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Agent-Based Simulations of Monetary Policy and Financial Markets

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Agent-Based Simulations of Monetary Policy and Financial Markets

Joeri Anton Schasfoort

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This thesis presents several agent-based models in which monetary policy and financial markets are simulated.

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Acknowledgments

Joeri Anton Schasfoort
Groningen
May 3, 2020

While this dissertation presents my research findings over the last four years, it was not written in isolation. In this section, I would like to acknowledge some of the most important people on which I relied to make this work possible.

First and foremost, I would like to thank Dirk Bezemer, my primary supervisor. The journey that led me towards this PhD started on Wednesday the 18th of 2012, when I sent him an e-mail asking if he would be willing to discuss with me how it could be possible that banks create money, a question that many of my Finance professors at the time could not answer. His answer was typical of his scientific ethos. Dirk deeply appreciates curiosity, but only if it comes with a willingness to 'do the work,' meaning that someone who sends a question to others has first done research on his/ her own. In his e-mail, Dirk briefly explained how banks created money and sent me some links for further reading. He emphasized that I should read those first before scheduling a meeting. It so happened that, I had just spent the entire Christmas holiday reading papers about the subject. After a brief e-mail back and forth, this became clear to him and he invited me for a meeting. This led to many subsequent meetings, a student assistant position, and eventually a YouTube film production called 'Debt: the good, the bad, and the ugly.' It also led him to endorse me for a PhD level Winter school in Agent-Based Modelling (ABM) at the University of Limerick. Finally, after a brief stint as an on-line course coordinator at Leiden University, he called over the phone me and said: "Joeri.. I might have a PhD position in agent-based modelling and I want you to apply."

I realized that I was extremely lucky because I was, on paper, not the right candidate for a PhD position. My university grades had been average. I had not

done the required 'research master,' and I had an unconventional career history which included student association board member, a student business research trip to Indonesia, founding an unsuccessful on-line retail company, a video production stunt, and on-line course coordinator roles at the universities of Leiden and Groningen. Yet, Dirk was confident that I would be able to do the PhD and so, after convincing the research school that I might be a feasible candidate, it happened. I was hired with the condition that I would do an extra year of classes in economics and agent-based modelling. I am immensely grateful for Dirk looking beyond my qualifications on paper and it fills me with joy that finishing this PhD proves that he was right to do so.

Second, I am grateful for the guidance of my second supervisor: Lex Hoogduin. I had worked with Lex to develop the on-line course: 'Decision Making in a Complex World.' The main message of this course –that the world is both complex and uncertain– left a deep impression on me and has certainly influenced this thesis. Lex is immensely intelligent and, at the same time, very open to ideas that are different to his own. This made him a great sparring partner, especially since we did not always agree on everything. For example, at the start of the PhD, Lex did not believe that making ABMs was very useful since the economy is far too complex and uncertain to capture with these simple models. Yet, he encouraged me to pursue the PhD anyway and pushed me to think about why my research was useful. Without him the part of the introduction about my research philosophy and the place of agent-based would surely not have been written.

Since neither of my primary supervisors had any experience in building ABMs, I desperately needed a third (unofficial) supervisor who had this experience. Indeed, without Antoine Godin, this thesis would never have materialized. I already knew Antoine from conferences and he was one of my teachers on the winter-school on ABM in Limerick. After I was awarded the PhD position, Dirk had arranged that I would visit the university of Limerick to work on my first chapter there –under Antoine's guidance. It must be said that Antoine is a dedicated supervisor with a pretty intense work ethic (meaning that he works day and night) and a mind that is fast as lightning. Needless to say, it was exhilarating to work under his guidance. Furthermore, since Antoine mixes work with pleasure, it was great fun to join him in pubs, and at his house for drinks, food and lengthy discussions. I look back on our work together with intense joy and will forever be grateful for his mentorship.

Furthermore, I would like to thank the following professors for helping me out at crucial points during the thesis. To write the third chapter, the advice of Lammertjan Dam and Jan Jacobs were crucial. Lammertjan helped me in finding my way through the literature on market efficiency and Jan Jacobs helped me considerably by checking that my understanding of using the estimation procedures were correct. For the final

chapter of this thesis, I would like to thank Andreas Steiner for providing input in how to best combine central bank quantitative easing with investor portfolio balancing behaviour.

During this PhD, and in the run-up to it, I was lucky enough to have visited several places. Here, I met many interesting people who inspired me to write my thesis and made the process much more enjoyable. At the start of the PhD, I was an active member of the Young Scholars Initiative (YSI) of the Institute for New Economic Thinking. From this group, I would especially like to thank Jay Pocklington, Nils Rochowicz, and Renate Marold, with whom I had the pleasure to organise an academic conference at the Dutch Central Bank. Furthermore, meeting with Asgeir Torfason, Elham Saeidinezhad, Lu Liu, Johannes Tiemer, Winnie Chen, and Paola D’Orazio made the YSI events a joy to attend. Finally, during my time at YSI, I made the connections which enabled me to visit three interesting places while writing my dissertation: Limerick, Kingston, and Cape Town.

First, in the spring of 2015, I visited the research group –at the time known as ‘the lads’– of Stephen Kinsella at the University of Limerick. I am very grateful for his willingness to host me there. Besides working intensively here with Antoine Godin, I was lucky to work here with Alessandro Caiani, Hamid Raza, and Apostolos Fasianos. I am grateful that Apostolos Fasianos was willing to host me for a weekend in Dublin. Furthermore, I thank Hamid Raza for travelling with me on several road-trips. These experiences made the visit unforgettable. For my second visit, I joined Antoine at his new university: Kingston University, London, in 2016. While two week visit was brief, I am grateful to have met Severin Reissl there and for having visited the Bank of England with Antoine. Finally, in 2018, I visited the research group of Co-Pierre Georg at the University of Cape Town. Not only am I grateful to Co-Pierre for receiving me there, I am really excited to work with him as a post-doctoral research fellow next. I had an amazing time in Cape Town, and look back with joy on working with Tina Koziol and Jesper Riedler and grateful for the great outings and time I had there with Sabine Bertram, Allan Davids, Adrián Carro, Suraj Shekhar, Daniel Opolot, and my amazing room-mate / host Gary Hopkins.

While working on the PhD in exotic locations such as Limerick and Cape Town *obviously* increased the quality of this thesis, it must be recognized that the majority of it has been written in Groningen. Next, I acknowledge my dear colleagues who have inspired me, worked with me, and have lifted my spirit in Groningen. As any Groningen PhD candidate will tell you, good room mates are essential. I was blessed to have them. In the first half of my PhD, I benefited enormously from being in a room with master programmer and all-round happy talker, Reitze Gouma. He helped me immensely in learning to code and learning how to deal with the big datasets that ABMs can produce. In the second half of my PhD, I was room mates with Stefan

Pahl and Daan Freeman. Both, Daan and Stefan have helped me to keep my spirit high during the stressful last years of the PhD. Along with Maite, Toby, Tobias, Juliette, Nikos, Duc, Ferdinand, Romina, Johannes, Bert, Timon, Fred, Aobo, they were always there if I wanted to test my ideas, have lunch, go to the pub, go cycling, or watch Game of Thrones. Finally, I greatly appreciate the support that I, as a PhD student, received from all university support and administrative staff, especially from the SOM research school and the Gemmmies (secretariat of the Global Economics and Management department).

Luckily, working on the PhD was not everything I did at the University of Groningen. The people who helped me do some side activities, which kept me sane, also need to be recognized. First, I thank the people from the computer programming volunteer group and especially Christopher Stockermans, with whom I worked on an ABM project which preceded my second chapter. Second, a big thanks to the members of the PhD committee with whom I enjoyed organising several PhD events. Third, I thank Inge Hovius for helping me obtain my University Teaching Qualification (UTQ / BKO). Finally, I would like to thank Stefan Lundberg, Thomas van Galen and Theo Kocken at Cardano for interesting discussions that made me think about possible practical applications for ABMs.

On a more personal level, I would like to thank my family for believing in me and supporting me throughout the PhD process. Since I was young, my parents have always stimulated me to follow my curiosity. I would not have pursued exploring a small part of the world (economics) at the PhD level if it was not for their support and encouragement. Finally, right at the start of the PhD process, I met the love of my life Ine Noben. Whenever I doubted myself, she reassured me that I shouldn't. Whenever I was lost in the confusion of many interlocking thoughts, she would help me re-structure them. Most of all, whenever I was down, she was there to cheer me up along with Henry, our beautiful cat.

Before moving on to the scientific part of this thesis, I stress that no dissertation can be seen as the product of its writer and his/ her loved ones, colleagues, and mentors alone. Every scientific work builds on the collective effort of thousands of scientists worldwide. These scientists have created the foundations upon which this thesis builds, such as computer programming, monetary theory, model validation, and so on. Likewise, I hope that this thesis will also serve as the foundation for many new scientific works.

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Since the 2008 financial crisis, economic modelling has been criticized for its excessive simplifications (Phelps, 2007; Farmer and Foley, 2009; Rodrik, 2015; Romer, 2016; Armstrong, 2017; Blanchard, 2018). This has led to the call by Haldane and Turrell (2018) to bring modelling methodologies from other disciplines to economics.

This thesis contributes to the fields of monetary policy and financial market research by applying one of the most popular of these methodologies, agent-based modelling (ABM) (Haldane and Turrell, 2019) to four distinct research questions. These research questions are:

1. How do central bank interest rate changes affect inflation in the short term?
2. Is it plausible that stock prices have become decoupled from their fundamental value?
3. How does stock market volatility affect wealth inequality?
4. How can central bank balance sheet policy best be used to stabilize asset prices?

These questions are all situated in the fields of either monetary policy or financial markets. I focus on these two fields because the models within them have been at the centre of the above-mentioned criticism (Battiston et al., 2016). Each question is explored in a separate chapter.

Before providing a brief overview of these chapters, the next sections cover the research philosophy that underpins this thesis. First, I discuss how I view the world, my research ontology. After that, I describe how I believe that the world can be understood, my research epistemology. Then, I move on to discuss how I believe that the ABM methodology can help us understand the world.

1.1 Ontology

This thesis is built on the view that the economy is a social complex system. Social complex systems are systems which consist of interacting individuals who change their

actions and strategies in response to the outcome they mutually create (Arthur, 2013). Economic patterns such as economic growth and inflation are emergent phenomena because they emerge out of the interactions of individual actors (Kirman, 2016).

Seen as a complex system, the economy is always in a state of flux, constantly evolving and changing. That being said, the state of flux is often relatively stable and can, in some cases, be approximated by an equilibrium or steady state. According to Bosker et al. (2007), complex systems are often characterized by multiple possible steady states, especially in the presence of positive feedback loops or increasing returns. The steady state a complex system finds itself in depends on the path towards that steady state. Tiny changes in initial conditions might cause the system to end up in a radically different steady state (Li and Yorke, 1975). Once a system ends up in a steady state, it might be so resilient to changes that it will take considerable shocks for the system to move to another steady state. This is also known as a ‘lock-in’ (Arthur, 1989). On the other hand, if a system’s resilience is decreasing, it might reach a tipping point and suddenly change behaviour or move to another steady state (Battiston et al., 2016).

A complex system can be seen as consisting of three distinct levels (Dopfer, Foster, and Potts, 2004): the micro (individuals), meso (rules) and macro (system) levels. At each level, different types of decisions and interactions take place. For example, in a macroeconomic system, one can identify interactions among sectors at the macro-level; markets as social network structures at the meso-level; and the strategic choices of single firms and households at the micro level.

At the micro level, actors are viewed as boundedly rational (Simon, 1972). This means that their rationality is limited by the general tractability of the decision problem, the cognitive limitations of the actor, and the time available to make the decision (Simon, 1991). Individuals generally do not optimize their utility (Arthur, 2010). Rather, people engage in cognitive processes such as social comparison, imitation and repetitive behaviour (habits) in order to efficiently use their limited cognitive resources (Jager et al., 2000).

Complex economic systems overlap with other complex systems but not always in a hierarchical way. Rather, these overlapping systems can be described as a panarchy (Holling 2001), referring to a structure in which systems are interlinked in continual adaptive cycles of growth, accumulation, restructuring, and renewal. Thus, complex systems have complex systems above and below them. At the same time, they are part of multiple overlapping complex systems. For example, the stock market is a complex system. The economy is a complex system which encapsulates the stock market. A trading firm, with its multiple employees, is a complex system that operates within the stock market. Finally, the stock market is part of both the global financial system and of the city in which it is located, two overlapping complex systems.

1.2 Epistemology

How can we hope to ever understand the set of overlapping complex systems that is the economy? My belief is that, because models are a simplification of reality, they can be used to uncover the causal mechanisms behind economic patterns. Once the causal mechanisms are known, these models can help us make predictions about the world.

That being said, because the economy is so incredibly complex, I agree with Rodrik (2015) in that it is impossible to derive economic models which are universally valid. This view is in line in the famous saying by Box (1976) that all models are wrong, but some models are useful. But what does it mean that a model is useful? Here, I follow the instrumentalist vision and state that a model is useful if it can make predictions about the world that help us make better decisions.

Even though I believe that models can make accurate predictions about the economy, I am sceptical about the degree to which they can do so. Hayek (1964) gives three reasons for why they might not be able to predict as much as we would like. First, the number of variables required to explain a complex economic phenomenon is often so large that it is practically (and perhaps even theoretically) impossible to model it. Second, the overlapping of complex systems can lead to unexpected interactions that were not anticipated in the model. Finally, many complex systems show sensitivity to initial conditions which would make it very unlikely that models are calibrated with the right initial conditions to produce useful forecasts.

When discussing these concerns, Gaus (2007) asserts that, while they might apply to certain economic problems, the economy is not so complex a system to make any predictions about it at all. As an argument for this, he refers to the work of Tetlock (2017). In his study, Tetlock (ibid.) asked several economists –informed by economic models– to predict future events and found that their predictions were more precise and accurate than those of both uninformed undergraduates and chimpanzees, be it not by a very wide margin. Furthermore, Gaus (2007) asserts that, while the predictions of economic models might not be very accurate, economists can make reliable predictions of what will definitely not happen. To clarify this, he compares economics to evolutionary biology. While an evolutionary biologist cannot predict the exact evolution of horses, he or she can accurately predict that they will not grow wings in the coming decade. This is a forecast about what will (not) happen to Y if X changes, also known as a conditional forecast.

These types of forecasts can be distinguished from unconditional forecasts (Wren-Lewis, 2014). Unconditional forecasts are about the value of Y, depending on the forecasts of all X variables which can influence Y. Unconditional forecasts are much more difficult than conditional forecasts because they are much more precise. Not

surprisingly, unconditional forecasts derived from economic models often perform poorly (Edge et al., 2010; Giacomini, 2015). On the other hand, conditional forecasts made by economic models have fared much better, especially those made by smaller models. For example, economic models such as that of Athey and Ellison (2011) and Agarwal, Athey, and Yang (2009) made the conditional forecasts that specific auction designs would lead to higher profits in the advertising market. On the basis of these models, big technology companies adjusted their auctions and consequently started making more revenue. Therefore, big technology companies have increasingly started to hire PhD economists (Athey and Luca, 2019) who produce formal economic models that can help design more efficient markets.

The advantage of producing formal economic models is that in a formal model the complete logic of the proposed mechanism is out in the open and both its internal and external validity can be evaluated. Internal validity means that there are no errors in the logic of the model. By showing a causal mechanism in a model you are showing that the proposed mechanism is possible in the world of the model (Epstein, 2006). External validity means that the proposed mechanism that works in the model also works in the real world. When discussing external validity, there are two important aspects: input and output validity (Windrum, Fagiolo, and Moneta, 2007). Input validity refers to how realistic input parameters and behavioural equations are. Output validity refers to how close model output patterns are to empirically observed patterns.

In this thesis, I follow an instrumentalist approach to external validity. Since the goal is that the model should produce accurate unconditional forecasts, a model has sufficient output validity if the model delivers the best (most precise and reliable) forecasts for the mechanism of interest. Once that point has been reached, model inputs are realistic enough and thus there is also sufficient input validity.

However, in practice, it is often not possible to determine if forecasts are optimal. They might work very well for a while but fail when there is a tipping point in the system dynamics. To reduce the chance of this happening, the modeller might want to build a buffer with regards to both input and output validity. For input validity, this means that the modeller should strive for realistic inputs. With regards to output validity, the model should be able to make forecasts about system mechanisms or patterns that are not the mechanism of interest. If the model is able to accurately forecast multiple variables, it is more likely that the model makes reliable predictions about the pattern of interest. What types of patterns should be replicated to increase our confidence in model forecasts is an open issue, see e.g. Lamperti (2017) and Fagiolo et al. (2019). In this thesis, I follow the pattern-oriented modelling approach to output validation (Grimm et al., 2005). Following this approach, a model is sufficiently validated if it is able to replicate key patterns (also known as stylized

facts) that are associated with the system of interest.

To summarize, I believe that a diverse set of economic models that have been sufficiently validated can help us understand our complex world. In the next section, I discuss what makes the ABM methodology unique and when ABMs are the appropriate methodology to use.

1.3 Methodology: agent-based modelling

ABM is a class of computer models in which the interactions of autonomous agents¹ are simulated over time. ABM can be traced back to the 60s and 70s (Von Neumann and Burks, 1966; Conway, 1970; Schelling, 1971). As computational power increased in the 90s and early 2000s, it slowly started to become more popular in economics. But ABM only really took off after conventional models came under fire for failing to help foresee the global financial crisis. This is when calls like the one of Farmer and Foley (2009), urging economists to seriously consider ABM as a complementary approach, became more common.

The key characteristics that distinguishes ABM from other modelling approaches is that both individual agents and their interactions are explicitly modelled. Modelling every individual agent means that, compared to other modelling methodologies, ABMs are relatively complex.

Following my epistemological position, one should pick the modelling methodology that provides the best forecasts for the problem of interest. However, if two models deliver (nearly) identical forecasts, I apply the criterion of Sun (2006), who states that a model should be used that is as simple as possible, but not more so. Based on the characteristics of ABMs, I identify two situations in which the ABM methodology is likely to make better forecasts than other modelling methodologies.

The first situation is when differences (heterogeneity) of many agent characteristics are simultaneously important. While, many modelling techniques are able to incorporate some heterogeneity in agent characteristics (Kirman, 2006), they typically struggle to incorporate heterogeneity on multiple levels because it makes them harder to solve (Algan, Allais, and Den Haan, 2008) and understand (Hommes, 2006). In contrast, adding heterogeneity in an ABM is as simple as adding a state variable to an agent. The added heterogeneity of a single variable only marginally increases the difficulty to understand or simulate the model.

The second situation is when the structure of interactions –the market mechanism– is important. Most economic models assume that markets are in equilibrium. This

¹In computer science, autonomous agents are software programs which respond to states and events in their environment independent from direct instruction by the owner of the agent (Bösser, 2001).

means that the price of a service or good is at the intersection of the supply and demand curves. Typically, these models do not explicitly model how the equilibrium comes about. This can be problematic if the modeller is interested in questions that directly concern the market mechanism such as questions about liquidity, tipping points, and price formation. In these cases, there are modelling techniques besides ABM that explicitly model the market mechanism and thus might be able to answer these types of questions, e.g. market-micro structure models (Ait-Sahalia and Sağlam, 2017) and Heterogeneous Agent Models (HAMs) (Dieci and He, 2018). However, these models usually only feature a single market which is still highly stylized. For example, the market mechanism in most HAMs and market-micro structure models is a single market maker that only deals in a single asset. On the other hand, ABMs feature a plethora of different market mechanisms such as dealer (Bookstaber, Paddrik, and Tivnan, 2018), limit-order-books (Chiarella and Iori, 2002), decentralised matching (Ricchetti, Russo, and Gallegati, 2015), and Walrasian auctioneers (Koziol, Riedler, and Schasfoort, 2019). They might even feature several different market mechanisms in one model (Dawid et al., 2012).

Both heterogeneity on multiple levels and differences in market structures have been identified as areas in which economic models can be improved. Heterogeneity has been identified as important for studying monetary policy (Yellen, 2016) and the financial sector (LeBaron, 2006). Furthermore, there is disagreement about how appropriate the equilibrium assumption is in both finance (Lo, 2017) and monetary economics (Vines and Wills, 2018). It is therefore not surprising that ABMs have become more popular in both fields. For a comprehensive overview of recent developments in these fields, I refer to Hommes and LeBaron (2018). That being said, in the next section I provide a few highlights.

1.3.1 ABMs and monetary policy

The effects of monetary policy are typically evaluated in Dynamic Stochastic General Equilibrium (DSGE) models. While these models have been criticized for failing to include enough agent heterogeneity (Colander et al., 2008), there are now many DSGE models that include heterogeneous agents in one way or another (De Grauwe, 2012a; Kaplan, Moll, and Violante, 2018; Auclert, 2019).

However, Fagiolo and Roventini (2017) state that the heterogeneity in these models is typically still limited to two types of predetermined agents. For example, in the DSGE model of Gertler and Kiyotaki (2010) financial frictions stemming from information differences (heterogeneity) between borrowers and lenders increase the severity of a credit quality shock and the time it takes for the economy to recover from this shock. In this model, financial frictions are a shock accelerator. The policy

implication is that, in times of crisis, the central bank should support lenders. On the other hand, in the ABM of Riccetti, Russo, and Gallegati (2016) there is heterogeneity on many levels. It features both heterogeneous firms –with regards to their debt and leverage– and banks which are heterogeneous banks in their interest rates, capital, and clients. Therefore, in their model, there are three accelerators instead of one. The first operates through the stock market; the second through leverage; and the third operates through the bank client network. This means that focusing policy on one accelerator only is not sufficient and might even produce unwanted spill-over effects through the other accelerators.

Regarding their structure, DSGE models have come under fire about whether they form an accurate enough representation of how the economy works (Blanchard, 2016). Some of the most important criticisms follow. De Grauwe (2012b) claims that by not including empirically observed expectation structures DSGE make inaccurate claims about the nature of deep downturns. Lindé (2018) states that DSGE models have relied too heavily on the assumption of perfect markets. Finally, Romer (2016) argues that DSGE models have been relying too much on external shocks to generate interesting dynamics. While most of these criticisms have been addressed by individual DSGE models, the ABM methodology is flexible enough to simultaneously address them. Adding a realistic model structure can lead to very different policy implications. For example, the model of Gualdi et al. (2017) features agents with heterogeneous expectations, imperfect markets, and at the same time it generates economic downturns endogenously. They show that central bank interest changes can actually generate economic downturns if the timing is wrong.

1.3.2 ABMs and financial markets

Instead of being dominated by one methodology, the financial markets modelling toolbox includes a wide variety of different (complementary) models such as portfolio balance models (Christensen and Krogstrup, 2016), market micro-structure models (Ho and Stoll, 1981; Glosten and Milgrom, 1985; Ait-Sahalia and Sağlam, 2017), network models (Allen, Babus, and Carletti, 2010), and heterogeneous agent models (Dieci and He, 2018).

Just as in the field of monetary policy, many of these established modelling methodologies include agents which are heterogeneous with regards to only a few aspects. So, ABMs have been able to provide new insights when heterogeneity with regards to many characteristics is necessary. For example, agents in the ABM of Chiarella and Iori (2002) are heterogeneous with regards to their expectations but also their trading horizon, market entrance frequency, and order placement. On top of that, the orders they place are heterogeneous with regards to their price, volume,

and duration. This set-up makes it possible to study how a market micro structure variable such as order duration affects volatility. The authors find that a higher average order duration is associated with lower price volatility because it increases market liquidity.

ABMs have also been useful in cases where a more detailed market structure was needed. For example, among other questions, Chiarella, Iori, and Perelló (2009) try to explain large sudden price movements with an ABM that features a realistic order-book based market structure with agent behaviour that is based on portfolio balancing and heterogeneous expectations. They show that large sudden price changes can be explained by the presence of large gaps in the order book.

1.4 Thesis outline

In the next chapters, I use the ABM methodology to help answer four research questions in which heterogeneity on multiple levels or detailed market structure is important. In line with my epistemology, the ABMs will be used to make conditional forecasts.

1.4.1 Chapter 2: interest policy transmission

In this chapter, together with Antoine Godin, Dirk Bezemer, Alessandro Caiani, and Stephen Kinsella, I explore how central bank interest rate changes affect inflation in the short term? We identify eight transmission channels and present an agent-based macroeconomic model based on Caiani et al. (2016), extended with an inter-bank market. We analyse the effects of interest rate shocks on inflation for four of the transmission channels.

Our justification for building an ABM to study the transmission mechanism is that, because we model individual agents which interact in markets that might not be in equilibrium at the same time, we are able to explore interest transmission at a much more granular level than has been done before. We wanted to explore if this model would produce the same predictions about the relationship between interest rate changes and inflation as popular DSGE models.

This was not the case. In our ABM, interest rate changes have a small effect on inflation because interest rate pass-through to costs, consumption, investment and bank lending is rather weak. The reason for this weak pass-through is that non-interest rate factors play a bigger role in most agent decisions. For the cost channel, interest rate costs are a much smaller component to costs than labour costs. For the investment channel, investment decisions are more heavily influenced by real factors such as sales than by interest rates. Also, for consumption, agents do not just believe

that the central bank will be effective at controlling inflation, they need to see it first. Furthermore, while interest rate increases encourage saving, they also provide extra income for savers, which will start spending more. As a result, aggregate consumption does not change much in response to interest rate changes. The only channel through which interest rate changes do significantly affect inflation is the bank lending channel. If the central bank interest rate reaches a certain threshold, and firms are relatively homogeneous, an interest rate increase can trigger a sudden credit crunch, which causes deflation.

1.4.2 Chapter 3: stock market efficiency

In the third chapter, I explore whether a "stock price decoupling scenario" is plausible. A stock price decoupling scenario means that stock prices do not revert to fundamentals as frequently as most behavioural models would predict. I define plausibility as being consistent with the main stylized facts of stock market returns. My main finding is that adding a mean-reversion component to the usual trend-following and fundamentalist expectation components allows the model to jointly replicate the moments associated with decoupling as well as the stylized facts. This is largely a result of mean-reversion expectations replacing fundamentalist expectations.

The ABM approach made sense here because the question deals with potential heterogeneity at multiple levels and the importance of each of these variables were unknown. The flexibility of the ABM methodology allowed for easy experimentation with different configurations of expectation heterogeneity. However, extensive sensitivity analyses revealed that a decoupling can be explained purely by replacing the fundamentalist expectations by simple mean-reversion expectations. The detailed market structure was not necessary in this case. Applying the philosophy that the model should be as simple as possible, a next step would be to apply a simpler modelling approach, such as heterogeneous agent modelling, to this problem.

1.4.3 Chapter 4: asset price volatility and inequality

In this chapter, I explore how stock market volatility affects wealth inequality. First, I present a simple two trader example in which random trading always leads to wealth inequality because at a certain point one of the two traders is no longer wealthy enough to trade. In this example, increased price volatility increases trading profits which accelerates the move to this unequal state. After that, I employ an ABM to find out if the same dynamic holds in a multi-agent setting. The ABM methodology makes sense here because heterogeneity at two levels is important: wealth and expectations. Furthermore, because inequality forms through trading, I needed to model the market structure in detail.

Therefore, the chapter presents an agent-based stock market model with a hundred noise traders with heterogeneous wealth. Simulation experiments show that the trading system lead to a highly unequal state as the wealth of more and more traders becomes so low that they have to stop trading. Increasing price volatility accelerates the movement towards this state, confirming that the same dynamic holds in a multi-agent setting.

1.4.4 Chapter 5: unconventional monetary policy and asset price stability

In chapter five, I explore how the central bank balance sheet can best be used to reduce asset price volatility. Here, I chose ABM to study this issue because it is able to incorporate heterogeneity with regards to both expectations and balance sheets. Furthermore, because there are extrapolative expectations, a non-equilibrium market mechanism was needed.

Using a financial market ABM with a central bank agent, I simulate three policy rules. These are: (1) a Buyer of Last Resort (BLR) rule which uses quantitative easing to dampen asset price down-swings; (2) a Seller of Last Resort (SLR) rule that uses quantitative tightening to prevent excessive asset price upswings; and (3) a Buyer and Seller of Last Resort rule that combines the BLR and SLR rules. Simulations reveal that the BLR and SLR rules do not increase financial stability but merely distort asset values. If the central bank wants to stabilize asset prices it will have to commit to acting as both a buyer and seller of last resort.

Chapter 2

Interest policy transmission

Abstract

In this chapter¹, we explore the variety of monetary interest policy transmission channels in an agent-based macroeconomic model. We identify eight transmission channels and present a macroeconomic model, based on Caiani et al. (2016), extended with an inter-bank market. We then analyse model simulation results of interest rate shocks in terms of GDP and inflation for four of the transmission channels. We find these effects to be small, in line with the view that monetary policy is a weak tool to control inflation.

The recent behaviour of inflation is ‘a mystery’ to central bankers according to ex Federal Reserve Chair Janet Yellen (Yellen, 2017). One contributing reason may be the structure of the New Keynesian Dynamics Stochastic General Equilibrium (DSGE) models typically used to guide interest rate policy by the central bank (Blanchard, 2016). Dissatisfaction with their unrealistic assumptions is now widespread (Caballero, 2010; Romer, 2016; Stiglitz, 2017). In other words, there is uncertainty about how monetary policy influences individual price setting behaviour which is captured by inflation headlines. Therefore, Blanchard (2016) calls for the economics profession to explore different model types.

As spelled out in the introduction of this thesis, agent-based models (ABMs) are a promising alternative if market mechanisms are not well described using the equilibrium simplification or if heterogeneity is important. Monetary policy transmission is usually studied in general equilibrium models which feature agents with limited heterogeneity. However, it is uncertain how these simplifications affect our understanding of the transmission mechanism. Therefore, in this chapter, we revisit the issue using an agent-based model.

Fagiolo and Roventini (2017) provide an overview of AB models which have been applied to study the effects of monetary policy. Monetary policy transmission is modelled in different ways across these models. For example, in Raberto, Teglioni, and Cincotti (2008), Salle, Yıldızoğlu, and Sénégas (2013), Salle (2015), Dosi et al.

¹This chapter has been published in *Advances in Complex Systems* under the name: Monetary policy transmission in a macroeconomic agent-based model (Schasfoort et al., 2017).

(2015), and Popoyan, Napoletano, and Roventini (2017) the central bank inflation target influences household inflation expectations, feeding into wage demands, costs, and output prices. In Delli Gatti and Desiderio (2015) higher policy rates lead to credit rationing on the supply side and decreased credit demand. In many models central bank rates affect household consumption through wealth effects (Gualdi et al., 2015; Salle, 2015), or changes in the propensity to consume (Bouchaud et al., 2017).

Thus, different models implement different channels. In order to enhance the comparability of findings in the agent-based literature, we present a taxonomy of monetary policy transmission channels. We then simulate four transmission channels in a modified version of the Caiani et al. (2016) benchmark model. We highlight a variety of behavioural and structural assumptions which affect outcomes in terms of GDP and inflation. Model outcomes are consistent with a relatively small efficacy of monetary policy in controlling inflation.

2.1 Transmission Channels

In practice, interest rate policy by the central bank means changing two rates: one as a compensation for depositing reserves and another charged to counter parties who borrow reserves from the central bank. Together, these are known as the Standing Lending Facilities (SLF). Lee and Sarkar (2017) provide a detailed discussion of the institutional differences for major central banks.

Typically, central banks change the interest rate based on an inflation target. The transmission of monetary policy refers to the process of interest rate changes working their way through the economy, ultimately to affect the rate of inflation (Bank of Canada, 2012). There are several channels through which this transmission can occur.

First, in the expectations channel, private sector behaviour depends on the expected course of monetary policy, as well as on the current policy. Agents might change their behaviour as they anticipate the effects of monetary policy (Bernanke, 2005). For example, inflation expectations might directly influence household consumption and firm pricing decisions. If households expect higher inflation in the future, they increase consumption now, increasing inflationary pressures. Or, if firms expect higher inflation in the future, they might increase their prices now. Figure 2.1 summarizes these effects.

Different from the expectations channel, the other transmission channels describe behavioural changes in response to changes in current interest rates. For these channels to work, it is vital that SLF rate changes induce changes in other key interest rates in the economy. This is known in the literature as interest rate pass-through (Von Borstel, Eickmeier, and Krippner, 2016).

Figure 2.1: Expectations channel

If there is some pass-through, the literature identifies at least seven channels by which changes in policy rates affect inflation: a bank lending channel (Disyatat, 2011), a balance sheet channel (Bernanke and Gertler, 1989), an investment channel (Mojon, Smets, and Vermeulen, 2002), an asset price channel (Bernanke and Gertler, 1995), a consumption channel (Lettau, Ludvigson, and Steindel, 2002), a cost channel (Barth and Ramey, 2002), and an exchange rate channel (Svensson, 1999).

The bank lending and balance sheet channels, collectively known as the credit channel, describe how banks reduce credit supply after a policy rate hike. According to the bank lending channel, as banks' funding costs increase and their profitability falls, they reduce the quantity of credit they are willing to lend (Disyatat, 2011). Through the balance sheet channel, an increase in interest rate lowers firms' future revenues, reducing the net worth of firms. In response, banks reduce the credit supply to these firms.

On the credit demand side, firms' desire to invest might decrease as a consequence of monetary policy tightening. The investment channel (Mishkin, 1995) describes how higher bank lending rates discourage business investment by reducing the value of investment, and therefore the value of assets reflecting these investments. This asset price channel suggests that the resulting decrease in firms' net worth reduces investment demand by firms (Mishkin, 1996).

In the consumption channel (Mishkin, 1995), changes in interest rates might affect household consumption decisions through a wealth effect, as interest rate hikes affect asset values. (Lettau, Ludvigson, and Steindel, 2002). Also, a rate increase makes it more worthwhile to save, decreasing the propensity to consume.

In addition, Barth and Ramey (2002) propose the existence of a cost channel in which changes in interest rates transmit to changes in funding costs for firms which then translate into higher output prices.

With the exception of the cost channel and the wealth effect in the consumption channel, in all of the channels described above, SLF policy rate increases are expected to reduce GDP relative to its potential level, thereby increasing the output gap (Gali, 2002) and reducing inflationary pressures.

Figure 2.2 provides an overview of all interest rate channels and shows that the net effect of these channels combined is *not* clear *a priori*. The strength of individual effects is unknown, effects may have opposite signs, and there may be interaction effects between different channels. For example, increased consumption through the consumption channel might amplify the balance sheet channel: it causes an increase in firms' net-worth.

This makes it challenging to open the 'black box' of conditions in which policy transmission does or does not occur (Bernanke and Gertler, 1995). Nonetheless, we will attempt to take a peek inside the black box and simulate an interest rate hike in an agent-based model in which the consumption, investment, bank lending, and cost channel are active.

2.2 The Model

To analyse monetary policy transmission, we modify the Caiani et al. (2016) benchmark model of a closed economy (i.e. without foreign or 'rest of the world' sector).

First, we add the ability to shock the central bank SLF policy rates. To simulate interest rate pass-through, we add an inter-bank market in which banks operate between the central bank determined upper and lower limits. We also add and change several behavioural rules related to bank lending, interest rates, firm pricing, dividends, liquidity, and capital ratios. Finally, to distinguish more between short-term and long-term debt, we change the time-scale so that periods represent months instead of quarters, we updated interest rates accordingly. The updated model is able to simulate the bank lending channel, investment channel, consumption channel, and cost channel along with their interactions.

The balance sheet channel is not operational in the model because banks do not discount the value of collateral. The asset price channel does not exist because firm investment decisions are based on desired growth of output which in turn is based on real factors. Then, they try to finance investment with retained earnings before turning to loans. Therefore, a reduction in net-worth does not reduce investment demand. Finally, inflation expectations are formed adaptively, as a consequence of past inflation. Consequently, there is no expectations channel through which the central bank can influence agent expectations directly. We implement the model using the Java Macro Agent-Based (JMAB) package².

²The source code for this model can be found at: <https://github.com/S120/Interbank>

Figure 2.2: Domestic monetary policy transmission channels

2.2.1 Agents

There are six types of agents x : households hh , firms f (divided into consumption goods firms cf and capital goods firms kf), banks b , a central bank cb , and a government g . All agents have state variables which are represented by a matrix V_x . Table A.1 (in the Appendix) provides an overview of the state variables V_x and their domains. In the notation of variables, subscripts indicate the agent and time step of the variable. Superscripts indicate if the variable or parameter refers to another variable, or is an expectation (e), demanded (d), supplied (s), or targeted (tr) variable.

2.2.2 Markets

All markets use a common matching protocol. This lets a demand agent observe a random subset of suppliers, the size of which is determined by parameter χ representing information asymmetry in that market. Demand agents pick the supplier who offers the best price; but if the demand agent has a previous supplier it sticks to this supplier with a probability of changing suppliers $(1 - \theta^{\Delta k})$,

$$\theta^{\Delta k} = \begin{cases} e^{\frac{\epsilon p_* p_k}{p_*}} & \text{if } p_* > p_k \\ 0 & \text{otherwise} \end{cases}, \quad (2.1)$$

where ϵ represents the intensity of choice, p_* the lowest observed supplier price, and p_k the price of the selected supplier. In case the preferred supplier has run out of inventory, the agent picks the supplier with the next best price. If the agent demand was filled or the supplier has run out of inventory, the protocol stops. In some markets, when the supplier has run out of inventory, the demand agent can select a new random supplier from the subset. Figure 2.3 below depicts the market matching protocol.

Figure 2.3: Market matching protocol

2.2.3 Simulation overview

We simulate agent actions and interactions over t periods. As a consequence of these actions and interactions, the state variables of the agents are immediately updated. Unless stated otherwise, agents are processed in a random order. Each

period represents a month in which we simulate the following sequence of events:

1. expectation formation,
2. firms' output determination,
3. banks write down non-performing loans,
4. firms' price determination,
5. capital goods market - first interaction,
6. investment demand,
7. bank's internal interest rates,
8. deposit rates,
9. credit demand,
10. firms' labour demand,
11. credit market interactions,
12. labour supply,
13. government labour demand,
14. central bank policy,
15. labour market interactions,
16. firms' production,
17. consumption demand,
18. consumption goods market interaction,
19. capital goods market - second interaction,
20. tax rate determination
21. payments on obligations,
22. deposit market interactions,
23. defaults,
24. bond market - first interaction,

- 25. interbank market interactions,
- 26. central bank bond demand,
- 27. bond market - second interaction,
- 28. central bank lending facilities.

2.2.4 Simulation scheduling

In this section, we describe in detail the simulation algorithm for every period. Agents are boundedly rational (Gigerenzer and Selten, 2002). They can observe their own state variables, the values of their state variables in the previous period, and some state variables of other agents. In their decision making, they follow simple heuristics based on limited information.

Expectation formation

At the start of every period, each agent computes expected values for state variables in V_x based on the simple adaptive rule:

$$V_{x,t}^e = V_{x,t-1}^e + \gamma(V_{x,t-1} - V_{x,t-1}^e), \quad (2.2)$$

where γ is an adaptive parameter.

Firms' output determination

Firms compute an output target, $o_{f,t}^{tr}$, by subtracting current inventories $X = \{KG, CG\}$ (capital or consumption goods depending on firm type), from the inventories needed to satisfy expected sales, $y_{f,t}^e$, and a percentage inventory buffer, $G_{f,t}^{tr}$

$$o_{f,t}^{tr} = y_t^e(1 + G_{f,t}^{tr}) - X_t \quad \text{with} \quad X = \{KG, CG\}. \quad (2.3)$$

Banks write down non-performing loans

In the next step, banks remove any loans from bankrupt debtors, $n_{b,t}^L$, from their balance sheets.

$$L_{b,t} = L_{b,t-1} - n_{b,t}^L. \quad (2.4)$$

If the debtor is a consumption firm, the bank recovers collateral C by forcing its sale, from which it recovers the proceeds, $C = KG_{cf}$. Since capital firms do not have collateral, the loss from their bad loans is fully borne by banks, who try to diminish this through sale of the firms' physical capital to households.

Firms' price determination

To determine output prices $p_{f,t}$, firms often take into account costs as well as market conditions (Alvarez and Hernando, 2005). Firms apply a mark-up $v_{x,t}^{uc}$ over their expected unit labour costs ($uc_{f,t}^e$) times the foreseen amount of labour $l_{f,t}^{tr}$, plus the interest payments over the last period, all divided by the targeted output level.

$$p_{f,t} = \left(1 + v_{x,t}^{uc}\right) \frac{uc_{f,t}^e l_{f,t}^{tr} + i_{f,t-1}^L L_{f,t}}{o_{xt}^t}. \quad (2.5)$$

Firms revise their mark-up adaptively depending on their inventory and capacity utilization, reflecting market conditions. If current inventory $G_{x,t-1}$, or output capacity o_{t-1} are below (above) targets $G_{f,t}^{tr}$, o_{t-1}^* , the mark-up is increased (decreased) by a stochastic amount FN^1 drawn from a folded normal distribution with parameters $\mu_{FN^1}, \sigma_{FN^1}^1$,

$$v_{x,t}^{ulc} = \begin{cases} v_{x,t-1}^{ulc} (1 + FN^1) & \text{if } \frac{CG_{x,t-1}}{y_{x,t-1}} \leq G_{f,t}^{tr} \text{ or } \frac{o_{t-1}}{o_{t-1}^*} \geq G_{f,t}^{tr} \\ v_{x,t-1}^{ulc} (1 - FN^1) & \text{otherwise} \end{cases} \quad (2.6)$$

Capital market - first interaction

Consumption firms try to find the cheapest capital supplier. They observe a subset of suppliers and then select the cheapest, following the market procedure presented in Figure 2.3.

Investment demand

Consumption firms now determine investment demand. They target a desired production capacity rate of growth $\kappa_{cf,t}^{tr}$ based on their target rate of capacity utilization $u_{c,t}^{tr}$ and the previous period rate of return on capital, $r_{c,t-1}$:

$$\kappa_{cf,t}^{tr} = \Omega_1 \frac{r_{cf,t-1} - \bar{r}}{\bar{r}} + \Omega_2 \frac{u_{cf,t}^{tr} - \bar{u}}{\bar{u}}. \quad (2.7)$$

Firms then derive demand for capital goods $kg_{c,t}^t r$ based on their target output growth, taking into account capital replacement. This results in their nominal investment demand $KG_{c,t}^d$ as the product of units of capital demanded and the price asked by the chosen supplier $p_{k,t}$.

$$KG_{c,t}^d = p_{k,t} kg_{c,t}^d. \quad (2.8)$$

Bank's internal interest rates

In the next step, banks determine their internal interest rate on loans, $i_{b,t}^L$. First, banks calculate their funding rate $fc_b = \overline{(i_b^A + i_b^{IB} + i_b^D)}$. To this rate they either add or subtract a stochastic amount FN^2 . This depends on whether they meet their capital ratio target. Thus, well capitalized banks decrease their rate to attract more borrowers and vice versa.

$$i_{b,t}^L = \begin{cases} fc_{b,t}(1 + FN^2) & \text{if } CR_{b,t} < CR_{b,t}^{tr} \\ fc_{b,t}(1 - FN^2) & \text{otherwise} \end{cases}, \quad (2.9)$$

where the capital ratio is calculated by dividing equity value by the value of assets, $CR = \frac{E}{R+B+L}$. Bank credit supply is limited only by demand, regulation, and bank's own rationing policy McLeay, Radia, and Thomas, 2014 as explained below.

Deposit rates

Banks try to attract deposits by setting deposit interest rates $i_{b,t}^D$ based on the values of their liquidity ratio, $LR = \frac{R}{D}$, funding costs, fc , and profitability, r :

$$\chi^{LR} = \begin{cases} 1 & \text{if } \frac{(LR_t - LR_t^t)}{(LR_t^t)} \geq 0 \\ -1 & \text{otherwise} \end{cases}; \quad (2.10)$$

$$\chi^{fc} = \begin{cases} 1 & \text{if } \Delta fc_b \geq 0 \\ -1 & \text{otherwise} \end{cases}; \quad (2.11)$$

$$\chi^r = \begin{cases} 1 & \text{if } \Delta r_t \geq 0 \\ -1 & \text{otherwise} \end{cases}. \quad (2.12)$$

If the combined values are sufficiently small, a bank will attempt to attract deposits by increasing its interest rate by the stochastic term FN^2 . Otherwise, it will decrease the rate.

$$i_{b,t}^D = \begin{cases} i_{b,t-1}^D (1 + FN^2) & \text{if } \chi^{LR} + \chi^r + \chi^{fu} \geq 0 \\ i_{b,t-1}^D (1 - FN^2) & \text{otherwise} \end{cases}. \quad (2.13)$$

Credit demand

Then, firms compute their need for credit, $L_{f,t}^d$. They compute their expected expenditures as nominal desired investment, $I_{f,t}^{tr}$, plus the dividends they expect to distribute, $dv_{f,t}^e$, plus the labour use, $l_{f,t}lc_{f,t}$. Then, adhering to the pecking order theory, they try to fund investment using their operating cash flows and deposits $D_{f,t}$ first. Furthermore, firms try to keep an extra liquidity buffer for loan payments ζ^w . The remainder is asked on the credit markets.

$$L_{c,t}^d = \max\{I_{f,t}^d + dv_{f,t}^e + \zeta^w l_{f,t}lc_{f,t} - OCF_{f,t}^e - D_{f,t}, 0\}, \quad (2.14)$$

where OCF represents operating cash flows after taxes, which is computed as after-tax profits plus capital amortization costs, minus changes in inventories and debt repayments.

Labour demand

Firms hire workers. Capital goods firms calculate the output level they can achieve based on their capital stock, and then set labour hiring needs $\Delta l_{kf,t}^d$. If negative, some random workers are laid off until there are just enough to produce the target output.

$$\Delta l_{k,t}^d = \frac{o_{ck,t}^t}{\lambda_l}, \quad (2.15)$$

where λ_l is the productivity of labour.

Consumption firms review their desired capacity utilization, $u_{cf,t}$ and calculate their labour demand as

$$l_{cf,t}^d = u_{cf,t}^{tr} \frac{KG_{cf,t}}{\delta}, \quad (2.16)$$

where δ is the constant capital labour ratio and $u_{cf,t}$ is the rate of capacity utilization needed to produce the target level of output $u_{cf,t} = \min\left(1, \frac{o_{cf,t}^{tr}}{\lambda_k KG_{cf,t}}\right)$.

Credit market

Firms then enter the credit market and request a loan from the cheapest supplier. The bank responds by calculating expected profit r^e as the net present value of future cash flows minus the expected loss:

$$r^e = \sum_{n=1}^m \frac{ds(i)}{(1+i^L)^n} - \Delta L - (LGD * \theta^{df} * L), \quad (2.17)$$

where $LGD = \frac{L-C}{L}$, is the loss given default, $ds = (i_{b,t}^L + \frac{1}{n})L_f$ is the debt service, and $\theta^{df} = \frac{1}{1+exp(\frac{OCF_{f,t}-\beta ds}{ds})}$ is the probability of default, where β is a parameter of risk aversion. If expected profit is positive, banks grant the loan in full. Otherwise, the loan is denied.

Labour supply

Households which are unemployed for longer than their threshold, $m_{hh,t} > \phi^m$ update their desired wage $w_{hh,t}^{tr}$ by subtracting stochastic amount FN^3 from the last periods' level. Employed households increase their asked wage by this stochastic amount,

$$w_{hh,t}^{tr} = \begin{cases} w_{hh,t-1}(1 - FN^3) & \text{if } \sum_{n=1}^4 m_{hh,t-n} > \phi^m \\ w_{hh,t-1}(1 + FN^3) & \text{otherwise} \end{cases}. \quad (2.18)$$

Additionally, every period a share of workers ι^u , leave their current employer and look for a new job.

Government labour demand

The government is committed to hiring a constant number of households, l_g^d . Government labour demand is therefore equal to the labour turnover share ζ^u ,

$$l_{g,t}^d = l_{g,t-1} \zeta^u. \quad (2.19)$$

Central bank policy

The supply of central bank advances is not limited or rationed. The central bank has a fixed lending facility rate $i_{cb,t}^R$. To study the effects of interest rate changes in isolation, in periods t_{mon} in which monetary policy changes occur, the lending facility rate changes by an amount Ψ_{mon} .

$$i_{cb,t}^R = \begin{cases} i_{cb,t-1}^R + \Psi_{mon} & \text{if } t = t_{mon} \\ i_{cb,t-1}^R & \text{otherwise} \end{cases}. \quad (2.20)$$

Much like the Bank of England (2012), it sets the rate on advances $i_{cb,t}^A$ as a mark-up, Ψ_{iR} over the official bank rate,

$$i_{cb,t}^A = i_{cb,t}^R + \Psi_{iR}. \quad (2.21)$$

The central bank also sets a countercyclical capital buffer based on the credit-to-GDP ratio (European System Risk Board, 2014), in line with the Basel III capital requirements:

$$CR_t^{tr} = \begin{cases} CR_{t-1}^{tr} + \Psi_{pru} & \text{if } \frac{L_t}{Y_t} > \phi^{pru} \\ CR_{t-1}^{tr} - \Psi_{pru} & \text{if } \frac{L_t}{Y_t} < \phi^{pru} \\ CR_{t-1}^{tr} & \text{otherwise} \end{cases}, \quad (2.22)$$

where Y is nominal GDP. The central bank also aims to minimize systemic liquidity risk, defined as a situation in which banks' normal funding and refinancing channels fail (ibid.), prompting the central bank to act as lender of last resort. Therefore, it sets a countercyclical liquidity ratio target based on total private credit L_t to GDP.

$$LR_t^T = \begin{cases} LR_{t-1}^T + \Psi_{pru} & \text{if } \frac{L_t}{Y_t} > \phi^{pru} \\ LR_{t-1}^T - \Psi_{pru} & \text{if } \frac{L_t}{Y_t} < \phi^{pru} \\ LR_{t-1}^T & \text{otherwise} \end{cases}. \quad (2.23)$$

Labour market

Now potential employers and employees enter the labour market. Employers select the employee with the lowest wage demands, according to the market selection algorithm.

Production

Consumption firms produce consumption goods, using their most productive capital goods first. Since they already chose the amount of labour necessary for production, they produce using all available labour and capital.

$$\Delta CG_{cf,t} = \lambda_{cf,t} KG_{cf,t} \lambda_k. \quad (2.24)$$

Capital firms produce according to:

$$\Delta KG_{kf,t} = \lambda_l l_{kf,t}. \quad (2.25)$$

Consumption demand

Households set desired consumption $c_{hh,t}^d$ as a fixed share α^y of their expected net income plus a share α^q of their expected net wealth, $D_{hh,t} + CG_{hh,t}$. The propensity to consume out of wealth responds to interest rate changes $\alpha_t^q = \alpha_{t-1}^q + i_t - i_{t-1}$. Both income and wealth are adjusted for expected inflation $\Delta p_{cf,t}^{e,CG}$.

$$c_{hh,t}^d = \alpha^y \frac{y_{hh,t}^e}{\Delta p_{cf,t}^{e,CG}} + \alpha^q \frac{q_{hh,t}^e}{\Delta p_{cf,t}^{e,CG}}. \quad (2.26)$$

Consumption market

In the consumption market, consumers are matched to the cheapest consumption firm according to the common matching protocol.

Capital market - round 2

With the supplier fixed and credit obtained, consumption firms enter the capital market again to purchase their desired capital goods.

2.2.5 Tax rate determination

To limit the government debt to GDP ratio, the government updates its tax rate every period.

$$mp_t^{tr} = \begin{cases} mp_{t-1}^{tr} + adj_{pru} & \text{if } \frac{B_t}{Y_t} > \phi^{pru} \\ mp_{t-1}^{tr} - adj_{pru} & \text{if } \frac{B_t}{Y_t} < \phi^{pru} \\ mp_{t-1}^{tr} & \text{otherwise} \end{cases}, \quad (2.27)$$

Payment on obligations

Then, interactions take place as a consequence of equity, credit, deposits, and other contractual claims. There are several types of credit claims in the model. Banks have loan claims on firms, interbank claims on other banks, and they may own government bonds. The central bank may own government bonds and in addition might have lent

reserves to deficit banks in the form of advances. Every period, these credit claims cause repayment and interest payments from debtors to creditors.

There are two types of transferable debt claims in the model. Banks and the government hold reserves at the central bank. Households and firms hold deposit accounts at banks. This leads to payments of interest on these claims. Furthermore, reserves and deposits are used to settle payments by the government; reserves are used for inter-bank payments; deposits are used to settle household and firm payments.

Finally, some debt claims are off-balance sheet but are implied by contracts. These are tax, social benefits, and wage claims. Households, banks and firms are all obliged to pay income taxes to the government; all employers (the government, firms and banks) are obliged to pay wages to their household employees. The government has an obligation to pay social security to unemployed households.

We now describe the payments due on every obligation, j , in every set of obligations, P . First, firms pay interests due on outstanding loans to banks, where each individual loans carries its own interest rate.

$$\Delta D_{f,t} = - \sum_{j \in P} i_{j,f,t}^L L_{j,f,t}. \quad (2.28)$$

Then, firms and the government pay wages to each household employee j , in its set of employees M .

$$\Delta D_{x,t} = - \sum_{j \in P} w_{j,x,t}. \quad (2.29)$$

The government pays unemployment benefits to unemployed workers at a fixed rate ν_m of average wage.

$$\Delta D_{x,t} = - \sum_{n \in P} \nu_m \bar{w}. \quad (2.30)$$

The government pays interest i^B on its outstanding bonds:

$$\Delta D_{g,t} = \sum_{j \in P} i_{j,x,t}^B B_{j,x,t}. \quad (2.31)$$

The central bank pays interest over outstanding reserves:

$$\Delta R_{g,t} = \sum_{j \in P} i_{j,cb,t}^R R_{j,x,t}. \quad (2.32)$$

Banks pay interest to the central bank on outstanding advances,

$$\Delta R_{b,t} = - \sum_{j \in P} i_{cb,t}^A A_{j,b,t}, \quad (2.33)$$

and on inter-bank loans,

$$\Delta R_{b,t} = - \sum_{j \in P} i_{j,b,t}^{IB} I B_{j,b,t}. \quad (2.34)$$

Banks also pay interest to households and firms over their deposit liabilities, as the agreed interest rate $i_{b,t-1}^D$ times the deposit $D_{x,t-1}$.

$$\Delta D_{b,t} = \sum_{j \in P} i_{j,b,t-1}^D D_{j,t-1}. \quad (2.35)$$

At the end of each period, the central bank calculates its profits $r_{cb,t}$ by subtracting the interest it pays on excess reserve deposits $i^R R_{b,t-1}$ from the interest receipts on government bonds $\bar{i}^B B_{t-1}$ and from advances $\bar{i}_{cb,t}^A A_{cb,t}$.

$$r_{cb,t} = \bar{i}^B B_{t-1} + \bar{i}_{cb,t}^A A_{cb,t} - i^R R_{b,t-1}. \quad (2.36)$$

After that, the central bank transfers its profit to the government.

$$\Delta R_{b,t} = r_{cb,t}. \quad (2.37)$$

Firms pay dividends to their capital suppliers by multiplying their after-tax profit with the dividend pay-out ratio:

$$\Delta D_{f,t} = \rho_x r_{f,t}. \quad (2.38)$$

They distribute these dividends among households proportionally to net wealth. Banks determine the amount of dividends they distribute based on their desired capital ratio,

$$\Delta D_{f,t} = \begin{cases} (1 + \alpha^\rho) \rho_b r & \text{if } CR_{bt} > CR_t^T \\ \rho_b r_{b,t} & \text{otherwise} \end{cases}. \quad (2.39)$$

After that, firms pay taxes to the government by multiplying their profits by the tax rate.

$$\Delta D_{f,t} = \tau^r r. \quad (2.40)$$

Finally, households pay a flat tax rate τ^y over their wages $w_{hh,t}$, dividends $dv_{hh,t}$ and interest received on deposits $i_{b,t-1}^D D_{hh,t-1}$,

$$\Delta D_{hh,t} = \tau_y \left(w_{hh,t} + dv_{hh,t} + i_{b,t-1}^D D_{hh,t-1} \right). \quad (2.41)$$

Deposit market

In the next step, consumers switch banks if they observe a more favourable deposit rate than the one they receive from their current bank.

Bankruptcies

If, at any point, a firm's or a bank's assets minus its liabilities are below zero, it enters a state of default,

$$df_{f,t} = \begin{cases} True & \text{if } D_f + CG_f + KG_f - L_f < 0 \\ False & \text{otherwise} \end{cases}, \quad (2.42)$$

$$df_b = \begin{cases} True & \text{if } R_b + IB_b + L_b + B_b - D_b - A_b < 0 \\ False & \text{otherwise} \end{cases}. \quad (2.43)$$

If in default, firms and banks are bailed in by their household owners and their depositors, see Caiani et al. (2016) for an extended description of this process. This happens so that the total number of firms and banks remains constant.

Bond supply

The government calculates its deficit as tax revenues plus central bank profits, minus wages, unemployment benefits and interest on bonds. To cover the deficit, it issues bonds to the amount ΔB_t at a fixed price p^B .

$$\Delta B_{g,t}^s = \frac{tx_{g,t} + r_{cb,t} - \sum_{j \in l_{g,t}} wl_j - um_t d_t - i^b B_{t-1}}{p^B}. \quad (2.44)$$

Bond market

Banks try to buy government bonds with their excess reserves.

$$B_{b,t}^d = \begin{cases} LR_{b,t} - LR_{b,t}^t & \text{if } LR_{b,t} < LR_{b,t}^t \\ 0 & \text{otherwise} \end{cases} . \quad (2.45)$$

Inter-bank market

After that, if a bank still has excess reserves, it determines its demand for reserves, or supply of inter-bank loans, on the inter-bank market as the difference between reserve requirement $R_{bt}^d = D_{bt}LR_{b,t}^d$ and current reserves R_{bt} :

$$IB_{bt}^s = (LR_{bt} - LR_{bt}^d) D_{bt}. \quad (2.46)$$

Subsequently, reserve-supplying banks adjust their mark-up on the price of reserves. This mark-up is the difference between their average generic interest rate $\bar{i}_{b,t}^L$ and the risk free reserve rate i_{bt}^R , divided by the maturity of credit η^L :

$$i_{bt}^{IB} = \frac{\bar{i}_{b,t}^L - i_{b,t}^R}{\bar{X}^L}, \quad (2.47)$$

Reserve-supplying and reserve-demanding banks are then matched on the inter-bank market according to the general matching protocol.

Government bond market -second interaction

Any bonds which were not purchased by private banks will then be purchased by the central bank, so that central bank demand for bonds will be equal to any government bond supply left:

$$\Delta B_{cb,t} = B_{g,t}^s. \quad (2.48)$$

Central bank lending facilities

Finally, if banks cannot obtain enough reserves on the inter-bank market, they borrow the remainder from the central bank as advances. The central bank always supplies the amount asked.

$$A_{b,t}^d = (LR_{b,t} - LR_{b,t}^d) D_{b,t} \quad (2.49)$$

2.2.6 Calibration

The parameter calibration is based on the calibration of the model presented by Caiani et al. (2016). Where possible, we have chosen parameter values that are the same. Compared to their model, we halved the number of household agents, because this does not alter the dynamics much while reducing computational time by roughly a third. We therefore initialize the model with 4,000 households, 100 consumption firms, 20 capital firms, 10 banks, a single central bank, and a single government.

Next, we apply the six-step strategy for initializing the model described in Caiani et al. (ibid.). For model consistency, it is important that for all agents, assets equal liabilities plus net worth. We determine initial values of all parameters and state variables consistent with an aggregate stock-flow consistent model in a steady state. Next, we distribute the aggregated variables homogeneously and symmetrically across agents. We create for the first period a 'memory' of fictitious past sales, past wages, past profits and so on, as the basis for backward-looking expectations. We also define a historical structure. That is, we assume that in the periods before the simulation starts, firms obtained loans and consumption firms invested in new capital to maintain their productive capacity.

We further assume that the real value (i.e. corrected for inflation) of the new loans or of the new capital goods was constant in each of these periods. Based on a constant inflation rate and an amortization schedules for capital goods and loans, we derive the outstanding value for each of these stocks, so that their total value sums up to the amount determined in the previous step. Using this set-up, no agent starts the simulation with an advantage over other agents. Initial values for variables are reported in Table A.2 and parameter values are reported in Table A.3 in the Appendix.

2.3 Results

To control for stochastic effects introduced in several equations and during the market matching mechanism, we run fifty³ Monte Carlo simulations of the baseline model.

2.3.1 Model dynamics

Starting from completely homogeneous initial conditions the models starts to evolve to a more heterogeneous distribution of firms, banks and households. The model does not converge to an equilibrium state in which all competing influences are exactly

³This is the standard number of simulation in this thesis. We have confirmed that the conclusions of this chapter do not change if more Monte Carlo simulations are performed.

balanced. Even though it is pretty stable, the simulated economy fits the description of Arthur (2013) and is always in a state of flux, constantly evolving and changing.

Business cycles

Figure 2.4 show the evolution of real GDP. The model generates endogenous business cycles which are characterized by pro-cyclical consumption and investment, see Figure 2.8 for a comparison of these properties to U.S. data. Following Eq. 2.8, consumption firms investment demand is driven by their desired rate of capacity growth, which in turn is driven by returns on capital and the current rate of capacity utilization. If consumption firms are not denied credit by banks, they will buy machines from capital firms. Investment by consumption firms drives down unemployment, both as consumption firms hire employees to work the machines and as capital firms hire employees to produce machines.

However, rising wages do not always translate into rising consumption. The trend in consumption is largely mirrored by the trend in net-income. Net-income is the sum of wage, dole, dividend, and interest income minus taxes. As households are both workers and capital owners, wages may rise at the expense of dividend income, balancing changes in net-income.

Figure 2.4 (top-left panel) shows that unemployment fluctuates between 0% and 12% on average. It might happen that, the economy temporarily reaches full employment. Such periods of full-employment are accompanied by stable consumption levels. Full employment puts a cap on the investment boom. Firms cannot expand production any further as they cannot hire new employees. At that point, any negative development in bank lending behaviour, firm profitability, or reversal of fortunes for investment driving firms might usher in a decrease in investment.

Once that happens, falling investment leads to falling sales for capital firms and a couple of them go bankrupt. This causes a reduction in household wealth and dividend income which in turn leads to falling consumption. Falling operating cash flows lead to a further reduction in investment demand and unemployment starts to rise.

Eventually investment downturns do turn around. Here heterogeneity plays a crucial role. While average capacity and return on capital decreases some firms continue to do well. These firms keep investing in a downturn. As weak firms de-investment is constrained at the depreciation rate of capital, the investment of strong firms might overtake the de-investment of the majority of smaller firms at a certain point. When this happens, the cycle reverses.

Figure 2.4: Monte Carlo average and standard deviation of: (top-left) real GDP, (top-right) unemployment, (bottom-left) real investment, and (bottom-right) real consumption.

Consumer price inflation

During the simulation the evolution of consumer prices switches twice from deflation to inflation.

To understand inflation dynamics, we start by inspecting the pricing behaviour of consumption firms. Eq. 2.5 shows that pricing behaviour is determined by cost prices and an inventory based mark-up (Eq. 2.6). The costs price term depends on several factors: labour costs and debt-service costs over desired output. At any point in time inflation is driven by the combination of these two factors.

During the first phase, prices generally fall. To understand the initial deflation, we inspect changes in firm-mark ups -mark-up inflation- and cost prices -cost price inflation. The fall in cost prices is largely driven by a drop in debt-service levels, as real investment is largely funded by retained earnings. With low unemployment, wages increase across the board.

Then, while deflation is stable, its drivers change. Falling real sales cause profits to decrease. This forces firms to borrow more to invest, increasing debt service costs. Along with continued wage increases, firms' cost price increases. At the same time, falling real sales and expanding capacity cause firms' mark-ups to decrease, causing overall prices to continue to fall.

As profitability and capacity utilization shrink, firms invest less. Near the end of the first deflationary phase, this dampens mark-up deflation until it eventually flips to mark-up inflation. This ushers in the start of an inflationary phase.

As real desired consumption is significantly above output capacity, firms increase their mark-ups. As firms are profitable and operate above desired capacity utilization, they start investing heavily, steadily increasing debt service costs. At the same time, unemployment is low and wages are increasing steadily.

A tipping point in mark-up inflation occurs as the economy hits full employment, slowing demand growth. The increase in debt-service costs as a result of increased investment keeps overall inflation high for a while.

This persistent inflation decreases real demand. As demand drops, sales and investment follow. This then affects the two primary inflation drivers. Cost prices start to decline along with debt service and, as firms start producing under desired capacity levels, mark-ups start falling as well, ushering in another deflationary phase.

In this phase, mark-up deflation is the primary driver of consumer price deflation. Even as demand starts to recover, firm capacity utilization is consistently below target. General price deflation is a consequence of mark-up deflation. Cost prices increase during this period. Cost price inflation is somewhat more stable with a constantly increasing wage bill as its primary driver. Along with the wage bill, nominal consumption and sales also increase.

Finally, the model enters a new inflationary phase. Both mark-up and cost price inflation pick up and contribute roughly the same to overall inflation. In this phase, the behaviour of mark-up inflation is quite different from the first inflationary phase. Firms are still substantially below capacity. However, as real sales slowly increase, firms increase output, leaving inventories very small. As a result, firms start investing more. Over the course of this phase, while nominal consumption is still rising due to fast rising consumer prices, real consumption starts dropping. Output follows and so does the need for further investment. As investment drops, firms start firing employees. Figure 2.5 shows the changes in mark-up and cost-price components along with inflation in each phase.

The labour market

Household wages are largely determined by the amount asked by households following Eq. 2.18. Because, unemployment is always relatively low, nominal wages increase over the simulation.

Financial markets

Loan interest rates generally increase over the course of the simulation because capital ratios are consistently below target until they stabilize when bank profitability rises as a consequence of increased interest rates. When capital ratios are above target, banks no longer try to raise their prices to increase capital. As a result, loan rates stabilize.

Figure 2.5: Changes in consumer prices, and its components: (top-left) phase 1, (top-right) phase 2, (bottom-left) phase 3, and (bottom-right) phase 4.

Furthermore, deposit rates are generally stable until funding costs of banks start to fall. The interbank rate converges to the loan rate mark-up when liquidity ratios are consistently above target. Finally, following Eq. 2.17, banks ration credit quite consistently throughout the simulation. As expected, upturns in credit rationing largely coincide with upturns in investment demand. The beginning of the simulation stands out though, when capital firms do not yet have sufficient operating cash flows and are thus disproportionately denied credit.

Balance sheets

Figure 2.7 shows how aggregate sector stocks evolve over the course of the simulation. We observe wealth accumulation by households and, to a lesser extent, capital firms. The flip side is government debt accumulation. Interbank loans are not visible in this overview as they net out on the banking sector balance sheet. Furthermore, while loans are important to firms, they are dwarfed by the amount of bonds and reserves which banks hold.

Figure 2.6: Average and standard deviation of: (top-left) loan rates, (top-right) deposit rates, (bottom-left) interbank rates, and (bottom-right) constrained credit.

Figure 2.7: Sectoral balance sheet compositions of (1) consumption firms, (2) households, (3) capital firms, (4) banks, (5) the central bank, and (6) the government.

2.3.2 Validation

As the purpose of our model is to illustrate the workings of four monetary transmission channels in an agent-based macroeconomic model, we perform a validation exercise in which we check if the model is able to replicate basic statistical properties of macroeconomic time series. We compare autocorrelation and cross-correlation properties of simulated time series for real-GDP, real investment, real consumption and unemployment with those of the United States.

From the Federal Reserve Economic Data (FRED) database, we retrieve data for unemployment, real GDP, real consumption, and real investment. Like the artificial time-series, the observed data covers a period of 33 years (approximately 400 months). Since the observed data is quarterly, we transform our simulated data series to a

quarterly time-scale first. Then, we apply a HP (Hodrick and Prescott, 1997) filter to separate the cyclical and trend components for both the actual and simulated data series. Following Caiani et al. (2016), we compare the moments for the cyclical component of the time series.

Figure 2.8 shows the simulated and observed auto-correlations and cross-correlations of the cyclical series with real-GDP. In spite of the model not being calibrated to fit this data, the model is able to replicate these properties reasonably well, similar⁴ to the benchmark model (ibid.). The auto-correlation structure of simulated and observed times series both have strong first order autocorrelations. Furthermore, as in the real-world data, simulated consumption and investment are pro-cyclical while unemployment is counter-cyclical. These dynamics are robust across multiple Monte-Carlo simulations.

Figure 2.8: Auto- and cross correlations of (from left to right) real GDP, real investment, unemployment, and real consumption for U.S. and simulated data (Monte Carlo average and standard deviations).

We do note that while the model appears to reach a steady state, this is not sustainable over longer simulation windows due to the build-up of debt. However, since our focus is on the monetary transmission channel in the medium to short run, this does not invalidate the experiments presented in the next section.

⁴the main differences come from the time-scale change.

2.3.3 Monetary transmission

We run several experiments to probe the effects of a monetary policy rate hike on key variables. We are interested in variables from interest-rate pass-through, the bank lending channel L^s , the investment channel I^D , consumption channel C_{hh}^D , the cost channel $i^L L$, and finally prices p_{CG} .

At different points in time, we apply a change to the deposit facility rate, and with it the marginal lending facility rate (see Eq. 2.21) at different shock sizes. Combining these, we perform sixteen unique experiments. For every experiment, we run fifteen⁵ Monte Carlo simulations.

Table 2.1 shows the Monte Carlo average effect of each rate hike, Ψ_{mon} , at times t_{mon} , on each variable, averaged over 40 periods after the shock. Using a two-sided t-test, we measure if the Monte-Carlo Average over these period was significantly (at 5 percent significance level) different from the baseline, marked with a * in the table.

⁵This amount chosen to keep computational time in check while still producing robust results.

Interest rate pass-through

The monetary transmission mechanism starts when the monetary policy shock influences the interbank market, see Figure 2.9 for an impression of how this works. Following Eq. 2.47, banks determine their interbank ask price i_b^{IB} as the difference between the rate they charge on loans and the risk free rate corrected for maturity. The central bank rate hike increases banks' funding costs through the interbank market by increasing the cost of advances. As the risk free rate rises, interbank rates follow. Table 2.1 shows the impact of all shocks on interbank rates is positive and significant.

Figure 2.9: Monte Carlo average and standard deviations inter-bank rates in the standing lending facility corridor with shock Ψ_{mon}^4 , for t_{mon}^1 (top-left), t_{mon}^2 (top-right), t_{mon}^3 (bottom-left), and t_{mon}^4 (bottom-right).

Banks set deposit rates according to Eq. 2.13, increasing or decreasing their rates based on profitability, χ^p , liquidity, χ^{LR} , and funding costs, χ^{fu} . Of these, only funding costs are directly affected. These increase, especially for those banks who derive a large part of their funding from advances or interbank loans. Yet, as in our simulation, banks do not rely heavily on either. Pass through is limited. Furthermore, as the interest rate affects profitability and liquidity through other variables, pass-through to deposit rates is uncertain, sometimes positive, sometimes negative, mostly insignificant.

Regarding loan rates, banks follow Eq. 2.9 and respond to changes in their funding costs and capital ratio relative to their targeted capital ratio. As funding costs

increase, loan rates increase. However, interbank and advances rates are only a small part of the total funding cost mix for banks. Deposits are a much more important source of funding. The effects of the rate hike on the difference between actual and target capital ratios is not straightforward. Therefore, similar to deposit rates, pass-through to loan rates is limited and uncertain.

The bank lending channel

The bank lending channel describes how monetary policy affects the credit supply. Following Eq. 2.17, banks only extend credit if they believe the expected return is bigger than the expected loss. The central bank rate hike influences the expected return, since cash flows are now discounted at a higher rate. Therefore, if the bank interest rate is increased above a threshold after which it is no longer profitable to lend, banks constrain credit. The effect is especially non-linear if firms have similar cash flows and collateral values. Indirectly, the rate hike also influences the interest rates on loans and therefore the debt service and the value of collateral. However, since interest-rate pass through is weak, this effect is similarly weak.

Therefore, in our simulations, monetary policy is only effective when firms are relatively homogeneous, at t_{mon}^1 , and when the hike is big enough, at Ψ_{mon}^3 or Ψ_{mon}^4 . The rate hike increases banks' discount factor, making it so that from one moment to the next most firm credit applications are negatively valued. In other simulations, these thresholds are not crossed and as a result constrained credit is not significantly different from the baseline simulation.

The investment channel

In our model, firm investment decisions are motivated by real factors. Following Eq. 2.7, firms determine a desired rate of growth based on expected profit and capacity utilization. Both are indirectly affected by interest changes. Following Eq. 2.14, firms try to finance their investment first with equity. All terms in this equation are indirectly affected by the changes in deposit and loan interest rates. Furthermore, weak bank rate pass-through reduces the potency of the investment channel.

Table 2.1 shows that the effects of monetary policy on desired investment is not clear cut. In the case of an early rate hike, investment demand actually increases for high rate hikes. This happens because credit is constrained in this scenario. Denied credit applications leave the firms demanding credit.

The consumption channel

In the model, monetary policy influences households' desired consumption directly by changing the propensity to consume out of wealth, and the absolute value of wealth

and income (Eq. 2.26).

If interest-rate pass-through to deposits was positive: higher interest rates on deposits would make consumption less attractive relative to saving. On the other hand, increased interest rates receipts on deposit holdings would increase household income and wealth. Note that, since there is no household lending in the model, this effect is always positive. These sub-mechanisms have opposite signs. A change in interest payments on deposits causes increased income and consumption while at the same time increasing the willingness to hold deposits rather than spending on consumption.

Furthermore, the effect of expected inflation depends on actual inflation, which in turn depends on the strength of all transmission channels. The strength and sign of the effect of the rate hike thus depends on the change in propensity to consume, the importance of interest rate income for households and the total effect on inflation. The net effect is typically very small since interest payments compared to other income are so small. Table 2.1 shows the effects of monetary policy on desired real consumption which are typically small and indirect. Notably, the early rate hikes do impact desired consumption significantly but primarily as the sudden credit crunch causes an early downturn in the business cycle.

The cost channel

In our model, the cost channel operates as firms follow Eq. 2.5. Firms prices are a mark-up of unit labour and interest rate costs. Changes in interest rates charged by banks result in changes interest payments for firms. However, as pass-through is weak this effect is also weak. Conflicting mechanisms are at work, since credit is rationed at higher interest rates, higher rates lead to reduced debt-service costs for firms. Even if banks would pass-through increased interest rates, overall costs would fall. The strength of the cost channel thus depends greatly on the size of interest costs compared to other costs, the amount of credit rationed through the bank lending channel, and the other interaction effects. Table 2.1, therefore, shows that increased interest rates on average reduce firms' debt-service costs.

Inflation

We now analyse the effects of the shock on inflation. Table 2.1 shows that monetary policy rate hikes can cause higher, lower or virtually unchanged consumer prices, depending on the circumstances. Because of the various simultaneous interaction effects, it is difficult to determine the effects on inflation in most experiments. However, as interest-rate pass through is very weak, monetary policy has no significant effect on consumer prices.

2.4 Summary and Discussion

In this paper, we reviewed several policy transmission channels for monetary policy. Based on existing literature, we identified eight channels. An expectations channel, which operates purely through agent expectations, and seven interest rate based channels: the bank lending, balance sheet, investment, asset-price, consumption, cost, and exchange rate channels. For these last six channels, we argued that the amount of interest rate pass-through is of importance.

To illustrate how several transmission channels can interact in an agent-based model, we presented a modified version of the Caiani et al. (2016) benchmark model which includes an interbank market and four transmission channels: the bank lending channel, investment channel, consumption channel, and the cost channel. Using this model, we simulated the transmission of an interest rate shock through these channels.

The bank lending model is the strongest channel in our model as a consequence of the structural and behavioural assumptions we made. Regarding our structural assumptions, the balance sheet and asset price channels are not modelled since the lack of a stock market makes it difficult to calculate the market value of a firm's equity. Similarly, the consumption channel is weak because there are no asset markets that can be inflated to boost consumption and there is no household lending. The investment channel is weak because we assume that firm investment decisions are primarily driven by non-interest rate factors and the bank lending channel is strong because we assume banks make net-present value type calculations when rationing credit.

In our model, monetary policy is not very effective at controlling inflation. Several consequences of a monetary policy shock stand out. First, the bank lending channel appears the strongest. Second, monetary policy effects are non-linear. Monetary policy non-linearity in our model comes from agent heterogeneity and macroeconomic feedback effects. In the bank lending channel, the lack of agent heterogeneity causes non-linearity. Once the interest rate reaches a certain threshold the majority of firm credit applications will not be funded.

This is also a contributing factor to the relevance of timing for policy effects. As firm heterogeneity increases the effects of larger monetary policy shocks get less extreme. Also contributing to this is that price changes have different drivers over the course of the simulation. Inflation is driven by slack in the consumer goods market —via the mark-up— or by slack in the labour market —via the labour costs— or by changes in debt-service costs. These are not equally affected by changes in monetary policy rates. Furthermore, while the simulated economy shows some resilience to small shocks, large shocks can change its macroeconomic dynamics significantly.

When monetary policy does not cause a credit crunch through the bank lending

channel, we find that the effects of monetary policy are weak. This is consistent with the view that monetary policy is a far less effective tool to control inflation than is commonly predicted by DSGE models (Arestis and Sawyer, 1998; Arestis and Sawyer, 2008).

Yet, we are cautious to translate these findings to policy advice, as our model might not be an accurate representation of the real world. Notably, it is lacking important asset markets such as the stock and housing markets. Furthermore, there is no foreign sector which nullifies the exchange rate channel.

When we compare our findings with those of contemporary agent-based monetary models, we see that they reach widely diverging conclusions. Models which assume a strong direct monetary policy transmission through the expectations channel come to the conclusion that the monetary policy rule has a strong effect on inflation (Raberto, Teglio, and Cincotti, 2008) (Salle, Yıldızoğlu, and Sénégas, 2013), (Salle, 2015), (Dosi et al., 2015), (Popoyan, Napoletano, and Roventini, 2017).

In contrast to the experiments Delli Gatti et al. (2011) performed, Delli Gatti and Desiderio (2015) find a clear non-neutrality of monetary policy once they include an investment channel: firm credit demand is decreasing step-wise with the interest rate. Finally, in the model of Bouchaud et al. (2017) a high number of transmission channels are active. First is the expectations channel, which assumes that individual expectations are formed using both the central bank target and actually realised inflation. Through this channel the central banks' inflation target and its credibility directly influence household consumption and firm pricing decisions. Furthermore, firms hiring and firing decisions are influenced by the interest rate through financial fragility, which increases if interest rates rise. Since both models assume interest pass-through is one-to-one, monetary policy has a major impact on the modelled economies.

If we compare these findings to our own it becomes apparent that the transmission channels that we chose to model have a major influence on model conclusions about the effectiveness of monetary policy. Therefore, it is important modellers take into account empirical work on the potency of different channels. After all, channels long taken for granted might not always hold. We refer to interesting work on the ability of central banks to anchor inflation expectations (Mankiw, Reis, and Wolfers, 2003; Kumar et al., 2015) and on interest rate pass-through which is typically less than one-to-one (Kleimeier and Sander, 2006).

In future work, we want to add more empirically grounded channels. Furthermore, we want to validate the model, presented here, in more detail. First, we want our model to reproduce empirical regularities on different time scales. Furthermore, we would like to assess if the model is able to reproduce causal structures among aggregate variables similar to the causal structures that can be found in the real-world.

Other options for future work include following clusters of firms, bank and households through simulation time, observing how their balance sheets and activities change due to the Central Bank rate shock, and due to their interactions with other agents. This heterogeneity in response is key to understanding aggregate impacts, as Yellen (2016) stressed.

Other promising avenues are to observe the effects of negative rate shocks and even negative interest rates at different points in time. Furthermore, extending the economy with an asset market and household debt would uncover other important channels. Yet another extension of the analysis is to take the simulation data and tease out the key patterns and correlations with econometric methods. This is one way to assess the role of channels of monetary policy transmission in this artificial economy, just as is often done with actual data.

		t_{mon}^1	t_{mon}^2	t_{mon}^3	t_{mon}^4
i_b^{IB}	Ψ_{mon}^1	0.49*	1.42*	2.76*	5.01*
	Ψ_{mon}^2	1.95*	3.81*	6.49*	11.00*
	Ψ_{mon}^3	3.42*	6.21*	10.23*	16.99*
	Ψ_{mon}^4	4.88*	8.60*	13.96*	22.98*
i_b^D	Ψ_{mon}^1	0.00	-0.00	0.00	0.00
	Ψ_{mon}^2	0.00	0.0001*	0.00	0.00
	Ψ_{mon}^3	0.00	-0.0001*	0.00	0.00
	Ψ_{mon}^4	0.0001*	0.00	0.00	0.0001*
i_b^L	Ψ_{mon}^1	0.00	0.00	0.00	0.00
	Ψ_{mon}^2	0.00	0.00	0.00	0.00
	Ψ_{mon}^3	-0.04*	0.00	0.00	0.00
	Ψ_{mon}^4	0.13*	0.00	0.00	0.00
L^s	Ψ_{mon}^1	0.20	0.00	0.31	-0.02
	Ψ_{mon}^2	0.48*	0.00	0.53*	-0.01
	Ψ_{mon}^3	14.15*	0.00	0.54*	0.04
	Ψ_{mon}^4	43.49*	0.00	0.87*	0.03
I^D	Ψ_{mon}^1	0.04	0.03	0.02*	0.03
	Ψ_{mon}^2	0.06	0.03	0.03	0.03
	Ψ_{mon}^3	0.16*	0.04*	0.05	0.03
	Ψ_{mon}^4	0.45*	0.07	0.05	0.04*
C_{hh}^D	Ψ_{mon}^1	0.00	0.00	0.00	0.00
	Ψ_{mon}^2	0.00	-0.01*	0.00	0.00
	Ψ_{mon}^3	-0.01*	-0.002*	0.00	0.00
	Ψ_{mon}^4	0.02*	0.003*	0.002*	0.00
$i^L L$	Ψ_{mon}^1	0.00	0.00	0.00	0.00
	Ψ_{mon}^2	0.00	-0.02*	-0.01*	-0.01*
	Ψ_{mon}^3	-0.18*	-0.03*	-0.03*	-0.03*
	Ψ_{mon}^4	0.65*	0.08*	0.04*	0.04*
pCG	Ψ_{mon}^1	0.00	0.00	0.00	0.00
	Ψ_{mon}^2	0.00	0.00	0.00	0.00
	Ψ_{mon}^3	0.00	0.00	0.00	0.00
	Ψ_{mon}^4	0.01*	0.00	0.00	0.00

Table 2.1: Average 40 period impact of monetary policy rate hikes on selected variables, at different points in time, * notes a significant (0.05) deviation from the baseline. We apply shocks of size: $\Psi_{mon}^{1,2,3,4} = 0.001, 0.002, 0.003, 0.004$; at times: $t_{mon}^{1,2,3,4} = 63, 166, 258, 355$

Chapter 3

Stock market efficiency

Abstract

In this chapter¹, I explore whether a ‘decoupling scenario’, in which stock prices fluctuate around their fundamental value less frequently than behavioural models predict, is still consistent with the stylized facts of stock market returns: no autocorrelation, volatility clustering, long memory, and fat tails. Applying the method of simulated moments reveals that adding a mean-reversion component to the behavioural chartist-fundamentalist model allows it to jointly replicate the moments associated with decoupling as well as the stylized facts. A global sensitivity analysis on the relative popularity of trading strategies shows that this is largely a result of mean-reversion expectations replacing fundamentalist expectations.

This chapter contributes to the ongoing debate about market efficiency. A key question is whether stock prices converge to the present value of future dividends - ‘the fundamental value’. There are two competing positions on this issue (Asness and Liew, 2014; Campbell, 2014). The Fama (1963) efficient market hypothesis states that stock prices equal fundamental value and the behavioural finance hypothesis predicts that prices fluctuates (frequently) around the fundamental value (Thaler, 2016).

Shiller (2014) modifies the behavioural hypothesis by stating that there might be longer market phases in which market prices deviate from the fundamental value. In these phases, stock prices do not mean-revert to their fundamental value. They can become decoupled from their fundamentals for extended periods of time because it might take successful fundamentalist investors many years to acquire enough wealth to bring the price back to its fundamental value. In the meantime, the market is dominated by ordinary traders. This would imply that stock prices fluctuate around their fundamental value far less frequently than behavioural models would predict. I name this scenario the ‘decoupling scenario.’

¹This chapter builds on the ideas first presented in an Economics E-journal discussion paper under the name: Fundamentals unknown: momentum, mean-reversion and price-to-earnings trading in an artificial stock market (Schasfoort and Stockermans, 2017).

This paper explores if the decoupling scenario is consistent with the stylized facts of financial markets: low daily return predictability (Samuelson, 1965; Cont, 2005; Stanley, Plerou, and Gabaix, 2008), excess volatility (fat tails) in the returns distribution (Shiller, 1981) (Gu, Chen, and Zhou, 2008), return predictability at longer time horizons (long memory) and returns volatility clustering (Cont, 2001; Gould et al., 2013). The behavioural chartist-fundamentalist model serves as my baseline because it can jointly replicate these stylized facts (Franke and Westerhoff, 2012; Bertella et al., 2014; Fischer and Riedler, 2014; Chiarella, Iori, and Perelló, 2009; Chiarella et al., 2017). However, because this model predicts that prices mean-revert to the fundamental value it needs to be extended.

Therefore, in this paper, I extend the behavioural model by introducing a new type of trading: mean-reversion trading. By adding mean-reversion trading to the standard trend-following strategy, the model now features the two main flavours of profitable technical trading strategies (Serban, 2010). In most behavioural models, the presence of trend-following strategies help explain long-memory and volatility clustering while some strategies that expect the price to mean-revert to the fundamental keep the price from becoming excessively volatile. In calibrated version of models that are consistent with the stylized facts, there are so many fundamentalist traders that price developments are, in the long-term, coupled to the trajectory of the fundamental value. Removing them would create 'decoupling' but also would mean that the stylized facts can no longer be replicated because trend-following would become the dominant strategy. Some form of mean reversion is needed. Therefore, replacing some of the fundamentalist traders with naive mean-reversion traders allows my model to replicate a decoupling between price and fundamentals while still being able to replicate the stylized facts.

Before formulating the model, I present the data from which I compute the disconnect between prices and fundamentals along with the other stylized facts. Then, I explore the model dynamics through Monte-Carlo Simulations. I estimate the model's parameters on empirical data and show that the inclusion of mean-reversion trading improves the models ability to jointly replicate decoupling and the stylized facts. By varying the relative popularity of trading strategies in a sensitivity analysis, I show that this result is primarily obtained by replacing the fundamentalist expectation component with the mean-reversion expectation component.

3.1 Data and stylized facts

To judge the model's ability to produce a price decoupling from fundamentals while replicating the stylized facts, I quantify both empirically.

The data comes from three sources. The first source is daily data on nominal

prices from the S&P500 starting on the 1st of August 2008 and ending on the 16th of August 2018 (2509 observations) from the Federal Reserve of St. Louis database². The second source is Robert Shiller's database³ (Shiller, 2000) on historical data on monthly S&P 500 prices and dividends. The last source is the macro history database⁴ (Jordà, Schularick, and Taylor, 2017) from which I extract historical data on annual short-term interest rates. Table 3.1 presents the descriptive statistics of this data.

Table 3.1: Descriptive statistics data of S&P500 and U.S. interest data.

Moment	Returns	Real Prices	Dividends	T-bill rate
Count	2487	1771	1770	146
Mean	0.0	516.59	15.35	4.09
Standard deviation	0.01	556.28	8.67	2.93
Min	-0.09	68.22	5.03	0.09
Max	0.12	2836.53	51.0	16.39

To quantify the disconnect between prices and fundamentals, the fundamental value is needed. I calculate it using the fixed equity premium net present value model (Campbell and Shiller, 1988; Shiller, 2014). It states that the fundamental value is the sum of discounted future dividend rates

$$F_t = \sum_{t=1}^{\kappa} \frac{D_t}{(1 + i_t + r)^{t+1}}, \quad (3.1)$$

where D_t is the dividend and i_t is the short-term interest rate, while r represents the equity price premium, κ represents the horizon which I set to the point at which $\frac{D_t}{(1+i_t+r)^t} < 0.01$. Using this equation, I calculate the ex-post fundamental value of the S&P500. Because I have annual short-term interest rate data and monthly dividends, I assume the annual interest rate holds for all months in the year.

The unobserved (stable) discount rate needed to determine the fundamental value is often calculated as the average discount rate implied by market prices⁵. However,

²<https://fred.stlouisfed.org/series/SP500>

³<http://www.econ.yale.edu/shiller/data/ie.data.xls>

⁴<http://www.macrohistory.net/JST/JSTmoneyR3.xlsx>

⁵For example, when calculating ex-post fundamental values for the S&P500 stock index using actual subsequent real dividends and a time-varying interest rate, Shiller (2014) estimates the equity premium such that it is equal to the average observed returns. Similarly, Boswijk, Hommes, and Manzan (2007) estimates the discount rate so that it fits the observed average dividend yield.

the implied assumption, that arbitrage is effective, is contested (Shleifer and Vishny, 1997; Mitchell, Pulvino, and Stafford, 2002; Gromb and Vayanos, 2010). I relax this assumption by assuming the unobserved (stable) discount rate to be constant at 5.2, the level of the equity risk premium estimated by Avdis and Wachter (2017).

I apply the augmented Engel-Granger test (Engle and Granger, 1987) to measure how much the price tends to mean-revert to the fundamental value. The resulting co-integration or ‘decoupling moment’ reflects the disconnect between the two series.

Then, the other stylized facts of stock market returns, are approximated as follows. Calculating the average autocorrelation over 25 lags and over the first and fifth lag measures the (un)predictability of returns. Excess kurtosis proxies excess volatility, or fat tails in the returns. Long memory is measured as the autocorrelation of absolute returns at lag 10, 25, 50 and 100. Volatility clustering is measured as the average autocorrelation of absolute returns over 25 lags.

Table 3.2 shows the resulting moments and confidence intervals. A bootstrapped time series is the basis for calculating the confidence intervals, see Appendix B.1.

Since the 95% confidence interval of the decoupling moment is larger than zero, there is a significant disconnect between prices and the fundamental value. The other moments are in line with the widely reported findings of no autocorrelation, volatility clustering, long memory, and fat tails in the returns.

Table 3.2: Moments: empirical values and lower and upper value of the confidence interval (CI).

Moment	Value	CI low	CI high
Decoupling	-3.396	-7.091	0.299
Average autocorrelation	-0.011	-0.015	-0.006
Autocorrelation lag 1	-0.079	-0.129	-0.029
Autocorrelation lag 5	-0.071	-0.124	-0.018
Absolute average autocorrelation	0.323	0.134	0.511
Kurtosis	12.613	2.89	22.337
Absolute autocorrelation lag 10	0.311	0.199	0.424
Absolute autocorrelation lag 25	0.256	0.109	0.404
Absolute autocorrelation lag 50	0.159	0.062	0.257
Absolute autocorrelation lag 100	0.148	0.035	0.261

3.2 The model

In this section the model is formulated. It extends the agent-based model of Chiarella and Iori (2002) with a stochastic fundamental and a mean-reversion expectations component.

The risky asset, which represents a traded stock market index, has an intrinsic or fundamental value equal to discounted future dividends, F_t . In contrast to Chiarella and Iori (ibid.), where the fundamental value is constant, it follows a random walk

$$F_{t+1} = F_t + \epsilon_t^F, \quad (3.2)$$

where $\epsilon_t^F \sim N(0, \sigma^F)$, and $F_{t+1} \geq 0$. In each period $t \in T$, the price of the risky asset is determined by a limit-order book which matches buy and sell orders submitted by a random set of agents, of size ι drawn from a population of agents of size N .

Before entering the market, each agent determines its expected asset price as a weighted average of fundamental value f , trend-following (momentum) mm , individual noise ns , and a mean-reversion component mr . The weights of these components, represented by $N \times 1$ vectors of weights $w^* := (w^f, w^{mm}, w^{mr}, w^{ns})$, are drawn from random normal distributions: $w^f \sim N(0, \sigma^f)$, $w^{mm} \sim N(0, \sigma^{mm})$, $w^{mr} \sim N(0, \sigma^{mr})$, and $w^{ns} \sim N(0, \sigma^{ns})$. The weights are subsequently normalized.

Each agent x determines expected returns r as

$$E_{x,t}[r_{t+1}] = w_x^f \frac{p_t^f - p_t}{p_t} + w_x^{mm} \bar{r}_{x,t} - w_x^{mr} \bar{r}_{x,t} + w_x^{ns} \epsilon_{x,t}^{ns}, \quad (3.3)$$

where p_t^f is the fundamental price. $\epsilon_{x,t}^{ns} \sim N(0, \sigma^{\epsilon^{ns}})$ is an agent-specific noise component drawn from a normal distribution each period. This reflects the heterogeneous expectations of the agents. $\bar{r}_{x,t}$ is the average historical spot return. Because arbitrage opportunities are assumed to be limited, the expectation formation rules for the agents are constant. For every agent the average spot return is calculated over its specific horizon $\phi_x \in \{1, \phi^{max}\}$ as:

$$\bar{r}_{x,t} = \frac{1}{\phi_x} \sum_{j=1}^{\phi_x} \frac{p_{t-j} - p_{t-j-1}}{p_{t-j-1}}. \quad (3.4)$$

Each agent converts its expected return to an expected price by multiplying it by the current price:

$$E_{x,t}[p_{t+1}] = p_t \exp(E_{x,t}[r_{t+1}]). \quad (3.5)$$

If the agent's expected price is larger (smaller) than the current price it will submit a bid b (ask a) order at price:

$$p_{x,t}^b = E_{x,t}[p_{t+1}](1 - \gamma_x) \text{ and } p_{x,t}^a = E_{x,t}[p_{t+1}](1 + \gamma_x), \quad (3.6)$$

where $p_{x,t}^b, p_{x,t}^a > 0$,

where $\gamma_x \sim N(1, \sigma^\gamma)$ reflects heterogeneity in order-book positioning. It is drawn from a normal distribution.

Then, the order volume is drawn from a normal distribution, $v_x \sim N(0, \sigma^v)$ and the order is entered into the limit-order book. The best (highest) bid p_t^{b*} and best (lowest) ask price p_t^{a*} are updated and, the best bid in the order book is matched to the best ask price. If the best bid price is higher than the best ask price $p_t^{b*} > p_t^{a*}$ both orders are matched at the best ask price:

$$p_t = p_t^{a*}, \quad (3.7)$$

The transaction volume is equal to the lowest of the two orders:

$$v_t = \min(v_t^{b*}, v_t^{a*}). \quad (3.8)$$

This volume is then subtracted from the two orders. If that results in an order volume reaching zero, it is removed from the order book. The matching procedure is repeated until there are no more remaining orders which can be matched.

To prevent orders from lingering in the order book, the age of the offers in the limit order book increases by one every period. When an order reaches the expiration time ζ , it is removed from the order book.

3.3 Model dynamics

This section evaluates whether the addition of the mean-reversion chartism component $w_x^{mr} \bar{r}_{x,t}$ to Equation 3.3 allows the model to jointly replicate the decoupling moment as well as the moments which reflect the stylized facts.

The dynamics of the model are explored using Monte Carlo Simulation methods (Hammersley, 2013)⁶. The standard number of Monte Carlo Simulations is $N_r = 15^7$.

⁶The code used for these computational experiments is available on-line at: <https://github.com/joerischafoort/sim-fin-abm>.

⁷Doing this amount of simulations limits the influence of randomness without demanding too much computational resources.

First, I calibrate observable parameters using the data and estimate the rest of the parameters using the method of simulated moments (MSM) (Franke, 2009). Then, I test the model's ability to match the moments and compare its performance to a version of the model without mean-reversion where $w_x^{mr} = 0$. Finally, I perform two experiments in which I vary the relative strength of mean-reversion trading versus trend-following and fundamentalism and explore how this affects the moments.

3.3.1 Parameter calibration and estimation

I calibrate observable parameters using the data. Simulation time T is set equal to the length of the shortest data time series. The initial fundamental value and the standard deviation of its return are obtained from the previously calculated fundamental value. The standard deviation of the spread is set equal to the value reported by Riordan and Storkenmaier (2012).

The values of the unobserved parameters are uncertain and will need to be estimated. Estimating them requires fewer parameters than moments. Therefore, I first reduce the set of uncertain parameters to those which are most important in determining the moments of interest.

Application of the enhanced Morris Method (Morris, 1991) as in Campolongo, Cariboni, and Saltelli (2007), suggest that the two least influential parameters are the number of traders, which are fixed at $N_l = 1000$, and the standard deviation of volume, which is set at $\sigma^v = 7$, see Appendix B.2 for the full results of the Morris Method. The remaining uncertain parameters are now defined to be contained in vector θ .

Table 3.3 presents an overview of the model parameters. The table shows values for the calibrated parameters and bounds for the uncertain parameters.

With the number of uncertain parameters less than the number of moments to be explained, we are now ready to estimate the parameters in vector θ . To do so, I follow the MSM procedure as set out in detail by Franke and Westerhoff (2012). This yields parameter values of the model which minimize the function:

$$J(m^{sim}, m^{emp}) = (m^{sim} - m^{emp})' W (m^{sim} - m^{emp}), \quad (3.9)$$

where m^{emp} is a vector containing the empirical moments described in Table 3.2, m^{sim} the model-generated moments vector, and W the weighting matrix. The purpose of the weighting matrix is that moments with low variance and those which correlate with each other have lower weights. Therefore, following Franke and Westerhoff (2016), I set the weighting matrix equal to the inverse of the variance-covariance matrix of the bootstrapped moments.

Table 3.3: Model parameters. Important uncertain parameters are italic. Their values are bounds which are shown as lower, upper.

Symbol	Description	Values
N_r	number of runs	15
T	total periods of simulation time	1235
F_0	initial fundamental value	166
σ^F	standard deviation ΔF	0.053
σ^γ	standard deviation maximum spread	0.004
N_l	number of traders	1000
σ^v	standard deviation volume	7
ι	<i>trader sample size</i>	1, 100
σ^{ϵ^n}	<i>standard deviation noise component</i>	0.05, 0.30
σ^f	<i>standard deviation fundamental weight</i>	0, 100
σ^{mm}	<i>standard deviation momentum weight</i>	0, 100
σ^e	<i>standard deviation noise weight</i>	0, 100
σ^{mr}	<i>standard deviation mean-reversion weight</i>	0, 100
ϕ^{max}	<i>maximum horizon length</i>	5, 30
ζ	<i>order expiration days</i>	5, 100

Given that the model moments vector m^{sim} is a function of the parameters θ , it can be rewritten as $m(\theta, S)$ and the minimization problem can be formalized as:

$$\arg \min_{\theta} J(m(\theta, S), m^{emp}), \quad (3.10)$$

where S is the simulation time horizon used for the estimation procedure. To increase the robustness of the estimation, it is common practice to set the simulation time to be ten times the empirical time series length $S = 10T$ (Franke, 2009; Franke and Westerhoff, 2012).

To solve the minimization problem of Equation 3.10, I employ an evolutionary algorithm (Thiele, Kurth, and Grimm, 2014) which I describe in detail in Appendix B.3. Table 3.4 shows the resulting estimated parameters.

3.3.2 Empirical performance

I primarily use Equation 3.9 to measure how well the model is able to match the moments. Since it is a cost function, I will refer to its outcome as its J-cost. The

Table 3.4: Estimated parameters.

Symbol	Description	Values
ι	trader sample size	19
σ^{ϵ^n}	standard deviation noise component	0.11
σ^v	standard deviation volume	7
σ^f	standard deviation fundamental weight	8.49
σ^{mm}	standard deviation momentum weight	43.06
σ^e	standard deviation noise weight	73.28
σ^{mr}	standard deviation mean-reversion weight	93.64
ϕ^{max}	maximum horizon length	10

model with mean-reversion (MR) will be compared to an estimated version of the model without the mean-reversion component which I refer to as the ‘no mean-reversion model’ (NMR). To control for the effects of randomness, I simulate both models 5000 times. As its empirical counterparts, I use the 5000 bootstrapped time-series used in the estimation procedure.

Following (Franke and Westerhoff, 2012), I compare the distribution of J-costs of the MR and NMR models to the distribution of J-costs of the bootstrapped data and its 95% confidence interval. I calculate the p-value of both models as the quantile of the simulated J-costs at which the empirical J-95% interval lies. As a robustness check, I also perform a pairwise comparison of both individual and pooled simulations. For the pairwise comparison, I compare the J-cost of MR and NMR for each individual Monte-Carlo run. During each comparison, the model with the lowest cost is awarded a point. This yields a ratio of model wins which I shall refer to as the pairwise score. For the pool wise comparison, I divide the J-costs of both models into non-overlapping pools of size 10 and calculate the average J-cost for each pool. Counting how often one model wins a pool compared to the other yields the pool wise score.

To gain a deeper insight into the generation of individual moments, I calculate the Moments Coverage Ratio (MCR) (ibid.) for every moment. The MCR measures the percentage of times the simulated moment is within the confidence bounds of its empirical counterpart. As a yardstick, I also calculate the MCRs for the bootstrapped empirical data series.

Table 3.5 provides an overview of J-cost performance and MCRs of both models and the bootstrapped data, bold values highlight a superior model performance. The MR model outperforms the NMR model on the P-value, pairwise, and pool wise scores. Furthermore, the decoupling MCR shows that the MR model is able to

produce a superior decoupling from fundamentals while still being able to produce the main stylized facts of financial markets which are also produced by the Chiarella and Iori (2002) model.

This provides an answer to the primary question of this paper: the decoupling scenario is consistent with the stylized facts of stock market returns.

Table 3.5: Performance of the benchmark model without mean-reversion (NMR), the model with a mean-reversion component (MR) and bootstrapped empirical data. The best score is bold.

Indicator	NMR	MR	Empirical
P-value	0.0003	0.0007	-
Pairwise score	0.33	0.67	-
Pool wise score	0.50	0.50	-
<i>Moment Coverage Ratios</i>			
Average autocorrelation	98.0	94.0	95.06
Autocorrelation lag 1	94.0	41.0	95.08
Autocorrelation lag 5	74.0	78.0	95.78
Average autocorrelation abs	0.0	0.0	94.64
Kurtosis	94.0	92.0	91.76
Autocorrelation abs lag 10	0.0	0.0	91.52
Autocorrelation abs lag 25	1.0	0.0	90.22
Autocorrelation abs lag 50	1.0	4.0	86.60
Autocorrelation abs lag 100	1.0	0.0	72.80
Decoupling	0.0	54.0	98.02

3.3.3 Experiments: the relative popularity of mean-reversion trading

Even though we established mean-reversion trading improves the models ability to match the moments, the mechanisms through which this happens are unknown. Therefore, in this section, I explore how the impact of increased popularity of mean-reversion trading versus the other two trading strategies; trend-following and fundamentalism⁸ affects the moments.

⁸I exclude the noise trading component because, rather than a strategy, it reflects heterogeneity of expectations.

I perform two experiments. In the first experiment, I increase the weight of the mean-reversion component at the expense of the fundamentalist component with parameter w^{mr^f} . In the second experiment, I increase the mean-reversion weight versus the trend-following weight with parameter w^{mr-mm} . In both cases, I keep the rest of the expectations constant at their estimated level.

Table 3.6 shows the parameter values and bounds that will be used for the experiments. To make this set-up work, I keep the other expectation components constant at their estimated levels. The rest of the uncertain parameters of Table 3.3 remain uncertain.

Table 3.6: Experiment parameters.

Symbol	Description	Values
<i>Experiment 1</i>		
w^{mr^f}	mean-reversion versus fundamentalism	(0, 100)
$\sigma^{mr} + \sigma^f$	total mean-reversion and fundamentalism	102.13
<i>Experiment 2</i>		
w^{mr-mm}	mean-reversion versus chartism	(0, 100)
$\sigma^{mr} + \sigma^{mm}$	total of mean-reversion and chartism	136.7

To account for this uncertainty, I sample the parameter space containing the parameter of interest for the experiment and the uncertain parameters for both experiments using Latin Hypercube Sampling (McKay, Beckman, and Conover, 1979; Saltelli et al., 2008). Then, I simulate the model with $N_r = 5$ on the sampled sets of parameters.

To measure the strength of the impact as a consequence of changes of the parameter, Marino et al. (2008) and Thiele, Kurth, and Grimm (2014) recommend performing a partial correlation analysis if the relationship is expected to be linear, a partial ranked correlation analysis if the relationship is expected to be non-linear but monotonic, and a variance decomposition technique if the relationship is expected to be non-monotonic.

Experiment 1: mean-reversion expectations replace fundamentalist expectations

For the first experiment, Figure 3.1 shows scatter plots of the relation between the J-score, every MCR and the parameter w^{mr^f} . It reveals that all three types of

relationships exist.

Figure 3.1: Scatter plots comparing the weight of the mean-reversion component over fundamentalist w^{mrf} to the J-score and moment coverage ratios of the simulated model moments.

The impacts of changes in w^{mrf} on the J-cost seems linear and monotonic. The Pearson's correlation coefficient between these two variables reveals a negative correlation of -0.43 implying that increasing the fraction of mean-reversion trading to fundamentalism decreases (improves) the J-cost. Second, increasing w^{mrf} seems to have a positive but non-linear effect on the MCR of the autocorrelation and decoupling moments. To deal with the non-linearity of the relationship, I calculate Spearman's correlation coefficient which transforms the data to ranks first. The resulting correlation coefficients imply that increasing w^{mrf} is associated with a 0.41 higher autocorrelation MCR and 0.49 higher decoupling MCR across the parameter space.

Because the relationship between w^{mrf} and the other MCRs seems either non-monotonic or non-existent, I apply a variance decomposition technique to assess their sensitivity to a change in w^{mrf} . To this end, I apply the Extended Fourier amplitude sensitivity test (eFast) (Cukier et al., 1973; Saltelli, Tarantola, and Chan, 1999) which uses Fourier series expansion to measure the strength of the influence of inputs on the model output. According to Thiele, Kurth, and Grimm (2014), it delivers all information needed for a comprehensive global sensitivity analysis while being more robust than the somewhat more extensive Sobol's method (Sobol, 2001; Saltelli et al., 2010) at low sample sizes.

The eFast analysis yields two measures of parameter sensitivity: first-order sensitivity $S1$ and a total sensitivity index ST . The latter takes into account the interaction effects with changes in the other uncertain parameters. Figure 3.2 shows the effects. In line with the findings of the estimation procedure, the model is not likely to replicate the average and lag 10 absolute autocorrelation which results in a low impact on the variance. The first-order effects on the J-cost, autocorrelation and co-integration moments are most pronounced. For the rest of the moments there seem to be strong overall sensitivity to changes in the uncertain parameters but low first order sensitivity to w^{mrf} , in line with what can be seen in Figure 3.1.

Experiment 2: mean-reversion expectations replace chartist expectations

Figure 3.3 provides the initial scatter plot overview of the relationships between w^{mr-mm} the J-cost and the MCRs.

Because for this experiment the relationship between w^{mr-mm} and the model output seems either non-monotonic or non-existent, I directly perform the eFast sensitivity analysis.

Figure 3.4 show the outcome of the sensitivity analysis. The blue bars indicate that there is some variability in the model's ability to capture the moments. This is largely the result of the other uncertain parameters because the absence of orange bars shows that the first order effects of w^{mr-mm} on model output are mostly non-existent.

Figure 3.2: Results of eFAST sensitivity analysis. Contribution of changes in the weight of the mean-reversion component over fundamental component w^{mrf} to variance in output for the J-score and several moment coverage ratios for model moments. S1 measures the first-degree sensitivity whereas ST measures the total sensitivity to changes in all uncertain parameters.

Figure 3.3: Scatter plots comparing the weight of the mean-reversion component over chartists w^{mr-mm} to the J-score and moment coverage ratios of the simulated model moments.

Figure 3.4: Results of eFAST sensitivity analysis for the second experiment. Contribution of changes in the weight of the mean-reversion component over chartist component w^{mr-mm} to variance in output for the J-score and several moment coverage ratios for model moments. S1 measures the first-degree sensitivity whereas ST measures the total sensitivity to changes in all uncertain parameters.

Evaluation of the experiments

The results of the experiments show that the improvement of the models' ability to capture the moments is largely a result of mean-reversion expectations replacing fundamentalist expectations. Particularly, replacing fundamentalist expectations with mean-reversion expectations increases the models ability to reproduce the observed autocorrelation and decoupling with the fundamental value.

3.4 Conclusion

In this paper, I set out to explore whether the 'decoupling scenario' is plausible. Specifically, I wanted to find out if a behavioural model which generates longer price fluctuations around the fundamental value is consistent with the main stylized facts of financial markets.

The answer to that question is a resounding yes. The estimated mean-reversion trading model presented in this paper generates a decoupling between prices and fundamentals. This does not limit its ability to replicate the stylized facts of no autocorrelation, volatility clustering, fat tails, and long memory in returns.

It does so by introducing a mean-reversion chartism component alongside the standard trend-following chartist component. In the chartist fundamentalist framework, the chartist component is mainly responsible for fat tails and volatility clustering in the returns while the fundamentalist component prevents them from being excessively large. In my model, the mean-reversion component, like the fundamentalist component, counteracts the chartist forces. However, because it is not tied to the fundamental value, the model price and fundamental values become decoupled.

I conclude that the Shiller (2014) suggestion that in financial markets prices and the unobserved fundamental value can be structurally decoupled for extended periods of time is plausible. This could have important policy implications because it implies the current market with its high share of algorithmic and index trading might no longer be effectively channelling funds to the most productive investments. The scenario therefore warrants further exploration.

Chapter 4

Asset volatility and inequality

Abstract

This chapter explores how volatility in stock markets affects wealth inequality. It first presents a stylized two trader example that demonstrates that random trading always leads to a situation of great wealth inequality because at a certain point one of the two traders is no longer wealthy enough to trade. In this example, increased price volatility increases trading profits that accelerates the move to this unequal state. The chapter then shows that this same dynamic holds in a multi-agent setting. It presents an agent-based stock market model with a hundred noise traders that are heterogeneous with regards to their wealth. Simulation experiments show that the trading system leads to a highly unequal state as the wealth of more and more traders becomes so low that they have to stop trading. Increasing price volatility accelerates the movement towards this state.

Does pure stock market volatility increase wealth inequality? This is the question that I will explore in this chapter. This question has not yet been answered by other research which has, so far, only considered the effects of changes in the level of stock prices and reached a consensus that rising stock prices lead to increased wealth inequality while falling stock prices have the opposite effect (Adam and Tzamourani, 2016; Colciago, Samarina, and Haan, 2019). By extension, pure volatility –where stock prices both rise and fall– should have a neutral effect on inequality. However, this story leaves out one important feature of stock markets: trading.

There are a couple of regularities in trading. First, if someone makes a profitable trade, someone else must have made a loss-making trade. Second, bigger price volatility translates to bigger trading profits and losses. Finally, traders need wealth to make trading profits, any trader who sees its wealth drop to a level below the price of a single stock can no longer trade.

The combination of these three elements implies that asset trading in a system of traders with noisy expectations will continue until wealth inequality is so big that trading stops. I will refer to this outcome as the unequal steady state. Increasing price volatility speeds up this process because it increases the size of trading profits

(and losses). In doing so, it accelerates the speed at which the system is moving towards the unequal steady state.

To see how this works, imagine a highly stylized two player trading game. The only difference between these two traders is that they form different expectations. Every turn t , these traders form the opposite expectation about the price movement of a risky asset. In every turn four events take place. At the start of a turn, (1) traders form expectations. Trader 1 expects that the price will appreciate by an amount α while trader 2 expects that the asset price will depreciate by the same amount. As a consequence, (2) trader 1 buys a quantity of risky assets Q while trader 2 sells a quantity of risky assets Q . Next, (3) both traders have a 50% chance that their respective price prediction is realized. Finally, (4) they will both exit the trade. This means that trader 1 sells at the new price and trader 2 buys at the new price. In the process, one of the traders has generated trading profits while the other has generated losses of size $\pi = \alpha Q$.

So, every turn t , trader 1 has a 50% percent chance of making a trading profit and a 50% chance of making a trading loss. If trader 1 has a profit of size π , trader 2 has a loss of size π and vice versa. Both traders start with an amount of wealth W_0 . If trader 1 makes a trading profit π , then its wealth will increase to $W + \pi$. In the next turn, trader 1 can again make a profit or loss of size π and see its wealth evolve to either $W + 2\pi$ or to W , both with a 50% probability. The next period this process repeats. The game stops if, after the price change, the trader that had sold the stock is no longer able to buy it back because the price has risen too much. At that point no more trading profits can be generated.

The left panel of Figure 4.1 shows the possible evolution of wealth for trader 1 in this scenario. At each point in time the probability of the trader wealth being in that state is shown in parentheses. As can be seen, the probability that the distribution of wealth is as equal as its starting state is decreasing over time, while the probability that the game is in one of the unequal steady states increases. For example, at $t = 2$ the chance that the game is still being played, a state in which the distribution of wealth is equal, is 0.5 while at $t = 4$ this chance is only 0.25.

The right panel of Figure 4.1 shows that, if the price volatility is twice as high, and by extension trading profits are twice as high, the trading game will end after 1 turn. At that point trader 1 has either lost or doubled its wealth. In both cases, wealth is concentrated in the hands of one trader. Increased volatility thus increases the speed at which the system moves towards the unequal steady state.

Figure 4.1: Evolution of wealth W of trader 1 in a two-player trading game. The probability of wealth increasing or decreasing is 0.5. t indicates time. The probabilities of ending up at a certain node are indicated in parentheses. The game stops if the level of wealth of trader 1 hits the bottom line, at which it is no longer able to buy back the stock it had sold because the price has risen too much. The game also stops if the wealth of trader 1 has reached the top of the graph, implying that trader 2 is no longer wealthy enough to buy back its stock. Left panel: volatility of profits is π , Right panel: volatility of profits is 2π .

Next, I will investigate if this relationship still holds in a more realistic multi-agent setting. The next section presents an ABM which contains noise traders who are heterogeneous with regards to their wealth. I use this model to test the three main predictions of the two trader example: (1) a speculative trading market moves to an unequal steady state, (2) as the situation progresses more and more traders stop trading because their wealth has hit the lower bound, and (3) increasing price volatility increases the speed at which the model moves to the unequal steady state.

My main result is that these predictions hold in the multi-agent setting. The model always ends up in the unequal steady state as more and more traders become so poor that they stop trading. Increasing price volatility, by increasing noise in price expectations, accelerates the speed with which the system moves to the unequal steady state. Before presenting the results in detail, the next section presents the model.

4.1 The model

The model contains a set of heterogeneous noise traders N_x who hold a portfolio of two assets: a risk-free asset M (money) and a risky asset S (stocks). In each time period $t \in T$, a random subset of traders of size ι enters the market. Then, each of the traders in the subset form their return expectations $E_{x,t}[r_{t+1}]$ for the next period $t + 1$. These expectations are formed by an individual noise component $\epsilon_{x,t}$ which is randomly drawn from a normal distribution with zero mean and standard deviation σ^ϵ :

$$E_{x,t}[r_{t+1}] = \epsilon_{x,t}. \quad (4.1)$$

Furthermore, each agent forms an expectation of the volatility of returns V which is equal to the return volatility that it observes over its horizon ϕ_x :

$$E_{x,t}[V_{t+1}] = \frac{1}{\phi_x} \sum_{j=1}^{\phi_x} [r_{t-j} - \bar{r}_{x,t}]^2, \quad (4.2)$$

where $\bar{r}_{x,\eta} = \frac{1}{\phi_x} \sum_{j=1}^{\phi_x} \ln(\frac{p_{\eta-j}}{p_{\eta-j-1}})$ is the average observed return.

Using both return and volatility expectations, agents compute the weights of money and stocks that optimize the following mean variance utility function:

$$w_{a,t}^* = \arg \max_w w' E_{x,t}[r_{t+1}] - 0.5 \alpha_x E_{x,t}[V_{t+1}], \quad (4.3)$$

where $w_{a,t}^* := (w_{x,t}^S, w_{x,t}^M)$ is the vector of optimal weights of assets, $\alpha_x \sim N(0, \sigma^\alpha)$ is the agent's individual risk aversion, and $E_{x,t}[r_{t+1}] = (E_{x,t}[r_{t+1}^S], 0)$ is the vector of expected returns for stocks and money. There are two constraints: a no short selling constraint $w_{d,t}^* \geq 0$ and a budget constraint $w_{d,t}^* = 1$.

The price level $p_{x,t}$ at which the agent will submit an order to the market is drawn from a normal distribution with mean $E_{x,t}[p_{t+1}]$ and standard deviation σ^p . With this price, the agent determines its demand for stocks $\Delta S_{x,t}$ as follows:

$$\Delta S_{x,t} = \frac{M_{x,t}}{p_{x,t}} + (w_{x,t}^S - 1)S_{x,t}. \quad (4.4)$$

If $\Delta S_{x,t}$ is positive (negative) the agent will submit a bid (ask) order to the order book with volume $\Delta S_{x,t}$ and price $p_{x,t}$. As the order is entered into the limit-order

book, the highest bid price p_t^{b*} and lowest ask price p_t^{a*} are updated. If $p_t^{b*} > p_t^{a*}$, these orders are matched at the price of the ask order:

$$p_t^* = p_t^{a*}, \quad (4.5)$$

and volume of the order v_t^* with the lowest volume:

$$v_t^* = \min(v_t^{b*}, v_t^{a*}). \quad (4.6)$$

Trading takes place between the agents to whom the matched orders belonged. An amount of money $p_t^* v_t^*$ is subtracted from the account of the trader who submitted the bid order and is added to that of the trader who submitted the ask order. In return, an amount of stocks v_t^* is added to the bid owner and subtracted from the ask owner. Note that, because of the constraints in equation 4.3, the amount of stocks and money, which traders own, will never become negative as a result of trading.

After trading between the agents, volume v_t^* is subtracted from both orders. If, as a result, the remaining volume of either order reaches zero, that order is removed from the order book. The matching procedure is repeated until there are no more remaining orders that satisfy the condition $p_t^{b*} > p_t^{a*}$.

4.2 Calibration

The model presented above is a highly stylized representation of the actual stock market because it serves to test if the two-trader relationship between stock price volatility and wealth inequality can be translated to a multi-agent setting. In line with that modelling philosophy, I set the number of traders $N_x = 1000$ and the trader sample size $\iota = 10$. These simplifications keep the computational time in check and do not change the conclusions presented in the results section.

The rest of the parameters will be calibrated using both direct and indirect calibration methods (Windrum, Fagiolo, and Moneta, 2007). Direct calibration means that parameters are set to values which are reported in the literature or can be directly inferred from the data. I use direct calibration where possible. The parameters for which this is not possible are uncertain. I set their values using indirect calibration. This means that their values are estimated so that the main stylized facts produced by the model correspond as closely as possible to their empirical counterparts.

To calibrate some of the parameters and to calculate the empirical moments, I use monthly data on inflation adjusted prices and the price to dividends ratio. These

were obtained from the database of Shiller (2000)¹. Observations start on the 31st of December 1952 and end on the 31st of December 2018 (600 observations).

The following parameters were calibrated using direct calibration. Assuming that the market is on average efficient, I set the initial price p_0 equal to its average price 1101.11. The initial amount of stocks distributed to every agent S_0 is set equal to the amount of stocks in the Vanguard S&P index fund divided by the number of agents at 81. I set the base risk aversion α equal to 0.7 (Kim and Lee, 2012). Then, I set the standard deviation of the spread $\sigma^p = 0.004$ (Riordan and Storkenmaier, 2012). Finally, the maximum horizon length $\phi^{max} = 100$, which is equal to the Churn estimate of Cella, Ellul, and Giannetti (2013) multiplied by T .

The standard deviation of the noise expectations component σ^ϵ (volatility) is uncertain because it is not observable. Using the Method of Simulated Moments indirect calibration approach (Franke and Westerhoff, 2012), I aim to set their values so that the model produces price returns that are in line with those of the S&P500. Formally, I minimize the following quadratic loss function:

$$J(m^{sim}, m^{emp}) = (m^{sim} - m^{emp})'W(m^{sim} - m^{emp}), \quad (4.7)$$

where m^{emp} and m^{sim} are vectors containing the empirical and model generated moments respectively, and the weighting matrix W is the co-variance matrix of the bootstrapped returns.

The moments in m are chosen to reflect some basic moments of stock price returns: its average value and its average autocorrelation of over 25 lags. Especially this last moment is important because autocorrelation of returns that is close to zero implies limited predictability of returns and therefore no obvious arbitrage opportunities (Samuelson, 1965).

Equation 4.7 is minimized using a version of the Nelder–Mead simplex algorithm (Nelder and Mead, 1965) which restricts input parameters to positive values only². To prevent the algorithm from getting stuck in a local optimum, I sample the complete parameter space ten times using Latin Hypercube Sampling methods (McKay, Beckman, and Conover, 1979). Each of the sampled parameter sets serve as a starting point for the optimization algorithm. At the end of this procedure, I select the algorithm which produced the lowest cost score. The estimated parameter is $\sigma^\epsilon = 0.1953$.

¹<http://www.econ.yale.edu/shiller/data/ie.data.xls>

²The constrained Nelder–Mead algorithm can be found at github.com/alexblaessle/constrNMPy

4.3 Results

This section provides an overview of the simulation results. First, I discuss the dynamics of the baseline simulation. For these, the dynamics of the price and fundamental value of the asset are observed along with the evolution of wealth inequality. Then, I construct two experiments to see how price volatility affects inequality and to discover the mechanism that drives it.

To measure inequality in agent wealth $W_{x,t} = p_t S_{x,t} + M_{x,t}$, I use two well-known inequality metrics. I use the Gini coefficient to measure the overall level of inequality and the Palma ratio (Palma, 2011) to measure inequality between the richest and poorest agents. The Gini coefficient is the most commonly used measure of inequality. It can take values between 0 and 1, where 0 represents perfect equality and 1 represents perfect inequality. The Palma ratio measures the ratio of the richest 10% of the agent's share of wealth over the share of the poorest 40% of the agents.

4.3.1 The model consistently ends up in an unequal steady state

To uncover if the model moves towards an unequal steady state, I simulate $N = 50$ Monte Carlo runs until the Gini coefficient is above 80%. If this is the case, the simulation stops at T_{max} ³. The result of this set-up is that, on average T_{max} is 6554 with a 95% confidence interval (6052, 7056).

Figure 4.2 shows that the noise trader model indeed moves towards an unequal low-trade steady state. The figure depicts average values and 95% confidence intervals. The top left panels show that the price, while volatile, is relatively stable. However, notably, it starts to become more volatile as volumes decrease and the order book becomes thinner. In the top right panel, it can be seen that on average trading volume declines. The bottom panels depict how both the Gini coefficient and the Palma ratio consistently increase over the course of the simulations.

³At this point this simulation is technically not yet in the unequal steady state, but I stop here to keep computational time manageable.

Figure 4.2: Baseline dynamics. The top-left panel shows the evolution of the price of the risky asset. The top-right panel shows the volume that is traded each period. The bottom panels show the evolution of wealth inequality as measured by the Gini coefficient (left) and Palma ratio (right). The solid line represents the average effect and the dotted lines indicate 95% confidence intervals.

4.3.2 Traders are increasingly too poor to trade

Figure 4.3 depicts that, as the simulation progresses, more and more traders rack up so many trading losses that it is difficult for them to recover. The graph displays the fraction of traders which, together, own 10% of total wealth. At this level of wealth trading becomes extremely difficult for them. They cannot trade much to recover from these losses for two reasons. First, they do not have the required wealth to support their trading activities. Second, as more and more traders fail to recover, demand for trading also decreases. This decreases upward and downward mobility within the wealth distribution.

Figure 4.3: Fraction of traders out of the game, proxied by less than 10% ownership of total wealth. The solid line represents the average effect and the dotted lines indicate 95% confidence intervals.

4.3.3 Increasing volatility leads to more inequality

To find out whether asset price volatility increases inequality, I construct an experiment in which the standard deviation of the noise component σ^ϵ (volatility) will be gradually increased from its calibrated value to 0.5 in steps of 0.05. This will increase the volatility of the asset price which should make the model end up in the steady state at T_{max} more quickly. Thus, T_{max} should decrease as volatility increases. On average, this type of volatility does not create price inflation since the average value of the noise component is zero. For each experiment, the model is simulated with $N = 15$ different Monte Carlo seeds.

Figure 4.4 demonstrates that increasing price volatility indeed decreases the average T_{max} . As σ^ϵ increases from 0.05 to 0.3, the average T_{max} decreases from 8614 to 1343.

4.4 Sensitivity analysis

Like in Chapter 3, I apply the Extended Fourier amplitude sensitivity test (eFast) (Cukier et al., 1973; Saltelli, Tarantola, and Chan, 1999) to measure how sensitive changes in inequality are to changes in the parameters that are not of primary interest. These are the sample size ι , risk aversion α , max spread σ^p , horizon ϕ , and volatility σ^ϵ .

To perform the sensitivity analysis, I sampled the parameter space using the eFast

Figure 4.4: Effect of an increase in volatility through the standard deviation of the noise component of return expectations σ^ϵ on the period at which the model ends up in the steady state. The solid line represents the average effect and the dotted lines indicate the 95% confidence intervals.

sampler of Herman and Usher (2017), sampling between minimum and maximum values of 50% around the values reported in the calibration section. This generates 500 parameter sets. Next, the model was simulated for each of these parameter sets with 5 Monte Carlo simulations, making for a total of 2500 simulations. Because this became too computationally intensive, I changed the set-up of the model so that it stops at $T = 800$. Then, instead of measuring the parameter impact on T_{max} , I measure the sensitivity of the Gini coefficient that is measured at the end of the simulation.

Figure 4.5 shows the results of the sensitivity analysis. The black bars show the first order sensitivity of the Gini coefficient to changes in the different parameters. Confirming that the results in the previous section are robust to changes in other parameters, the Gini coefficient responds most to changes in volatility σ^ϵ . The second most influential parameter is the trader sample size ι . Sensitivity to ι can be explained by the fact that if this parameter is increased the amount of trades increase every turn. This effectively speeds up the simulation. Therefore, increasing ι leads to more inequality.

The dashed bars represent the total sensitivity index. This index takes into account interaction effects with the other uncertain parameters. Notably, this does not change the order of importance of the parameters. Inequality is still the most sensitive to changes in volatility and second to changes in the trader sample size.

Figure 4.5: eFast sensitivity analysis results: black bars represent the first order sensitivity of the Gini coefficient to the various parameters; dashed bars represent total sensitivity which includes interaction effects. The bars represent the following parameters: sample size ι , risk aversion α , max spread σ^p , horizon ϕ^{max} , and volatility refers to the standard deviation of the noise parameter σ^ϵ .

4.5 Model validity

Since my results have been shown in a stylized simulation model, I briefly address why some of my simplifying assumptions do not invalidate the prediction that increased volatility increases wealth inequality. My argument consists of two aspects: input and output validity.

Regarding input validity, agent-behaviour and market structure have both been modelled after their empirical counterparts. The investment behaviour of the agents is based on portfolio balancing micro foundations (Tobin, 1958) which are well established in the literature (Hau and Rey, 2005). Furthermore, the market micro structure of the model is based on the electronic limit-order book, a popular matching algorithm which is used in more than half of global stock markets (Gould et al., 2013). Furthermore, while the assumption of noise expectations is a major simplification, it does not change the results. In previous versions of the model, I tested

if increased disagreement about the fundamental value or trend-following expectations would also result in more inequality. Following my epistemological position described in the thesis introduction, I removed these features from the model to make the model as simple as possible while generating the same results. Finally, I note that in the real world the lower bound for traders can be extended in multiple ways. For example, traders could borrow or unite what is left of their capital in a fund that trades for them. However, even in those cases there is a lower bound of wealth at which traders can no longer trade.

With regards to output validity, the model is able to replicate price series that are in line with the most important stylized fact of stock markets: no arbitrage. The model returns are characterized by an autocorrelation structure close to zero.

4.6 Conclusion

The simulations have shown that increasing stock price volatility increases the speed at which a system of noise traders moves towards an unequal steady state. Increased price volatility increases both profits and losses. This results in higher inequality because, over time, some traders will see their wealth reduced to such low levels that they can no longer trade. This also decreases the opportunity for other traders to trade, decreasing both volume and trader mobility in the wealth distribution.

These are important new insights given that literature on how stock prices influence wealth inequality has so far only considered the effect of asset price inflation. My findings have implications for policy makers who are concerned with financial stability and inequality. For example, central bankers, who have so far focussed on the distributional consequences of asset price inflation, should also take into account the distributional consequences of asset price volatility. To prevent increased inequality, they might even consider stabilizing asset prices through monetary policy, an issue that I will explore in the next chapter. A second example are financial regulators concerned with increased volatility as a consequence of high-frequency trading, they now have more reason for concern as this increase in volatility has distributional consequences.

The model presented in this chapter offers many possibilities for extensions which will make it applicable to particular policy concerns. For example, the model could be extended with a trend-following expectations component, this will lead to volatility and will increase inequality even more drastically. Other interesting extensions would be to test the above-mentioned policy considerations by adding a central bank or high-frequency traders to the model.

Chapter 5

Unconventional monetary policy and asset price stability

Abstract

In this chapter¹, I explore how central bank balance sheet policy can best be used to stabilize asset prices. I formulate three policy rules that central banks can use to do so: (1) a Buyer of Last Resort (BLR) rule which uses quantitative easing to dampen asset price falls; (2) a Seller of Last Resort (SLR) rule that uses quantitative tightening to prevent asset price booms; and (3) a Buyer and Seller of Last Resort (BSLR) rule that combines the BLR and SLR rules. These rules are simulated in an agent-based financial market model with endogenous asset price cycles. Simulations reveal that only the BSLR rule stabilizes asset prices. The BLR and SLR rules do not increase financial stability but merely change average asset prices.

This chapter contributes to the literature on unconventional² monetary policy by exploring how the central bank balance sheet can be used to increase financial stability. This is a deviation from current thinking which has so far focussed on using the central bank balance sheet to manipulate inflation by changing long-term asset prices. The effectiveness of unconventional monetary policy for this purpose remains disputed, especially in the long-term (Gambacorta, Hofmann, and Peersman, 2014) and for European countries (Papadamou, Kyriazis, and Tzeremes, 2019).

Therefore, in this chapter, I explore whether the central bank balance sheet can instead be used for financial stability purposes. Greenwood, Hanson, and Stein (2018) argue that the central bank should maintain a large balance sheet to make sure that there are enough safe short-term claims. I expand that arguments by suggesting that central banks can actively use an enlarged balance sheet to lean against the wind using APPs. Specifically, I explore how it can be used to stabilize asset prices. Three specific policy rules are formulated. Following these rules, the central bank will act

¹This chapter is a spin-off project from a project I worked on with Tina Koziol and Jesper Riedler which led to a paper called: Euro Area Quantitative Easing in a Portfolio Balance Model with Heterogeneous Agents and Assets (Koziol, Riedler, and Schasfoort, 2019).

²A term that includes all non-interest rate policies but is mainly used to refer to balance sheet policies.

as (1) a Buyer of Last Resort (BLR), (2) a Seller of Last Resort (SLR), or (3) a Buyer and Seller of Last Resort (BSLR). Following the BLR rule means buying assets using Quantitative Easing (QE) if asset prices fall too far below their fundamental value. Following the SLR rule means selling assets using Quantitative Tightening (QT) if asset prices rise too far above their fundamental value. The BSLR combines both rules. Using this rule the central bank will buy assets if their price falls too far below their fundamental value and sells assets if it rises too far above it.

I put these rules to the test in an agent-based model (ABM). The reason for turning to the ABM methodology is that while portfolio balance models (Christensen and Krogstrup, 2016) feature individual balance sheets, and Heterogeneous Agent Models (HAM) (Dieci and He, 2018) feature excess asset price volatility, they do not feature both jointly. Therefore, this paper presents a model which does. The model features a central bank that continuously buys assets by expanding the size of its balance sheet because this corresponds to the period to which the data was available. Thanks to this set-up, the model produces empirically plausible asset price volatility.

To study the asset stabilization rules, I build several counter-factual configurations in which the central bank uses either the BLR, SLR or BSLR rule. I contrast these to a benchmark configuration in which there is no central bank intervention. As a robustness check, I perform a global sensitivity analysis in which I vary all uncertain parameters. After that, a simulation experiment is conducted in which I increase the amount of assets that the central bank will buy or sell every period. For each rule, I evaluate how it affects average asset price levels and volatility.

My main result is that the central bank balance sheet can only be used to decrease asset price volatility if the central bank follows the BSLR rule. Applying this rule, the central bank reduces extreme asset price movements. Average asset prices are not affected because buying and selling assets balance out which leaves the size of the central bank balance sheet relatively stable. In contrast, applying just QE using the BLR rule raises average asset prices above their fundamental value while the SLR rule decreases average asset prices below their fundamental value. This occurs because money and risky assets are imperfect substitutes. If the central bank increases the supply of (base)money and decreases the supply of assets, the price of risky assets will increase as traders keep a diversified portfolio. Therefore, these rules change the level, not just the volatility, of asset prices.

The paper proceeds as follows. After discussing related models in the next section, I present the model in section 5.2. Section 5.3 contains the calibration procedure. Section 5.4 presents model dynamics. In Section 5.5, I present the three policy rules that can guide balance sheet policy in targeting asset prices. I first test these policy rules in the counter-factual version of the model and then construct experiments in which I increase the size of the central bank balance sheet that is available in the

three policy scenarios. In Section 5.6 the empirical validity of the model is discussed and Section 5.7 contains the conclusion.

5.1 Related models

In this chapter, I combine two types of models: portfolio balance models and Heterogeneous Agent Models (HAMs). Therefore, before presenting the model, I first review the literature around these models.

Portfolio balance models have been developed to understand one of the most important channels of central bank balance sheet policies: the portfolio balance channel.

While there are six channels through which QE can influence asset prices (Haldane et al., 2016), I focus on the portfolio balance channel for two reasons. The first reason is that, when QE was introduced, policy makers put forward the portfolio balance model as the key transmission channel through which QE would work (Joyce, Liu, and Tonks, 2017). The second reason is that the portfolio balance channel has since been recognized as a key channel in the empirical literature (Kuttner, 2018).

In the portfolio balance channels, QE reduces the supply of risky assets while increasing the supply of money. From the perspective of investors these two assets are imperfect substitutes due to different risk aversions or due to different preferences for maturity. The result is upward price pressure on the risky asset (Fratzscher, Lo Duca, and Straub, 2018).

To understand how this transmission channel affects steady-state asset prices, several portfolio balance models have been proposed. While all of these models build on the seminal model presented by Tobin (1958), they differ in what the source of this imperfect substitution is. In Joyce et al. (2011) the source of imperfect substitution is heterogeneity in agent risk aversion. In, Vayanos and Vila (2009) investors prefer different maturity structures. The models presented by Christensen and Krogstrup (2016) and Christensen and Krogstrup (2018) highlight another portfolio balance effect: a reserve induced effect. There, the effect of the reduction in bonds is amplified by an equal increase in central bank reserves which creates additional deposits.

All portfolio balance models only consider the long-term price effects of QE. They all assume that agents have rational expectations. So by assumption, QE has no effect on asset price volatility.

In contrast, Heterogeneous Agent Models (HAMs) are able to explain excess volatility (Hommes, 2011). HAMs feature traders with fundamentalist and trend-following expectation components. Agents with fundamentalist expectations expect the price to mean revert to its fundamental value. Agents with trend-following expectations expect that price trends will continue. HAMs have shown that the interplay between these two expectation types can explain a wide variety of stylized facts about

asset returns. Besides excess volatility, HAMs have been able to explain high trading volume, clustered volatility, and fat tails in returns (Hommes, 2006).

Thanks to this explanatory power, these models have been applied to a wide variety of issues (Dieci and He, 2018). However, HAMs are not used to study the impact of central bank balance sheet policies on asset prices. These models typically do not explicitly model the stocks of assets and money. Therefore, the next section presents an agent-based model which features both heterogeneous expectations and individual balance sheets.

5.2 The model

The model is an agent-based model with a central bank agent, inspired by the HAM and portfolio balance frameworks. The central bank agent can perform quantitative easing by buying risky assets A with newly created money M .

Traders in the set of agents N_x hold a portfolio that contains a combination of money and risky assets. For the latter, they form expectations about its return and volatility for the next period. Based on these expectations, they use mean-variance portfolio optimization to determine which shares of their wealth they wish to hold in money and in risky assets. Traders are heterogeneous with regards to their expectations, trading horizons, risk-aversions, and learning abilities. Their expectations consist of three components: a fundamentalist component, a trend-following component, and a noise component. Supply and demand are matched using a limit-order book.

The model operates on a discrete time-scale which represents days, T . Every time period $t \in T$, the fundamental value F_t of the risky asset is updated following:

$$F_{t+1} = F_t + \epsilon_t^F, \quad (5.1)$$

where $\epsilon_t^F \sim N(0, \sigma^\epsilon)$, and $F_{t+1} \geq 0$.

Two other events occur during each period t . First, the central bank determines its demand and submits a corresponding order to the order book. Second, a random subset of traders of size ι determine their expectations, demand and submit orders to the order book. Whenever a bid (ask) order is submitted, it is matched to an ask (bid) order. In the following subsections, I describe the model elements in more detail.

5.2.1 The central bank

The balance sheet of the central bank cb might at any point in time have risky assets A on the asset side of its balance sheet and money M and capital C on the liability side. Figure 5.1 demonstrates what its balance sheet structure looks like.

Figure 5.1: Central bank balance sheet.

Assets		Liabilities	
Risky asset	$p_t A_{cb,t}$	(Base)Money	$M_{cb,t}$
		Capital	$C_{cb,t}$

Capital is exogenous to the model and merely reflects the difference between the $p_t A_{cb,t}$ and $M_{cb,t}$. Since the central bank cannot default, its capital can be negative.

The central bank starts with assets equal to its target $A_{cb,t}^*$. To reflect that QE is taking place, this target is increased each period between the start and end of the simulation with an amount $\frac{\gamma A}{T}$. It funds asset purchases by expanding the monetary base $M_{cb,t}$ by an amount equal to the value of the purchased assets. The reverse applies if the central bank sells assets it takes money out of circulation.

Every period t , its supply (demand) depends on its inventory $A_{cb,t-1}$ and its target $A_{cb,t}^*$, i.e.

$$\Delta A_{cb,t} = A_{cb,t}^* - A_{cb,t-1}. \quad (5.2)$$

The central bank will submit a bid or ask order with volume $\Delta A_{cb,t}$ to the order book. To maximise the chance that the order is executed it will be submitted at the price of the best order³ of the opposite type.

$$p_{cb,t} = p_t^*, \quad (5.3)$$

where p_t^* is the lowest ask price if the central bank submits a bid order and the highest bid price if it submits an ask order.

5.2.2 Traders

After the central bank has submitted its orders to the order book, traders enter the market.

³Note that even though traders have not yet entered the market, there are still unfulfilled orders from previous periods in the order book.

Asset price expectations are determined by the weights of three expectation components which are contained in vector $w_{x,t}$: a fundamental value component with weight w_x^1 , a trend-following component with weight w_x^2 , and a noise component with weight $w_x^3 = 1 - (w_x^1 + w_x^2)$. I initialize the values of these expectation weights using parameter W^3 , which represents the aggregate weight of noisy expectations of all traders, and parameter λ which determines the ratio of aggregate trend-following expectations W^2 as $\lambda(1 - W^3)$ and the aggregate weight of fundamentalist expectations W^1 as $(1 - \lambda)(1 - W^3)$. Initially, aggregate weights are randomly distributed across the agents, forming their individual weights.

When an investor enters the market, it updates its weight components through learning with agent-specific probability ν_x which is drawn from the distribution: $\sim N(0, \sigma^\nu)$. If learning takes place, the agent observes the expectation component vector of wealthy trader z which was randomly selected from a set of the wealthiest traders of size ι . The trader learns from the wealthy trader by setting all its expectation weights in vector $w_{x,t}$ equal to the average of the vector $w_{x,z,t}$, which contains the current expectation weights of the trader and the expectation weights w_z of the wealthy trader:

$$w_{x,t} = \frac{1}{N} \sum_i^N w_{i,z,t}. \quad (5.4)$$

As part of the evolutionary learning algorithm, every trader has a probability of ν_x to update one random expectation component to a new value drawn from the original probability distribution $\sim N(0, \sigma^{w^*})$.

After learning has taken place, agents calculate expected returns on the risky asset $E_{x,t}[r_{t+1}]$ as:

$$E_{x,t}[r_{t+1}] = w_x^1 \frac{1}{\beta \phi_x} \ln\left(\frac{F_t}{p_t}\right) + w_x^2 \bar{r}_{x,t} + w_x^3 \epsilon_{x,t}, \quad (5.5)$$

where p_t is the average price of the highest bid and lowest ask order in the order book⁴, β is a multiplier which represents how quickly the price is expected to return to the fundamental value, $\epsilon_{x,t} \sim N(0, \sigma^\epsilon)$ is a noise parameter drawn from a normal distribution, ϕ_x is the number of periods over which a trader can remember previous asset returns that is drawn from a uniform distribution between 0 and ϕ^{max} , and $\bar{r}_{x,t}$ is the average historical return of the asset over horizon ϕ_x . It is calculated as follows

⁴If there are no orders in the order book: $p_t = p_{t-1}$.

$$\bar{r}_{x,t} = \frac{1}{\phi_x} \sum_{j=1}^{\phi_x} \ln\left(\frac{p_{t-j}}{p_{t-j-1}}\right). \quad (5.6)$$

Next, the trader calculates the expected price as

$$\mathbb{E}_{x,t}[p_{t+1}] = p_t \exp(\mathbb{E}_{x,t}[r_{t+1}]), \quad (5.7)$$

and expected volatility of returns V as

$$\mathbb{E}_{x,t}[V_{t+1}] = \frac{1}{\phi_x} \sum_{j=1}^{\phi_x} [r_{t-j} - \bar{r}_{x,t}]^2. \quad (5.8)$$

With these expectations traders can compute the optimal weights of money and assets that they wish to hold using the following mean variance function:

$$g_{x,t}^* = \arg \max_w w' \mathbb{E}_{x,t}[r_{t+1}] - 0.5\alpha_x \mathbb{E}_{x,t}[V_{t+1}], \quad (5.9)$$

where $g_{x,t}^* := (g_{x,t}^A, g_{x,t}^M)$ are the trader's optimal weights of assets and money, $\alpha_x \sim N(0, \sigma^\alpha)$ is the trader's individual risk aversion, $\mathbb{E}_{x,t}[r_{t+1}] = (\mathbb{E}_{x,t}[r_{t+1}], 0)$ is the vector of expected returns for the risky asset and money. Portfolio optimization is constrained by a no short selling constraint $g_{x,t}^A \geq 0$ and a budget constraint $g_{x,t}^M \geq 0$.

Next, the agent determines the price level $p_{x,t}$ at which it will submit a bid or ask order to the market. The price is drawn randomly from a normal distribution with mean $\mathbb{E}_{x,t}[p_{t+1}]$ and standard deviation σ^p . Using the optimal weights, the investor computes its demand for the risky asset $\Delta A_{x,t}$ as follows

$$\Delta A_{x,t} = \frac{w_{x,t}^A (A_{x,t} p_{x,t} + M_{x,t}) - A_{x,t-1} p_{x,t}}{p_{x,t}}, \quad (5.10)$$

making demand the difference between the desired balance sheet position (resulting from the optimal weights) and its inventory at the start of period t .

The agent will then submit a bid or ask order to the order book depending on whether $\Delta A_{x,t}$ is positive or negative respectively. The order has a volume $\Delta A_{x,t}$ and price $p_{x,t}$.

5.2.3 Market clearing

Once the orders by the central bank and investors have been submitted, the order book will match the orders. First, the orders with the highest bid price p_t^{b*} and lowest ask price p_t^{a*} are matched at the price of the ask order:

$$p_t = p_t^{a*}. \quad (5.11)$$

The volume of the transaction v_t is set at:

$$v_t = \min(v_t^{b*}, v_t^{a*}), \quad (5.12)$$

given that $p_t^{b*} > p_t^{a*}$.

When the orders are matched, the owner of the bid order subtracts $p_t v_t$ money from its account while the owner of the ask order adds this amount to its money stock. In return, an amount of assets v_t is added to the portfolio of the bid owner and subtracted from that of the ask owner⁵.

After trading has taken place, volume v_t is subtracted from both orders. An order is removed from the order book if the remaining volume of either orders is depleted. The matching procedure is repeated until there are no more remaining orders that satisfy the condition $p_t^{b*} > p_t^{a*}$.

5.3 Calibration

Following the approach in previous chapters, I use a mix of direct and indirect calibration. For both, I calibrate the model to past observations in which the central bank was performing QE to drive up asset prices.

My approach seeks to balance computational simplicity with a grounding in empirical observations. To ensure that I can do sufficient Monte Carlo simulations, I limit the simulation time to $T = 600$.

Following the calibration procedure of Chapter 3, I set the amount of investor agents N_x to be 1000, agent subset per period $\iota = 19$, initial fundamental value of the risky asset F_0 to 166 and the standard deviations of its evolution $\epsilon_t^F = 0.053$.

Each agent receives a number of shares $A_{0,x}$ between 0 and 740, drawn from a uniform distribution and a quantity of money $M_{0,x} = F_0 \kappa A_{0,x}$, where $\kappa = 2.2$ has been chosen so that on average the price of the risky asset is equal to its fundamental value.

⁵Thanks to the constraints on equation 5.9, the amount of assets and money will never be negative.

The total size of the balance sheet the central bank can employ $\gamma = 0.16$. This value was obtained from Koziol, Riedler, and Schasfoort (2019) (KRS) and is based on the Quantitative Easing programme of the European Central Bank (ECB). During the programme, approximately 16% of total eligible bonds outstanding were purchased by the ECB. To determine the initial quantity of bonds, I again use the calculations presented by Koziol, Riedler, and Schasfoort (ibid.). They report shares of market capitalization of total Euro assets, with 74% representing bonds. Applying these shares to the total quantity of assets, I initialize the quantity of bond portfolios B_0 at 740.

Like in Chapter 3, I follow Chiarella, Iori, and Perelló (2009) (CIP) in setting the maximum horizon ϕ^{max} to be 200 and set the standard deviation of the spread σ^p equal to 0.004, following Riordan and Storkenmaier (2012) (RS). Table 5.1 provides an overview of the calibrated parameters and their sources.

Table 5.1: Calibrated parameters. The calibration source abbreviations are as follows: - indicates that these parameter values were chosen by the authors to limit computational complexity and to set prices equal to the fundamental value; CH3 refers to calibration in CH3, KRS refers to Koziol, Riedler, and Schasfoort (2019); CIP refers to Chiarella, Iori, and Perelló (2009); RS refers to Riordan and Storkenmaier (2012)

Symbol	Description	Source	Value
T	simulation time	-	600
κ	money multiplier	-	2.2
N_x	number of investor agents	CH3	1000
ι	trader sample size	CH3	19
F_0	initial fundamental value	CH3	166
ϵ_t^F	standard deviation fundamental	CH3	0.053
$A_{0,x}$	initial assets	KRS	740
γ	percentage of asset to be bought	KRS	0.16
ϕ^{max}	maximum horizon length	CIP	200
σ^p	standard deviation spread	RS	0.004

The rest of the parameters are uncertain and will be estimated. Before doing so, I define the most important stylized facts associated with asset prices. These are (1) low daily return predictability measured by low autocorrelation of returns (Stanley, Plerou, and Gabaix, 2008), (2) volatility clustering measured by autocorrelation in absolute returns (Cont, 2001), (3) fat tails (Gu, Chen, and Zhou, 2008) measured

by excess kurtosis, and (4) long memory (Cont, 2005) measured using the Hurst exponent.

Because the risky asset is eligible for QE, it can be seen to represent a portfolio of highly rated bonds. Therefore, I select all U.S. and European bond indexes with A ratings and higher from the Federal Reserve Economic Data (FRED) website around the time of QE programs. In total, I collected 18 bond indexes. Observations start on the 17th of April 2010 and end on the 31st of January 2018. I use daily data, leaving us with 2058 observations for each bond index.

I estimate the uncertain parameters using the same procedure as described in Chapter 4. The only difference is that, since there are multiple assets, I derive the variance co-variance matrix directly from the observed data. The parameter bounds and estimates for the uncertain parameters are shown in table 5.2.

Table 5.2: Estimated parameters. The parameters were estimated using the method of simulated moments procedure as described by Franke and Westerhoff (2012).

Symbol	Description	Bounds	Estimate
σ^ϵ	standard deviation noise	0.03, 0.09	0.073
W_0^3	initial aggregate noise weight	0.02, 0.15	0.149
λ_0	initial share trend followers	0.02, 0.60	0.23
α	base risk aversion	0.05, 3.00	1.17
β	horizon multiplier	1.0, 5.0	1.66
v	learning mutation intensity	0.05, 0.50	0.31
σ^ν	average learning probability	0.01, 0.80	0.3

5.4 Model dynamics with QE

The model with QE is characterized by rising asset prices and consistent trading volume. Figure 5.2 provides an overview of the price-to-fundamentals (PF) ratio generated by the model. The left panel shows that QE pushes up prices above their fundamental values. This is in line with what the portfolio balance model predicts. The right panel shows that there is continuous trading activity over the course of the simulations.

The set-up of the model mimics reality which has seen a long period of sustained QE and rising asset prices. In the next section, I explore a counterfactual in which the central bank targets asset price stability.

Figure 5.2: Model dynamics. The left panel shows average PF ratio and 95% confidence intervals (dotted lines), the right panel shows average trading volume.

5.5 Targeting asset price stability

Having calibrated the model to historical data in which the central bank was following an inflation targeting framework, in this section, I explore the scenario of interest in which the central bank seeks to stabilize asset prices. I formally define the following policy rules: (1) a Buyer of Last Resort (BLR) rule, (2) a Seller of Last Resort (SLR) rule, and (3) a Buyer and Seller of Last Resort (BSLR) rule.

The BLR rule is defined as follows:

$$A_{cb,t}^* = \begin{cases} (1 + \gamma)A_{cb,t-1}^* & \text{if } \frac{p_t}{F_t} < 1 - \theta \\ A_{cb,t-1}^* & \text{otherwise} \end{cases}, \quad (5.13)$$

where θ determines how far the central bank tolerates PF ratio deviations from 1 and γ determines the size of the intervention. The value of $\theta = 0.05$ was chosen as a reference value, it could not be calibrated directly because an asset stability targeting rule does not exist yet. The value of $\gamma = 0.024$ was calibrated to the 60 billion (2.4 %) average monthly purchased by the ECB that led to a total of 2.532 billion assets on the ECB balance sheet by the end of September 2018 (Baltensperger and Bowen, 2018).

Next, I define the SLR rule as:

$$A_{cb,t}^* = \begin{cases} (1 - \gamma)A_{cb,t-1}^* & \text{if } \frac{p_t}{F_t} > 1 + \theta \\ A_{cb,t-1}^* & \text{otherwise} \end{cases}. \quad (5.14)$$

Finally, following the BSLR rule, the central bank acts as a buyer and seller of last resort by employing QE when the price is below the fundamental value and QT when the price is above it:

$$A_{cb,t}^* = \begin{cases} (1 - \gamma)A_{cb,t-1}^* & \text{if } \frac{p_t}{F_t} > 1 + \theta \\ (1 + \gamma)A_{cb,t-1}^* & \text{if } \frac{p_t}{F_t} < 1 - \theta \\ A_{cb,t-1}^* & \text{otherwise} \end{cases} \quad (5.15)$$

To analyse the impact of the policy rules, I first remove the constant QE from the model that was necessary to match the data of the last years. Then, I establish a benchmark in which the central bank does not use any of the balance sheet policy rules. Next, I compare this benchmark configuration to each of the three policy rules.

Figure 5.3 provides an overview of the average PF ratios of these scenarios. For each scenario the bottom panel indicates the size of the central bank balance sheet that is a result of central bank policy.

Figure 5.3: Balance sheet rule dynamics. The top panels depict the average asset price for the three policy rules and the no-rule benchmark, the bottom panels show balance sheets items of the central bank.

As the left column of Table 5.3 demonstrates, the BLR rule raises average PF ratios. The average PF ratio in BLR simulations is 0.0064 higher than the benchmark, this is not significant at the 5% level. Through the portfolio balance channel, QE shifts prices permanently upwards. Similarly, the SLR rule reduces the average PF ratios downwards by 0.0381, which is significant at the 5% level. Finally, average PF ratios in the BSLR configurations are 0.0003 higher than in the benchmark. This is not significant at the 5% level.

Next, I evaluate how each rule impacts asset price volatility which is measured using the relative standard deviation. The relative standard deviation is the standard deviation of the PF ratio divided by the average PF ratio, $\frac{\sigma}{\bar{p}f}$. The reason I use this measure is that the different policies also affect average PF ratios, making the standard deviations alone hard to compare.

I find that the average volatility in the BLR scenario is a bit higher and that of the SLR is a bit lower than in the benchmark scenario. However, both are within the 95% confidence intervals of the benchmark scenario. On the other hand, in the BSLR scenario relative volatility of the PF ratio is 0.0095 lower than in the benchmark. This effect is significant at the 5% level. In the next section, I will explore if these results are robust to variations in the uncertain parameters.

Table 5.3: Average price to fundamentals (PF) ratio, $\bar{p}f$, and relative standard deviation, $\frac{\sigma}{\bar{p}f}$, for the benchmark no-rule configuration and the buyer of last resort (BLR), seller of last resort (SLR), and buyer and seller of last resort (BSLR) policy rules. Volatility is defined as the standard deviation of the cyclical component of the PF ratio, corrected for the price level. Confidence intervals are in brackets.

Scenario	$\bar{p}f$	$\frac{\sigma}{\bar{p}f}$
Benchmark	1.0335 (1.0118, 1.0552)	0.0389 (0.0318, 0.0460)
BLR	1.0399 (1.0227, 1.0571)	0.0392 (0.0315, 0.0469)
SLR	0.9954 (0.9841, 1.0068)	0.0330 (0.0248, 0.0413)
BSLR	1.0038 (0.9998, 1.0079)	0.0294 (0.0262, 0.0327)

5.5.1 Robustness of the results

To test the robustness of the result that only the BSLR rule reduces asset price volatility, I perform a global sensitivity analysis in which I vary the uncertain parameters presented in Table 5.2. The uncertain parameters were sampled using the Latin Hypercube sampler of Herman and Usher (2017), where the bounds used for in the estimation procedure are the minimum and maximum values. This process generates 50 unique parameter sets. Next, I simulate the model for each of these parameter sets with 5 Monte Carlo simulations.

The result of the sensitivity analysis is that, compared to the benchmark, the BSLR scenario is on average associated with a 0.017 reduction in the relative standard deviation of the PF ratio. On the other hand, the BLR scenario was associated with a 0.021 increase in relative volatility and the SLR scenario with a 0.0053 decrease of relative volatility. All of these findings were significant at the 5% level. Thus, even when controlling for the changes in the uncertain parameters, the BSLR rule is the most effective at decreasing asset price volatility.

5.5.2 Sensitivity to program size

Finally, I explore how the different rules affect volatility if their potency is slowly increased. In an experiment, I check the sensitivity of how effective the rules are to the amount of buying / selling power the central bank has to implement its rule. To do so, I increase the parameter γ from zero to 0.4 in increments of 0.01. γ represents the size of the balance sheet that is available to perform QE or QT in a period⁶. For every increment, like in the experiments of previous chapters, I simulate 15 Monte Carlo Simulation runs. I perform three versions of this experiment, one for each policy rule.

Figure 5.4 presents the results for the BLR configuration. In line with previous results, the left panel demonstrates that as the potential size of QE increases, the average PF ratio during the simulation is increased. This effect becomes weaker as γ increases. This happens because if asset prices hit a certain level, the central bank will apply QE less often, because even though the PF ratio might fall just as far as before, it will not fall to the intervention level. The right panel shows that volatility of the cyclical component of the PF ratio increases slightly.

I perform the same experiment for the SLR scenario. The left panel of Figure 5.5 demonstrates that as γ increases the average PF ratio decreases. The right panel demonstrates, that while the volatility of the PF ratio only decreases somewhat on average.

This brings us to the BSLR rule. The left panel of Figure 5.6 shows that the average PF ratio decreases a bit by this policy rule while volatility is reduced on average and confidence intervals tighten. This rule becomes more effective as γ increases and the central bank has more buying / selling power to reverse the price trend.

⁶I note that this does not mean that this amount of the central bank balance sheet is used. There might not be sufficient demand or supply in that period so the central bank order might not be fully filled.

Figure 5.4: BLR scenario effect of increasing γ on price to fundamental ratios levels (left panel) and volatility (right panel). The black line represents the Monte Carlo average. Dotted lines indicate 95% confidence intervals.

Figure 5.5: SLR scenario effect of increasing γ on price to fundamental ratios levels (left panel) and volatility (right panel). The black line represents the Monte Carlo average. Dotted lines indicate 95% confidence intervals.

Figure 5.6: BSLR scenario effect of increasing γ on price to fundamental ratios levels (left panel) and volatility (right panel). The black line represents the Monte Carlo average. Dotted lines indicate 95% confidence intervals.

5.6 Discussion on model validity

In the process of modelling, I made several simplifying assumptions that could influence the validity of the model. First, the model does not consider macroeconomic spill overs such as capital flows to other countries, other asset classes, or real investment. Also, the modelled financial market is highly stylized. It features only one asset. If there are multiple assets, it becomes important which asset the central bank buys or sells. Furthermore, asset price cycles in different asset classes might not coincide. This can complicate the use of the BSLR rule because buying one asset, that is below fundamental value, might cause another asset, which is above fundamental, to rise even more. Another limitation is that, my results rely on the concept of the fundamental value, which is the net present value of future cash flows. However, in real life, there is not one fundamental value, it might not exist, or alternatively there might be multiple fundamental values, one for each agent. Even if we accept that the fundamental value exists, it is problematic to assume the central bank knows what it is. Since real world central banks typically do not know the fundamental value of assets, they should be able to estimate the fundamental value reliably in able to target it using the BSLR rule. Finally, the agents are myopic and are not able to anticipate central bank policy decisions. Given these limitations, I will only limit my extrapolations of the results to the financial market impact.

I argue that the model is a valid representation of a financial market. My argument consists of two aspects. First, the model uses inputs that are grounded in observed behaviour and market micro structure. Second, when calibrated to the recent past, in a version with consistent QE, the model can replicate the most important stylized facts of financial markets.

With regards to the inputs, agent-behaviour and market structure have both been modelled after their empirical counterparts. The fundamentalist and trend-following expectation components are the two most common expectation components measured in surveys (Menkhoff and Schmidt, 2005; Menkhoff, 2010) and in experiments (Haruvy, Lahav, and Noussair, 2007; Hommes, 2011) on trading expectations. In line with the adaptive market hypothesis of Lo (2004), traders do not have perfect foresight but they learn from their mistakes via adaptive learning, just as they do in the model. The portfolio composition behaviour of the agents is based on solid portfolio balancing micro foundations (Tobin, 1958). Finally, the market micro-structure is based on the electronic limit-order book, a popular matching algorithm which is used in more than half of global stock markets (Gould et al., 2013).

With regards to model outputs, the model is able to produce price dynamics that are not significantly different from observed asset price series. The model is able to replicate the moments described in the calibration section: (1) low autocorrelation

of returns, (2) autocorrelation in absolute returns, (3) excess kurtosis, and (4) the Hurst exponent.

First, I consider the structure of the auto-correlation of returns and absolute returns. Figure 5.7 shows that for most lags the average autocorrelation of returns and absolute returns are within the 95% confidence bands of the empirical autocorrelations. On average autocorrelation of returns over 25 lags is 0.06 which falls within the empirical confidence interval of (0.02, 0.08) and autocorrelation of absolute returns is 0.08, which is also within the empirical confidence interval of (0.04, 0.10).

Figure 5.7: Autocorrelation of returns. The left panel shows the average autocorrelation of returns, and the right panel shows the average auto-correlation of absolute returns. For both, the dotted lines indicate 95% confidence intervals.

Then, I consider the kurtosis of the returns. For the simulations, I record an average excess kurtosis of 4.35. This falls within the empirical 95% confidence interval of (-2.39, 10.33). Finally, I record an average Hurst exponent (Hurst, 1951) of 0.75 which is also inside the empirical confidence interval of (0.62, 0.81).

Like in Chapter 3, I calculate the Moment Coverage Ratio (MCR) for the simulated and empirical moments. The results are presented in Table 5.4.

Table 5.4: Moment coverage ratios of the model and empirical data.

Moment	Model	Empirical
Average autocorrelation	98.0	88.9
Average autocorrelation abs	1.0	94.4
Kurtosis	98.0	94.4
Hurst	0.92	1.0

5.7 Conclusion

Using an agent-based simulation model, I have explored whether the central bank balance sheet can be employed to stabilize asset prices and, if so, how best to do this. Simulations show that the central bank balance sheet can be used to stabilize asset prices. The best way to do this is by following the Buyer and Seller of Last Resort (BSLR) rule in which the central bank commits to buying assets if they are too low and selling them if they are too high. This insight can be the start of a new research agenda which considers using the central bank balance sheet for financial stability purposes rather than for spurring inflation.

Appendix A

Tables and list of symbols chapter 2

Symbol	Description	Possible values
id_x	Unique agent identifier	1 - 8121
D_x	Amount of deposits	0 - ∞
CG_x	Amount of consumption goods	0 - ∞
KG_x	Amount of capital goods	0 - ∞
L_x	Amount of loans	0 - ∞
R_x	Amount of reserves	0 - ∞
B_x	Amount of bonds	0 - ∞
A_x	Amount of advances	0 - ∞
IB_x	Amount of interbank loans	0 - ∞
df_x	Indicates whether an agent has defaulted	True, False
ep_{hh}	Identifier of the employer	Bank, firm, or government
l_x	List of identities of workers	List of households
vc	Variable costs	0 - ∞
lc	Unit labour costs	0 - ∞
o	Output	0 - ∞
u	Capacity utilization	0% - 100%
y	Sales	0 - ∞
k	Selected supplier	Firm identifier
n_b^L	Non performing loans	List of loans
i_b^L	Internal benchmark rate bank charges on loans	0% - 100%
i_b^D	Rate on deposits	0% - 100%
i_b^{IB}	Rate for extending an interbank loan	0% - 100%
CR	Capital adequacy ratio	0% - 100%
LR	Liquidity ratio	0% - 100%
p^B	Face value at which the government is willing to release bonds	100%
i^B	The percentage the government pays on the face value of government bonds	0% - 100%
i^R	Rate on central bank reserve deposits	-10% - 10%
CR	Capital adequacy ratio	0% - 100%
LR	Liquidity Ratio	0% - 100%

Table A.1: Agent State Variable Domains

Symbol	Description	Initial value
ΔY_{ss}	Nominal rate of growth in the steady state	0.0024
$Popsiz_{hh}$	Number of households	4000
$Popsiz_{cf}$	Number of consumption firms	100
$Popsiz_{kf}$	Number of capital firms	20
$Popsiz_b$	Number of banks	10
$Popsiz_g$	Number of governments	1
$Popsiz_{cb}$	Number of central banks	1
$l_{kf,cf,g}$	Consumption firms initial workers	500, 2600, 780
m	Initial unemployment	0.08
$p_{kf,cf}$	Goods prices by type	1.2625, 0.1643
$i_b^{L,D,A,B,R}$	Initial interest rate on debt	0.0024, 0.0008, 0.0008, 0.0008, 0
CR^{tr}, LR^{tr}	Initial banks' target prudential measure	0.08422, 0.1551
i_{cb}^R	CB interest rate on reserves (bank rate)	0
w	Initial wages	5
$\Delta p^C G$	Inflation	0.00246627
ρ_{hh}	Dividends received	1022.7246
Y	Nominal GDP	18303.8210132755
$r_{kf,cf,b}$	Profits received by sector	18.68515, 1102.4699, 47.1388
$y_{kf,cf}$	Sales by sector	2525, 15778.8210
$uc_{kf,cf}$	Unit costs by sector	1.25, 0.1494
$OCF_{kf,cf}$	Operating cash flows for firms	17.5140, 2100.9267
A	Initial quantity of advances	0
$B_{c,cb}$	Bonds held by sector	269845.1258, 56965.5549
$L_{kf,cf}$	Initial loans per sector	1990.5041, 42037.8831
$R_{b,g}$	Reserves held by sector	56965.5549, 0
$D_{hh,kf,cf}$	Initial deposits per sector	352630.6774, 2500, 12000
$G_{kf,cf}$	Initial inventory per sector	200, 9600
KG_{cf}	Initial machines	120000
Ψ_{cf}^{uc}	Initial mark-up on unit labour costs for consumption firms	0.3188
Ψ_{kf}^{uc}	Initial mark-up on unit labour costs for capital firms	0.075

Table A.2: Global Variables

Symbol	Description	Initial value
$\alpha^{q,y}$	Propensity to consume out of wealth, income	0.25, 0.38581
α^ρ	Propensity to distribute dividends out of excess capital	0.2
β	Risk aversion	0.01
γ	Adaptive expectations weight	0.25
$\epsilon^D = \epsilon^L = \epsilon^B$	Intensity of choice in the deposit, credit, and interbank markets	2.00687
$\epsilon^{CF} = \epsilon^{KF}$	Intensity of choice in the consumption and capital goods markets	1.50515
$\eta^{L,B,M}$	Loans, Bonds, Machines duration	20, 5, 20
$\theta^{\Delta k}$	given a a 15% and 20% price difference between old and new	50%
θ^{df}	Probability of default	free
ι_{cf}	Haircut on defaulted firms' capital value	0.5
$\iota^{u,w}$	Share of workers leaving their employer, wage costs kept as a liquidity buffer	0.01, 1
κ_{cf}^{tr}	Desired capacity rate of growth	free
λ	Productivity of labour for capital, consumption firms	2, 1
$G_{f,t}^{tr}$	inventory buffer target	0.1
$u_{c,t}^{tr}$	Desired rate of capacity utilization	0.8
ξ	Number of potential partners interbank market, goods markets, deposit and credit markets, labour market	10, 5, 3, 10
ρ	Dividend pay-out ratio firms, banks	0.9, 0.6
ν_m	unemployment benefits as a share of average wage	0.3
$\tau^y = \tau^r$	Tax rate on income and profit	0.18
ϕ^u	Unemployment threshold (wage revision function)	0.08
ϕ^{pru}	Prudential threshold	0.1
ϕ^{mon}	Monetary threshold	0.01
$\rho^{CG,KG,D,L,W}$	Information asymmetry in consumption / capital goods, credit / deposit and labour markets	5, 3, 10
v_{pru}	Policy mark-up for prudential policy	0.0025
v_{iR}	Bank rate mark-up	0.025
Ω_1	Profit rate weight (Investment function)	0.01
Ω_2	Capacity utilization rate weight (Investment function)	0.02
$\mu_{FN^x}, \sigma_{FN^x}^2$	Folded normal distribution mean and standard deviation of all FN parameters	(1, 0.0094)

Table A.3: Initialization of Parameters

Symbols

b	banks
c	consumption
cb	central bank
cf	consumption goods firms
C	collateral
CR	capital ratio
d	demand
df	default
dv	dividends
ds	debt service
D	deposits
e	expected
f	firms
fc	funding rate
FN^1	stochastic mark-up component firm prices
FN^2	stochastic mark-up component bank rates
FN^3	stochastic mark-up component household wages
g	government
G	Firm inventory buffer
hh	households
i	interest rate
I	investment
j	iterator variable
kf	capital goods firm
kg	capital goods
KG	demand for capital goods

l	labour
L	loans
LR	liquidity ratio
LGD	loss given default
m	unemployment
M	employees
n	non-performing loans
o	output
OCF	operating cash flows
p	price
P	set of obligations
q	wealth
r	return or profitability
R	reserves
s	supply
t	time
tr	target
u	utilization of capacity
uc	unit labour cost
V	state variables
w	wages
x	agent
X	inventory of capital or consumption goods
y	sales
Y	nominal GDP
α	propensity to consume
β	risk aversion
γ	adaptive learning parameter
δ	capital labour ratio
Δ	difference between two periods
ϵ	intensity of choice
ζ	buffer parameter
η	credit maturity
θ	probability
ι	share
κ	growth rate
λ	productivity
μ	average
ν	unemployment rate

ρ	information asymmetry
σ	standard deviation
τ	tax rate
v	mark-up
χ	determinant of bank rates
Ψ	shock

Appendix B

Appendices chapter 3

B.1 Block bootstrap procedure

To calculate the confidence intervals for model parameters, I perform a block bootstrap on the data from which I extract the confidence intervals of the moments. To do so reliably, I make a distinction between moments which are recorded over different time lengths and perform three separate bootstrap procedures.

I follow the approach set out by Franke and Westerhoff (2012). That means that I divide the original data into blocks of size b . Then, randomly sampling from these blocks without replacement, I create 5000 unique new time series.

To ensure the diversity of these time series, ideally, there are plenty of blocks. Therefore, for returns, I calculate the moments related to the predictability, volatility clustering and fat tails using block size $b = 250$. Because of the longer fundamental data series length, I create time series of the returns of the historical price and fundamental value for the decoupling moment with block size $b = 205$. However, to capture some of the longer term moments related to long memory, I needed to use a bigger block size of $b = 625$ on the nominal returns series.

B.2 Sensitivity to parameters

To assess parameter importance, I subject the uncertain parameters to a screening analysis which delivers measures of the relative importance of every parameter for every moment (Ginot et al., 2006). A screening method cannot quantify the strength of the effects. Instead, it will rank parameters by their importance (Thiele, Kurth, and Grimm, 2014).

The screening method I apply here is the enhanced Morris method (Morris, 1991) of Campolongo, Cariboni, and Saltelli (2007). According to Thiele, Kurth, and Grimm (2014), this is the most suitable method for ABMs because it does not require knowledge of the signs of the relationships between parameters and output in advance.

Given a set of model outputs simulated over a sample of the full parameter space, the enhanced Morris method will yield three measures for every output, parameter

pair: the mean effect μ , the enhanced mean effect μ^* , and the standard deviation σ . μ gives an indication of the average effect of varying the parameter on the output. The enhanced μ^* does the same while taking into account the effects of opposite signs which occur if the relationship is non-monotonic. Finally, σ measures the variance in the output which occurs when varying the input parameter.

Combining these measures can yield the following insights about the relationship between the parameter and model output of interest. High μ and high μ^* means that the parameter is of importance. Low μ and high μ^* indicates that the parameter is of importance and that this relationship is non-monotonic. The combination of μ^* and σ provides information about non-linear and or interaction effects. Low μ^* and high σ indicates that a parameters effect on output is non-linear and/or dependent on other parameter values. If both indicators are low (high) both the first-order and interaction effects are weak (strong). Finally, high μ^* and low σ indicates that the effect is strong and this is mainly a first-order effect.

Using the Campolongo, Cariboni, and Saltelli (2007) sampling tool, I sample 5000 different combinations of the uncertain parameters within the bounds declared in Table 5.1. Then, I simulate 2 runs of the model for every parameter set in the sample. Table B.1 presents an overview of the ranked importance of parameters.

To find the most influential parameters overall, I sum the ranks for μ^* for each parameter over all moments. This yields the following ranking of overall importance:

1. σ^e weight random,
2. ι trader sample size,
3. σ^f weight fundamentalists,
4. ζ maximum order expiration ticks,
5. σ^{ϵ^n} standard deviation of noise ,
6. σ^{mr} weight mean-reversion,
7. σ^{mm} weight momentum,
8. ϕ^{max} maximum horizon,
9. N_l number of traders,
10. σ^v standard deviation of volume.

Besides total importance, the Morris Method also provides information about the importance of parameter uncertainty for individual moments. The autocorrelation

moments are mostly influenced by changes in the trader sample size, weight of the random component and the weight of the fundamentalist component. While surprising at first, this last component makes sense since the fundamental follows an AR(1) process. Regarding the volatility clustering moment, absolute autocorrelation is mostly influenced by the trader sample size, random weight and expiration time of orders. The heavy tails moment, kurtosis, is primarily influenced by changes in the random weight, trader sample size and standard deviation of noise. For the long memory moments the overall biggest influencers are sample size, weight of the random component, and the random component. There is some heterogeneity between the different lag sizes. Notably, the chartist component and horizon components are important for absolute autocorrelation at longer lags. Finally, for our moment of primary interest: the decoupling between prices and fundamentals, the fundamentalist component is the most important determinant.

The primary goal of the sensitivity analysis was to determine which uncertain parameters could be safely discarded for the model estimation. To make the decision, I follow the set of criteria: the parameter must not be one of the expectation components; the parameter must not be a top three determinant for the groups of moments; the parameter should be near the bottom of the list for overall impact. After applying these criteria, I determine the number of traders N_l and the standard deviation of volume σ^v are the least important parameters.

B.3 Evolutionary algorithm

The evolutionary optimization algorithm starts out with an initial set (population) of 500 parameters which was sampled from within the bounds of κ using Latin Hypercube Sampling (LHS) methods (McKay, Beckman, and Conover, 1979). LHS has become the sampling method of choice for ABMs because of its ability to sample the parameter space efficiently (Thiele, Kurth, and Grimm, 2014). Then, I simulate the model using Monte Carlo methods varying the seed of the random number generator N_r times for all parameter sets in the population and calculate its J-value using Equation (4.7). A lower J-function is better and stands for a higher fitness of the simulation. 30% of the fittest simulations and a 20% of random simulation become parents which are combined to create a set of children. Then, 10% of parameters mutate at random in 10% of the parents. The resulting set of parameters is the next generation which will be simulated. I repeat this procedure until the average population costs reaches a steady state.

Table B.1: Results of the Morris Method. Impact ranks of the parameters: ι trader sample size, σ^{ϵ^n} standard deviation of noise, σ^v standard deviation of volume, σ^f weight fundamentalists, σ^{mm} weight momentum, σ^e weight random, σ^{mr} weight mean-reversion, ϕ^{max} maximum horizon, N_l number of traders, ζ maximum order expiration ticks on different simulated model moments, where μ measures the average parameter impact, μ^* measures the average adjusted impact and σ measures the variance in impact.

Moment		ι	σ^{ϵ^n}	σ^v	σ^f	σ^{mm}	σ^e	σ^{mr}	ϕ^{max}	N_l	ζ
Autocorrelation	μ	1	8	4	9	2	10	7	6	5	3
	μ^*	3	5	9	2	6	1	4	8	10	7
	σ	4	5	9	2	6	1	3	8	10	7
Autocor1	μ	7	6	3	10	1	8	2	3	5	9
	μ^*	3	4	8	1	6	2	6	9	10	5
	σ	4	3	8	2	5	1	5	9	10	7
Autocor5	μ	1	8	4	9	3	10	7	5	6	2
	μ^*	3	4	10	2	7	1	5	8	9	6
	σ	3	4	9	2	7	1	5	8	10	6
Abs autocor	μ	2	9	7	3	4	10	5	8	6	1
	μ^*	4	3	10	5	6	1	6	8	9	1
	σ	4	3	10	5	6	1	7	8	9	2
Kurtosis	μ	9	8	7	3	6	10	2	5	4	1
	μ^*	2	4	7	6	3	1	8	9	10	5
	σ	3	4	5	7	2	1	9	8	10	6
Abs autocor 10	μ	2	9	6	3	4	10	5	8	7	1
	μ^*	4	3	10	5	7	1	7	6	9	2
	σ	4	2	10	5	7	1	7	6	9	2
Abs autocor 25	μ	2	9	4	4	2	10	7	4	8	1
	μ^*	3	4	10	4	7	1	9	6	7	2
	σ	3	2	10	3	7	1	9	6	7	5
Abs autocor 50	μ	2	9	6	10	4	6	3	6	5	1
	μ^*	1	7	10	5	8	1	5	4	3	8
	σ	2	5	10	7	8	1	5	4	3	9
Abs autocor 100	μ	1	6	2	7	7	2	9	10	2	5
	μ^*	1	8	10	5	9	2	5	4	2	5
	σ	1	8	10	5	9	1	5	4	3	5
Decoupling	μ	8	7	4	10	1	9	3	6	5	2
	μ^*	2	5	10	1	7	3	6	9	8	4
	σ	2	5	10	1	6	3	7	8	9	4

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Samenvatting

Deze thesis past een nieuwe modelleringsmethode –individueel gebaseerd modelleren (IBM)– toe op een viertal onderzoeksvragen. In het eerste hoofdstuk –de introductie– bespreek ik dat IBM een relatief nieuwe model methodologie is waarin individuele actoren (bijvoorbeeld bedrijven, huishoudens, of personen) en hun interacties expliciet worden gemodelleerd. Deze techniek is vooral geschikt als de individuen in een systeem op verschillende niveaus van elkaar verschillen en/ of als interactiestructuur in detail gemodelleerd moet worden. Daarom pas ik in deze thesis de techniek toe op vier onderzoeksvragen waar deze aspecten op het eerste gezicht van belang leken. De onderzoeksvragen zijn:

1. Hoe beïnvloeden veranderingen in de beleidsrente de inflatie op de korte/ middellange termijn?
2. Is het aannemelijk dat aandelenprijzen ontkoppeld zijn van de onderliggende 'fundamentele' waarde?
3. Hoe beïnvloedt volatiliteit in de aandelenmarkt de ongelijkheid van vermogen?
4. Hoe kan de centrale bank haar balans inzetten om de prijs van financiële instrumenten te stabiliseren?

Elk van deze onderzoeksvragen zal apart worden behandeld in een hoofdstuk. In ieder hoofdstuk gebruik ik de IBM-methodologie om de onderzoeksvraag te beantwoorden.

Hoofdstuk twee is geschreven met Antoine Godin, Dirk Bezemer, Alessandro Ciani, en Stephen Kinsella. Samen met hen bestudeer ik hoe de beleidsrente van de centrale bank de inflatie beïnvloedt op de korte/ middellange termijn. Eerst identificeren we verschillende transmissiekanalen over hoe de rente beslissing van de centrale bank

andere actoren in de economie beïnvloed. Dan maken we een macro-economische IBM die is gebaseerd op het model van Caiani et al. (2016), maar uitgebreid is met een interbancaire markt. Met dit model analyseren we de effecten van een renteschok door vier transmissiekanaalen: het kosten kanaal, het investeringskanaal, het consumptie kanaal, en het bankleningen kanaal.

In dit geval was het nuttig om een complexe IBM te bouwen omdat in de macro-economie markten lang niet altijd tegelijk in evenwicht zijn. Het is daarom niet duidelijk hoe de populaire aanname van evenwicht op alle markten onze conclusie zou beïnvloeden. Daarnaast is er de laatste tijd in de macro-economie steeds meer oog gekomen voor het belang van verschillen tussen individuen en de invloed die dit heeft op het rentebeleid. We vergelijken de uitkomsten van ons model met dat van populaire modellen die uitgaan van enkele representatieve individuen en algemeen marktevenwicht.

Onze bevinding is dat de veranderde aannames in ons model een grote invloed hebben op de conclusies van het model. In tegenstelling tot populaire evenwichtsmodellen voorspelt ons model dat het rente-instrument maar weinig invloed heeft op de korte-termijn inflatie. Dit komt omdat andere factoren in ons model van groter belang zijn voor de beslissingen van individuen dan rente factoren. Zo zijn voor de investeringsbeslissingen van bedrijven vooral reële factoren als vraag en loonkosten van belang. Voor de consument gaan we er van uit dat hij/zij niet zomaar het doel van de centrale bank serieus neemt maar zijn/haar verwachtingen aanpast naarmate de gerealiseerde inflatie afwijkt van verwachtingen. Een verhoging van de rente zorgt daarom wel voor wat meer geld in de zakken van de consumenten, maar tegelijkertijd worden ze aangemoedigd om meer te sparen en minder uit te geven. Als gevolg van deze tegenstrijdige krachten heeft een renteverandering maar weinig effect op consumptieve bestedingen. Het meest sterke transmissiekanaal is het bankleningen kanaal. Als de rente te ver stijgt zal dit de winstgevendheid van bankleningen verlagen. Als bedrijven sterk op elkaar lijken is er een bepaald punt waarop banken plots geen geld meer uitlenen. Dit kan de economie flink afremmen en heeft daarom ook een effect op inflatie. Hierdoor is de rente een zeer bot instrument en is de centrale bank niet, zoals voorspeld door evenwichtsmodellen, goed in staat om de inflatie met grote precisie te controleren door de rente te veranderen.

In hoofdstuk drie onderzoek ik of een scenario waarin aandelenprijzen zich ontkoppelen van de fundamentele waarde aannemelijk is. In zo'n scenario keren de aandelenprijzen niet meer terug naar de 'fundamentele' waarde, die wordt bepaald door de dividenden van de aandelen. Ik definieer aannemelijkheid als: in lijn met een aantal statistische feiten die we kennen van aandelen markten.

Mijn belangrijkste bevinding is dat het toevoegen van een naïeve verwachtingscomponent, die terugkeert naar de gemiddelde prijs voorspelt, aan de gebruikelijke ex-

trapolerende en fundamentalistische component een ontkoppeling kan verklaren. De ontkoppeling wordt sterker naarmate de naïeve terugkeer verwachtingen de fundamentalistische verwachtingen vervangen. Dit model reproduceert dan nog steeds de statistische feiten. Het scenario is daarom plausibel.

In dit geval leek de IBM aanpak geschikt omdat er sprake was van grote verschillen tussen agenten. Echter, een gevoeligheidsanalyse laat zien dat het ook mogelijk zou moeten zijn om ditzelfde effect te reproduceren in een meer simpel model waarin niet alle individuen expliciet worden gemodelleerd. De gedetailleerde marktstructuur van dit model is overbodig. Een volgende stap zou daarom zijn om een simpeler techniek op dit probleem toe te passen.

In het vierde hoofdstuk, verken ik de relatie tussen de volatiliteit van aandelenprijzen en de vermogensongelijkheid tussen aandelenhandelaren. Eerst presenteer ik een simpel voorbeeld met twee handelaren.

Elke beurt in de simulatie vormen deze handelaren eerst tegengestelde verwachtingen. Als de ene handelaar denkt dat de prijs zal zakken dan denkt de ander dat deze zal stijgen. De handelaar die denkt dat de prijs zal stijgen zal een aandeel willen kopen terwijl de andere een aandeel zal willen verkopen. Daarna vindt er een prijsrealisatie plaats. De kans is gelijk dat deze is gestegen of gedaald met een bepaald bedrag. Daarna zullen beide handelaren winst of verlies nemen en het aandeel respectievelijk weer verkopen/ terugkopen voor de nieuwe prijs. Ze boeken dan een winst of verlies. Als één van beide handelaren te weinig geld heeft om het in die beurt verkochte aandeel weer terug te kopen, stopt het spel. In zo'n situatie is het slechts een kwestie van tijd dat het spel stopt omdat één van beide handelaren toevallig zonder geld zit.

Vervolgens kijk ik in een IBM of deze dynamiek ook standhoudt als er duizend handelaren zijn die handelen via een realistisch marktmechanisme. De IBM-methode is een logische keuze omdat de handelaren verschillen met betrekking tot het geld, de aandelen en de verwachtingen die ze hebben. Daarnaast, omdat de ongelijkheid tot stand komt door de handel, is het nuttig om deze handel expliciet te simuleren. Simulaties laten zien dat zo'n systeem alsmaar ongelijker wordt, totdat er geen handel meer plaats vindt. Meer volatiliteit in de prijs, gecreëerd door meer volatiliteit in de verwachtingen van handelaren, zorgt ervoor dat het systeem sneller ongelijk wordt. Dit bevestigt dat deze dynamiek ook in een systeem met meerdere handelaren standhoudt.

In het vijfde, en laatste, hoofdstuk onderzoek ik hoe de balans van de centrale bank mogelijk zou kunnen worden gebruikt om de markt voor financiële instrumenten meer stabiel te maken. Het model bestaat uit een centrale bank en meerdere handelaren. Net als bij de vorige hoofdstukken is de IBM-methodologie geschikt om deze vraag te behandelen, omdat er sprake is van veel verschillen tussen de indi-

viduen. De handelaren verschillen van elkaar met betrekking tot de balansstructuur en verwachtingen. Daarnaast is dit een vraagstuk met betrekking tot stabiliteit wat lastig te bestuderen is in een model met evenwichtsmechanisme.

In de simulaties verken ik drie mogelijke gedragsregels die de centrale bank kan gebruiken om financiële instabiliteit tegen te gaan. De eerste gedragsregel beschrijft hoe de centrale bank financiële instrumenten koopt als de prijs te ver onder de fundamentele waarde komt. De tweede gedragsregel beschrijft het tegenovergestelde. Gebruikmakend van deze regel verkoopt de centrale bank instrumenten als de prijs te ver boven de fundamentele waarde ligt. De derde regel combineert deze beide regels. In dit geval koopt de centrale bank instrumenten als de prijs te laag is en verkoopt ze deze instrumenten weer als de prijs te hoog is. De simulaties laten zien dat de eerste twee regels de gemiddelde prijs niet stabiliseren maar deze naar een hoger, respectievelijk lager, niveau brengt. De derde gedragsregel is geschikt om de prijs te stabiliseren zonder de gemiddelde prijs te beïnvloeden.