t \\ e_1\omega_t^{y,c}y_{t-1} + e_2r_t - e_2\omega_t^{\pi,c}\pi_{t-1} + e_2\chi_t &= \eta\chi_t + \kappa\eta(1-\nu^*)d_t. \end{aligned} \tag{1.7.24}$$

Plugging in the Taylor rule and solving for χ_t yields the <u>fourth state equation</u>:

$$\begin{aligned} (e_2-\eta)\chi_t = &- e_2\phi_\pi\pi_t - e_2\phi_y y_t + \kappa\eta(1-\nu^*)d_t + e_2\omega_t^{\pi,c}\pi_{t-1} - e_1\omega_t^{y,c}y_{t-1} \\ &- e_2\epsilon_t^r - e_2\phi_r r_{t-1} - e_2\phi_s s_t. \end{aligned} \tag{1.7.25}$$

The stock market

$$s_t = s_{t-1} + (1-\omega_t^{s,c})D_t^f + \omega_t^{s,c}D_t^c + c_{\Lambda,y}y_t - c_{\Lambda,r}r_t - c_{\Lambda,s}s_t + \epsilon_t^s. \tag{1.7.26}$$

Plug in Taylor rule, substitute D_t^c and D_t^f for equations 1.7.19 and 1.7.20 respectively and rearrange to reach the <u>fifth state equation</u>:

$$[1 + c_{\Lambda,s} + c_{\Lambda,r}\phi_s]s_t = [1 - (1-\omega_t^{s,c})]s_{t-1} + \epsilon_t^s + [c_{\Lambda,y} - c_{\Lambda,r}\phi_y]y_t - c_{\Lambda,r}\phi_\pi\pi_t - c_{\Lambda,r}\epsilon_t^r - c_{\Lambda,r}\phi_r r_{t-1}. \tag{1.7.27}$$

The state space representation

The state space representation then reads:

$$\begin{pmatrix} \pi_t \\ y_t \\ d_t \\ \chi_t \\ s_t \end{pmatrix} = \mathbf{A}_t^{-1}\mathbf{B_t} \begin{pmatrix} \pi_{t-1} \\ y_{t-1} \\ d_{t-1} \\ \chi_{t-1} \\ s_{t-1} \end{pmatrix} + \mathbf{A}_t^{-1}\mathbf{C_t} \tag{1.7.28}$$

where:

$$A_t = \begin{pmatrix} 1 & -b_2 & 0 & 0 & 0 \\ -(d_3+e_2)\phi_\pi & 1-d_1-\phi_y d_3-\phi_y e_2 & 0 & -e_2 & -d_3\phi_s - e_2\phi_s \\ A_{3,1} & A_{3,2} & 1 & 0 & A_{3,5} \\ \phi_\pi e_2 & \phi_y e_2 & -\kappa\eta(1-\nu^*) & e_2-\eta & e_2\phi_s \\ c_{\Lambda,r}\phi_\pi & c_{\Lambda,r}\phi_y - c_{\Lambda,y} & 0 & 0 & 1+c_{\Lambda,s}+c_{\Lambda,r}\phi_s \end{pmatrix}$$

where $A_{3,1} = d_{t-1} - c_{\Lambda,r}s_{t-1}\phi_\pi + \sum \pi_{t-1}c_{\Lambda,r}\phi_\pi - c_{\Lambda,s}\sum \pi_{t-1} + c_{\Lambda,s}s_{t-1} - l_{t-1} + d_3\phi_\pi$

$A_{3,2} = -1 + s_{t-1}c_{\Lambda,s} - c_{\Lambda,r}s_{t-1}\phi_y - \sum \pi_{t-1}c_{\Lambda,y} + \phi_y \sum \pi_{t-1}c_{\Lambda,r} + d_1 + \phi_y d_3$ and

$A_{3,5} = -c_{\Lambda,r}\phi_s - c_{\Lambda,s}s_{t-1} + \sum \pi_{t-1}c_{\Lambda,r}\phi_s + c_{\Lambda,s}\sum \pi_{t-1} + d_3\phi_s$.

$$B_t = \begin{pmatrix} b_1 * \omega_t^{\pi,c} & 0 & 0 & 0 & 0 \\ -(d_3+e_2+d_4)\omega_t^{\pi,c} & (d_2+e_1)\omega_t^{y,c} & 0 & 0 & d_4\omega_t^{s,c} \\ d_3\omega_t^{\pi,c} + d_4\omega_t^{\pi,c} & -d_2\omega_t^{c,y} & r_{t-1} & 0 & B_{3,5} \\ e_2\omega_t^{\pi,c} & -e_1\omega_t^{y,c} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-\omega_t^{s,f} \end{pmatrix}$$

where $B_{3,5} = \Lambda_{t-1} - c_{\Lambda,s}\sum \pi_{t-1} + s_{t-1}\omega_t^{f,s} - \omega_t^{f,s}\sum \pi_{t-1} - d_4\omega_t^{c,s} + c_{\Lambda,r}\phi_r r_{t-1} + c_{\Lambda,r}\epsilon_t^r$ and

$$C_t = \begin{pmatrix} \epsilon_t^\pi \\ (d_3+e_2)\phi_r r_{t-1} + (d_3+e_2)\epsilon_t^r \\ -\sum \pi_{t-1}\Lambda_{t-1} - \sum \pi_{t-1}c_{\Lambda,r}\epsilon_t^r - \sum \pi_{t-1}c_{\Lambda,r}r_{t-1}\phi_r + c_{\Lambda,s}[\sum \pi_{t-1}]^2 - \rho_{t-1}l_{t-1} - d_3\phi_r r_{t-1} - d_3\epsilon_t^r \\ -e_2\epsilon_t^r - e_2\phi_r r_{t-1} \\ \epsilon_t^s - c_{\Lambda,r}\epsilon_t^r - c_{\Lambda,r}\phi_r r_{t-1} \end{pmatrix}.$$

Impulse Response Analysis

To calculate the impulse response functions, we follow the steps of the experiment discussed in Lengnick and Wohltmann (2013). These steps are described as follows:

1. Generate model dynamics for one particular random seed.
2. Generate the dynamics again with the same random seed, but with e.g. ϵ^r_{50} increased by 0.5. In other words, at time $t = 50$, the value of the interest rate shock is higher than the same shock at the same time in the previous step with an amount +0.5.
3. Calculate the difference between the trajectories of steps 1 and 2 which gives the isolated impact of the additional cost shock.
4. Repeat steps 1-3 for 10000 times.

Chapter 2

Monetary Policy, Stock Prices and Temporal Aggregation in a New Keynesian Model with Behavioural Expectations[1]

[1] This Chapter is based on joint work with Prof. Dr. Christian R. Proaño.

2.1 Introduction

While in the great majority of macroeconomic models the frequencies of the Data Generation Process (DGP) and the Data Collection Process (DCP) are implicitly or explicitly assumed to be the same, "[t]here is simply no reason to believe that the frequency at which economic time series are collected coincides with the frequency at which economic agents make decisions" (Christiano and Eichenbaum, 1987, p.64). In the case of macroeconomic aggregates such as the economy's GDP, in particular, data is collected and reported much less frequently than it is generated, due to the substantial costs of such processes. This situation, in which a variable's evolution through time cannot be observed at all dates it is generated, is known as *temporal aggregation* and has been widely investigated – mostly from the time series analysis perspective –, by e.g. Theil (1954), Mundlak (1961), Sims (1971), Zellner and Montmarquette (1971), Stock (1987), Marcet (1991), Marcellino (1999), and more recently, by Chan (2022).

In spite of the potential usefulness of averaging or summarizing high frequency data into lower frequencies e.g. in eliminating high frequency noise that may obscure more relevant behaviour, theory predicts that temporal aggregation leads to non-trivial losses of information about the underlying data processes, especially with regards to their true statistical properties (Rossana and Seater, 1995). Further, temporal aggregation and the choice of sampling frequency are especially relevant when assessing the persistence of macroeconomic aggregates (Paya et al., 2007), modelling the dynamics of asset price volatility (Perron and Shi, 2020), studying spill-over effects of financial uncertainty shocks on the real economy (Ferrara and Guérin, 2018), or assessing the adequateness of monetary policy rules (Bayar, 2014).

While temporal aggregation is particularly relevant for macroeconomic data, financial market data is, by contrast, readily available at frequencies that are almost as high as that of their DGP. As a result, the information set available to the public and policy-makers consists of data of different frequencies: financial market data is available, in general, at high frequencies, and macroeconomic data at lower frequencies. While this issue is widely acknowledged, there is no clear consensus on how macroeconomic and financial data should be linked consistently in a theoretical model, instead of simply assuming a uniform frequency for all macroeconomic and financial variables, as it is usually done in the great majority of the macroeconomic models (see e.g. Woodford, 2003), as recently pointed out by Christensen et al. (2016).

Against this background, the main objective of the present paper is to analyse to what extent the macroeconomic and financial stability of an economy would be affected by a monetary policy rule that reacts to daily (available) stock prices, instead of using only their quarterly averages (to match the frequency of macroeconomic variables), and so losing intra-quarter information. We analyse this issue from a behavioural macroeconomic perspective, starting with the premise that agents, due to cognitive or informational constraints, use simple expectational rules-of-thumb to forecast macroeconomic and financial variables instead of using model-consistent or "rational" expectations in the sense of Muth (1961). Accordingly, the availability of data will significantly determine or constrain the updating frequency of their expectations, what will in turn have non-trivial effects on the dynamics of the economy. Just to be clear: Our objective is not to argue for a monetary policy rate that would react on daily basis in response to stock price fluctuations, but instead to quantify the informational "losses" from temporal aggregation from a theoretical perspective, and to indirectly highlight the importance of econometric mixed-frequency techniques as e.g. discussed in Carriero et al. (2015) for real-time nowcasting and policy-making.

The role of asset prices in the monetary policy design has been widely investigated in the literature, also from a behavioural perspective, see e.g. Kontonikas and Ioannidis (2005), Kontonikas and Montagnoli (2006), Bask (2012), Westerhoff (2012), Naimzada and Pireddu (2013) and Caines and Winkler (2018). However, the debate upon whether monetary policy should respond to asset prices/bubbles is hardly settled. Economists who argue against this proposal, stress that asset prices are too volatile, too unrelated to the real economy, and/or with misalignments that are difficult to detect. Further, a wrong response (e.g. over responding) may lead to excess output volatility (see, e.g., Gertler et al. 1998 and Cogley 1999). Bernanke and Gertler (1999, 2001) state that price stability and financial stability are complementary; by stabilizing prices and output, the monetary authority may also stabilize asset prices. In other words, responding to inflation and output captures the benefit of asset price targeting, without risking the costs (i.e. excess volatility, the baggage of the appearance of interfering in the workings of financial markets, etc.). On the other hand, Gilchrist and Leahy (2002), for instance, assert that all these concerns would appear to argue for caution in using asset price information, rather than ignoring such information. They, as well as e.g. Gilchrist and Saito (n.d.) and Dong et al. (2020), explain that, whether targeting asset prices (or asset bubbles) is beneficial, depends on the information structure of the economy, the particular interest rate rule adopted by the central bank and/or the type of shocks hitting the economy, an argument that is also supported by our analysis.

Relevantly, Chen and Phelan (2021) suggest that financial sector considerations alone justify at least an additional rate cut during a financial crisis beyond what would be implied by a standard Taylor rule responding to output gaps. More specifically, policies that combine leaning against the wind in good times, with accommodative rates during financial distress, can substantially improve stability. Further, the consequences of monetary policy for financial stability are state-dependent: the stability benefits of monetary policy depend critically on the timing, with the greatest potential benefits coming when rate cuts occur during financial crises. In another approach, Caballero and Simsek (2022) design a model where monetary policy operates through financial markets: the central bank affects asset prices, which in turn affects aggregate demand with a delay.

We investigate our research question by incorporating temporal aggregation of real macroeconomic variables in the New Keynesian model developed by Airaudo et al. (2015), while assuming that the economy's overall DGP is of a daily frequency, and that agents use simple expectational rules-of-thumb based on observed data. We show that the effect of temporal aggregation in the real sector can be reduced through an interest policy rule that reacts to the daily available stock market prices. In our mixed-frequency dynamic framework, the daily available financial data can serve as a proxy for the real data, which is assumed to be available on a quarterly basis only. Moderately targeting this "proxy" can simultaneously stabilize the financial sector as well as the real sector, on which data is available with a significant delay. We thus provide a further argument for monetary policy to take asset prices fluctuations into account.

The remainder of this paper is organized as follows. In section 2.2 we present our mixed-frequency behavioural macroeconomic model, and describe in detail the assumed Data Collection Process. In section 2.3 we conduct some dynamic adjustments and discuss the results of our numerical exercises. In section 2.4, we investigate the rationale of targeting asset prices by the monetary authorities. In section 2.5 we draw some final conclusions from this study.

2.2 Theoretical Framework

2.2.1 The Original Model by Airaudo et al. (2015)

The starting point for our analysis is the theoretical New Keynesian model developed by Airaudo et al. (2015), see also Nisticò (2012). The frequency of this model, as well as of the great majority of the macroeconomic models specified in discrete time, is a quarterly one (Airaudo et al., 2015, p. 1287). In our representation of the model, and to distinguish between the quarterly frequency adopted in this model and the mixed frequency that will be assumed in the rest of the paper, we denote by q the quarterly time index, and use the subscript t to denote daily frequency. Further, let T^q denote the number of "trading days", i.e. days with economic activity, in a quarter. Following Lengnick and Wohltmann (2013, 2016), we assume for simplicity that there is no economic activity (stock market trading, goods production, etc.) on the weekends, so that $T^q = 64 \approx 3 \cdot 30 \cdot \frac{5}{7}$ days per quarter. This implies that a quarter (q) is defined to contain the days $64(q-1)+1, \ldots, 64q$.

In a nutshell, the model developed by Airaudo et al. (2015) is a New Keynesian DSGE model with financial markets and an indefinite number of cohorts of non-Ricardian agents who survive between any two subsequent periods with constant probability $1-\gamma$, where γ is the turnover ratio. A non-zero turnover ratio in financial markets between long-time traders (holding assets) and newcomers (entering the market with no assets) makes financial markets intertemporally incomplete, and hence partially hinders the agents' traditional consumption smoothing schedule. As a result, the wedge between the current and the expected level of aggregate consumption is driven not only by the ex ante real interest rate, as in the standard New Keynesian model, but also by the market value of financial wealth, since the latter is responsible for the difference between the consumption level of long-time traders and newcomers. Airaudo et al. (2015) call the mechanism through which stock price fluctuations feedback into real activity via their wealth effects on consumption the *Financial Wealth Channel* (FWC).

Using the quarterly time index q, the log-linearised version of the Airaudo et al. (2015) model is described below. The demand-side block, the supply-side block, the financial-side block and the forward-looking Taylor rule are respectively presented by (see Airaudo et al., 2015 eqs. 20-26):

$$
\begin{aligned}
y_q &= \frac{1}{1+\psi}E_q y_{q+1} + \frac{\psi}{1+\psi}s_q - \frac{1}{1+\psi}(r_q - E_q\pi_{q+1}) && (2.2.1)\\
\pi_q &= \tilde{\beta}E_q\pi_{q+1} + \kappa(1+\chi)(y_q - z_q) && (2.2.2)\\
s_q &= \tilde{\beta}E_q s_{q+1} - \lambda E_q y_{q+1} - (r_q + E_q\pi_{q+1}) + \varphi z_q && (2.2.3)\\
r_q &= \phi_\pi E_q\pi_{q+1} + \phi_s E_q s_{q+1} && (2.2.4)
\end{aligned}
$$

where y_q represents the aggregate demand (=aggregate output), π_q the price inflation rate, r_q the policy nominal interest rate and s_q the stock price in a quarter q, all represented as percentage deviations of the original variables from their respective steady-state values, that is, $x_q = \log(X_q/X)$. $z_q = \rho_z \cdot z_{q-1} + \nu_q$ is an AR(1) technology shock, where $\rho_z \in (0,1)$ and ν_q is an i.i.d. disturbance. The FWC (i.e. effect of stock price fluctuations on the real activity) is captured by the term $(\frac{\psi}{1+\psi})$. $\tilde{\beta} \equiv \frac{\beta}{1+\psi}$ is the discount factor β adjusted for a positive turnover ratio γ. The composite coefficient ψ is equal to:

$$\psi \equiv \gamma\frac{1-\beta(1-\gamma)}{(1-\gamma)\epsilon}\frac{1+r}{r}$$

where ϵ is the elasticity of substitution across differentiated goods and r is the steady state real interest rate. The latter is equal to (see Airaudo et al., 2015, p.1300):

$$
\begin{aligned}
r &= f(\beta,\gamma,\epsilon)\\
&= \frac{(1-\gamma)(1-\beta) + \frac{\gamma[1-\beta(1-\gamma)]}{\epsilon} + \sqrt{\Psi}}{2\beta(1-\gamma)} \text{ where} && (2.2.5)\\
\Psi &\equiv \left[(1-\gamma)(1-\beta) + \frac{\gamma[1-\beta(1-\gamma)]}{\epsilon}\right]^2 + 4\,\frac{\gamma[1-\beta(1-\gamma)]\beta(1-\gamma)}{\epsilon} > 0.
\end{aligned}
$$

Finally,

$$\kappa \equiv \frac{(1-\theta)\left(1-\theta\tilde{\beta}\right)}{\theta}$$
$$\lambda \equiv (1-\tilde{\beta})[(\epsilon-1)(1+\chi)-1] \quad \text{and} \quad \varphi \equiv (1-\tilde{\beta})(\epsilon-1)(1+\chi)\rho_z$$

where θ is the Calvo price stickiness probability, and $\chi \equiv \frac{N}{1-N}$ is the inverse of the (steady-state) Frisch elasticity of labour supply N.

The relevance of the turnover rate γ in the model is easily outlined: A non-zero value for γ establishes the feedback between the stock market and the real economy. As the turnover rate goes to zero, only infinitely lived traders operate in the market, $\psi \to 0$, $\tilde{\beta} \to \beta$, the FWC vanishes (i.e. $\frac{\psi}{1+\psi} \to 0$) and the model collapses to the benchmark New Keynesian model where there is no rationale for monetary policy to target stock prices (see e.g. Bernanke and Gertler, 2001, Bullard and Schaling, 2002 and Carlstrom and Fuerst, 2007).

2.2.2 A Mixed-Frequency Representation of the Model

In the following, we explain the mechanism through which we alter the representation of the model's frequency to incorporate and analyse the issue of temporal aggregation. More specifically, we adopt a mixed frequency framework in which financial and policy data is generated and collected daily, while real data is generated daily, but collected only quarterly. As will be made clear below, a mixed frequency framework is capable of capturing such a delay in collecting data relative to its generation process.

The log linearised mixed-frequency version of the model is described by:

$$y_t = \frac{1}{1+\psi}\tilde{E}_q y_{q+1} + \frac{\psi}{1+\psi}s_t - \frac{1}{1+\psi}(r_t - \tilde{E}_q \pi_{q+1}) \tag{2.2.6}$$
$$\pi_t = \tilde{\beta}\tilde{E}_q \pi_{q+1} + \kappa(1+\chi)(y_t - z_t) \tag{2.2.7}$$
$$s_t = \tilde{\beta}^d \tilde{E}_t s_{t+1} - \lambda \tilde{E}_q y_{q+1} - (r_t + \tilde{E}_q \pi_{q+1}) + \varphi z_t \tag{2.2.8}$$
$$r_t = \phi_\pi \tilde{E}_q \pi_{q+1} + \phi_s \tilde{E}_t s_{t+1} \tag{2.2.9}$$

where the subscript t indicates the daily generation of the variable (i.e. the daily stance of the deviation from the quarterly steady state) and the tilde above the expectation operator indicates boundedly rational, backward-looking expectations. Naturally, these backward-looking expectations depend on already collected information about the model variables. Since the DCP for the real variables (i.e. output and inflation) is of a quarterly frequency, expectations are also updated only once in a quarter, hence the subscript q in $\tilde{E}_q y_{q+1}$ and $\tilde{E}_q \pi_{q+1}$. On the other hand, data on the stock market is available on daily basis. Expectation of stock price is therefore daily updated; hence the subscript t in $\tilde{E}_t s_{t+1}$. $\tilde{\beta}^d$ is the discount factor $\tilde{\beta}$ adjusted for a daily frequency. It is equal to $\tilde{\beta}^{\frac{1}{64}}$.[2]

Similar to the baseline scenario in Airaudo et al. (2015), the policy rate reacts to expected inflation and the expected stock price. It is straightforward to observe that the frequency of the policy rate depends on the value of ϕ_s: a non-zero value for ϕ_s implies that the policy rate is set on a daily frequency, while for $\phi_s = 0$, the policy rate is set once every quarter, as it is a function of expected price inflation only, which itself is – by assumption – updated only once every quarter.

Further, the technology shock process is specified as follows

$$z_t = \rho_z^d z_{t-1} + \iota_t \nu_t \tag{2.2.10}$$

where ι_t is a random process that takes the value of 1 with a probability $\frac{1}{T^q}$ and 0 with a probability $1 - \frac{1}{T^q} = \frac{63}{64}$, and $\rho_z^d = \rho_z^{\frac{1}{T^q}}$. This way, a shock occurs on average once per quarter, analogous to a standard quarterly frequency model (e.g. Airaudo et al. 2015) and its persistence is equivalent to the persistence assumed in the quarterly frequency version.

Randomizing the day within the quarter, when a shock may occur, enlarges the scope of relevance of studying day to day updates of the model economy rather than simply the quarterly frequency version. To see this clearly, observe how equations (2.2.7) and (2.2.8) state that a shock arriving at any day t has an immediate effect on the inflation rate and the stock price, respectively. The change in the latter also immediately affects aggregate output (see equation 2.2.6). Following that, as will be later discussed (see equations 2.2.14 and 2.2.20 below), the expected stock price reacts to a change in the stock price with a one day delay. Further, at a non zero value for ϕ_s, the policy rate reacts immediately to the change in the (expected) stock price (see equation 2.2.9). Output, inflation rate and the stock price are by turn instantly impacted, and so forth. Our mixed frequency model can capture these updates as they happen, and then capture the effect of the real data when it is collected and made available at the end of the quarter. A homogeneous frequency (i.e. quarterly) model assumes that all these updates happen at a single point in time, and is unable to study such a gradual escalation in the dynamics portrayed here.

Finally, along the lines of e.g. De Grauwe (2011, 2012), we assume that agents are either targeters or naive regarding their expectations formation. Targeters expect a variable to return to its steady state value in the next period or, put differently, the variable's deviation from its steady state to be zero. On the other hand, naive agents expect the future value of a variable to be equal to the last known value for that variable. As within the days of a given quarter, data on the current quarter for output

[2] Equivalently, one can calculate the steady state daily real interest rate, $r^d = (1 + r)^{\frac{1}{64}} - 1$. Then, $\tilde{\beta}^d = \frac{1}{1+r^d}$.

and inflation is unavailable, agents use the most recent available data, i.e. data on the last quarter, to make expectations about the next quarter, i.e.

$$\text{Targeting expectations: } \tilde{\mathrm{E}}_q^{\text{tar}}\left[x_{q+1}\right] = 0 \qquad x \in \{y, \pi\} \tag{2.2.11}$$

$$\text{Naive expectations: } \tilde{\mathrm{E}}_q^{\text{naive}}\left[x_{q+1}\right] = x_{q-1}. \tag{2.2.12}$$

For the stock price, in contrast, agents can use the stock price of yesterday to make expectations concerning the stock price tomorrow:

$$\text{Targeting expectations: } \tilde{\mathrm{E}}_t^{\text{tar}}\left[s_{t+1}\right] = 0 \tag{2.2.13}$$

$$\text{Naive expectations: } \tilde{\mathrm{E}}_t^{\text{naive}}\left[s_{t+1}\right] = s_{t-1}. \tag{2.2.14}$$

The attractivity of a given heuristic A^j, $j \in \{\text{targeters}, \text{naive}\}$, is defined as a geometric sum of past squared expectation errors (cf. De Grauwe, 2010, 2011). Again, the quarter availability of data for the real sector means that agents can evaluate the performance of a given heuristic only once per quarter. On the other hand a daily evaluation of the stock expectation heuristics is possible:

$$A_q^{x,j} = -\left(x_{q-1} - E_{q-2}^j x_{q-1}\right)^2 + \zeta\, A_{q-1}^{x,j} \qquad x \in \{y, \pi\} \tag{2.2.15}$$

$$A_t^{s,j} = -\left(s_{t-1} - E_{t-2}^j s_{t-1}\right)^2 + \zeta\, A_{t-1}^{s,j} \tag{2.2.16}$$

where $0 \leq \zeta < 1$ is a memory coefficient. A lower value for ζ indicates a higher speed with which agents forget about the past.

As it is usual in the behavioural finance literature, the fractions of agents ω^j for the two heuristics are determined via a Brock and Hommes (1997, 1998) discrete choice approach (see also Westerhoff, 2012; Franke and Westerhoff, 2012; and De Grauwe, 2011):[3]

$$\omega_q^{x,j} = \frac{\exp\left(\mu A_q^{x,j}\right)}{\exp\left(\mu A_q^{x,\text{tar}}\right) + \exp\left(\mu A_q^{x,\text{naive}}\right)} \qquad x \in \{y, \pi\} \tag{2.2.17}$$

$$\omega_t^{s,j} = \frac{\exp\left(\mu A_t^{s,j}\right)}{\exp\left(\mu A_t^{s,\text{tar}}\right) + \exp\left(\mu A_t^{s,\text{naive}}\right)} \tag{2.2.18}$$

with μ being the intensity of choice parameter.

Market expectations are then given by a weighted average of the two heuristics:

$$\tilde{\mathrm{E}}_q\left[x_{q+1}\right] = \omega_q^{\text{x,tar}} \tilde{\mathrm{E}}_q^{\text{x,tar}}\left[x_{q+1}\right] + \omega_q^{\text{x,naive}}\, \tilde{\mathrm{E}}_q^{\text{x,naive}}\left[x_{q+1}\right] \tag{2.2.19}$$

$$\tilde{\mathrm{E}}_t\left[s_{t+1}\right] = \omega_t^{\text{s,tar}} \tilde{\mathrm{E}}_t^{\text{s,tar}}\left[s_{t+1}\right] + \omega_t^{\text{s,naive}}\, \tilde{\mathrm{E}}_t^{\text{s,naive}}\left[s_{t+1}\right]. \tag{2.2.20}$$

[3]See e.g. Alfarano and Milaković (2009) for insights on the categorization of models with behavioural heterogeneity and herding in financial markets.

We now turn to the description of the assumed data collection process and how this feeds back into the expectations mechanism.

2.2.3 Data Collection Process under Temporal Aggregation

As the last day of a quarter q (i.e. day $t = 64 \cdot q$) is reached, data for that quarter is published. At this point, the last generated value for a variable represents its quarterly collected value,[4] namely:

$$\text{DCP:} \quad y_q = y_{t=64\cdot q} \tag{2.2.21}$$

$$\text{DCP:} \quad \pi_q = \pi_{t=64\cdot q}. \tag{2.2.22}$$

For the (unobservable) technology shock, the quarterly value can be thought of as the shock persistent from the last quarter plus the sum of newly arrived shocks within the quarter:

$$\text{DCP:} \quad z_q = \rho_z z_{q-1} + \sum_{t-63}^{t} (\iota_t \cdot \nu_t). \tag{2.2.23}$$

When data concerning the quarter has been collected, agents evaluate the attractivity of the different expectations heuristics, update their corresponding choices and take their economic decisions accordingly.

Despite of its simplicity, this assumed DCP enables us to represent and highlight different important features. First, and foremost, the model explicitly accounts for mismatches between Data Generation and Data Collection processes. Such mismatches make studying the role of expectations even more relevant: how do expectations based on delayed information affect real, financial and monetary variables as they evolve day to day, and vice versa? Second, in our model, an interest rate policy that targets the stock market does not need to wait for the new quarter to begin to react to stock price fluctuations, which are available on a daily basis. And third, as technology shocks can occur any day within a quarter, and not necessarily at the beginning of a new quarter, the discrepancy between the DCP and the DGP is even stronger. In the next section, we numerically study how these features interact, and compare the dynamics resulted from these interactions to the dynamics obtained from the standard quarterly frequency model.

[4] See Bayar (2014) for insights on the outperformance of end of period values compared to average values in the monetary policy design. In our framework, end of period values are preferred to average values because the first allow for decisions (e.g. expectations formation and policy rate setting) that are based on the exact stance of the real variables at the beginning of the new quarter rather than on average values from the previous quarter, which are no longer relevant (see Figures 2.1 and 2.2 for a visual illustration). Further, end of quarter values are consistent with our assumption regarding the data generation process (see Section 2.2.2).

2.3 Model Analysis

2.3.1 Calibration

The baseline parameter values used in our numerical simulations are summarized in Table 2.1. Mostly, we adopt the calibration values of Airaudo et al. (2015). For the behavioural parameters, we follow Lengnick and Wohltmann (2016).

Table 2.1: Baseline simulation parameter values. ANZ (2015) stands for Airaudo, Nisticó and Zanna (2015), and LW (2016) for Lengnick and Wohltmann (2016).

Parameter	Value	Source
Main Parameters		
number of days per quarter	$T^q = 64$	LW (2016)
turnover ratio	$\gamma = 0.05$	ANZ (2015)
intertemporal discount factor	$\beta = 0.99$	ANZ (2015)
β adjusted for a positive turnover	$\tilde{\beta} = 0.96$	ANZ (2015)
elasticity of substitution between intermediate goods	$\epsilon = 2.3$	ANZ (2015)
the inverse of the Frisch elasticity of labor supply	$\chi = 0.25$	ANZ (2015)
Calvo price stickiness probability	$\theta = 0.91$	ANZ (2015)
ss of quarterly real interest rate	$r = 0.043$	ANZ (2015)
composite parameter κ	$\kappa = 0.011$	ANZ (2015)
composite parameter ψ	$\psi = 0.03$	ANZ (2015)
composite parameter λ	$\lambda = 0.0259$	ANZ (2015)
composite parameter ϕ	$\phi = 0.047$	ANZ (2015)
composite parameter Ψ	$\Psi = 0.005$	ANZ (2015)
Monetary Policy		
coefficient of inflation	$\phi_\pi = 2$	ANZ (2015)
coefficient of stock price	$\phi_s = 0.0$	ANZ (2015)
Bounded Rationality, Learning		
memory coefficient	$\zeta = 0.5$	LW (2016)
intensity of choice	$\gamma = 10$	LW (2016)
Technology Shock		
shock persistence (quarterly)	$\rho_z = 0.7$	LW (2016)
standard deviation shock technology	$\sigma_z = 0.15$	LW (2016)

Temporal aggregation in our model is exemplary illustrated in Figure 2.1. The dotted lines represent the day to day evolution of price inflation, output and the underlying technology shock. Given data

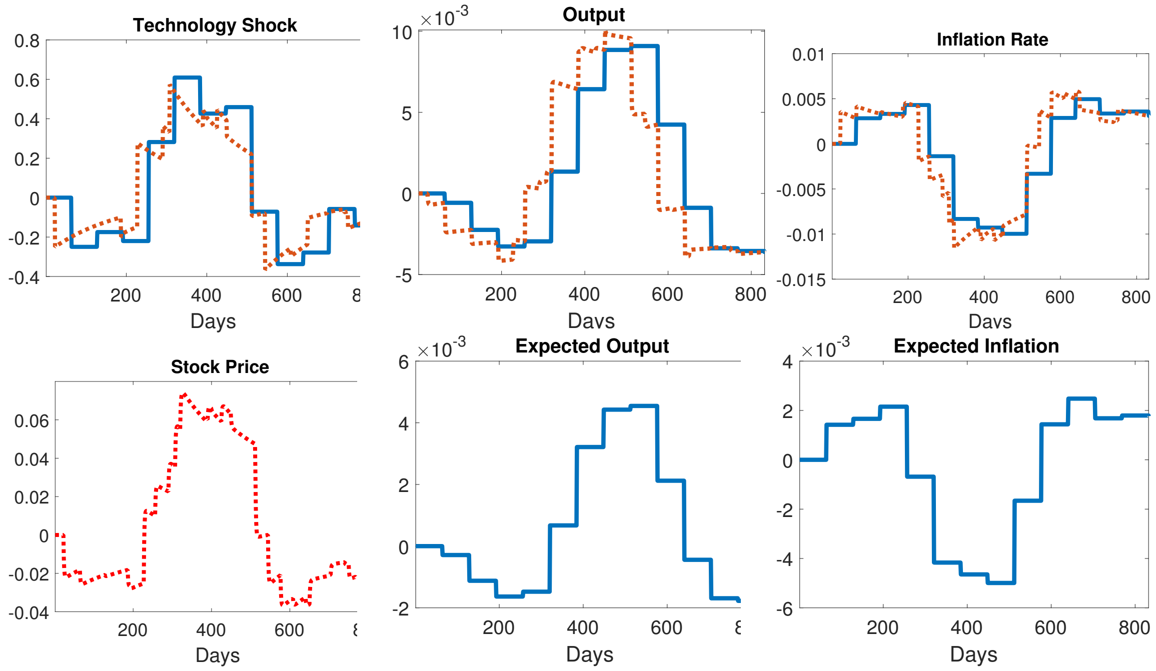

Figure 2.1: Temporal aggregation in the real sector. The dotted line shows the day-to-day generation of the variable. The solid line shows the quarterly collected values.

collection and processing costs, this data is assumed not to be observable on a daily basis, and becomes only available to, or observable by, the public at the end of the quarter, in an aggregated form. The solid line corresponds to this quarterly published data. Further, as only quarterly figures of price inflation and output are in the information set of the agents, expectational rules of thumb (equations 2.2.11 and 2.2.12) are only updated once at the beginning of the quarter, delivering aggregate expectations of output and inflation of a quarterly frequency.

In Figure 2.2, we illustrate the capability of our mixed-frequency framework to produce quarterly collected values that are comparable to the values obtained from the quarterly frequency model. More specifically, Figure 2.2 illustrates the IRFs (Impulse Response Functions) of the quarterly values of output, inflation and the technology shock from our mixed frequency model (the model as in equations 2.2.6 to 2.2.9) as well as the quarterly frequency model (the model as in equations 2.2.1 to 2.2.4, under heterogeneous boundedly rational expectations) in response to a one standard deviation technology shock. As will be later in more details explained, a positive technology shock induces a positive reaction by output and the stock price, and a negative reaction by the inflation rate. As it can be observed, both representations of the model deliver results that are qualitatively, and to some extent quantitatively, similar. However, the delayed and incomplete information availability that characterizes the mixed-frequency framework, causes a (seemingly)[5] weaker response of the model variables to the shock, compared to the quarterly frequency framework where information is complete and always "delivered on time".

Indeed, as we can observe in the figure, when the shock arrives on the last, rather than the first, day of the quarter, the effect of temporal aggregation is minimized and the quarterly values from our model are almost identical to that from a quarterly frequency model.

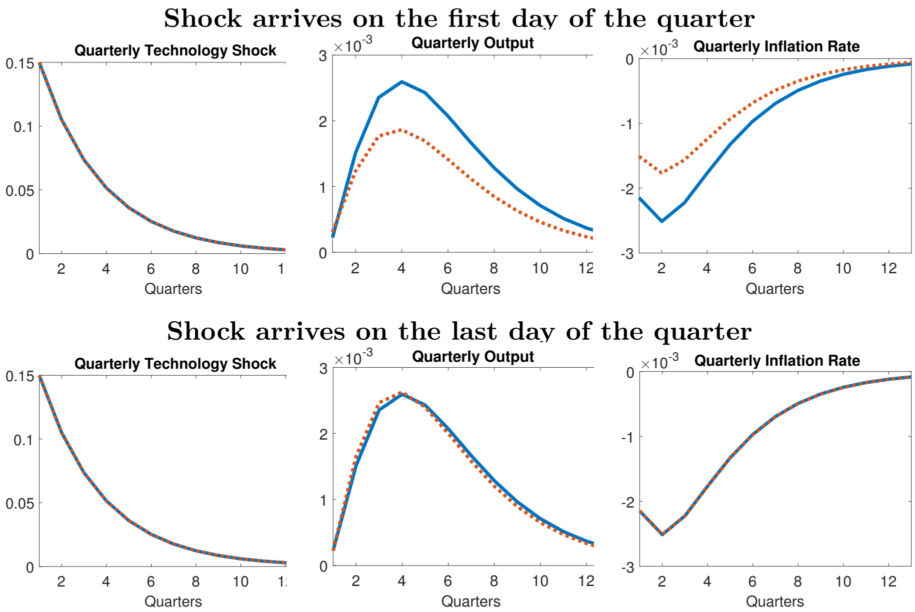

Figure 2.2: Impulse responses to a one standard deviation technology shock. Solid line: the quarterly frequency model. Dotted line: the mixed frequency model.

2.3.2 The Role of Expectational Rules-of-Thumb

Figure 2.3 illustrates the dynamic adjustments of the quarterly-frequency model variables to a one standard deviation technology shock under different values for the turnover ratio γ (0, 0,05 and 0.13)[6] for two cases: 1) rational (forward-looking) expectations and 2) boundedly rational (backward-looking) expectations as specified in Section 2.2.2.

When the turnover ratio is equal to zero, the FWC does not exist; the shock affects output solely through the policy rate reaction to the inflation rate; stock price movements have no effect on output and therefore there is no rationale for the monetary policy to react to stock price developments. At a

[5] "Seemingly" in the sense that these response graphs show only what is *collected*, not what is actually *generated*.

[6] Airaudo et al. (2015) restrict their analysis to the range [0, 0.13] for the value of γ, with a benchmark of $\gamma = 0.05$.

positive turnover ratio, the effect of a technology shock on the model variables is strengthened through the FWC: output is affected both by the policy rate and stock price movements, as illustrated in the second and third rows in Figure 2.3.

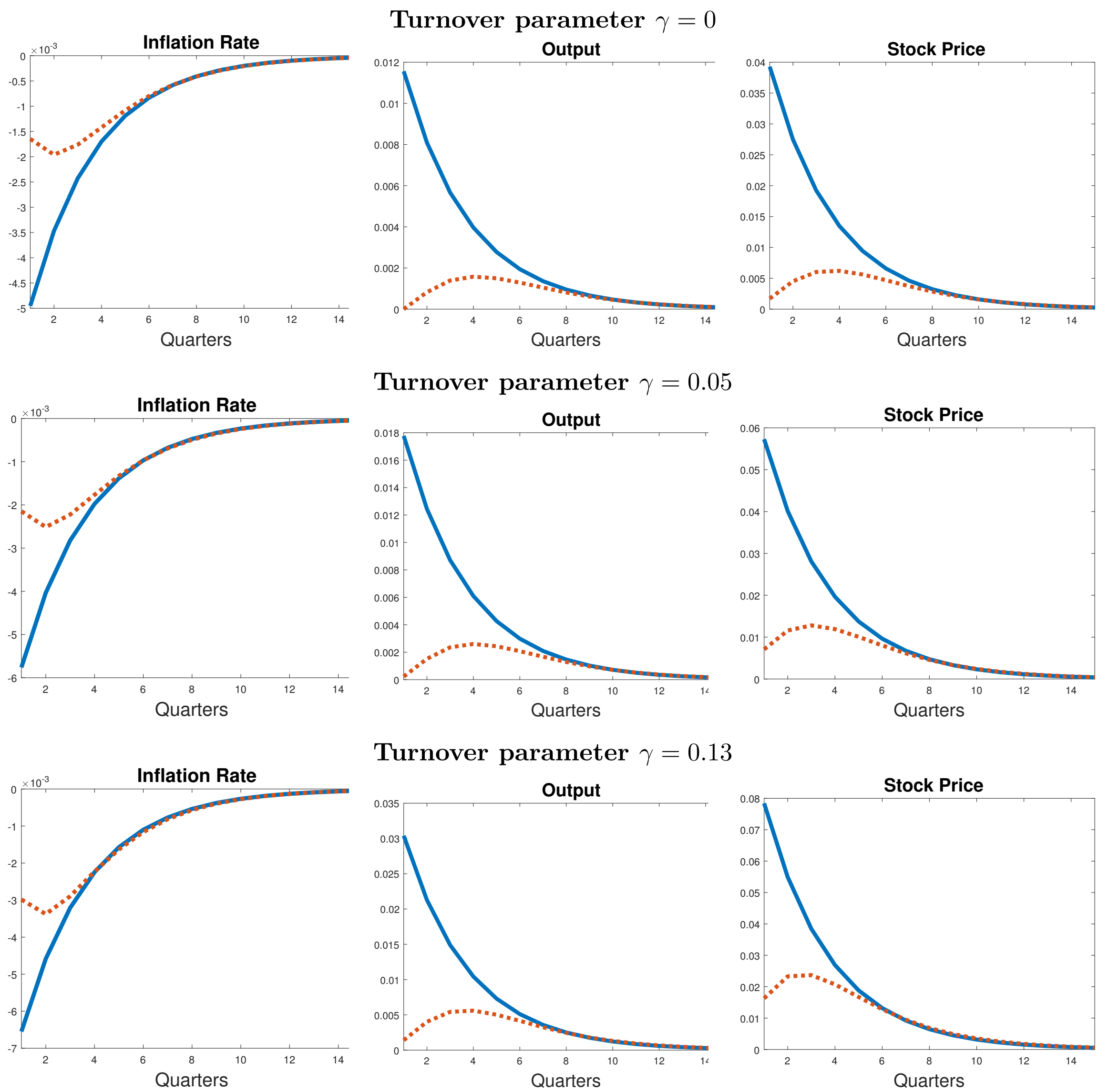

Figure 2.3: Impulse responses of the quarterly-frequency model variables to a one standard deviation technology shock under rational expectations (solid line) and backward looking expectations (dotted line).

Backward looking, boundedly rational expectations significantly weaken the technology shock impact on the model: regardless of the value of the turnover ratio, the real and financial reactions to the technology shock are mild, compared to the scenario with rational expectations. This can be attributed

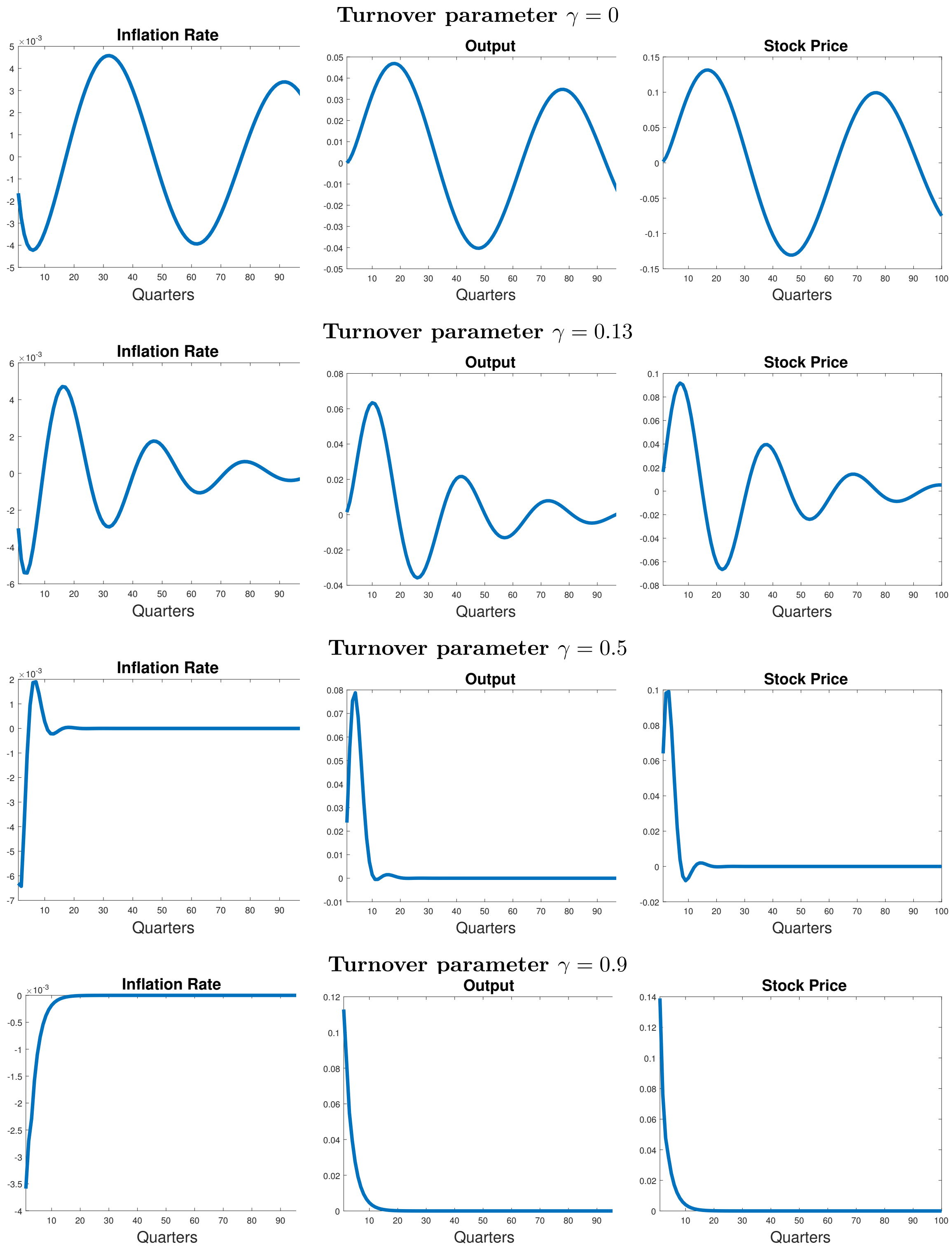

Figure 2.4: Impulse responses of the quarterly-frequency model variables to a one standard deviation technology shock under naive expectations.

to the stabilizing effect of the targeting expectations. To illustrate this more clearly, Figure 2.4 shows the quarterly model's dynamic adjustments under the assumption of only naive (no targeting) expectations, i.e. $E_q x_{q+1} = x_{q-1}$, where $x \in \{y, \pi, s\}$. As it can be clearly observed, for $\gamma = 0$ (no FWC), an exogenous technology shock triggers, in the absence of the stabilizing targeting expectations and with only the more persistent (purely backward looking) naive expectations, cyclical dynamics that only slowly fade out.

We can observe that the FWC works in opposite direction to the backward-looking, naive expectations: the higher the value of the turnover ratio, the less cyclical the reaction to the shock is, and the sooner it fades out. At $\gamma = 0.9$, there are no cyclical dynamics, the model variables monotonically return to the steady state following the initial reaction, despite the fact that only naive expectations are considered. The reason for this, is that the turnover ratio influences not only (positively) the direct effect of stock prices on the output gap (given by the term $\frac{\psi}{1+\psi}$ in equation 2.2.6), but also (negatively) the effect of expected output gap and real interest rate per the term $\frac{1}{1+\psi}$ in equation (2.2.6). In other words, a high turnover ratio can counteract the destabilizing effect of naive expectations in the model but, at the same time, may also decrease the effectiveness of the traditional interest rate channel of monetary policy.

2.4 The Performance of a Daily Leaning against the Wind Policy under Temporal Aggregation

2.4.1 Targeting the Stock Price: Daily vs Quarterly Values

We begin by addressing the question of whether the policy rate should react to daily stock price fluctuations or, instead, to aggregate quarterised values, e.g. the average (expected) stock price in a quarter. For this purpose, we perform a Monte Carlo experiment to obtain simulated variances of the key variables of the model.

Figure 2.5 illustrates the result of a Monte Carlo experiment of 10,000 runs under different values for the policy parameters ϕ_π and ϕ_s. The rest of the parameters have the values of the baseline calibration as described in Table 2.1. Variances of (generated values of) output, inflation rate and the stock price are illustrated under three different modelling scenarios: 1) the quarterly frequency model (basically, the model as in equations 2.2.1 to 2.2.4 under bounded rationality), 2) our mixed-frequency version of the model (the model as in equations 2.2.6 to 2.2.9) with daily reaction to the expected stock price (i.e. $\phi_s \tilde{E}_t s_{t+1}$) and 3) the mixed-frequency model with quarterly reaction to the expected stock price

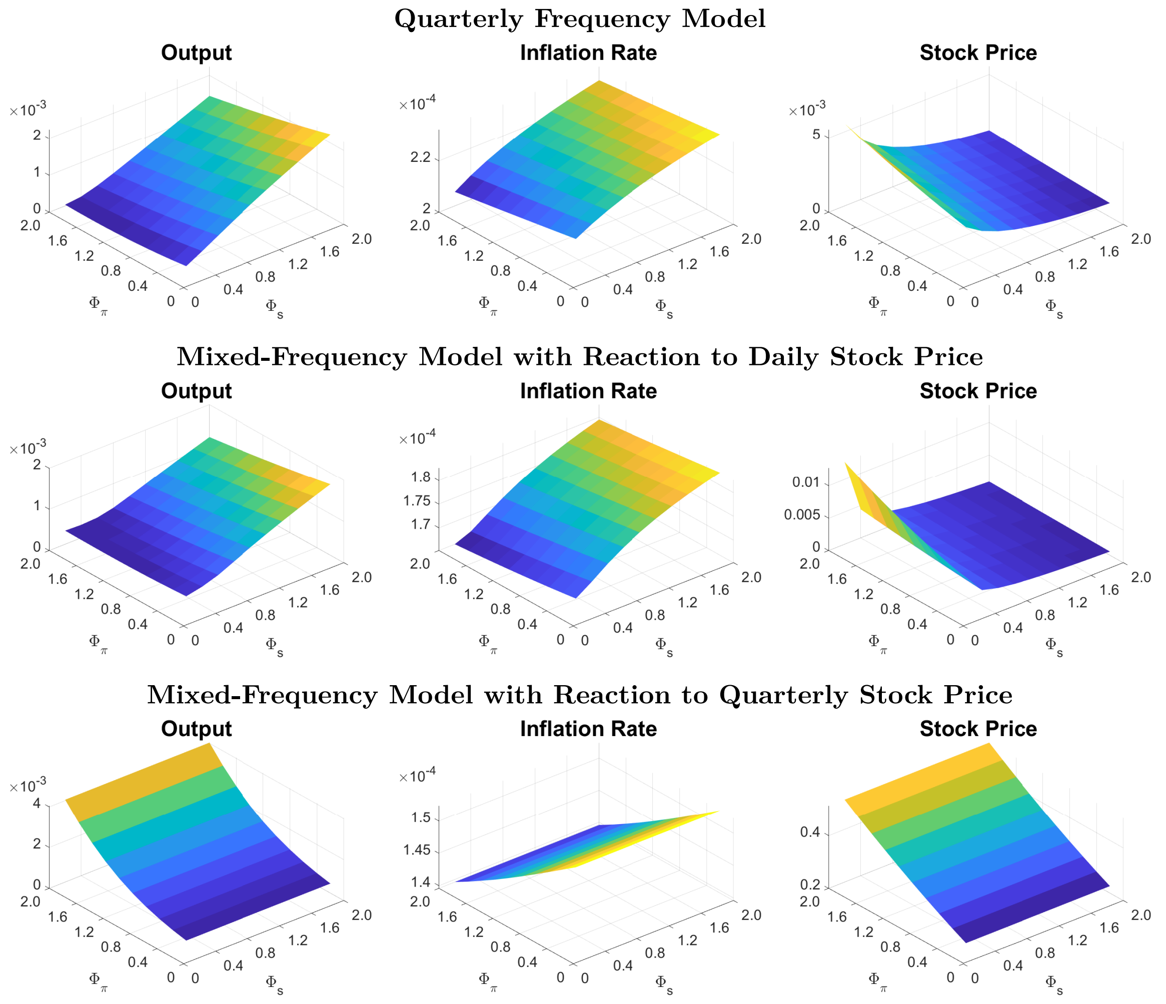

Figure 2.5: A Monte Carlo experiment of 10000 runs, each for 40 quarters (2560 days). Illustrated are the variances of output, inflation and the stock price at different values for the policy parameters ϕ_π and ϕ_s. $\sigma_z = 0.5$.

(i.e. $\phi_s \tilde{E}_q s_{q+1}$).[7]

The first pronounced feature of Figure 2.5 is the great similarity between the first two scenarios (i.e. first two rows): small values of ϕ_s (namely $\phi_s \approx 0.2$) stabilize both the stock price and output; higher values of ϕ_s further stabilize the stock price on the expenses of higher variability in output and inflation; higher values of ϕ_π stabilize the real sector with a slight loss in the stability of the stock price. By contrast, the third scenario delivers completely different results: On the one hand, the value of ϕ_s has a trivial effect on the stability of the real or financial variables. On the other hand, a strong

[7]To achieve consistency, s_q is calculated similarly to y_q and π_q, and $\tilde{E}_q s_{q+1}$ is calculated similarly to $\tilde{E}_q y_{q+1}$ and $\tilde{E}_q \pi_{q+1}$.

reaction to inflation (illustrated by high values of ϕ_π) greatly stabilizes inflation but simultaneously destabilizes the stock market. That, in turn, leads to output instability.

This result can be explained as follows: when the policy rate is strongly reacting to inflation without properly reacting to stock prices (i.e. a delayed reaction due to the quarterly frequency of the reaction), the stock market is made unstable (see equation 2.2.8). The positive effect of the stabilized inflation rate on the stability of output is outweighed by the negative effect of the unstable stock prices. Aggregate output is thus destabilized as a result of a policy rate that strongly targets inflation rate without properly reacting to stock price fluctuations.

The similarity between the first and second cases delivers a focally significant point: in our mixed frequency model, in which data collection mismatches in the real sector exist, a policy rate that reacts to the daily available information on the stock price can successfully stabilize the stock market and to some extent neutralize the effect of such a data mismatch in the real sector. This success is to the extent that the model can deliver results that are similar to the scenario in which data collection mismatches are ignored altogether and a homogeneous frequency concerning data generation and collection for both the real and the financial sectors is assumed.

In Figure 2.6 we illustrate in more detail the effect the value of ϕ_s has on the dynamics of the model and the stability of both the real and the financial sectors, particularly in response to a technology shock. Therein the simulation results of our mixed-frequency model with daily reaction to stock prices for 40 quarters (2560 days) under three different policy scenarios: a) no reaction to the stock price ($\phi_s = 0$, dashed line), b) a moderate daily reaction to the expected stock price ($\phi_s = 0.2$, dotted line) and c) a strong daily reaction to the expected stock price ($\phi_s = 1$, solid line).

As we can observe, when the policy rate does not react to the stock price, output and the stock price move relatively strongly in the same direction as, and inflation moves in the opposite direction to, the technology shock. This result is not surprising; better technology means lower prices, higher production and more appreciated stocks. At the other end of the policy spectrum, a strong reaction of the policy rate to the stock price, highly stabilises the stock market on the expenses of a highly unstable output which now moves in the opposite direction to technology updates. In other words, the effect of the strong reaction of the policy rate to stock prices outweighs the effect of the technology shock that it leads output to negatively co-move with technology.

A moderate policy reaction delivers the most optimal results in terms of output stability: output can be observed relatively close to the steady state all over the time line. At the same time, such a policy moderately stabilises the stock price: the dotted line, which corresponds to this moderate policy, falls between the solid line, which corresponds to strong reaction to the stock price and the dashed line, which corresponds to no reaction to the stock price.

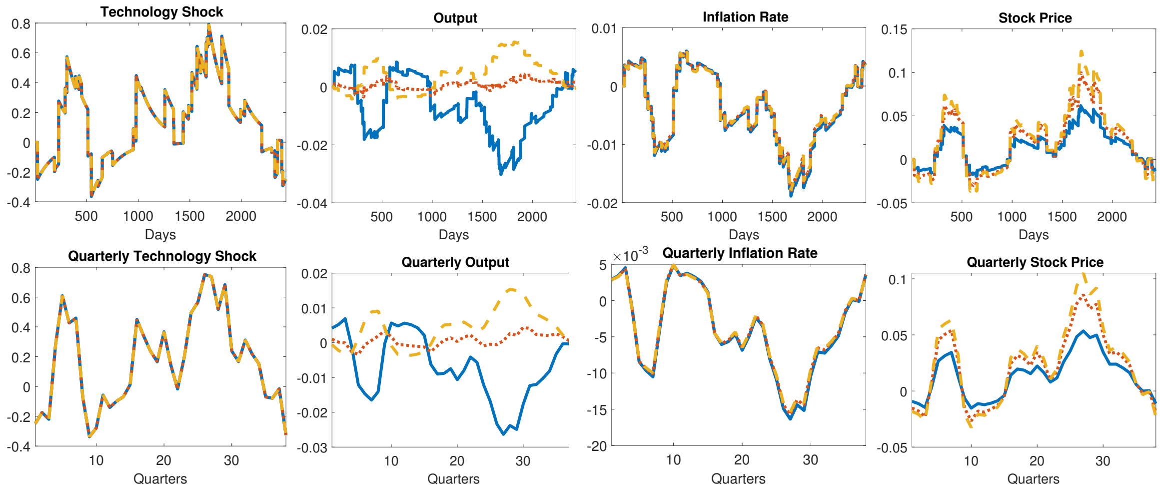

Figure 2.6: A simulation of the mixed frequency model (with daily reaction to the stock price) for 40 quarters (2560 days). The solid line represents a relatively strong reaction to the stock price (ϕ_s =1). The dotted line represents a moderate reaction to the stock price (ϕ_s =0.2). The dashed line represents no reaction to the stock price ($\phi_s = 0$).

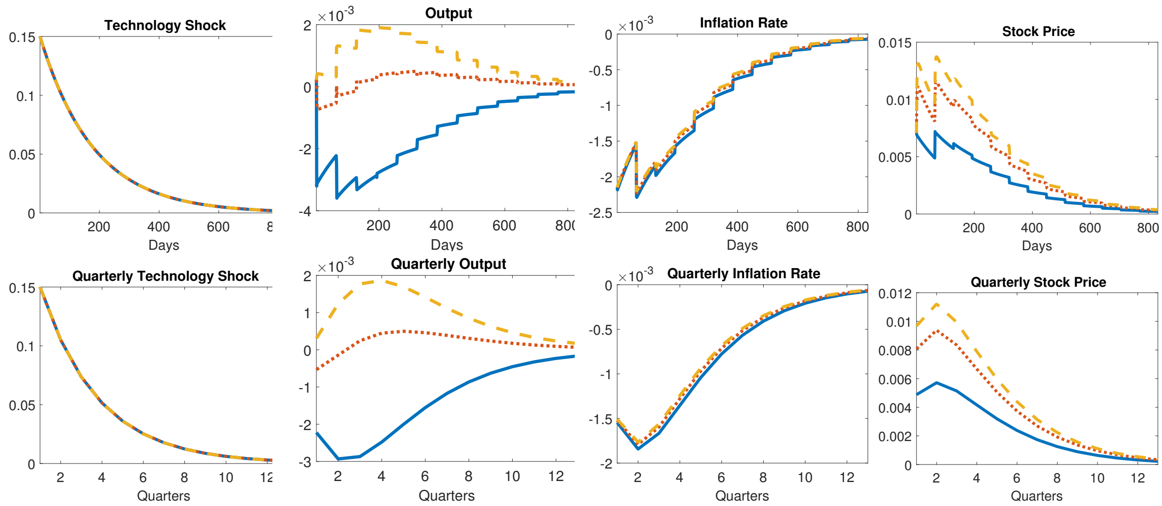

Figure 2.7: Impulse responses of the mixed frequency model (with daily reaction to the stock price) to a one standard deviation technology shock. The solid line represents a relatively strong reaction to the stock price (ϕ_s =1). The dotted line represents a moderate reaction to the stock price (ϕ_s =0.2). The dashed line represents no reaction to the stock price ($\phi_s = 0$).

Figure 2.7, which shows the model's dynamic adjustments to a one standard deviation technology shock, delivers analogous results: a strong reaction to the stock price highly stabilises the stock market and more than offsets the positive effect of technology on output; a moderate reaction to the stock price fairly stabilises the stock market and provides the most stabilised output levels. These findings strengths the ones we obtained from the previous exercise: when intra-quarter data on inflation and output is not available, the policy rate can successfully stabilise the real sector together with the stock market by moderately reacting to stock prices.

2.4.2 Output vs. Stock Price Stabilization

Finally, Figure 2.8 displays the results for the case where the forward-looking policy rule also responds to expected future output, that is,

$$r_t = \phi_\pi E_q \pi_{q+1} + \phi_s E_t s_{t+1} + \phi_y E_q y_{q+1}$$

for the mixed frequency model and

$$r_q = \phi_\pi E_q \pi_{q+1} + \phi_s E_q s_{q+1} + \phi_y E_q y_{q+1}$$

for the quarterly frequency model, for three different values for the turnover ratio γ: 0, 0.05 and 0.13.

By observing variances of the quarterly frequency model (first row), one can notice that the value of ϕ_y that achieves the most stable output (lowest variance) decreases, the stronger the FWC (i.e. the higher the value of γ) is, and that at any value for the policy parameters, output is more volatile at higher values for γ. The FWC narrows the scope for output response by the policy rate and increases the validity of responding to the stock price. This is in line with the findings of Airaudo et al. (2015), and with our discussion of Figure 2.4.

The second row, which presents the mixed-frequency model, delivers considerably different results. First, responding to output is fairly ineffective in stabilizing output. Put different, temporal aggregation, which means that the policy rate can only respond to quarterly updated output expectations, negatively influences the effect of such response on the output volatility. Second, responding to the stock price, upon which data is daily available, is not irrelevant for output volatility. Even at $\gamma = 0$, i.e. no FWC, a policy response to the stock price is still an effective tool to stabilize output, since when intra-quarter real data is not available, stock price movements reflect unobserved real fluctuations and/or events (e.g. the arrival of a technology shock). Under these circumstances, a moderate policy reaction to the stock price is also, indirectly, a reaction to output. Recall that, as previously illustrated in Figures 2.6 and 2.7, at low values for ϕ_s, both output and stock prices positively co-move with technology shocks.

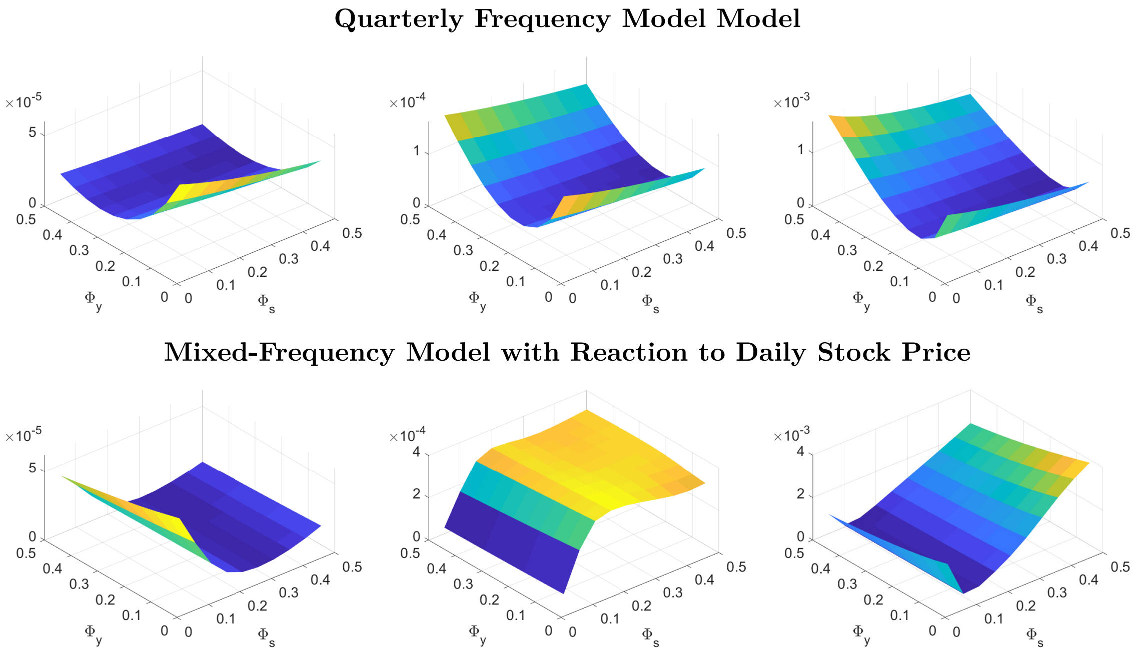

Figure 2.8: A Monte Carlo experiment of 10000 runs, each for 40 quarters (2560 days). Output variances under three different values for the turnover ratio γ: $\gamma = 0$ (first column), $\gamma = 0.05$ (second column), and $\gamma = 0.13$ (third column). $\sigma_z = 0.5$.

2.5 Concluding Remarks

We investigated the rationale for why the central bank should move the interest rate in response to stock price movements in a mixed frequency macroeconomic model with boundedly rational expectations and a discrepancy between data collection and data generation processes. We showed how a moderate, high frequency (i.e. daily) policy response to the stock price can play a significant role not only in the stabilization of the stock market, but also of the real sector, especially when real data are temporally aggregated. Further, we illustrated the role of backward-looking naive and targeting expectations on the model dynamics, compared to forward looking rational expectations: targeting expectations are highly stabilizing and weaken the spill-over effect between the real and the financial sectors compared to rational expectations, and naive expectations lead to cyclical long lasting dynamics following an exogenous shock.

It is very important to note here that these results are primarily the product of the model's assumptions, specifically, assumptions regarding data availability, type of shock and source of financial volatility. Our model considers solely technology (i.e. real) shocks, which are assumed to hit the economy, on average, once per quarter. The stock price, as well as the real variables, move *only* in reaction to such shocks. In other words, there are no other sources for stock price volatility (e.g. trading noise, speculations, etc.). When information about the shock or the real variables is not properly available (i.e. available only in an aggregated form and with a delay), the central bank indirectly targets these latter variables by reacting to the high-frequently observed stock price. In such a context, the stock price acts as a proxy to the actual state of the economy. This concept has been previously emphasized by Gilchrist and Leahy (2002, p. 83): “Asset prices aggregate information from diverse sources in a timely matter and are obvious candidates to be proxies of the underlying state of the economy.”

While our analysis does not argue for a daily revision or setting of the policy rate in the real world, it does highlight the importance of mixed-frequency econometric techniques that allow to incorporate high-frequency financial market data into the assessment of the current state of the economy, and by extension the updating of expectations or forecast at more frequent intervals.

Chapter 3

Optimism, Pessimism and Panics in a Macroeconomic Model with a Banking Sector[1]

[1] The paper is available on SSRN.

3.1 Introduction

Post Global Financial Crisis (GFC) macro-financial literature (e.g. Gertler and Gilchrist, 2018; Duffie, 2019) has extensively accentuated the contrast between the complex, fragile and inherently risky pre crisis financial sector in the real world, on the one hand, and the prevailing macroeconomic models at that time, that failed to represent such a complex sector or anticipate the effect its disruption could have on the macroeconomy, on the other hand.

Further, the GFC has greatly highlighted the importance of the inclusion of psychological factors and boundedly rational behaviour in the macro-financial analysis. Lack of objectivity, failure to learn from past mistakes, over confidence and unrealistic optimism are not trivial when trying to understand financial decisions as well as financial panics and their implications for the macroeconomy (see Gärling et al. 2009; de Meza and Dawson 2021; Beaudry and Willems 2022).

Against this background, the purpose of this paper is to model banking crises in a behavioural macroeconomic context. Bank defaults, which lead to devastating effects on investment and output, are caused by panics that prevail when boundedly rational agents asses that banks are too leveraged and therefore prone to fail.

Despite the general acceptance of bounded rationality and behavioural inclinations, there is no academic consensus on a theory or a right formula to quantify behavioural aspects of expectations such as optimism, pessimism and extrapolative biases (Concetto and Ravazzolo, 2019). This highlights the need for simple models that are easy to explain and employ but still able to capture, to a fair extent, the heterogeneity and biasedness of expectations (see Fuster et al. 2012). In this paper, I utilize insights from behavioural macroeconomics as well as macro-financial literature to characterize an economy that is vulnerable to system-wide panics: agents form boundedly rational expectations and news may induce waves of optimism or pessimism in an economy where banks are unregulated, risky and subject to runs.

Starting from Gertler, Kiyotaki and Prestipino (2020*a*) (GKP), I replace rational expectations with boundedly rational (static) expectations. Such backward-looking expectations intensify the dynamics, amplify the effect of negative exogenous shocks on the model economy and most importantly, increase the probability of panics, compared to the scenario with rational expectations. Further, I construct a mechanism of breaking down static expectations into optimistic and pessimistic expectations (which are always static on average). Banks then must take into consideration the prevailing optimism/pessimism when they are solving for the profit-maximizing leverage multiple, which in turn motivates a limit on the banks' ability to increase their leverage.

As described by GKP, bank runs are discrete and sudden in nature, their occurrence, though relatively rare, leads to devastating aggregate effects and extended contractions in the real activity. Modelling bank runs thus requires capturing such disturbing nature of panics as well as the circumstances that make an economy vulnerable to such panics in some instances but not in others. In the paper at hand, several numerical exercises that illustrate the characteristics of bank runs are conducted. They show that when a bank run equilibrium is not feasible, the model economy can fairly survive a mildly negative capital quality shock, with no major disturbance to the financial or real activities. In contrast, when bank runs are feasible, a small-sized negative shock can induce a bank panic that translates into a deep recession, as witnessed e.g. in the GFC. Finally, news-driven booms, during which optimism prevails and banks appetite for risk increases, can lead to subsequent financial and real busts, even in absence of any capital shocks.

The rest of the paper is organised as follows. Section 3.2 presents insights from relevant literature. Section 3.3 describes the macroeconomic model of GKP. Section 3.4 demonstrates the behavioural problem I designed, and tracks its effect on the banker's maximization problem. Section 3.5 presents the calibration, an overview of the model dynamics as well as the results of some numerical exercises. Section 3.6 concludes.

3.2 Literature Review

It has been more than a decade since the GFC erupted. Nevertheless, neither the argumentation surrounding the crisis nor the efforts to understand it are settled. The debate upon whether financial crises are always products of (or preceded by) panics,[2] greatly dominated the macro-financial research that followed the crisis. For instance, Bordo and Landon-Lane (2010) revisit the *illiquidity-versus-insolvency* debate in the banking crises of the 1930s and provide empirical evidence that these banking crises largely reflected contagious illiquidity (panic) shocks. Nonetheless, they also stress that endogenous insolvency was important between the panic episodes. In other words, insolvency and illiquidity intervened with one another creating the crises that we observed. This notion was previously featured by Diamond and Rajan (2005) a few years prior to the crisis, when they documented how liquidity and solvency problems interact and cause each other, making it hard to determine the definite cause of a crisis.

[2] There are different approaches to define a bank panic/run. In the *early withdrawal* approach by Diamond and Dybvig (1983), during a bank run, depositors rush to withdraw their deposits because they expect the bank to fail. Gertler et al. (2020*a*) define a panic or run as a self-fulfilling failure of creditors to *roll over* their short-term credit (i.e. deposits) to banks.

Bernanke (2018) and Baron et al. (2021) provide a thorough review of literature on financial crises without panics. This literature stresses that panics do not need to happen for crises to unfold. At the other end of the scale, (Diamond and Dybvig, 1983, p.401) state that 'bank runs are a common feature of the extreme crises that have played a prominent role in monetary history.' They model bank runs as the *direct cause* of the real economic damage that follows a financial crisis rather than simply reflecting other problems (e.g. distress in money supply or loss of collateral). Gertler et al. (2020*a*) follow their lead and present an economy where insolvencies are rare, and require exceptionally large negative fundamental shocks to happen, to the extent that the probability of such an event can be considered negligible. They model banking crises as a sole product of fire sales of bank assets in the wake of a panic and show that they can mimic financial crisis events with such a model. Perhaps the most explicit advocation for the pivotal role played by bank panics came from Gorton and Calomiris (2000) years before the crisis, when they stated that the history of U.S. banking regulation can be written largely as a history of government and private responses to banking panics.

The debate on the cause of financial crises opens to another: if it is indeed panics that cause banks to fail, how can such panics be induced in a macro-financial framework? Classically, Diamond and Dybvig (1983) introduced panics in the form of self-fulfilling sunspot events.[3] In a series of papers, Gertler et al. (2016*a*,*b*, 2020*a*,*b*,*c*) also adopt a mechanism where the feasibility of a run depends on a realization of a sunspot. Differently, Dang et al. (2020) design a framework where unexpected news or events turn information-insensitive debt into information-sensitive. Such a shift induces a panic and thus a crisis.

Another equally important, but less academically controversial, issue is modelling the booms that precede the crises. On that matter, Gertler et al. (2020*c*) state that banking crises are usually preceded by credit booms, but also, credit booms often do not result in crises. Put differently, almost every crisis is preceded by a boom but only some booms are followed by crises. Similarly, Gorton and Ordonez (2020) differentiate between good booms (not followed by crises) and bad booms (followed by crises). In that sense, macroprudential policy would have a central role: weighing the benefits of preventing a crisis against the costs of stopping a good boom.

The 'good booms, bad booms' argument put together with the 'this time is different' synonym (Reinhart and Rogoff, 2009), which describes investors failing to see crises coming because they do not recognize similarities among the different pre-crisis bubbles, constitute a valid explanation to puzzling questions like: *Why do investors repeat the same mistakes?* And *why do we see repeated patterns of crises?* An investor, institutional or private, would simply think: 'I know that the last boom was *bad* and ended in a crisis, but *this time is different.* It will be a *good boom*, with no crisis'. As a result,

[3] events that exhibit self-fulfilling dependence on extrinsic variables, i.e., *animal spirits*, see Branch et al. (2022).

financial crises, which are supposed to be rare, occur quite often (see Gennaioli et al. 2015).

3.3 Model

This paper builds on the model by Gertler, Kiyotaki and Prestipino (2020*a*) (hereafter GKP) by incorporating bounded rationality and allowing behavioural rules to influence banking decisions. In this section, the key elements of GKP's model economy, namely, the model's outline, households and bankers are described, as these are the elements that are necessary to be explained before proceeding with the description of my modification in the following section.

3.3.1 Outline and Households

The baseline framework is a standard New Keynesian model with investment. Each household consists of a continuum of members with measure unity. Within the household there are $1-f$ workers and f bankers. Every period, there exists a probability $1-\sigma$ a banker exits, and immediately turns into a worker. Upon exit, a banker transfers all the outstanding accumulated earnings to the household. Within the household, there is perfect consumption sharing. To keep the population of each occupation constant, each period, $(1-\sigma)f$ workers become bankers. The household provides new bankers with a one-time-only wealth transfer e_t.

Firms finance their capital as well as new investments by issuing a state-contingent claim on the earnings generated by the capital. These claims, which can be considered as equity, are either directly held by the less-efficient households or alternatively, intermediated by the more efficient bankers. Total amount of claims outstanding at the end of period t, S_t is the sum of both:

$$S_t = S_t^b + S_t^h \tag{3.3.1}$$

where, S_t^h is the quantity of claims held directly by households and S_t^b is the quantity intermediated by banks. Since firms exclusively finance capital through claims, total capital at the end of period t is equal to the total quantity of claims, S_t. The former is in turn defined as the sum of capital newly produced during period t and capital at the beginning of period t, K_t, that has not been exhausted (i.e. depreciated) in the production:

$$S_t = \Gamma(I_t) + (1-\delta)K_t \tag{3.3.2}$$

where $\Gamma(I_t)$ is an increasing and concave function in investment (I_t), and δ is the depreciation rate.

Capital entering the next period, K_{t+1} differs from capital at the end of the current period due to capital quality shocks that randomly transform the amount of capital available at $t+1$:[4]

$$K_{t+1} = \xi_{t+1} S_t \tag{3.3.3}$$

where

$$\xi_{t+1} = 1 - \rho_\xi + \rho_\xi \xi_t + \epsilon_{t+1} \tag{3.3.4}$$

where $0 \leq \rho_\xi < 1$ and ϵ_t is a normally distributed i.i.d. random variable with mean zero and standard deviation σ_ξ. The inefficiency of households compared to bankers as capital holders is captured by a *capital management cost* that takes the form of a utility cost and is a function of the share of households'-held capital to the total capital, i.e. S_t^h/S_t:

$$\varsigma(S_t^h, S_t) = \begin{cases} \frac{\chi}{2}(\frac{S_t^h}{S_t} - \gamma)^2 S_t & \text{if } \frac{S_t^h}{S_t} > \gamma > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{3.3.5}$$

Equation (3.3.5) states that households will pay zero utility cost if they hold a share of total claims up to γ. Beyond γ, $\varsigma(.)$ is increasing and convex in S_t^h/S_t. The capital management cost is a focal concept in the model: at $S_t^h/S_t \leq \gamma$, the economy is as efficient as it can most be. As the share of households'-held claims expands beyond γ, efficiency drops, and investment and output fall. In the event of a bank run, banks are forced to fire-sell their holdings. All claims are allocated from banks to the direct ownership of households. The utility cost is at its maximum level, cost of capital sharply rises and investment and output deeply contract. In other words, these utility costs capture the devastating effects of bank panics on the micro level, which directly lead to the aggregate effects that we observe (e.g. effects on investment and total output).[5]

Households save in the form of deposits at banks and direct claims on capital. Bank deposits at t are one period bonds that promise to pay a non-contingent gross real rate of return $\bar{R}_t$ in the absence of default. In the event of default, depositors receive a fraction x_t of the promised return, where the

[4] According to GKP, the advantage of the capital quality shock is that it can introduce an exogenous source of variation in the market value of bank assets, which will play a role in making banks vulnerable to panics. The disadvantage is that the shock has a direct supply effect on output by affecting the quantity of capital.

[5] As discussed by Bernanke (2018), much of the post GFC research on the role of credit factors in economic behaviour and economic analysis focused on the microeconomic level, documenting the importance of credit and balance sheet factors for the decisions of households, firms, and financial institutions (refer to the paper for a thorough literature review).

recovery rate $x_t \in [0,1)$ is the value of bank assets per unit of promised deposit obligations, as will be explained later.

Banks may default due to insolvency or illiquidity. The first occurs when banks obtain sufficiently negative return on their portfolios. The second occurs when creditors run forcing banks to liquidate assets at fire-sale prices. Similar to Diamond and Dybvig (1983), banks' insolvencies are rare in the GKP model (as well as in my modification of the model, as I will discuss later) and require exceptionally large exogenous shocks (e.g large negative capital quality shocks) to occur.

Let C_t be consumption, L_t labour supply, and $\beta \in (0,1)$ the household's subjective discount factor. Households' utility maximization problem is standard, except that utility is *punished* by the holding of capital ($\frac{S_t^h}{S_t}$) beyond γ:

$$U_t = E_t \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau-t} \left[\frac{C_\tau^{1-\gamma h}}{1-\gamma h} - \frac{L_\tau^{1+\varphi}}{1+\varphi} - \varsigma(S_\tau^h, S_\tau) \right] \right\} \tag{3.3.6}$$

where γh is the risk aversion parameter, φ is the inverse Frisch elasticity and E_t is the rational expectations operator.

Let Q_t be the relative price of capital, Z_t the rental rate on capital, w_t the real wage rate, T_t lump-sum taxes, B_t the real value of riskless bonds[6], R_t^n the associated riskless nominal rate and Π_t dividend distributions net transfers to new bankers, all of which the household takes as given. Then the household chooses C_t, L_t, S_t^h, B_t and deposits D_t to maximize expected utility subject to the budget constraint:

$$C_t + D_t + Q_t S_t^h + B_t = w_t L_t - T_t + \Pi_t + R_t D_{t-1} + \frac{R_{t-1}^n}{\pi_t} B_{t-1} + \xi_t [Z_t + (1-\delta) Q_t] S_{t-1}^h \tag{3.3.7}$$

where $\pi_t = \frac{P_t}{P_{t-1}}$ is the realized gross inflation rate at date t and R_t is the gross interest rate households *actually* receive in period t on their deposits from the previous period. The latter is equal to $\bar{R}_{t-1}$ in case of no default (i.e. households get what they were promised), and $x_t \bar{R}_{t-1}$ in case of default (i.e. households get less than what they were promised):

$$R_t = \begin{cases} \bar{R}_{t-1} & \text{no bank default at } t \\ x_t \bar{R}_{t-1} & \text{bank default at } t \end{cases} \tag{3.3.8}$$

where $0 \leq x_t < 1$.

[6] in zero supply. For further explanation, refer to GKP.

The first order conditions for labour, riskless bonds, deposits, and direct capital holding, are as follows:

$$w_t = (C_t)^{\gamma_h}(L_t)^{\varphi} \tag{3.3.9}$$

$$E_t\left[\left(\Lambda_{t+1}\frac{R_t^n}{\pi_{t+1}}\right)\right] = 1 \tag{3.3.10}$$

$$E_t\Lambda_{t+1}[\rho_t x_{t+1}\bar{R}_t + (1-\rho_t)\bar{R}_t] = 1 \tag{3.3.11}$$

$$E_t\left[\Lambda_{t+1}\xi_{t+1}\frac{Z_{t+1} + (1-\delta)Q_{t+1}}{Q_t + \frac{\partial}{\partial S_t^h}\varsigma(S_t^h, S_t)}\right] = 1 \tag{3.3.12}$$

where

$$E_t\Lambda_{t+1} = \beta(E_tC_{t+1})^{-\gamma_h}C_t^{\gamma_h} \tag{3.3.13}$$

$$\frac{\partial}{\partial S_t^h}\varsigma(S_t^h, S_t) = Max\left[\chi\left[\frac{S_t^h}{S_t} - \gamma\right], 0\right] \tag{3.3.14}$$

and ρ_t is the probability of bank default.[7,8]

Equations (3.3.9 and 3.3.10) are standard. Equation (3.3.11) shows that households take into account the probability of bank default (ρ_t) in the determination of the rate that should be promised by banks on their deposits, $\bar{R}_t$. In equation (3.3.12), one can see that Q_t is inversely related to the marginal utility cost of holding capital $\frac{\partial}{\partial S_t^h}\varsigma(.)$. When banks fail, the ownership of capital claims shifts entirely to households. The utility cost is at its maximum level and the price of capital sharply decreases.

3.3.2 Bankers

As described by (GKP, p.6): "The banking sector [characterized] corresponds best to the shadow banking system which was at the epicentre of the financial instability during the Great Recession. In particular, banks in the model are completely unregulated, hold long-term securities, issue short-term debt, and as a consequence are potentially subject to runs."

[7] Here, it is assumed that banks are identical, and therefore the probability of default is identical among them. Later, I show how the banker's optimization problem leads to identical banking decisions and therefore identical banks (i.e. all banks choose the same leverage so they have the same probability of default).

[8] Note that the subscript t in ρ_t indicates that such probability is calculated in period t, even if it effectively measures the probability of default in period $t+1$.

I delineate the banking sector through three steps: 1) defining the bankers' maximization problem, 2) describing the conditions for bank run and bank insolvency and 3) motivating a constraint on the banker's ability to raise funds. I follow GKP precisely in steps 1 and 2. Concerning step 3, I design a behavioural problem of optimism and pessimism that would motivate the constraint on the bankers' ability to raise funds (i.e. increase leverage multiple). Note that, similar to GKP, I use small letters to denote bank specific variables (e.g. net worth, capital claims intermediated by the bank, probability of default, leverage multiple and deposits). For the aggregate variables such as capital price, rate of return on investment, total capital claims, rental rate on capital, as well as aggregate bank net worth and aggregate deposits, I use capital letters.

Bankers' optimization problem

Each banker manages a financial intermediary with the objective of maximizing the expected utility of the household. During each period t, a continuing bank (either new or surviving) finances asset holdings, $Q_t s_t^b$, by issuing short-term deposits, d_t, to households as well as by using their own equity, or net worth, n_t:

$$Q_t s_t^b = d_t + n_t. \tag{3.3.15}$$

The net worth of surviving bankers, accordingly, is the gross return on assets net the cost of deposits:

$$n_t = R_t^b Q_{t-1} s_{t-1}^b - \bar{R}_{t-1} d_{t-1} \tag{3.3.16}$$

where R_t^b is the gross rate of return on capital intermediated by banks:

$$R_t^b = \xi_t \frac{Z_t + (1-\delta)Q_t}{Q_{t-1}}. \tag{3.3.17}$$

So long as n_t is strictly positive, the bank does not default. In this instance, it pays its promised rate $\bar{R}_{t-1}$. If the value of assets, $R_t^b Q_t s_{t-1}^b$, is below the promised repayments to depositors, $\bar{R}_{t-1} d_{t-1}$ (due to either a run or simply a bad realization of returns), n_t goes to zero and the bank defaults. It then pays creditors the product of the recovery rate x_t and $\bar{R}_{t-1}$, where x_t is given by:

$$x_t = \frac{R_t^b Q_{t-1} s_{t-1}^b}{\bar{R}_{t-1} d_{t-1}} < 1. \tag{3.3.18}$$

For each new banker at t, net worth simply equals the start-up equity e_t it receives from the household:

$$n_t = e_t. \tag{3.3.19}$$

The bank's leverage multiple is the ratio of a bank's assets to net-worth:

$$\phi_t = \frac{Q_t s_t^b}{n_t}. \tag{3.3.20}$$

One can then express the value of x_t as:

$$x_t = \frac{R_t^b}{\bar{R}_{t-1}} \frac{\phi_{t-1}}{\phi_{t-1} - 1}. \tag{3.3.21}$$

Combining the balance sheet constraint (equation 3.3.15) and the flow of funds constraint (equation 3.3.16) yields the expression for the evolution of the net worth for a surviving bank that does not default:

$$E_t(n_{t+1}) = E_t[(R_{t+1}^b - R_{t+1})\phi_t + R_{t+1}^b]n_t \tag{3.3.22}$$

where

$$E_t R_{t+1} = (1 - \rho_t)\bar{R}_t + \rho_t E_t x_{t+1} \bar{R}_t. \tag{3.3.23}$$

As explained in GKP, as long as there is a positive probability that the banker may be financially constrained at some point in the future, it will be optimal for the banker to delay dividend payments until exit. At this point, the dividend payout will simply be the accumulated net worth. Following this logic, the banker's objective is to maximize the expected net worth (equation 3.3.22).

By plugging equation (3.3.11) in (3.3.22), the banks' maximization problem can be represented as:

$$\max_{\phi_t} \left(E_t \left[\left[R_{t+1}^b - \frac{1}{\Lambda_{t+1}(\rho_t x_{t+1} + 1 - \rho_t)} \right] \phi_t + \frac{1}{\Lambda_{t+1}(\rho_t x_{t+1} + 1 - \rho_t)} \right] n_t \right). \tag{3.3.24}$$

Equivalently:

$$\max_{\phi_t} \left(\phi_t E_t R_{t+1}^b n_t - \frac{n_t \phi_t - n_t}{E_t[\Lambda_{t+1}(\rho_t x_{t+1} + 1 - \rho_t)]} \right). \tag{3.3.25}$$

By replacing x_{t+1} by the expression in equation (3.3.21), we reach:

$$\max_{\phi_t} \left(\phi_t E_t R_{t+1}^b n_t - \frac{n_t \phi_t - n_t}{E_t[\Lambda_{t+1}(\rho_t \frac{E_t R_{t+1}^b}{\bar{R}_t} \frac{\phi_t}{\phi_t - 1} + 1 - \rho_t)]} \right). \tag{3.3.26}$$

Conditions for bank default and aggregation of the financial sector

A bank may default as a result of insolvency or illiquidity. The first occurs when the bank endures a sufficiently negative return on its portfolio. The latter occurs when the bank's creditors run forcing the bank to liquidate (fire-sell) its assets. The conditions for bank insolvency are straightforward. If the value of the bank's assets turns less than its liabilities, the bank's net worth becomes negative (see equation 3.3.16). Since the net worth must be strictly positive for a bank to operate, this effectively leads to bank default. The bank then liquidates its assets, and pays its creditors the product of the recovery rate x_t (see equation 3.3.18) and the promised rate $\bar{R}_{t-1}$. The net worth goes to zero, and the bank simply functions no more. Since banks are identical, this scenario, if it happens, happens to all banks. Therefore bank failure here is a failure of the entire banking sector.[9] This may occur in the event of a sufficiently large negative shock to capital quality, which will directly lower the bank's rate of return on investment (R_t^b). Bank insolvency in that instance, occurs in absence of a run or a panic. As a result, the exogenous shock that leads to it must be big enough, unlike the case of a bank run, which can happen even when the exogenous shock is only slightly negative.

Similar to the case of insolvency, bank run, in GKP, is a run on the entire banking sector, not on individual banks; also a direct result of banks being identical. To specify conditions for bank runs, suppose that at the beginning of period t, the banking system is solvent: assets valued at the prevailing market prices exceed liabilities. The household must then decide whether to roll over deposits. As described by GKP, a self-fulfilling run equilibrium exists if and only if the household correctly believes that in the event all other depositors run, thus forcing the banking system into liquidation, the household will lose money if it rolls over its deposits individually. In other words, the return rate on deposits that will be achieved by the end of period t, if run occurs and assets are liquidated, is below the return rate promised in period $t-1$ (i.e. n_t becomes negative in the event of a run). If instead bank net worth is positive even at liquidation prices, a panic equilibrium would not exist.[10] GKP explain how bank panics, this way, are similar to the type described in Diamond and Dybvig (1983), with the exception that runs, in the model at hand, reflect a panic failure to roll over deposits as opposed to the early withdrawal mechanism in Diamond and Dybvig (1983).[11]

For a bank run to occur, 1) bank run equilibrium must exist *and* 2) it must be feasible. That being stated, we can specify the *first condition* for bank run to be that the recovery rate in case of liquidation,

[9] See, for instance, Lux and Westerhoff (2009) on the importance of systemic risk, systemic vulnerability and the "logic of collective activity" in the macro-financial context.

[10] Loewy (1991, 1998) states that, to provide a general equilibrium analysis of the macroeconomic effects of bank runs, it is necessary to have a model of financial intermediation in which there exist equilibria that correspond to both the presence and the absence of bank runs.

[11] It is assumed that households deposit funds in banks other than the ones they own.

x_t^* falls below unity:

$$x_t^* = \xi_t \frac{[(1-\delta)Q_t^* + Z_t^*]s_{t-1}^b}{\bar{R}_{t-1}d_{t-1}} = \frac{R_t^{b^*}}{\bar{R}_{t-1}} \frac{\phi_{t-1}}{\phi_{t-1}-1} < 1 \tag{3.3.27}$$

where Q_t^* is the asset liquidation price, Z_t^* is the rental rate on capital and R_t^* is the return on banks' assets, all conditional on a run. Since the liquidation price Q_t^* is below the normal market price Q_t (due to the high value of efficiency costs when all assets are held by households), a run may occur even if the bank is solvent at normal market prices. This explains why a small negative shock to the capital quality that would not cause insolvency, can cause a run.[12]

The *second condition*, feasibility of bank run, depends on the realization of a sunspot. Let ι_t be a binary sunspot variable that takes on a value of 1 with probability κ and a value of 0 with probability $1-\kappa$:

$$\iota_t = \begin{cases} 1 & \text{with probability } \kappa \\ 0 & \text{with probability } 1-\kappa. \end{cases} \tag{3.3.28}$$

In the event of $\iota_t = 1$, depositors coordinate on a run if a bank run equilibrium exists. Modelling bank run this way, stresses the two factors behind financial panics, the first factor is related to the performance of the banking sector itself (i.e. whether x_t^* is less than or greater than unity). The second component is totally exogenous and random, a sunspot process, which can be considered as the *bad luck* factor.

A direct result of bank default is the shifting of the entire ownership of capital claims to the hands of the private households. This can be expressed by: $S_t^h = S_t$. This means that S_t^b can take the following values, depending on whether or not a run occurs at t:

$$S_t^b = \begin{cases} \phi_t N_t Q_t^{-1} & \text{no bank default at } t \\ 0 & \text{bank default at } t. \end{cases} \tag{3.3.29}$$

[12]GKP show that the minimum capital quality required for the banking sector to avoid insolvency is lower than the minimum capital quality required for it to avoid a run: $\xi_t^I < \xi_t^R$.

Following a default in period t, the banking system then recapitalizes and therefore "re-exists" in period $t+1$. Further, during a run at t new bankers cannot set up business. Instead, they store their initial equity and enter in the following period along with the new bankers scheduled to begin at $t+1$. Starting from period $t+2$, the bank equity evolves according to the standard process. This can be summarized in the following expression for the aggregate net worth N_t:

$$N_t = \begin{cases} 0 & \text{bank default at } t \\ \zeta S_{t-1} + \sigma\zeta S_{t-2} & \text{bank default at } t-1 \\ \sigma[\xi_t(Z_t + (1-\delta)Q_t)S^b_{t-1} - \bar{R}_{t-1}d_{t-1}] + \zeta S_{t-1} & \text{otherwise.} \end{cases} \tag{3.3.30}$$

Notice that the household's transfer (e_t) to each new banker is proportionate to the stock of capital at the end of the previous period, S_{t-1}, with $e_t = \frac{\zeta}{(1-\sigma)f}S_{t-1}$. This is technically and computationally convenient as on aggregate, the transfer is calculated by multiplying e_t by the number of new bankers $(1-\sigma)f$, which will result in aggregate transfer being equal to ζS_{t-1}. The transfers from the banking sector to households on aggregate are then described by:

$$\Pi_t = \begin{cases} 0 & \text{bank default at } t \\ -[\zeta S_{t-1} + \sigma\zeta S_{t-2}] & \text{bank default at } t-1 \\ (1-\sigma)N_t - \zeta S_{t-1} & \text{otherwise.} \end{cases} \tag{3.3.31}$$

The actual rate of return on deposits realized in period t is given by:

$$R_t = \begin{cases} \bar{R}_{t-1} & \text{no bank default at } t \\ x_t\bar{R}_{t-1} & \text{bank default at } t. \end{cases} \tag{3.3.32}$$

The aggregate bank balance sheet is described by:

$$Q_t S^b_t = \phi_t N_t \tag{3.3.33}$$

and the aggregate deposit level by:

$$D_t = \begin{cases} (\phi_t - 1)N_t & \text{no bank default at } t \\ 0 & \text{bank default at } t. \end{cases} \tag{3.3.34}$$

Finally, the expected rate of return on banks' investment is given by:

$$E_t R^b_{t+1} = E_t\left[\xi_{t+1}\frac{Z_{t+1} + (1-\delta)Q_{t+1}}{Q_t}\right]. \tag{3.3.35}$$

3.4 Incorporating Optimism and Pessimism and Modifying the Banking Problem

Now I describe my modification of the GKP banking problem through the incorporation of boundedly rational expectations. I manage to show how the behavioural rules for expectations can play dual role in the model. First, they motivate a limit on the banks' ability to increase their leverage (i.e. expand their balance sheet). Second, they provide a context where the issue raised by GKP concerning 'the circumstances that make an economy vulnerable to panics in some instances but not in others' is addressed.

The first step followed to that end is to replace rational expectations in the model with static expectations, particularly:

$$\widetilde{E}_t(\Theta_{t+1}) = \Theta_t \quad \text{where } \Theta \in (\pi, C, Y, Z, Q) \tag{3.4.1}$$

where the tilde above the expectation operator ($\widetilde{E}$) indicates boundedly rational expectations, as in e.g. Lengnick and Wohltmann (2016). Further I assume that these static expectations are the result of optimistic and pessimistic expectations averaging out.[13] Below I explain how such a mechanism for expectations functions on the household level[14] and how it affects the banking problem:

- Assume that, within each household, half of the individuals are optimists and the other half are pessimists (i.e. $\omega^o = \omega^p = 0.5$, where ω is the fraction of optimists and pessimists within the representative household, and o and p refer to optimists and pessimists respectively).
- Optimists believe that positive past trends will continue, while negative past trends will be reversed, in the future. For instance, if the capital price has been rising, it will continue rising in the next period; if it has been falling, it will reverse its trend and start rising in the next period:

$$\widetilde{E}^o_t(Q_{t+1}) = \begin{cases} \theta(Q_t - Q_{t-1}) + Q_t & \text{if } Q_t - Q_{t-1} > 0 \\ -\theta(Q_t - Q_{t-1}) + Q_t & \text{if } Q_t - Q_{t-1} \leq 0. \end{cases} \tag{3.4.2}$$

- Pessimists, on the other hand, believe that negative past trends will continue, while positive trends will be reversed in the future. For instance, if the capital price has been falling, it will

[13] The idea is that when half the individuals expect tomorrow to be better than today, and the other half expect tomorrow to be worse than today, on average, tomorrow is expected to be similar to today: static expectations.

[14] It is then straightforward to expand the idea further to other sectors: expectations in all sectors are static and these static expectations are the result of optimism and pessimism averaging out.

continue falling in the next period; if it has been rising, it will reverse its trend and start falling in the next period:[15,16]

$$\widetilde{E}_t^p(Q_{t+1}) = \begin{cases} -\theta(Q_t - Q_{t-1}) + Q_t & \text{if } Q_t - Q_{t-1} > 0 \\ \theta(Q_t - Q_{t-1}) + Q_t & \text{if } Q_t - Q_{t-1} \leq 0 \end{cases} \tag{3.4.3}$$

where $0 \leq \theta < 1$.

- As the weight of optimists is equal to the wight of pessimists (equal 0.5), at ($Q_t \lesseqgtr Q_{t-1}$) the aggregate expectations are:

$$\begin{aligned} \widetilde{E}_t(Q_{t+1}) &= 0.5[\theta(Q_t - Q_{t-1}) + Q_t] + 0.5[-\theta(Q_t - Q_{t-1}) + Q_t] \\ &= Q_t \end{aligned} \tag{3.4.4}$$

  as previously stated in equation (3.4.1). Observe that at $\theta = 0$, there is no optimism or pessimism; only static expectations.

- Finally, assume that, within the household, decisions are based on the average expectations of its members.

Accordingly, optimists and pessimists will have different expectations for R^b_{t+1} and x_{t+1}:

$$\widetilde{E}_t^j(R^b_{t+1}) = E_t(\xi_{t+1}) \frac{\widetilde{E}_t^j(Z_{t+1}) + (1-\delta)\widetilde{E}_t^j(Q_{t+1})}{Q_t} \tag{3.4.5}$$

$$\begin{aligned} \widetilde{E}_t^j(x_{t+1}) &= \frac{\widetilde{E}_t^j(R^b_{t+1}) Q_t S^b_t}{\bar{R}_t D_t} \\ &= \frac{\widetilde{E}_t^j(R^b_{t+1})}{\bar{R}_t} \frac{\phi_t}{\phi_t - 1} \end{aligned} \tag{3.4.6}$$

where $j \in (o, p)$. Note that the expectation of the future capital quality ($E_t \xi_{t+1}$) remains rational as the latter follows an exogenous AR(1) process (see equation 3.3.4).

[15] Gibson and Sanbonmatsu (2004) explain how optimists demonstrate an attentional bias for positive information, whereas pessimists demonstrate an attentional bias for negative information. In addition, even when faced with clearly negative information, optimists tend to reframe this information in positive ways.

[16] See also Schmitt and Westerhoff (2016), who explain how when stock prices are increasing, optimism (i.e. the believe that the prices will keep increasing) can be accompanied by a fear of regret of missing out on speculative profits. On the other hand, there is also the sense of common wisdom that dictates that stock markets cannot grow forever.

By equating the expression in equation (3.4.6) to unity, we can solve for the bank leverage levels for optimists and pessimists, beyond which they would expect a bank insolvency.[17] I denote these by ϕ_t^o and ϕ_t^p respectively:

$$\frac{\phi_t^j}{\phi_t^j - 1} = \frac{\bar{R}_t}{\widetilde{E}_t^j(R_{t+1}^b)} \quad j \in (o, p). \tag{3.4.7}$$

Optimists have higher expectations for the capital price, $\widetilde{E}_t Q_{t+1}$, and the rental rate on capital, $\widetilde{E}_t Z_{t+1}$, than pessimists (see equations 3.4.2 and 3.4.3), and as a result, higher expectations for future banks' performance (return on assets, $\widetilde{E}_t R_{t+1}^b$). Therefore, optimists' expectations allow for a larger leverage level:

$$1 \leq \phi_t^p \leq \phi_t^o. \tag{3.4.8}$$

At equilibrium, both optimists and pessimists have (correctly) static expectations for Q_{t+1} and Z_{t+1} (i.e. $\widetilde{E}_t^j Q_{t+1} = Q$ & $\widetilde{E}_t^j Z_{t+1} = Z$). Therefore $\phi^o = \phi^p$, at the steady state.

Depending on the value of the leverage a bank chooses, the probability of default, due to insolvency is assumed to be:

$$\rho_t = \begin{cases} 0 & \text{if } 1 \leq \phi_t \leq \phi_t^p \\ \omega^p & \text{if } \phi_t^p < \phi_t \leq \phi_t^o \\ 1 & \text{if } \phi_t^o < \phi_t. \end{cases} \tag{3.4.9}$$

The case where banks operate at $\phi_t > \phi_t^o$ is excluded as it is not possible for a bank to operate when all the households' members (and hence the entire economy) expect it to default. Therefore equation (3.4.9) can be reduced to:

$$\rho_t = \begin{cases} 0 & \text{if } 1 \leq \phi_t \leq \phi_t^p \\ \omega^p & \text{if } \phi_t^p < \phi_t \leq \phi_t^o. \end{cases} \tag{3.4.10}$$

The bank's maximization problem (expressed before in equation 3.3.26) can now be represented by:

$$\max_{\phi_t} \begin{cases} \phi_t \widetilde{E}_t R_{t+1}^b n_t - \frac{n_t\phi_t - n_t}{\widetilde{E}_t \Lambda_{t+1}(\omega^p \frac{\widetilde{E}_t R_{t+1}^b}{\bar{R}_t}\frac{\phi_t}{\phi_t - 1} + 1 - \omega^p)} & \text{if } \phi_t > \phi_t^p \\ \phi_t \widetilde{E}_t R_{t+1}^b n_t - \frac{n_t\phi_t - n_t}{\widetilde{E}_t \Lambda_{t+1}} & \text{if } \phi_t \leqslant \phi_t^p. \end{cases} \tag{3.4.11}$$

[17] The idea here is analogous to GKP. They focus on calculating the level of capital quality below which a default would happen. Here, I focus on calculating the leverage multiple value, above which a default would happen.

Equation (3.4.11) shows that, when the level of leverage is not higher than ϕ_t^p, banks are not punished by raising the leverage: as long as $\widetilde{E}_t R_{t+1}^b$ is higher than $\frac{1}{\widetilde{E}_t \Lambda_{t+1}}$ (as it is in the steady state), expected net worth is strictly increasing in ϕ_t. Therefore, banks will keep their leverage at the highest possible level (i.e. ϕ_t=ϕ_t^p). Beyond ϕ_t^p, the probability of default becomes positive (= ω^p) and higher leverage levels become costly, because of the compensation banks have to pay in terms of higher rates promised on deposits. This highlights the fact that the choice of leverage has a direct as well as an indirect effect on the objective function. The latter effect materializes through the impact of the chosen leverage level on the probability of default.

Taking the first derivative of the first line in (3.4.11) with respect to ϕ_t, equating the result to zero, dividing both sides by (n_t) and finally simplifying lead to the level of leverage that maximizes expected net worth, $\phi_t^{\max}$:

$$\widetilde{E}_t R_{t+1}^b - \frac{2\widetilde{E}_t \Lambda_{t+1} \omega^p \frac{\widetilde{E}_t R_{t+1}^b}{\bar{R}_t} \frac{\phi_t^{\max}}{\phi_t^{\max}-1} + (1-\omega^p - \omega^p \frac{\widetilde{E}_t R_{t+1}^b}{\bar{R}_t})\widetilde{E}_t \Lambda_{t+1}}{\left[\widetilde{E}_t \Lambda_{t+1}\left(\omega^p \frac{\widetilde{E}_t R_{t+1}^b}{\bar{R}_t} \phi_t^{\max}(\phi_t^{\max}-1)^{-1} + 1 - \omega^p\right)\right]^2} = 0. \tag{3.4.12}$$

Then, the following equation manifests the possibilities for the level of leverage ϕ_t:

$$\phi_t = \begin{cases} \phi_t^{\max} & \text{if } \phi_t^p \leq \phi_t^{\max} \leq \phi_t^o \\ \phi_t^o & \text{if } \phi_t^{\max} > \phi_t^o \\ \phi_t^p & \text{if } \phi_t^{\max} < \phi_t^p. \end{cases} \tag{3.4.13}$$

Banks will choose a leverage level higher than ϕ_t^p only if the compensation, in terms of a higher rate of return on deposits, is low enough. If the compensation is too high (because ω^p is too high or $E_t x_{t+1}$ is too low), banks will choose a level of leverage equal to ϕ_t^p. The nonlinear problem is implemented through a mechanism that captures both the direct and the indirect effect of ϕ_t on the objective function as follows: equation (3.4.12) is solved for ϕ_t^{max}. If ϕ_t^{max} is higher than ϕ_t^p it means that it is profitable for the banks to take such a high leverage even with the compensation they have to pay to the depositors. If ϕ_t^{max} is lower than ϕ_t^p it means that the compensation is too high. As discussed before, at any level of leverage lower than or equal to ϕ_t^p, raising the leverage level will not be at any cost to the bank, leverage is thus set equal to ϕ_t^p. Figure 3.1 virtually illustrates the possible value range for ϕ_t.

We can notice that the optimal leverage multiple is independent of bank-specific factors (i.e. independent of bank's net worth n_t). As a result, the level of leverage that maximizes the expected net

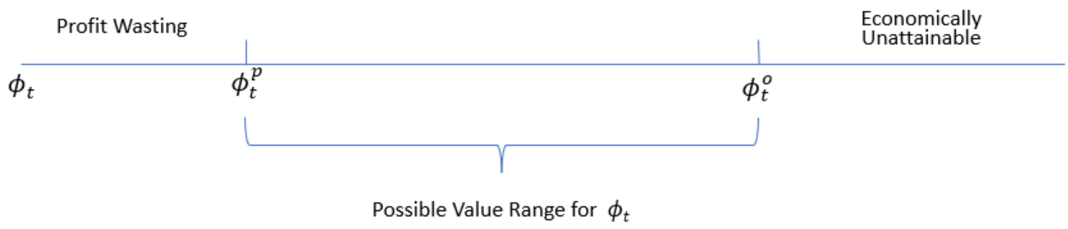

Figure 3.1: The limit on banks' choice of leverage

worth is homogeneous across banks. This implies that the default probability, the promised rate on deposits, $\bar{R}_t$, and the (expected) recovery rate are all independent of bank's specific characteristics.

It is important to notice here that the optimistic and pessimistic expectations for the model's variables altered the model exclusively via their influence on the banking problem through the mechanism explained above. Beyond that, optimism and pessimism have no further effect on the model as they always average out into static expectations on the aggregate level. In other words, there are no other channels through which optimism and pessimism affect the model's outcome other than the banking problem channel (see equations 3.4.1 and 3.4.4 as well as the appendix for a full insight).

The rest of the model, precisely, production, market clearing and monetary policy, follows GKP entirely. There is a production sector consisting of producers of final goods, intermediate goods, and capital goods. Prices are sticky in the intermediate goods sector. Finally, there is a central bank that conducts monetary policy through the variation of the short run interest rate following a Taylor rule. To avoid unnecessary repetition, the reader is referred to GKP for a detailed illustration. Final equations regarding these sectors, which are necessary for the description of the equilibrium, are included in the appendix.

3.5 Numerical Exercises

3.5.1 Calibration

Table 3.1 reports the calibration. It chiefly follows GKP. The last column of the table provides the motive behind the choice of values. Note that letters without the subscript t denote steady state values.

Table 3.1: Baseline parametrization

Parameter	Description	Value	Target
		Standard parameters	
A	Technology Parameter	11.3	$Y = 2.25$
a	Inv. Technology	0.53	$Q = 1$
b	Inv. Technology	-0.0083	$\Gamma(I) = I$
η	Elasticity of Q w.r.t. I	0.25	Literature
α	Capital Share	0.33	$\frac{I}{K} = 0.025$
δ	Capital Depreciation	0.025	$K = S$
β	Impatience	0.99	Risk Free Rate
γ_h	Risk Aversion	2	Literature
κ_π	Policy Response to Inflation	1.5	Literature
κ_y	Policy Response to Output	0.125	Literature
ϵ	Elasticity of Subst. across Varieties	1.06	$MC = \frac{\epsilon-1}{\epsilon}$
φ	Inverse Frisch Elasticity	0.5	Literature
ρ^r	Price Adj. Costs	1000	Slope of Phillips curve = 0.01
G	Government Expenditure	0.45	$\frac{G}{Y} = 0.2$
		Behavioural and financial intermediation parameters	
σ	Banker Survival Rate	0.93	$\phi = 10$
χ	Marginal HH Intermediation Costs	0.005	40% drop in investment in a panic
$\varkappa$	Sunspot Probability	0.15	GKP
ζ	New Banker Endowment	0.001	GKP
γ	Threshold for HH Intermediation Costs	0.61	GKP
θ	Expectations Parameter	0.2	ad hoc
σ_ξ	Standard Deviation of Innovation to Capital Quality	0.25%	40% drop in investment in a panic
ρ_ξ	Serial Correlation of Capital Quality	0.7	GKP

3.5.2 A General Overview of the Model Dynamics

Every period, there exists two possible "states of the world" for the model:

1. Banks do not default; the banking sector functions normally, and capital claims are shared among banks and households: $S^b_t > 0$ and $S^h_t + S^b_t = S_t$.
2. a) Banks default as a result of insolvency; banks fire-sell their capital holdings: $S^b_t = 0$ and $S^h_t = S_t$.
   b) Banks are solvent at prevailing prices, but they default as a result of a bank run; banks fire-sell their capital holdings: $S^b_t = 0$ and $S^h_t = S_t$.

The conditions for each state must be checked every period. This determines which state is the feasible state. Such a mechanism creates complicated nonlinear model dynamics.

3.5.3 Experiments

In this section, I perform several experiments to study the behaviour of the model under different scenarios. The first experiment pursues the assessment of the role of backward-looking expectations absent bank runs. The second experiment illustrates the effect of a bank run on the model economy. The third experiment simulates a scenario where news driven optimism leads to a rise in the leverage multiple that is followed by a panic and a subsequent real and financial bust.

No bank run: role of backward-looking expectations

Figure 3.2 shows the response of the economy to a negative one standard deviation (0.25%) shock to the quality of capital without runs.[18,19] The solid line is the model with optimistic and pessimistic expectations and the dotted line is the case where all expectations are rational (no static, optimistic or pessimistic expectations). In both cases, the shock reduces the return to capital, reducing investment and aggregate demand. In addition, the weakening of bank balance sheets amplifies the contraction in demand through the financial accelerator/credit cycle mechanism of Bernanke et al. (1999) and Kiyotaki and Moore (1997). Low asset returns following the shock cause bank net worth to decrease by up to 0.7% in the scenario with rational expectations, and 1.6% in the scenario with optimism and pessimism. In the case with rational expectations, and similar to GKP, as financial constraints tighten and asset prices decline, expected bank returns ($\widetilde{E}_t R^b_{t+1}$) slightly rise, allowing banks to increase their leverage multiple. In other words, leverage moves countercyclically. This leads to a decrease in efficiency costs and as a result, the overall effect of the negative shock on the model is diluted. In the case with backward-looking expectations however, the pessimistic view inhibits the rise in bank leverage even when average expected returns rise. Banks are thus "forced" to cut back their leverage, i.e. leverage is moving procyclically, leading to a decrease in bank demand on capital claims, increased levels of efficiency costs, lower capital prices and as a result, a deep contraction in investment. Overall, a 0.25% decline in the quality of capital results in a drop in investment by 1% in the case with rational expectations and 20% in the case with backward-looking expectations. One can see that, in comparison with the rational expectations scenario, backward-looking expectations, in particular pessimistic expectations, greatly amplify the negative effect of the shock through their effect on the banking problem.

[18] I use a smaller value for the standard deviation of innovation to capital quality than GKP, namely, 0.25% instead of 0.5% (see Table 3.1). The reason behind this is that the backward-looking expectations in the model massively intensify the effect of exogenous shocks.

[19] Bank runs are excluded by exogenously setting $\iota_t = 0$.

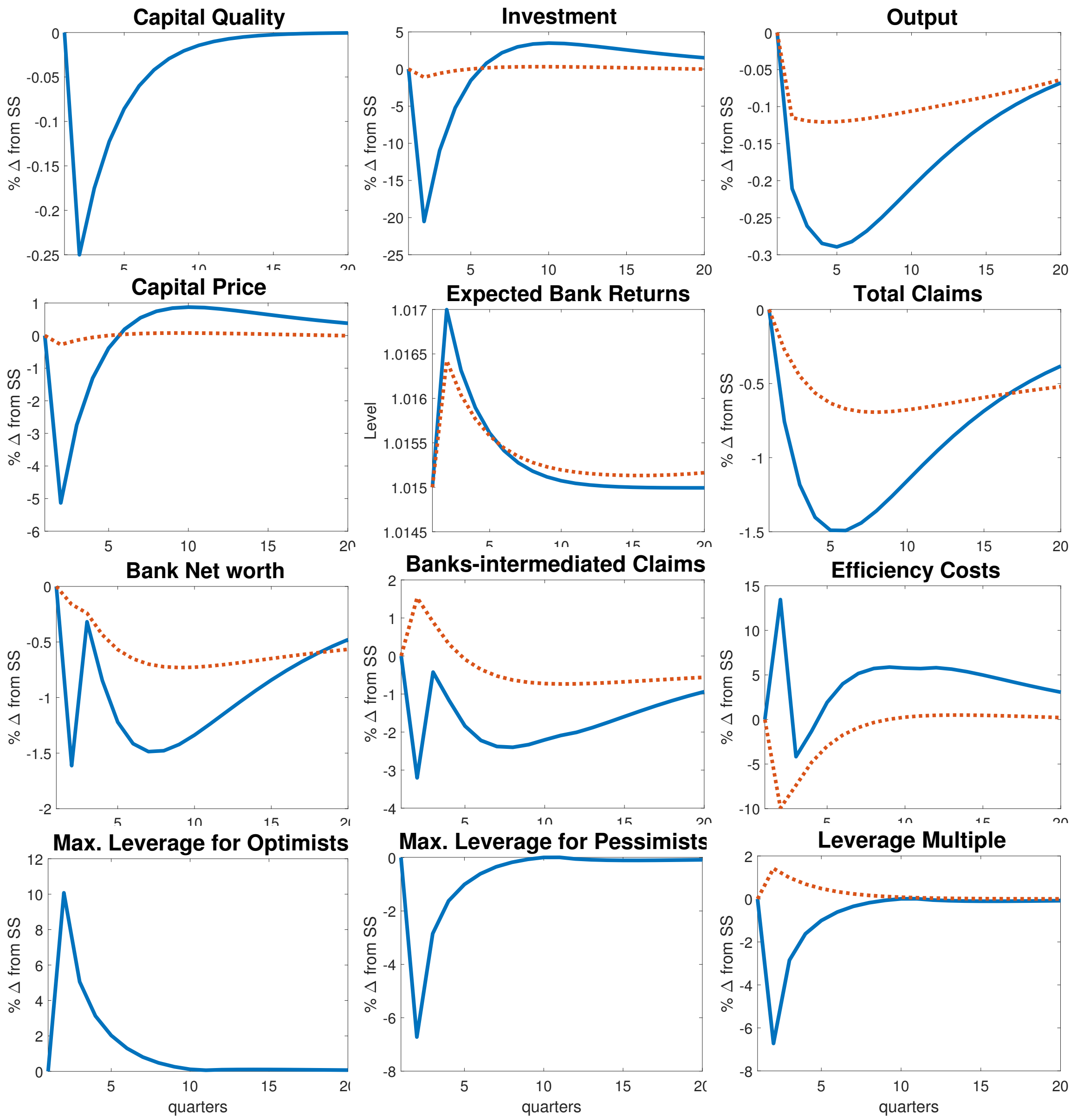

Figure 3.2: Response to a capital quality shock under no run scenario. The solid line is the model under backward-looking expectations. The dotted line illustrates the model under rational expectations.

Bank runs

Figure 3.3 shows the response of the economy to a negative one standard deviation (0.25%) shock to the quality of capital, with and without bank run. The solid line is the model under no run assumption (i.e. $\iota_t = 0$). It corresponds to the solid line in Figure 3.2. The dashed line is the case where a bank run is allowed in the first period ($\iota_1 = 1$). The graphs titled "Run" and "Insolvency" are designed to take the value of 1 when run or insolvency respectively occurs, and the value of 0 otherwise.

We can observe that, when a run equilibrium is feasible, the negative shock induces depositors to coordinate on a no rollover equilibrium. In other words, the shock causes x_t^* to drop below unity. As a result, a complete collapse of the banking sector follows: all bank assets are liquidated ($\frac{S_t^b}{S_t} \to 0$), net worth and deposits go to zero, and banks default. Asset prices drop 10%, to their liquidation value, investment drops 40% and output drops almost 0.4%.[20] We can also observe that the drop in investment in the presence of a run is about double the drop absent run, reflecting the inefficiency from the complete loss of banking services.

The dotted line in the figure represents the model under rational expectations, where a run is allowed in the first period. We can see however that no bank run occurs. In other words, the negative capital quality shock that induces a bank run in the model under pessimism and optimism, is not enough to induce a panic in the model under rational expectations.[21]

Finally, we can notice that the "insolvency" graph remains at zero in all three cases, which means that the conditions for insolvency are not satisfied: banks remain solvent at the prevailing market prices, even in the face of a negative capital quality shock. It is the panic (illiquidity) that leads to the failure of the banking sector, the drop in asset prices to their liquidation values and the accompanying devastating effect on the real economy.

A news driven credit boom that leads to a bust

In the previous exercise, the panic induced bust was created in the model by means of a negative shock to the quality of capital. In this exercise, I simulate a panic/bust event (1) absent any real exogenous shock[22] and (2) with a pre-crisis credit boom. I follow the lead of GKP and others by introducing optimistic beliefs about the return on capital that are eventually disappointed. Figure 3.4 illustrates an experiment where an optimistic news about a rise in the expected bank returns, $E_t R_{t+1}^b$, arrives in the economy creating a wave of overoptimism.[23] As time passes and such a rise in returns is not actually realized, agents loose hope. Unlike GKP, who model the loss of hope as being gradual, I, for simplicity, assume that the hope is lost once and for all after 12 periods.

[20] See equation (3.7.5) in the appendix which shows how the market value of capital (Q_t) governs investment dynamics.

[21] Therefore, the dotted line in Figure 2 corresponds to the dotted line in Figure 1. In the latter, bank run is exogenously disallowed, in the first, bank run is allowed but the shock is not big enough to induce it.

[22] On this matter, (Gorton and Ordoñez, 2014, p.343) state that "Financial Crises are hard to explain without resorting to large shocks. But the recent crisis[(i.e.the GFC)], for example, was not the result of a large shock."

[23] Gärling et al. (2009), for instance, explain how optimism leads to overreaction to news which in turn leads to increased trading volume and stock price volatility.

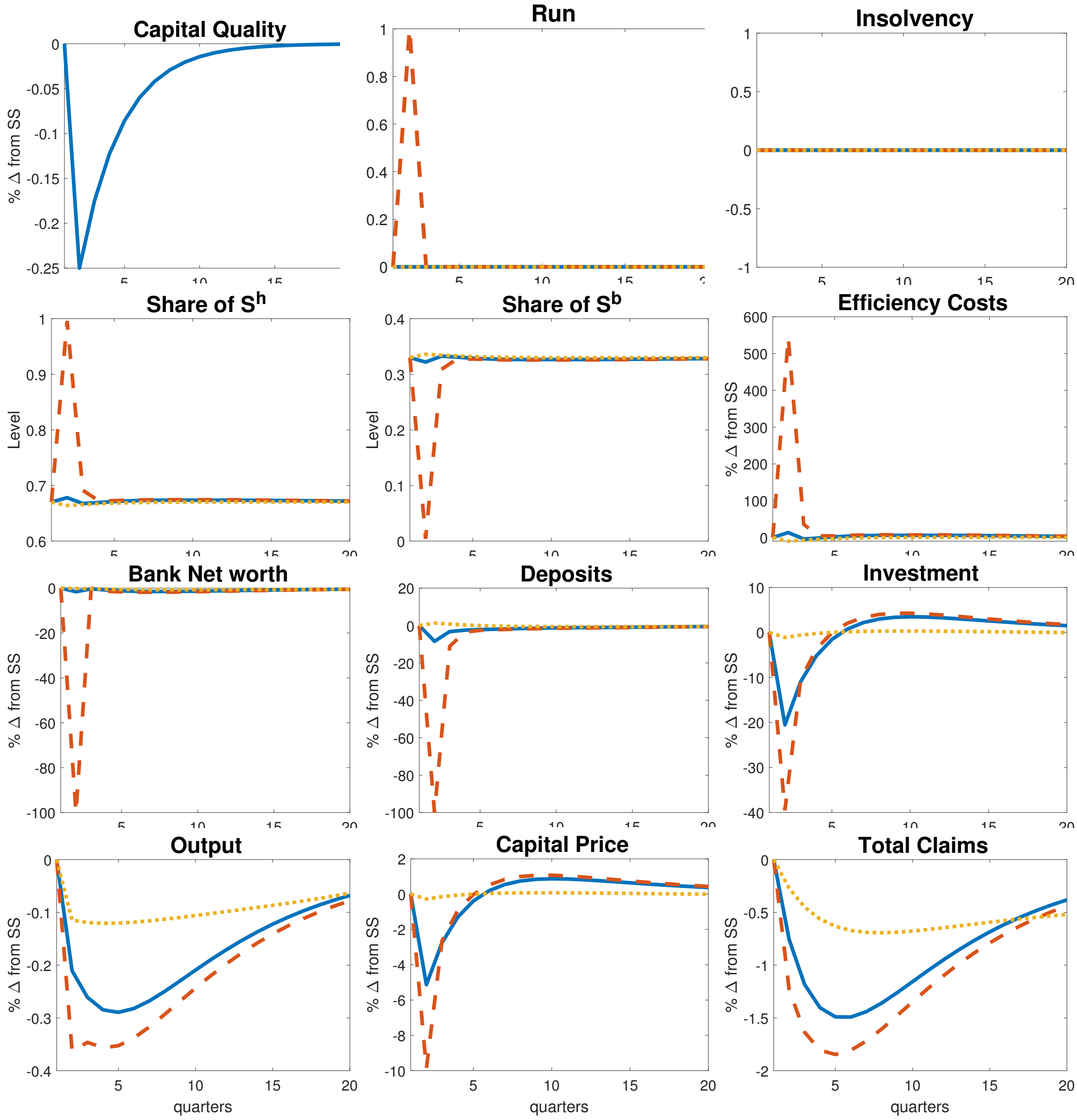

Figure 3.3: Response to a capital quality shock with and without bank run. The solid line is the model under no run assumption. The dashed line is the case where a bank run is allowed in the first period. The dotted line is the model under rational expectations, where a bank run is allowed in the first period.

The solid line shows a scenario where the news is only believed by banks. Households, whether optimists or pessimists, either do not believe the news, or simply do not receive it. Despite being optimistic, banks are restricted from raising their leverage multiple, as per the mechanism explained before in Section 3.4. The optimistic news cannot translate into a credit boom; the model stays at the steady state unaffected.

Differently, the dashed line shows a scenario where such news is received and believed by both households and banks. Banks now have the *marginal freedom* to raise their leverage multiple. Leverage increases by about 40%.[24] The share of bank intermediated claims expand, and therefore, efficiency costs drop. The credit boom is accompanied by a much less proportional real boom: investment increases by about 3% and output by less than 0.1% on average.

When hope is lost, it becomes clear to the creditors that banks are overleveraged and x_t^* falls below unity. When bank run is allowed ($\iota = 1$), a panic equilibrium both exists and is feasible. Banks are forced to fire-sell their assets, efficiency costs dramatically rise, capital price falls, and investment drops by more than 20%.

Note that this was a completely expectations-driven boom-bust event that happened absent any real disturbance to the economy.[25] Also note that in the absence of a capital quality shock, panics can be induced, but the downturn is very short lived (financial and real variables soon return to the steady state). In other words, this exercise can capture the severity of the initial downturn rather than the slowness of the recovery (see Bernanke, 2018, for more on that matter).

[24] The reader is referred to Figure 1 in Duffie (2019), which illustrates the build-up of leverage of the largest US investment banks and bank holding companies in the years prior to the GFC.

[25] See Di Bella and Grigoli (2019) on empirical evidence on the effect of expectations, namely turning more optimistic or pessimistic, on consumption and investment.

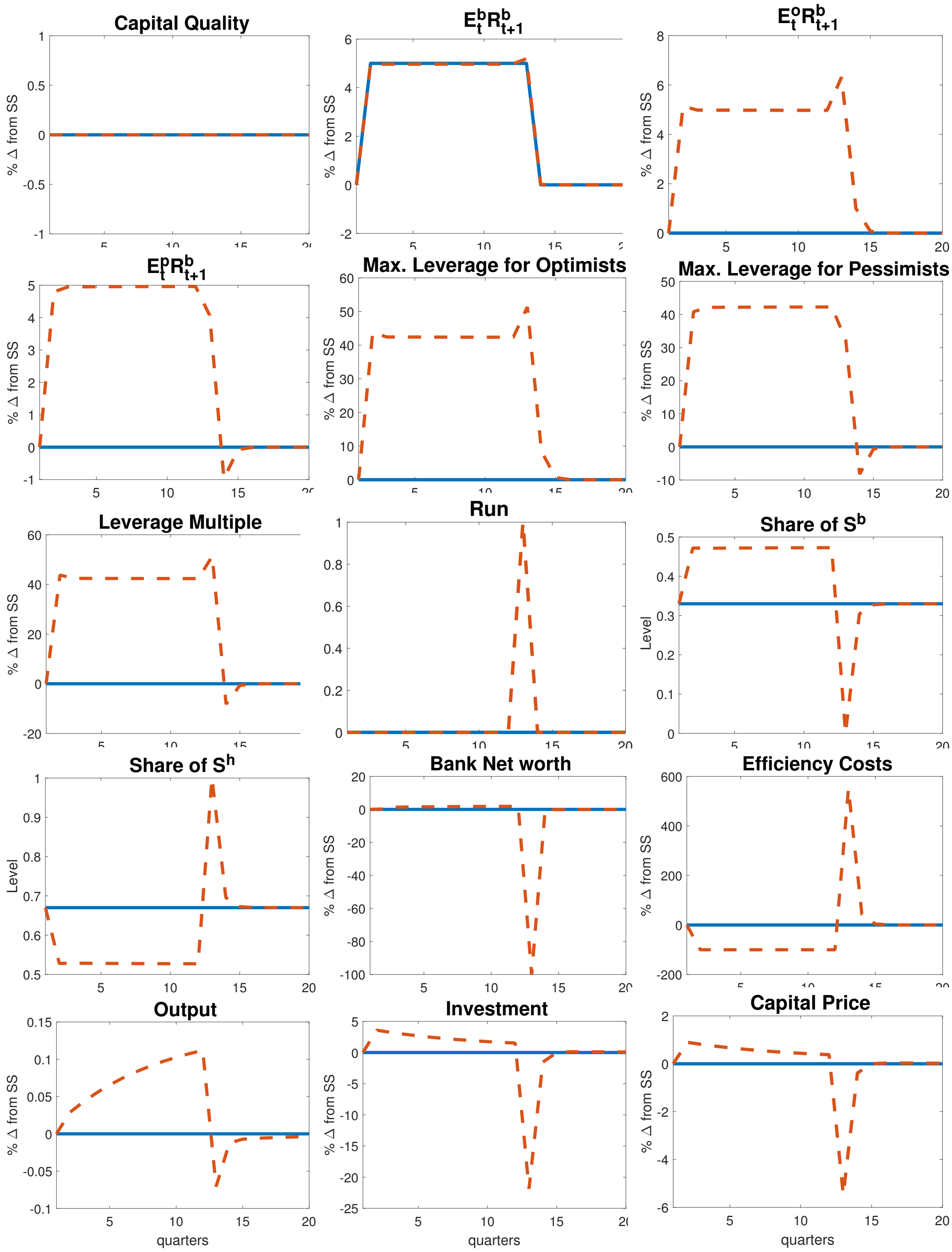

Figure 3.4: Overoptimistic news concerning bank yields. The solid line is the scenario where only bankers believe the news. The dashed line is the scenario where both households and bankers believe the news. Note: run is feasible in period 13 ($\iota_{13} = 1$).

3.6 Concluding Remarks

I have integrated behavioural expectations in a macroeconomic model where bank panics can occur, leading to devastating effects on the real activity. Bankers have to take into consideration the prevailing optimistic and pessimistic expectations when solving for the leverage multiple that maximizes expected net worth. A leverage multiple that is too low forgoes the possibility of a higher future net worth. A leverage multiple that is too high increases the probability of bank default according to the expectations of the depositing, boundedly rational households. The latter in turn raises the rate banks have to promise on deposits and, as a consequence, expected net worth is negatively impacted. Such a mechanism defines limitations on the unregulated, otherwise unrestricted banking sector, concerning its ability to increase its leverage.

I manage to show how as long as there exists an optimism-pessimism balance in the economy, banks are disabled from massively expanding their balance sheets and the banking sector stays moderately leveraged. When such an optimism-pessimism balance is disrupted by means of some overoptimistic news, banks are able to enormously increase their leverage and panics can follow. This can attributed to the following quote by (Hecht, 2013, p.173):

> Our survival and wellness require a balance between optimism and pessimism. Undue pessimism makes life miserable; however, excessive optimism can lead to dangerously risky behaviors.

3.7 Appendix to Chapter 3

Equations (3.7.1) to (3.7.36) of this appendix describe the model, showing the two states the model economy can take: 1) no default and 2) default. Equations (3.7.37) to (3.7.56) describe the model variables conditional on a bank run. Equations (3.7.1′) to (3.7.56′) illustrate the log linearised version of the model. Finally, Table 3.2 presents the steady state values of the model variables.

Producers

The capital stock for production is given by:

$$K_t = \xi_t S_{t-1}. \tag{3.7.1}$$

The capital quality shock is serially correlated as follows:

$$\xi_t = 1 - \rho_\xi + \rho_\xi \xi_{t-1} + \epsilon_t. \tag{3.7.2}$$

Capital at the end of period t is:

$$S_t = \Gamma(I_t) + (1-\delta)K_t \tag{3.7.3}$$

where the investment technology $\Gamma(I_t)$, is expressed as follows:

$$\Gamma(I_t) = a(I_t)^{1-\eta} + b. \tag{3.7.4}$$

Capital goods producers' first order condition for investment is:

$$Q_t(1-\eta)aI_t^{-\eta} = 1. \tag{3.7.5}$$

The first-order conditions for intermediate goods producers yield:

$$\frac{K_t}{L_t} = \frac{\alpha}{1-\alpha}\frac{w_t}{Z_t} \tag{3.7.6}$$

and the following relation for marginal cost:

$$MC_t = \frac{1}{A}\left(\frac{Z_t}{\alpha}\right)^{\alpha}\left(\frac{w_t}{1-\alpha}\right)^{1-\alpha}. \tag{3.7.7}$$

Phillip's curve is expressed by:

$$\pi_t(\pi_t - 1) = \frac{\epsilon}{\rho^r}\left(MC_t - \frac{\epsilon-1}{\epsilon}\right) + \widetilde{E}_t\left[\Lambda_{t+1}\frac{Y_{t+1}}{Y_t}(\pi_{t+1}-1)\pi_{t+1}\right] \tag{3.7.8}$$

where

$$\widetilde{E}\Lambda_{t+1} = \beta\left(\frac{\widetilde{E}_t C_{t+1}}{C_t}\right)^{-\gamma_h}. \tag{3.7.9}$$

Aggregate production is:

$$Y_t = AK_t^{\alpha}L_t^{1-\alpha}. \tag{3.7.10}$$

Households

First order conditions for labour, riskless bonds, deposits, and direct capital holding, respectively are:

$$w_t = (C_t)^{\gamma_h}(L_t)^{\varphi} \tag{3.7.11}$$

$$\widetilde{E}_t\left(\Lambda_{t+1}\frac{R_t^n}{\pi_{t+1}}\right) = 1 \tag{3.7.12}$$

$$\widetilde{E}_t\Lambda_{t+1}[\rho_t x_{t+1}\bar{R}_t + (1-\rho_t)\bar{R}_t] = 1 \tag{3.7.13}$$

$$\widetilde{E}_t\left[\Lambda_{t+1}\xi_{t+1}\frac{Z_{t+1} + (1-\delta)Q_{t+1}}{Q_t + \frac{\partial}{\partial S_t^h}\varsigma(S_t^h, S_t)}\right] = 1 \tag{3.7.14}$$

where

$$\frac{\partial}{\partial S_t^h}\varsigma(S_t^h, S_t) = Max\left[\chi\left[\frac{S_t^h}{S_t} - \gamma\right], 0\right]. \tag{3.7.15}$$

Bankers

Rate of return on bank assets is:

$$R_t^b = \xi_t\left(\frac{Z_t + (1-\delta)Q_t}{Q_{t-1}}\right) \tag{3.7.16}$$

and the expected rate is:

$$\widetilde{E}_t R_{t+1}^b = \widetilde{E}_t\left[\xi_{t+1}\frac{Z_{t+1} + (1-\delta)Q_{t+1}}{Q_t}\right]. \tag{3.7.17}$$

The aggregate capital holding of the banking sector is proportional to the aggregate net worth:

$$S_t^b = \begin{cases} \phi_t N_t Q_t^{-1} & \text{no bank default at } t \\ 0 & \text{bank default at } t. \end{cases} \tag{3.7.18}$$

The aggregate net worth of banks evolves as:

$$N_t = \begin{cases} 0 & \text{bank default at } t \\ \zeta S_{t-1} + \sigma\zeta S_{t-2} & \text{bank default at } t-1 \\ \sigma[\xi_t(Z_t + (1-\delta)Q_t)S_{t-1}^b - \bar{R}_{t-1}D_{t-1}] + \zeta S_{t-1} & \text{otherwise.} \end{cases} \tag{3.7.19}$$

Banks finance capital holdings by net worth and deposit, which implies:

$$D_t = \begin{cases} (\phi_t - 1)N_t & \text{no bank default at } t \\ 0 & \text{bank default at } t. \end{cases} \tag{3.7.20}$$

Aggregate transfers between households and bankers are given by:

$$\Pi_t = \begin{cases} 0 & \text{bank default at } t \\ -\zeta S_{t-1} - \sigma\zeta S_{t-2} & \text{bank default at } t-1 \\ (1-\sigma)\left[\xi_t(Z_t + (1-\delta)Q_t)S^b_{t-1} - \bar{R}_{t-1}D_{t-1}\right] & \text{otherwise.} \end{cases} \tag{3.7.21}$$

The recovery rate is:

$$x_t = \frac{R^b_t Q_{t-1} S^b_{t-1}}{\bar{R}_{t-1} D_{t-1}}. \tag{3.7.22}$$

As explained in the text, conditions for insolvency are checked first, then conditions for a run. The following two-step-calculation for the actual rate of return on deposits R_t holds:

$$R^a_t = \begin{cases} \bar{R}_{t-1} & \text{if } x_t \geqslant 1 \\ x_t \bar{R}_{t-1} & \text{if } x_t < 1 \end{cases} \tag{3.7.23}$$

$$R_t = \begin{cases} R^a_t & \text{if } x^*_t \geqslant 1 \text{ and/or } \iota_t = 0 \\ \bar{R}_{t-1} x_t & \text{if } x^*_t < 1 \text{ AND } \iota_t = 1 \end{cases} \tag{3.7.24}$$

where $x_t \in [0, 1)$ and x^*_t is the recovery rate conditional on a run. Note that if bank default is actually happening (line 2 in 3.7.23 or 3.7.24), $x_t = x^*_t$.

The bankers' maximization problem leads to:

$$\widetilde{E}_t R^b_{t+1} - \widetilde{E}_t \left[\frac{2\Lambda_{t+1}\omega^p \frac{R^b_{t+1}}{\bar{R}_t} \frac{\phi^{\max}_t}{\phi^{\max}_t - 1} + (1 - \omega^p - \omega^p \frac{R^b_{t+1}}{\bar{R}_t})\Lambda_{t+1}}{\left[\Lambda_{t+1}\left(\omega^p_t \frac{R^b_{t+1}}{\bar{R}_t} \phi^{\max}_t (\phi^{\max}_t - 1)^{-1} + 1 - \omega^p\right)\right]^2} \right] = 0. \tag{3.7.25}$$

Then, the bankers' choice for ϕ_t follows the rules described in the text. Namely:

$$\phi_t = \begin{cases} \phi^{\max}_t & \text{if } \phi^p_t \leq \phi^{\max}_t \leq \phi^o_t \\ \phi^o_t & \text{if } \phi^{\max}_t > \phi^o_t \\ \phi^p_t & \text{if } \phi^{\max}_t < \phi^p_t. \end{cases} \tag{3.7.26}$$

Market clearing

The market for capital holding implies:

$$S_t = S^b_t + S^h_t. \tag{3.7.27}$$

The final goods market clearing condition implies:

$$Y_t = C_t + I_t + \frac{\rho^r}{2}(\pi_t - 1)^2 Y_t + G. \tag{3.7.28}$$

The central bank's nominal rate on the riskless bond R_t^n is governed by the following Tylor rule:

$$R_t^n = \frac{1}{\beta}(\pi_t)^{\kappa_\pi}\left(\frac{MC_t}{\frac{\epsilon-1}{\epsilon}}\right)^{\kappa_y}. \tag{3.7.29}$$

Note that similar to GKP, I do not exogenously impose the zero lower bound on the nominal policy rate. Nevertheless, the rate never falls below zero in the simulation exercises discussed before.

Expectations

$$\widetilde{E}_t(\Theta_{t+1}) = \Theta_t, \quad \text{where } \Theta \in (\pi, C, Y, Z, Q). \tag{3.7.30}$$

Particularly for expectations of Q_{t+1},[26] optimistic expectations are:

$$\widetilde{E}_t^o(Q_{t+1}) = \begin{cases} \theta(Q_t - Q_{t-1}) + Q_t & \text{if } Q_t - Q_{t-1} > 0 \\ -\theta(Q_t - Q_{t-1}) + Q_t & \text{if } Q_t - Q_{t-1} \leq 0 \end{cases} \tag{3.7.31}$$

and pessimistic expectations are:

$$\widetilde{E}_t^p(Q_{t+1}) = \begin{cases} -\theta(Q_t - Q_{t-1}) + Q_t & \text{if } Q_t - Q_{t-1} > 0 \\ \theta(Q_t - Q_{t-1}) + Q_t & \text{if } Q_t - Q_{t-1} \leq 0. \end{cases} \tag{3.7.32}$$

Then the following is true for the expected rate of return on banks' assets:

$$\widetilde{E}_t^j R_{t+1}^b = E_t(\xi_{t+1}) \frac{\widetilde{E}_t^j(Z_{t+1}) + (1-\delta)\widetilde{E}_t^j(Q_{t+1})}{Q_t} \quad \text{where } j \in (o, p) \tag{3.7.33}$$

and the aggregate expected rate is:

$$\widetilde{E}_t R_{t+1}^b = \widetilde{E}_t\left[\xi_{t+1}\frac{Z_{t+1} + (1-\delta)Q_{t+1}}{Q_t}\right] = \omega^o \widetilde{E}_t^o R_{t+1}^b + \omega^p \widetilde{E}_t^p R_{t+1}^b. \tag{3.7.34}$$

It follows that optimists and pessimists respectively calculate that the levels of leverage beyond which banks would be insolvent is:

$$\phi_t^j = \frac{\bar{R}_t}{\widetilde{E}_t^j(R_{t+1}^b)}\left(\phi_t^j - 1\right) \quad \text{where } j \in (o, p). \tag{3.7.35}$$

Finally, expected capital quality is:

$$E_t \xi_{t+1} = 1 - \rho_\xi + \rho_\xi \xi_t + \epsilon_t. \tag{3.7.36}$$

[26] The same rules apply to $\widetilde{E}_t Z_{t+1}$. For the other variables, namely, π_{t+1}, C_{t+1} and Y_{t+1}, it is not important to explicitly state optimistic and pessimistic expectations as they have no influence on the model dynamics.

The model variables conditional on a run

As stated in the text, every period, depositors compute the recovery rate conditional on a run, x_t^*. If its value is less than unity AND the sunspot variable ι_t is equal to 1, run happens. Otherwise, a bank run is not feasible.

The following equations describe the model variables conditional on a run (with the asterisk referring to variables conditional on a run).

$$S_t^* = \Gamma(I_t^*) + (1-\delta)K_t \tag{3.7.37}$$

$$\Gamma(I_t^*) = a(I_t^*)^{1-\eta} + b \tag{3.7.38}$$

$$Q_t^*(1-\eta)aI_t^{*-\eta} = 1 \tag{3.7.39}$$

$$\frac{K_t}{L_t^*} = \frac{\alpha}{1-\alpha}\frac{w_t^*}{Z_t^*} \tag{3.7.40}$$

$$w_t^* = (C_t^*)^{\gamma_h}(L_t^*)^{\varphi} \tag{3.7.41}$$

$$Y_t^* = AK_t^{\alpha}L_t^{*1-\alpha} \tag{3.7.42}$$

$$\widetilde{E}_t^*(\Lambda_{t+1}\frac{R_t^{n*}}{\pi_{t+1}}) = 1 \tag{3.7.43}$$

$$\widetilde{E}_t^*\Lambda_{t+1} = \beta\left(\frac{\widetilde{E}_t^*C_{t+1}}{C_t^*}\right)^{-\gamma_h} \tag{3.7.44}$$

$$R_t^{n*} = \frac{1}{\beta}(\pi_t^*)^{\kappa_\pi}\left(\frac{MC_t^*}{\frac{\epsilon-1}{\epsilon}}\right)^{\kappa_y} \tag{3.7.45}$$

$$MC_t^* = \frac{1}{A}(\frac{Z_t^*}{\alpha})^{\alpha}(\frac{w_t^*}{1-\alpha})^{1-\alpha} \tag{3.7.46}$$

$$\pi_t^*(\pi_t^*-1) = \frac{\epsilon}{\rho^r}(MC_t^* - \frac{\epsilon-1}{\epsilon}) + \widetilde{E}_t^*\left[\Lambda_{t+1}\frac{Y_{t+1}}{Y_t^*}(\pi_{t+1}-1)\pi_{t+1}\right] \tag{3.7.47}$$

$$Y_t^* = C_t^* + I_t^* + \frac{\rho^r}{2}(\pi_t^*-1)^2Y_t^* + G \tag{3.7.48}$$

$$\widetilde{E}_t^*\left[\Lambda_{t+1}\xi_{t+1}\frac{Z_{t+1}+(1-\delta)Q_{t+1}}{Q_t^* + \frac{\partial}{\partial S_t^h}\varsigma(S_t^{h*}, S_t^*)}\right] = 1 \tag{3.7.49}$$

$$\frac{\partial}{\partial S_t^h}\varsigma(S_t^{h*}, S_t^*) = \chi(1-\gamma) \tag{3.7.50}$$

$$S_t^{b*} = 0 \tag{3.7.51}$$

$$N_t^* = 0 \tag{3.7.52}$$

$$D_t^* = 0 \tag{3.7.53}$$

$$S_t^{h*} = S_t^* \tag{3.7.54}$$

$$R_t^{b*} = \xi_t \left(\frac{Z_t^* + (1-\delta)Q_t^*}{Q_{t-1}} \right) \tag{3.7.55}$$

$$x_t^* = \xi_t \frac{[(1-\delta)Q_t^* + Z_t^*]S_{t-1}^b}{\bar{R}_{t-1}D_{t-1}} = R_t^{b^*} Q_{t-1} S_{t-1}^b \bar{R}_{t-1}^{-1} D_{t-1}^{-1} = \frac{R_t^{b^*}}{\bar{R}_{t-1}} \frac{\phi_{t-1}}{\phi_{t-1} - 1}. \tag{3.7.56}$$

Observe that for the computation of x_t^*, equations (3.7.37) to (3.7.55) must be computed.

Model linearisation

Equations (3.7.1) to (3.7.56) are linearised respectively as follows. A log-linearised variable is denoted by a prime and, as already mentioned, letters without the subscript t denote steady state values.[27]

$$K_t' = \xi_t' + S_{t-1}' \tag{3.7.1'}$$

$$\xi_t' = \rho \xi_{t-1}' + \epsilon_t \tag{3.7.2'}$$

$$S_t' = \Gamma \Gamma'(I_t') + (1-\delta)K_t' \tag{3.7.3'}$$

$$\Gamma'(I_t') = a(1-\eta)I^{-\eta} I_t' \tag{3.7.4'}$$

$$Q_t' = \eta I_t' \tag{3.7.5'}$$

$$K_t' = w_t' - Z_t' + L_t' \tag{3.7.6'}$$

$$MC_t' = \alpha Z_t' + (1-\alpha)w_t' \tag{3.7.7'}$$

$$\pi_t' = \Lambda \widetilde{E}_t \pi_{t+1}' + \frac{\epsilon - 1}{\rho^r} MC_t' \tag{3.7.8'}$$

$$\widetilde{E}_t \Lambda_{t+1}' = -\gamma_h \widetilde{E}_t C_{t+1}' + \gamma_h C_t' \tag{3.7.9'}$$

$$Y_t' = \alpha K_t' + (1-\alpha)L_t' \tag{3.7.10'}$$

[27] Note that I made use of the steady state values to shorten the equations (examples: $R^n \Lambda = \frac{1}{\beta}\beta = 1$, $\Gamma = I = \delta = 0.025$, and $K = S = \xi = Q = \pi = 1$).

$$w'_t = \gamma_h C'_t + \alpha L'_t \tag{3.7.11$'$}$$

$$R^{n\prime}_t + \widetilde{E}_t \Lambda'_{t+1} = \widetilde{E}_t \pi'_{t+1} \tag{3.7.12$'$}$$

$$\bar{R}'_t = -\widetilde{E}_t \Lambda'_{t+1} - x'_{t+1} \tag{3.7.13$'$}$$

$$\begin{aligned} Q'_t = \widetilde{E}_t \Lambda'_{t+1}[\Lambda Z + \Lambda(1-\delta)] + E_t \xi_{t+1}[\Lambda Z + \Lambda(1-\delta)] + \widetilde{E}_t Z'_{t+1} Z\Lambda + \\ \widetilde{E}_{t+1} Q'_{t+1}[\Lambda(1-\delta)] - \left(\frac{\partial}{\partial S^{h\prime}_t} \varsigma(S^{h\prime}_t, S'_t)\right)' \left(\frac{\partial}{\partial S^h_t} \varsigma(S^h, S)\right) \end{aligned} \tag{3.7.14$'$}$$

$$\left(\frac{\partial}{\partial S^{h\prime}_t} \varsigma(S^{h\prime}_t, S'_t)\right)' = \max\left[\chi \frac{S^h}{S} \left(\frac{\partial}{\partial S^{h\prime}_t} \varsigma\left(S^h, S\right)\right)^{-1} (S^{h\prime}_t - S'_t), -1\right] \tag{3.7.15$'$}$$

$$R^{b\prime}_t = R^{b^{-1}} \left[(Z+1-\delta)\xi'_t + ZZ'_t - (Z+1-\delta)Q'_{t-1} + (1-\delta)Q'_t\right] \tag{3.7.16$'$}$$

$$\widetilde{E}^b_t R^{b\prime}_{t+1} = R^{b^{-1}} \widetilde{E}_t \left(Z\xi'_{t+1} + ZZ'_{t+1} - (Z+1-\delta)Q'_t + (1-\delta)Q'_{t+1}\right) \tag{3.7.17$'$}$$

$$S^b_t = \begin{cases} \phi'_t + N'_t - Q'_t & \text{no bank default at } t \\ -1 & \text{bank default at } t \end{cases} \tag{3.7.18$'$}$$

$$N'_t = \begin{cases} -1 \quad \text{bank default at } t \\ \zeta S(S'_{t-1} + \sigma S'_{t-2}) N^{-1} \quad \text{bank default at } t-1 \\ \left[(\sigma Z S^b + \sigma(1-\delta)S^b)(\xi'_t + S^{b\prime}_{t-1}) + (Z\sigma S^b)Z'_t + \sigma(1-\delta)S^b Q'_t - \bar{R}D\sigma(\bar{R}'_{t-1} + D'_{t-1}) + SS'_{t-1}\right] N^{-1} \quad \text{otherwise} \end{cases} \tag{3.7.19$'$}$$

$$D'_t = \begin{cases} (\phi\phi'_t N + NN'_t(\phi - 1))D^{-1} & \text{no bank default at } t \\ -1 & \text{bank default at } t \end{cases} \tag{3.7.20$'$}$$

$$\Pi'_t = \begin{cases} -1 & \text{bank default at } t \\ \Pi^{-1}\left(-\zeta S(S'_{t-1} + \sigma S'_{t-2})\right) & \text{bank default at } t-1 \\ \Delta_t & \text{otherwise} \end{cases} \tag{3.7.21$'$}$$

where

$$\begin{aligned} &\Delta_t \\ &= \Pi^{-1}\left[\xi\xi'_t\left[(1-\sigma)ZS^b\xi'_t + (1-\sigma)(1-\delta)QS^b\right]\right. \\ &\quad + ZZ'_t[(1-\sigma)\xi S^b] + S^b S^{b\prime}_{t-1}[(1-\sigma)\xi Z + (1-\sigma)\xi(1-\delta)Q] + QQ'_t[(1-\sigma)\xi(1-\sigma)S^b] \\ &\quad \left. - \bar{R}\bar{R}'_{t-1}[D(1-\sigma)] - DD'_{t-1}\bar{R}(1-\sigma)\right] \end{aligned}$$

$$xx_t' = R^b Q S^b \bar{R}^{-1} D^{-1} (R_t^{b\prime} + Q_{t-1}' + S_{t-1}^{b\prime} - \bar{R}_{t-1}' - D_{t-1}') \tag{3.7.22'}$$

$$R_t^{a\prime} = \begin{cases} \bar{R}_{t-1}' & \text{if } x_t' \geqslant \frac{1-x}{x} \\ x_t' + \bar{R}_{t-1}' & \text{if } x_t' < \frac{1-x}{x} \end{cases} \tag{3.7.23'}$$

$$R_t' = \begin{cases} R_t^{a\prime} & \text{if } x_t^{*\prime} \geqslant \frac{1-x^*}{x^*} \\ x_t' + \bar{R}_{t-1}' & \text{if } x_t^{*\prime} < \frac{1-x^*}{x^*} \end{cases} \tag{3.7.24'}$$

$$\begin{aligned} &2(\phi^{max} - 1)^{-1} \phi^{max} \bar{R}^{-1} R^b \omega^p \Lambda \phi_t^{max\prime} [R^b \Lambda z - R^b \phi^{max} (\phi^{max} - 1)^{-1} z \Lambda - 1 + \phi^{max} (\phi^{max} - 1)^{-1}] = \\ &\Lambda \widetilde{E}_t \Lambda_{t+1}' [-\Lambda R^b z^2 + 2\omega^p R^b \bar{R}^{-1} \phi^{max} (\phi^{max} - 1)^{-1} + 1 - \omega^p - \omega^p R^b \bar{R}^{-1}] + \bar{R}^{-1} R^b \omega^p \Lambda \bar{R}_t' \\ &[2\Lambda z R^b \phi^{max} (\phi^{max} - 1)^{-1} - 2\phi^{max} (\phi^{max} - 1)^{-1} + 1] + R^b \Lambda \widetilde{E}_t R_{t+1}^{b\prime} [-\Lambda z^2 - 2R^b \Lambda \omega^p \bar{R}^{-1} \\ &\phi^{max} (\phi^{max} - 1)^{-1} z + 2\omega^p \bar{R}^{-1} \phi (\phi - 1)^{-1} - \omega^p \bar{R}^{-1}] \end{aligned} \tag{3.7.25'}$$

where

$$z = \omega^p R^b \bar{R}^{-1} \phi^{max} (\phi^{max} - 1)^{-1} + 1 - \omega^p$$

$$\phi_t' = \begin{cases} 0.5\phi_t^{\max\prime} - 0.5 & \text{if } \phi_t^{p\prime} \leq 0.5\phi_t^{\max\prime} - 0.5 \leq \phi_t^{o\prime} \\ \phi_t^{o\prime} & \text{if } 0.5\phi_t^{\max\prime} - 0.5 > \phi_t^{o\prime} \\ \phi_t^{p\prime} & \text{if } 0.5\phi_t^{\max\prime} - 0.5 < \phi_t^{p\prime} \end{cases} \tag{3.7.26'}$$

$$S_t' = \frac{S^b}{S} S_t^{b\prime} + \frac{S^h}{S} S_t^{h\prime} \tag{3.7.27'}$$

$$Y_t' = \frac{C}{Y} C_t' + \frac{I}{Y} I_t' \tag{3.7.28'}$$

$$R_t^{n\prime} = \kappa_\pi \pi_t' + \kappa_y MC_t' \tag{3.7.29'}$$

$$\widetilde{E}_t(\Theta_{t+1}') = \Theta_t' \quad \text{where } \Theta' \in (\pi', C', Y', Z', Q') \tag{3.7.30'}$$

$$\widetilde{E}_t^o(Q_{t+1}') = \begin{cases} \theta(Q_t' - Q_{t-1}') + Q_t' & \text{if } Q_t' - Q_{t-1}' > 0 \\ -\theta(Q_t' - Q_{t-1}') + Q_t' & \text{if } Q_t' - Q_{t-1}' \leq 0 \end{cases} \tag{3.7.31'}$$

$$\widetilde{E}_t^p(Q'_{t+1}) = \begin{cases} -\theta(Q'_t - Q'_{t-1}) + Q'_t & \text{if } Q'_t - Q'_{t-1} > 0 \\ \theta(Q'_t - Q'_{t-1}) + Q'_t & \text{if } Q'_t - Q'_{t-1} \leq 0 \end{cases} \tag{3.7.32$'$}$$

$$R^b \widetilde{E}_t^j R_{t+1}^{b\prime} = \widetilde{E}_t^j [Z\xi'_{t+1} + ZZ'_{t+1} - (Z + 1 - \delta)Q'_t + (1-\delta)Q'_{t+1}] \quad \text{where } j \in (o, p) \tag{3.7.33$'$}$$

$$R^b \widetilde{E}_t R_{t+1}^{b\prime} = \widetilde{E}_t [Z\xi'_{t+1} + ZZ'_{t+1} - (Z + 1 - \delta)Q'_t + (1-\delta)Q'_{t+1}] \tag{3.7.34$'$}$$

$$\phi^j \phi_t^{j\prime} = \bar{R}\bar{R}'_t [R^{b^j}]^{-1}[\phi^j - 1] - [R^{b^j}]^{-1} \widetilde{E}_t R_{t+1}^{j\prime} \bar{R}(\phi^j - 1) + \phi^j \phi_t^{j\prime} \bar{R}[R^{b^j}]^{-1} \quad \text{where } j \in (o, p) \tag{3.7.35$'$}$$

$$E_t \xi'_{t+1} = \rho_\xi \xi'_t + \epsilon_t \tag{3.7.36$'$}$$

$$S^* S_t^{*\prime} = \Gamma\Gamma'(I_t^{*\prime}) + (1-\delta)K'_t \tag{3.7.37$'$}$$

$$\Gamma^* \Gamma'(I_t^{*\prime}) = a(1-\eta) I^{*1-\eta} I_t^{*\prime} \tag{3.7.38$'$}$$

$$Q_t^{*\prime} = \eta I_t^{*\prime} \tag{3.7.39$'$}$$

$$K'_t = w_t^{*\prime} - Z_t^{*\prime} + L_t^{*\prime} \tag{3.7.40$'$}$$

$$w_t^{*\prime} = \gamma_h C_t^{*\prime} + \alpha L_t^{*\prime} \tag{3.7.41$'$}$$

$$Y_t^{*\prime} = \alpha K'_t + (1-\alpha) L_t^{*\prime} \tag{3.7.42$'$}$$

$$R_t^{n*\prime} + \widetilde{E}_t^* \Lambda'_{t+1} = \widetilde{E}_t^* \pi'_{t+1} \tag{3.7.43$'$}$$

$$\widetilde{E}_t^* \Lambda'_{t+1} = -\gamma_h \widetilde{E}_t^* C'_{t+1} + \gamma_h C_t^{*\prime} \tag{3.7.44$'$}$$

$$R_t^{n*\prime} = \kappa_\pi \pi_t^{*\prime} + \kappa_y MC_t^{*\prime} \tag{3.7.45$'$}$$

$$MC_t^{*\prime} = \alpha Z_t^{*\prime} + (1-\alpha) w_t^{*\prime} \tag{3.7.46$'$}$$

$$\begin{aligned} \pi^* \pi_t^{*\prime} = (2\pi^{*2} - \pi^*)\Lambda^* \widetilde{E}_t^{*\prime} \pi_{t+1} + \frac{\epsilon}{\rho^r} MC^* MC_t^{*\prime} + \Lambda^*(\pi^{*2} - \pi^*)\widetilde{E}_t^* \Lambda_{t+1} + (\Lambda^* \pi^{*2} \\ - \Lambda^* \pi^*) Y_t^{*\prime} - (\pi^{*2} - \pi^*)\Lambda^* E_t^* Y_{t+1} \end{aligned} \tag{3.7.47$'$}$$

$$Y^*(1+\pi^*\rho^r - \frac{\rho^r}{2}\pi^{*2} - \frac{\rho^r}{2})Y_t^{*\prime} = C^*C_t^{*\prime} + I^*I_t^{*\prime} + \pi^*(\rho^r Y^*\pi^* - \rho^r Y^*)\pi_t^{*\prime} \tag{3.7.48'}$$

$$\begin{aligned} Q^*Q_t^{*\prime} = {} & \widetilde{E}_t^*\Lambda_{t+1}'[\Lambda^*Z^* + \Lambda^*(1-\delta)Q^*] + E_t\xi_{t+1}[\Lambda^*Z^* + \Lambda^*(1-\delta)Q^*] + \widetilde{E}_t^* Z_{t+1}' Z^*\Lambda^* + \\ & \widetilde{E}_t^* Q_{t+1}'[\Lambda^*(1-\delta)Q^*] \end{aligned} \tag{3.7.49'}$$

$$\left(\frac{\partial}{\partial S_t^{h\prime}}\varsigma(S_t^{h*\prime}, S_t^{*\prime})\right)' = 0 \tag{3.7.50'}$$

$$S_t^{b*\prime} = 0 \tag{3.7.51'}$$

$$N_t^{*\prime} = 0 \tag{3.7.52'}$$

$$D_t^{*\prime} = 0 \tag{3.7.53'}$$

$$S_t^{h*\prime} = S_t^{*\prime} \tag{3.7.54'}$$

$$R_t^{b*\prime} = R^{b*^{-1}}\left[(Z^* + Q^* - \delta Q^*)\xi_t' + Z^*Z_t^{*\prime} - (Z^* + Q^* - \delta Q^*)Q_{t-1}' + (1-\delta)Q^*Q_t^{*\prime}\right] \tag{3.7.55'}$$

$$x^*x_t^{*\prime} = R^{b*}QS^b\bar{R}^{-1}D^{-1}(R_t^{b*\prime} + Q_{t-1}' + S_{t-1}^{b\prime} - \bar{R}_{t-1}' - D_{t-1}'). \tag{3.7.56'}$$

Steady state values

Table 3.2 illustrates the steady state values of the variables of the model.

Table 3.2: Steady state values

Variable at SS	Value	Description	Variable at SS	Value	Description
K	1	capital at the beginning of period t	ρ	0	probability of default
S	1	capital at the end of period t	R^a	$\frac{1}{\beta}$	a step to check insolvency
ξ	1	capital quality	x	1.12	recovery rate
$\Gamma(I)$	0.025	investment technology	$\phi^{o/p}$	10	max ϕ according to opt&pes**
I	0.025	investment	R^{b*}	0.9	R^b conditional on run
Z	0.04	rental rate on capital	Z^*	0.027	Z conditional on run
w	0.9	real wage rate	w^*	0.7	w conditional on run
L	0.09	labour supply	L^*	0.08	L conditional on run
Λ	β	stochastic discount factor	Λ^*	β	Λ conditional on run
C	1.775	consumption	C^*	1.59	C conditional on run
R^n	1.01	nominal rate on the riskless bond	${R^n}^*$	1.006	R^n conditional on run
MC	$\frac{(\epsilon-1)}{\epsilon}$	marginal cost	MC^*	0.04	MC conditional on run
π	1	realized gross inflation rate	π^*	0.996	π conditional on run
Y	2.25	total output	Y^*	2.09	Y conditional on run
$\bar{R}$	$\frac{1}{\beta}$	promised gross rate of return on deposits	Q^*	0.88	Q conditional on run
Q	1	relative price of capital	${S^b}^*$	0	S^b conditional on run
$\frac{\partial}{\partial S_t^h}\varsigma(S^h, S)$	$\chi(\frac{S^h}{S} - \gamma)$	marginal capital management cost	N^*	0	N conditional on run
S^b	0.33	bank owned capital claims	D^*	0	D conditional on run
N	0.03	banks' net worth	${S^h}^*$	0.99	S^h conditional on run
R	$\frac{1}{\beta}$	actual gross rate of return on deposits	$\frac{\partial}{\partial S_t^h}\varsigma({S^h}^*, S^*)$	$\chi(1-\gamma)$	$\frac{\partial}{\partial S_t^h}\varsigma$ conditional on run
D	0.297	total deposits	$\Gamma(I^*)$	0.016	Γ conditional on run
R^b	1.015	gross rate of return on banks' assets	Π^*	0	Π conditional on run
S^h	0.67	households' owned capital claims	I^*	0.016	I conditional on run
ϕ	10	banks' leverage multiple	S^*	0.99	S condition on run
$\phi^{\max}$	5	leverage maximizes expected net worth	x^*	0.97	x conditional on run
Π	0.0024	net transfers			

** Note that I multiplied the expected rate of return on bank investments according to optimists and pessimists (equation 3.7.33) by 0.89 to be able to get $\phi^p = \phi^o = \phi = 10$.

Bibliography

Adrian, T. and Liang, N. (2018), 'Monetary policy, financial conditions, and financial stability', *International Journal of Central Banking* **14**(1), 73–131.

Airaudo, M., Nisticó, S. and Zanna, L.-f. (2015), 'Learning, monetary policy, and asset prices', *Journal of Money, Credit and Banking* **47**(7), 1273–1307.

Alfarano, S. and Milaković, M. (2009), 'Network structure and n-dependence in agent-based herding models', *Journal of Economic Dynamics and Control* **33**(1), 78–92.

Anufriev, M. and Hommes, C. (2012), 'Evolution of market heuristics', *The Knowledge Engineering Review* **27**(2), 255–271.

Baron, M., Verner, E. and Xiong, W. (2021), 'Banking crises without panics', *The Quarterly Journal of Economics* **136**(1), 51–113.

Bask, M. (2012), 'Asset price misalignments and monetary policy', *International Journal of Finance and Economics* **17**(3), 221–241.

Bayar, O. (2014), 'Temporal aggregation and estimated monetary policy rules', *The B.E. Journal of Macroeconomics* **14**(1), 553–577.

Beaudry, P. and Willems, T. (2022), 'On the macroeconomic consequences of over-optimism', *American Economic Journal: Macroeconomics* **14**(1), 38–59.

Bernanke, B. and Blinder, A. (1988), 'Credit, money and aggregate demand', *American Economic Review* **78**, 435–39.

Bernanke, B. and Gertler, M. (1989), 'Agency costs, net worth, and business fluctuations', *American Economic Review* **79**(1), 14–31.

Bernanke, B. and Gertler, M. (1995), 'Inside the black box: The credit channel of monetary policy transmission', *Journal of Economic Perspectives* **9**(4), 27–48.

Bernanke, B. and Gertler, M. (2001), 'Should central banks respond to movements in asset prices?', *American Economic Review* **91**(2), 253–57.

Bernanke, B., Gertler, M. and Gilchrist, S. (1999), The financial accelerator in a quantitative business cycle framework, *in* J. B. Taylor and M. Woodford, eds, 'Handbook of Macroeconomics', 1st edn, Vol. 1, Part C, Elsevier, chapter 21, pp. 1341–1393.

Bernanke, B. S. (2018), 'The real effects of disrupted credit: Evidence from the global financial crisis', *Brookings Papers on Economic Activity* **49**(2 (Fall)), 251–342.

Bernanke, B. S. and Gertler, M. (1999), 'Monetary policy and asset price volatility', *Economic Review* **84**(Q IV), 17–51.

Bordo, M. and Landon-Lane, J. (2010), 'The banking panics in the united states in the 1930s: Some lessons for today', *Oxford Review of Economic Policy* **26**(3), 486–509.

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

Branch, W. A., McGough, B. and Zhu, M. (2022), 'Statistical sunspots', *Theoretical Economics* **17**(1), 291–329.

Branch, W. and McGough, B. (2010), 'Dynamic predictor selection in a New Keynesian model with heterogeneous expectations', *Journal of Economic Dynamics and Control* **34**(8), 1492–1508.

Brock, W. and Hommes, C. (1997), 'A rational route to randomness', *Econometrica* **65**, 1059–1095.

Brock, W. and Hommes, C. (1998), 'Heterogeneous beliefs and routes to chaos in a simple asset pricing model', *Journal of Economic Dynamics and Control* **22**, 1235 – 1274.

Brunnermeier, M. and Sannikov, Y. (2014), 'A macroeconomic model with a financial sector', *American Economic Review* **104**(2), 379–421.

Bullard, J. and Schaling, E. (2002), 'Why the fed should ignore the stock market', *Federal Reserve Bank of St. Louis Review* **84**, 35–42.

Caballero, R. J. (2010), 'Macroeconomics after the crisis: Time to deal with the pretense-of-knowledge syndrom', *Journal of Economic Perspectives* **24**(4), 85–102.

Caballero, R. J. and Simsek, A. (2022), Monetary policy and asset price overshooting: A rationale for the wall/main street disconnect, CESifo Working Paper Series 9632, CESifo.

Caines, C. C. and Winkler, F. (2018), Asset price learning and optimal monetary policy, International Finance Discussion Papers 1236, Board of Governors of the Federal Reserve System (U.S.).

Carlstrom, C. T. and Fuerst, T. S. (2007), 'Asset prices, nominal rigidities, and monetary policy', *Review of Economic Dynamics* **10**(2), 256–275.

Carriero, A., Clark, T. and Marcellino, M. (2015), 'Realtime nowcasting with a bayesian mixed frequency model with stochastic volatility', *Journal of the Royal Statistical Society. Series A (Statistics in Society)* **178**, 837–862.

Chan, W.-S. (2022), 'On temporal aggregation of some nonlinear time-series models', *Econometrics and Statistics* **21**, 38–49.

Chen, W. and Phelan, G. (2021), Should monetary policy target financial stability?, Department of Economics Working Papers 2021-12, Department of Economics, Williams College.

Chiarella, C., Flaschel, P., Hartmann, F. and Proaño, C. R. (2012), 'Stock market booms, endogenous credit creation and the implications of broad and narrow banking for macroeconomic stability', *Journal of Economic Behavior and Organization* **83**, 410–23.

Christensen, B. J., Posch, O. and van der Wel, M. (2016), 'Estimating dynamic equilibrium models using mixed frequency macro and financial data', *Journal of Econometrics* **194**, 116–137.

Christiano, L. and Eichenbaum, M. (1987), 'Temporal aggregation and structural inference in macroeconomics', *Carnegie-Rochester Conference Series on Public Policy* **26**, 63–130.

Cogley, T. (1999), 'Should the fed take deliberate steps to deflate asset price bubbles?', *Economic Review* pp. 42–52.

Concetto, C. and Ravazzolo, F. (2019), 'Optimism in financial markets: Stock market returns and investor sentiments', *Journal of Risk and Financial Management* **12**, 85.

Dang, T., Gorton, G. and Holmström, B. (2020), 'The information view of financial crises', *Annual Review of Financial Economics* **12**, 39–65.

Darracq Paries, M., Karadi, P., Körner, J., Kok, C., Mazelis, F., Nikolov, K., Rancoita, E., Van der Ghote, A., Cozzi, G. and Weber, J. (2020), Macroprudential policy measures: macroeconomic impact and interaction with monetary policy, Working Paper Series 2376, European Central Bank.

de Bondt, G., Mojon, B. and Valla, N. (2005), Term structure and the sluggishness of retail bank rates in euro area countries, Working Paper 518, European Central Bank.

De Grauwe, P. (2010), 'The scientific foundation of dynamic stochastic general equilibrium (DSGE) models', *Public Choice* **144**(3-4), 413–443.

De Grauwe, P. (2011), 'Animal spirits and monetary policy', *Economic Theory* **47**(2-3), 423–457.

De Grauwe, P. (2012), 'Booms and busts in economic activity: A behavioral explanation', *Journal of Economic Behavior and Organization* **83**(3), 484–501.

De Grauwe, P. and Macchiarelli, C. (2015), 'Animal spirits and credit cycles', *Journal of Economic Dynamics and Control* **59**(C), 95–117.

de Meza, D. and Dawson, C. (2021), 'Neither an optimist nor a pessimist be: Mistaken expectations lower well-being', *Personality and Social Psychology Bulletin* **47**(4), 540–550.

Di Bella, G. and Grigoli, F. (2019), 'Optimism, pessimism, and short-term fluctuations', *Journal of Macroeconomics* **60**(C), 79–96.

Diamond, D. and Dybvig, P. (1983), 'Bank runs, deposit insurance, and liquidity', *Journal of Political Economy* **91**(3), 401–19.

Diamond, D. and Rajan, R. (2005), 'Liquidity shortages and banking crises', *Journal of Finance* **60**(2), 615–647.

Dong, F., Miao, J. and Wang, P. (2020), 'Asset bubbles and monetary policy', *Review of Economic Dynamics* **37 Supplement 1**, S68–S98.

Dou, W., Lo, A., Muley, A. and Uhlig, H. (2020), 'Macroeconomic models for monetary policy: A critical review from a finance perspective', *Annual Review of Financial Economics* **12**(1), 95–140.

Drechsler, I., Savov, A. and Schnabl, P. (2017), 'The deposits channel of monetary policy', *The Quarterly Journal of Economics* **132**(4), 1819–1876.

Duffie, D. (2019), 'Prone to fail: The pre-crisis financial system', *Journal of Economic Perspectives* **33**(1), 81–106.

Eickmeier, S., Kolb, B. and Prieto, E. (2018), Effects of bank capital requirement tightenings on inequality, Discussion Papers 54/2018, Deutsche Bundesbank.

Ferrara, L. and Guérin, P. (2018), 'What are the macroeconomic effects of high frequency uncertainty shocks?', *Journal of Applied Econometrics* **33**(5), 662–679.

Filardo, A. and Rungcharoenkitkul, P. (2016), A quantitative case for leaning against the wind, BIS Working Papers 594, Bank for International Settlements.

Franke, R. and Westerhoff, F. (2012), 'Structural stochastic volatility in asset pricing dynamics: Estimation and model contest', *Journal of Economic Dynamics and Control* **36**(8), 1193–1211.

Fuster, A., Hebert, B. and Laibson, D. (2012), 'Natural expectations, macroeconomic dynamics, and asset pricing', *NBER Macroeconomics Annual* **26**, 1–48.

Gambacorta, L. and Shin, H. S. (2018), ‘Why bank capital matters for monetary policy’, *Journal of Financial Intermediation* **35**(PB), 17–29.

Garcia Revelo, J. D., Lucotte, Y. and Pradines-Jobet, F. (2020), ‘Macroprudential and monetary policies: The need to dance the tango in harmony’, *Journal of International Money and Finance* **108**, 102–156.

Gärling, T., Kirchler, E., Lewis, A. and van Raaij, F. (2009), ‘Psychology, financial decision making, and financial crises’, *Psychological Science in the Public Interest* **10**(1), 1–47.

Gennaioli, N., Shleifer, A. and Vishny, R. (2015), ‘Neglected risks: The psychology of financial crises’, *American Economic Review* **105**(5), 310–14.

Gerali, A., Neri, S., Sessa, L. and Signoretti, F. (2010), ‘Credit and banking in a DSGE model of the euro area’, *Journal of Money, Credit and Banking* **42**(s1), 107–141.

Gertler, M. and Gilchrist, S. (2018), ‘What happened: Financial factors in the great recession’, *Journal of Economic Perspectives* **32**(3), 3–30.

Gertler, M., Issing, O. and Goodfriend, M. (1998), Asset prices and monetary policy: Four views, Center for Economic Policy Research, London.

Gertler, M., Kiyotaki, N. and Prestipino, A. (2016*a*), ‘Anticipated banking panics’, *American Economic Review* **106**(5), 554–59.

Gertler, M., Kiyotaki, N. and Prestipino, A. (2016*b*), Wholesale banking and bank runs in macroeconomic modeling of financial crises, Vol. 2, Elsevier, chapter 16, pp. 1345–1425.

Gertler, M., Kiyotaki, N. and Prestipino, A. (2020*a*), ‘A macroeconomic model with financial panics’, *Review of Economic Studies* **87**(1), 240–288.

Gertler, M., Kiyotaki, N. and Prestipino, A. (2020*b*), ‘Banking panics as endogenous disasters and the welfare gains from macroprudential policy’, *AEA Papers and Proceedings* **110**, 463–69.

Gertler, M., Kiyotaki, N. and Prestipino, A. (2020*c*), ‘Credit booms, financial crises, and macroprudential policy’, *Review of Economic Dynamics* **37**, 8–33.

Gibson, B. and Sanbonmatsu, D. (2004), ‘Optimism, pessimism, and gambling: The downside of optimism’, *Personality & Social Psychology Bulletin* **30**, 149–60.

Gigerenzer, G. (2002), *Bounded Rationality: The Adaptive Toolbox*, Vol. 1, 1st edn, The MIT Press, chapter 3, pp. 36–50.

Gigerenzer, G. (2018), The behavioural finance revolution, Edward Elgar Publishing, chapter 10, pp. 115–134.

Gilchrist, S. and Leahy, J. (2002), 'Monetary policy and asset prices', *Journal of Monetary Economics* **49**(1), 75–97.

Gilchrist, S. and Saito, M. (n.d.), Expectations, asset prices, and monetary policy: The role of learning.

Gilli, M., Maringer, D. and Winker, P. (2008), *Applications of Heuristics in Finance*, Springer, pp. 635–653.

Gorton, G. (1988), 'Banking panics and business cycles', *Oxford Economic Papers* **40**(4), 751–81.

Gorton, G. and Calomiris, C. W. (2000), *The Origins of Banking Panics: Models, Facts, and Bank Regulation*, Cambridge University Press, pp. 93–163.

Gorton, G. and Ordoñez, G. (2014), 'Collateral crises', *American Economic Review* **104**(2), 343–78.

Gorton, G. and Ordonez, G. (2020), 'Good booms, bad booms', *Journal of the European Economic Association* **18**(2), 618–665.

Gorton, G. and Winton, A. (2003), Financial intermediation, *in* G. Constantinides, M. Harris and R. M. Stulz, eds, 'Handbook of the Economics of Finance', 1st edn, Vol. 1, Part 1, Elsevier, chapter 08, pp. 431–552.

Gorton, G. and Winton, A. (2017), 'Liquidity provision, bank capital, and the macroeconomy', *Journal of Money, Credit and Banking* **49**(1), 5–37.

Gourio, F., Kashyap, A. K. and Sim, J. (2018), 'The trade offs in leaning against the wind', *IMF Economic Review* **66**(1), 70–115.

Harstad, R. M. and Selten, R. (2013), 'Bounded-rationality models: Tasks to become intellectually competitive', *Journal of Economic Literature* **51**(2), 496–511.

Hecht, D. (2013), 'The neural basis of optimism and pessimism', *Experimental Neurobiology* **22**, 173–199.

Ingrao, B. and Sardoni, C. (2019), *Banks and Finance in Modern Macroeconomics*, Edward Elgar Publishing.

Irving-Fisher-Committee (2021), *New Developments in Central Bank Statistics around the World*, number 5, Bank for International Settlements.

Kashyap, A. and Stein, J. (1994), Monetary policy and bank lending, *in* 'Monetary Policy', National Bureau of Economic Research, Inc, pp. 221–261.

Kiyotaki, N. and Moore, J. (1997), 'Credit cycles', *Journal of Political Economy* **105**(2), 211–48.

Klaes, M. and Sent, E.-M. (2005), ‘A conceptual history of the emergence of bounded rationality’, *History of Political Economy* **37**(1), 27–59.

Kontonikas, A. and Ioannidis, C. (2005), ‘Should monetary policy respond to asset price misalignments?’, *Economic Modelling* **22**, 1105–1121.

Kontonikas, A. and Montagnoli, A. (2006), ‘Optimal monetary policy and asset price misalignments’, *Scottish Journal of Political Economy* **53**, 636–654.

Kopecky, K. J. and VanHoose, D. (2004*a*), ‘Bank capital requirements and the monetary transmission mechanism’, *Journal of Macroeconomics* **26**(3), 443–464.

Kopecky, K. J. and VanHoose, D. (2004*b*), ‘A model of the monetary sector with and without binding capital requirements’, *Journal of Banking and Finance* **28**, 633–646.

Lambertini, L. and Uysal, P. I. (2014), Macroeconomic implications of bank capital requirements.

Lengnick, M. and Wohltmann, H.-W. (2013), ‘Agent-based financial markets and New Keynesian macroeconomics: A synthesis’, *Journal of Economic Interaction and Coordination* **8**, 1–32.

Lengnick, M. and Wohltmann, H.-W. (2016), ‘Optimal monetary policy in a New Keynesian model with animal spirits and financial markets’, *Journal of Economic Dynamics and Control* **64**(C), 148–165.

Lin, L. (2019), ‘Bank deposits and the stock market’, *The Review of Financial Studies* **33**, 2622–2658.

Loewy, M. (1991), ‘The macroeconomic effects of bank runs: An equilibrium analysis’, *Journal of Financial Intermediation* **1**(3), 242–256.

Loewy, M. (1998), ‘Information-based bank runs in a monetary economy’, *Journal of Macroeconomics* **20**(4), 681–702.

Lux, T. and Westerhoff, F. (2009), ‘Economics crisis’, *Nature Physics* **5**, 2–3.

Marcellino, M. (1999), ‘Some consequences of temporal aggregation in empirical analysis’, *Journal of Business and Economic Statistics* **17**, 129–136.

Marcet, A. (1991), Temporal aggregation of economic time series, *in* L. P. Hansen and T. J. Sargent, eds, ‘Rational Expectations Econometrics’, Westview Press, San Francisco, pp. 237–281.

Milani, F. (2017), ‘Learning about the interdependence between the macroeconomy and the stock market’, *International Review of Economics and Finance* **49**(C), 223–242.

Mousavi, S. and Gigerenzer, G. (2014), ‘Risk, uncertainty, and heuristics’, *Journal of Business Research* **67**(8), 1671–1678.

Mousavi, S. and Gigerenzer, G. (2017), 'Heuristics are tools for uncertainty', *Homo Oeconomicus: Journal of Behavioral and Institutional Economics* **34**(4), 361–379.

Mundlak, Y. (1961), 'Aggregation over time in distributed lag models', *International Economic Review* **2**, 154–163.

Muth, J. (1961), 'Rational expectations and the theory of price movements', *Econometrica* **29**(3), 315–335.

Naimzada, A. K. and Pireddu, M. (2013), 'Dynamic behavior of real and stock markets with varying degree of interaction', *DEMS Working Paper* **245**.

Nisticò, S. (2012), 'Monetary policy and stock-price dynamics in a dsge framework', *Journal of Macroeconomics* **34**(1), 126–146.

Paya, I., Duarte, A. and Holden, K. (2007), 'On the relationship between inflation persistence and temporal aggregation', *Journal of Money, Credit and Banking* **39**(6), 1521–1531.

Peek, J. and Rosengren, E. (1995), 'Is bank lending important for the transmission of monetary policy? an overview', *New England Economic Review* **39**(Nov), 3–11.

Perron, P. and Shi, W. (2020), 'Temporal aggregation and long memory for asset price volatility', *Journal of Risk and Financial Management* **13**(8), 1–18.

Proaño, C. R. (2011), 'Exchange rate determination, macroeconomic dynamics and stability under heterogeneous behavioral FX expectations', *Journal of Economic Behavior and Organization* **77**(2), 177–88.

Proaño, C. R. (2013), 'Monetary policy rules and macroeconomic stabilization in small open economies under behavioral FX trading: Insights from numerical simulations', *Manchester School* **81**(6), 992–1011.

Reinhart, C. and Rogoff, K. (2009), *This Time Is Different: Eight Centuries of Financial Folly*, 1st edn, Princeton University Press.

Romer, C. and Romer, D. (1990), 'New evidence on the monetary transmission mechanism', *Brookings Papers on Economic Activity* **1**, 149–214.

Rossana, R. J. and Seater, J. J. (1995), 'Temporal aggregation and economic time series', *Journal of Business & Economic Statistics* **13**(4), 441–451.

Samitas, A., Polyzos, S. and Siriopoulos, C. (2018), 'Brexit and financial stability: An agent-based simulation', *Economic Modelling* **69**, 181–192.

Schmitt, N. and Westerhoff, F. (2016), 'Stock market participation and endogenous boom-bust dynamics', *Economics Letters* **148**, 72–75.

Sims, C. A. (1971), 'Discrete approximations to continuous time distributed lags in econometrics', *Econometrica* **39**, 545–563.

Stock, J. H. (1987), 'Temporal aggregation and structural inference in macroeconomics: A comment', *Carnegie-Rochester Conference Series on Public Policy* **26**, 131–140.

Theil, H. (1954), *Linear Aggregation of Linear Economic Relations*, North-Holland, Amsterdam.

Tissot, B. and de Beer, B. (2020), Implications of covid-19 for official statistics: a central banking perspective, IFC Working Papers 20, Bank for International Settlements.

Van den Heuvel, S. (2002), 'Does bank capital matter for monetary transmission?', *Economic Policy Review* **8**(May), 259–265.

Van den Heuvel, S. (2006), The bank capital channel of monetary policy, 2006 Meeting Papers 512, Society for Economic Dynamics.

Westerhoff, F. (2008), 'The use of agent-based financial market models to test the effectiveness of regulatory policies', *Journal of Economics and Statistics* **228**(2-3), 195–227.

Westerhoff, F. (2012), 'Interactions between the real economy and the stock market: A simple agent-based approach', *Discrete Dynamics in Nature and Society* **2012**, 1–21.

Woodford, M. (2003), *Interest and Prices. Foundations of a Theory of Monetary Policy*, Princeton University Press, Princeton.

Woodford, M. (2010), 'Financial intermediation and macroeconomic analysis', *Journal of Economic Perspectives* **24**(4), 21–44.

Zellner, A. and Montmarquette, C. (1971), 'A study of some aspects of temporal aggregation problems in econometric analyses', *The Review of Economics and Statistics* **53**(4), 335–342.