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Doctoral Thesis

Heterogeneous agent models to determine spillover effects in the context of Quantitative Easing

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School of Economics

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Für meinen Vater.

Declaration of Authorship

I, Tina Koziol, hereby declare that the work on which this dissertation/thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I empower the university to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

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Abstract

We develop heterogeneous agent models to investigate financial spillover effects in the context of Quantitative Easing (QE). We consider these spillover effects from two perspectives. The first perspective studies spillovers within a network of *financial institutions*. The aim is to understand where amplification effects occur in the event of a shock. For this purpose, we calibrate a model of fire-sale contagion to the South African banking sector. We use cross-sectional balance sheet data for 29 South African banking institutions. Fire-sale externalities are pecuniary externalities that operate through prices. They pose a threat to the financial system because they amplify price shocks across assets and thus lead to liquidation spirals. In the first step, we investigate general shock propagation scenarios to an unsecured lending portfolio of a large bank and to a marketable asset held by all banks, i.e. South African government bonds. We rank individual banks according to their contribution to systemic risk and show the importance of cash liquidity buffers in reducing risk of fire-sale occurrences. Further, we find a critical threshold parameter which, if exceeded, makes the banking system highly unstable. In the second step, we build on findings presented by Cecchetti et al. (2017) that determine a relationship between Quantitative Easing and risk-taking behavior of financial institutions in emerging markets. Assuming that QE increases banks' leverage, we show that the fire-sale contagion channel becomes much more pronounced. The same shock to the government bond asset class leads to higher banking sector instability. The risk to banking sector losses is not linear, but rather increases exponentially with higher leverage ratios.

The second perspective of the dissertation considers spillovers between *financial markets* in the context of QE. We contribute to the literature that investigates the portfolio balance effect associated with QE. In essence, the portfolio balance channel is the consequence of an assumed imperfect substitutability of assets. To account for this, we develop a dynamic agent-based model to study international asset price spillover. Our two-country model features heterogeneity in assets and in investor preferences. Both are crucial for a meaningful model-based impact assessment of QE because preferences for asset maturity, asset class (bonds, equities and currencies) and whether an asset is issued at home or abroad can influence the substitutability of assets, and hence the portfolio balance effect of central bank asset purchases. We implement a novel pricing mechanism that allows us to approach market clearing prices. This allows us to take advantage of the flexibility of the agent-based methodology, while keeping the model comparable to more standard equilibrium-based portfolio balance models. We calibrate the two countries in our model to the Eurozone (EZ) and a representative sample of rest-of-the-world (ROW) countries in order to estimate the international impact of the ECB's asset purchase program announced in January 2015. For this purpose, we compile data on asset holdings of 15 374 EZ and 25 930 ROW open-end investment funds from the Morning Star Database, as well as data on investment portfolios of EZ and ROW banks from the ECB's Statistical Warehouse and Bankscope. When simulating our model, we find a negative impact of central bank asset purchases on both domestic and foreign returns. While the effects of QE on domestic bond yields and the exchange rate are rather modest and smaller than commonly assumed in the literature, they can cause domestic stock prices increase substantially. Somewhat surprisingly, however, we find that spillovers from portfolio balancing to the rest of the world are negligible.

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Abbreviations

ABM Agent-based model

ABSA Barclays Africa Group

AfricanB African Bank Group

APP Asset purchase program of the ECB

BOE Bank of England

BOJ Bank of Japan

CAPITEC Capitec Bank LTD

DeutscheB Deutsche Bank AG

ECB European Central Bank

EZ Eurozone

FNB Firstrand Bank LTD

FRED Federal Reserve Economic Data of the St. Louis Fed

HPC High performance Cluster

INVESTEC Investec Bank LTD

JPM JPMorgan Chase Bank

LSAP Large scale asset purchases

MMF Money Market Funds

NEDBANK Nedbank LTD

QE Quantitative Easing

ROW Rest-of-the-world

SBSA Standard Bank LTD

USD US Dollar currency

1 Introduction

"Well, the problem with QE is it works in practice, but it doesn't work in theory."

Ben Bernanke, former chair of the US Federal Reserve, January 2014[1]

The famous quote Ben Bernanke shared in conversation with the Brookings Institution in early 2014 captures the current puzzle surrounding Quantitative Easing (QE). QE is a central bank policy that involves large asset purchases in exchange for newly created reserves. It has been used extensively in advanced economies in the post-crisis area. Despite this, however, our understanding of the underlying transmission channels of QE is inadequate. In particular, the economic theory literature is lacking models that convincingly describe the relationship between QE, financial markets and financial institutions. The dissertation presented here seeks to contribute to this research gap. We focus on specific aspects of financial spillover in the context of QE and apply heterogeneous agent models to investigate channels of contagion. This chapter provides an overview of the main research questions and the methodological approach. Following a brief problem statement, we will highlight the scope and contributions of the dissertation and give an outline of the chapters that follow.

1.1 Background and problem statement

Large asset purchase programs known as Quantitative Easing represent a relatively new instrument in central bankers' toolkit to stimulate aggregate demand. First introduced in Japan in the early 2000s, QE is thought to ease credit conditions further when the short-term interest rate approaches its zero lower bound. Since the 2009 financial crisis, the US Fed, the Bank of England, the Bank of Japan, the Swiss National Bank, the Swedish Riksbank and the ECB bought a combined value in excess of 15 trillion USD (approx. 18% of world GDP), mostly in the form of sovereign bonds.[2] QE is part of a set of 'unconventional monetary policy' tools because it is distinct from the 'traditional' approach that focuses on the short term interest rate as main instrument to dampen out spikes in the business cycle. Instead, QE involves the expansion of central bank balance sheets through the acquisition of assets and hence a broadening of the money base. For example, the US Fed's balance sheet increased by 400% between the beginning of QE1 in 2009 and the tapering of QE3 in 2014. The problem with the QE approach - and this is what Bernanke was referring to - is that it doesn't work according to standard monetary theory. A famous result known as 'Wallace Neutrality' (Wallace, 1981) predicts that the composition and

[1] transcript of Brooking Institution conference, page 14,
https://www.brookings.edu/wp-content/uploads/2014/01/20140116_bernanke_remarks_transcript.pdf

[2] Authors own calculations based on FRED, BOJ, BOE, ECB balance sheet data

size of central bank balance sheet can have no effect on inflation or employment. Another result from Eggertsson and Woodford (2003), an important contribution in macro theory, finds central bank's purchases of market securities to be irrelevant per se for asset prices, inflation and demand.

Yet we can observe a correlation between QE announcements and movements in financial asset returns, particularly in the 10-year government bond yield. The growing literature on announcement effects finds evidence that central banks' QE announcements are reducing domestic government bond yields by sizable amounts (see e.g. Gagnon et al., 2011a; Bauer and Rudebusch, 2014; Krishnamurthy and Vissing-Jorgensen, 2011a; Kuttner, 2018, among others).

The dissertation focuses on two aspects of spillovers in the context of QE. The first raises the question of whether QE may contribute to instability in the banking sector by considering a specific channel of contagion, i.e. the channel of fire-sale externalities. The second deals with the relationship between QE and domestic and foreign asset returns for the example of Eurozone QE. For this purpose, we develop a dynamic portfolio balance model that accounts for heterogeneity in assets and investors. The model seeks to combine features of what are known as agent-based models with the equilibrium considerations of traditional economic models. The aims of this dissertation are threefold. The first aim is to determine conditions under which QE may affect stability of the banking sector of an emerging market. To address this question, a model of shock propagation is calibrated to the South African banking sector to investigate determinants of banking sector instability. The second aim is to develop a model framework that offers sufficient complexity to replicate real-world financial markets while maintaining computational tractability. The third and final aim is to conduct an extensive calibration and simulation study which allows for the quantification of QE-induced asset price effects. The focus here will be on the Euro area purchase program, as the research gap is wider than for the US programs and data is easily available. In working towards these aims, a number of contributions were made, which will be discussed below.

1.2 Scope and contribution of the study

The main research questions addressed in this study are as follows:

> How resilient is the South African banking sector to fire-sale externalities?
>
> Is banking sector stability affected by QE?
>
> Can spillover asset price effects be attributed to the portfolio balance effect of QE?
>
> How does the ECB's Asset Purchase Program (APP) affect domestic and foreign asset returns and the exchange rate through the portfolio balance channel?
>
> What are the policy implications for South African regulators concerned about financial stability of the banking sector?

The dissertation develops two models to address the research questions outlined above. The first model calibrates a model of fire-sale externalities in the South African banking sector to illustrate the resilience of the sector to amplification price effects. The analysis is carried out from the point of view of banks' balance sheet data. We demonstrate how balance sheet data sets can be analyzed in practice and simulate a shock propagation algorithm to identify vulnerabilities in this sector. The main contributions of the fire-sale contagion model are twofold. First, the Greenwood et al. (2015) model is extended by including a cash buffer and calibrated to the South African banking sector. General shock scenarios for specific asset classes are carried out to identify exposure to systemic risk in the banking sector in respect of common asset holdings. It is shown to what extent the South African banking sector is able to absorb price shocks. We rank individual banks according to their contribution to systemic risk and show the importance of cash liquidity buffers in reducing risk from fire-sale occurrences. A sensitivity analysis of results finds a critical illiquidity parameter for the shock scenario regarding SA government bonds. If shocks to this asset class lead to price effects larger than 10 basis points per 10 bn selling volumes (i.e. the illiquidity parameter $\rho > 1 \times 10^{-13}$), high systemic risk, which requires policy response, ensues. In addition, a detailed description of banks' balance sheets is used in a complementary fashion to give more insight into the distribution of banks' asset holdings. The tables presented illustrate common asset holdings which can be used to determine the exposure of banks' portfolios to asset write-downs at a specific date in time. Second, a scenario of fire-sale amplification is simulated in the context of QE. Here we build on findings by Cecchetti et al. (2017), who find that QE leads to an increase in leverage of financial institutions in emerging markets. Assuming that QE leads to higher risk-taking behavior of South African banks by means of increased leverage, the exposure to fire-sale externalities to asset losses increases substantially.

The second model presented in this dissertation is a dynamic portfolio balance model to investigate spillover effects by means of a two-country model. This model was developed together with two co-authors, Jesper Riedler and Joeri Schasfoort. At the heart of the model are portfolio optimising investors who allocate capital across a domestic and a foreign market. We then conduct a policy experiment in which the central bank of the domestic market conducts asset purchases in their market ranging from EUR200bn to EUR2.6tn. We contribute methodologically by including heterogeneous agents and assets, which we believe is crucial for a meaningful assessment of QE within the portfolio balance channel. To our knowledge, we are the first to demonstrate the effect of QE while accounting for:

- Endogenous outcome variables. QE-induced asset price and exchange rate effects are the result of agents' portfolio optimisation given the interaction of risk and return variables, availability of assets and expectations formation.
- Dynamic covariance structure. Our model allows for the interactions between variables over time. Agents take into account a time-varying variance-covariance structure of returns.

- Consideration of preferred habitat preferences. We introduce asset-specific preferred habitat parameters to account for heterogeneous investors' preferences for asset maturity, issuer nationality, default risk and inflation risk. These preferred habitat parameters are akin to the risk aversion parameter from the standard mean variance portfolio selection problem Markowitz (1952), however they conflate all the aforementioned preferences above.

- Computational tractability. A shortfall of many agent based models is their lack of tractability. We use a price-setting algorithm that finds daily equilibrium prices.

- Parsimonious modelling of maturity. We introduce heterogeneity in asset maturity by introducing constant repayment rates and a maturity parameter. In this manner, we can model equity portfolios (that never mature) and bond maturities with different repayment characteristics in a parsimonious manner.

- Empirical data. For the calibration of the model, we compile a global dataset of investment funds' and banks' balance sheets. We match the maturity profile of funds by applying our modelling approach to a holding sample of 15,374 open-ended investment funds. Furthermore, we calibrate our model to reflect preferred habitat preferences as revealed in investor holding positions.

- Result replication. Our framework gives us the advantage of conducting policy experiments in a 'lab environment'. We can replicate results and vary conditions (for example, examining what happens if the business cycle features higher defaults and hence, higher default risk) to investigate determinants of asset price effects.

- Quantification. Our policy experiment leads us to believe that asset price effects from portfolio balancing are smaller than what is commonly assumed in the literature. Breckenfelder et al. (2016) conduct a review of empirical studies on the ECB's APP and find a reduction in the domestic government bond yield of 37 - 88 bps. Our findings can be summarised as follows:

  EZ bonds: -16 bps in yields, +0.9% in price

  EZ equities: -50 bps in yields, +6.6% in price

  ROW bonds: -1 bps in yields, +0% in price

  ROW equities: -3 bps in yields, +0.4% in price

  EUR/ROW exchange rate: -0.4%

  One should note that the effect we measure is in respect of market EZ bond portfolios, market EZ equity portfolios etc. Our results are less pronounced than what is found in most event studies for the US, but they are in line with recent empirical results for the Euro area presented by Koijen et al. (2016). We discuss the underlying factors that play a role in this discrepancy in section 6.1.

The following section gives an overview of chapters, indicating which sections address which topics.

1.3 Organisation of the study

This study is divided into three parts. In PART I, we give a overview of the relevant literature strands on spillover between (1) financial institutions and (2) financial markets and their relevance to Quantitative Easing. Considering (1), we emphasize models of fire-sale contagion and their implications for systemic risk. Our first contribution is to draw together the two strands in the literature that highlight the importance of leverage as the threat for financial stability and the transmission of QE. In PART II of the dissertation we build on Cecchetti et al. (2017) findings and investigate vulnerabilities that arise in the South African banking system following higher leverage. We are the first to investigate the impact of the risk-taking channel on indirect fire-sale contagion for the example of South Africa. We propose an extension of the Greenwood et al. (2015) model to account for more realistic liquidation behavior. In section 3.3 we proceed to simulate asset price shocks to the system. The data is cross-sectional balance sheet data of 29 banks provided by the BA900 forms of the South African Reserve Bank. Subsequently, we consider the hypothesis of Cecchetti et al. (2017) and conduct shock scenarios assuming that QE leads to higher leverage within the banking system.

In PART III, we shift the focus from financial institutions to financial markets. Chapter 4 develops the heterogeneous agent model used to determine international asset price movements through the portfolio balance channel. Chapter 5 calibrates and simulates the model to the Eurozone's Quantitative Easing program. The results are discussed in section 5.3.

Last but not least, Chapter 6 presents conclusions and policy implications resulting from the findings of the dissertation and highlights areas that provide scope for future research.

PART I - Literature

2 Financial spillover literature in the context of QE

We start the analysis by reviewing the relevant literature. The aim of this chapter is to give an overview on the topic of QE and how it is related to the literature on financial spillover. In Section 2.3, we introduce agent-based modelling and discuss why it is a suitable methodology to address our research questions.

2.1 Quantitative Easing - a new tool for central bankers

The short-term interest rate has been the most important tool available to central bankers to conduct monetary policy. It determines the cost of credit in the domestic economy and greatly influences capital spending, consumption expenditure, inflation and the exchange rate. The transmission of monetary policy through the interest rate channel has played a major role in the economic literature in the last 50 years (Mishkin, 1995).
In the last decade, however, central banks faced a new challenge as policy rates reached the zero rate bound, but they still had to support the economy. When the financial crisis unfolded in November 2008, the US federal funds rate had already been reduced to close to zero. That's when the US Fed turned to unconventional monetary policy in the form of Quantitative Easing. In the first QE program, Large-Scale Asset Purchases (LSAP) 1, the US Fed bought USD 600bn mortgage-backed securities and bonds issued by government-sponsored firms. Overall, the US Fed would increase its balance sheet from USD 900 bn to USD 4.5 tn in three separate rounds of QE between 2008 and 2014. These actions were taken to "put downward pressure on longer-term interest rates, support mortgage markets, and help to make broader financial conditions more accommodative."[1] In addition, the Fed began to conduct 'forward guidance', i.e. it made explicit references to the likely path of short-term interest rate in its policy statements (Kuttner, 2018). Contrary to conventional monetary policy, the announcement of QE was never tied to a specific target in respect of lowering the long-term interest rate. One reason for this is that the transmission channel of QE was simply not known. The LSAP programs bought a variety of mortgage-backed securities and longer-term US Treasuries and the interest rate effect was not clear given a set of purchases. In fact, the transmission of QE policy is still the subject of much debate today with no clear consensus. All we know is that QE drastically changed the size and composition of major central bank balance sheets and that this correlated with a decline in long

[1] Federal Open Market Committee press release October 24, 2012

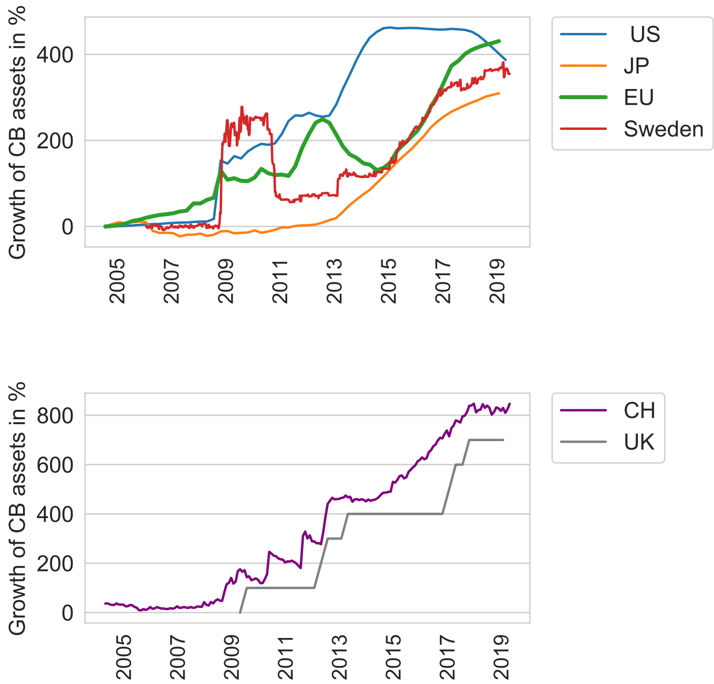


FIGURE 2.1: Growth in total assets of central banks of the US, Euro area, Sweden, Switzerland and Japan since 2005. For the UK, growth is measured from 2009 due to limited data availability. *Upper chart:* Growth in total assets of US Fed, ECB, Bank of Japan and Swedish Riksbank. *Lower chart:* Growth in total assets of Swiss National Bank and Bank of England. Source: FRED, Federal Reserve Bank of St Louis.

term interest rates (see Figure 2.4 on page 18). PART III of the dissertation presents a model to investigate whether this decline could have been a function of one particular transmission channel, i.e. portfolio balancing.

While QE played a major role in the crisis resolution in the US from 2008 onwards, it was first used by the **Bank of Japan** in the early 2000s. At the time, the Japanese economy experienced a series of challenges characterised by stagnant growth, deflation, distressed banks' balance sheets and near-zero interest rates. Krugman (1998) argues that Japan was in a liquidity trap, a situation where monetary policy becomes ineffective even though the nominal rate is close to zero. Krugman shows this by using a framework that was first introduced by John Hicks in 1937, incorporating the emergence of a liquidity trap in an IS-LM model (Hicks, 1937). Krugman's argument is that the wrong kind of economic shock can lead the economy into a bad equilibrium state in which real interest rates don't reach a low enough level to stimulate the economy. Demand is persistently low and the economy is stuck in a situation with a consistent and large output gap. Krugman estimated that the Japanese output gap exceeded 8% in 1998. Krugman's paper also proposed solutions for this situation in the form of large-scale borrowing and spending on the part of the government, as well as tolerating higher expected inflation in the future on the part of the central bank. This would cause a decline in real interest rates in the present and contribute towards stimulating demand. In short, the recipe was a radical expansionary monetary policy.

In fear of facing a deflationary spiral, the Japanese central bank committed to providing ample liquidity by means of creating additional reserves through QE until the deflation would end (Ueda, 2012). The rationale was that banks would be less constrained in terms of reserves available and would start lending out to the real sector. From March 2001, the Bank of Japan bought Yen 400 bn worth of assets per month, which was gradually increased to Yen 1200 bn by May 2004. QE was briefly lifted in March 2006, but eventually resumed in October 2010 in the wake of the global financial crisis (Dell'Ariccia et al., 2018). Mechanically, the QE of the US Fed and the QE of the Bank of Japan were quite similar. Both bought assets in large quantities by creating large amounts of extra reserves and expanding their balance sheets. However, Bernanke has stressed that the Fed's QE policy was different in the sense that they focused on the composition of the Fed's balance sheet and its effect on those assets, while the BOJ had the intention of increasing the money supply with the additional reserves (Bernanke, 2017).

The **Euro area** faced its own challenges when dealing with the aftermath of the global financial crisis from 2008 to 2009 and an unfolding sovereign debt crisis from 2010 to 2013. Early policy responses on the part of the ECB focused on the provision of liquidity in the form of Main Refinancing Operations (MROs), Long-term Refinancing Operations (LROs) and a broadening of the type of collateral allowed. These refinancing operations can be viewed as 'lender of last resort' actions in which the ECB makes credit available to distressed financial institutions (Dell'Ariccia et al., 2018). Only at the beginning of 2015, as growth in the Euro area stagnated and inflation was persistently below the 2% target, did the ECB start its own large-scale Asset Purchase Program (APP). Over the course of nearly four years, from March 2015 until the end of 2018, the ECB grew its assets by EUR 2.6 trillion by purchasing a mix of asset-backed securities, corporate bonds and government bonds.

As shown in Figure 2.1 and Figure 2.2, QE was an established monetary policy tool by the end of the 2010s in the US, Japan, the UK, the Euro area, Sweden and Switzerland. By 2019, the US Fed, the BOJ, the ECB and the Riksbank of Sweden grew their balance sheets between three and four times relative to their pre-2005 levels. The Bank of England and the Swiss National Bank expanded their balance sheet even more aggressively by 700% and 800% respectively. The combined value of total assets held by those central banks is well over USD 15 trillion, or more than 18% of global GDP today[2]. Central banks financed these USD 15 trillion by creating reserves in the banking system, most of which ended up as excess reserves on banks' balance sheets (Thornton, 2015).

The literature on QE is vast and the debate on its transmission channels is ongoing and intriguing. However, the aim of this dissertation is not to evaluate if QE was an effective monetary policy to stimulate the economy. We would need to dig deeper into the respective macro-economic and monetary theories. Instead, we consider QE from a *spillover* perspective with a special focus on two channels that will be at the centre of our heterogeneous agent models. In the next section we will discuss the financial spillover literature and establish the links that explain its relevance in the context of QE.

[2] Ovaska, Reuters Graphics http://fingfx.thomsonreuters.com/gfx/rngs/GLOBAL-CENTRALBANKS/010041ZQ4B7/index.html

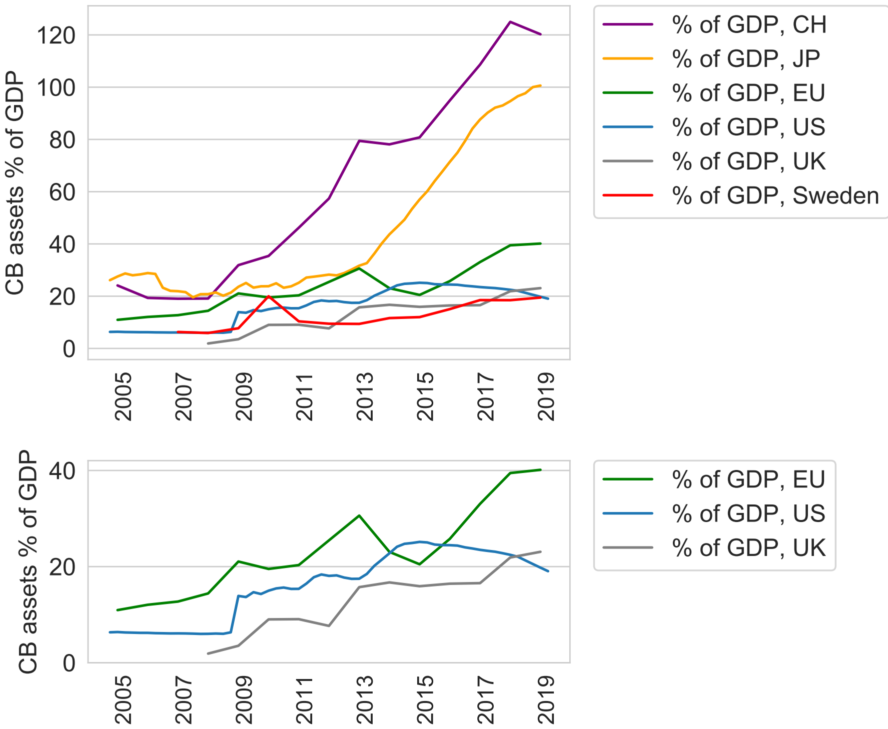


FIGURE 2.2: Central bank assets to GDP ratio for the US, Euro area, Sweden, Switzerland, Japan and UK. *Upper Chart:* All countries. *Lower chart:* 'Zooming' in on the EU, US and UK. Source: FRED, Federal Reserve Bank of St Louis.

2.2 Financial spillover

Financial spillovers are externalities that become more and more important in an increasingly integrated world economy. They can be positive or negative, but from a systemic risk perspective, a large literature is devoted to studying negative externalities that arise from growing financial integration (e.g. Berrospide et al., 2016; Glasserman and Young, 2016; Schnabl, 2012; Edison et al., 2002; Agénor and da Silva, 2018). In this context, financial spillovers are associated with the transmission of shocks across interconnected markets and financial institutions. The rising degree of integration of the global economy leads to new policy challenges, such as how to prevent contagion of financial volatility and boom and bust cycles.

At the same time, the effectiveness of Quantitative Easing as a new form of monetary policy has been discussed extensively in recent years (see Kuttner (2018) for a recent review, Neely (2015) for an affirmative view and Greenlaw et al. (2018) for a sceptical view). From a domestic perspective, an important question is whether QE decreases the yield of the safe asset, i.e. the 10-year government bond, and whether this supports the real economy (e.g. Schenkelberg and Watzka, 2013; Weale and Wieladek, 2016). From an international perspective, researchers and policymakers are concerned with the fact that QE may destabilise emerging markets by causing sudden reversals in capital flows and asset price bubbles (Raghuram, 2014).

Figure 2.3 shows the different channels that are being discussed in the QE literature and the literature on financial spillover between markets and institutions. It is important to note that these channels are interconnected and occur simultaneously, and disentangling them is inherently

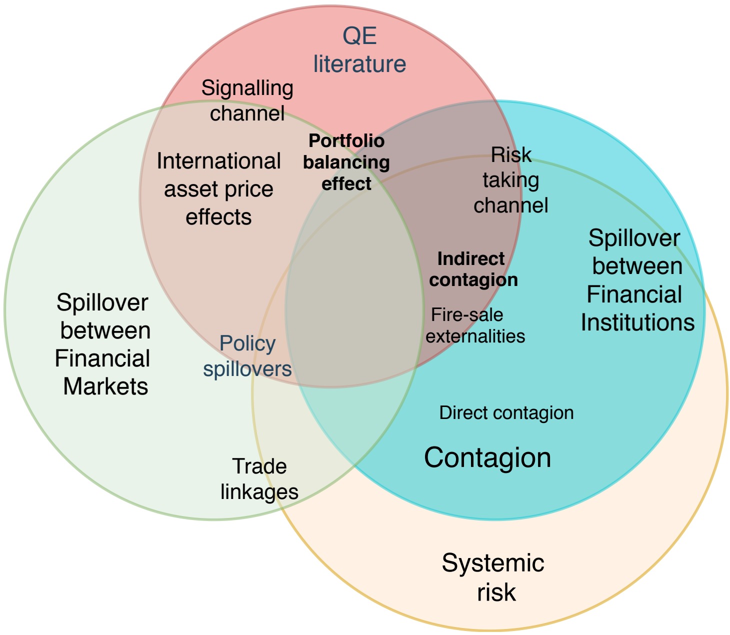


Figure 2.3: Red circle: QE literature overlaps with 'spillover between financial markets' and 'spillover between financial institutions'. Bold channels highlight the focus of the dissertation on portfolio balance channel and indirect contagion channel.

difficult.

The international asset price channel plays an important role within the 'market view'. Due to the ongoing international diversification and rising cross-border holdings, asset prices are correlated across geographical regions (Bekaert et al., 2011). In the context of QE, there are two channels that are highlighted to act as underlying transmission mechanisms for asset price effects: 1) the **portfolio balancing channel** and 2) the **signalling channel** (Bhattarai and Neely, 2016; Gagnon et al., 2011a; Krishnamurthy and Vissing-Jorgensen, 2011b). They are displayed at the 'borders' of respective circles in Figure 2.3 because they play a role in various strands, i.e domestic and international asset price effects, as well as market spillover and institutional spillover. The portfolio balance channel refers to the supply and demand effects which are associated with QE. When central banks buy certain assets on a large scale, the supply of that asset decreases. This may lead to changes in the price of the assets that were bought, as well as other assets in the market. For example, lower yields of bonds in one market may lead to substitution effects towards higher yielding assets in other market segments and/or geographical regions. However, it is not clear whether the portfolio balancing effect actually occurred and whether it resulted in significant changes in asset prices and returns. There are several points to consider. Farmer (2012, p.3) pointed out that 'much of the academic discussion concerning the effectiveness of qualitative easing has been conducted in the context of general equilibrium models where rational forward-looking agents are able to trade securities in a set of complete financial markets'. In this framework, central bank asset purchases represent a swap of one interest-bearing asset (government bond) for another (cash reserves) and are 'irrelevant, because complete markets transfer risk completely and efficiently' (ibid). Rational agents internalise this swap on the part of the central bank and adjust their positions to reverse the central bank intervention. Hence, a change in the composition and size of the central bank's balance sheet can't have an effect on asset prices (Eggertsson and Woodford, 2003; Wallace, 1981). In addition, one should note that on aggregate, banks are 'forced' to hold the reserves newly created by QE. It is impossible to get rid of reserves in the system as a whole, so the cash will end up on some banks' balance sheet. The portfolio balance channel plays an important role in this dissertation and will be discussed in more detail in Section 2.2.2.

The signalling channel refers to the fact that announcements about asset purchases affect **expectations** of market participants, which in turn feed back into asset prices. This channel is about the information that is contained in central bank decisions and is not directly linked to the purchase operations. For example, announcements about US QE programs may 'signal' continuing accommodative monetary policy leading to lower expected long-term interest rates in the US, which in turn may lead to lower expected long-term interest rates in emerging markets if other countries also pursue an accommodative monetary policy stance. These kind of policy spillovers are important within the literature for financial market spillover and are discussed, for example, by Mohanty (2014) in the context of QE and by Rey (2016) in a general way. The last sub-field in the left circle, 'Trade linkages', is an example of financial market spillover that are not directly relevant in the context of QE. This literature emphasises the role of trade in financial contagion, and emerged following a series of currency crises in the late 90s (Eichengreen et al., 1996; Caramazza et al., 2004; Glick and Rose, 1999). One of the findings of this literature is that contagion associated with currency crises spreads more easily between countries that are connected by international trade linkages than, for example, countries having similar macroeconomic conditions. The underlying transmission channel for these kind of spillovers is the exchange rate channel. For example, if one country suffers a speculative attack on its currency and experiences large currency depreciation, its exports become more competitive, which can lead to growing current account deficit with its trading partner. If this process becomes excessive, the trading partner could in turn experience a critical situation with its central bank depleting its foreign reserves and its currency depreciating to a degree that destabilises its banking system.

Financial spillovers between financial institutions are represented by the turquoise circle on the right-hand side in Figure 2.3. Within this literature, there is a focus on systemic risk arising from contagious processes within interconnected financial networks, with many papers focusing on the banking sector (two excellent reviews are presented in Summer, 2013; Glasserman and Young, 2016). Topics related to contagion in financial networks investigate the amplification of shocks through direct and indirect balance sheet linkages, price spillovers and risk-taking behaviour. Direct contagion typically focuses on the liability side of financial institutions and on how losses associated with defaulting debt contracts and receding liquidity spread across the interbank market (Upper and Worms, 2004), while indirect contagion focuses more on the asset side and the role of common asset holdings. Recent papers model contagion across different types of institutions like money market funds and banks (Cipriani et al., 2013), as well as banks and mutual funds (see e.g. Puy, 2016; Calimani et al., 2017; Baranova et al., 2017).

However, in the context of QE, the risk-taking channel is the most important channel within the literature on spillover between financial institutions (see e.g. Dell'ariccia et al., 2017; Rijckeghem and Weder, 2001; Rodnyansky and Darmouni, Rodnyansky and Darmouni). One aspect of this channel is bank lending. The bank lending channel describes the relationship between Quantitative Easing and banks' credit extension to domestic and international financial institutions and firms. Morais et al. (2019) show in the example of Mexico that British QE increased foreign credit supply to Mexican firms via institutional linkages. For the EU market, a recent paper by Grosse-Rueschkamp et al. (2019) demonstrates that Euro area QE resulted in higher risk-taking in corporate credit extension of European banks with low capitalisation ratios and high non-performing loans. For the US market, Kandrac and Schlusche (2017) show that US QE programs increased the share of risky loans on a sample of about 3000 US banks. Banks' risk-taking behaviour is also at the centre of attention in a paper by Cecchetti et al. (2017), who document that US QE led to increasing bank leverage in a sample of non-US banks.

PART II of the dissertation develops an agent-based model to study spillover effects between financial institutions in the context of QE. To do this, we build on Cecchetti et al. (2017)'s findings and investigate the role of banks' leverage in a price-shock propagation model for the South African banking sector. More specifically, we focus on one source of systemic risk and investigate the emergence of fire-sale externalities within the South African banking sector. Before we proceed, however, we will discuss the contagion channels that arise in financial networks in more detail in the next section.

2.2.1 Channels of contagion in financial networks

Even before the financial crisis researchers knew that systemic risk can arise in many forms. Triggers of systemic events include, for example, bank runs or large-scale loan defaults on the part of over-indebted households. However, systemic risk also resides "within" the financial system in the complex nature of the interconnected relationships between institutions which are not obvious to the observer. A large literature seeks to measure this kind of systemic risk by tracing amplification mechanisms that propagate shocks in those networks. These amplification effects can be direct or indirect and arise in different channels of contagion. Direct amplification typically occurs between financial institutions which are connected through bilateral contractual obligations (Brunnermeier and Pedersen, 2009). Interbank loans are one example of such direct balance sheet linkages which play a role in loss propagation. If one financial institution defaults on its liabilities, it adversely impacts the balance sheet of another financial institution, which triggers further losses and so on. This is referred to as domino contagion or *cascades of defaults*. The seminal paper in this field is Eisenberg and Noe (2001), which study how payment shortfalls spread in the banking sector following the bankruptcy of one or more individual institutions. Eisenberg and Noe (2001) show that under certain assumptions and given a network of nodes and interbank obligations, there exists a "unique clearing vector" that determines the damage of the insolvency shock. The framework provides a tool to quantify systemic losses by tracking how the initial default propagates across the system. To allow for the mathematical solutions, the model has simplified assumptions. For example, banks maximise the entropy of their linkages, which means that they spread their interbank exposures as evenly as possible across counterparties. Furthermore, there are no recovery rates; all payment obligations have equal priority and contagion can only arise from domestic exposures. Eisenberg and Noe (2001)'s framework was widely applied to model and quantify systemic losses from interbank default contagion and there exist many variations of the original model. Fischer (2014), for example, derives a more general case in which there are obligations with different seniority levels and simple derivatives. There is also an extensive literature investigating the effect of the network structure on such default cascades (see e.g. Gai et al., 2011; Acemoglu et al., 2015; Georg, 2013). The role of network structure is reviewed by Allen et al. (2010), who conclude that a system with a more complete set of connections may be less susceptible to contagion than those with an incomplete connection structure.

But financial systems are not only vulnerable to direct amplification effects that arise from insolvency contagion, but also to *indirect* amplification effects that can propagate through price shocks. To account for both direct and indirect amplifiers, Glasserman and Young (2015) use Eisenberg and Noe (2001)'s framework and expand it by introducing bankruptcy costs, market-to-market losses and confidence shocks. They find that the topology of the network is particularly important once bankruptcy costs are accounted for. When comparing direct with indirect amplification effects, they conclude that indirect effects from price drops associated with mark-to-market accounting may have a higher impact on systemic losses than pure "domino" effects from direct default contagion. This is because, in severe cases, large price declines lead to self-reinforcing liquidation spirals. When banks are in distress and want to cover their losses, they "dump" their assets on the market, which leads to excess supply and further depresses prices. Such price-mediated liquidation spirals are modeled as fire-sale externalities in the literature.

Fire-sale contagion

Fire-sale externalities are pecuniary externalities that operate through prices. They pose a threat to the financial system because they amplify price shocks across assets and thus lead to liquidation spirals. Post-crisis, they have received a lot of attention as researchers emphasised the role of fire-sales as a source of systemic risk. Shleifer and Vishny (2011) give a good overview and define fire-sales as forced sales of illiquid assets, which are traded at prices far below value and which propagate across various asset classes and institutions. Furthermore, they highlight that fire-sales are particularly potent as a destabilising factor in the financial sector because of financial institutions' vulnerability to sudden stops in their short-term financing. Even though the literature on fire-sales has been expanding recently, the models which are used to study these effects are set up in a similar way. Typically, there is a set of financial institutions which are holding common assets on their balance sheets and which are subject to a binding constraint, example, regarding their leverage capital requirements or risk-weighted capital requirements. There is an exogenous shock that hits the system and financial institutions start liquidating assets as their constraint is violated. This causes a drop in market prices and induces "second round" losses which potentially trigger further liquidations. An important assumption that drives these models concerns the price impact, i.e. how much the price moves given the liquidity and trading volumes of an asset. The table below serves as illustration of different fire-sale modelling approaches in the theoretical and empirical literature. It's noteworthy that most theoretical contributions are able to integrate into multiple contagion channels using stylised balance sheets. In empirical papers, researchers apply fire-sale algorithms on more realistic balance sheets, but use simpler model frameworks.

In their theoretical work, Cifuentes et al. (2005) use an exponential price impact in a system of banks that engage in fire-sales following a shock to one tradeable asset. If liquidation gains of this asset are not sufficient, banks start selling the illiquid asset to restore their fixed risk-weighted capital ratio. If they still can't bring their capital ratio back within required levels, banks will default and trigger direct contagion to its counterparties. By employing Eisenberg and Noe (2001)'s framework, Cifuentes et al. (2005) are able to determine equilibrium payments between banks and equilibrium prices of assets. Nier et al. (2007) construct an artificial banking system and investigate contagion probability in a network of banks with an exponential price impact function. Fire-sales occur in the event of a bank default as all assets of the insolvent bank are dumped on the market. Caccioli et al. (2014) use a similar approach where an insolvency of one institution triggers fire-sales and default contagion within a network of banks. In their stylized model, they find that banking systems are stable below a critical value of leverage and become more and more unstable as leverage increases above this value. In a recent ECB working paper, Calimani et al. (2017) simulate a financial system with banks and asset managers, label shadow banks, and investigate contagion from fire-sale externalities and interbank default contagion across different types of financial institutions. They model an interbank loan market with endogenous interest rates and introduce a liquidity shock to financial institutions. Interestingly, they find that the shadow banking sector is able to absorb small shocks better than the traditional banking sector, largely due to the fact that they are less burdened by regulatory constraints.

Table 2.1: Fire-sale modelling approaches

Authors	**Financial institutions**	**Fire-sale trigger**	**Price impact**	**Data**	**Channels**
Cifuentes et al. (2005)	Banks	Shock to marketable asset violates constant risk-weighted capital ratio constraint	Exponential	Simulated	Fire-sale and default contagion
Greenwood et al. (2015)	Banks	Shock to GIPS bonds violates constant leverage ratio constraint	Linear	Empirical data on European Banking sector	Fire-sale contagion
Caccioli et al. (2014)	Banks	Insolvency of one bank or large price shock to a random asset	Linear	Simulated	Fire-sale and default contagion
Nier et al. (2007)	Banks	Defaulting bank's assets are sold on the market	Exponential	Simulated	Fire-sale and default contagion
Cont and Schaanning (2017)	Banks	Shock to non marketable asset	Concave function depending on market depth	Empirical data on European Banking sector	Fire-sale contagion
Calimani et al. (2017)	Banks and Asset Managers	Critical liquidity shock to bank, i.e. withdrawal of funding which cannot be offset by cash buffer or call-back of bank lending	Endogenous clearing price for non-liquid asset	Simulated	Fire-sale and interbank liquidity contagion

QE, leverage and fire-sale contagion as pitfalls for financial stability

Fire-sale externalities occur in situations where financial institutions experience sudden constraints, e.g. a large liquidity requirement, which lead to forced liquidation of assets. A trigger for such a condition is a large exogenous shock, for example, a bankruptcy of a major investment bank as we have seen with Lehman Brothers in 2008. An unconventional monetary policy in the form of Quantitative Easing is unlikely to cause such an event. In the last decade, QE was implemented in the US, UK, Japan, Canada, Sweden, Eurozone and Switzerland. During this time, we have not seen evidence that central bank purchase programs would cause liquidation spirals in banking systems. However, QE may affect fire-sale spillover indirectly through changing risk-taking behavior of financial institutions. Borio and Zhu (2012) were among the first to highlight the link between accommodative monetary policy and risk-taking. They coined the term "risk-taking channel", which describes the effects that work through the risk appetite of financial intermediaries. One way to investigate the relationship between risk-taking and monetary policy is to determine how monetary policy influences leverage. In fact, Bruno and Shin (2015) argue that bank leverage acts as the linchpin of the risk-taking channel of monetary policy. Using quarterly data from 1995 to 2012, they show that, following an expansionary shock to US monetary policy, higher leverage of international banks increases cross-border bank capital flows. In respect of Quantitative Easing, Cecchetti et al. (2017) conduct an empirical analysis of the link between the Fed's QE and leverage ratios of US and non US banks. They find significant evidence of QE increasing leverage in both bank and non-bank financial intermediaries outside of the US. This suggests that through the role of leverage, QE may have detrimental effects for financial stability. It has been shown empirically by Gourinchas and Obstfeld (2012) in an extensive study on data from 1973 to 2010 that a rapid increase in leverage stood out as a significant factor in predicting financial crises for both developed countries and emerging markets. In a similar way, Schularick and Taylor (2012) use data on 14 developed countries from 1870 to 2008 and come to the conclusion that leverage plays an important role in contributing towards financial vulnerability, especially leverage within the banking sector.

Our first contribution is to draw together the two strands in the literature that highlight the importance of leverage as the common thread for financial stability and the transmission of unconventional monetary policy. In PART II of the dissertation we build on Cecchetti et al. (2017)'s findings and investigate vulnerabilities that arise in the South African banking system following higher leverage. We are the first to investigate the impact of the risk-taking channel on indirect fire-sale contagion for the example of South Africa.

2.2.2 Channels of contagion through international asset price effects

PART III of the dissertation develops a dynamic heterogeneous agent model to determine price spillover in the context of QE. The aim of this section is to review the literature that looks at the link between QE and financial markets, particularly in respect of asset returns. There are two main channels that are being discussed that could potentially move asset prices: the signalling channel and the portfolio balance channel.

The signalling channel

The signalling channel considers the fact that central bank communication of asset purchases affects market participants' expectations. For example, central banks' QE announcements can be interpreted as a commitment to keeping an accommodative stance of monetary policy. This may signal more favourable macro-economic conditions in the future and higher firm output and dividends, which feed back into the pricing kernel of equities. In more general terms, Cochrane (2009) advocates that the price of any asset equals the expected future payoff x discounted by a factor m, i.e. $p_t = E[m_{t+1}x_{t+1}]$. QE can then work through the signalling channel by changing either the discount factor or the expected income stream.

In the case of bonds, the expected future income stream is known due to the 'fixed' coupon and principal repayment. The discount rate, however, may change in the future, for example if the short term interest rate rises. This implied interest rate risk is higher, the higher the uncertainty and the longer the time to maturity. In addition, the discount rate may be affected by the perceived default risk of the asset issuer which can vary over time. High risk requires compensation, which is why higher default probability increases the discount factor, which results in lower bond prices.

Government bonds

In theory, the default risk for government bonds is 0 because governments can always raise taxes to fulfill their financial obligations. To investigate the relationship between QE and government bond returns, it is common to focus on the 10-year bond because it is the risk-free long-term interest rate in the market. The analysis of the 10-year bond yields plays an important role in the QE literature. The upper row in Figure 2.4 shows the correlation between movements in long-term interest rates in the US and Germany with periods of balance sheets' expansion (grey shaded area). Overall, there is a downward trend in long-term interest rates; however, it is not entirely clear what happens during the implementation of QE. In the US, in particular, it seems that long-term interest rates increased during the US Fed's large-scale asset purchases (LSAP). The empirical challenge is to infer causality between QE and asset price movements in the face of many confounding factors and endogeneity problems, for example in respect to simultaneity and omitted variables.

In an attempt to curb endogeneity issues, a large strand of literature uses an event study approach when investigating the impact of QE announcements on bond yields. In these papers, high frequency data is used on a narrow window around central banks' asset purchase announcements or implementation days. Some of those studies inform their regression with models that decompose the yield into an component reflecting the average expected short term interest rate and a risk premium component (see e.g. Krishnamurthy and Vissing-Jorgensen, 2011a; Krishnamurthy et al., 2017; Christensen and Krogstrup, 2018). This approach can be traced back to amended versions of the expectation hypothesis of the term structure of interest rates. Term structure models are derived from a no-arbitrage argument and determine long-term interest rates to be the average expected short-term interest rate plus a risk premium (Cox et al., 1985). Researchers

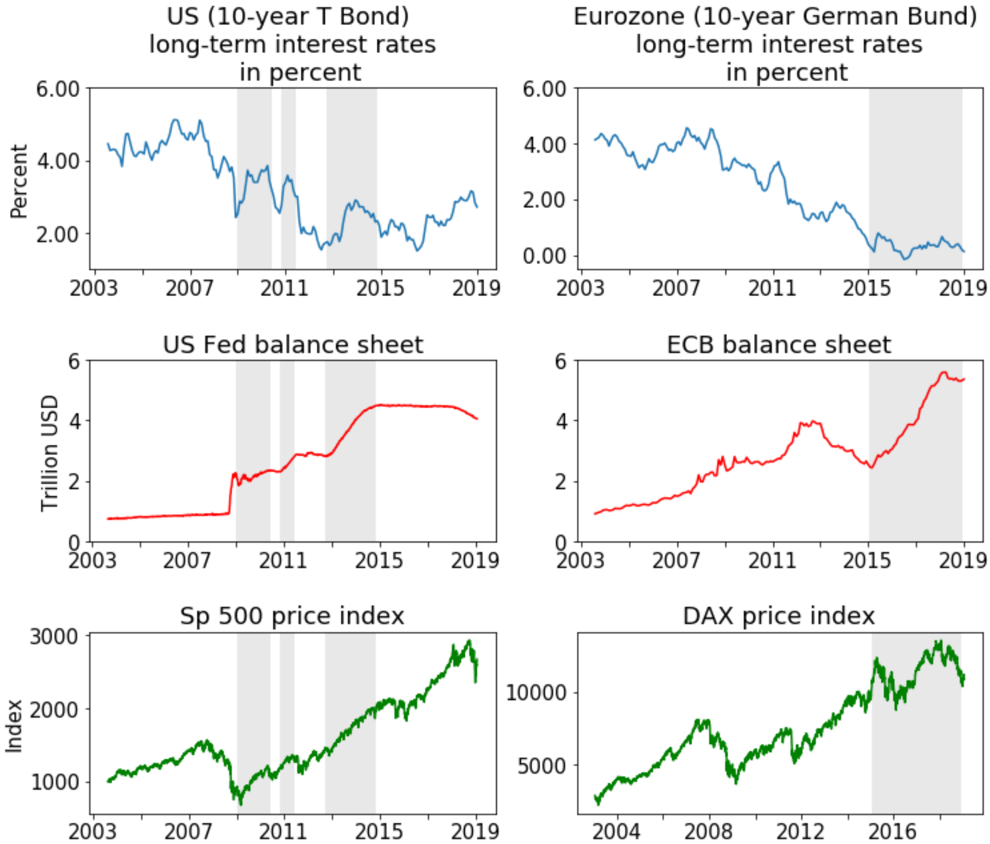


FIGURE 2.4: *Left:* US long-term interest rates (10 year Treasury bond) in percent (top), US Fed balance sheet in trillion USD (middle) and US S&P500 Equity price index (bottom). *Right:* Long-term interest rate of the 10 year German Bund in percent (top), ECB's total assets in in trillion USD (middle) and DAX stock market price index (bottom). Shaded areas indicate periods of balance sheet expansion during the US Fed's Q1 to Q3 program and the ECB's APP. Source: FRED, Federal Reserve of St Louis.

seek to identify the signalling channel by tracing changes in the expectation component of the yield around QE announcements. In the case where not the expectation component, but the risk premium is affected, the underlying channel is presumed to be the portfolio balance channel. The portfolio balance channel plays an important role in this dissertation and is be the focus of the next section.

The portfolio balance channel

The portfolio balance effect is the other main channel in discussion of whether QE affects financial asset returns. In fact, when QE was introduced in the US and UK in the wake of the crisis, policymakers stated that they anticipate this to be the main channel to lower long-term interest rates (see e.g Bernanke, 2008; Dale, 2010).
The hypothesis behind the portfolio balance effect is that central bank purchases affect quantities of assets available in the market, which will lead to changes in assets' expected returns. One underlying assumption of this is that assets are imperfect substitutes allowing for investors to have different downward-sloping demand curves. This is why it is also referred to as channel of *imperfect asset substitution* (Kuttner, 2018). To give two examples, pension funds can have a higher preference for assets of longer maturity and hedge funds can be particularly demanding of assets with high price volatility.

Theory
Even though policymakers were anticipating the portfolio balance effect, its existence is contested in the economic theory literature (Thornton, 2012). This is because there are several theoretical frameworks in which a relationship between relative asset supplies and their expected return is not possible.

First, from the perspective of the consumption-based asset pricing approach in the macro literature, the pricing kernel of an asset depends on its expected state-contingent cash flows and their relation to households' state-contingent income. If we think of QE as a swap of assets between the central bank and the private sector in the sense that one public sector liability ('government bond') is exchanged for another ('bank reserves'), this should not affect expectations of households' income stream. Hence, asset prices remain unaffected. A Ricardian equivalence type argument is furthermore invoked to show that asset purchases by the central bank do not change households' overall exposure to desired assets (Woodford, 2012).

This means macroeconomic theory is rather bleak regarding the effectiveness of QE. Shifts in the supply of bonds are shown to be irrelevant within the frameworks of Wallace (1981) and Eggertsson and Woodford (2003). However, there are some newer New-Keynesian models where central bank asset purchases can affect interest rates. For example, Andrés et al. (2004) incorporate portfolio adjustment costs and heterogeneous preferences for assets of different maturities into a DSGE framework and show that central bank asset purchases can impact yields. Chen et al. (2012) use a similar approach and show that the effectiveness of QE to stimulate the economy depends on the degree of market segmentation between short-term and long-term bonds.

Second, there is also skepticism from the perspective of conventional term structure models of interest rates. In most standard term structure models, demand curves for bonds are flat and investors view bonds of different maturities as perfect substitutes. Any additional risk associated with longer term assets is entirely compensated by the term premium. Changes in relative asset supplies do not affect the assets' risk nor the risk aversion of investors, hence no portfolio balancing channel can materialize (Doh, 2010).

So where does the portfolio balance effect come from? It appears in a class of models - so-called 'portfolio balance models' - that can be traced back to Tobin (1958). By letting risk-averse households optimise the composition of a portfolio comprising riskless but low-yielding cash and risky but higher-yielding bonds, Tobin's model provided a microfoundation for the liquidity preference, which was a standard component of macroeconomic models at the time. In equilibrium, lower yields on bonds would elicit a rebalancing of the portfolio towards cash and thereby explain the inverse relation between the demand for cash and the interest rate on bonds from Keynes' liquidity preference theory.

Whereas Tobin's original model dealt with the substitution between money and bonds, portfolio balance models, in a more general way, describe a class of arbitrage-free models in which the relative amounts of assets held by investors matter for the term structure of interest rates and other asset prices. Investors' objective function optimises the overall return and risk of their portfolio. This works in a way that expected returns and prices are adjusted to make investors willing to hold whatever securities are outstanding in each period. In aggregate, total asset holdings of investors are constrained to be the same as the available exogenous asset supplies of each asset. Variants of portfolio balancing have been incorporated in Walsh (1982); Piazzesi and Schneider (2007); Joyce et al. (2011); Neely (2015).

A model presented by Vayanos and Vila (2009) shows how the supply of assets of different maturities affect the term structure when interest rates are determined through the interaction of preferred habitat investors and risk averse arbitrageurs with mean-variance preferences. One of the implications of Vayanos and Vila (2009)'s model is that asset purchases are more effective in reducing long-term yields when risk aversion of arbitrageurs is high. Variations of Vayanos and Vila (2009)'s model have been calibrated to US data and find that the change in Treasury debt supply following QE has predictive power for determining the decline in bond yields (e.g. Hamilton and Wu, 2012; Greenwood and Vayanos, 2014; Doh, 2010).

Empirically, there seems to be little doubt that asset purchasing programs by major central banks had at least some effect on yields directly after they were announced. In respect of methodological approaches, researchers have used event studies and Vector autoregression (VAR) models, as well as calibrated Dynamic stochastic general equilibrium (DSGE) models (Bhattarai and Neely (2016)).

As previously mentioned, event studies that use high frequency data to quantify the changes in bond yields around QE announcements are particularly popular in the financial market research of QE. Table 2.2.2 on page 22 provides an overview of such event study findings for US-based purchase programs. The largest effect is associated with the announcement of the initial QE1 program, which caused US Treasury yields to decline by approx. 100 bps, while subsequent QE announcements lead to a decline between 14 and 40 bps (see Krishnamurthy and Vissing-Jorgensen, 2012; Gagnon et al., 2011a; Ehlers, 2012).Given the recency of the APP, there is much less research on the effect of Eurozone QE. Only a few papers study the effects of the ECB's asset purchase program (APP) that was announced in January 2015. Event studies quantifying the effect of the APP on euro area 10-year government bonds estimate that yields declined by between 30 bps and 70 bps (see Motto et al., 2015; Breckenfelder et al., 2016; De Santis, 2016). Koijen et al. (2016) show the changes in securities' holdings of domestic and foreign investors per asset class, sector and region over the seven quarters following the ECB's announcement. They find that the ECB's purchases of government bonds were mainly accommodated by foreign investors, who provided 70% of the ECB's asset purchases, and to a lesser degree by euro area banks and mutual fund investors. In addition, Koijen et al. (2016) show that insurance companies and pension funds reacted by buying bonds with similar maturities as the ECB, thereby amplifying the reduction in government bond supply.

Empirical work

Notwithstanding the growing evidence of QE's role in impacting asset prices, the dominating channel through which prices are affected and the persistence of effects are controversial. While many empirical studies associate the impact of QE with the change in asset supply associated with the portfolio balance effect (see e.g. Neely, 2015; Joyce et al., 2011; Gagnon et al., 2011b; Stefania and King, 2013)), a few associate the effects with a signaling channel (e.g. Bauer and Rudebusch, 2014; Bauer and Neely, 2012). Krishnamurthy and Vissing-Jorgensen (2011a) for example, find that the signaling channel plays the primary role in the decline of US Treasury yields in connection to the US-based QE2 program, while the portfolio balancing channel was responsible for lowering Mortgage Backed Securities (MBS) rates and corporate bond yields in connection to the QE1 program.

US	Announced	EUR	Measured effect	per 100 bn EUR	Paper
LSAP QE1	Initial announcement		10-year US Treasuries		
	- 25. November 2008				
	- 600bn US Dollar MBS	471bn	i) -22bs	-4.9 bps	i) Gagnon et al (2011), Table 1 page 19
			ii) - 36bps	-7.6 bps	ii) Krishnamurthy & Vissing-Jorgenson (2011), p.230
			iii)- 23.1bps	-4.9 bps	iii) Bauer & Neely (2014), p.39 Table 4
LSAP QE1	- 18 March 2009		i) - 47bps	- 5.8 bps	i) Gagnon et al (2011),Table 1 page 19
	750 bn USD MBS	804.6bn	ii) - 41 bps	- 5.2 bps	ii) Krishnamurthy & Vissing-Jorgenson (2011), p.230
	300 bn USD US Treasuries		iii) - 50.5bps	-6.3 bps	iii) Bauer & Neely (2014), p.39 Table 4
	= 1050 bn USD				
			Cumulative effect		
			iv) 91 bps cumulative		
			across 8 ann. in	- 7.1 bps	iv) Gagnon et al (2011),Table 1 page 19
			baseline events		
			v) 107 bps cumulative		
			across 5 ann. events		
			vi) -122.8bps	- 8.4bps	v) Krishnamurthy & Vissing-Jorgenson (2011), p.230
				- 9.6bps	vi) Bauer & Neely (2014), p.39 Table 4
LSAP QE 2	03-Nov-10		Cumulatively across ann. 8/10 and		
	- USD600bn US Treasuries	439.4bn	9/21 2010		
			i) -30bps	-6.8 bps	i) Krishnamurthy & Vissing-Jorgenson (2011), p.248*
			ii) -40bps	- 9.1 bps	ii) Ehlers (2012), p.249*
			iii) -45 bps	- 10.2 bps	iii) D'Amico eta l. (2012)
LSAP QE 3	22 Aug 2012 & 13 Sept 2012				
	- 40bn USD MBS monthly	137.1 bn	i) -14.0 bps	-10.2 bps	i) Bauer and Neely (2014), p.39 Table 4
	-40 bn USD US T monthly,				
	- gradually reduced to 10bn monthly				
	- stopped December 2014				

Table 2.2: Overview of empirical findings on the impact of US QE on government bonds. Author's own calculations.

Other papers try to separate the two effects by comparing event study results with results implied by a portfolio model. For the UK, Joyce et al. (2011) calibrate a portfolio choice model to determine the impact of the Bank of England's purchases on domestic returns for government and corporate bonds, equities and cash. By estimating a VAR impulse response function, Joyce et al. (2011) conclude that through the portfolio balance channel, British QE led to a decline in gilt yields in the range between 30 and 85 bps. Expanding the portfolio model to an international scale, Neely (2015) evaluates the impact of US QE on international long term interest rates and exchange rates. He also back-tests his empirical findings with a portfolio model, lending support to the existence of the portfolio balance channel. Expected foreign returns are adjusted by expected inflation and expected exchange rate changes, assuming that long run purchasing power parity holds. The US Fed's LSAP purchases are introduced through a swap of US government bonds for the risk-free liquidity asset, leading to declines in domestic and international bond yields ranging from 35 and 144 bps and a US Dollar depreciation between 3.5% and 7.8%.

An alternative model of portfolio balancing is presented by Christensen and Krogstrup (2017), who argue that the supply-side induced portfolio balance effect can be amplified by the fact that QE leads to an expansion of bank balance sheets when transactions are done with non-bank entities because of additional deposits that are created. The authors refer to this as reserve-side induced portfolio balance effect of QE and present empirical evidence that the Swiss National Bank's asset purchases lowered the yield of the Swiss 10-year bond by 28 bps through this channel.
Beside the difficulty of disentangling the impact channel of QE announcements, identifying the information that drives changes in investor behavior is not straightforward either. Greenlaw et al. (2018) have raised the concern that empirical results derived from event studies may overstate the effect of QE. The authors doubt that only effects of monetary policy announcements, rather than other economic news, are measured. Event studies assume that any impact within the narrow window around an announcement event is solely associated with market participants reaction to QE announcements. However, when Greenlaw et al. (2018) consider a larger than usual sample of possible events, they find that announcements by the US Fed have not played a major role in changing yields and that the initial impact, if measurable, did not persist.

A number of studies has focused on the effect of QE on capital flows to emerging markets (see e.g. Aizenman et al., 2016; Mishra et al., 2014; Eichengreen and Gupta, 2015). Chen et al. (2012) show a significant "expansionary impact" of US QE on asset prices in Asia and Latin America in the short and medium term. Focusing on the tapering announcement of QE, Eichengreen and Gupta (2015) find strong negative pressure on forex and equity rates in emerging markets, alluding to capital outflows following QE tapering announcements. According to these authors, the effect was the more pronounced, the larger and more developed the the emerging market indicating that investors were able to "better rebalance their portfolio" (ibid., p.1). A similar result is presented in Aizenman et al. (2016)'s quasi-event study, which finds that financially developed countries were more significantly impacted by tapering news announcements, as least in the short term.

2.3 Agent-based models for contagion modelling

This section provides a brief introduction to the topic of agent-based models (ABM) to illustrate why this approach is suited for the analysis. Agent-based modelling is a computational methodology that focuses on the interaction of autonomous agents within a system. The methodology has received growing attention in the last two decades, and even more in the wake of the crisis which has demonstrated a glaring need for new economic models and thinking. While still regarded with skepticism by the mainstream, ABMs present an alternative approach to the representative agent paradigm found in general equilibrium models such as DSGE models.

In essence, agent-based models incorporate micro-founded behaviour of rational or bounded-rational agents, who interact according to a given set of rules. Agents' decision rules and characteristics are often heterogenous, e.g. in respect of their preferences or expectations. The agent-based framework is highly suited to include learning behaviour in agents' decision rules. Some examples of advanced learning techniques include neural networks or evolutionary algorithms (Bonabeau, 2002). Adaptive behaviour of agents may cause them to evolve and one may observe unanticipated phenomena that emerge dynamically over time, such as asset price bubbles or regional segregation of households with similar demographics (Lux, 1995; Boswijk et al., 2007; Schelling, 1971).
It's important to note that ABMs come in many forms and that not all agent-based models include adaption and learning. Applications within economics are particularly prominent for **financial market** models and models of **networks**. This dissertation presents a study of ABM applications in both of these fields, with PART II being an example of a network ABM of financial institutions and PART III being the case of a financial market ABM.

ABM applications to financial markets have been successful in the sense that they could reproduce stylised empirical facts like fat tails in returns, clustered volatility and herding behavior (see e.g. LeBaron, 2001; Chen et al., 2012)). There are equilibrium and disequilibrium models in the literature. Among the latter group, Beja and Goldman (1980) were the first to model a financial market with a market maker adjusting excess demand stemming from traders with diverging beliefs about asset prices. Examples of disequilibrium models which build on the distinction between fundamentalists and chartists include Day and Huang (1990) and Chiarella (1992), who show that the involvement of chartists/speculators above a certain threshold destabilises the market. Farmer and Joshi (2002) present a log-linear price impact function and explain how clustered volatility can arise with the emergence of different trading strategies. In the group of equilibrium models, De Grauwe and Rovira Kaltwasser (2012) model an exchange rate in the presence of fundamentalists and chartists where the proportions of the strategies evolve endogenously over time.

Another literature strand where ABMs are a popular methodological approach is network theory (e.g. Amblard, 2002; Tesfatsion, 2006), particularly in respect of modelling endogenous development of network structure through adaptive behaviour. An important research question is concerned with how specific structural features of the network (e.g. size, centrality, interconnectedness) influence the stability of the studied system. In the context of financial systems, de-stabilising factors concern the propagation (or contagion) of information, portfolio similarity (e.g. Elliott et al., 2018; Georg et al., 2019), price shocks (Bookstaber et al., 2018), debt defaults (Georg, 2013) and liquidation spirals (Calimani et al., 2017). One of the most pressing questions concerns the identification of conditions that render financial networks prone to either risk-sharing (i.e. with favorable consequences for stability) or loss amplification (i.e. with unfavorable consequences for stability). Against this backdrop, a number of network ABMs have contributed with insightful results and policy recommendations. Applying a dynamic network model with endogenous network formation (Georg, 2013) shows that in "higher interconnected networks, shocks will spread more rapidly, which implies a higher fragility of the system once the tipping point is reached".[3] The author recommends central bank intervention in the short term due to its stabilising effect on the financial system, but not in the long term. In the case of static network structure,Ladley (2013) models an exogenous network topology, but endogenous bank behaviour and interest rate formation to study systemic events in a banking system. He finds that risk-sharing and amplification depend crucially on the size of the shock. For large shocks, a network displaying higher connectivity in the form of more inter-bank lending relationships provides a 'channel of failure' and aggravates the situation. For small shocks, however, the author finds the opposite effect. Furthermore, he finds that a deposit insurance is the most effective policy to reduce the cost of negative network externalities and thus, benefit network stability.

2.3.1 Complexity and realism vs tractability

ABMs are built from the perspective of looking at the economy as a complex evolving system. It is common to include a set of realistic and flexible assumptions regarding agents' behaviors and interactions. Examples of such assumption can be limited information or bounded rationality. The realism in agent-based models is an attempt to achieve empirical understanding and replication (see Tesfatsion, 2006). However, the more one tries to incorporate realistic assumptions into the model, the more complex the system becomes.

This may lead to over-complicated models featuring multiple equilibria or out-of equilibrium solutions. Simulation results are not as clear cut as in closed-form solutions and may have ambiguous comparative statics. This is because ABMs are not required ex-ante to be analytically solvable. Thus, one of the main criticism ABMs face has to do with their lack of tractability.

We believe it's important to balance advantages gained from incorporating realistic assumptions with a a minimum form of tractability in the ABM framework. This is why our spillover model in PART III is solved numerically through an adaptive algorithm that finds daily market clearing prices. The simulation converges to a long-term equilibrium which represents the 'steady-state' we base our analysis on.

[3](Georg, 2013, page 27).

To summarise, agent-based models are an alternative to conventional economic models when studying problems around heterogeneity, complexity and non-linearity. For our research question that studies QE-induced spillover effects on financial markets, we believe it to be best approach to account for heterogeneity in assets and investors. This, as we have seen in the previous chapter, is absolutely crucial when studying the portfolio balance channel of imperfect asset substitution associated with QE. In respect of studying spillover effects within financial networks, the agent-based model in PART II accounts for non-linearity in how shocks propagate through the South African banking sector. We will present this model in the following chapter.

PART II - QE and spillover within a network of financial institutions

This chapter develops the first heterogeneous agent model to investigate financial spillover effects. More specifically, we analyse the propagation of fire-sale spillovers in the context of QE. We build on findings presented by Cecchetti et al. (2017) that determine a relationship between QE and risk-taking behavior by financial institutions. Cecchetti et al. (2017) show that banks' leverage in respect of asset-to-equity ratios increased on average for a sample of non-US banks following QE programs by the US Fed. We conduct a hypothetical exercise and assume that QE increases SA banks' leverage after December 2015 and perform a sensitivity analysis to the leverage parameter in our model to investigate how this may affect banking sector stability.

This chapter contributes to a growing literature on contagion and spillover mechanism in financial networks. To understand price shock propagation, we implement a model of asset fire-sale contagion across 29 South African banking institutions. We focus the analysis on the banking sector due to its central role in the South African financial system. Banks still make up the largest share of total assets in the South African financial system, even though the non-bank sector is growing (Kemp, 2017). We simulate shocks on banks' assets, which trigger 1) a direct effect corresponding to the change in asset value driven by each bank's individual exposure and 2) an indirect contagion effect corresponding to the impact of the shock on each individual bank's equity through deleveraging of other banks. The model shows how the combination of these two effects leads to asset sale spillovers across banks. In essence, the paper calibrates a stress-testing exercise for South African banks and quantifies how the banking sector absorbs asset shocks. Last, but not least, a discussion of how QE impacts spillover effects completes the analysis.

3 A model of fire-sale propagation for the South African banking sector

The purpose of this chapter is to calibrate a network model studying price shock amplification processes to banks' balance sheet data to determine the conditions under which QE may affect fire-sale contagion. It's important to note that this section does not consider QE-induced price effects, but how QE might influence the conditions for which price shock amplification processes destabilise a network of banks. Section 3.1 presents Greenwood et al. (2015)'s model of liquidation spirals and extends it by including a cash liquidity buffer. Greenwood et al. (2015)'s original model abstracts from the fact that banks can use a small fraction of their asset side - their cash,

albeit low in magnitude - before they are forced to liquidate assets.
Section 3.2 provides an overview of the data set, before general shock scenarios are carried out in Section 3.3 to demonstrate determinants of systemic risk. Finally, we conduct shock scenarios in the context of QE and highlight the role of leverage in the analysis. Here we build on findings from Cecchetti et al. (2017) that show how US QE lead to an increase in foreign banks' leverage ratios. The chapter concludes with a summary of results in section 3.5.

The literature most relevant to this chapter deals with the application of fire-sale externality models to empirical data. Greenwood et al. (2015) have been one of the first to fit an indirect contagion model to empirical data. Their framework uses a constant holding structure and fixed leverage ratio to study the effect of a debt haircut for European sovereign bonds on capital losses in the European banking system. Duarte and Eisenbach (2013) apply Greenwood et al.'s model to a panel data analysis of US broker-dealer banks to investigate the effect of price declines in assets financed by repurchase-agreements. They find that a 1% decline in the price of all assets financed with repos leads to losses owing to fire-sale spillovers accumulating to 8% of total equity. Greenwood et al. (2015)'s framework is also the basis of Cont and Schaanning (2017)'s recent stress-test analysis of the European banking sector. They extend the original framework by introducing asymmetric liquidation behaviour and a concave price impact function which depends on assets' market depth and selling volumes. They perform a stress-test on the European banking sector and show that the quantification of systemic losses based on those kind of indirect fire-sale contagion effects yields substantially different results to traditional stress-test methods.

3.1 Model - Extension of Greenwood et al. 2015

3.1.1 Banks' balance sheets

The starting point for our analysis is the framework of Greenwood et al. (2015). Assume a set of n banks $B = \{1, ..., n\}$ and k asset classes $K = \{1, ..., k\}$, with $K = \{C, LB, TB\}$. We define a subset of asset classes Cash $C = \{k^c\}$, trading book assets $TB = \{1, ..., k^{tb}\}$ and loan book assets $LB = \{1, ..., k^{lb}\}$. Each individual bank b_i has total assets a_i with portfolio weight w_k on asset k such that $\sum_k w_k = 1$. On the liability side, bank i has debt d_i and equity capital e_i, resulting in leverage $l_i = d_i/e_i$.

Balance sheet

	Asset	Liabilities
$a_i = \sum_k w_k a_i$	Cash $w_{k^c}\ a_i$	Equity e_i
	$LB\ w_{k^{lb}}\ a_i$	Debt d_i
	$TB\ w_{k^{tb}}\ a_i$	

3.1.2 Algorithm

Assume an initial exogenous shock hits the banking system, triggering the following process:[1]

1. *Direct exposure*: In time t, every bank holding the shocked assets incurs direct losses which can be quantified by

$$a_{i,t} \sum_k w_{i,k,t} f_{k,t} \text{ for bank } b_i \tag{3.1.1}$$

where $f_{k,t} \in [\,\text{-}1,\, 0\,]$ is the devaluation shock on asset k. The bank can be hit with shocks on multiple asset classes, which is why the product of the portfolio weight and the shock value per asset class is summed up before multiplying by total assets $a_{i,t}$. This impact on a bank's assets reduces equity on the liability side, which leads to an increase in the bank's leverage ratio. An important assumption of the model is *leverage targeting*, i.e. banks maintain a constant leverage ratio over time. This assumption is backed by Adrian and Shin (2010), who provide some empirical evidence that large financial institutions maintain fairly stable levels of leverage in the medium term. The change in the binding leverage ratio[2] will prompt banks to become active in the market.

2. *Cash buffer*: Greenwood et al. (2015) assume that banks immediately pay off debt to return to their initial leverage ratio l_i in response to the direct losses. A convenient modelling feature that follows from their assumption is that portfolio weights of the k assets are held constant, i.e. banks sell assets in such manner that keeps their portfolio composition the same throughout the de-leveraging phase. However, we believe it is more realistic to assume that banks first use their cash liquidity buffer to pay off their debt before liquidating assets. Thus, portfolio weights are allowed to fluctuate in our model. The critical value determining the shortfall that bank i needs to cover by de-leveraging is given by

$$\Gamma_{i,t}: \quad d_{i,t} - \Big(\; l_i \quad \max\{e_{i,t} - a_{i,t} \sum_k w_{i,k,t} f_{k,t}; 0\}\Big)^3 \tag{3.1.2}$$

$$\text{with } \Gamma_{i,t} \in [0, d_{i,t}] \quad \text{and}$$

$$\Gamma_{i,t} > 0 \quad \text{if} \quad f_{k,t} < 0$$

$$\Gamma_{i,t} = 0 \quad \text{if} \quad f_{k,t} = 0$$

The intuition behind equation 3.1.2 is as follows: if the direct exposure is 0 because the shock is 0%, the shortfall bank i needs to cover is also 0. This is because, in the absence of a shock on balance sheets, the composition of the liability side does not change, i.e. equity does not change and the difference between the previous period's debt and next period's debt is also 0. If the shock is negative, the shortfall will be larger than 0 with its maximum being the previous period's level of debt.[4]

[1] The description of the framework is similar to Duarte and Eisenbach (2013), pp. 5-9

[2] This constraint is not given by regulators in our simulation. For sake of simplicity, we assume that banks become active as soon as they move away from initial leverage conditions. An interesting extension of the model could be to investigate spillover in the case of additional regulatory leverage restrictions.

[3] It is theoretically possible that equity is wiped out entirely by a very large shock; thus the max operator limits losses to 0, i.e. there is no negative equity

[4] One should note here that we define $f_{k,t} \in [\,\text{-}1,\, 0\,]$.

3. *Fire-sales*: For an individual bank i, the algorithm checks two conditions that can occur in the face of a shock $f_{k,t}$ on its balance sheet. If the shock is too large and cash buffers are depleted, bank i starts selling assets immediately in proportion to its weights $w_{i,k,t}$ as in Greenwood et al. (2015)[5]. In the second case, if the bank is able to absorb the shock, neither fire-sales nor spillover to other banks occur, but the balance sheet composition changes in response to how cash is used. To facilitate the reader's understanding, we define de-leveraging volumes at three levels: the bank level (i.e. across all asset classes for bank i), the bank-asset level (i.e. bank i's selling volumes for only asset k) and the system-wide de-leveraging of asset k. At the bank level, if the individual shortfall is larger than the bank's cash liquidity buffer, the bank's total de-leveraging amount is determined by the product of its leverage and its direct exposure:

$$\textit{De-leveraging}_{i,t} = \begin{cases} \underbrace{l_i}_{\text{leverage}} \underbrace{a_{i,t} \sum_k w_{i,k,t} f_{k,t}}_{\text{direct exposure}} & \text{if} \quad \Gamma_{i,t} > \underbrace{a_{i,t} w^c_{i,k,t}}_{\text{cash liquidity buffer}} \\ 0 & \text{else} \end{cases} \tag{3.1.3}$$

Focusing on only asset k, the amount sold at the bank level amounts to:

$$\textit{De-leveraging}_{i,k,t} = \begin{cases} \underbrace{\tilde{w}_{i,k,\cdot}}_{\text{weight for asset k}} \quad \underbrace{l_i}_{\text{leverage}} \underbrace{a_{i,t} \sum_k w_{i,k,t} f_{k,t}}_{\text{direct exposure}} & \text{if} \quad \Gamma_{i,t} > \underbrace{a_{i,t} w^c_{i,k,t}}_{\text{cash liquidity buffer}} \\ 0 & \text{else} \end{cases} \tag{3.1.4}$$

with $\tilde{w}_{i,k,\cdot}$ being the adjusted portfolio weight for asset k after cash operations have been taken into account (see equation (3.1.4)).

Thirdly, we sum up the bank-level selling volumes for asset k across all banks to get to the system-wide fire-sales for asset k:

$$\textit{De-leveraging}_{k,t} = \sum_i \tilde{w}_{i,k,\cdot} \quad l_i \quad a_{i,t} \sum_k w_{i,k,t} f_{k,t} \tag{3.1.5}$$

Note that the first term $\tilde{w}_{i,k,\cdot}$ in 3.1.4 and 3.1.5 contains the intermediate adjusted weights that follow from cash operations. We define their derivation in equation 3.1.10; however, the adjustment of the liability side is the first in the law of motion as described below.

How are balance sheets adjusted?

Whenever cash liquidity buffers are used, weights are adjusted proportionately according to the new total assets of bank i, which in turn depend on how equity and debt are affected by the direct exposure and the pay-off of debt obligations. Equity and debt in $t+1$ are

[5] As in Greenwood et al. (2015), we assume that these selling volumes are accommodated in the market at the initial step at no price discount

defined by:

$$e_{i,t+1} = max\{e_{i,t} - a_{i,t} \sum_k w_{i,k,t} f_{k,t}; 0\} \tag{3.1.6}$$

$$d_{i,t+1} = max\{l_i \;\; e_{i,t+1} \;\; ; 0\} \tag{3.1.7}$$

The sum of adjusted equity and updated debt gives total assets of bank i in $t+1$ as

$$a_{i,t+1} = \max\{d_{i,t+1} + e_{i,t+1}, 0\} \tag{3.1.8}$$

On the asset side, cash is reduced by how much of the shortfall $\Gamma_{i,t}$ can be covered. In $t+1$, its value is determined by debt pay-offs transactions. The maximum amount that is payable is $\Gamma_{i,t}$, hence new cash positions in $t+1$ amount to:

$$c_{i,t+1} = \begin{cases} 0 & \text{if} \quad \Gamma_{i,t} \geq \underbrace{a_{i,t} w^c_{i,k,t}}_{\text{cash liquidity buffer}} \\ c_{i,t} - \Gamma_{i,t} & \text{else} \end{cases}$$

$$\text{with } c_t = a_{i,t} w^c_{i,k,t}$$

In the case that the cash buffer is not sufficient to de-leverage, $c_{i,t+1}$ is 0. Alternatively, the new cash position is the difference between the previous period's amount and Γ_i, t.

The next step is the intermediate update of portfolio weights $\sum_k w_{i,k} = 1$. As in Greenwood et al. (2015), we assume that asset weights determine how much of each asset is sold in the de-leveraging process. This assumption is a drastic simplification as selling behaviour is more complex in real markets. However, it is a necessary building block which helps to gauge the extent of overlapping portfolios in the sector, while still being simple enough to allow for data calibration. While in Greenwood et al. (2015), weights are constant, we allow for fluctuations due to cash transactions. The update process takes place between t and $t+1$, which is why 'intermediate' adjusted weights are denoted with $\tilde{w}_{i,k,\cdot}$. Starting with cash, the intermediate portfolio weight is given by the ratio of the target positions:

$$\tilde{w}^c_{i,k,\cdot} = \frac{c_{i,t+1}}{a_{i,t+1}} \tag{3.1.9}$$

Since $\tilde{w}^c_{i,k,\cdot}$ is smaller than $w^c_{i,k,t}$ $\forall f_{k,t} < 0$, the difference needs to be accounted for so that $\sum_k w_k = 1$. For sake of simplicity, we distribute the difference proportional to the existing weights. Consider the correction factor $\tau = \frac{w^c_{i,t} - \tilde{w}^c_{i,k,\cdot}}{k-1}$, so that the remaining intermediate weights are given by

$$w_{i,k,\cdot} = w_{i,k \neq c,t} + \tau \qquad \forall f_{k,t} < 0 \tag{3.1.10}$$

To re-iterate the law of motion, the intermediate weights are used in the determination of fire-sale volumes in the de-leveraging process described in equations 3.1.3 -3.1.5. Once transactions materialise, the intermediate weights become the new weights for the period $t+1$.

System-wide de-leveraging

We now turn to the spillover effects that arise from system-wide de-leveraging. Recall from equation 3.1.5 that the amount of asset k that is sold across all banks is given by

$$\textit{De-leveraging}_{k,t} = \sum_i \tilde{w}_{i,k,\cdot} \quad l_i \quad a_{i,t} \sum_k w_{i,k,t} f_{k,t}$$

The direct exposure of bank i is multiplied by its leverage to determine the shortfall that bank i needs to cover through asset sales if cash buffers are depleted. This shortfall is multiplied by asset k's portfolio weight $w_{i,k,t}$ to determine the proportional amount that bank i sells of asset k. The sales are summed up over all banks, leading to a total amount $\textit{De-leveraging}_{k,t}$, i.e. the system-wide fire-sales of asset k following the initial shock $f_{k,t}$. The equity of bank i is reduced by direct exposure $a_{i,t} \sum_k w_{i,k,t} f_k$, while debt is paid off according to $l_i(a_{i,t} \sum_k w_{i,k,t} f_{k,t})$.

4. *Price impact*: The cumulative sales lead to a price effect $\upsilon(\rho_k, \textit{De-leveraging}_{k,t})$ which depends on the liquidity parameter ρ_k and the selling volumes $\textit{De-leveraging}_{k,t}$. The assumption is that an exogenous buyer steps in to accommodate the selling volumes at the fire-sold price.

5. *Spillover losses*: The price effect leads to further losses on banks' balance sheets. These are the *indirect* spillover losses arising from common asset holdings. Our analysis is particularly concerned with these kind of spillover losses, as they represent the amplification mechanism in the centre of the fire-sale contagion channel. It is possible to describe total spillover losses for asset k by

$$SP_{k,t} = \sum_i (a_{i,t} \sum_k \tilde{w}_{i,k,\cdot}) \underbrace{\left[\rho_k \sum_i \tilde{w}_{i,k,\cdot} l_i a_{i,t} \sum_k w_{i,k,t} f_{k,t} \right]}_{f*} \tag{3.1.11}$$

where the expression inside the square brackets can be interpreted as second round shock f^*_k on asset k. The routine from *3.* is repeated to determine the system-wide losses $SP_{k,t}$ for asset k, which result only from the second round fire-sale price-shock f^*_k. Summing up second-round sales across all asset classes gives us the system-wide spillover losses

$$\lambda_t = \sum_k SP_{k,t} \tag{3.1.12}$$

In the next step, we capture the fragility of the banking system to fire-sale spillovers by putting λ_t in relation to pre-shock banking sector equity $E_= \sum_i e_{i,t}$:

$$AV_t = \frac{\lambda_t}{E_{t-1}} \tag{3.1.13}$$

Greenwood et al. (2015) call this the *Aggregate Vulnerability* of the banking system to the preceding shock. It is further possible to break down AV into every bank's contribution to the overall losses in the banking system attributable to *indirect spillover losses*, i.e. $AV_t = \sum_i S_{i,t}$. To conclude, the *systemicness* of a bank depends on four factors and is higher, the more connected the bank is (connectedness is high when the bank owns large illiquid amounts of assets which are also held by other banks), the bigger the bank, the more leveraged the bank (l_i) and the larger the shock the bank faces.
The next section introduces some general characteristics of the South African banking system and presents the data used in the simulation.

3.2 Data

This section presents a descriptive overview of the data to highlight main attributes of the South African banking sector. All observations are taken from December 2015. The 29 banks in the data set own a total of R4.8 tn assets (USD319 bn[6]), which is about 118% of South Africa's nominal GDP.[7] A key characteristic of the banking system is its high concentration of assets among few individual banks. The 4 largest retail banks, Standard Bank (SBSA), First National Bank FNB, Barclays Africa Group (ABSA) and NEDBANK, account for approx. 78% of total assets in the sector. The gini coefficient measuring the concentration of assets among market participants is 0.8, whereas the Herfindahl-Hirschmann Index is 0.18, indicative of low competitiveness in the sector.

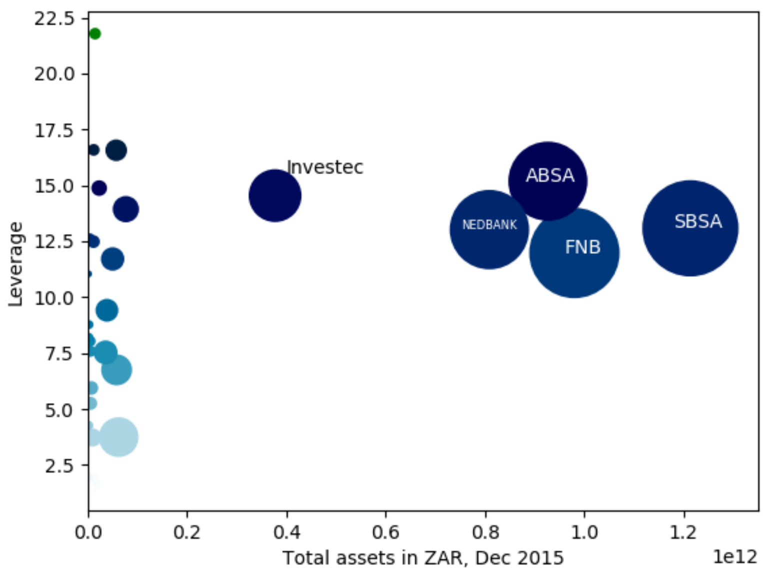


FIGURE 3.1: Bank size and leverage for 29 South African banks. Leverage is defined as the ratio of total debt over equity as reported in balance sheets. Dot sizes correspond to bank size in terms of total assets.

[6]Exchange rate is 15.0 per USD average for December 2015
[7]year end 2015

Figure 3.1 depicts the relationship between banks' size and leverage ratios. Details about aggregate banking data are also presented in Table 3.7 on page 54: SBSA is the largest bank with R1.2 tn worth of assets, followed by FNB (R980 bn), ABSA (R927 bn), NEDBANK (R808 bn) and Investec (R377 bn). The remaining 13 banks account for R480 bn of assets in the sector. Leverage is defined as the ratio of bank debt over equity and ranges between 12 (FNB) to 15.2 (ABSA) for the 5 largest banks. Although ABSA ranks 3rd in terms of total assets, they hold the largest amount of household deposits, i.e. R167 bn or 18% of its total balance sheet. This compares to SBSA having 12%, or R142 bn, of its assets financed by household deposits. It's noteworthy that this ratio is nearly 60% (R36 bn) for SA's fasted growing retail bank CAPITEC.

Banks' assets are categorised as depicted in Table 3.1 on page 36. We aggregate 23 asset classes, of which 12 are loan book assets, 9 are trading book assets, one is cash and the remaining assets are summarised as non-financial assets[8]. Figure 3.2 on page 35 shows the aggregate composition of balance sheets according to these overall classes, while Figures 3.3 and 3.5, as well as Figure 3.15 on page 53 show banks' individual holdings in specific asset classes. The broad composition of balance sheets is comparable across banks; large retail banks hold more than 70% of assets in their loan book, the largest share of which can be attributed to household mortgages. Citibank's assets are about evenly split between loan book and trading book assets, with corporate unsecured lending and foreign currency loans as the largest items in the loan book, and SA government bonds and asset-backed securities as the main components in the trading book. Investment banks DeutscheB, JPM and the micro-credit bank hold a larger share of their portfolio in the trading book, largely due to their investment in securitisation and asset-backed securities, as well as in SA treasury bills. In respect of cash, Capitec holds the highest relative share at 5.8%, while other retail banks hold between 2% to 3% of their assets in cash.

[8] We don't account for off-balance sheet items due to data availability

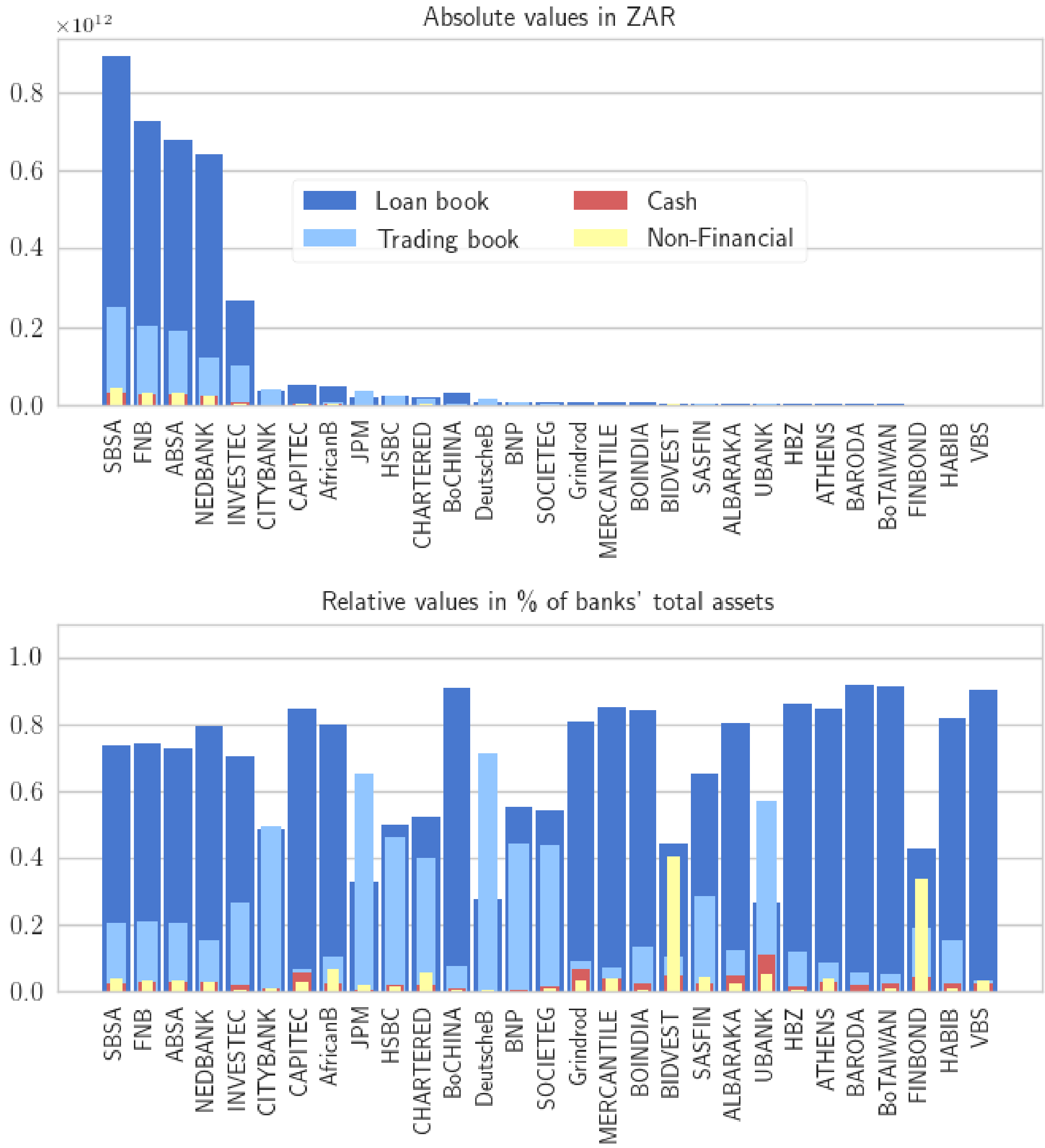


Figure 3.2: Broad composition of banks' assets. *Upper bar chart* Absolute volumes of main balance sheet components Non-financial, Cash, Loan book and Trading book for 29 banks in the sample. *Lower bar chart* Relative share of main balance sheet components per bank. The sum of shares is 1.

Table 3.1: Asset classes

Disaggregation of banks' balance sheet items in Cash, Non-financial assets, Loan book assets and Trading book assets as reported in BA 900 forms

Weight	*Asset class*	*Loan book assets*				*Trading book assets*			
w^c	Cash	w_1^{lb}	SA Interbank deposits	w_7^{lb}	Household instalment credit	w_1^{tb}	SA Central and provincial government bond	w_7^{tb}	Derivative instruments
w^{nf}	Non-financial assets	w_2^{lb}	Rand Deposits with and loans to foreign banks	w_8^{lb}	Corporate mortgage credit	w_2^{tb}	Other public-sector bonds	w_8^{tb}	Treasury bills, SA Reserve Bank bills, Land Bank bills
		w_3^{lb}	Loans granted under repo agreement	w_9^{lb}	Household mortgage credit	w_3^{tb}	Private sector bonds	w_9^{tb}	Other investments
		w_4^{lb}	Foreign currency loans and advances	w_{10}^{lb}	Unsecured lending corporate	w_4^{tb}	Equity holdings in subsidiaries and joint ventures		
		w_5^{lb}	Redeemable preference shares	w_{11}^{lb}	Unsecured lending household	w_5^{tb}	Listed and unlisted equities		
		w_6^{lb}	Corporate instalment credit	w_{12}^{lb}	Other credit (i.e. Credit card + leasing + Overdraft + factoring debt)	w_6^{tb}	Securitisation/ asset-backed securities		

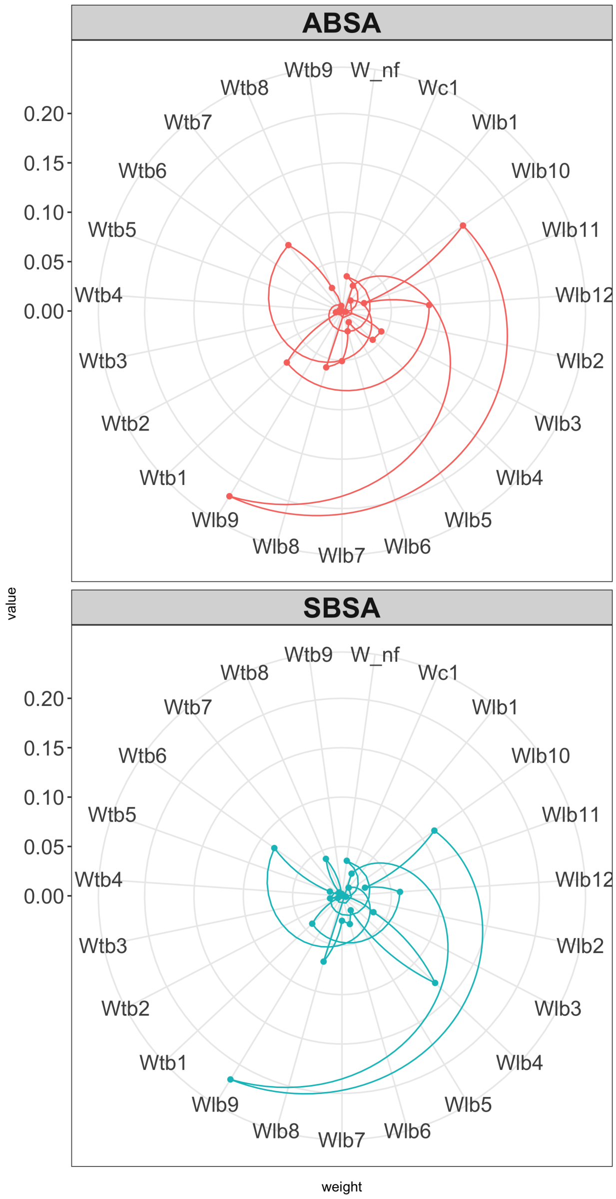


FIGURE 3.3: ABSA and SBSA portfolio weights for Non-financial assets Wnf, Cash Wc, Loan book assets *Wlbi* and Trading book assets *Wtbi* in clock-wise direction. The more peripheral, the higher the portfolio share. Weights are 0 in the centre and increase by 0.05 (5%) per every latitude until a maximum of 0.2 (20%). There is a striking similarity in holding pattern. Both banks have large exposure in *Wlb9*, i.e. household mortgage credit, and *Wlb10*, i.e. Unsecured corporate lending.

Furthermore, we use radar charts to detect potential holding patterns across the 5 largest retail banks, as well as African Bank, Capitec and Deutsche Bank. Figure 3.3 on page 37 shows the individual portfolio weights for ABSA and SBSA as a fraction of their total assets, while Figure 3.5 and 3.15 on page 39 and 53 'zoom in' on the remainder of the aforementioned banks. ABSA and SBSA have striking similarities in the composition of their asset side. Apart from household mortgages (w_9^{lb}), ABSA's and SBSA's main exposure concerns corporate unsecured lending (w_{10}^{lb}) with 15% and 11.5% of their assets held in this category, as well as corporate mortgage credit

(w_8^{lb}) with portfolio weights of 5.9% and 6.9% respectively. The second largest weight in SBSA's portfolio is foreign currency loans (w_4^{lb}) at 13% of total assets, while "other credit"[9] (w_{12}^{lb}) is the third largest category for ABSA, FNB and INVESTEC, which each investing about 9% of their balance sheets in this asset class. Furthermore, both FNB and Nedbank's 4th largest item on the asset side is household instalment credit (w_7^{lb}) with about 9% of their balance sheets tied in this asset class. Nedbank and Investec's exposure to corporate mortgage credit (w_8^{lb}) is slightly higher than the other banks at approx. 9% of total assets. Both AfricanB and Capitec have

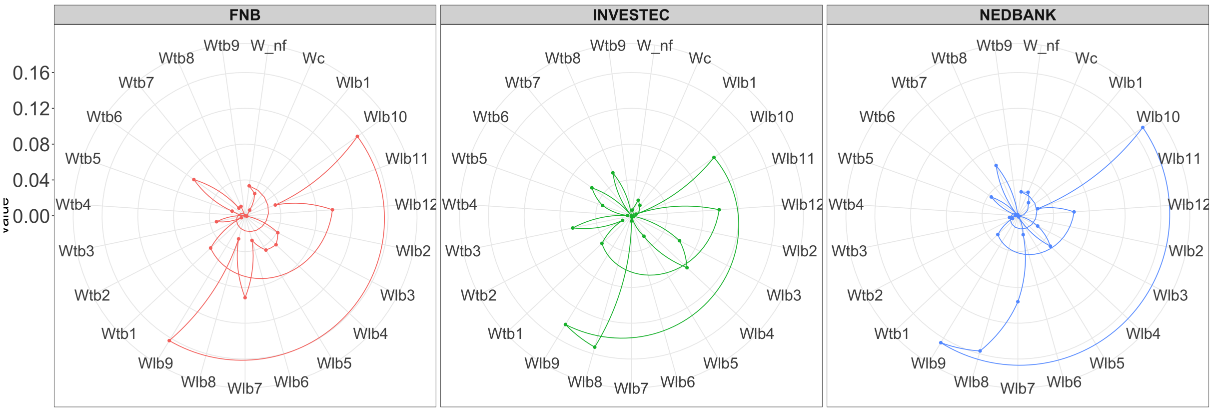


FIGURE 3.4: FNB, Investec and Nedbank portfolio weights for assets Wnf, Cash Wc, Loan book assets $Wlbi$ and Trading book assets $Wtbi$ in clock-wise direction. The more central, the lower the portfolio weight. Weights are 0 in the center and increase by 0.04 (4%) per every latitude until a maximum weight of 0.16 (16%)

large exposure to household unsecured lending (w_{12}^{lb}) at nearly 60% of their balance sheets, while having a second dominant asset class. In the case of African Bank, 16% of its assets are in "Other credit" (w_{12}^{lb}), which includes leasing, credit card and overdraft credit. This means that African Bank has more than 75% of its balance sheet in asset classes that are sensitive to households' ability to service debt.

In respect of trading book items, the largest components are SA government bonds (w_1^{tb}), private sector bonds (w_3^{tb}), as well as 'securitisation/asset-backed securities', derivative instruments and SA treasury bills (w_6^{tb} to w_8^{tb}). ABSA has the largest portfolio weight in SA government bonds (w_1^{tb}, 7.6%), while Investec's largest exposure is in private sector bonds (w_3^{tb}, 7%). ABSA has no exposure in securitisation/asset-backed securities (w_6^{tb}), while SBSA and FNB invest 8.4% and 7.0% in this asset class respectively. ABSA is the only one of the larger retail banks with considerable exposure to derivative instruments (w_7^{tb}), at 8.6% of total assets. Last, but not least, Nedbank and Investec have 6.1% and 5.2% of their assets invested in w_8^{tb}, i.e. treasury bills, SA Reserve Bank bills and land bank bills. The radar charts show interesting similarities between FNB, Investec and Nedbank, and in particular, the role of w_{10}^{lb}, w_9^{lb}, w_{12}^{lb}, and in the case of Nedbank and Investec, w_8^{lb}. These findings are further summarised in Table 3.2, which shows large banks' main asset classes, of which they hold more than 5% as a fraction of their balance

[9]i.e. the asset class that combines leasing, credit card, overdraft and factoring debt

sheet. It's noteworthy that Capitec and African Bank are by far the least diversified retail banks in terms of their asset side composition.

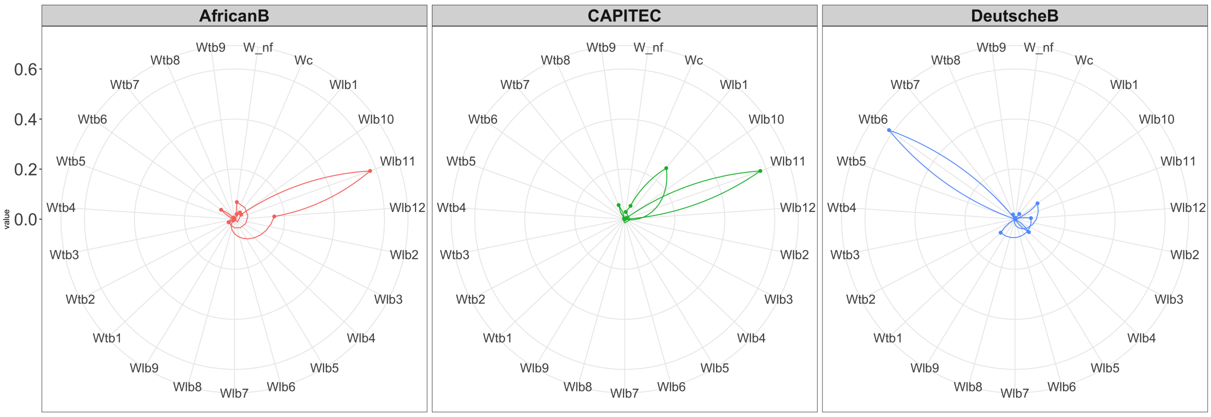


FIGURE 3.5: African Bank, Capitec and Deutsche Bank portfolio weights for Non-financial assets $W\text{nf}$, Cash $W\text{c}$, Loan book assets $Wlbi$ and Trading book assets $Wtbi$ in clock-wise direction. The more peripheral, the higher the portfolio weight. Weights are 0 in the center and increase by 0.2 (20%) per every latitude until a maximum weight of 0.6 (60%).

TABLE 3.2: Selected banks' Loan book asset classes. x indicates a proportion larger than 5% of total assets.

Loan book items	w_1^{lb} SA Interbank deposits, loans and advances	w_4^{lb} Foreign currency loans and advances	w_7^{lb} Household instalment credit	w_8^{lb} Corporate mortgages	w_9^{lb} Household mortgages	w_{10}^{lb} Corporate Unsecured lending	w_{11}^{lb} Households Unsecured lending	w_{12}^{lb} Other credit (credit card, leasing, overdraft, factor debt)
ABSA				x	x	x		x
SBSA		x	x	x	x	x		x
NEDBANK		x	x	x	x	x		x
FNB			x		x	x		x
INVESTEC		x		x	x	x		x
CAPITEC	x						x	
AfricanB							x	x
DeutscheB						x		x

TABLE 3.3: Selected banks' Trading book asset classes. x indicates a proportion larger than 5% of total assets. Balance sheet categories as reported in the BA 900 forms.

Trading book items	w_1^{tb} SA Central & provincial government bond	w_3^{tb} Private sector bonds	w_6^{tb} Securitisation, asset-backed securities	w_7^{tb} Derivative instruments	w_8^{tb} Treasury bills, SA Reserve Bank bills, Land Bank bills
ABSA	x			x	
SBSA			x		
NEDBANK					x
FNB			x		
INVESTEC	x	x	x		x
CAPITEC					
AfricanB					
DeutscheB	x		x		

In light of the events surrounding the bursting of the unsecured lending bubble, it is worthwhile to have a brief look at the relationship between banks' holding of unsecured loans and their deposit sources. This may shed further light onto the interconnectedness between banks and non-banks, a topic recently emphasized as source of systemic risk. As previously mentioned, the majority of banks' deposits stem from the household sector, i.e. on average about 15% of total liabilities across the 5 largest banks. However, bank deposits can also be attributed to the financial sector, i.e. coming from insurers, pension funds, money market funds (MMF) and investment funds. Figure 3.16 on page 54 plots the proportion of assets in unsecured lending against the proportion of liabilities attributable to MMFs, insurers & pension funds and investment funds' deposits. Only banks with deposits larger than 0.1% of total liabilities in a certain category are displayed in the chart. First, it stands out that African Bank and Capitec have by far the highest exposure in unsecured lending expressed as a proportion of total assets, which is why they are located in the upper half of the charts. Second, deposits from insurers and pension funds (lower chart) and MMFs (upper right chart) only play a minor role. The largest proportion of MMF deposits is 0.03 for both FNB and African Bank. Out of the sample of 29 banks, only 6 banks have MMF deposits larger than 0.1% of their liabilities. In respect of deposits from insurers and pension funds, the proportions are also fairly small with a maximum of 0.05, i.e, 5% of total liabilities held in this form of deposit. In the third category, deposits from investment funds, proportions are slightly higher. Investec, operating in the asset management segment, has the highest share with 21% of deposits from investment funds. SBSA, Nedbank and ABSA receive between 10% and 16% of their liabilities from investment funds' deposits which is a considerable amount.
Nedbank, for example, has the same relative share of its liabilities in investment funds' deposits as it does in deposits from the household sector (16%). ABSA also has 16% of its liabilities in investment funds' deposits, which is only 2 percentage points less than the 18% stemming from household deposits. For SBSA, the relative share of fund manger deposit is 10% of total liabilities, and for African Banks it's 17%. Capitec's interconnectedness in terms of financial sector deposits is not very large, having 0.3% of liabilities in MMF deposit, 1% in investment

fund deposits and 1% in insurer and pension fund deposits. One should note that the interconnectedness between banks and non-banks does not only affect deposits, but also bank bonds held as securities on the part of non-banks. Figure 3.16 serves merely as a broad indication. Perhaps the most striking finding is that African Bank still has a high share of liabilities from MMFs and investment banks in comparison to other banks.

To summarise, section 3.2 reviewed the key characteristics of the South African banking system and explored similarities in banks' holding patterns. The sector is highly concentrated with the 4 largest banks holding 78% of assets and displaying similar leverage ratios ranging between 12 and 15 when defined as debt over equity. ABSA and SBSA have a relatively high degree of matching asset holdings. Nedbank, FNB and Investec are also three institutions which display similarities in their balance sheet composition. Furthermore, African Bank and Capitec are the least diversified retail banks and have a high exposure to household unsecured lending credit. SA government bonds and 'securitisation/asset-backed securities' are the most important components of the trading book.

3.3 Simulating fire-sale externalities

In this chapter, we study general shock scenarios to quantify systemic losses arising from the fire-sale contagion channel. The aim of the simulation is to assess individual banks' contribution to overall fragility of the financial system conditional on certain shock scenarios. Furthermore, the results are used to relate the outcome to structural characteristics of the system.

3.3.1 Parameters

The simulation has $N = 29$ banks and $K = 23$ asset classes. The illiquidity parameter ρ_k, which determines the knock-on price effects is chosen to be in the same region as in Greenwood et al. (2015). Greenwood et al. (2015) use 10^{-13}, which means that a selling volume of 10 bn leads to a price drop of 0,1%, or 10 basis points. The estimate is empirically found in studies from the European bond market (see Duffie, 2010). The sensitivity analysis in the second part of the chapter shows that this is a reasonable parameter.

Scenario 1: The largest bank suffers defaults in its unsecured lending portfolio

3.3.2 Selection of shocks

This section describes the shock scenarios conducted to identify determinants of banking sector fragility. We start by shocking a loan portfolio of an individual bank and move on to shocks to the marketable portfolio.

Individual bank

The largest bank in the system is SBSA with approx. R1.2 tn total assets. As the unsecured lending category is the part of the loan book that is most exposed to defaults, we study knock-on

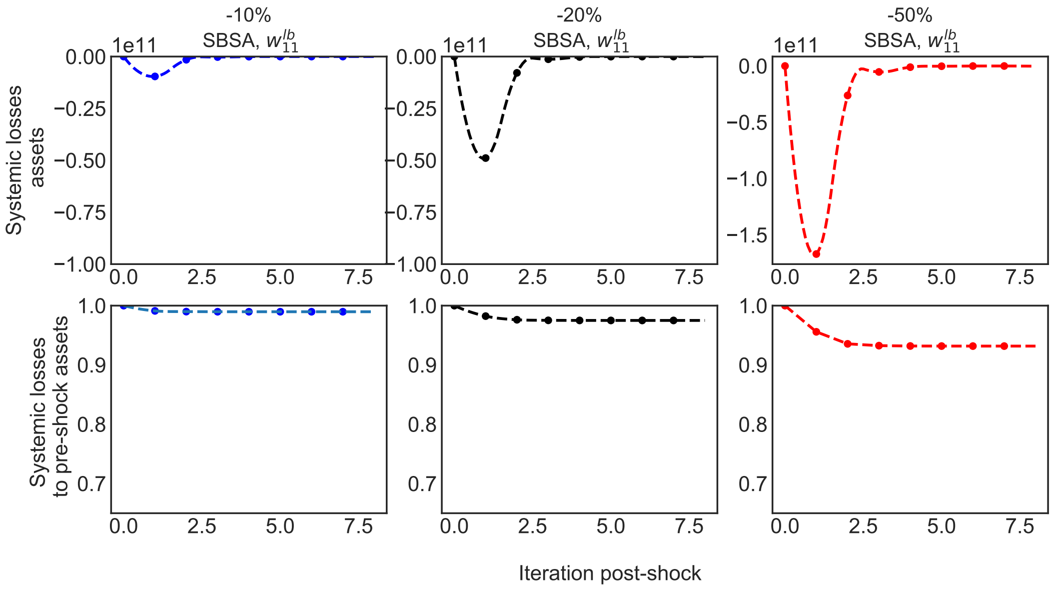


FIGURE 3.6: Systemic asset losses over multiple rounds following a shock on SBSA's household unsecured lending portfolio. Left: Initial de-valuation shock is 10%. Middle: 20% de-valuation Right: 50% de-valuation. Lower charts show the effect of on total assets in the banking system (1 is 100% pre-shock assets). Source: Author's simulation based on SARB BA 900 forms' balance sheet data.

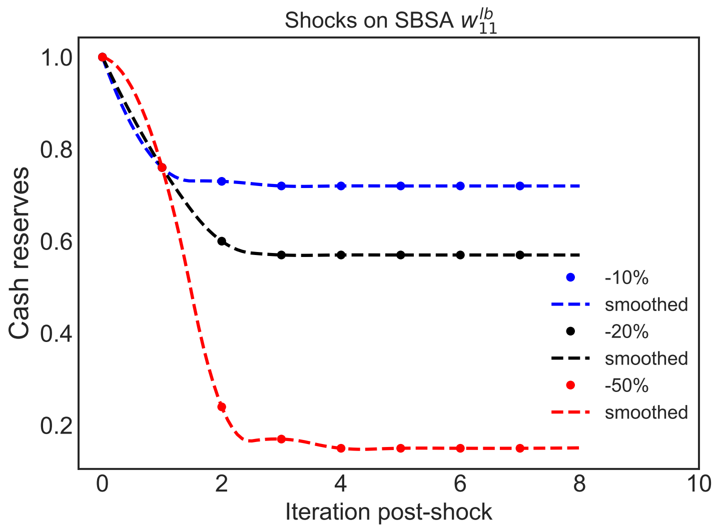


FIGURE 3.7: Cash liquidity buffers as a proportion of total pre-shock cash positions. For example, a 10% shock on SBSA's w_{11}^{lb} leads to a decline of total banking system cash reserves to 80% of total pre-shock cash reserves. Source: Author's simulation based on SARB BA 900 forms' balance sheet data.

effects from a devaluation shock of -10%, -20% and -50%. The number of periods post-shock is large enough so that the system reaches a steady state. Results are shown in Figure 3.6. In all three cases, systemic losses peak in the first iteration post-shock and level off in subsequent periods. As can be seen in the chart, a 10% shock leads to systemic asset losses of 0.1×10^{11}, i.e. R 10 bn following the initial impact. This figure increases to 0.5×10^{11} (R 50 bn) for a 20% shock (middle chart) and 1.6×10^{11} (R 160 bn) for a 50% shock (top right chart), respectively. These losses can be attributed to Standard Bank's direct exposure to defaults in the unsecured lending segment, as well as to deleveraging effects on the part of other banks. The cumulative effect on total assets as a share of pre-shock assets in the banking system is shown in the lower charts in Figure 3.6. A 10% shock reduces pre-shock banking system assets by 1%, a 20% shock by 3% and a 50% shock by 7%. Thus, from the perspective of a fire-sale contagion channel, defaulting unsecured loans on the part of SBSA have a muted effect on the stability in the South African banking sector overall. This finding can be explained by inspecting banks' cash reserves and individual selling behaviour.

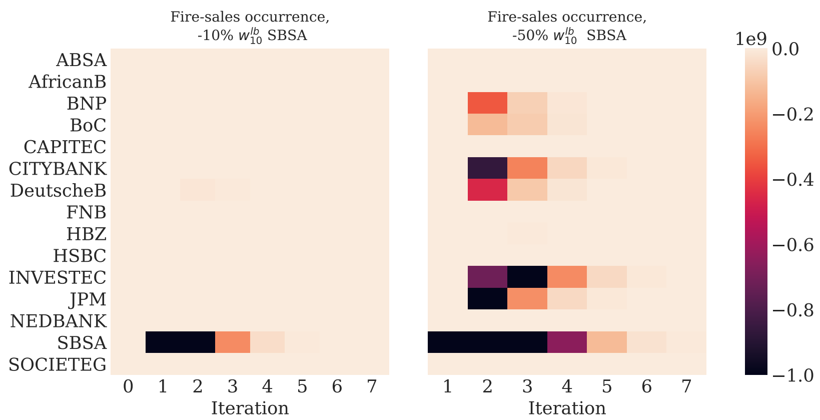


FIGURE 3.8: Asset sales per bank over multiple rounds. Initial impact is a 10% (left chart) and a 50% (right chart) de-valuation shock on w^{lb}_{11} of SBSA. Color shades range from 0 to R1 bn. Source: Author's simulation based on SARB BA 900 forms' balance sheet data.

Figure 3.7 on page 42 displays the evolution of cash liquidity reserves in the banking system for a given shock. De-leveraging by fire-selling assets only occurs if individual banks' cash buffers are fully depleted. Furthermore, the heat map in Figure 3.8 above shows the occurrence of fire-sales by each bank. The darkest colour displays asset sales in the order of R1 bn and shades reach a lighter colour every R200 m. For a small price shock of -10% (left chart), only SBSA is forced to de-leverage by selling assets. All other banks display no occurrence of fire-sales because feedback price effects are small enough to be absorbed by banks' liquidity buffers. In a large shock scenario of 50% devaluation on SBSA's w^{lb}_{11}, however, there are fire-sale externalities which cause losses across financial institutions and asset classes, i.e. BNP, JP Morgan (JPM), Deutsche Bank (DeutscheB) and Bank of China (BoC), who 'dump' assets on the market because they no longer can use cash to pay back debt contracts necessary to de-leverage their balance sheet size. One should note that large retail banks ABSA, FNB, Investec and Nedbank are unaffected, even in the large shock scenario. This is the primary reason why systemic losses are muted overall in

Figure 3.6.

Multiple banks

In the next step, we shock the price of w_1^{tb} to stress-test banks' resilience to South African government bond price shocks. SA government bonds are particularly sensitive to perceived political risk. For example, a sudden price decline could occur if a large number of international investors exits this security class on account of higher expected default risk on the part of the South African government.

Consider Figure 3.9 below which shows the volatility of the 10-year Government Bond (R186). Within the last 20 years, there were extreme price movements on 4 days: a 20% price drop on 28 January 2004 and 4 January 2008, as well as a 30% and 20% increase on 13 November 2006 and 23 January 2015, respectively.

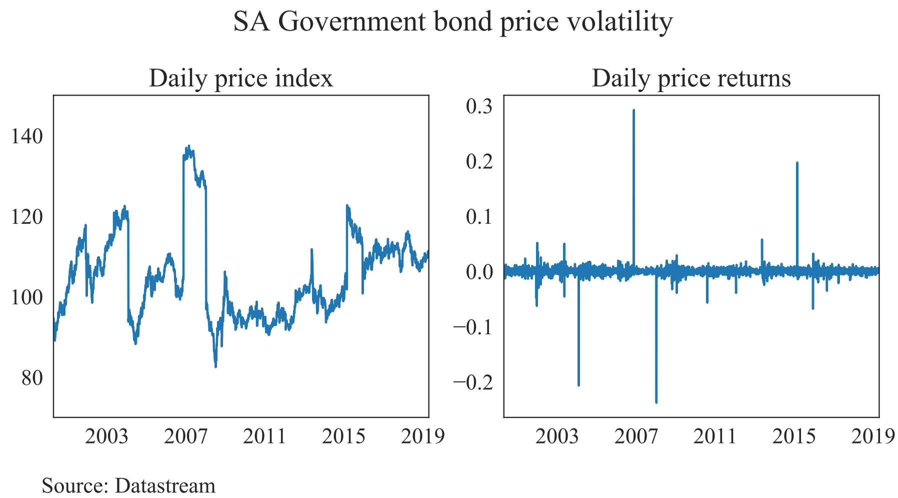


FIGURE 3.9: *Left chart:* R186 10-year bond daily price index. *Right chart:* Daily returns

We take these extreme values as orientation for our marketable asset shock simulations. In Figure 3.10, we see that a 10%, 20% and 50% shock on w_1^{tb} leads to systemic losses of 11% and 21% of total assets in the banking sector after 4 iterations. Hypothetically, an even larger shock of 50% sees total assets in the system drop to about 49%. These sizable effects can be attributed to the fact that the initial impact hits all banks (instead of just one as in the previous scenario), which have to de-leverage as their cash liquidity buffers are not enough to down-size their balance sheets (see also Figure 3.7 on page 42). Hence, in all three scenarios, cash buffers are depleted after the first price shock hits balance sheets. One should note here that price drops in SA government bonds and sharp declines in banks' cash reserves will lead to additional stress from the perspective of banks' liquidity requirements. These liquidity-related stress dynamics are not explicitly modeled in this paper.

Scenario 2: Price shocks on SA government bonds

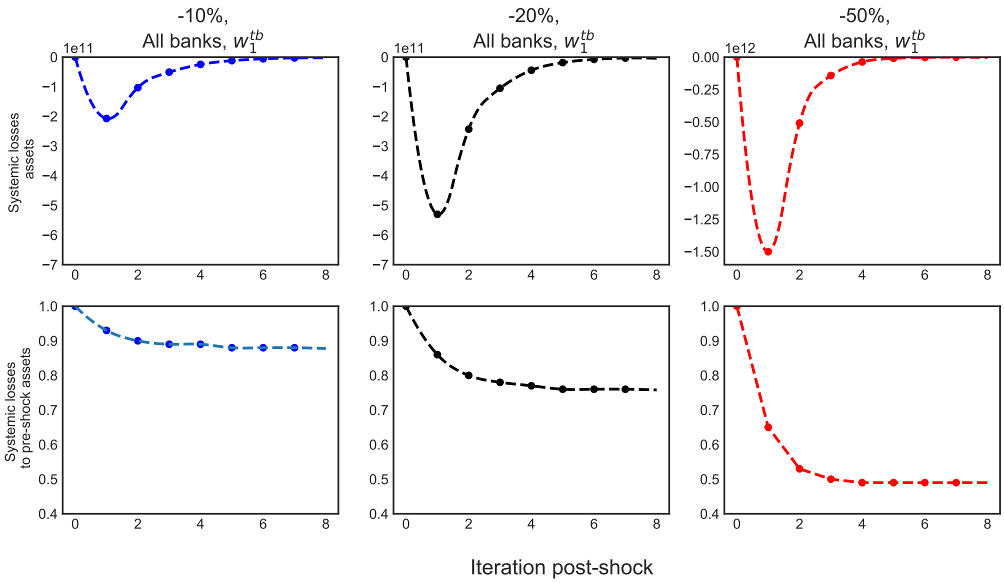


FIGURE 3.10: Systemic losses over multiple post shock iterations, w_1^{tb} all banks. Left: All banks suffer a 10% price shock on their holdings of w_1^{tb} (SA government bonds). Middle: All banks suffer a 20% price shock on w_1^{tb}. Right: All banks suffer a 50% price shock on w_1^{tb}. Lower charts show the effect of the shock on total assets in the banking system (as a fraction of pre-shock assets). Source: Author's simulation based on SARB BA 900 forms balance sheet data.

TABLE 3.4: Aggregate Vulnerability. Fraction of banking system equity wiped out in response to shock f_{t-1} by banks' fire-selling

Period	AV
1 to 2	-16.50%
2 to 3	-5.60%
3 to 4	-1.50%
4 to 5	-0.40%
5 to 6	-0.10%
6 to 7	-0.03%

Table 3.4 quantifies the knock-on effects arising from fire-sale externalities for the large shock scenario of a 50% price drop of SA government bonds. AV is the Aggregate Vulnerability, i.e. the percentage of total banking system equity wiped out *only* by feedback price effects. Equity losses from fire-sale externalities dissipate sharply after the second iteration and reach a steady state in period 7.

The question arises as to which bank contributes more to systemic losses under the displayed shock scenarios. To shed light on this, the heat map in Figure3.11 displays fire-sales for each bank for the 10% and 50% shock on SA government bonds. Feedback price effects are caused mainly by banks in the upper chart, with the heaviest and most prolonged selling occurring for the largest banks ABSA, SBSA, Nedbank, FNB, Investec. African Bank does not experience any stress in the small shock scenario, but contributes to systemic losses in excess of R2 bn given a -50% shock. Interestingly, Capitec does not liquidate any of its assets even in the large shock scenario, which can be attributed to two reasons. First, they have no asset holdings in w_1^{tb}, and thus, no direct exposure to the initial shock. Second, the feedback price effects, which occur in subsequent iterations and which affect other asset classes as well, are absorbed by their cash buffers.

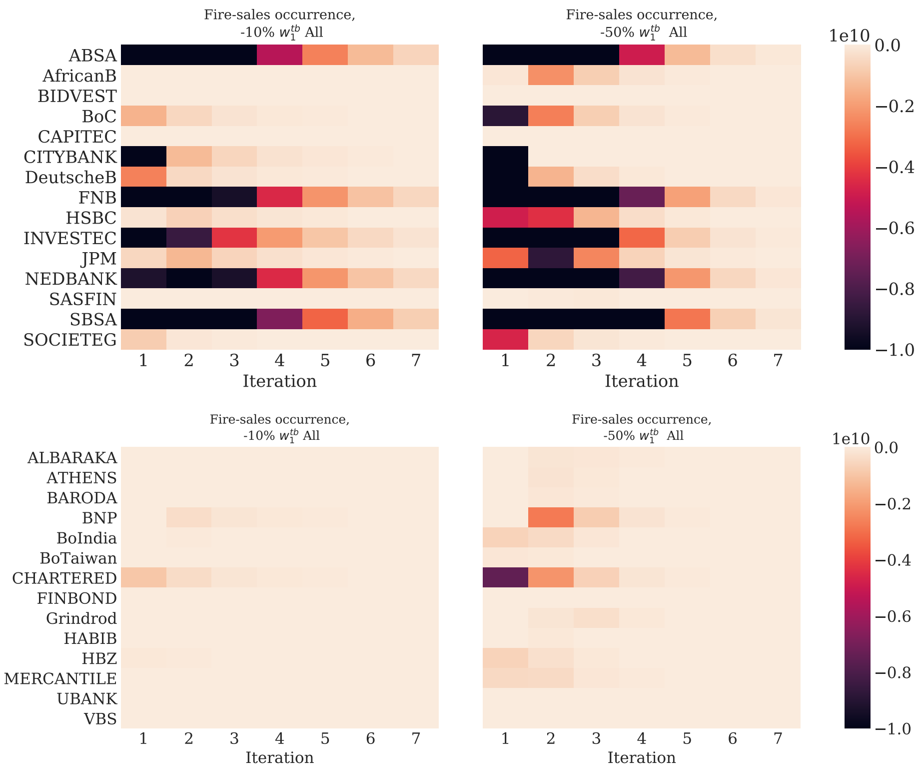


FIGURE 3.11: Asset sales per bank post-shock. All banks holding SA Government bonds in their investment book are affected by a 10% (left chart) and 50% (right chart) price shock on w_1^{tb}. *Upper chart* shows asset sales for the 15 largest banks. Color shades range from 0 to R10 bn. Source: Author's simulation based on SARB BA 900 forms' balance sheet data.

Furthermore, it is important to relate the impact of price shocks to direct and indirect effects in the stress-test simulation. For this purpose Table 3.5 shows banks' contribution to total banking

TABLE 3.5: Bank's relative contribution to direct and indirect systemic equity losses in the 50% shock scenario on w_1^{tb}. The direct impact is the initial 50% price shock to all banks holding w_1^{tb} (SA government bonds). ABSA suffers largest direct losses (30% of all). The indirect contagion arises from banks' de-leveraging and fire-selling. SBSA suffers largest indirect equity losses (30% of all banking system equity losses) in each feed-back round. Note that only the 12 largest contributors are shown.

	Direct impact		Indirect contagion effect
SBSA	21%	SBSA	30%
NEDBANK	10%	NEDBANK	22%
FNB	22%	FNB	21%
ABSA	30%	ABSA	12%
INVESTEC	7%	INVESTEC	8%
CITYBANK	6%	CITYBANK	0%
JPM	0.2%	JPM	1%
HSBC	0.4%	HSBC	1%
BoC	1%	BoC	1%
AfricanB	0.2%	AfricanB	1%
CHARTERED	1%	CHARTERED	1%
CAPITEC	0%	CAPITEC	1%

sector equity losses for the two categories. ABSA suffers the largest equity losses from the initial impact (30% of total), which can be explained by their large direct exposure to w_1^{tb} highlighted in the data section. Nedbank's direct losses from the price shock are about 10% of total system equity losses, while SBSA's and FNB's direct losses account for 21% and 22% of total direct losses respectively. However, in respect of *indirect* losses arising from the fire-sale externality channel, SBSA ranks first with a 30% contribution to total losses and ABSA ranks fourth, accounting for 12% of total system equity losses. Nedbank's role in the de-leveraging rounds is more pronounced, representing the second most systemic bank in this respect, and is one notch above FNB and below SBSA. The reason for SBSA and Nedbank being more important for feedback price effects can be attributed to their leverage and connectedness, i.e. they own large amount of assets also held by other banks.

3.3.3 Sensitivity analysis

The stress-test simulations in the previous section have shown that large government bond price shocks lead to sizable equity losses in the South African banking system due to de-leveraging behaviour of banks. When modelling feedback price effects, however, it's important to inspect the sensitivity of results to parameter variation. The fire-sale externalities measured in the simulation depend on the illiquidity parameter ρ used to determine feedback price drops as a function of selling volumes. Hence, we repeated the shock simulation for a wide range of illiquidity parameters. Figure 3.12 shows the cumulative effect on total equity in the banking sector given a 10%, 30%, 50%, 70% and 90% shock on SA government bond prices and conditional on the illiquidity parameter. For example, a 50% shock (blue line) at 4×10^{-14} leads to cumulative equity losses of 41%. However, the same shock leads to 100% banking system equity losses for a

parameter exceeding 3×10^{-13}.
As the chart shows, there is a critical value for the illiquidity parameter at which the slope for cumulative losses increases sharply across all shock scenarios, i.e. 1×10^{-13}. If the price effect for bond price shocks exceeds this threshold value, the South African banking system becomes highly unstable.

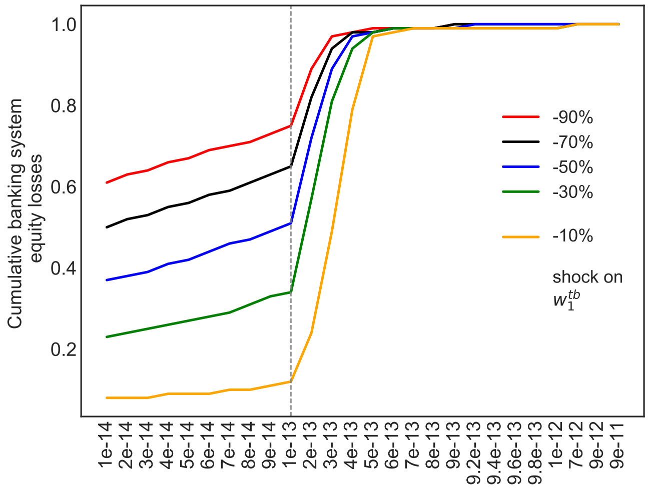


FIGURE 3.12: Cumulative banking system equity losses conditional on illiquidity parameter; following a 10%, 30%, 50%, 70% and 90% shock on SA government bond prices.

3.4 QE Scenario

Scenario 3: 20% price decline in SA government bonds under higher leverage

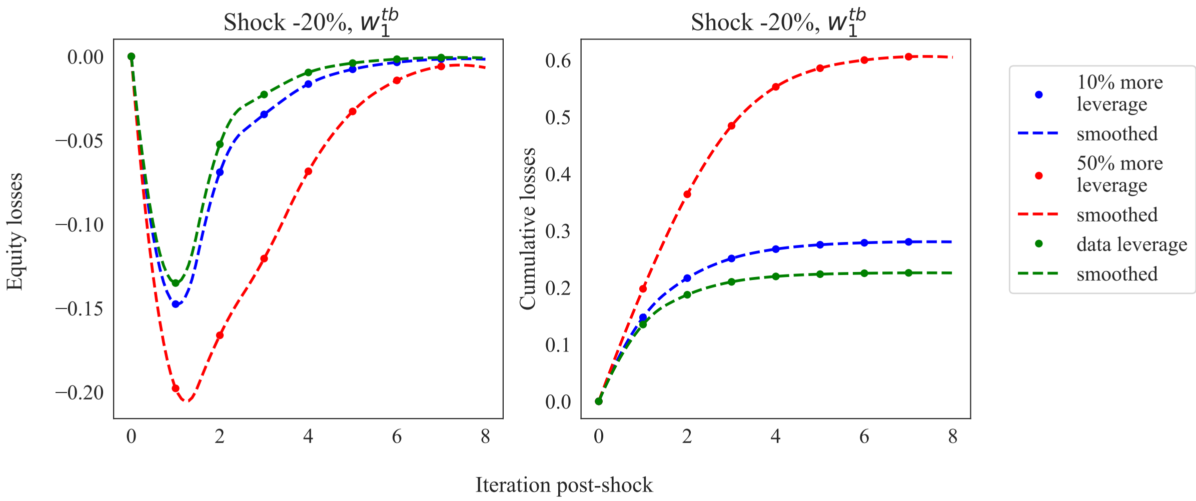


FIGURE 3.13: Equity losses for increased leverage ratios and a 20% SA Government bond price shock. *Left chart:* System-wide equity losses at each liquidation step *Right chart:* System-wide cumulative equity losses

As demonstrated in Section 3.3.2, a 20% price decline is an extreme scenario which resulted in substantial bank de-leveraging. The green line in Figure 3.13 shows the effect under the conditions found in the data. Given those leverage ratios, fire-sale contagion erases approximately 22.5% of equity in the system. The initial impact accounts for about 13% of those losses, while feedback amplification effects compound losses in the magnitude of 9%. If all banks displayed a 10% higher leverage, cumulative equity losses would amount to a marginally higher 28%. The selling patterns for the case of the 10% higher leverage are similar to those of the leverage present in the data.

However, the picture changes for a situation where banks display 50% more leverage. Indirect amplification losses are now much higher than losses from the initial impact. Fire-sale contagion contributes to two thirds of total losses, leading to high banking sector instability. This is because the relative higher leverage of the large banks means that they need to de-leverage a much larger critical amount to keep their (now higher) debt-to-equity ratio constant. Naturally, this raises the question as to how much leverage is too much. To investigate this, we conducted a range of simulation while varying the shock size and the leverage parameter. The results can be seen in Figure 3.14 which shows how total banking sector assets evolve (y-axis) following an initial price shock to SA government bonds (line graphs) and varying leverage from 0 to 2.5 times the current leverage present in the data (x-axis). One should note that the price shocks are artificially high for demonstration purposes. While the upper chart 'zooms' in on leverage ratios smaller than 1.0 times the current ratios, the lower chart shows what happens in the range from 1.0 to 2.5 times the current levels. It becomes apparent that the risk to banking sector asset losses are not linear, but increase exponentially with higher leverage ratios. Considering the lower chart and price declines from 10% to 30%, a system with 1.5 times current levels is very exposed. If one considers banks' leverage ratios that are twice as high as current levels, price shocks become catastrophic to the system.

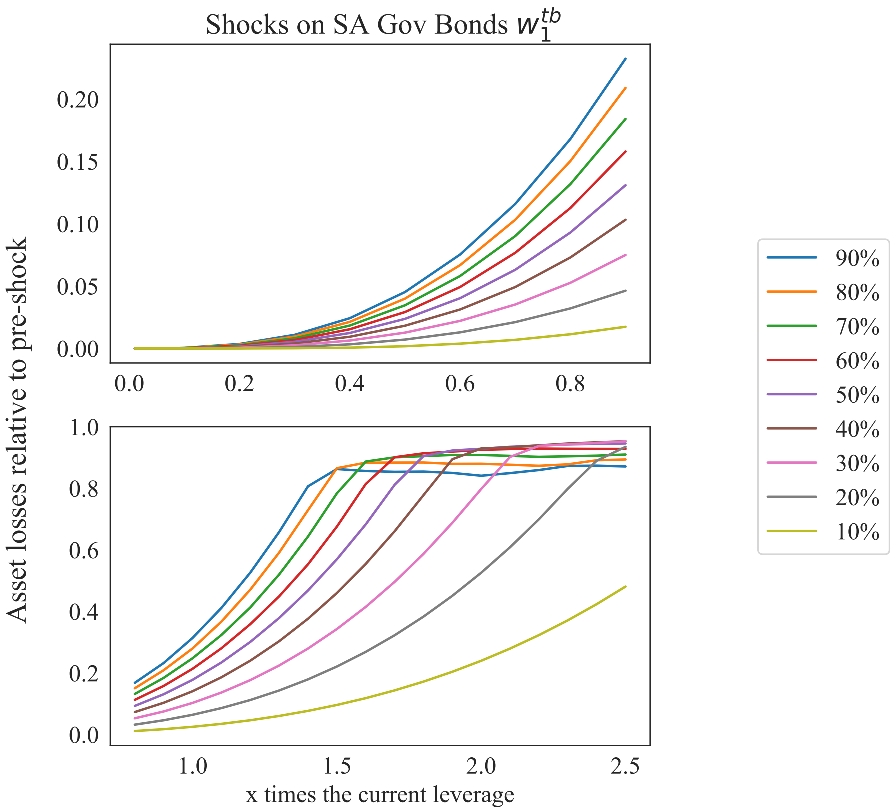


FIGURE 3.14: Sensitivity analysis of the leverage parameter. X-axis depicts x *times* the current leverage in the banking system. Y-axis shows asset losses relative to pre-shock total assets in the sector. *Upper chart:* Leverage ratios are 0 to 0.8 times larger than current ratios. *Lower chart:* Leverage ratios are 0 to 2.5 times larger than current values. Line graphs are hypothetical shock scenarios ranging from 10% to 90% price decline to government bonds.

3.5 Conclusion

This chapter used a model-based approach to show how spillovers within the South African banking sector arise from fire-sale externalities. A detailed description of banks' balance sheets is used in a complementary fashion to give insight into the distribution of banks' asset holdings. The presentation of tables illustrates patterns of asset holdings which can be used to determine the exposure of individual banks' portfolios to asset write-downs. In the main section we calibrated a model of asset fire-sale propagation to South African balance sheet data to investigate spillovers arising from a specific channel of contagion. Banks are 'forced' to liquidate part of their portfolio given a large enough price shock, as they are subject to a maximum leverage constraint. We follow Greenwood et al. (2015) and model this constraint as constant leverage constraint, but include a consideration of a cash liquidity buffer in banks' decision rule. We show how the liquidity buffer contributes to shock absorption in our simulation study. A second factor conducive to shock absorption is the fact that the banking system displays a relatively high concentration with the largest 4 banks comprising nearly 80% of assets. It was shown that large defaults to the household mortgage credit portfolio of one of those banks did not lead to feedback amplification losses.

However, we also demonstrate that the banking sector is more exposed to fire-sale externalities in the event of large price shocks to a marketable asset. Focusing our analysis on South African government bonds, we show that most banks are able to absorb price shocks up to a critical threshold illiquidity. Last, but not least, we have shown that the fire-sale contagion channel becomes much more pronounced in the context of QE. The same shock to the government bond asset class leads to much higher banking sector instability, assuming that QE leads to a condition of banks taking up higher leverage.

3.6 Annex - PART II

TABLE 3.6: Asset classes. Banks' asset side has 23 components. Author's classification of categories reported in the SARB's BA 900 forms.

Weight	Asset class
w^c	Cash
w_1^{lb}	SA Interbank deposits, loans and advances
w_2^{lb}	Rand Deposits with and loans to foreign banks
w_3^{lb}	Loans granted under repo agreement
w_4^{lb}	Foreign currency loans and advances
w_5^{lb}	Redeemable preference shares
w_6^{lb}	Corporate instalment credit
w_7^{lb}	Household instalment credit
w_8^{lb}	Corporate mortgage credit
w_9^{lb}	Household mortgage credit
w_{10}^{lb}	Unsecured lending corporate
w_{11}^{lb}	Unsecured lending household
w_{12}^{lb}	Other credit (i.e. Credit card + leasing + Overdarft + factoring debt)
w_1^{tb}	Central and provincial government bond
w_2^{tb}	Other public-sector bonds
w_3^{tb}	Private sector bonds
w_4^{tb}	Equity holdings in subsidiaries and joint ventures
w_5^{tb}	Listed and unlisted equities
w_6^{tb}	Securitisation/ asset-backed securities
w_7^{tb}	Derivative instruments
w_8^{tb}	Treasury bills, SA Reserve Bank bills, Land Bank bills
w_9^{tb}	Other investments
w^{nf}	Non-financial assets
Weights	w^c Cash , w_i^{tb} Trading book asset, w_i^{lb} Loan book asset, w^{nf}Non-financial assets

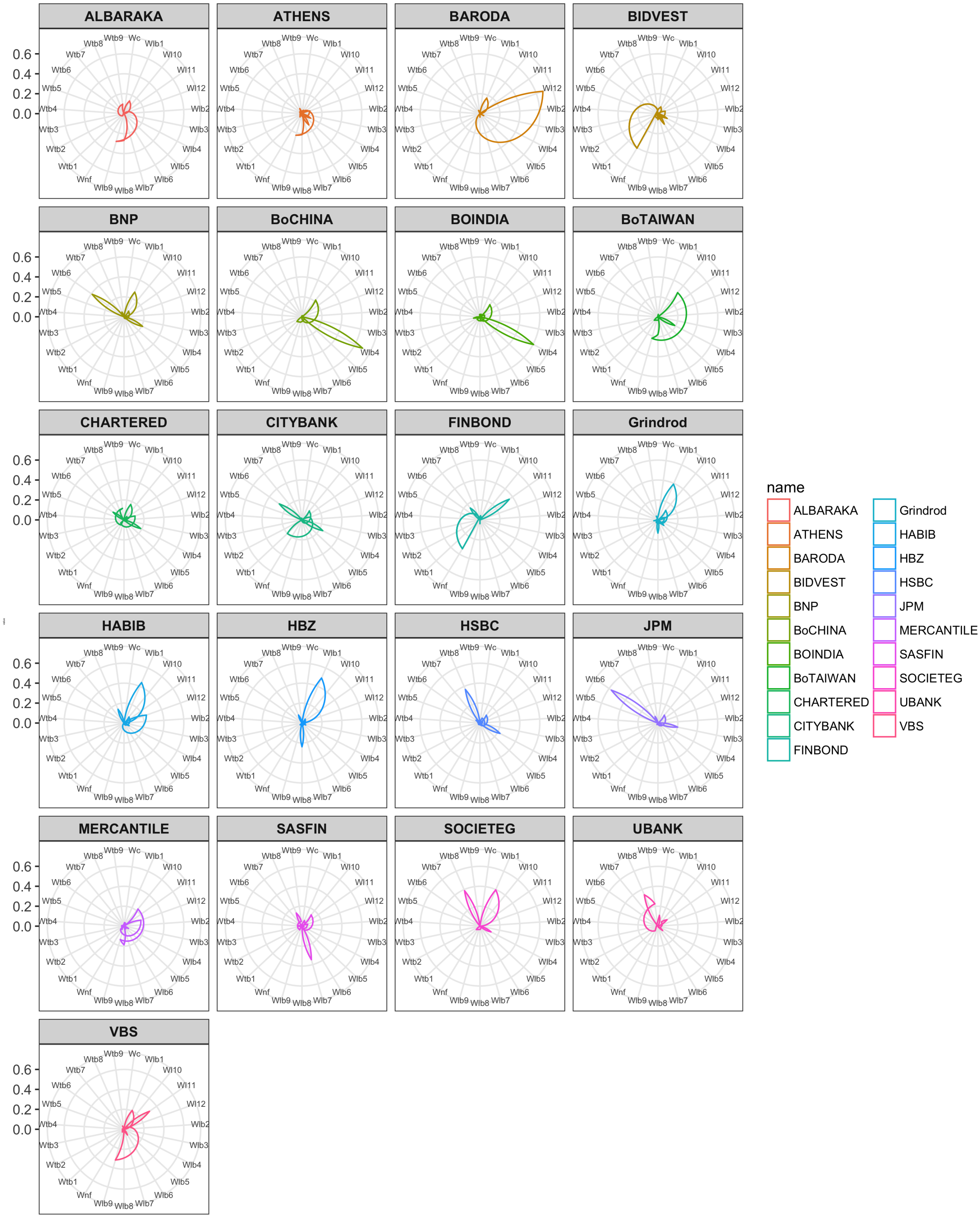


FIGURE 3.15: Bank portfolio weights for Non-financial assets Wnf, Cash Wc, Loan book assets $Wlbi$ and Trading book assets $Wtbi$. The more peripheral, the higher the portfolio weight. Weights are 0 in the center and increase by 0.2 (20%) per every latitude until a maximum weight of 0.6 (60%). Asset weights $w^c, w_i^{lb}, w_i^{tb}, w_{nf}$

Table 3.7: Selected banks aggregate data. Observation as of 31 December 2015 as reported the SARB's BA900 forms. Total assets in R bn, Leverage ratio (debt over equity), Loan book aggregates all loan book balance sheet items, trading book aggregates all balance sheet items held for investment.

Bank	**Total assets in R bn**	**Leverage**	**Equity**	**Debt in R bn**	**HH deposits in R bn**	**HH deposits % of total**	**Loan book % of total**	**Trading book % of total**
SBSA	1,213.5	13.1	86.2	1,127	142.3	0.12	0.74	0.21
FNB	979.9	12.0	75.5	904	150.3	0.15	0.74	0.21
ABSA	926.5	15.2	57.3	869	166.7	0.18	0.73	0.21
NEDBANK	808.7	13.0	57.7	751	131.7	0.16	0.79	0.15
INVESTEC	377.0	14.5	24.3	353	64.8	0.17	0.71	0.27
CITYBANK	76.5	13.9	5.1	71	-	-	0.49	0.50
CAPITEC	62.0	3.7	13.1	49	36.5	0.59	0.85	0.07
AfricanB	57.9	6.8	7.5	50	0.1	0.00	0.80	0.11
JPM	57.0	16.6	3.2	54	-	-	0.33	0.65
HSBC	49.8	11.7	3.9	46	-	-	0.50	0.46
Chartered	38.4	9.4	3.7	35	-	-	0.53	0.40
BoC	35.6	7.5	4.2	31	0.1	0.00	0.91	0.07
DeutscheB	22.8	14.9	1.4	21	-	-	0.28	0.72
BNP	14.5	21.8	0.6	14	-	-	0.55	0.44
SocieteG	11.7	16.6	0.7	11	-	-	0.54	0.44
Grindrod	11.3	12.5	0.8	10	5.4	0.48	0.81	0.09

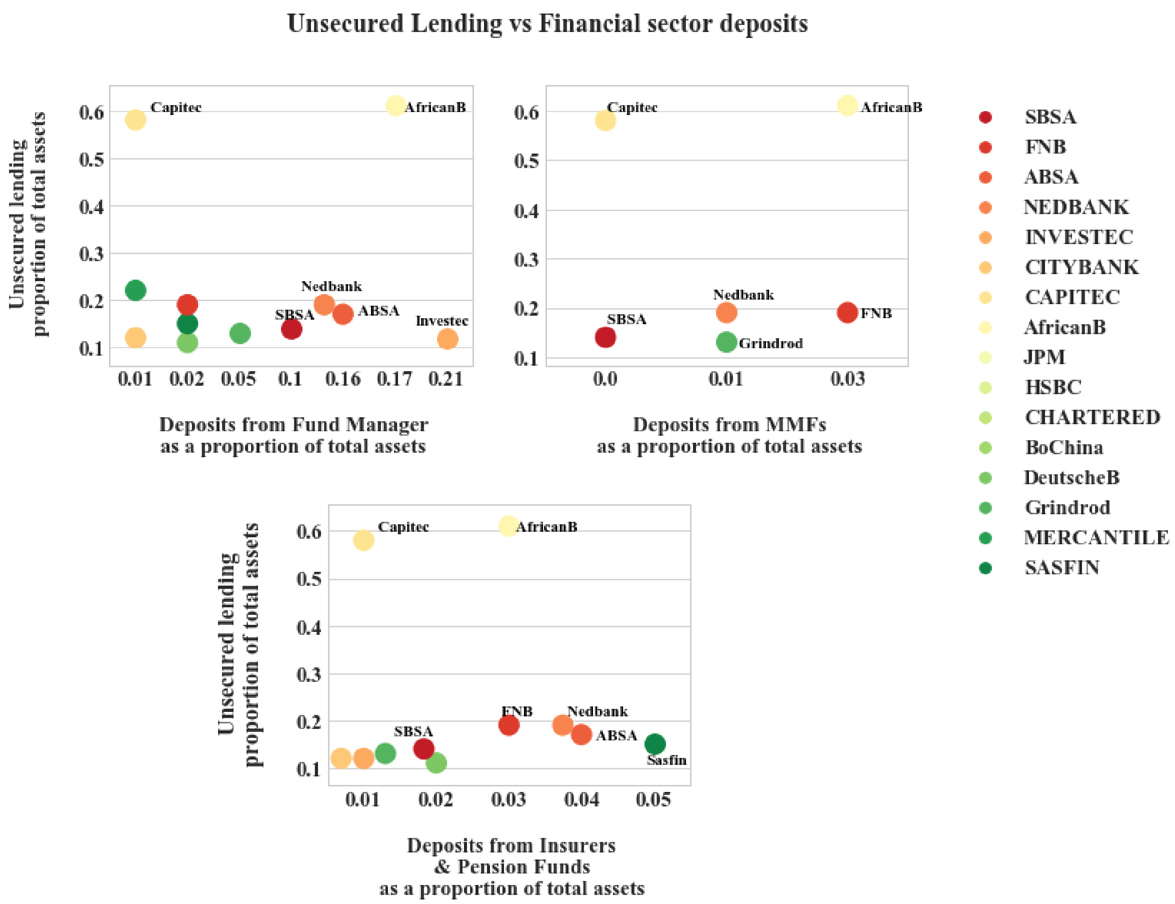


Figure 3.16: Financial sector deposits vs Unsecured lending. The x axis displays each banks' proportion of total liabilities attributable to deposits from Investment funds/Fund manager (top left chart), Money Market Funds(top right) and Insurers and Pension Funds (bottom chart). The y axis shows proportion of assets tied in unsecured lending.

PART III - QE and spillover effects on *financial markets*

4 A spillover model with heterogeneous agents and assets[1]

In PART III we shift the focus from spillovers within financial networks to asset price spillovers that operate through the portfolio balance channel of QE. At the center of the portfolio balance channel is the assumption that assets are imperfect substitutes for investors, e.g. due to segmented markets, regulation restricting the type of asset that can be bought or home bias, i.e. the preference to hold domestic assets. To accommodate this, we present an agent-based model specifically designed to incorporate heterogeneity in assets and agents. The model is developed in the next section and in Chapter 5, we conduct policy experiments to quantify the effect of Eurozone QE on international asset returns.

4.1 Model framework

This section presents a dynamic heterogeneous agent model that was specifically developed to account for heterogeneity in assets and agents. In its present form, we introduce a two-country set up, but the framework can be extended to feature more countries as well.

The model schematized in Figure 4.1 comprises the following: country $\mathcal{D}$ populated by investor agents $d \in \{1, 2, ..., n^d\}$ and country $\mathcal{F}$ populated by investor agents $f \in \{1, 2, ..., n^f\}$. Both countries have local financial markets in which investors can trade shares of asset portfolios $D \in \{1, 2, ..., n^D\}$ issued in country $\mathcal{D}$ and $F \in \{1, 2, ..., n^F\}$ issued in country $\mathcal{F}$. Introducing portfolios of assets instead of individual assets reduces computational complexity and facilitates a parsimonious modeling of asset maturity. Capital can flow freely between the two countries at endogenous exchange rates $X^{\mathcal{DF}}$ and $X^{\mathcal{FD}}$, with $X^{\mathcal{FD}} = 1/X^{\mathcal{DF}}$. The exchange rate $X^{\mathcal{DF}}$ defines the number of units of country $\mathcal{D}$'s currency that can be purchased with one unit of country $\mathcal{F}$'s currency. Thus an increase in $X^{\mathcal{DF}}$ corresponds to an appreciation of country $\mathcal{F}$'s currency vis-à-vis country $\mathcal{D}$'s currency. A central bank agent in country $\mathcal{D}$ can intervene in financial markets by buying and selling shares in portfolio D.[2] In the following we describe agent behavior from the point of view of an agent from country $\mathcal{D}$, which we will refer to as the domestic country. We will furthermore not use superscripts D and F to indicate a domestic or foreign portfolio in equations that apply to portfolios of both countries.

[1] This chapter is part of the working paper Koziol et al. (2019), 'Euro Area Quantitative Easing in a Portfolio Balance Model with Heterogeneous Agents and Assets'

[2] We assume that only the domestic central bank does QE.

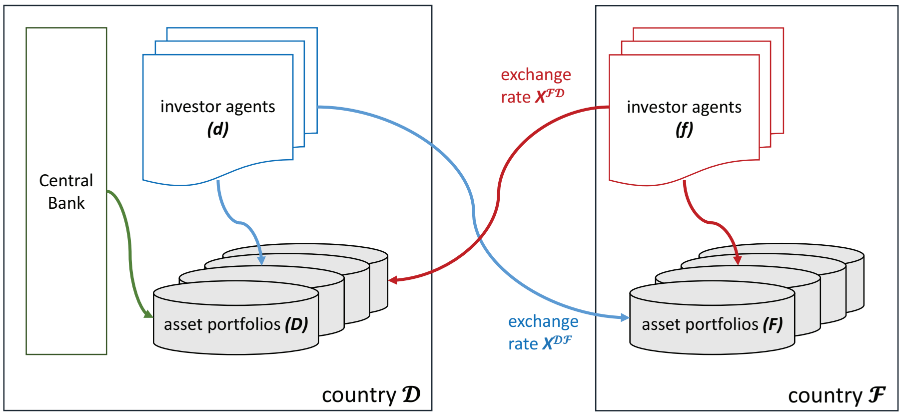


FIGURE 4.1: Model overview.

4.1.1 Sequence overview

To help the reader understand model dynamics before going into a detailed description, we present the algorithm in a simplified form in Figure 4.2.
The timing of the model includes two separate loops: an inter-day loop that governs the events from day t to $t + 1$ and an intra-day loop which finds market clearing prices. At the start of the day, investors form expectations about asset returns and optimise their portfolio according to mean-variance preferences. A recursive log impact price function adjusts prices until a stopping criteria δ is satisfied, meaning that demand and supply come sufficiently close. Our model features simultaneous clearing of three markets: the domestic market, the foreign market and the exchange rate market. Subsequent to finding equilibrium prices, transaction take place and balance sheets are adjusted. Profit and maturity related factors occur overnight, before the sequence starts again. Eventually, the algorithm converges to a long-term steady state.

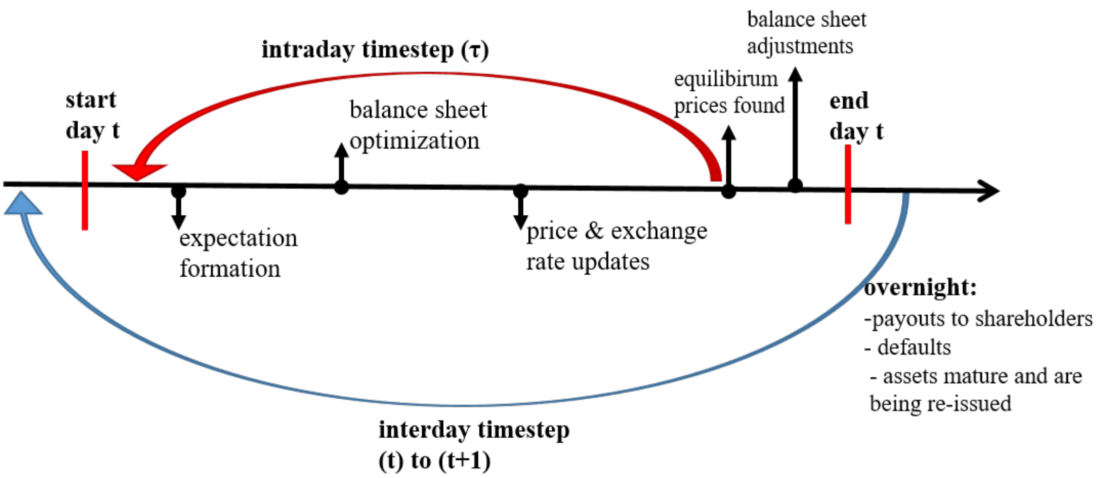


FIGURE 4.2: Model timing.

We will now proceed with the description of agents and assets.

4.1.2 Investor balance sheets

A domestic investor agent d has the following balance sheet structure:

Assets		Liabilities	
Domestic Asset Portfolios,	$\sum_{D=1}^{n^D} Q_{d,t}^{D} P_t^D$	Capital,	$S_{d,t}$
Foreign Asset Portfolios,	$\sum_{F=1}^{n^F} Q_{d,t}^{F} (P_t^F X_t^{\mathcal{DF}})$		
Domestic Cash,	$C_{d,t}^{\mathcal{D}}$		
Foreign Cash,	$C_{d,t}^{\mathcal{F}} X_t^{\mathcal{DF}}$		

with $Q_{d,t} \in \mathbb{R}^+$ denoting the quantity of shares held in a portfolio by agent d at time t and P_t being the market price of one share in the portfolio. Agents can hold cash in domestic and foreign currency ($C_{d,t}^{\mathcal{D}}$ and $C_{d,t}^{\mathcal{F}}$) and fund themselves through capital $S_{d,t}$, which they receive as an endowment in $t = 0$. For the sake of simplicity, we abstract from any liability side management by agents. We thereby assume that any portfolio balancing is, on average, not due to adjustments in the capital structure of agents.

4.1.3 Heterogeneous assets

The asset portfolios of a country can differ with regard to their maturity structure, as well as the default rate of underlying assets. As agents consider expected real returns, the location of the asset portfolio determines its inflation risk.

Defaults

We assume that a fraction Ω of the asset portfolio instantly defaults overnight. Default risk is one of two exogenous risk factors that enter the model, the other one being inflation. We model defaults as stochastic process whose distribution is known by investor agents. See section 5.1.4 on page 71 and Equation 5.1.2 on page 71 for more details.

Inflation

Agents consider expected real returns, so inflation risk enters the model by deflating expected nominal returns by an expected inflation rate which is modeled as a simple normally distributed random variable $\pi_t \sim \mathcal{N}(\mathrm{E}[\pi], \sigma^{\pi})$ with constant mean and variance. We describe in section 5.1.4 how we calibrate inflation risk to the domestic and foreign market.

Maturity

Maturity is introduced through an exogenously set repayment rate $(1-m)$ on outstanding assets in a portfolio. The parameter $m \in [0, 1]$ can be interpreted as a maturity parameter, with $m = 0$ meaning that all assets inside the portfolio mature overnight, whereas $m = 1$ would entail that assets never mature.[3]

[3] Hatchondo and Martinez (2009) pioneered this one-parameter model of maturity within a standard macro model. However, rather than assuming a constant repayment rate on bonds, they assume a perpetual bond with constantly declining coupon payments. Bond duration is computed with the Macaulay definition of duration, which focuses on cash flow rather than redemption. Our modeling of maturity is identical to that in Riedler and Brückbauer (2017).

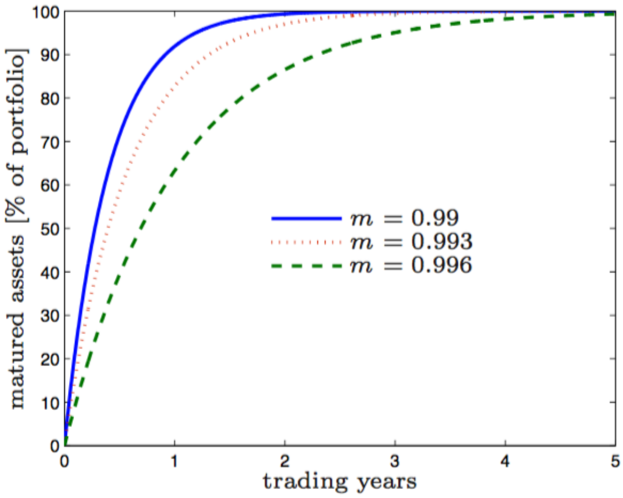


FIGURE 4.3: Exemplary maturity structures of a portfolio of assets for different values of m.

Figure 4.3 exemplarily shows the maturity structure of portfolios for different values of m. The higher the m, the lower the repayment rate $(1-m)$, the longer it takes for the portfolio to mature. Given $m = 0.996$, for example, the asset portfolio will have (hypothetically) matured approximately after 5 trading years from the current point in time. Note that although assets mature, the overall supply of outstanding shares is held constant by introducing an underwriter agent who instantly re-issues the maturing portfolio shares. This is a convenient way for us to deal with maturity risk without having to model maturity dates over time.

Section 5.4.1 in the appendix is devoted to a more detailed discussion on the appropriateness of modeling maturity through a constant repayment rate and its relation to the term structure of interest rates.

4.1.4 Asset performance

For an overview of performance-related variables, consider the following table:

Π_t^D	profit per portfolio share	V^D	nominal value of portfolio
$\bar{Q}^D$	portfolio shares issued	P_t^D	price of portfolio share
ρ^D	interest on portfolio share	Ω_t	default rate
m	maturity parameter	$(1-m)$	constant repayment rate
out_t	percentage outstanding	mat_t	percentage maturing

TABLE 4.1: Performance related variables for asset portfolios

There are five effects that can have an impact on an investor agent's performance. For the sake of simplicity, we assume that the events associated with these effects, i.e. interest payments, principal repayments, defaults, price movements and exchange rate movements, happen overnight (i.e. in the logical second before period t) and become public knowledge at the beginning of each period. We can compute the profit $\Pi_{d,t}$ that has accrued overnight by adding the performance effects associated with each portfolio share and unit of cash, i.e.

$$\Pi_{d,t} = \sum_{D=1}^{n^D} Q^D_{d,t-1}\Pi^D_t + \sum_{F=1}^{n^F} Q^F_{d,t-1}\Pi^F_t + C^{\mathcal{D}}_{d,t-1}\Pi^{C^{\mathcal{D}}}_t + C^{\mathcal{F}}_{d,t-1}\Pi^{C^{\mathcal{F}}}_t \tag{4.1.1}$$

Not all shares of a portfolio of assets are subject to the same performance effects. For the sake of a clearer presentation, we define three factors that indicate these different shares:

- The factor out_t defines the percentage of performing outstanding portfolio shares at the beginning of period t relative to the portfolio shares held at the end of period $t-1$.
- We define the factor mat_t as the percentage of performing portfolio shares that matured overnight.
- all_t defines all performing portfolio shares, i.e. those that have not defaulted overnight

So that

$$\begin{aligned} out_t &:= m(1-\Omega_t) \\ mat_t &:= (1-m)(1-\Omega_t) \\ all_t &:= out_t + mat_t = (1-\Omega_t) \end{aligned}$$

Note that the factors are time-dependent because they take into account the stochastic default rate of assets in a portfolio. The profit that accrues for one share in a portfolio denominated in domestic currency is computed as follows:

$$\Pi^D_t = \underbrace{mat^D_t(\frac{V^D}{\bar{Q}^D} - P^D_{t-1})}_{\text{repayment effect}} + \underbrace{out^D_t(P^D_t - P^D_{t-1})}_{\text{price effect}} + \underbrace{all^D_t\frac{V^D}{\bar{Q}^D}\rho^D}_{\text{interest effect}} - \underbrace{\Omega^D_t P^D_{t-1}}_{\text{default effect}} \tag{4.1.2}$$

For the sake of simplicity, the face value of the assets in a portfolio V, the total number of portfolio shares $\bar{Q}$ and the interest rate ρ paid per portfolio share are modelled as constants.[4] We furthermore assume that the loss given default of assets in the portfolio is 100%, i.e. shareholders incur losses of P_{t-1} for each defaulting portfolio share. The principal repayments and interest payments depend on the face value of a portfolio share, not its past valuation. When considering portfolios denominated in foreign currency, exchange rate movements between $t-1$ and t will influence the repayment and price effect. Interest rates will be valued at the current exchange rate, while losses due to default are written off at last period's exchange rate:

$$\begin{aligned} \Pi^F_t = & \underbrace{mat^F_t(X^{\mathcal{DF}}_t\frac{V^F}{\bar{Q}^F} - X^{\mathcal{DF}}_{t-1}P^F_{t-1})}_{\text{repayment effect}} + \underbrace{out^F_t(X^{\mathcal{DF}}_t P^F_t - X^{\mathcal{DF}}_{t-1}P^F_{t-1})}_{\text{price effect}} + \\ & + \underbrace{all^F_t X^{\mathcal{DF}}_t\frac{V^F}{\bar{Q}^F}\rho^F}_{\text{interest effect}} - \underbrace{\Omega^F_t X^{\mathcal{DF}}_{t-1}P^F_{t-1}}_{\text{default effect}}, \end{aligned} \tag{4.1.3}$$

[4] An exogenous underwriter-agent, which instantly reissues defaulting and maturing assets is introduced in Section 4.1.7 in order to keep face values and quantities of portfolio shares constant.

While all cash positions pay an interest rate, the valuation of foreign cash positions are also affected by exchange rate movements:

$$\Pi_t^{C^{\mathcal{D}}} = \rho^{C^{\mathcal{D}}} \text{ and } \Pi_t^{C^{\mathcal{F}}} = X_t^{\mathcal{DF}} \rho^{C^{\mathcal{F}}} + X_t^{\mathcal{DF}} - X_{t-1}^{\mathcal{DF}}. \tag{4.1.4}$$

For the sake of simplicity, we model interest rates payed on cash in their respective currency as constants $\rho^{C^{\mathcal{D}}}$ and $\rho^{C^{\mathcal{F}}}$.

Given the profit $\Pi_{d,t}$ agent d accrued overnight, the first decision an agent has to make is whether to retain or to pay profits out to shareholders. In order to avoid dealing with economic growth issues within the model, we assume that all performance effects that materialise in a period (i.e. all, expect for the price effect) are paid out to shareholders. Payouts are made in both domestic and foreign currency according to the following equation:[5]

$$\begin{aligned} D_{d,t}^{\mathcal{D}} &= C_{d,t-1}^{\mathcal{D}} \rho^{C^{\mathcal{D}}} + \sum_{D=1}^{n^D} Q_{d,t-1}^{D} \left(mat_t^D \left(\frac{V^D}{\bar{Q}^D} - P_{t-1}^D\right) + all_t^D \frac{V^D}{\bar{Q}^D} \rho - \Omega_t^D P_{t-1}^D \right) \\ D_{d,t}^{\mathcal{F}} &= C_{d,t-1}^{\mathcal{F}} \rho^{C^{\mathcal{F}}} + \sum_{F=1}^{n^F} Q_{d,t-1}^{F} \left(mat_t^F \left(\frac{V^F}{\bar{Q}^F} - P_{t-1}^F\right) + all_t^F \frac{V^F}{\bar{Q}^F} \rho - \Omega_t^F P_{t-1}^F \right) \end{aligned} \tag{4.1.5}$$

The law of motion for the value of capital amounts to:

$$S_{d,t} = S_{d,t-1} + \Pi_{d,t} - D_{d,t}^{\mathcal{D}} - X_t^{\mathcal{DF}} D_{d,t}^{\mathcal{F}}. \tag{4.1.6}$$

4.1.5 Expectation Formation

Realised nominal returns on a portfolio share can be computed by dividing the profit per share that accrued overnight by last period's price. Taking into account an exogenous stochastic process for domestic and foreign inflation $\pi_t^{\mathcal{D}}$ and $\pi_t^{\mathcal{F}}$ respectively and defining $\mathrm{E}_{d,t}[\cdot]$ as agent d's expectation of the variable in brackets at time t, the expected real returns of domestic and foreign portfolios amount to:

$$\underset{d,t}{\mathrm{E}}[r_{t+1}^D] = \frac{1 + \mathrm{E}_{d,t}[\Pi_{t+1}^D]/P_t^D}{1 + \mathrm{E}_{d,t}[\pi_{t+1}^{\mathcal{D}}]} - 1 \quad \text{and} \quad \underset{d,t}{\mathrm{E}}[r_{t+1}^F] = \frac{1 + \mathrm{E}_{d,t}[\Pi_{t+1}^F]/(X_t^{\mathcal{DF}} P_t^F)}{1 + \mathrm{E}_{d,t}[\pi_{t+1}^{\mathcal{D}}]} - 1 \tag{4.1.7}$$

Analogously, real domestic and foreign cash returns amount to:

$$\underset{d,t}{\mathrm{E}}\left[r^{C^{\mathcal{D}}}{}_{t+1}\right] = \frac{1 + \mathrm{E}_{d,t}\left[\Pi_{t+1}^{C^{\mathcal{D}}}\right]}{1 + \mathrm{E}_{d,t}[\pi_{t+1}^{\mathcal{D}}]} - 1 \quad \text{and} \quad \underset{d,t}{\mathrm{E}}\left[r^{C^{\mathcal{D}}}{}_{t+1}\right] = \frac{1 + \mathrm{E}_{d,t}\left[\Pi_{t+1}^{C^{\mathcal{D}}}\right]/X_t^{\mathcal{DF}}}{1 + \mathrm{E}_{d,t}[\pi_{t+1}^{\mathcal{D}}]} - 1 \tag{4.1.8}$$

Since nominal profits in period $t+1$ depend on prices, exchange rates and default rates that only materialise overnight, agents need to form expectations regarding their realisation. All other variables are assumed to be constant by agents. For the sake of simplicity, we assume that agents know the stochastic process behind default rates, i.e. $\mathrm{E}_{d,t}[\Omega_{t+1}] = \mu_t^{\Omega}$, with μ_t^{Ω} being the first

[5] When payouts are negative, agents do not receive funds, but rather retain future positive payouts until losses have been compensated.

moment of the true default rate process.[6] We furthermore assume that agents are myopic and believe in efficient asset markets, i.e. $\mathrm{E}_{d,t}[P_{t+1}] = P_t$. Exchange rates expectations, on the other hand, are anchored in economic fundamentals.[7] Agents believe the exchange rate will eventually revert to the purchasing power parity ($\bar{X}_t^{\mathcal{DF}}$):

$$\underset{d,t}{\mathrm{E}}[X_{t+1}^{\mathcal{DF}}] = X_t^{\mathcal{DF}} + \eta \left(\underset{d,t}{\mathrm{E}}[\bar{X}_{t+1}^{\mathcal{DF}}] - X_t^{\mathcal{DF}} \right), \text{ with } \underset{d,t}{\mathrm{E}}[\bar{X}_{t+1}^{\mathcal{DF}}] = \bar{X}^{\mathcal{DF}} \frac{1 + \mathrm{E}_{d,t}[\pi_{t+1}^{\mathcal{F}}]}{1 + \mathrm{E}_{d,t}[\pi_{t+1}^{\mathcal{D}}]} \tag{4.1.9}$$

The parameter η, which, for instance, depends on the responsiveness of a country's exports and imports to changes in exchange rates, defines the expected convergence speed towards the purchasing power parity. Expectations of purchasing power parity change with changes in expected inflation. In order to take into account the risk of their investments, agents compute estimates of variance and covariances of historic real returns. We generally define an agent's estimate of the covariance between variables r^x and r^y as

$$\hat{\mathrm{Cov}}_{d,t}(r^x, r^y) := \hat{\mathrm{M}}_{d,t}\left[\left(r_{t-1}^x - \hat{\mathrm{M}}_{d,t-1}[r^x, \phi] \right) \left(r_{t-1}^y - \hat{\mathrm{M}}_{d,t-1}[r^y, \phi] \right), \phi \right]. \tag{4.1.10}$$

with the operator

$$\hat{\mathrm{M}}_t[x, \phi] := (1 - \phi)\hat{\mathrm{M}}_{t-1}[x, \phi] + \phi x_t, \tag{4.1.11}$$

defining the exponentially weighted moving average of variable x. The parameter $\phi \in [0, 1]$ determines how much weight is given to the most recent observation.

4.1.6 Balance Sheet Optimisation

Investor agents optimise their asset holdings by computing the relative weights of the portfolios on their balance sheet, that optimises a mean variance utility function:

$$\mathbf{w}_{d,t}^* = \arg\max_{\mathbf{w}} \mathbf{w}' \mathrm{E}_{d,t}[\mathbf{r}_{d,t+1}] - 0.5\mathbf{w}' \left(\boldsymbol{\lambda}_d' \boldsymbol{\Sigma}_{d,t} \boldsymbol{\lambda}_d \right) \mathbf{w} \qquad \text{s.t.} \tag{4.1.12}$$

$$\mathbf{w} \geq 0 \quad \text{and} \quad \mathbf{w'1} = 1, \tag{4.1.13}$$

with $\mathbf{w}_{d,t}^* := (\mathbf{w}_{d,t}^D, \mathbf{w}_{d,t}^F, \mathbf{w}_{d,t}^C)'$ being the $N \times 1$ vector of optimal weights, $\mathrm{E}_{d,t}[\mathbf{r}_{d,t+1}] = (\mathrm{E}_{d,t}[\mathbf{r}_{d,t+1}^D], \mathrm{E}_{d,t}[\mathbf{r}_{d,t+1}^F], \mathrm{E}_{d,t}[\mathbf{r}_{d,t+1}^C])'$ being the $N \times 1$ vector of expected returns and $\boldsymbol{\Sigma}_d$ being the estimate of the $N \times N$-covariance matrix of returns. Note that $N = n^D + n^F + 2$ because $\mathbf{w}_{d,t}^D$, $\mathbf{w}_{d,t}^F$ and $\mathbf{w}_{d,t}^C$ are themselves vectors containing the optimal weights of n^D domestic asset portfolios $w_{d,t}^D$, n^F foreign asset portfolios $w_{d,t}^F$ and 2 cash positions $w_{d,t}^{C^{\mathcal{D}}}$ and $w_{d,t}^{C^{\mathcal{F}}}$. Analogously,

[6] Including heterogeneous expectations about default rates is feasible within the model. We refrain from implementing them because it would require $n^d \gg 1$, which substantially increases computation time with apparent benefit for the simulations conducted.

[7] When agents believe that the expected exchange rate movement is zero, i.e. $\mathrm{E}_{d,t}[X_{t+1}^{\mathcal{DF}}] = X_t^{\mathcal{DF}}$, it can easily be shown that the expected return of an investment in a foreign asset is independent of the exchange rate level. This would lead to unrealistic exchange rate dynamics with excessive volatility.

$\mathrm{E}_{d,t}[\mathbf{r}^D_{d,t+1}], \mathrm{E}_{d,t}[\mathbf{r}^F_{d,t+1}]$ and $\mathrm{E}_{d,t+\tau}[\mathbf{r}^C_{d,t+1}]$ are themselves vectors of the corresponding expected returns.

The vector $\boldsymbol{\lambda}_d := \sqrt{(\boldsymbol{\lambda}^D_d, \boldsymbol{\lambda}^F_d, \boldsymbol{\lambda}^C_d)'}$ assigns specific risk aversions to all assets, with $\boldsymbol{\lambda}^D_d$, $\boldsymbol{\lambda}^F_d$ $\boldsymbol{\lambda}^C_d$ being $1 \times n^D$, $1 \times n^F$ and 1×2 vectors specifying the risk aversion assigned to individual domestic and foreign portfolios, as well as domestic and foreign currencies, respectively. Including asset specific risk aversions is a simple way to account for idiosyncratic preferences of agents for certain assets that cannot be explained by their risk-return profile nor associated transaction costs. The substitutability of available assets crucially depends on agents' preferences for certain maturities, asset types (e.g. equities vs. bonds) and issuer nationality (home bias).

Equation (4.1.13) contains two constraints: a no-short-selling constraint[8] and a budget constraint (the sum of weights must be equal to 100%).

An agent's demand for the domestic and foreign portfolios, as well as currencies, is a function of the optimal weights:

$$\Delta Q^D_{d,t} = \frac{w^D_{d,t} S_{d,t}}{P^D_{d,t}} - out^D_t Q^D_{d,t-1} \tag{4.1.14}$$

$$\Delta Q^F_{d,t} = \frac{w^F_{d,t} S_{d,t}}{X^{\mathcal{DF}}_t P^F_{d,t}} - out^F_t Q^F_{d,t-1} \tag{4.1.15}$$

$$\Delta C^{\mathcal{D}}_{d,t} = w^{C^{\mathcal{D}}}_{d,t} S_{d,t} - \left(\underbrace{C^{\mathcal{D}}_{d,t-1}(1+\rho^{C^{\mathcal{D}}})}_{\text{previous cash + interest}} - \underbrace{D^{\mathcal{D}}_{d,t}}_{\text{payouts}} + \underbrace{\sum_{D=1}^{n^D} (mat^D_t + all^D_t \rho^D) Q^D_{d,t-1} \frac{V^D}{\bar{Q}^D}}_{\text{principal and interest payments}} \right) \tag{4.1.16}$$

$$\Delta C^{\mathcal{F}}_{d,t} = \frac{w^{C^{\mathcal{F}}}_{d,t} S_{d,t}}{X^{\mathcal{DF}}_t} - \left(C^{\mathcal{F}}_{d,t-1}(1+\rho^{C^{\mathcal{F}}}) - D^{\mathcal{F}}_{d,t} + \sum_{F=1}^{n^F} (mat^F_t + all^F_t \rho^F) Q^F_{d,t-1} \frac{V^F}{\bar{Q}^F} \right) \tag{4.1.17}$$

Note that demand is the difference between the desired balance sheet position (resulting from the optimal weights) and its inventory at the start of period t. For portfolios, the inventory is simply the quantity held at the end of last period reduced by shares that have defaulted or matured overnight, while for currency the inventory takes into account overnight interest payments, principal repayments and payouts.

4.1.7 Price and Exchange Rate Adjustments

In equilibrium, prices and exchange rates need to take values that simultaneously clear the markets of n^D domestic portfolios, n^F foreign portfolios and two currencies. Achieving simultaneous market clearing can be challenging with standard numerical techniques. We circumvent these challenges by employing a price-setting algorithm that takes into account the economic intuition that excess demand should increase prices and excess supply should reduce them. The flow chart in Figure 4.4 illustrates how the algorithm, which we adopt from Riedler and Brückbauer (2017), works for any variable V_t for which economic intuition (formulated as a recursive impact function) informs the direction in which that variable is updated. In case of price adjustments,

[8] We follow Levich et al. (1999) with this assumption, who argue that short selling plays only a minor role in real funds' investment decisions.

we use the following impact function starting with last period's prices ($P_{t^*} = P_{t-1}$):[9]

$$\log(P_{t^*}) = \log(P_{t^*}) + \gamma \frac{\Delta Q_{t^*}}{\bar{Q}}, \tag{4.1.18}$$

with γ being the intensity with which prices change and

$$\Delta Q_{t^*} = \sum_{d=1}^{n^d} \Delta Q_{d,t^*} + \sum_{f=1}^{n^f} \Delta Q_{f,t^*} + \Delta Q_{U,t} + \Delta Q_{CB,t} \tag{4.1.19}$$

being excess demand (excess supply if $\Delta Q_{t^*} < 0$) for a portfolio of assets at the hypothetical price of P_{t^*}. Expectations of returns $\mathrm{E}_{d,t^*}[r_{t+1}]$ and prices $\mathrm{E}_{d,t^*}[P_{t+1}]$, covariance estimates $\hat{\mathrm{Cov}}_{t^*}(\cdot)$, payouts D_{d,t^*} and balance sheet size S_{d,t^*} all need to be updated with the hypothetical price when computing demand. Excess demand in Eq. (4.1.18) is normalised by the total quantity of portfolio shares $\bar{Q}$ in circulation for a more convenient calibration of the intensity parameter γ.[10]

Monetary policy enters the model through the central bank agent's demand $\Delta Q_{CB,t}$ for assets in Eq. (4.1.19), while an exogenous underwriter agent reissues maturing and defaulting portfolio shares by supplying $\Delta Q_{U,t} \leq 0$. Note that neither the central bank demand nor the underwriter supply change during the iterative price setting algorithm. The demand of the central bank depends on its inventory $Q_{CB,t-1}$ and the amount $Q^*_{CB,t}$ it desires to hold in period t, i.e.

$$\Delta Q_{CB,t} = Q^*_{CB,t} - out_t Q_{CB,t-1}. \tag{4.1.20}$$

The underwriter agent, on the other hand, will supply all portfolio shares in its inventory and all shares that have matured or defaulted overnight:

$$\Delta Q_{U,t} = -\left(out_t Q_{U,t-1} + (mat_t + \Omega_t)\bar{Q}\right) \tag{4.1.21}$$

The exchange rate is updated using the same iterative algorithm used to adjust price, but with the following recursive logarithmic impact function initialised at $X^{\mathcal{DF}}_{t^*} = X^{\mathcal{DF}}_{t-1}$:

$$\log(X^{\mathcal{DF}}_{t^*}) = \log(X^{\mathcal{DF}}_{t^*}) + \gamma^{EX} \frac{\Delta K^{\mathcal{DF}}_{t*}}{\sum_{d=1}^{n^d} S_{d,t^*} + \sum_{f=1}^{n^f} S_{f,t^*} X^{\mathcal{DF}}_{t^*}}, \tag{4.1.22}$$

[9] We add a star to the index of variables to differentiate between values within and outside of the price setting algorithm.

[10] The normalisation by the total quantity of portfolio shares means that when every agent wants to sell their shares in one portfolio, the price will fall by γ between two steps of the algorithm. The value of the intensity parameter is crucial to the efficiency of the pricing algorithm. If the value is too large, ΔQ_{t^*} may jump between positive and negative values without convergence towards the equilibrium price. If γ is too small, on the other hand, the number of iterations needed for prices to reach equilibrium can be unacceptably large. We allow for the intensity parameter to adapt within simulations. Specifically, we divide γ by three after ten jumps of ΔQ between positive and negative values. We multiply γ by 1.1 if no jump in ΔQ has occurred for 20 consecutive iterations.

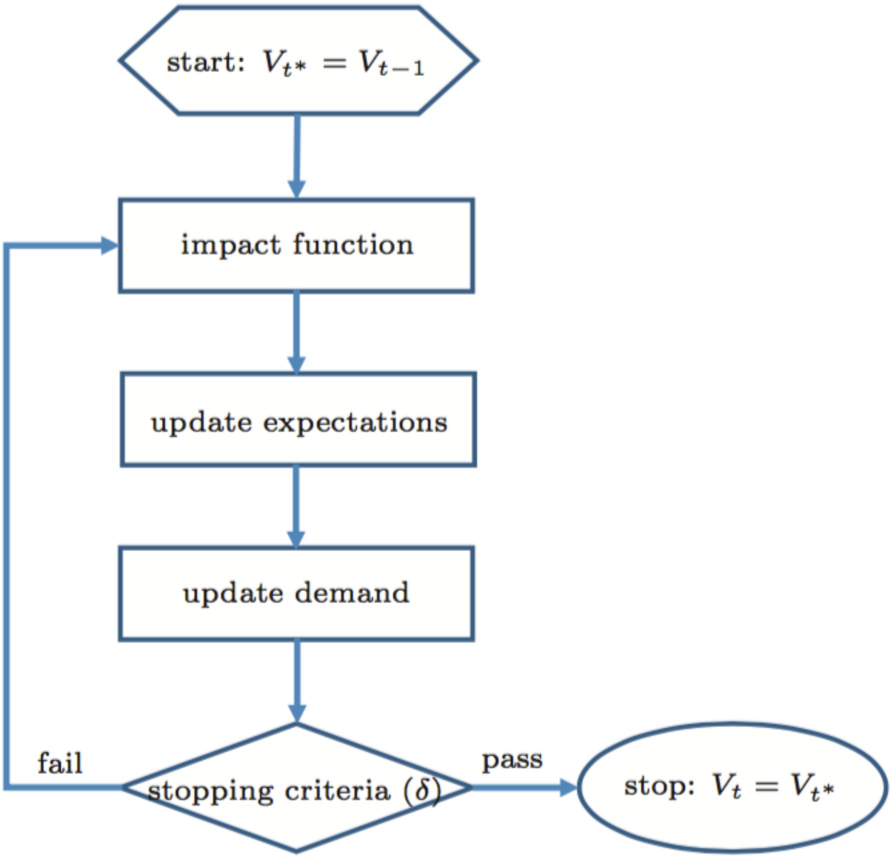


FIGURE 4.4: Pricing algorithm.

with the parameter γ^{EX} defining the intensity of adjustments and

$$\Delta K_{t^*}^{\mathcal{DF}} = \sum_{d=1}^{n^d} \left(\Delta C_{d,t^*}^{\mathcal{F}} + \sum_{F=1}^{n^F} \Delta Q_{d,t^*}^{F} P_{t^*}^{F} \right) X_{t^*}^{\mathcal{DF}} - \sum_{f=1}^{n^f} \left(\Delta C_{f,t^*}^{\mathcal{D}} + \sum_{D=1}^{n^D} \Delta Q_{f,t^*}^{D} P_{t^*}^{D} \right) \tag{4.1.23}$$

being a measure of desired net capital flows into country $\mathcal{F}$ denominated in country $\mathcal{D}$'s currency. Analogous to normalising excess demand in Eq. (4.1.18), we normalise, for convenience, desired net capital flows by the exchange rate adjusted balance sheet size of all agents.

The algorithm schematised in Figure 4.4 can produce prices and exchange rates that come arbitrarily close to the values that clear their respective market. Since market clearing is achieved when $\delta_{t^*}^{\{D,F\}} := \Delta Q_{t^*}^{\{D,F\}} / \bar{Q}^{\{D,F\}}$ for all portfolios and $\delta_{t^*}^{X} := \Delta K_{t*}^{\mathcal{DF}} / (\sum_{d=1}^{n^d} S_{d,t^*} + \sum_{f=1}^{n^f} S_{f,t^*} X_{t^*}^{\mathcal{DF}})$ in the foreign exchange market are zero, it is sensible to exit the algorithm when all these variables go below the bound b, i.e.

$$\delta := \begin{cases} \text{pass} & \text{if } \bigwedge_{D=1}^{n^D} (\delta_{t^*}^{D} \leq b) \wedge \bigwedge_{F=1}^{n^F} (\delta_{t^*}^{F} \leq b) \wedge (\delta_{t^*}^{X} \leq b) \\ \text{fail} & \text{else} \end{cases} \tag{4.1.24}$$

The higher b, the quicker the stopping criteria δ is met and the further prices and the exchange rate are from their market clearing values. Figure 4.1.7 illustrates this trade-off between computational complexity and achieving market clearing prices and exchange rates. We measure computational complexity as the average number of iterations needed before the stopping criteria δ is reached.

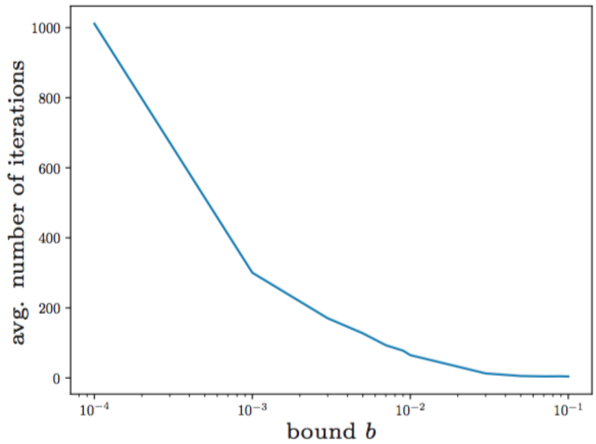


FIGURE 4.5: Trade-off between computational complexity and achieving market clearing.

When the stopping criteria δ is satisfied, final prices and exchange rates are determined, i.e. $P_t = P_{t^*}$ and $X_t^{\mathcal{DF}} = X_{t^*}^{\mathcal{DF}} + \epsilon_t^X$. Note that we add an error term to the exchange rate in order to account for exchange rate movements that are not driven by transactions in financial assets.

4.1.8 Balance Sheet Adjustments

Once prices and the exchange rate have adjusted to a satisfactory extent, agents sell and buy portfolio shares and trade cash on foreign exchange markets. The consequence of using the pricing algorithm presented in the previous section is that new balance sheet positions can, in an unsystematic way, slightly deviate from the positions implied by agents' balance sheet optimisation. Updating the asset side of investor agents' balance sheets thus requires taking into account excess demand and supply in shares of portfolios as well as cash payments that result from transactions in portfolio shares. The computations that lead to the new balance sheet positions are described in Appendix 5.4.2.

5 Simulation study[1]

The previous section developed a model that yields endogenous price and exchange rates movements while allowing for heterogeneity in assets in respect of maturities, default rates and inflation risk. To understand the effect of QE in this framework, we calibrate our model to a domestic market consisting of the Eurozone (EZ) and a foreign market consisting of a sample of rest-of-the-world countries. Calibrated variables include balance sheet positions, interest rates, dividend yields, the maturity profile of bond portfolios, inflation risk and default risk. Both regions comprise two agents, which are calibrated to match investment behaviour of funds and banks. Agents can trade two asset portfolios per region representing bonds (sovereign and corporate) and equities. We use several data sources in order to get the model as close to the data as possible.

Programming of the algorithm was done in python. We used UCT's High performance Cluster (HPC) as the algorithm that determines equilibrium prices is very computation intensive.

5.1 Portfolio balance effects from Eurozone QE

5.1.1 Agents' asset holdings

Agents' balance sheet positions are calibrated to financial asset holdings of world-wide investment funds and banking institutions. While there is substantial heterogeneity within the group of a region's funds and banks respectively, we model EZ banks and EZ funds, as well as ROW banks and ROW funds as representative agents for their respective industry, i.e. two agents per region. Our framework does not limit the number of agents included per region. However, data availability and computational complexity provide good reason to start with representative agents.

Our sample of investment funds include equity funds, bond funds, mixed funds and hedge funds. For the sake of simplicity, we exclude real estate funds, money market funds, pension funds and insurance companies. Although the investment behavior of these institutions could very well lead to a portfolio re-balancing effect in response to QE, we assume that mean-variance portfolio optimisation would be a poor representation of that behaviour.[2] All data points are taken from

[1] This chapter is part of the working paper Koziol et al. (2019), 'Euro Area Quantitative Easing in a Portfolio Balance Model with Heterogeneous Agents and Assets'

[2] The insurance and pension fund sector (ICPF) exhibits demand functions for bonds that are distinct from the rest of the investment fund sector. Due to their long-term obligations and duration gap management, the ICPF sector has an upward sloping demand function for long-term bonds, i.e. when the price of the long-term bond increases, the duration gap of any given bond portfolio increases as well and the ICPF investor reacts by purchasing additional long-term assets to match the longer duration of their liabilities Domanski et al. (2015).

Q4 2014. Table 5.2 provides an overview of the balance sheet positions, while Table 5.12 in the appendix provides details on the data sources used. While we assume that all equity and debt securities on funds' balance sheets are held for investment purposes and therefore subject to portfolio optimisation, banks may have other reasons to hold securities (e.g. to use as collateral in exchange for central bank liquidity). To account for this, we only include bank assets that are categorised as "trading assets" and "available for sale". Calibrating currency positions for funds and banks is more problematic. We are unable to distinguish cash positions held for transactional purposes and for investment purposes. For the sake of simplicity, we assume that all cash positions on funds' balance sheets are the result of portfolio optimisation while only excess reserves held by banks qualify as such.

5.1.2 Interest Rates, Dividends and Inflation

Table 5.1 shows the values used in simulations for EZ and ROW nominal interest rates for the respective bond portfolios and currencies, as well as nominal dividends for equity portfolios. Furthermore, since agents in our model consider real returns instead of nominal return when making investment decisions, we set agents' inflation expectations to inflation forecasts at the end of 2014 for the year 2015.[3] The nominal rates on currency are set to central bank deposit facility rates for the EZ and the ROW that were effective at the end 2014. The nominal rate for bond portfolios and dividends (as percent of an equity portfolio's face value) are calibrated in such a way, that agents' initial expected returns at $t = 0$ for the respective portfolios match empirical returns for stocks and bonds. For the calibration of expected bond returns, we use yield to maturity data from comprehensive S&P sovereign and corporate bond indices (see Table 5.17 in the appendix for details). We take a simple average of corporate and sovereign yields to determine the expected return of bond portfolios in the model.[4] Expected returns on equity portfolios are calibrated by using estimates of equity premia and risk-free rates for corresponding geographical regions (see Table 5.15 in the appendix). Note that we assume a constant dividend rate just as we assume a constant nominal interest rate on bond portfolios. While this assumption would be problematic for an individual stock, it seems reasonable for a comprehensive portfolio of stocks.

5.1.3 Preferences

We assume that funds' and banks' preferences are revealed by their asset holdings (Table 5.2) at prevailing interest rates (Table 5.1). In our model, these preferences come in the form of asset-specific risk aversion parameters. Since changing the risk aversion parameters can have an influence on returns and their variation, we need to use the iterative algorithm schematized in Figure 5.1. The calibration algorithm starts by simulating the model with arbitrary parameters for bonds' nominal interest rates, for equities' nominal dividend rates and for asset-specific risk aversions. The dynamics created in this simulation give agents an idea of the variance and

[3] See Table 5.14 in the appendix for the weighting of ROW countries to obtain representative nominal rates and inflation rates

[4] Public and private debt securities have very similar market capitalisations in the Eurozone and in our sample of ROW countries.

	Nominal rate Cash	Nominal rate Bond portfolio	Nominal rate Equity portfolio	Expected Inflation
EZ	-0.20%	0.93%	5.73%	1%
ROW	0.85%	1.92%	4.33%	2.1%

TABLE 5.1: Nominal interest rates for asset portfolios. EZ cash rate is the ECB's deposit facility as of Dec 2014. The ROW cash rate is the market-cap weighted average of our sample of ROW countries. See Table 5.14 for details of weighting and deposit rate per individual countries. Nominal rates for bond and equity portfolios are calibrated to yield to maturity values for domestic and foreign market indices (see Table 5.17 for details) and equity risk premia (see Table 5.15) respectively. Expected inflation values are sourced from the ECB's inflation forecast for the Eurozone and the OECD's inflation forecast for the rest-of-the-world respectively (5.14).

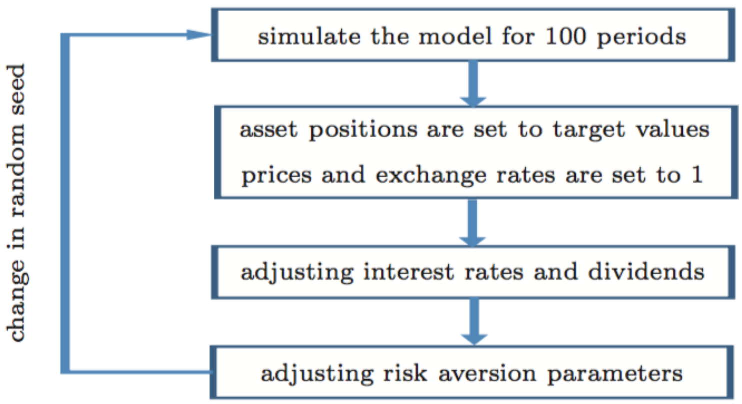


FIGURE 5.1: Calibration algorithm.

Trillion EUR		Debt Securities (DS)			Equities (Eq)			Currencies (C)			Computed Total Assets
		EZ DS	ROW DS	sum DS	EZ Eq	ROW Eq	sum Eq.	EZ C	ROW C	sum C	
Eurozone Investors	Funds	1.961	1.651	3.612	0.930	1.821	2.751	0.411	0.218	0.629	6.992
	Banks	3.204	0.656	3.860	0.571	0.075	0.646	0.08	0.016	0.096	4.602
ROW Investors	Funds	0.263	7.045	7.308	0.556	8.461	9.017	0.063	1.202	1.265	17.59
	Banks	0.568	10.009	10.577	0.078	1.692	1.770	0.136	2.4	2.536	14.883
Computed Market Size		5.996	19.361	25.357	2.135	12.049	14.184	0.69	3.836	4.526	44.067

TABLE 5.2: Balance sheet positions of funds and banks residing in the Eurozone and in the rest-of-the-world in trillion EUR. *Sources:* ECB Investment fund balance sheet statistics, CBD2, Bankscope, IMF Coordinated Portfolio Investment Survey, Morning Star Direct, Fred database and FSB Global Shadow Banking Monitoring Report.For more details for computation methods and source details see Table 5.16 and Table 5.12 in the annex.

covariances of returns associated with each asset. In a second step, asset holdings per agent are set to their target values documented in Table 5.2 and, for the sake of convenience, prices and exchange rates are set to 1. We then adjust nominal interest rates for bonds and nominal dividend rates for equities so that the expected returns for the respective assets are identical with the data from Table 5.1. The next step is the main part of the calibration algorithm. We adjust the asset-specific risk aversion parameters for each agent so that they are willing to hold their targeted asset portfolio at the given expectations of returns. In order to adjust the asset-specific risk aversion parameters, we use the algorithm in Figure 4.4 employed to adjust prices and exchange rates within a simulation. We thereby make use of the economic intuition that an increase in asset-specific risk aversion should decrease the demand for that asset. We use the following recursive impact function to calibrate risk aversions to asset A, which could be a portfolio or a currency:

$$\log(\lambda_d^A) = \log(\lambda_d^A) + \gamma \left(\frac{w_{d,0}^A S_{d,0} - Q_{d,0}^A}{Q_{d,0}^A} \right), \tag{5.1.1}$$

with $w_{d,0}^A S_{d,0}$ being the demand for asset A according to agent d's balance sheet optimization, $Q_{d,0}^A$ being the targeted amount and γ being the intensity parameter that adjusts the risk aversion. Once the risk parameters for all agents have been adjusted, the model is again simulated for 100 periods and the procedure is repeated. Note that whenever the model is simulated for 100 periods, we change the random seed to ensure that the risk aversion parameters are not only valid for a particular manifestation of the exogenous stochastic variables. We iterate the algorithm 500 times to allow for risk aversion parameters to stabilise.

Table 5.3 documents the calibration outcome for risk aversion parameters, while Table 5.4 shows the standard deviation in percent of the parameters in the last 100 iterations of the calibration algorithm. Thereby it becomes clear that there is substantial uncertainty about the true preferences of agents. The uncertainty is most salient for risk aversion towards the currencies, with risk aversion parameters deviating from their means on average by 31% to 246%, while the other risk aversion parameters vary from 4% to 13%. Note that the uncertainty about the correct risk aversion parameters for currencies, reflects our uncertainty about agents' holdings of currencies for non-transactional purposes mentioned in Section 5.1.1. Since the risk aversion parameters can generally only be calibrated jointly, it is also likely that it is the uncertainty about currency holdings that is driving the uncertainty about risk aversion towards other assets.

Strikingly, the asset-specific risk aversion parameters in Table 5.3 are consistently higher than the typical single-digit estimates of risk aversion found in the literature. For the bond and equity portfolios the parameters range from 16.36 to 1317.90. While this seems unusual, it is more likely to indicate missing risk factors than it is to reflect a general problem with our calibration approach. Note that inflation risk and default risk are the only factors determining risk in the model. Other factors, such as uncertainty about future interest rates or political uncertainty, are not represented. Furthermore, the agents in the model are rather cool-headed and not inclined to overreact to changing conditions, which would generate more price volatility. The estimates of risk aversion parameters suggest that the assumed risk exposure (in the form of expected variances and covariances of returns) resulting from agents' expectation formation and trading behavior under exogenous default rate and inflation processes (see next subsection) are

Investors	Assets available for investment: Euro area Bond Portfolio	Euro area Equity Portfolio	Rest-of-the-World Bond Portfolio	Rest-of-the World Equity Portfolio	Euro area Currency	Rest-of-the-World Currency
Euro Funds	119.35	63.22	41.09	28.21	13,233.67	126.69
Euro Banks	93.54	52.11	263.28	175.05	19860.89	142.80
ROW Funds	486.37	249.71	22.82	16.36	1646.41	80.41
ROW Banks	1317.90	719.87	54.51	40.27	3071.84	830

TABLE 5.3: Risk aversion parameters of investor agents for assets.

Investors	Assets available for investment: Euro area Bond Portfolio	Euro area Equity Portfolio	Rest-of-the-World Bond Portfolio	Rest-of-the World Equity Portfolio	Euro area Currency	Rest-of-the-World Currency
Euro Funds	7	7	4	5	31	128
Euro Banks	5	6	6	9	49	227
ROW Funds	13	11	4	5	87	246
ROW Banks	12	12	5	5	49	183

TABLE 5.4: Standard deviation in percent of risk aversion parameters for the last 100 iterations of the calibration algorithm.

one order of magnitude lower than in reality. Note that this conjecture cannot easily be tested by looking at historical variations and correlations in returns, as they may differ systematically from expectations of risk exposures.

5.1.4 Stochastic Processes

Default risk and inflation risk are the only two risk factors that are exogenous to our model. They are modeled with random variables in order to produce realistic dynamics of endogenous variables such as prices and returns. Inflation risk is modeled as a simple normally distributed random variable $\pi_t \sim \mathcal{N}(\mathrm{E}[\pi], \sigma^\pi)$ with constant mean and variance. The mean $\mathrm{E}[\pi]$ is the region-specific inflation forecast and the standard deviation being calibrated to match that of inflation data for the respective regions from of the past 20 years, i.e. 1997 to 2017.[5] All calibration results for the stochastic processes are documented in Table 5.5.

For the calibration of default risk, we use data on global default events from the S&P 2017 Annual Global Corporate Default Study and Rating Transitions (see SP2017, 2018, p.5). Lacking granular data on default events for different regions, we distribute the number of events per year to the EZ and ROW region according to their relative total market capitalization. From this data basis, we estimate the parameters of the following AR(1) process:

$$\ln(\mathrm{E}[e_t]) = \ln(\mathrm{E}[e_{t-1}])(1-\psi_e) + \psi_e \ln(\mathrm{E}[\bar{e}]) + \epsilon_t^e, \tag{5.1.2}$$

with $\mathrm{E}[e_t]$ being the expected number of default events occurring on day t, $\bar{e}$ being the sample average number of events per day (i.e. the yearly average divided by 250), and $\epsilon_t^e \sim \mathcal{N}(0, \sigma^e)$

[5] ROW data is taken from the IMF World Economic Outlook and weighted according to market capitalisations as documented in Table 5.11 of the appendix.

	inflation process parameters		default process parameters				
	E[π]	σ^{π}	$\bar{e}$	ψ_e	σ^e	ω^{DS}	ω^{Eq}
EZ	1%	1%	15/250	0.0011	0.00176	$\frac{0.5}{250}\%$	$\frac{2}{250}\%$
ROW	2.1%	0.7%	75/250	0.0014	0.01132		

TABLE 5.5: Stochastic inflation and default processes parameters.

being a normally distributed error term with zero mean and standard deviation σ^e. Since realized default events can only be a natural number, we draw e_t from a Poisson distribution with mean $\text{E}[e_t]$. The parameters of the process in Eq. (5.1.2) are estimated in order to minimize the distance between the data and the stochastic process for the first order autocorrelation $A(\cdot)$ and variance $var(\cdot)$, i.e.

$$\hat{\psi}_e, \hat{\sigma}^e = \underset{\psi_e, \sigma^e}{\arg\min} \left((A(e_{\text{yearly}}) - A(\text{data}))^2 + (var(e_{\text{yearly}}) - var(\text{data}))^2 \right) \tag{5.1.3}$$

Since the data on default events is available on a yearly basis, while our model simulates daily data, we aggregate defaults over 250 days in order to obtain yearly default events for the numerical estimation of Eq. (5.1.3).

Although we assume that equity and bond portfolios of a region are subject to the same default event process, default rates Ω_t do take into account the different risk characteristics of equities and bonds. The difference in default rates for bonds and equities results from differences in the loss rate ω per default event, with $\Omega_t = e_t * \omega$. While sovereigns do not issue equity, the bond portfolio contains a 50:50 mix of corporate bonds and sovereign bonds, which for the sake of simplicity we assume to be free of default risk. Furthermore, it is reasonable to assume a 100% loss given default for equities, whereas 50% of a defaulting corporate bond can typically be recovered (c.p. e.g. Jacobs, 2009, p. 43). With the simplifying assumption that one default event always affects $\frac{2}{250}\%$ of assets in the equity portfolios and corporate part of the bond portfolios, we arrive at our values for loss rates documented in Table 5.5, i.e. $\omega^{\text{Eq}} = 1 * \frac{2}{250}\%$ for equity portfolios and $\omega^{\text{DS}} = 0.5 * 0.5 * \frac{2}{250}\% = \frac{0.5}{250}\%$ for bond portfolios.[6]

5.1.5 Portfolio Maturity

The average portfolio maturity parameter m is calibrated by reconstructing a portfolio that matches the maturity profile of a representative Euro area investment fund. We compile data from a sample of 15374 open-end investment funds resident in the Euro area from the Morning Star database. Table 5.6 contains information on the remaining maturities of fixed income securities held by the representative fund.

Under the assumption that the maturity dates are distributed equally within a maturity bin, we can fit the data to our model. Figure 5.2 shows the maturity structure of the representative fund from Table 5.6 and a fitted portfolio with a constant repayment rate. The maturity parameter that best fits the data is $m = 0.99936$, which corresponds to an average maturity of 6.25 years. Fitting the data to more than one portfolio with different maturity parameters only

[6]The assumed $\frac{2}{250}\%$ of affected assets per default event means that on average 2% of corporate bond and equity issuers default each year, which is in line with the data in SP2017 (2018).

remaining maturity	% of total assets
0-1 year	11.5
1-3 years	22.7
3-5 years	21.7
5-7 years	15.0
7-10 years	15.1
10-15 years	4.6
15-20 years	1.9
20-30 years	4.4
30-40 years	3.1

TABLE 5.6: Maturity profile of fixed income securities of a representative open-end euro area investment fund in December 2014.

slightly increases the fit. Since stocks do not mature, we set their maturity parameter of equity portfolios to one.

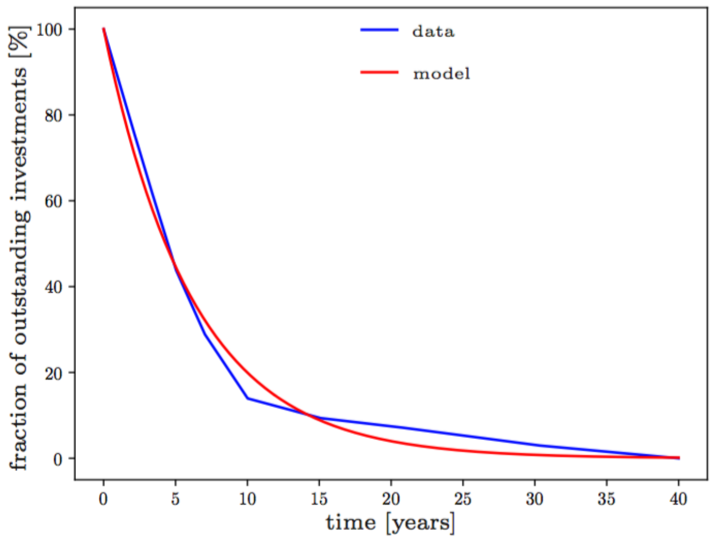


FIGURE 5.2: Maturity structure of a representative Euro area open-end investment fund compared to the maturity structure of a fitted model portfolio.

5.1.6 Other Parameters

Of the three parameters that remain uncalibrated, the expected convergence speed (η from Eq. (4.1.9)) of the exchange rate towards its purchasing power parity (PPP) is arguably the most influential. Low values will lead to excess exchange rate volatility, while high values will tie the exchange rate to its PPP. We choose a convergence speed of 15% annually, which we take from Rogoff (1996).

For the memory parameter ψ in Eq. (4.1.10), which determines how much weight is given to the latest observation when agents update their return-covariances estimates, there is no data nor a literature that we can draw on for calibration purposes. If excessive weight (e.g. $\geq 1\%$, in our model) is given to the latest observations, agents will replace large parts of their balance sheet holdings with high frequency. This can lead to self-reinforcing dynamics, where large shifts in holdings increase return volatility, which in turn increases trade volumes. The emergence of such destabilising dynamics is unlikely to produce interesting insights, as it ensues not from a realistic representation of investor behaviour, but rather from an unrealistically high sensitivity of optimal portfolio weights derived from a mean-variance utility function. A memory parameter $\psi = 0.1\%$ is chosen to ensure the stability of the model.

The bound b from Eq. (4.1.24), which determines how close prices and the exchange rate need to come to their respective market clearing values before the stopping criteria of the pricing algorithm schematised in Figure 4.4 is reached. We set $b = 0.01$, which leads to reasonable simulation times. This choice means that, at most, excess demand for an asset is $\pm 1\%$ of total quantity of that asset. Furthermore, excess demand for the respective foreign currency is at most $\pm 1\%$ of total assets.

5.2 Results

We conduct a series of experiments to analyse the impact of central bank asset purchases on international returns and the exchange rate. Thereby we compare simulation outcomes for a range of QE volumes to a benchmark, where the central bank does not interfere in asset markets. We simulate asset purchases from 200 bn EUR to 2.6 tn EUR, whereby the purchase volume refers to the nominal value of EZ debt securities. Each simulation run lasts for 1000 periods, i.e. 4 trading years, and is repeated 20 times with different random seeds. The repetition of simulations is important to make sure that results are valid for different manifestations of stochastic processes; in particular the default processes, which reflect different states of the economy.

5.2.1 Asset Returns and Prices

To obtain estimates of the portfolio balance effect of QE on asset returns, we regress the change between return expectations with and without central bank purchases on the size of these purchases. In order to avoid that serial correlation in the simulated data affects standard errors, we use a cross-section of observations per random seed by averaging data points across time, which leads to 260 independently distributed observations and the following regression equation:

$$\underset{\text{seed}}{\Delta} \mathrm{E}[r|_{\mathrm{QE}}] = \alpha + \beta \frac{\mathrm{QE}}{100\text{bn EUR}} + \epsilon_{\text{seed}}, \quad \text{with}$$
$$\underset{\text{seed}}{\Delta} \mathrm{E}[r|_{\mathrm{QE}}] = \left(\underset{\text{seed}}{\mathrm{E}}[r|_{\mathrm{QE}}] - \underset{\text{seed}}{\mathrm{E}}[r|_{\mathrm{QE}=0}] \right) * 250 * 100 * 100 \tag{5.2.1}$$

Note that we use annualised returns (approximated by multiplying by 250) and multiply by 10^4 to obtain results in basis points. We use return expectations instead of observed daily returns to isolate yield effects from price movements. We do this to avoid transitory increases in prices to influence the impact on yields. To isolate the yield effect, the target variable is the return a new investor would expect to get from investing in an asset. Expectations in our model are unbiased. All quantitative results refers to the expected returns. Furthermore, we use EZ agents' expectations of EZ bond and equity portfolio returns and ROW agents' expectations of ROW bond and equity portfolio returns. This prevents exchange rate expectations being reflected in

VARIABLES	(1) EZ bond portfolio	(2) EZ equity portfolio	(3) EZ currency
QE	-0.598***	-1.96***	0.206***
	(0.000124)	(0.000489)	(0.000119)
Constant	-0.178	0.787	0.742***
	(0.180)	(0.280)	(0.166)
Observations	260	260	260
R-squared	0.897	0.866	0.515

VARIABLES	(4) ROW bond portfolio	(5) ROW equity portfolio	(6) ROW currency
QE	-0.0271***	-0.143***	-0.205***
	(3.67e-05)	(0.000233)	(0.000118)
Constant	0.0420	0.145	-0.745***
	(0.0604)	(0.381)	(0.165)
Observations	260	260	260
R-squared	0.162	0.116	0.515

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.7: OLS regressions of QE on expected return variables with heteroskedasticity robust standard errors. *Upper half:* QE effects on domestic assets. *Lower half:* QE effects on foreign assets.

return expectations. The impact of QE on exchange rate expectations is documented in ROW agents' expectations of EZ currency returns and EZ agents' expectations of ROW currency returns.

Table 5.7 shows the impact of QE on returns in basis points per 100 bn EUR of central bank purchases. All effects are statistically highly significant, but rather low in magnitude. The yield of the EZ bond portfolio declines on average about 0.6 basis point for each 100 bn EUR the central bank purchases of that portfolio. The low standard error on the coefficient indicates that the relationship between purchases and bond returns is well described by the linear regression. The constant is not statistically significant from zero, which is consistent with what is expected because the effect on yields by definition is zero if no QE is implemented. With a reduction of 1.96 bps per 100 bn EUR of purchases, the effect of QE is strongest on domestic equity returns. The positive impact on expected returns on the EZ currency indicates that the Euro depreciates with the central bank's asset purchases. ROW-agents assume that the Euro will eventually revert back to its PPP value and therefore expect a higher return in comparison to the scenario without central bank intervention.

We do find a statistically significant spillover into the foreign asset markets. The effects per 100 bn EUR of the central bank's purchases on the expected returns of the ROW bond portfolio and the ROW equity portfolio are -0.03 bps and -0.14 bps, respectively. Thus, the impact of

VARIABLES	(1) EZ bond portfolio	(2) EZ equity portfolio	(3) ROW bond portfolio	(4) ROW equity portfolio
QE	0.0348***	0.260***	0.0014***	0.0152***
	(7.22e-06)	(6.39e-05)	(2.00e-06)	(2.54e-05)
Constant	0.00867	-0.180***	-0.00228	-0.0155
	(0.0104)	(0.0987)	(0.00328)	(0.0416)
Observations	260	260	260	260
R-squared	0.897	0.869	0.161	0.115

VARIABLES	(5) exchange rate
QE	0.0138***
	(7.92e-06)
Constant	0.0495***
	(0.0110)
Observations	260
R^2	0.515

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 5.8: OLS regressions of QE on price variables with heteroskedasticity robust standard errors.

QE on foreign bond and equity returns, although statistically significant at the 1% level, is economically negligible.

Under our assumption that banks and funds represent the investors that are most likely to be responsible for a portfolio balance effect of QE, we can use the regression results to estimate the effects of the ECB's expanded asset purchase program (APP). Given that the ECB bought approximately 2.6 tn EUR of Eurozone debt securities between March 2015 and December 2018, our model predicts a reduction of annualised EZ bond returns of approximately 15.6 bps and a reduction of EZ equity returns of approximately 50.9 bps. While these reductions in returns are arguably too small to significantly stimulate the economy, they can have more substantial wealth effects, which are a consequence of QE induced price changes.

Table 5.8 shows the results of regressing percentage price differences between simulations with and without QE.[7] The price impact on the EZ equity portfolio is by far the biggest, with an increase of 0.26% per 100 bn EUR of purchased EZ bond portfolio shares. Extrapolating this to the size of the ECB's APP predicts that the portfolio balance channel would increase EZ equity prices by approximately 6.8%. When comparing the 6.8% increase in equity prices with the annualised 15.6 bps decrease in expected bond yields, it seems fair to say that the portfolio

[7]The dependent variable is $\Delta P_{\text{seed, QE}} = \frac{P_{\text{seed, QE}} - P_{\text{seed,QE=0}}}{P_{\text{seed,QE=0}}}$, while the independent variable is the volume of EZ bond purchases.

balance effect of the ECB's APP is of greater benefit to shareholders than to issuers of debt securities.

EZ bond prices only increase by 0.035% per 100 bn EUR of purchased bonds. This is not surprising as there is a tighter relationship between the return and the price of assets with limited maturity. The relation between the exchange rate and the expected return on currency, on the other hand, is determined by the expected convergence speed (the parameter η in Eq. 4.1.9) towards the PPP. Hence, the predicted 0.0138% depreciation of the EUR vis-a-vis the basket of ROW currencies per 100 bn EUR of asset purchases (amounting to approx. 0.36% for the entire APP) reflects our calibration choice of $\eta = 15\%$ per year. Note that a lower (higher) expected convergence speed would lead to a stronger (weaker) depreciation without directly affecting how QE impacts expected currency returns documented in Table 5.7.

5.2.2 Variation in Return and Price Effects

Although the regressions with averaged data provide estimates of the impact of QE on returns and prices with high confidence, there is a significant amount of variation in the effects when comparing individual observations. Table 5.9 documents the distribution of return and price effects for asset purchases worth 100 bn EUR. Note that all QE-effects apart from those on EZ bond returns and prices range from negative to positive values within the 5th and 95th percentile of the distribution. This indicates the difficulty of empirically measuring the portfolio balance effect when it is phased in slowly. It is unclear why the portfolio balance effect differs so strongly between observations. We find, however, that the state of the model economy, which we can measure by looking at stochastic default probabilities, does not have a significant effect on the magnitude and direction of the portfolio balance effect.

QE-effect	Variable	Mean	Standard deviation	5% percentile	95% percentile
	exp. return EZ bonds	-0.62	0.33	-1.09	-0.22
Yields:	exp. return EZ equities	-1.88	1.56	-3.84	0.15
Effect in bps	exp. return EZ currency	0.28	0.32	-0.09	0.82
per 100 bn EUR	exp. return ROW bonds	-0.02	0.12	-0.16	0.13
assets bought	exp. return ROW equities	-0.13	0.78	-1.09	0.89
	exp. return ROW currency	-0.28	0.32	-0.81	0.09
Prices:	EZ bond price	0.036	0.019	0.012	0.063
Effect	EZ equity price	0.242	0.195	-0.018	0.488
in percentage	ROW bond price	0.001	0.006	-0.007	0.009
per 100 bn EUR	ROW equity price	0.014	0.086	-0.096	0.119
assets bought	exchange rate	0.019	0.022	-0.006	0.054

TABLE 5.9: Distribution of the QE effect on expected returns and prices following a 100 bn purchase of EZ bond assets. Sample moments are computed from 260,000 simulated observations (i.e. the average from 14 experiments with QE ranging from 200 bn EUR to 2600 bn EUR that last for 1000 days and are repeated 20 times with different random seeds).

5.2.3 Who Sells to the Central Bank?

Table 5.10 shows how agents re-balance their portfolios on the first day of asset purchases by the central bank. The upper panel documents the changes in market value, while the lower panel displays the change relative to agents' previous asset holdings. Note that sales of the EZ bond portfolio by agents do not add up to 100 bn EUR, but approximately 80 bn EUR. This is the case because the exit condition in the pricing algorithm is often satisfied before the central bank succeeds in purchasing all its desired assets. While the central bank purchases the remaining assets in the following days, we only show the results after the first day in order to avoid measuring portfolio re-balancing due to exogenously changing economic conditions (i.e. default probabilities).

We find that all agents decrease their holdings of EZ bonds and increase their holdings of EZ currency in response to QE. In relative terms, the ROW agents are more eager to sell their EZ bonds to the central bank. ROW funds sell 11.1% and ROW banks 2.3% of their EZ bonds per 100 bn EUR of EZ bonds demanded by the central bank. EZ funds and banks, who initially hold a higher share of EZ bonds, only sell 1.1% and 0.5%, respectively. The reason why ROW agents are more inclined to decrease their balance sheet share in EZ bonds, which is consistent with the data (see Koijen et al., 2016), is the increased attractiveness of the EZ currency. From the perspective of ROW agents, an expected appreciation of their currency increases the expected returns on EZ assets. However, since expected yields on EZ bonds and EZ equities decline at the same time, it is the investment in EZ currency that promises a higher return after QE. From the perspective of the EZ agents, holding Euros is also more attractive under QE than without it. This is the case because the expected return on holding Euros does not change with QE, while the expected returns on all other assets, domestic or foreign decline under QE. From the perspective of EZ investors, foreign expected returns decline because agents expect the ROW currency basket to depreciate in order to reach its PPP.

Change in holdings per 100bn		EZ bond	EZ equity	EZ currency	ROW bond	ROW equity	ROW currency
		EZ			Rest-of-the-World		
EZ	funds	-21.1 (8.5)	-1.3 (1.4)	22.4 (9.3)	-6.0 (11.2)	-3e-3 (0.03)	6.0 (11.3)
	banks	-16.7(9.8)	-1.1 (1.2)	16.4 (10.7)	-0.4 (1.9)	0.19 (0.3)	1.6 (5.3)
ROW	funds	-28.7 (13.9)	1.2 (1.6)	28.5 (12.5)	1.5 (6.1)	-0.1 (0.3)	-2.4 (7.1)
	banks	-13.2 (5.9)	1.2 (0.9)	12.3 (5.2)	4.4 (7.4)	-0.1 (0.2)	-4.6 (7.5)
Change in % per 100bn							
EZ	funds	-1.1 (0.4)	-0.1(0.2)	5.5 (2.3)	-0.3 (0.7)	-2e4 (0.00)	3.7 (7.0)
	banks	-0.5(0.3)	-0.2(0.2)	20.9 (13.4)	-0.1 (0.3)	0.3 (0.4)	70.0 (273.5)
ROW	funds	-11.1 (5.5)	0.2 (0.3)	42.9 (18.2)	0.02 (0.1)	-1e-3 (0.0)	-0.2 (0.6)
	banks	-2.3 (1.1)	1.5(1.1)	8.9 (3.8)	0.04 (0.07)	-0.01 (0.01)	-0.2 (0.3)

TABLE 5.10: Change in agents' balance sheet positions on the day QE is implemented. Values are means across 20 seeds, standard deviations in parentheses. *Upper half:* Difference in the market value of absolute asset holdings per 100bn EUR of asset purchases by the central bank. *Lower half:* percentage difference in asset holdings per 100bn EUR of asset purchases by the central bank.

5.3 Conclusion

We develop a portfolio model to analyse the impact of QE on international asset returns. Our model differs from those in the literature by allowing for heterogeneity in asset characteristics and agent preferences. Including these two domains of heterogeneity is crucial in order to capture the substitutability of assets from the perspective of investors. Data clearly shows that the raw variance and covariance of returns, which are the sole determinant of asset substitutability in other portfolio models, are not sufficient to explain investor behavior. Home bias, preferences for certain asset classes and asset maturity, which we include as a characteristic of assets, all contribute in determining asset substitutability.

We calibrate our model to represent banks and investment funds from the Eurozone (EZ) and a sample of rest-of-the-world (ROW) countries. In simulations we find that the portfolio balance effect in response to QE is rather modest when compared to empirical results from event studies of QE announcements. For 2.6 tn EUR of asset purchases, our model predicts a reduction in EZ bond yields of 15.6 basis points and a reduction in EZ equity returns of 50.9 basis points. Equity prices, on the other hand, are predicted to be 6.8% higher under the ECB's extended asset purchasing program than they would otherwise be. Furthermore, we find that ROW investors sell a much higher relative share of their EZ holdings to the central bank than domestic investors, particularly ROW funds. This can be explained by a higher attractiveness to hold EZ currency from the perspective of ROW investors than what would be the case without QE.

5.4 Annex - PART I

5.4.1 Maturity Parameter and Term Structure

Maturity of asset portfolios is modelled through a constant repayment rate $(1-m)$ on outstanding assets. In section 5.1.5, we describe how we calibrate the parameter m to match the maturity profile of Euro area bond portfolios. Figure 5.2 shows how the maturity structure we find in the data compares to our fitted portfolio with constant repayment rate. The plot shows the percentage of current portfolio still outstanding on any given date in the future. It becomes clear from Figure 5.2 that the portfolio within the model implicitly contains many securities with differing maturity dates. Hypothetically, a portfolio with maturity parameter $0 < m < 1$ comprises at least one security for each possible future maturity date. The expected return $r(m)$ on that portfolio is therefore a function of the yield curve $r(t)$ of underlying hypothetical securities:

$$r(m) = \sum_{t=1}^{\infty}(1-m)m^{t-1}r(t), \tag{5.4.1}$$

with $(1-m)m^{t-1}$ denoting the portfolio shares that mature on date t. Under certain conditions, $r(t)$ can be approximated by simulating the model with varying maturity parameters. Note, however, that the return $r(m)$ on a portfolio of average maturity T_m is generally not the same as the sport rate $r(t = T_m)$ of an individual security that matures at date T_m, with:

$$T_m = \sum_{t=1}^{\infty}(1-m)m^{t-1}t = \frac{1}{1-m}, \tag{5.4.2}$$

The ability to approximate $r(t)$ crucially depends on the assumption about its functional form. Specifically, $r(t)$ must lead to convergence of the infinite sum in Eq. 5.4.1. Conveniently, the most common parametric yield curve models used by central banks, i.e. the Nelson & Siegel model $r^{\text{N\&S}}(t)$ as well as its more flexible extension, the Svensson model $r^{\text{Sv}}(t)$, satisfy the convergence condition.

$$r^{\text{N\&S}}(t) = \beta_0 + \beta_1 \frac{1-\exp(\frac{-t}{\tau_1})}{\frac{t}{\tau_1}} + \beta_2\left(\frac{1-\exp(\frac{-t}{\tau_1})}{\frac{t}{\tau_1}} - \exp(\frac{-t}{\tau_1})\right) \tag{5.4.3}$$

$$r^{\text{Sv}}(t) = r^{\text{N\&S}}(t) + \beta_3\left(\frac{1-\exp(\frac{-t}{\tau_2})}{\frac{t}{\tau_2}} - \exp(\frac{-t}{\tau_2})\right) \tag{5.4.4}$$

With

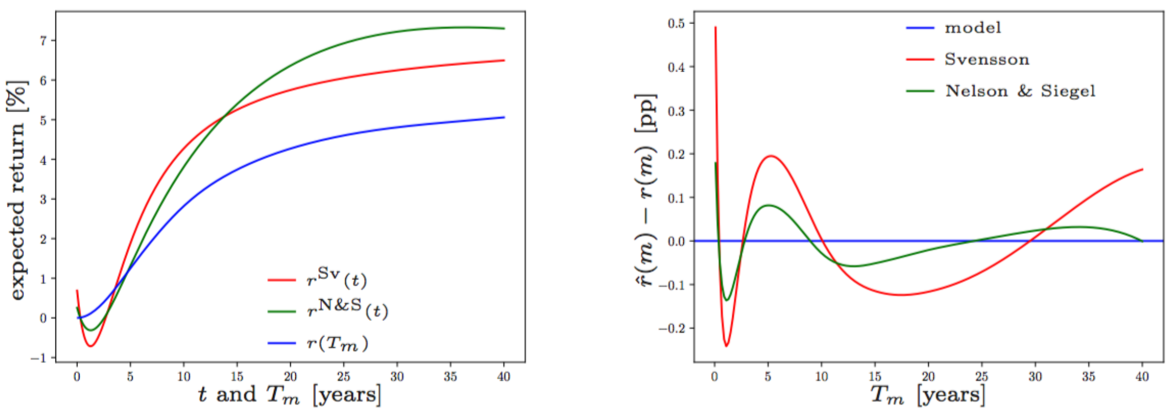
$$\begin{aligned}\hat{r}^{\text{N\&S}}(m) &= \sum_{t=1}^{\infty}(1-m)m^{t-1}r^{\text{N\&S}}(t) \\ &= \beta_0 + \frac{(\beta_1\tau_1 + \beta_2\tau_1)(m-1)(\log(1-m) - \log(1-\exp(\frac{-1}{\tau_1})m)}{m} + \frac{\beta_2(m-1)}{\exp(\frac{1}{\tau_1}) - m}\end{aligned} \tag{5.4.5}$$

$$\hat{r}^{\text{Sv}}(m) = \hat{r}^{\text{N\&S}}(m) + \frac{\beta_3\tau_2(m-1)(\log(1-m) - \log(1-\exp(\frac{-1}{\tau_2})m)}{m} + \frac{\beta_3(m-1)}{\exp(\frac{1}{\tau_2}) - m} \tag{5.4.6}$$

defining the estimate of a portfolio's return, we choose the parameters of the Nelson & Siegel and Svensson yield curve models so that they minimise the sum of squared differences to the portfolio returns obtained in simulations, i.e.

$$\{\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\tau}_1, \hat{\tau}_2\} = \underset{\{\beta_0,\beta_1,\beta_2,\beta_3,\tau_1,\tau_2\}}{\arg\min} \sum_m \Big(r(m) - \hat{r}^{\{\text{N\&S,Sv}\}}(m)\Big)^2 \tag{5.4.7}$$

Figure 5.3(a) shows the yield curves $r(t)$ implied by exemplary simulated data $r(m)$ for the Nelson & Siegel and Svensson models. Unsurprisingly, the fit of the Svensson model, which has two additional parameters, better fits the simulated data as displayed in Figure 5.3(b). Both models struggle most to fit the very short-end of $r(m)$. In particular, the inverted yield curve on the short-end seems to be an artifact of the curve fitting exercise. Such an inversion is typically interpreted as the market's expectation of an upcoming reduction in central bank interest rates, which, for the sake of simplicity, is not considered by agents in our model.



(a) portfolio vs. individual security yield curve

(b) goodness of fit

FIGURE 5.3: Relation between the yield curve of securities portfolios, characterised by a maturity T_m and the yield curve of hypothetical individual securities with remaining maturity t.

Equations (5.4.5) and (5.4.6) can also be used to compute the yield curve $r(m)$ implied by yield curves fitted to real bond data. Figure 5.4(a) e.g. plots the Svensson model representation of the yield curve estimated with euro area sovereign bonds, which is published on a daily basis by the European Central Bank. On the basis of these transformed real data yield curves, model portfolio return dynamics can be reconstructed for calibration and validation purposes. Figure 5.4(b) plots the time series of two hypothetical portfolios with different maturity parameters that are reconstructed from ECB yield curve data.

5.4.2 Updating Balance Sheets

Excess demand and supply of portfolio shares need to be taken into account when updating balance sheets. We define $\mathcal{Q}_+ := \{d, f, CB | \Delta Q_{\{d,f,CB\},t} \geq 0\}$ and $\mathcal{Q}_- := \{d, f, CB, U | \Delta Q_{\{d,f,CB,U\},t} < 0\}$ as the sets identifying domestic, foreign, central bank and the

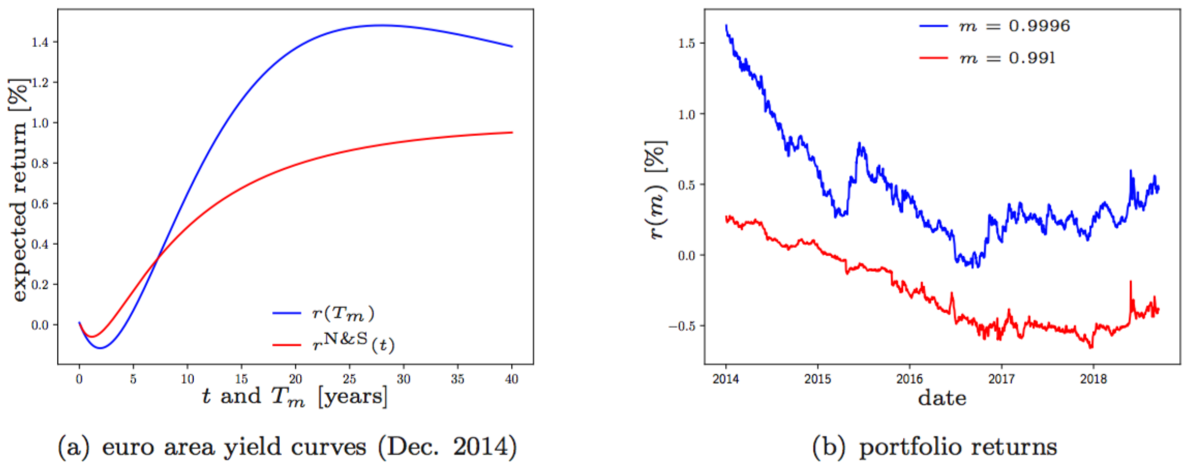


FIGURE 5.4: Transforming euro area sovereign bond yield curve into model yield curves and model portfolio return time series.

underwriter agents' demand and supply of portfolio shares, respectively. The factors correcting for excess demand π_t and excess supply of a portfolio of assets ν_t proportionately distribute the mismatch across agents:

$$\pi_t = 1 - \frac{\Delta Q_t}{\sum_{j \in \mathcal{Q}_+} \Delta Q_{j,t}} \quad \text{and} \quad \nu_t = 1 - \frac{\Delta Q_t}{\sum_{j \in \mathcal{Q}_-} \Delta Q_{j,t}} \tag{5.4.8}$$

with ΔQ_t being the aggregate excess demand for a portfolio of assets. The factors in Eq. (5.4.8) imply that if there is, for example, an excess demand of 10%, all agents that want to buy those portfolio shares will only be able to acquire 90% of their original demand. With the correction factors we compute the new quantities of portfolio shares agents hold on their balance sheet at the end of period t:

$$Q_{d,t} = \begin{cases} out_t Q_{d,t-1} + \Delta Q_{d,t} \pi_t & \text{if} \quad \Delta Q_{d,t} \geq 0 \text{ and } \Delta Q_t \geq 0 \\ out_t Q_{d,t-1} + \Delta Q_{d,t} \nu_t & \text{if} \quad \Delta Q_{d,t} < 0 \text{ and } \Delta Q_t < 0 \\ out_t Q_{d,t-1} + \Delta Q_{d,t} & \text{else} \end{cases} \tag{5.4.9}$$

The updates of central bank agent's inventory follows the logic of investor agents' new balance sheet positions, i.e.

$$Q_{CB,t} = \begin{cases} out_t Q_{CB,t-1} + \Delta Q_{CB,t} \pi_t & \text{if} \quad \Delta Q_{CB,t} \geq 0 \text{ and } \Delta Q_t \geq 0 \\ out_t Q_{CB,t-1} + \Delta Q_{CB,t} \nu_t & \text{if} \quad \Delta Q_{CB,t} < 0 \text{ and } \Delta Q_t < 0 \\ out_t Q_{CB,t-1} + \Delta Q_{CB,t} & \text{else} \end{cases} \tag{5.4.10}$$

while the underwriter agent, which always tries to sell its entire inventory, does not need to consider the case of positive excess demand:

$$Q_{U,t} = \begin{cases} \Delta Q_{U,t}(\nu_t - 1) & \text{if} \quad \Delta Q_t < 0 \\ 0 & \text{else.} \end{cases} \tag{5.4.11}$$

Transactions in portfolio shares can lead to changes in the inventory of domestic and foreign currency holdings of investor agents, which in turn impact their demand for currency. We define

$$\Delta \tilde{C}^{\mathcal{D}}_{d,t} = \Delta C^{\mathcal{D}}_{d,t} - \sum_{D=1}^{n^D} \underbrace{(out^D_t Q^D_{d,t-1} - Q^D_{d,t})P^D_t}_{\text{asset transactions}} \quad \text{and} \tag{5.4.12}$$

$$\Delta \tilde{C}^{\mathcal{F}}_{d,t} = \Delta C^{\mathcal{F}}_{d,t} - \sum_{F=1}^{n^F} (out^F_t Q^F_{d,t-1} - Q^F_{d,t})P^F_t \tag{5.4.13}$$

as the updated respective domestic and foreign demand for cash after assets have been traded, and $\tilde{C}^{\mathcal{D}}_{d,t} = w^{C^{\mathcal{D}}}_{d,t} S_{d,t} - \Delta \tilde{C}^{\mathcal{D}}_{d,t}$ and $\tilde{C}^{\mathcal{F}}_{d,t} = w^{C^{\mathcal{F}}}_{d,t} S_{d,t}/X^{\mathcal{DF}}_t - \Delta \tilde{C}^{\mathcal{F}}_{d,t}$ as the updated respective domestic and foreign cash inventories. Cash demand needs to be updated a second time as it does not take into account the fact that an agent can only buy currency if it is able to supply an equally valued amount of a different currency. More generally, an agent will only engage in a foreign exchange transaction if its demands for the domestic and foreign currency are of opposite signs (i.e. one currency is demanded, the other supplied); and the volume of the aspired cash transaction is limited by what an agent demands or supplies of the respective other currency. Taking this into account, the final demand for a currency at the end of period t amounts to:

$$\Delta \tilde{\tilde{C}}^{\mathcal{D}}_{d,t} = \begin{cases} \text{sgn}(\Delta \tilde{C}^{\mathcal{D}}_{d,t}) \cdot \min\left\{ |\Delta \tilde{C}^{\mathcal{D}}_{d,t}|, |X^{\mathcal{DF}}_t \Delta \tilde{C}^{\mathcal{F}}_{d,t}| \right\} & \text{if} \quad \text{sgn}(\Delta \tilde{C}^{\mathcal{D}}_{d,t}) \neq \text{sgn}(\Delta \tilde{C}^{\mathcal{F}}_{d,t}) \\ 0 & \text{else} \end{cases} \tag{5.4.14}$$

$$\Delta \tilde{\tilde{C}}^{\mathcal{F}}_{d,t} = \begin{cases} \text{sgn}(\Delta \tilde{C}^{\mathcal{F}}_{d,t}) \cdot \min\left\{ |\Delta \tilde{C}^{\mathcal{F}}_{d,t}|, |X^{\mathcal{FD}}_t \Delta \tilde{C}^{\mathcal{D}}_{d,t}| \right\} & \text{if} \quad \text{sgn}(\Delta \tilde{C}^{\mathcal{D}}_{d,t}) \neq \text{sgn}(\Delta \tilde{C}^{\mathcal{F}}_{d,t}) \\ 0 & \text{else} \end{cases}, \tag{5.4.15}$$

with sgn($\cdot$) denoting the sign or signum function, which extracts the sign of the respective updated cash demands.

Analogous to Eq. (5.4.8) for transactions in portfolio share, we compute correcting factors for cash transactions, i.e.

$$\pi^C_t = 1 - \frac{\Delta \tilde{\tilde{C}}_t}{\sum_{j \in \mathcal{C}_+} \Delta \tilde{\tilde{C}}_{j,t}} \quad \text{and} \quad \nu^C_t = 1 - \frac{\Delta \tilde{\tilde{C}}_t}{\sum_{j \in \mathcal{C}_-} \Delta \tilde{\tilde{C}}_{j,t}}, \tag{5.4.16}$$

with $\mathcal{C}_+ := \{d, f | \Delta \tilde{\tilde{C}}_{\{d,f\},t} \geq 0\}$ and $\mathcal{C}_- := \{d, f | \Delta \tilde{\tilde{C}}_{\{d,f\},t} < 0\}$ defining the sets that identify the agents demanding and supplying cash. Excess demand for domestic and foreign currency is computed as

$$\Delta \tilde{\tilde{C}}^{\mathcal{D}}_t = \textstyle\sum_{d=1}^{n^d} \Delta \tilde{\tilde{C}}^{\mathcal{D}}_{d,t} + \sum_{f=1}^{n^f} \Delta \tilde{\tilde{C}}^{\mathcal{D}}_{f,t} \text{ and } \Delta \tilde{\tilde{C}}^{\mathcal{F}}_t = \sum_{d=1}^{n^d} \Delta \tilde{\tilde{C}}^{\mathcal{F}}_{d,t} + \sum_{f=1}^{n^f} \Delta \tilde{\tilde{C}}^{\mathcal{F}}_{f,t}, \text{ respectively.}$$

These are used to compute positions of domestic and foreign cash on balance sheets similar to asset positions, i.e.:

$$C_{d,t} = \begin{cases} \tilde{C}_{d,t} + \Delta\tilde{\tilde{C}}_{d,t}\pi_t^C & \text{if} \quad \Delta\tilde{\tilde{C}}_{d,t} \geq 0 \text{ and } \Delta\tilde{\tilde{C}}_t \geq 0 \\ \tilde{C}_{d,t} + \Delta\tilde{\tilde{C}}_{d,t}\nu_t^C & \text{if} \quad \Delta\tilde{\tilde{C}}_{d,t} < 0 \text{ and } \Delta\tilde{\tilde{C}}_t < 0 \\ \tilde{C}_{d,t} + \Delta\tilde{\tilde{C}}_{d,t} & \text{else} \end{cases} \tag{5.4.17}$$

5.4.3 Calibration tables

	Debt securities outstanding (BIS) Tn EUR	Stock market Capitalisation (World Bank) Tn EUR	Total Market Capitalisation Tn EUR	
Euro area	16.62	5.71	22.33	
	Tn EUR	Tn EUR	Tn EUR	Weight in ROW Sample
Total ROW	56.84	43.14	99.98	1.00
United States	29.96	21.94	51.91	0.519
United Kingdom	5.14	2.88	8.02	0.080
Australia	1.22	1.07	2.30	0.023
Brazil	1.65	0.70	2.35	0.024
Canada	1.35	1.75	3.10	0.031
Switzerland	0.27	1.25	1.52	0.015
China	4.74	5.00	9.75	0.097
Colombia	0.07	0.12	0.19	0.002
Hungary	0.06	0.01	0.07	0.001
Indonesia	0.11	0.35	0.47	0.005
India	0.56	1.30	1.86	0.019
Israel	0.16	0.17	0.33	0.003
Japan	9.12	3.65	12.77	0.128
Korea	1.20	1.01	2.21	0.022
Mexico	0.50	0.40	0.90	0.009
Norway	0.19	0.18	0.37	0.004
New Zealand	0.05	0.06	0.11	0.001
Russia	0.15	0.32	0.47	0.005
Turkey	0.16	0.18	0.35	0.003
South Africa	0.17	0.78	0.95	0.009

TABLE 5.11: Market capitalisation weights used for computation of Rest-of-the-World inflation, interest rates and expected returns

Bond indices

Description for Table 5.17: Computation of domestic and foreign market yield to maturity used in calibration of expected bond returns. Eurozone: We compute a simple average yield to maturity by using the S&P Eurozone Investment Grade Corporate Bond Index and the S&P Eurozone Developed Sovereign Bond Index as of 29 December 2014. Rest-of-the-world: We approximate the rest-of-the-world yield to maturity by combining the yield to maturity of i) a bond index excluding the US with ii) a bond index with the US to form a world bond index and iii) adjust this by the Euro area value. i) The row-ex US yield to maturity is an equally weighted average of the S&P International Corporate Bond Index and the S&P International Sovereign Ex-US Bond Index as of 29 December 2014, of 1.44%. ii) The US yield to maturity is the equally weighted average of the S&P US Treasury Bond Index and the S&P 500 Investment Grade Corporate Bond Index, of 2.06%. The combined world yield to maturity is the sum of i) and ii), weighted by their relative market size (59% for the rest-of-the-world-ex-US and 41% for the US), i.e. $0.59 * 1.44 + 0.41 * 2.06 = 1.69$. Lastly, we adjust the yield to maturity of our computed world bond index by the Eurozone value, which leads to $(1.69\% - 0.93\% * 0.23)/0.77 = 1.92\%$ for approximated yield to maturity of the foreign market in our simulation. Source: S&P Bond Indices.

	Data Source	Data Description
A	ECB Investment fund balance sheet statistics	Eurozone funds' holdings in debt securities and equities, by counterparty region.
B	ECB Consolidated banking statistics CBD2 and Securities holding statistics SHS	Debt securities holdings of banks resident in the Eurozone area from the ECB's CBD2. Home bond bias calculated from SHS.
C	Inferred from Bankscope	Bankscope data on Rest-of-the-world banking sector securities, i.e. available-for-sale and trading securities, shows a 2.47 larger investment portfolio than for Eurozone banks.
D	FSB Global Shadow Banking Monitoring Report 2015	Global shadow banking sector without Money Market Funds, Real estate funds and Eurozone funds
I	IMF Coordinated Portfolio Investment Survey (CPIS)	Cross-holdings of equities and debt securities in the global banking sector, i.e. 'Deposit-taking institutions except Central banks'
M^1	Morning Star Direct	Calculated by multiplying total Rest-of-the-world assets (see D above) with regional weight for Eurozone debt securities compiled from Morning Star Direct. Morning Star asset class and regional weights are based on a sample of open-end investment funds (see Table 5.13).
M^2	Morning Star Direct	Calculated by using weights in Eurozone equity securities in Rest-of-the-world sample compiled from Morning Star and total equity assets computed in M^4
M^3	Morning Star Direct	Computed by using debt securities weight in Rest-of-the-world sample compiled from Morning Star
M^4	Morning Star Direct	Computed by multiplying total Rest-of-the-world assets (see D) with equity securities weight compiled from Morning Star Direct
M^5	Morning Star Direct	Eurozone and Rest-of-the-World funds' cash positions are calculated by cash securities weights compiled from Morning Star Direct (see also Table 5.13)
R	Residual	Computed from remaining category values
RES	ECB Statistical Warehouse, Federal Reserve Bank of St. Louis FRED database	Central Bank Reserve assets (ECB, Bank of England and US Fed)
T	ECB Investment fund Statistics and Morning Star Direct	We take the sum of equities and debt securities holdings by Euro area investment funds statistics

Table 5.12: Data Sources for Funds and Banks' Balance Sheet Positions used in Table 5.16

	Sample definition	Portfolio Shares
Domestic Market Morning Star Sample	Euro area, 15374 open-end investment funds domiciled in the Euro area; Rescaling total assets to only include cash, equities and bonds Eurozone countries: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Slovenia, Slovakia, Spain	- Equity share: 0.44 - Bond share: 0.47 - Cash share: 0.09 - Out of all cash assets, 65.3% are domestic cash and 34.4% are foreign cash
Foreign Market Morning Star Sample	Rest-of-the-world area, 25930 open-end investment funds, Countries: Argentina, Australia, Bermuda, Botswana, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark,Hong Kong, Hungary, India, Indonesia, Israel, Japan, Kuwait, Lebanon, Liechtenstein, Malaysia, Mexico, Monaco, Namibia, New Zealand, Norway, Oman, Pakistan, Peru, Philippines, Puerto Rico, Poland, Russia, Singapore, South Africa, South Korea, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, United States, Venezuela, Vietnam. Rescaling total assets to only include cash, equities and bonds	- Equity share: 0.51 - Bond share: 0.41 - Cash share: 0.08 - Out of all bond assets, 4% are invested in Euro area bonds - Out of all equity assets, 6% are invested in Euro area equities - Out of all cash assets, 5% are Euros

Table 5.13: Sample definition and portfolio shares of Euro area and Rest-of-the-world open-end investment funds collected from Morning Star. The portfolio shares are used in the calibration of the global balance sheet positions of funds.

Country	Inflation	Deposit rate	Market cap weight	Weighted deposit rate	Weighted inflation
United States	1.612	0.250	0.519	0.1298	0.837
United Kingdom	1.461	0	0.080	0	0.117
Japan	2.760	0.415	0.128	0.0530	0.352
China	1.988	0.350	0.097	0.0341	0.194
Brazil	6.329	10.024	0.024	0.2359	0.149
Canada	1.920	0.550	0.031	0.0170	0.059
Australia	2.513	2.904	0.023	0.0667	0.058
Colombia	2.905	4.089	0.002	0.0079	0.006
Hungary	-0.197	1.777	0.001	0.0012	0.000
India	5.800	5.500	0.019	0.1024	0.108
Indonesia	6.395	6.750	0.005	0.0314	0.030
Israel	0.476	0.798	0.003	0.0026	0.002
Korea	1.275	2.536	0.022	0.0560	0.028
Mexico	4.022	0.840	0.009	0.0076	0.036
New Zealand	1.220	3.250	0.001	0.0037	0.001
Norway	2.042	0.490	0.004	0.0018	0.008
Russia	7.824	6.042	0.005	0.0283	0.037
South Africa	6.090	4.801	0.009	0.0454	0.058
Switzerland	-0.012	0.020	0.015	0.0003	0.000
Turkey	8.855	7.500	0.003	0.0261	0.031
SUM			1.000	0.85	2.1

TABLE 5.14: Rest-of-the-world inflation and deposit rates. Deposit rates are sourced from the World bank development indicators, Fred database of the Federal Reserve of St. Louis, Bank of Japan, Bank of England, Norge Bank and Hungarian Central bank for December 2014. Inflation is the inflation forecast by the OECD for 2015 at the end of 2014.

	Equity premium	Equity return	Risk-free rate	Equity Market Weight	Market cap Tn USD
World	4.50	7.01	2.51	1.00	57.50
EZ	5.73	6.27	0.54	0.12	7.00
Rest-of-the-world	4.33	7.11	2.78	0.88	50.50
US			2.17		26.33
Japan			0.33		4.38
UK			1.76		3.46
Switzerland			3.66		1.50
South Africa			7.96		0.93
Mexico			6.01		0.48
Poland			2.54		0.17
Hungary			3.54		0.01
Russia			14.09		0.39
Brazil			12.43		0.84
India			7.86		1.56
Hong Kong			1.92		3.23
South Korea			2.61		1.21
China			3.66		6.00

TABLE 5.15: Equity premia and risk free rate of the Eurozone and rest-of-the-world. The Eurozone equity premium is sourced from Absolute Strategy Research, as of 31 Dec 2014. The risk-free rate is the 10-year government bond for geographical regions and provided by Datastream. Equity market capitalisation is taken from the World Bank Development indicators and World Federation of Exchanges database in 2014 US dollars.

Trillion EUR		Debt Securities (DS)			Equities (Eq)			Currencies (C)			Computed Total Assets
		EZ DS	ROW DS	sum DS	EZ Eq	ROW Eq	sum Eq.	EZ C	ROW C	sum C	
Eurozone Investors	Funds	1.961	1.651	3.612	0.930	1.821	2.751	0.411	0.218	0.629	6.992
	Banks	3.204	0.656	3.860	0.571	0.075	0.646	0.08	0.016	0.096	4.602
ROW Investors	Funds	0.263	7.045	7.308	0.556	8.461	9.017	0.063	1.202	1.265	17.59
	Banks	0.568	10.009	10.577	0.078	1.692	1.770	0.136	2.4	2.536	14.883
Computed Market Size		5.996	19.361	25.357	2.135	12.049	14.184	0.69	3.836	4.526	44.067

		Debt Securities (DS)			Equities (Eq)			Currencies (C)			Computed Total Assets
		EZ DS	ROW DS	sum DS	EZ Eq	ROW Eq	sum Eq.	EZ C	ROW C	sum C	
Eurozone Investors	Funds	A	R	A	A	R	A	M^5	M^5	M^5	T
	Banks	B	R	B	R	I	B	RES	RES	RES	$\sum$
ROW Investors	Funds	M^1	R	M^2	M^3	R	M^4	M^5	M^5	M^5	D
	Banks	I	R	C	I	R	C	RES	RES	RES	$\sum$
Computed Market Size		$\sum$	$\sum$	$\sum$	$\sum$	$\sum$	$\sum$	$\sum$	$\sum$	$\sum$	$\sum$

TABLE 5.16: *Upper Table*: Euro area and Rest-of-the-World balance Sheet positions in Trillion EUR. *Lower Table*: Data sources used in the compilation of balance sheet positions. Symbols are explained in Table 5.12.

Region	International - Ex US		Eurozone		US	
Index name	S&P International Corporate Bond Index	S&P International Sovereign Ex-U.S. Bond Index	S&P Eurozone Investment Grade Corporate Bond Index	S&P Eurozone Developed Sovereign Bond Index	S&P U.S. Treasury Bond Index	S&P 500 Investment Grade Corporate Bond Index
Description	ex-US	ex-US developed world	Investment grade bonds	Euro area sovereign bonds	US treasury bonds	US investment grade corporate bonds
Date	2014/12/29	2014/12/29	2014/12/29	2014/12/29	2014/12/29	2014/12/29
Yield to maturity	2.01	0.87	1.05	0.81	1.21	2.91
	Weighted average 50:50 1.44		Weighted average 50:50 0.93		Weighted average 50:50 2.06	
Relative Market Cap	0.59		0.23		0.41	
Weight Row	0.77					
World Yield	1.69					
Row yield	1.92					
Euro area	0.93					

Table 5.17: Computation of domestic and foreign market yield to maturity used in calibration of expected bond returns. Eurozone: We compute a simple average yield to maturity by using the S&P Eurozone Investment Grade Corporate Bond Index and the S&P Eurozone Developed Sovereign Bond Index as of 29 December 2014. Rest-of-the-world: We approximate the rest-of-the-world yield to maturity by combining the yield to maturity of i) a bond index excluding the US with ii) a bond index with the US to form a world bond index and iii) adjust this by the Euro area value. i) The row-ex US yield to maturity is an equally weighted average of the S&P International Corporate Bond Index and the S&P International Sovereign Ex-US Bond Index as of 29 December 2014, of 1.44%. ii) The US yield to maturity is the equally weighted average of the S&P US Treasury Bond Index and the S&P 500 Investment Grade Corporate Bond Index, of 2.06%. The combined world yield to maturity is the sum of i) and ii), weighted by their relative market size (59% for the rest-of-the-world-ex-US and 41% for the US), i.e. $0.59 * 1.44 + 0.41 * 2.06 = 1.69$. Lastly, we adjust the yield to maturity of our computed world bond index by the Eurozone value, which leads to $(1.69\% - 0.93\% * 0.23)/0.77 = 1.92\%$ for approximated yield to maturity of the foreign market in our simulation. Source: S&P Bond Indices.

Simulation Parameters

Agents Parameters			
Variable	*Description*	*Value*	*Source*
$\boldsymbol{\lambda}_d$	Domestic and foreign investors' risk aversion (preferred habitat) preference for domestic & foreign assets	Table 5.3	Calibration outcome
Asset Parameters			
Π^{C^D}	**Euro area**: Interest on cash,	-0.2 %	ECB Statistical Warehouse, Deposit facility Dec 2014
C^D	Domestic currency quantity	690	Table 5.16
Π^{C^F}	**Rest-of-the-World**: Interest on cash,	0.85%	Deposit interest rate, World Bank, World Development indicators; & Central banks'statistics Market-cap weighted average with weights from Table 5.13 and refTab:BS
C^F	Foreign currency quantity	3836	Row central banks' balance sheet (Table 5.16)
m_{bond}	Maturity parameter, Bond portfolio	0.99936	Morning Star Direct, calibrated to the maturity profile of open-end investment funds (Table 5.6)
m_{eq}	Maturity parameter, Equity portfolio	1	Equities never mature
	Euro area bond portfolio		
Q^D, V^D, ρ	Quantity, Face Value Nominal interest	5996, 0.005%	Table 5.16 Calibration outcome
	Euro area equity portfolio		
Q^D, V^D, ρ	Quantity, Face Value Nominal interet	2135, 0.03%	Table 5.16 Calibration outcome
	Row area bond portfolio		
Q^F, V^F, ρ	Quantity, Face Value Nominal interest	19361 0.00943%	Table 5.16 Calibration outcome
	Row equity portfolio		
Q^F, V^F, ρ	Quantity, Face Value Nominal interest	12049 0.0361%	Table 5.16 Calibration outcome
η	Foreign exchange reversion rate to purchasing power parity	15% annually	Rogoff (1996)
δ	Convergence parameter indicative of market clearing	1%	
ϕ	Memory parameter updating of the covariance matrix	0.001	

TABLE 5.18: Simulation parameters

MODEL COMPOSITION 1) Profits Description of model equations

Equation 4.1.1, page 59

$$\Pi_{d,t} = \sum_{D=1}^{n^D} Q^D_{d,t-1}\Pi^D_t + \sum_{F=1}^{n^F} Q^F_{d,t-1}\Pi^F_t + C^{\mathcal{D}}_{d,t-1}\Pi^{C^{\mathcal{D}}}_t + C^{\mathcal{F}}_{d,t-1}\Pi^{C^{\mathcal{F}}}_t$$

Overall profit for domestic agent d at time t, which is the sum of profit per portfolio share times quantities held and the profit from holding currency

Equation 4.1.4, page 59 Domestic profit per portfolio share

$$\Pi^D_t = \underbrace{mat^D_t(\frac{V^D}{\bar{Q}^D} - P^D_{t-1})}_{\text{repayment effect}} + \underbrace{out^D_t(P^D_t - P^D_{t-1})}_{\text{price effect}} + \underbrace{all^D_t\frac{V^D}{\bar{Q}^D}\rho^D}_{\text{interest effect}} - \underbrace{\Omega^D_t P^D_{t-1}}_{\text{default effect}}$$

Profit that accrues for one share in a portfolio D denominated in domestic currency from the perspective of domestic agent (i.e. no exchange rate effect)

$mat^{D_t} = (1-m)(1-\Omega_t)$ — the percentage of performing portfolio shares that matured overnight

$out_t = m(1-\Omega_t)$ — the percentage of performing outstanding portfolio shares at the beginning of period t relative to the portfolio shares held at the end of period $t-1$

$all_t = out_t + mat_t = (1-\Omega_t)$ — all performing portfolio shares, i.e. those that have not defaulted overnight

Name	Type	Description
Π^D_t, (Π^F_t)	flow variable	profit per domestic (foreign) portfolio share
$\Pi^{C^D}_t$, $(\Pi^{C^F}_t)$	flow variable	profit per unit of domestic (foreign) cash held
C^D_t, (C^F_t)	flow variable	Domestic (foreign) cash quantities held
V^D,(V^F)	parameter	nominal value of portfolio
P^D_t, (P^F_t)	state variable	price of portfolio share
Ω^D_t, (Ω^F_t)	parameter	default rate per portfolio share
$\bar{Q}^D$, $(\bar{Q}^F)$	parameter	total portfolio shares issued
ρ^D, (ρ^F)	parameter	interest on portfolio share

MODEL COMPOSITION 1) Profits continued

Equation 4.1.3, page 59 Foreign profit and cash profit

$$\Pi_t^F = \underbrace{mat_t^F(X_t^{\mathcal{DF}}\frac{V^F}{\bar{Q}^F} - X_{t-1}^{\mathcal{DF}}P_{t-1}^F)}_{\text{repayment effect}} + \underbrace{out_t^F(X_t^{\mathcal{DF}}P_t^F - X_{t-1}^{\mathcal{DF}}P_{t-1}^F)}_{\text{price effect}} + \underbrace{all_t^F X_t^{\mathcal{DF}}\frac{V^F}{\bar{Q}^F}\rho^F}_{\text{interest effect}} - \underbrace{\Omega_t^F X_{t-1}^{\mathcal{DF}}P_{t-1}^F}_{\text{default effect}}$$

Profit per share of foreign portfolio F for domestic agent d at time t

$$\Pi_t^{C^\mathcal{D}} = \rho^{C^\mathcal{D}} \text{ and } \Pi_t^{C^\mathcal{F}} = X_t^{\mathcal{DF}}\rho^{C^\mathcal{F}} + X_t^{\mathcal{DF}} - X_{t-1}^{\mathcal{DF}}$$

Profit per unit of domestic and foreign cash from a domestic agent perspective, i.e. the interest paid on bank reserves for domestic cash and the interest on foreign reserves adjusted for exchange rate gains/losses for foreign cash

Equation 4.1.5, page 60 Domestic and foreign payouts and resulting capital position

$$\mathrm{D}_{d,t}^\mathcal{D} = C_{d,t-1}^\mathcal{D}\rho^{C^\mathcal{D}} + \sum_{D=1}^{n^D} Q_{d,t-1}^D\left(mat_t^D(\tfrac{V^D}{\bar{Q}^D} - P_{t-1}^D) + all_t^D\tfrac{V^D}{\bar{Q}^D}\rho - \Omega_t^D P_{t-1}^D\right)$$
$$\mathrm{D}_{d,t}^\mathcal{F} = C_{d,t-1}^\mathcal{F}\rho^{C^\mathcal{F}} + \sum_{F=1}^{n^F} Q_{d,t-1}^F\left(mat_t^F(\tfrac{V^F}{\bar{Q}^F} - P_{t-1}^F) + all_t^F\tfrac{V^F}{\bar{Q}^F}\rho - \Omega_t^F P_{t-1}^F\right)$$

To avoid dealing with economic growth issues within the model, we assume that all performance effects that materialise in a period (i.e. all, expect for the price effect) are payed out to shareholders. Payouts are made in both domestic and foreign currency

$$\mathrm{S}_{d,t} = S_{d,t-1} + \Pi_{d,t} - D_{d,t}^\mathcal{D} - X_t^{\mathcal{DF}}D_{d,t}^\mathcal{F}$$

The value of capital after payouts are being made

Name	Type	Description
X^{DF},$X^{\mathcal{FD}}$	state variable	exchange rates with $X^{\mathcal{FD}} = 1/X^{\mathcal{DF}}$
S_d	state variable	Capital (total liability side of agents)

MODEL COMPOSITION 2) Expectation Formation

Equation 4.1.7, page 60 — Expected return on foreign & domestic pf ,

$$\mathrm{E}_{d,t}[r^D_{t+1}] = \frac{1+\mathrm{E}_{d,t}[\Pi^D_{t+1}]/P^D_t}{1+\mathrm{E}_{d,t}[\pi^{\mathcal{D}}_{t+1}]} - 1$$

and

$$\mathrm{E}_{d,t}[r^F_{t+1}] = \frac{1+\mathrm{E}_{d,t}[\Pi^F_{t+1}]/(X^{\mathcal{DF}}_t P^F_t)}{1+\mathrm{E}_{d,t}[\pi^{\mathcal{D}}_{t+1}]} - 1$$

$$\mathrm{E}_{d,t}\left[r^{C^{\mathcal{D}}}_{t+1}\right] = \frac{1+\mathrm{E}_{d,t}\left[\Pi^{C^{\mathcal{D}}}_{t+1}\right]}{1+\mathrm{E}_{d,t}[\pi^{\mathcal{D}}_{t+1}]} - 1 \quad \text{and} \quad \mathrm{E}_{d,t}\left[r^{C^{\mathcal{D}}}_{t+1}\right] = \frac{1+\mathrm{E}_{d,t}\left[\Pi^{C^{\mathcal{D}}}_{t+1}\right]/X^{\mathcal{DF}}_t}{1+\mathrm{E}_{d,t}[\pi^{\mathcal{D}}_{t+1}]} - 1$$

From the perspective of the domestic agent, expected real returns of domestic and foreign portfolios are computed taking into account an exogenous stochastic process for domestic and foreign inflation $\pi^{\mathcal{D}}_t$ and $\pi^{\mathcal{F}}_t$ respectively

Realised nominal returns on a portfolio share can be computed by dividing the profit per share that accrued overnight by last period's price.

Agents need to form expectations about factors that influence nominal profits, i.e.

a) prices

$\mathrm{E}_{d,t}[P_{t+1}] = P_t$, i.e. myopic agents believe in efficient asset markets

b) exchange rates

Agents believe the exchange rate will revert to purchasing power parity $\bar{X}^{\mathcal{DF}}$ in the long run

$\mathrm{E}_{d,t}[X^{\mathcal{DF}}_{t+1}] = X^{\mathcal{DF}}_t + \eta\left(\mathrm{E}_{d,t}[\bar{X}^{\mathcal{DF}}_{t+1}] - X^{\mathcal{DF}}_t\right)$

$$\text{with} \quad \mathrm{E}_{d,t}[\bar{X}^{\mathcal{DF}}_{t+1}] = \bar{X}^{\mathcal{DF}} \frac{1+\mathrm{E}_{d,t}[\pi^{\mathcal{F}}_{t+1}]}{1+\mathrm{E}_{d,t}[\pi^{\mathcal{D}}_{t+1}]}$$

and η as expected convergence speed towards the purchasing power parity

c) default rates

Agents know the stochastic process behind default rates, i.e. $\mathrm{E}_{d,t}[\Omega_{t+1}] = \mu^{\Omega}_t$, with μ^{Ω}_t being the first moment of the true default rate process

d) risk

$$\hat{\mathrm{Cov}}_{d,t}(r^x, r^y) = \hat{\mathrm{M}}_{d,t}\left[\left(r^x_{t-1} - \hat{\mathrm{M}}_{d,t-1}[r^x, \phi]\right)\left(r^y_{t-1} - \hat{\mathrm{M}}_{d,t-1}[r^y, \phi]\right), \phi\right]$$

Agents compute estimates of variance and covariances of historic real returns through adaptive expectations. The parameter $\phi \in [0, 1]$ determines how much weight is given to the most recent observation

with the operator $\hat{\mathrm{M}}_t[x, \phi] = (1-\phi)\hat{\mathrm{M}}_{t-1}[x, \phi] + \phi x_t$ as the exponentially weighted moving average of variable x

MODEL COMPOSITION 3) Balance Sheet Optimisation

Agents' optimisation problem

$$\mathrm{w}^*_{d,t} = \arg\max_{\mathbf{w}} \mathbf{w}'\mathrm{E}_{d,t}[\mathbf{r}_{d,t+1}] - 0.5\mathbf{w}'\left(\boldsymbol{\lambda}_d'\boldsymbol{\Sigma}_{d,t}\boldsymbol{\lambda}_d\right)\mathbf{w}$$

$$\text{s.t.}\mathbf{w} \geq 0 \quad \text{and} \quad \mathbf{w}'\mathbf{1} = 1$$

Agents calculate optimal weights according to the constrained mean-variance optimisation problem shown on the left. Determining factors are the expected returns for the domestic and foreign portfolio, for the domestic and foreign cash, the covariance matrix of returns and the assets specific risk aversion parameters. There are two constraints, a no short selling constraint and a budget constraint (the sum of weights must be equal to 100%).

Variable	Description
$\mathbf{w}^*_{d,t} := (\mathbf{w}^D_{d,t}, \mathbf{w}^F_{d,t}, \mathbf{w}^C_{d,t})'$	$N \times 1$ vector of optimal weights
$\mathrm{E}_{d,t}[\mathbf{r}_{d,t+1}] = (\mathrm{E}_{d,t}[\mathbf{r}^D_{d,t+1}], \mathrm{E}_{d,t}[\mathbf{r}^F_{d,t+1}], \mathrm{E}_{d,t}[\mathbf{r}^C_{d,t+1}])'$	$N \times 1$ vector of expected returns
$\boldsymbol{\Sigma}_d$	$N \times N$-covariance matrix of returns
$\boldsymbol{\lambda}_d := \sqrt{(\boldsymbol{\lambda}^D_d, \boldsymbol{\lambda}^F_d, \boldsymbol{\lambda}^C_d)'}$	vector of asset specific risk aversion

Agent's demand for portfolio quantities as well as currencies are functions of the optimal weights:

$$\Delta Q^D_{d,t} = \frac{w^D_{d,t} S_{d,t}}{P^D_{d,t}} - out^D_t Q^D_{d,t-1}$$

$$\Delta Q^F_{d,t} = \frac{w^F_{d,t} S_{d,t}}{X^{\mathcal{DF}}_t P^F_{d,t}} - out^F_t Q^F_{d,t-1}$$

$$\Delta C^{\mathcal{F}}_{d,t} = \frac{w^{C^{\mathcal{F}}}_{d,t} S_{d,t}}{X^{\mathcal{DF}}_t} - \left(C^{\mathcal{F}}_{d,t-1}(1+\rho^{C^{\mathcal{F}}}) - D^{\mathcal{F}}_{d,t} + \sum_{F=1}^{n^F}(mat^F_t + all^F_t \rho^F) Q^F_{d,t-1} \frac{V^F}{\bar{Q}^F}\right)$$

$$\Delta C^{\mathcal{D}}_{d,t} = w^{C^{\mathcal{D}}}_{d,t} S_{d,t} - \left(\underbrace{C^{\mathcal{D}}_{d,t-1}(1+\rho^{C^{\mathcal{D}}})}_{\text{previous cash + interest}} - \underbrace{D^{\mathcal{D}}_{d,t}}_{\text{payouts}} + \sum_{D=1}^{n^D} \underbrace{(mat^D_t + all^D_t \rho^D) Q^D_{d,t-1} \frac{V^D}{\bar{Q}^D}}_{\text{principal and interest payments}} \right)$$

The demand is the difference between the desired balance sheet position (resulting from the optimal weights) and its inventory at the start of period t. For portfolios, the inventory is simply the quantity held at the end of last period reduced by shares that have defaulted or matured overnight, while for currency, the inventory takes into account overnight interest payments, principal repayments and payouts

MODEL COMPOSITION 4) Price adjustment	Prices and exchange rates need to take values that simultaneously clear the markets of n^D domestic portfolios, n^F foreign portfolios and two currencies.
$\log(P_{t^*}) = \log(P_{t^*}) + \gamma \frac{\Delta Q_{t^*}}{\bar{Q}}$, with $\Delta Q_{t^*} = \sum_{d=1}^{n^d} \Delta Q_{d,t^*} + \sum_{f=1}^{n^f} \Delta Q_{f,t^*} + \Delta Q_{U,t} + \Delta Q_{CB,t}$	We employ a price-setting algorithm that takes into account the economic intuition that excess demand should increase prices and excess supply should reduce them. For prices we use a recursive impact function starting with last period's prices as shown on the left. We add a star to the index of variables to differentiate between values within and outside of the price setting algorithm ($P_{t^*} = P_{t-1}$).

Variable	
γ	intensity of adjustment
ΔQ_{t^*}	Total market excess demand (excess supply if $\Delta Q_{t^*} < 0$) for a portfolio of assets at the hypothetical price of P_{t^*}. Expectations of returns $\mathrm{E}_{d,t^*}[r_{t+1}]$ and prices $\mathrm{E}_{d,t^*}[P_{t+1}]$, covariance estimates $\hat{\mathrm{Cov}}_{t^*}(\cdot)$, payouts D_{d,t^*} and balance sheet size S_{d,t^*} all need to be updated with the hypothetical price when computing demand. The excess demand is normalized by the total quantity of portfolio shares $\bar{Q}$ in circulation for a more convenient calibration of the intensity parameter γ. The normalization by the total quantity of portfolio shares means that when every agent wants to sell their shares in one portfolio, then the price will fall by γ between two steps of the algorithm.
$\Delta Q_{CB,t}$	Monetary policy enters the model through the central bank agent's demand. The demand of the central bank depends on it's inventory $Q_{CB,t-1}$ and the amount $Q^*_{CB,t}$ it desires to hold in period t, i.e.$\Delta Q_{CB,t} = Q^*_{CB,t} - out_t Q_{CB,t-1}$. The central bank's demand does not change during the intra-day iterative price setting algorithm.
$\Delta Q_{U,t} \leq 0$	An exogenous underwriter agent reissues maturing and defaulting portfolio shares by suppling $\Delta Q_{U,t} \leq 0$. The underwriter's supply does not change during the intra-day iterative price setting algorithm.
$\Delta Q_{d,t}$, $(\Delta Q_{f,t})$	Demand/supply for a type of asset from domestic (foreign) investor agents.

MODEL COMPOSITION 5) Exchange rate adjustment

$$X^{\mathcal{DF}}_{t^*} = X^{\mathcal{DF}}_{t-1} :$$

$$\log(X^{\mathcal{DF}}_{t^*}) = \log(X^{\mathcal{DF}}_{t^*}) + \gamma^{EX} \frac{\Delta K^{\mathcal{DF}}_{t*}}{\sum_{d=1}^{n^d} S_{d,t^*} + \sum_{f=1}^{n^f} S_{f,t^*} X^{\mathcal{DF}}_{t^*}}$$

$$\text{with } \Delta K^{\mathcal{DF}}_{t^*} = \sum_{d=1}^{n^d} \left(\Delta C^{\mathcal{F}}_{d,t^*} + \sum_{F=1}^{n^F} \Delta Q^F_{d,t^*} P^F_{t^*} \right) X^{\mathcal{DF}}_{t^*} - \sum_{f=1}^{n^f} \left(\Delta C^{\mathcal{D}}_{f,t^*} + \sum_{D=1}^{n^D} \Delta Q^D_{f,t^*} P^D_{t^*} \right)$$

The exchange rate is updated using the recursive logarithmic impact function on the left. The exchange rate clears the foreign exchange market, domestic demand for foreign assets must equal foreign demand of domestic assets.

Market clearing

$$\delta := \begin{cases} \text{pass} & \text{if } \bigwedge_{D=1}^{n^D} (\delta^D_{t^*} \leq b) \wedge \bigwedge_{F=1}^{n^F} (\delta^F_{t^*} \leq b) \wedge (\delta^X_{t^*} \leq b) \\ \text{fail} & \text{else} \end{cases}$$

Since market clearing is achieved when $\delta^{\{D,F\}}_{t^*} := \Delta Q^{\{D,F\}}_{t^*} / \bar{Q}^{\{D,F\}}$ for all portfolios and $\delta^X_{t^*} := \Delta K^{\mathcal{DF}}_{t*} / (\sum_{d=1}^{n^d} S_{d,t^*} + \sum_{f=1}^{n^f} S_{f,t^*} X^{\mathcal{DF}}_{t^*})$ in the foreign exchange market are zero, it is sensible to exit the algorithm when all these variables go below the bound b. The higher b, the quicker the stopping criteria δ is met and the further prices and the exchange rate are from their market clearing values.

Variable	
γ^{EX}	intensity of adjustment
$\Delta K^{\mathcal{DF}}_{t^*}$	measure of desired net capital flows into country $\mathcal{F}$ denominated in country $\mathcal{D}$'s currency. We normalise desired net capital flows by the exchange rate adjusted balance sheet size of all agents
δ	Passing criteria for the difference between demand and supply on asset markets and the foreign exchange market
b	Threshold parameter determining how close overall demand equals overall supply

MODEL COMPOSITION **6) Balance Sheet Adjustments** Asset positions

$\mathcal{Q}_+ := \{d, f, CB|\Delta Q_{\{d,f,CB\},t} \geq 0\}$, $\mathcal{Q}_- := \{d, f, CB, U|\Delta Q_{\{d,f,CB,U\},t} < 0\}$

Correction factors for assets:

$$\pi_t = 1 - \frac{\Delta Q_t}{\sum_{j\in\mathcal{Q}_+} \Delta Q_{j,t}} \quad \text{and} \quad \nu_t = 1 - \frac{\Delta Q_t}{\sum_{j\in\mathcal{Q}_-} \Delta Q_{j,t}}$$

New quantities of portfolio shares at the end of period t:

$$\mathrm{Q}_{d,t} = \begin{cases} out_t Q_{d,t-1} + \Delta Q_{d,t}\pi_t & \text{if} \quad \Delta Q_{d,t} \geq 0 \text{ and } \Delta Q_t \geq 0 \\ out_t Q_{d,t-1} + \Delta Q_{d,t}\nu_t & \text{if} \quad \Delta Q_{d,t} < 0 \text{ and } \Delta Q_t < 0 \\ out_t Q_{d,t-1} + \Delta Q_{d,t} & \text{else} \end{cases}$$

$$\mathrm{Q}_{CB,t} = \begin{cases} out_t Q_{CB,t-1} + \Delta Q_{CB,t}\pi_t & \text{if} \quad \Delta Q_{CB,t} \geq 0 \text{ and } \Delta Q_t \geq 0 \\ out_t Q_{CB,t-1} + \Delta Q_{CB,t}\nu_t & \text{if} \quad \Delta Q_{CB,t} < 0 \text{ and } \Delta Q_t < 0 \\ out_t Q_{CB,t-1} + \Delta Q_{CB,t} & \text{else} \end{cases}$$

$$\mathrm{Q}_{U,t} = \begin{cases} \Delta Q_{U,t}(\nu_t - 1) & \text{if} \quad \Delta Q_t < 0 \\ 0 & \text{else.} \end{cases}$$

Once prices and the exchange rate have adjusted, agents sell and buy portfolio shares and trade cash on foreign exchange markets. New balance sheet positions can slightly deviate from agents' desired positions implied by their balance sheet optimisation. Updating the asset side of investor agents' balance sheets thus requires taking into account excess demand and supply in shares of portfolios as well as cash payments that result from transactions in portfolio shares. We take excess demand and supply into account by using correction factors π_t for excess demand and ν_t for excess supply of a portfolio of assets. These factors proportionately distribute the mismatch across agents.

The factors imply that if there is, for example, an excess demand of 10%, all agents that want to buy those portfolio shares will only be able to acquire 90% of their original demand. For the investor agents and the central bank agent, the new quantities are computed by adding the product of the appropriate correction factor and their excess demand/supply to the outstanding fraction of previous period's quantities. The underwriter agent, which always tries to sell its entire inventory, does not need to consider the case of positive excess demand.

Variable	Description
$\mathcal{Q}_+$, ($\mathcal{Q}_-$):	the sets identifying domestic, foreign, central bank and the underwriter agents' demand (supply) of portfolio shares
$\Delta Q_t \geq 0$, ($\Delta Q_t < 0$):	aggregate excess demand (supply) for an asset portfolio
π_t, ν_t:	π_t for excess demand and ν_t for excess supply of a portfolio of assets

MODEL COMPOSITION **6) Balance Sheet Adjustments** **continued** Cash corrections and final positions after trading

After the trading, we can define the new currency demand:

$$\Delta\tilde{C}^{\mathcal{D}}_{d,t} = \Delta C^{\mathcal{D}}_{d,t} - \sum_{D=1}^{n^D} \underbrace{(out^D_t Q^D_{d,t-1} - Q^D_{d,t})P^D_t}_{\text{asset transactions}}$$

$$\text{and} \quad \Delta\tilde{C}^{\mathcal{F}}_{d,t} = \Delta C^{\mathcal{F}}_{d,t} - \sum_{F=1}^{n^F}(out^F_t Q^F_{d,t-1} - Q^F_{d,t})P^F_t$$

Transactions in portfolio shares can lead to changes in the inventory of domestic and foreign currency holdings of investor agents, which in turn impact their demand for currency. The updated respective domestic and foreign demand for cash after assets have been traded is defined on the left,with $\tilde{C}^{\mathcal{D}}_{d,t} = w^{C^{\mathcal{D}}}_{d,t} S_{d,t} - \Delta\tilde{C}^{\mathcal{D}}_{d,t}$ and $\tilde{C}^{\mathcal{F}}_{d,t} = w^{C^{\mathcal{F}}}_{d,t} S_{d,t}/X^{\mathcal{DF}}_t - \Delta\tilde{C}^{\mathcal{F}}_{d,t}$ as the updated respective domestic and foreign cash inventories.

Adjusting for the fact, that cross-border transactions can only occur if currency demanded is the same as currency supplied, the final demand/ supply at the end of period t is:

$$\Delta\tilde{\tilde{C}}^{\mathcal{D}}_{d,t} = \begin{cases} \text{sgn}(\Delta\tilde{C}^{\mathcal{D}}_{d,t}) \cdot \min\left\{|\Delta\tilde{C}^{\mathcal{D}}_{d,t}|, |X^{\mathcal{DF}}_t \Delta\tilde{C}^{\mathcal{F}}_{d,t}|\right\} & \text{if} \quad \text{sgn}(\Delta\tilde{C}^{\mathcal{D}}_{d,t}) \neq \text{sgn}(\Delta\tilde{C}^{\mathcal{F}}_{d,t}) \\ 0 & \text{else} \end{cases}$$

$$\Delta\tilde{\tilde{C}}^{\mathcal{F}}_{d,t} = \begin{cases} \text{sgn}(\Delta\tilde{C}^{\mathcal{F}}_{d,t}) \cdot \min\left\{|\Delta\tilde{C}^{\mathcal{F}}_{d,t}|, |X^{\mathcal{FD}}_t \Delta\tilde{C}^{\mathcal{D}}_{d,t}|\right\} & \text{if} \quad \text{sgn}(\Delta\tilde{C}^{\mathcal{D}}_{d,t}) \neq \text{sgn}(\Delta\tilde{C}^{\mathcal{F}}_{d,t}) \\ 0 & \text{else} \end{cases}$$

with sgn(·) denoting the sign or signum function, which extracts the sign of the respective updated cash demands.

Cash demand needs to be updated a second time as it does not take into account the fact that an agent can only buy currency if it is able to supply an equally valued amount of a different currency. Generally, an agent will only engage in a foreign exchange transaction if its demands for the domestic and foreign currency are of opposite signs (i.e. one currency is demanded, the other supplied); and the volume of the aspired cash transaction is limited by what an agent demands or supplies of the respective other currency.

Correction factors for cash are:

$$\pi^C_t = 1 - \frac{\Delta\tilde{\tilde{C}}_t}{\sum_{j\in\mathcal{C}_+} \Delta\tilde{\tilde{C}}_{j,t}} \quad \text{and} \quad \nu^C_t = 1 - \frac{\Delta\tilde{\tilde{C}}_t}{\sum_{j\in\mathcal{C}_-} \Delta\tilde{\tilde{C}}_{j,t}}$$

with $\mathcal{C}_+ := \{d, f|\Delta\tilde{\tilde{C}}_{\{d,f\},t} \geq 0\}$ and $\mathcal{C}_- := \{d, f|\Delta\tilde{\tilde{C}}_{\{d,f\},t} < 0\}$ defining the sets that identify the agents demanding and supplying cash.

To allocate excess demand or supply in the currency market, we use correction factors as defined on the left. The intuition is that if there is an excess demand of 10%, all agents that want to buy currency will only be able to acquire 90% of their original demand. The factors are multiplied with each agents' individual excess position (demand or supply) to arrive at the final currency position (see below)

Finally, new quantities of domestic and foreign cash on balance sheets are computed with 'excess positions' and corrections factors

$$\text{C}_{d,t} = \begin{cases} \tilde{C}_{d,t} + \Delta\tilde{\tilde{C}}_{d,t}\pi^C_t & \text{if} \quad \Delta\tilde{\tilde{C}}_{d,t} \geq 0 \text{ and } \Delta\tilde{\tilde{C}}_t \geq 0 \\ \tilde{C}_{d,t} + \Delta\tilde{\tilde{C}}_{d,t}\nu^C_t & \text{if} \quad \Delta\tilde{\tilde{C}}_{d,t} < 0 \text{ and } \Delta\tilde{\tilde{C}}_t < 0 \\ \tilde{C}_{d,t} + \Delta\tilde{\tilde{C}}_{d,t} & \text{else} \end{cases}$$

$$\text{with} \quad \Delta\tilde{\tilde{C}}^{\mathcal{D}}_t = \sum_{d=1}^{n^d} \Delta\tilde{\tilde{C}}^{\mathcal{D}}_{d,t} + \sum_{f=1}^{n^f} \Delta\tilde{\tilde{C}}^{\mathcal{D}}_{f,t} \text{ and } \quad \Delta\tilde{\tilde{C}}^{\mathcal{F}}_t = \sum_{d=1}^{n^d} \Delta\tilde{\tilde{C}}^{\mathcal{F}}_{d,t} + \sum_{f=1}^{n^f} \Delta\tilde{\tilde{C}}^{\mathcal{F}}_{f,t}$$

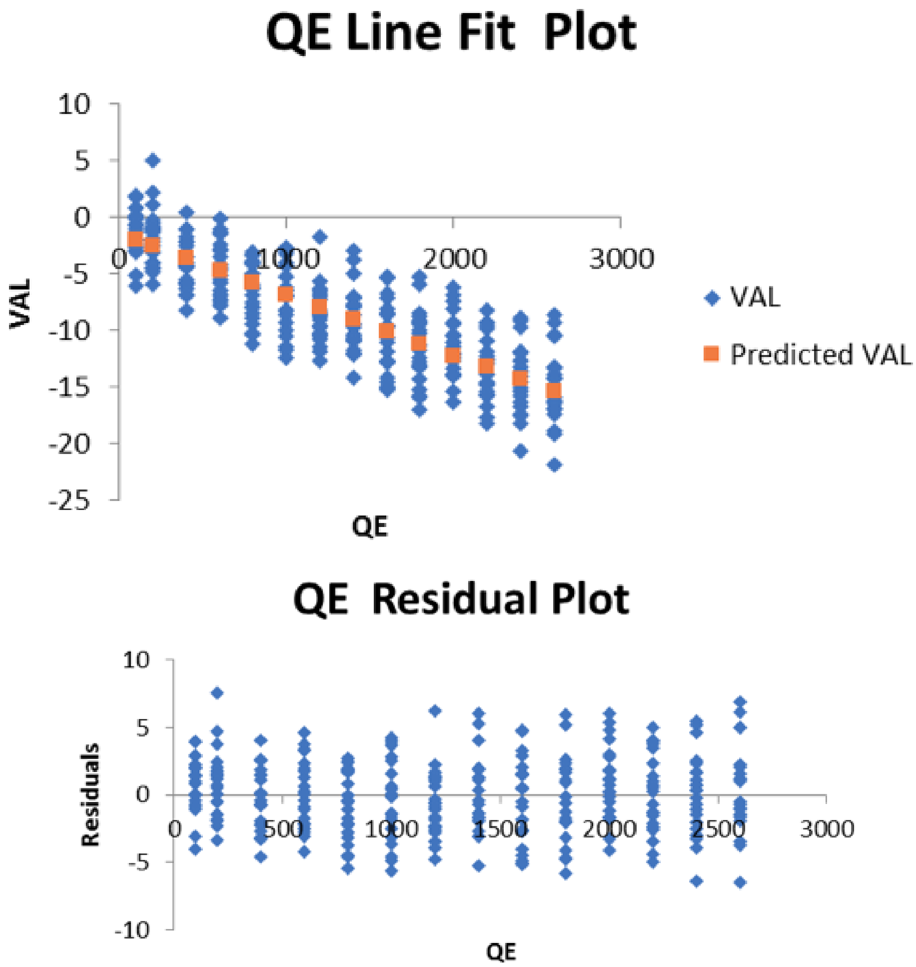


FIGURE 5.5: Regression diagnostics for Table 5.7 on page 75, column 1. The coefficient captures the marginal effect of 100bn EUR of QE magnitude (i.e. the asset purchases by the domestic central bank) on the domestic bond portfolio. VAL is the difference in the expected return an investor faces when buying the domestic bond portfolio with and without QE. The expected return of the EZ bond portfolio declines on average about 0.6 basis point for each 100 bn EUR the central bank purchases of that portfolio. The simulation includes levels of asset purchases, i.e. magnitude 'jumps', from 200 bn EUR to 2.6 tn EUR. The relationship between QE and the domestic bond returns is linear because there is no discernible pattern of the residuals from the linear predicted value.

6 Conclusions and policy implications

Quantitative Easing has become a prevalent policy instrument for central banks in the US, Eurozone, UK, Japan, Switzerland and Sweden in the last decade. While the period of unconventional monetary policy was accompanied by declining long-term interest rates in those countries, the transmission mechanisms of QE are not clear. This dissertation focused on specific aspects of financial spillover in the context of QE and applied heterogeneous agent models to investigate channels of contagion. This chapter summarises our main findings and presents recommendations for policymakers concerned with financial sector stability. Finally, Section 6.3 identifies areas that provide scope for further research.

6.1 Summary of findings

The first aim of the study was to investigate conditions under which QE may affect stability in a network of financial institutions. Chapter 3 in PART II addressed these questions by calibrating a spillover model of asset price shock propagation. In essence, Chapter 3 conducted stress-test simulations on South African banks to study the emergence of liquidation spirals on the back of banks' de-leveraging behaviour. We employ a network model that extends the framework proposed by Greenwood et al. (2015) by including a cash buffer. Systemic risk via fire-sale contagion is compared across two types of shocks; one to a non-marketable asset of an individual bank, and the other to a marketable asset held by all banks. In the first scenario, the largest bank, Standard Bank (SBSA), suffers defaults in its unsecured lending portfolio causing distress for SBSA which is forced to de-leverage by fire-selling. However, the volumes of SBSA's asset sales are not large enough to cause de-stabilising feedback effects in the form of large scale second-round fire-sales. The main reason for this is that knock-on price effects can be absorbed by cash liquidity buffers of most other banks. There are a few banks that are forced to de-leverage in the case of 50% shock, i.e. JP Morgan, BNP, Bank of China, Citybank, Deutsche Bank and Investec. However, there is no contagion to the three other large banks, ABSA, FNB and Nedbank, for any of the devaluation shocks to SBSA's unsecured lending portfolio studied in the stress-test. This is the primary reason why cumulative banking system asset losses are minimal in this scenario. Only if fire-sales affect cash buffers and de-leveraging behaviour of these large banks do losses become systemically relevant. One could argue that the characteristic of the South African banking system to be highly concentrated amongst SBSA, ABSA, Nedbank and FNB has a positive absorptive effect on financial system stability. This is the case as long as these banks are not involved in de-leveraging rounds.

A different picture emerges in the case of a shock to the marketable asset, or more specifically, to SA government bonds. Here, most banks are involved in de-leveraging from the initial impact as cash liquidity buffers are depleted. In the case of a large shock of 50% to SA government bonds, more than 16% of banking sector equity gets wiped out in secondary de-leveraging and fire-selling rounds. SBSA contributes most to the fire-sale externality risk due to the magnitude of its down-sizing. The second most systemic bank in the fire-sale contagion context is Nedbank, closely followed by FNB. African Bank and Capitec play no role in the fire-sale price shock propagation. They are, however, the least diversified retail banks, as shown in section 3.2, which makes them highly exposed to fallouts in their unsecured lending portfolio. We rank individual banks according to their contribution to systemic risk and show the importance of cash liquidity buffers in reducing risk to fire-sale occurrences. Last, but not least, we find a critical threshold parameter, which, if exceeded, makes the banking system highly unstable. A sensitivity analysis of results finds a critical illiquidity parameter for the shock scenario regarding SA government bonds. If shocks to this asset class lead to a price effect larger than 1×10^{-13}, high systemic risk, which requires policy response, ensues. Finally, we have shown that the fire-sale contagion channel becomes much more pronounced in the context of QE. The same shock to the government bond asset class leads to much higher banking sector instability, assuming that QE leads to a condition of banks taking up higher leverage. The risk to banking sector losses is not linear, but increases exponentially with higher leverage ratios.

The second aim of the study was to ascertain whether spillover asset price affects can be attributed to the portfolio balance channel of Euro area QE. In Chapter 2 we highlighted that the bulk of empirical studies (e.g. Krishnamurthy and Vissing-Jorgensen, 2012; Gagnon et al., 2011a; Ehlers, 2012; Joyce et al., 2011; Neely, 2015; Breckenfelder et al., 2016) finds sizable asset price effects in the wake of QE announcements and that policy makers emphasised the role of the portfolio balance channel as justification for QE. However, this stands in contrast to the theoretical literature incorporating the composition and allocation of public sector debt in the consumption-based asset pricing approach of macro models (Wallace, 1981; Eggertsson and Woodford, 2003; Woodford, 2012). Overall, portfolio balance effects of QE are still contested in the literature (Thornton, 2012).

In face of the research gap looking for models explaining QE-induced portfolio balance effects, we developed a dynamic agent-based model with heterogeneous assets and investors (Chapter 4). This novel approach is suited to address the research question because it specifically models assets as imperfect substitutes. Our two-country spillover model is complex and computationally intensive, but this is required to capture heterogeneity in assets in terms of maturity, default and inflation risk, as well as in preferred habitat preferences of investors. The core of the model is about how central bank purchases impact mean-variance investors who allocate their capital across a domestic and foreign market. Asset substitutability is determined by the risk-return profile reflected in expected returns and covariance-variance structure of returns. An adaptive algorithm solves the model numerically which allows us to keep computational tractability.

The third aim of the dissertation was to conduct an extensive simulation study to quantify QE-induced portfolio balance effects in the Eurozone and compare our estimates with those of the literature. The design of the simulation study was justified by incorporating theoretical and practical considerations. Chapter 5 calibrated the model to a two-country market with the Eurozone (EZ) representing the domestic market and a sample of rest-of-the world (ROW) countries as foreign market. It was important to capture a sample representing the global market size for portfolios of EZ and ROW bonds, equities and currencies. For this purpose, we compiled data on asset holdings of 15 374 EZ and 25 930 ROW open-end *investment funds* from the Morning Star Database, as well as data on investment portfolios of EZ and ROW *banks* from the ECB's Statistical Warehouse, Bankscope and other sources detailed in Table 5.12 on page 87. The simulation study finds significant portfolio balance effects for the domestic market, albeit smaller than what could have been assumed from QE announcement studies. The average effect of EUR100bn asset purchases of the EZ central bank is a decline in the expected return of the EZ bond portfolio of 0.6 basis points, which means that the APP (EUR 2.6tn) led to an overall reduction of 15.6 basis points in domestic bond returns. This result is broadly in line with empirical work of Koijen et al. (2016) who find that the ECB's APP caused a decline of about 14 basis points in the yield of the 10-year government bond. Perhaps the most interesting result pertains to domestic equities, where the effect is 7 times stronger than for domestic bonds and the APP leads to 6.6% higher prices of the EZ equity portfolio.

Somewhat surprisingly, we don't find economically meaningful spillover effects in respect of foreign asset returns for our sample of ROW countries. While the impact of the APP program is statistically significant, price effects on ROW equities and bonds are negligible at +0.4% and +0.04% in total, respectively. When comparing these results with the empirical findings from the spillover literature, it turns out that we cannot confirm the notion that QE influenced foreign asset prices in an economically meaningful way, at least not in respect of portfolio-balancing-induced price effects of the APP. In addition, domestic asset prices were impacted to a smaller degree than what was found by Motto et al. (2015); Breckenfelder et al. (2016); De Santis (2016) or what was found for US programs by Gagnon et al. (2011a); Stefania and King (2013); Neely (2015).

Do our findings contradict the conventional knowledge about the relationship between QE and financial asset prices? There are several points to consider. First, the empirical spillover literature focuses on US-based QE (Aizenman et al., 2016; Mishra et al., 2014; Eichengreen and Gupta, 2015; Chen et al., 2012) due to its relatively higher importance for the world economy. It is possible that the portfolio balance effect from the US FED's LSAP programs were significantly higher than what we find for the APP, and thus, we need to calibrate our model to the US market to compare these findings. Second, event studies that don't specifically disentangle the underlying transmission channels may be measuring the signalling channel associated with QE programs in the US and not the portfolio balance channel. Last, but not least, there is the possibility that it is not the QE, per se, that is driving those empirical estimates of price effects on financial markets. Greenlaw et al. (2018) have argued that event studies determining large QE-induced effects suffer from an identification problem, i.e. it is unclear whether markets react to news on central bank asset purchases or news regarding underlying economic fundamentals.

Thus, Greenlaw et al. (2018) conclude that the effect of the US program itself on interest rates is likely smaller than what many event studies claim.

Overall, our findings seem to be in line with Greenlaw et al. (2018)'s skepticism, at least in the context of the ECB's APP. Our results lead us to believe that QE-induced asset price effects are not irrelevant, but only small in magnitude on the domestic market. Spillovers from portfolio balancing to the rest-of-the-world are negligible.

6.2 Policy implications

The following policy implications can be deduced from the findings of this study. First, our findings suggest that the effectiveness of Euro area QE in lowering long-term interest rates **through the portfolio balance channel** must be regarded with skepticism. While finding a clear relationship between asset purchases and rising prices for global bond and equity portfolios, the magnitude of the effect is rather small. From a domestic market perspective, it is not clear to us that policymakers should engage in massive asset purchase programs if the primary intention is to ease conditions through lowering long-term interest rates in a meaningful way. Apart from portfolio balancing, it is possible that QE works through changing expectations of market participants. However, as Eggertsson and Woodford (2003) point out, if the aim of monetary policy is to lower the expected path of short-term rates, QE should not be the first choice. An alternative measure is forward guidance, i.e. the credible and consistent communication about the future course of monetary policy. The effectiveness of forward guidance is not part of the analysis of this dissertation. However, it has been shown in many studies that explicit forward guidance has been a successful tool to lower various interest rates. This would be conducive to increasing economic activity and inflation (see for instance Campbell et al., 2012; Gavin et al., 2013; Swanson and Williams, 2014; Gertler and Karadi, 2015; Giannoni et al., 2015).

Second, from a foreign market perspective, portfolio balance effects from Euro Area Quantitative Easing are not, per se, a threat to financial markets in terms of contributing to higher price volatility abroad. Policymakers should be more concerned with the effect of QE on the risk-taking behaviour of banks in respect of their leverage ratio. We demonstrated how higher leverage in banks amplifies shock propagation in Section 3.4. It is important to monitor the development of leverage in the banking system in the medium term, particularly of those banks that are too big to fail.

Third, to mitigate the risk of fire-sale propagation in banking systems, the findings of Chapter 5 point to two crisis intervention instruments. First, the provision of emergency liquidity is important during a crisis to reduce the likelihood of banks' asset liquidation. We demonstrated the importance of cash liquidity buffers to dampen banks' de-leveraging spirals through fire-sales. Second, the results suggest that regulators put maximum leverage requirements on hold during times of stress. Maximum leverage is a regulatory instrument that prevents high risk-taking behaviour *ex-ante*. In times of stress, however, this regulation has the potential to aggravate the situation by incentivising de-leveraging through asset liquidation. To lessen these amplification effects, banks should be allowed to have larger than normal leverage ratios **temporarily** until systemic risk subsides.

6.3 Further research areas

There are a number of research possibilities which could be pursued further. The network model studying price shock amplification processes in Chapter 3 uses cross-sectional balance sheet data from December 2015. The simulation study can be extended by considering more time points to determine the exposure to systemic risk over time. It was found that increased leverage has detrimental effects for financial stability in South Africa by increasing risk to fire-sale amplification losses. More research needs to be done on how banks' leverage changed over time and on what drove these changes. Second, an extension of the fire-sale algorithm to more complex assumptions needs to be investigated. This includes the incorporation of a binding liquidity constraint in banks' de-leveraging behaviour. One of the shock scenarios was to study amplification processes in the event of a shock to SA government bonds. However, government bonds are used by banks as highly liquid assets to comply with liquidity regulation. Ideally, the fire-sale model should include a liquidity constraint in the sense that banks are not able to sell off asset without considering their liquidity position. Some additional analyses in respect of the fire-sale algorithm will be valuable in order to obtain alternative estimates. Greenwood et al. (2015)'s model, which we have extended in this dissertation by including a cash buffer, was among the first models to be put to empirical data. Greenwood et al. (2015) use a constant holding structure and fixed leverage ratio to study the effect of a debt haircut for European sovereign bonds on capital losses in the European banking system. They find that a one percent decline in the price of all assets financed with repos leads to losses owing to fire-sale spillovers accumulating to eight percent of total equity. Cont and Schaanning (2017) extend Greenwood et al. (2015)'s framework by including a more complex concave price impact function which depends on assets' market depth and selling volumes. The advantage of this approach is that the illiquidity parameter is much more asset specific than the 'one-size-fits-all' approach in Greenwood et al. (2015) framework. In fire-sale algorithms, adequate modelling of the illiquidity parameter is still an open question. More empirical investigation is needed to determine values that are appropriate for respective market conditions. This idea should be pursued further to allow for a more accurate estimation of systemic losses given certain shock scenarios.

Our results from PART III suggest that the portfolio balance channel does not lead to economically meaningful spillover effects of Eurozone QE into the rest of the world. The calibration of the model to the two markets, Eurozone and the rest of the world, took substantial time and effort to match our model variables of assets available in the market with global holdings of bonds, equities and currency. A first possible addition is to extend the data by including asset holding from the insurance and pension fund sector (ICPF). We have not yet compiled data for the ICPF sector, thus the simulation of the model on an extended data set could be a valuable robustness test. Furthermore, it would be a valuable extension to simulate specific estimates for a country, e.g. South Africa. For this, one needs to calibrate the spillover model to a three-country setup with EZ as domestic market and two foreign markets with one representing South Africa and the other representing the rest of the world without EZ and South Africa. It's important to capture all investment opportunities for the agents globally to calibrate preference parameters adequately. Last but not least, it will be valuable to obtain estimates for US based QE programs. The literature on asset price effects for US LSAP programs is much larger and we could contribute by providing model-based estimates calibrated to US holding data. This will give further indication of our estimation accuracy of the portfolio balance channel.

Bibliography

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015). Systemic risk and stability in financial networks. *American Economic Review 105*(2), 564–608.

Adrian, T. and H. S. Shin (2010). Liquidity and leverage. *Journal of Financial Intermediation 19*(3), 418–437.

Agénor, P.-R. and L. A. P. da Silva (2018, April). *Financial spillovers, spillbacks, and the scope for international macroprudential policy coordination.* Number 97 in BIS Papers. Bank for International Settlements.

Aizenman, J., M. Binici, and M. M. Hutchison (2016). The transmission of federal reserve tapering news to emerging financial markets. *International Journal of Central Banking 12*(2), 317–356.

Allen, F., A. Babus, and E. Carletti (2010). Financial Connections and Systemic Risks. *Working Paper National Bureau of Economic Research No.16177*, 1–43.

Amblard, F. (2002). Which ties to choose? A survey of social networks models for agent-based social simulations. In *Proceedings of the 2002 SCS International Conference On Artificial Intelligence, Simulation and Planning in High Autonomy Systems*, pp. 253–258. Citeseer.

Andrés, J., D. Lopez-Salido, and E. Nelson (2004). Tobin's imperfect asset substitution in optimizing general equilibrium. Working Papers 2004-003, Federal Reserve Bank of St. Louis.

Baranova, Y., J. Coen, J. Noss, P. Lowe, and L. Silvestri (2017, July). Simulating stress across the financial system: the resilience of corporate bond markets and the role of investment funds. Bank of England Financial Stability Papers 42, Bank of England.

Bauer, M. and C. Neely (2012). International channels of the Fed's unconventional monetary policy. (2012-028).

Bauer, M. and G. Rudebusch (2014). The Signaling Channel for Federal Reserve Bond Purchases. *International Journal of Central Banking 10*(3), 233–289.

Beja, A. and M. B. Goldman (1980). On The Dynamic Behavior of Prices in Disequilibrium. *Journal of Finance 35*(2), 235–248.

Bekaert, G., C. Harvey, C. Lundblad, and S. Siegel (2011). What segments equity markets? *Review of Financial Studies 24*(12), 3841–3890.

Bernanke, B. S. (2008). Federal Reserve policies in the financial crisis: a speech at the Greater Austin Chamber of Commerce, Austin, Texas, December 1, 2008. Technical report.

Bernanke, B. S. (2017, November). The Mayekawa Lecture: Some Reflections on Japanese Monetary Policy. *Monetary and Economic Studies 35*, 23–38.

Berrospide, J. M., L. K. Black, and W. R. Keeton (2016, August). The Cross-Market Spillover of Economic Shocks through Multimarket Banks. *Journal of Money, Credit and Banking 48*(5), 957–988.

Bhattarai, S. and C. Neely (2016). A Survey of the Empirical Literature on U.S. Unconventional Monetary Policy. *Federal Reserve Bank of St. Louis Working Paper Series 2016-021A*, 1–47.

Bonabeau, E. (2002, 06). Agent-Based Modeling: Methods And Techniques for Simulating Human Systems. *Proceedings of the National Academy of Sciences of the United States of America 99 Suppl 3*, 7280–7.

Bookstaber, R., M. Paddrik, and B. Tivnan (2018). An agent-based model for financial vulnerability. *Journal of Economic Interaction and Coordination 13*(2), 433–466.

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

Boswijk, H. P., C. Hommes, and S. Manzan (2007). Behavioral heterogeneity in stock prices. *Journal of Economic Dynamics and Control 31*(6), 1938–1970.

Breckenfelder, J., F. De Fiore, P. Andrade, P. Karadi, and O. Tristani (2016). The ECB's asset purchase programme: an early assessment. *European Central Bank, Working Paper Series* (1956).

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Bruno, V. and H. S. Shin (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics 71*(C), 119–132.

Caccioli, F., M. Shrestha, C. Moore, and J. D. Farmer (2014). Stability analysis of financial contagion due to overlapping portfolios. *Journal of Banking and Finance 46*(1), 233–245.

Calimani, S., G. Hałaj, and D. Żochowski (2017, June). Simulating fire-sales in a banking and shadow banking system. ESRB Working Paper Series 46, European Systemic Risk Board.

Campbell, J., C. L. Evans, J. Fisher, and A. Justiniano (2012). Macroeconomic effects of federal reserve forward guidance. *Brookings Papers on Economic Activity 43*(1 (Spring)), 1–80.

Caramazza, F., L. Ricci, and R. Salgado (2004). International financial contagion in currency crises. *Journal of International Money and Finance 23*(1), 51 – 70.

Cecchetti, S., T. M. Griffoli, and M. Narita (2017, March). Does Prolonged Monetary Policy Easing Increase Financial Vulnerability? IMF Working Papers 17/65, International Monetary Fund.

Chen, H., V. Cúrdia, and A. Ferrero (2012, October). The macroeconomic effects of large-scale asset purchase programs. Working Paper Series 2012-22, Federal Reserve Bank of San Francisco.

Chen, S.-H., C.-L. Chang, and Y.-R. Du (2012). Agent-based economic models and econometrics. *The Knowledge Engineering Review 27*(02), 187–219.

Chiarella, C. (1992). The dynamics of speculative behaviour. *Annals of Operations Research 37*(1), 101–123.

Christensen, J. and S. Krogstrup (2017). A Portfolio Model of Quantitative Easing. (2016-12).

Christensen, J. H. and S. Krogstrup (2018). Transmission of quantitative easing: The role of central bank reserves. *The Economic Journal*.

Cifuentes, R., G. Ferrucci, and H. S. Shin (2005). Liquidity Risk and Contagion. *Journal of the European Economic Association 3*(2/3), pp. 556–566.

Cipriani, M., A. Martin, and B. M. Parigi (2013). Money market funds intermediation, bank instability, and contagion. *FRB of New York Staff Report* (599).

Cochrane, J. H. (2009). *Asset pricing: Revised edition.* Princeton university press.

Cont, R. and E. Schaanning (2017). Fire sales, indirect contagion and systemic stress testing. *SSRN Electronic Journal*, 1–50.

Cox, J. , J. E. Ingersoll Jr, and S. A. Ross (1985). A Theory of the Term Structure of Interest Rates. *Econometrica 53*(2), 385–408.

Dale, S. (2010). Qe - one year on. *Remarks at the CIMF and MMF Conference on "New Instruments of Monetary Policy: The Challenges,"*.

Day, R. H. and W. Huang (1990). Bulls, bears and market sheep. *Journal of Economic Behavior and Organization 14*(3), 299–329.

De Grauwe, P. and P. Rovira Kaltwasser (2012). The Exchange Rate in a Behavioral Finance Framework. In *Handbook of Exchange Rates*, pp. 111–132.

De Santis, R. A. (2016, July). Impact of the asset purchase programme on euro area government bond yields using market news. Working Paper Series 1939, European Central Bank.

Dell'ariccia, G., L. Laeven, and G. A. Suarez (2017). Bank Leverage and Monetary Policy's Risk-Taking Channel: Evidence from the United States. *The Journal of Finance 72*(2), 613–654.

Dell'Ariccia, G., P. Rabanal, and D. Sandri (2018). Unconventional monetary policies in the euro area, Japan, and the United Kingdom. *Journal of Economic Perspectives 32*(4), 147–72.

Doh, T. (2010). The efficacy of large-scale asset purchases at the zero lower bound. *Economic Review* (Q II), 5–34.

Domanski, D., H. S. Shin, and V. Sushko (2015). The hunt for duration: not waving but drowning? BIS Working Papers 519, Bank for International Settlements.

Duarte, F. and T. M. Eisenbach (2013). Fire-Sale Spillovers and Systemic Risk. *SSRN Electronic Journal* (FRB of New York Staff Report No. 645), 76.

Duffie, D. (2010). Asset Price Dynamics with Slow-Moving Capital. *Journal of Finance LXV*(4), 1–35.

Edison, H., R. Levine, L. Ricci, and T. Slok (2002). International financial integration and economic growth. *Journal of International Money and Finance 21*(6), 749–776.

Eggertsson, G. B. and M. Woodford (2003). The Zero Bound On Interest Rates And Optimal Monetary Policy. *Brookings Papers on Economic Activity 34*(1), 139–235.

Ehlers, T. (2012). The effectiveness of the Federal Reserve's Maturity Extension Program - Operation Twist 2: the portfolio rebalancing channel and public debt management. *65*, 245–255.

Eichengreen, B. and P. Gupta (2015). Tapering talk: The impact of expectations of reduced Federal Reserve security purchases on emerging markets. *Emerging Markets Review 25*, 1–15.

Eichengreen, B., A. K. Rose, and C. Wyplosz (1996, July). Contagious Currency Crises. NBER Working Papers 5681, National Bureau of Economic Research, Inc.

Eisenberg, L. and T. H. Noe (2001). Systemic Risk in Financial Systems. *Management Science 47*(2), 236–249.

Elliott, M., J. Hazell, and C.-P. Georg (2018). Systemic Risk-Shifting in Financial Networks. *Working Paper available at SSRN 2658249*.

Farmer, J. D. and S. Joshi (2002). The price dynamics of common trading strategies. *Journal of Economic Behavior and Organization 49*(2), 149–171.

Farmer, R. E. (2012, September). Qualitative Easing: How it Works and Why it Matters. Working Paper 18421, National Bureau of Economic Research.

Fischer, T. (2014). No-arbitrage pricing under systemic risk: Accounting for cross-ownership. *Mathematical Finance 24*(1), 97–124.

Gagnon, J., M. Raskin, J. Remache, and B. Sack (2011a, March). The Financial Market Effects of the Federal Reserve's Large-Scale Asset Purchases. *International Journal of Central Banking 7*(1), 3–43.

Gagnon, J., M. Raskin, J. Remache, and B. P. Sack (2011b). Large-scale asset purchases by the federal reserve: did they work? *Economic Policy Review* (May), 41–59.

Gai, P., A. Haldane, and S. Kapadia (2011). Complexity, concentration and contagion. *Journal of Monetary Economics 58*(5), 453–470.

Gavin, W. T., B. D. Keen, A. Richter, and N. Throckmorton (2013). The stimulative effect of forward guidance. Technical report.

Georg, C. P. (2013). The effect of the interbank network structure on contagion and common shocks. *Journal of Banking and Finance 37*(7), 2216–2228.

Georg, C.-P., D. Pierret, and S. Steffen (2019). Similar Investors. *Working Paper available at SSRN 3250826*.

Gertler, M. and P. Karadi (2015, January). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics 7*(1), 44–76.

Giannoni, M., C. Patterson, and M. D. Negro (2015). The Forward Guidance Puzzle. Technical report.

Glasserman, P. and H. P. Young (2015). How likely is contagion in financial networks? *Journal of Banking and Finance 50*, 383–399.

Glasserman, P. and H. P. Young (2016). Contagion in Financial Networks. *Journal of Economic Literature 54*(3), 779–831.

Glick, R. and A. K. Rose (1999). Contagion and trade: Why are currency crises regional? *Journal of International Money and Finance 18*(4), 603 – 617.

Gourinchas, P.-O. and M. Obstfeld (2012, January). Stories of the Twentieth Century for the Twenty-First. *American Economic Journal: Macroeconomics 4*(1), 226–265.

Greenlaw, D., J. D. Hamilton, E. Harris, and K. D. West (2018, June). A Skeptical View of the Impact of the Fed's Balance Sheet. Working Paper 24687, National Bureau of Economic Research.

Greenwood, R., A. Landier, and D. Thesmar (2015). Vulnerable banks. *Journal of Financial Economics 115*(3), 471–485.

Greenwood, R. and D. Vayanos (2014). Bond Supply and Excess Bond Returns. *Review of Financial Studies 27*(3), 663–713.

Grosse-Rueschkamp, B., S. Steffen, and D. Streitz (2019). A Capital Structure Channel of Monetary Policy. *Journal of Financial Economics*.

Hamilton, J. and J. C. Wu (2012). The Effectiveness of Alternative Monetary Policy Tools in a Zero Lower Bound Environment. *Journal of Money, Credit and Banking 44*, 3–46.

Hatchondo, J. C. and L. Martinez (2009). Long-duration bonds and sovereign defaults. *Journal of international Economics 79*(1), 117–125.

Hicks, J. R. (1937). Mr. Keynes and the "Classics": A suggested interpretation. *Econometrica*.

Jacobs, M. (2009). An empirical study of the returns on defaulted debt and the discount rate for loss-given-default. *Available at SSRN*.

Joyce, M. A. S., A. Lasaosa, I. Stevens, and M. Tong (2011). The Financial Market Impact of Quantitative Easing in the United Kingdom. *International Journal of Central Banking 7*(3), 113–161.

Kandrac, J. and B. Schlusche (2017, October). Quantitative Easing and Bank Risk Taking: Evidence from Lending. Finance and Economics Discussion Series 2017-125, Board of Governors of the Federal Reserve System (US).

Kemp, E. (2017). Measuring shadow banking activities and exploring its interconnectedness with banks in South Africa. *South African Reserve Bank - Occasional Paper Series* (December), 1–28.

Koijen, R. S., F. Koulischer, B. Nguyen, and M. Yogo (2016). Quantitative Easing in the Euro Area: The Dynamics of Risk Exposures and the Impact on Asset Prices. *Banque de France, Working paper series*.

Koziol, T., J. Riedler, and J. Schasfoort (2019). Euro Area Quantitative Easing in a Portfolio Balance Model with Heterogeneous Agents and Assets. *Available at SSRN*.

Krishnamurthy, A., S. Nagel, and A. Vissing-Jorgensen (2017, November). ECB Policies Involving Government Bond Purchases: Impact and Channels. NBER Working Papers 23985, National Bureau of Economic Research, Inc.

Krishnamurthy, A. and A. Vissing-Jorgensen (2011a). The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy. *Brookings Papers on Economic Activity 42*(2 (Fall)), 215–287.

Krishnamurthy, A. and A. Vissing-Jorgensen (2011b). The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy. *Brookings Papers on Economic Activity 42*(2 (Fall)), 215–287.

Krishnamurthy, A. and A. Vissing-Jorgensen (2012). The Aggregate Demand for Treasury Debt. *Journal of Political Economy 120*(2), 233 – 267.

Krugman, P. R. (1998). It's Baaack: Japan's Slump and the Return of the Liquidity Trap. *Brookings Papers on Economic Activity 29*(2), 137–206.

Kuttner, K. N. (2018). Outside the Box: Unconventional Monetary Policy in the Great Recession and Beyond. *Journal of Economic Perspectives 32*(4), 121–46.

Ladley, D. (2013). Contagion and risk-sharing on the inter-bank market. *Journal of Economic Dynamics and Control 37*(7), 1384–1400.

LeBaron, B. (2001). A builder's guide to agent-based financial markets. *Quantitative Finance 1*(2), 254–261.

Levich, R., G. S. Hayt, and B. A. Ripston (1999, 01). 1998 Survey of Derivatives and Risk Management Practices by U.S. Institutional Investors. *New York University, Leonard N.*

Stern School of Business-, New York University, Leonard N. Stern School Finance Department Working Paper Seires.

Lux, T. (1995). Herd behaviour, bubbles and crashes. *Economic Journal 105*(431), 881–96.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance 7*(1), 77–91.

Mishkin, F. S. (1995, Fall). Symposium on the Monetary Transmission Mechanism. *Journal of Economic Perspectives 9*(4), 3–10.

Mishra, P., K. Moriyama, P. N'Diaye, and L. Nguyen (2014). The Impact of Fed Tapering Announcements on Emerging Markets. *IMF Working Paper No. 14/109*, 1–34.

Mohanty, M. S. (2014). The transmission of unconventional monetary policy to the emerging markets-An overview. *BIS Paper* (78a).

Morais, B., J.-L. Peydró, J. Roldán-Peña, and C. Ruiz-Ortega (2019). The International Bank Lending Channel of Monetary Policy Rates and QE: Credit Supply, Reach-for-Yield, and Real Effects. *The Journal of Finance 74*(1), 55–90.

Motto, R., C. Altavilla, and G. Carboni (2015). Asset Purchase Programmes and Financial Markets: Lessons from the Euro Area. *European Central Bank,Working Paper Series* (1864).

Neely, C. (2015). Unconventional monetary policy had large international effects. *Journal of Banking Finance 52*(C), 101–111.

Nier, E., J. Yang, T. Yorulmazer, and A. Alentorn (2007). Network models and financial stability. *Journal of Economic Dynamics and Control 31*(6), 2033–2060.

Piazzesi, M. and M. Schneider (2007, 04-05). Asset Prices and Asset Quantities. *Journal of the European Economic Association 5*(2-3), 380–389.

Puy, D. (2016). Mutual funds flows and the geography of contagion. *Journal of International Money and Finance 60*, 73 – 93.

Raghuram, R. (2014). Global Monetary Policy: A View from Emerging Markets.

Rey, H. (2016, May). International Channels of Transmission of Monetary Policy and the Mundellian Trilemma. *IMF Economic Review 64*(1), 6–35.

Riedler, J. and F. Brückbauer (2017). Evaluating regulation within an artificial financial system - a framework and its application to the liquidity coverage ratio regulation. *ZEW discussion papers 17*.

Rijckeghem, C. V. and B. Weder (2001). Sources of contagion: is it finance or trade? *Journal of International Economics 54*(2), 293 – 308.

Rodnyansky, A. and O. M. Darmouni. The Effects of Quantitative Easing on Bank Lending Behavior.

Rogoff, K. (1996). The Purchasing Power Parity Puzzle. *Journal of Economic Literature 34*(2), 647–668.

Schelling, T. C. (1971). Dynamic models of segregation. *J. Math. Sociol. 1*(2), 143–186.

Schenkelberg, H. and S. Watzka (2013). Real effects of quantitative easing at the zero lower bound: Structural VAR-based evidence from Japan. *Journal of International Money and Finance 33*, 327 – 357.

Schnabl, P. (2012). The international transmission of bank liquidity shocks: Evidence from an emerging market. *The Journal of Finance 67*(3), 897–932.

Schularick, M. and A. M. Taylor (2012, April). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review 102*(2), 1029–1061.

Shleifer, A. and R. Vishny (2011). Fire Sales in Finance and Macroeconomics. *Journal of Economic Perspectives 25*(1), 29–48.

SP2017 (2018). SP Annual global corporate default study 2017. Technical report.

Stefania, D. and T. King (2013). Flow and stock effects of large-scale treasury purchases: Evidence on the importance of local supply. *Journal of Financial Economics 108*(2), 425–448.

Summer, M. (2013). Financial Contagion and Network Analysis. *Annual Review of Financial Economics 5*(1), 277–297.

Swanson, E. T. and J. C. Williams (2014, October). Measuring the Effect of the Zero Lower Bound on Medium- and Longer-Term Interest Rates. *American Economic Review 104*(10), 3154–3185.

Tesfatsion, L. (2006). Agent-Based Computational Economics: A Constructive Approach to Economic Theory. Computing in Economics and Finance 2006 527, Society for Computational Economics.

Thornton, D. (2012). Evidence on the portfolio balance channel of quantitative easing. Working Papers 2012-015, Federal Reserve Bank of St. Louis.

Thornton, D. L. (2015). Requiem for QE. *Policy Analysis 783*, 464–85.

Tobin, J. (1958). Liquidity Preference as Behavior Towards Risk. *Review of Economic Studies 25*(2), 65–86.

Ueda, K. (2012). Japan's Deflation and the Bank of Japan's Experience with Nontraditional Monetary Policy. *Journal of Money, Credit and Banking*.

Upper, C. and A. Worms (2004). Estimating bilateral exposures in the German interbank market: Is there a danger of contagion? *European Economic Review 48*(4), 827–849.

Vayanos, D. and J.-L. Vila (2009, November). A Preferred-Habitat Model of the Term Structure of Interest Rates. Working Paper 15487, National Bureau of Economic Research.

Wallace, N. (1981). A Modigliani-Miller Theorem for Open-Market Operations. *American Economic Review 71*(3), 267–74.

Walsh, C. E. (1982). Asset substitutability and monetary policy : An alternative characterization. *Journal of Monetary Economics 9*(1), 59–71.

Weale, M. and T. Wieladek (2016). What are the macroeconomic effects of asset purchases? *Journal of Monetary Economics 79*, 81 – 93.

Woodford, M. (2012). Methods of policy accommodation at the interest-rate lower bound. *Proceedings - Economic Policy Symposium - Jackson Hole*, 185–288.