Essays on Macroeconomic Dynamics, Credit Intermediation and Financial Stability

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For any errors or inadequacies that may remain in this work, of course, the responsibility is entirely my own.

Preface

I hereby declare that this dissertation is the result of my own work and includes nothing that is an outcome of work done in collaboration except where specifically indicated in the text. It is not substantially the same as any other work that I have submitted or will be submitting for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution. This thesis does not exceed the prescribed word limit of 60,000 words.

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Summary

This dissertation consists of three chapters. In the first chapter, we study the role of financial frictions on the demand side of the economy. In particular, we study the interaction between firm and household credit constraints over the business cycle. We construct a real business cycle model with explicit modeling of price and quantity side of housing. This allows us to include both firm and household financing frictions. The model is estimated for the U.S economy using quarterly data on key macroeconomic variables over the period 1970 - 2006. Household and firm financial accelerators operate primarily through movement in house and capital prices respectively. We find clear evidence of the operation of a financial accelerator mechanism, whereby shocks to the economy are amplified most in the presence of both types of frictions, as opposed to just firm or household frictions. Over the business cycle, total factor productivity shocks in the non-housing sector explain about half of the volatility of GDP and consumption. However, cyclical variations in housing investment and housing prices are predominantly explained by housing preference and housing technology shocks. Finally, spillovers from household financing frictions are mostly concentrated in consumption. However, they also affect business investment via its impact on the demand for capital and consequently its price.

The second chapter focuses on financial frictions on the supply side. We study the role of bank capital in the transmission of shocks to the economy. Given the evolutionary change in the financial services industry and the growth of shadow banking in the decades prior to the global recession, we characterize credit intermediation with a heterogeneous banking sector comprised of traditional retail and shadow banking. We approach the shadow banking system from a regulation perspective wherein commercial banks have incentives to transfer loans from on- to off-balance sheet to gain regulatory relief. Since bank capital is costly, banks cover part of their funding needs by loan sale in the secondary market. Furthermore, these transferred loans are bundled together and converted into liquid asset backed securities. Commercial banks' effective return is subject to their monitoring effort, which is unobservable and hence introduces a moral hazard problem in loan sale. This limits the amount of

loan sold in the secondary market. We find that loan sale and securitization enhances credit intermediation in normal times and improves the resilience of the system to productivity shocks. However, it also exposes the economy to shocks emerging in the financial system. In response to financial market shocks, the government via its backstop program, can ameliorate its impact on the economy. Finally, we compare the model economy with Basel I and Basel II capital requirement and find that business cycle fluctuations are amplified under Basel II regime. Furthermore, in response to a negative productivity shock there is a transfer of loans from on to off balance sheet under Basel II rules with procyclical capital constraints. This points towards a need for countercyclical capital requirement as being implemented under Basel III accord.

In the third chapter, we focus on the question of trade off between price and financial stability goals for the conduct of monetary policy. The recent crisis has generated renewed interest in Hayekian theory and Minsky's instability hypothesis, which claims that accommodative monetary policy can be harmful for an economy by promoting excessive risk taking – the so called risk taking channel of monetary policy transmission. Risk Taking Channel has been documented for the U.S and Euro area and we investigate the presence of this in Asia. Using annual and quarterly data on publicly listed banks in Asia, we find that when interest rates are too low - lower than a benchmark - bank risk increases. Furthermore, there is also a case for greater supervision and capital stringency to alleviate risk taking.

Introduction

This dissertation is on understanding macroeconomic propagation in the presence of financial frictions. Following the global financial crisis of 2007, there has been a renewed interest in understanding the demand and more specifically the supply side of credit intermediation. Moreover, the macro-financial linkages and interconnectedness of macroeconomic and financial stability have come to the forefront. This dissertation, through three main chapters, provides an insight into macroeconomic dynamics in the presence of financial frictions on demand and supply side of credit intermediation. It also explores the linkages between the real and the financial economy and the dual goals of macroeconomic and financial stability.

The recent financial turmoil has called for a need to understand the role of financial frictions in propagating shocks and to develop approaches to embed these frictions in the macro models of central banks. In chapter 1, we study the macroeconomic dynamics resulting from financial frictions on the demand side, more specifically on households and firms. Existing literature looks at financial frictions on household and firm side in isolation, thereby missing any interaction between household and firm leverage in propagation of shocks. We construct a model with heterogeneous production of housing and non-housing that allows for studying the dynamics between residential and non-residential investment. This also allows us to analyze the nature of interaction between firm and household financing constraints over the business cycle.

In chapter 2, we focus on the supply side dynamics of credit intermediation. Following the global recession of 2007, many papers have attempted to understand the role played by the financial system in credit generation and growth. We add to the existing literature by incorporating a heterogeneous banking sector, comprising of traditional commercial banking and shadow banking. Shadow banking emerged as a product of growth in innovation, financial technology and regulation in the decades prior to the crisis. Our model provides a more realistic setup to understand the macro-financial linkages between the financial sector and real economic activity. It also allows us to analyze the link between macroeconomic stability, financial stability and regulation.

Finally in chapter 3, we delve deeper into the question of tradeoff between macroeconomic and financial stability. In particular, we look at the link between monetary policy and financial stability. Policymakers and researchers have questioned the reasons behind the crisis, trying to provide some explanations on the forces behind the fragility of the global financial system. Among the many potential causes of the crisis, a contentious one amongst economists is the contribution of the accommodative monetary policy to the build up of the crisis. Some economists argue that a prolonged period of extremely low interest rates and lax liquidity conditions encouraged financial institutions to take on more risk i.e. the so-called 'risk taking' channel of monetary policy transmission. In chapter 3, we contribute to the empirical literature on the risk taking channel by analyzing the risk taking behavior of banks in Asian economies. This also fills a notable gap in the existing literature that is mostly confined to the developed western economies, particularly of the U.S and Europe.

Chapter 1 focuses on the role of demand side frictions in propagation of shocks and macroeconomic volatility. Financial frictions on the firm side have been widely documented starting from Bernanke and Gertler (1989), Bernanke, Gertler and Gilchrist (henceforth BGG) (1999), Kiyotaki and Moore (1997). More recently papers including Iacoviello (2005), Iacoviello and Neri (2010) and Justiniano et. al. (2013) have explored housing market dynamics and their spillovers to the macroeconomy. The composition of households' balance sheets and assets such as housing, play a significant role in shaping the transmission mechanism. In this chapter, we add to the existing literature, by jointly studying the interaction between household and firm debt dynamics in a business cycle model. Studying household and firm financial frictions in isolation assumes that they are independent of each other. However, recent literature suggests that household balance sheet shocks have a substantial effect on aggregate economic activity and employment. For example, Mian and Sufi (2009, 2011) and Haltenhof (2014) document the role of household financing constraints on aggregate economic activity and employment.

We begin with a multi-sector production economy with housing and non-housing goods. On the supply side of the model, firms engage in joint production of housing and non-housing goods. The non-housing sector produces consumption goods using capital and labour and the housing sector produces new homes using capital, labour, intermediate business input and land. Firms hire labour and purchase capital using their net worth and by borrowing from the financial intermediary as in BGG (1999). The demand side of the model embodies financial frictions for both household and firms. Financial frictions for households appear in the form of borrowing based on collateralisable assets (housing). For firms, our model generates endogenous external finance premium as a function of the firms' leverage.

We use quarterly data for the U.S on six key macroeconomic variables (consumption, non-residential investment, residential investment, house prices, hours worked (consumption sector) and hours worked (housing sector)) for the period 1970 – 2006 to estimate the model using Bayesian techniques.

We find merit in including both household and firm financial frictions in a general equilibrium model. As compared to a model with only firm or household financial frictions, joint analysis of both leads to a greater amplification of shocks to GDP, consumption and investment. For example, the response of output and consumption to a non-housing technology shock is more than twice as large in a model with both kind of frictions as compared to a model with only one of the two frictions. Firms' financial accelerator operates via the procyclical impact of capital prices on its net worth. As the net worth increases with rising capital prices, the external finance premium facing firms falls. Household financial accelerator on the other hand operates primarily through the movement in house prices, which affects their borrowing capacity. Our model finds two unique ways in which firms' and households' financial constraints interact with each other. First, is via the loan market equilibrium condition: as the financial constraint on households tighten, their demand for loans fall, causing a downward pressure on interest rate. This reduces the cost of borrowing external funds for the firms. This would suggest a negative relationship between firm and household credit frictions as seen in Solomon (2010). The second effect operates through the impact of house prices on housing demand and investment. As house prices decrease (due to a negative housing demand shock for instance), the demand for housing and housing investment decreases. This further reduces the demand for housing capital and capital price. A decline in capital price worsens the net worth position of firms and therefore their terms of credit. Thus, a fall in households' borrowing capacity in this case also worsens firms credit condition. Overall in our model, the second effect dominates, providing evidence to the claim that there is a positive interaction between firm and household credit market constraints.

We also find very strong household wealth effects in our model, wherein shocks to housing wealth (house prices) have a substantial effect on household non-housing consumption. This is in line with the results of Mian and Sufi (2011) who find that money extracted from increased home equity is not used to purchase new real estate or pay down high credit card balance, suggesting that borrowed funds maybe used for real outlays. Finally, we also look at the factors affecting cyclical variation in aggregate variables at business cycle frequencies. We find that a productivity shock in the non-housing sector accounts for about half of the variation in GDP and consumption and about 15 percent of the variation in investment. Variations in housing investment and prices are however primarily explained by housing technology (supply) and housing preference (demand) shocks. Finally, financial shocks in the form of investment and entrepreneur risk shock are prime candidate for explaining variation in business investment.

The financial accelerator and the collateral constraint frameworks discussed in chapter 1 assume that borrowers could obtain funds directly from lenders without much of a role for the financial intermediaries. Introducing a banking sector into DSGE models provides an additional avenue for incorporating financial frictions specifically linked to the costs of intermediation, balance sheets of financial intermediaries, and their risk management behavior. Furthermore, credit channels and financial intermediaries embedded in macroeconomic models help explain dynamics of the business cycle capturing the inherent procyclicality of the financial system. The banking sector has been ignored in most DSGE models developed in the literature, except for some recent papers. In these, the analysis is mostly focused on commercial/retail banking without any emphasis on non bank financial intermediation, comprising of the so-called shadow banking, which grew in prominence prior to the great recession. The principal motivation for chapter 2 is therefore, to explicitly model the behavior of financial intermediaries, whereby we allow for a heterogeneous setup with both commercial and shadow banking.

We begin our analysis by understanding the reasons for the growth of shadow banking prior to the financial crisis. The growth in innovation, financial technology, regulation and competition in the decades prior to the crisis, led to an evolutionary change in the whole financial services industry. In particular, there was a marked shift from the usual originate-to-hold model of commercial banking to originate-to-distribute model of financial intermediation. While in the former model credit, maturity and liquidity transformation occurred on the balance sheets of a bank, in the latter, instead of holding loans on the balance sheets, banks could easily transfer them off the balance sheets. This led to the emergence of a new financial entity - Special Purpose Vehicles (SPV) or Off Balance Sheet Entities (OBSE) where these loans are transferred. Even though shadow banking comprises of a myriad of financial structures and institutions, we focus on OBSE as the sole entity of shadow banking in our model. This choice makes the model tractable and also allows us to focus on the existence of shadow banking from a regulatory perspective, which forms the central theme of this chapter.

We motivate the existence of shadow banking from both demand and supply side. On the supply side of the system, commercial banks could not compete with finance companies and broker-dealers that are not subject to as tight capital constraints as the former is. Thus, the presence of regulatory arbitrage marked a shift from traditional loan issuance and funding (originate-to-hold) to an originate-to-distribute model whereby loans are shifted from bank balance sheet to shadow banks. These loans were then pooled, underwritten and sold as rated asset backed securities linked to the loan portfolio. The originate-to-distribute model helped traditional banks to manage risks, provided regulatory benefits and also freed up capital, which was used to issue further loans to the private sector. On the demand side, we look at the market for the products of shadow banking i.e. the asset-backed securities. Managed funds and other institutional investors are important risk takers through investment in securities and other market debt instruments. Greenwood, Hanson, and Stein

(2012) and Pozsar (2011) argue that the total balances of the institutional cash investors significantly exceed the (inelastic) supply of short-term government debt and insured deposits. Therefore, institutional investors, such as managed funds who do not have any access to safe, short term and interest earning investment, became major players as shadow bank depositors.

The banking system in our model consists of retail and shadow banking. Retail banks collect deposits, raise bank capital and make loans (a part of which is sold in the secondary market). The effective return on bank portfolio depends on the monitoring effort exerted by banks. We further assume that the level of bank monitoring services is unobservable so that the bank and loan buyers cannot write contracts that are contingent on the level of the effort. Therefore, loan sales involve a moral hazard problem, namely, that the bank may not exert the monitoring effort at the most efficient level. This limits the amount of loan sold in the secondary market. Banks are also subject to idiosyncratic risk similar to entrepreneurs in the BGG framework. This introduces aggregate default in the banking sector as banks whose idiosyncratic risk falls below a certain threshold cannot service their deposits and hence declare default. The returns from defaulting banks are expropriated by the deposit insurance agency, who service the deposits from failed banks by levying lump sum taxes on households. The banks are therefore subject to a minimum capital regulatory constraint to limit the losses incurred due to failing banks. An important motivation for incorporating bank balance sheets with capital into the model framework is that it facilitates analysis of financial stability issues and assessing the implications of prudential regulatory measures affecting bank capital. The shadow bank on the other hand is not subject to regulatory constraint. The shadow bank undertakes the securitization process whereby the transferred loans are converted into marketable liquid asset-backed securities. To avoid adding too many agents in our model, we designate households as the final investors in these securities.

Our results indicate that the inclusion of shadow banking enhances credit intermediation and resilience of the financial system to productivity shocks. However, it increases the vulnerability of the economy to shocks emerging in the financial system. The recent financial crisis brought to light the perverse effect of financial shocks on the supply side of credit intermediation. In particular, an increase in the riskiness of commercial banks, leads to a shift of larger proportion of loans to the secondary market thereby increasing the moral hazard associated with bank monitoring and lowering the effective return on bank portfolio.

We further analyze the efficacy of government backstop programs in containing the crisis. In this regard, we evaluate the impact of direct loan purchase by the government. Active government credit policy is effective in ameliorating the adverse impact of risk shock on the economy.

Finally, we draw our focus to the macro-financial linkages of prudential regulation. In analyzing the impact of capital regulation on macroeconomic dynamics, we compare the Basel I and Basel II framework. We find that the impact of a negative technology shock on output, investment and capital price is amplified under procyclical Basel II regime. Furthermore, an increase in capital requirement under Basel II leads to a higher securitization and shift of loans from on to off balance sheets. This leads to a greater tendency to move to the unregulated sector in response to a negative shock under Basel II regime. Furthermore, it also reduces the overall return on bank portfolio by increasing the moral hazard problem associated with bank monitoring.

To reiterate, chapter 1 focuses on the financial accelerator or broad credit channel of monetary policy transmission wherein financial friction on the demand side amplifies shocks affecting the real economy. Chapter 2 reviews the influence of capital regulation on bank-behavior. A key issue here is the degree to which capital regulation both reflects and influences the measurement, management and pricing of risk. It summarizes what is known about the "bank capital" channel, i.e. the impact on the transmission mechanism that operates through the threat of breaching minimum capital requirements. It further analyzes the evolution of shadow banking from regulation perspective and provides a theoretical model to understand the interaction between traditional and shadow banking as well as the link between macroeconomic and financial stability. In chapter 3, we further this discussion on the link or trade-offs between macroeconomic and financial stability. Here, we study a more recently understood channel of monetary transmission – the 'bank risk-taking channel'.

During the pre-crisis period, central banks mostly disregarded the financial stability aspect, since the conventional wisdom suggested that the design of monetary policy was to maintain price stability. Developments in the credit transfer techniques that came with financial innovation were often regarded as contributing to financial stability (Duffie (2008), Altunbas et. al. (2014)). However, following the global financial crisis, the view that monetary policy actions may have consequences on financial stability has gained popularity. Further, questions regarding the role of financial stability considerations in monetary policy decisions and the ways to modify the existing monetary policy frameworks taking into account macro imbalances, have gathered strong prominence.

In light of these developments, the debate over the relationship between monetary policy and financial stability has intensified. The question of how monetary policy affects banks' risk-taking incentives is key to the aforementioned policy debate. This led to the emergence of the theory of risk-taking channel of monetary policy transmission (Borio and Zhu (2012), Rajan (2006)). In short, risk-taking channel posits that an expansionary monetary policy for a prolonged period of time can have an impact on risk perceptions or attitudes of banks. It relates to how changes in interest rates affect either risk perceptions or risk-tolerance of financial intermediaries. In this case, the result is not only an increase in lending in line with the traditional transmission mechanisms, but the risk-taking channel also implies an increase in riskiness of lending, i.e. a deterioration in the quality of portfolios. Thus the risk taking channel posits that monetary policy actions could contribute to the buildup of financial imbalances via its impact on risk attitudes, which could eventually result in a financial crisis.

The risk-taking channel of monetary policy transmission, even though fairly new, has garnered substantial attention, as manifested in recent papers – both theoretical and empirical. Empirical literature on the risk-taking channel has thus far focused mostly on the US and the euro area. Chapter 3 therefore fills an important gap in this literature by examining the impact of low interest rates in 10 Asian economies (the

People's Republic of China (PRC); Hong Kong, China; India; Indonesia; the Republic of Korea; Malaysia; the Philippines; Singapore; Taipei,China; and Thailand) from 2000 to 2011. Emerging Asia is an interesting case because during the global financial crisis a persistent interest rate differential remained between the relatively higher interest rate in the emerging economies and that of the advanced economies. The search-for-yield in this case led to a surge in capital flows into the emerging economies buoying domestic economic and financial conditions. The appropriate stabilization strategy would be to tighten policy (let interest rates rise), yet this was seldom done in order to discourage further capital inflows and hold the exchange rate relatively steady. This has led to lower than appropriate interest rates in these economies.

We empirically test for the existence of the risk-taking channel by analyzing the panel of banks in Asia using both annual and quarterly data. For annual data, we employ four different risk indicators incorporating both market based and accounting based measures of risk.

1. Idiosyncratic bank risk from an estimated CAPM model using daily individual bank return index and daily stock market return index for each country

2. The Z-score, which measures bank soundness in terms of insolvency risk or distance to default is calculated with data obtained from Bankscope. In essence, the z-score measures the lower bound in which expected returns need to drop in order to exhaust the bank's equity.

3. The ratio of non-performing loans to total loans.

4. Volatility of return on bank assets, measured by standard deviation of return on bank assets.

Furthermore we use two interest rate gaps for monetary policy stance as per Altunbas et al. (2014) in calculating the deviation of policy rate from some benchmark level;

1. Taylor gap, computed as the difference between the actual nominal interest rates and that generated from a Taylor-type equation.

2. Natural gap, which is the difference between the real short-term interest rate and the natural rate (or more accurately the trend rate).

If the bank risk-taking channel is operational, we expect the coefficient on interest rate gap to be negative, meaning low interest rates (lower than some benchmark) increase bank risk-taking. We also include other variables to account and control for other determinants of bank risk taking. These include macroeconomic controls (output growth, yield curve, exchange rate volatility, stock market index and debt/GDP ratio), bank specific controls (size, profitability, liquidity and capitalization) and regulatory controls (capital stringency, supervisory power and market discipline). Given the dynamic nature of bank risk we utilize a dynamic panel data model, which is estimated using a System GMM approach along the lines of Arellano- Bover (1995)/ Blundell-Bond (1998).

We find evidence of an operational bank risk-taking channel. In particular, we find that when interest rates are "too low"—lower than a benchmark—bank risk increases. This result is robust to other factors, which might have influenced banks' risk-taking behavior, namely, general economic conditions, bank specific characteristics, country specific market risk, and the regulatory environment. There is also some evidence suggesting the positive role of regulatory environment in ameliorating bank risk taking. We find the increase in bank risk in response to lax monetary policy to be lower in the case of Asia as compared to advanced economies like the US and euro area (for example Altunbas et. al (2014)), however the estimates are closer to findings in some other emerging market economies (Ozsuca and Akbostancı (2016)). The results are robust to various specifications, for example considering a subsample by excluding China, Hong Kong and Singapore from the sample where interest rates are not the main policy instrument.

The effects of short-term interest rate on banks' risk tolerance can be very brisk therefore we add to our analysis of an annual data model by including a specification for quarterly data. Due to lack of accounting data at quarterly frequency, we have to rely on a market-based indicator of bank risk (idiosyncratic bank risk from an estimated CAPM model) computed from quarterly data on individual banks from Bloomberg. Quarterly model offers more nuanced results wherein we can distinguish between the two opposing ways in which interest rates can affect bank risk taking as suggested by Jimenez et. al. (2014). In the short term (contemporaneous effect), low interest rates, by reducing the probability of default on existing loans, lead to a fall in the risk of banks' portfolio. Over time, however, banks start to undertake more risky operations and lending to projects with a higher probability of default.

Thus, the results from this chapter suggest that the conduct of monetary policy is not independent from the goal of achieving financial stability and therefore it is important to explicitly model financial stability considerations in macro models. Furthermore, for emerging market economies in particular, which are not insulated from low interest rates in advanced economies, it might be instructive to let the exchange rate move more flexibly. If not, they might find themselves in a position where the low interest rates in advanced economies can lead to low interest rates in these economies too. This would not only encourage bank risk taking but also interfere with the domestic stabilization goals.

1 Household and Firm Leverage in Business Cycle Model

This chapter studies the role of credit and demand side frictions in business cycle fluctuations. In particular, we model the interaction between firm and household credit constraints over the business cycle. Using data on the U.S to estimate the model with Bayesian techniques, we find a clear evidence of an operating financial accelerator mechanism, whereby shocks to the economy are amplified by the presence of credit frictions. Inclusion of both firm and household financing constraints, as opposed to just one of them, amplifies the impact of exogenous shocks on GDP, investment and consumption. Regarding the importance of various shocks in explaining macroeconomic fluctuations, we find that total factor productivity shock in non-housing sector explains more than 40 percent of the fluctuations in GDP and consumption, however housing demand and supply shocks explain most of the cyclical variation in housing investment and housing prices. Investment shocks are an important driver in explaining variation of non-housing and housing investment. Finally, we find substantial spillovers from housing market to the real economy, predominantly to non-housing consumption, due to the wealth effect of house prices.

1.1 Introduction

The view that financial structure and the performance of credit markets may be important to understand the macroeconomy dates back to Gurley and Shaw (1955). Thereafter it has been reconsidered in the last 50 years in a growing number of studies. The common feature of these contributions is the idea that the way in which agents finance their activities, have access to financial markets and choose contractual arrangements is mostly relevant to understanding the business cycle. The recent financial turmoil of 2007 has further brought to light the importance of financial propagation in macroeconomic volatility. In particular, the housing market has come to the spotlight. Financial propagation, often called the financial accelerator mechanism, implies that the presence of credit market frictions can amplify the impact of exogenous shocks on business cycles by affecting the financial health of borrowers (firms and households).

Traditionally, most papers have analyzed the importance of credit constraints on the firm or the entrepreneur side. Bernanke, Gertler and Gilchrist, henceforth BGG (1999) and Carlstrom and Fuerst (1997) study frameworks in which credit market imperfections arise because there is asymmetric information between entrepreneurs and banks. This asymmetry translates into external borrowing being more expensive than internal financing. The costly state verification approach proposed by these studies is used extensively in the literature thereafter (Christiano et. al. (2014); Christensen and Dib (2008) among others). However, more recently there has been an emerging interest in modeling relation between household debt and the macroeconomy, particularly in the U.S (Iacoviello and Neri (2010), Justiniano, Primiceri and Tambalotti (2013)). Since household debt in the U.S. is held primarily in the form of mortgages, these models impose a collateral constraint that limits debt to a fraction of home values. As a consequence, house prices play a crucial role in the dynamics of debt, a connection that is evident in the data. Studying firm and household debt in isolation however assumes that they are independent of each other. If both household and firm credit constraints independently generate their own financial accelerator, there is a possibility of a positive interaction between the two. This paper by integrating both household and firm debt in a dynamic stochastic general equilibrium (DSGE) model aims at answering few related questions - what is the interplay between credit market frictions faced by firms and households in generating business cycle fluctuations? what is the role played by productivity and financial shocks over the business cycle?

Poor household financial conditions can affect firms' activity via various channels. First, through the impact of a negative shock to household balance sheet on aggregate economic activity and employment. Mian and Sufi (2012) examine the role of the aggregate demand channel in the decline in U.S employment from 2007 to 2009. A drop in aggregate demand driven by shocks to household balance sheet caused a substantial decline in the U.S employment over this period. They further found that employment losses in response to balance sheet shocks are higher in the U.S counties with high household leverage. Therefore, worse household financial condition by affecting the aggregate economic activity, can accentuate the impact of firm financial constraints through the usual financial accelerator channel. Another channel relates to the impact of households' terms of borrowing on the durable goods industry. The decade prior to the great recession witnessed an increased availability of consumer loans collateralised with residential properties. Mian and Sufi (2011) estimate that the average U.S homeowner extracted 25 to 30 cents for every dollar increase in home equity from 2002 to 2006[1]. Changes to consumers' access to credit affects employment, particularly in industries producing goods that are purchased with consumer loans. Haltenhof et al. (2014) find that between 2007 and 2010 the decline in home equity extraction explains about 10 percent of the decline in employment in the durable goods industries. Their results also suggest that changes in lending standards on commercial and industrial loans and the availability of home equity lines of credit affect notably the manufacturing employment and net firm dynamics. The evidence though does not necessarily represent a causal link from worse household financial frictions to tightening of firm financial constraints; it points towards the need to better understand the interaction and dynamics of firm and household leverage and their impact on propagation mechanisms.

We construct our model on the lines of Iacoviello and Neri (2010) with heterogeneous production sector and introduce an active role for evolution of firms' net worth and their financial leverage. On the supply side of the model, firms engage in joint production of housing and non-housing goods. The non-housing sector produces consumption good using capital and labour and the housing sector produces new homes using capital, labour, intermediate business input and land. Firms hire labour and purchase capital using their net worth and borrowing from the financial intermediary as in BGG (1999). Firms are ex-post heterogeneous and differ in their realization of the idiosyncratic shock. This results in an external finance premium

[1]Mian and Sufi (2011) find that money extracted from increased home equity is not used to purchase new real estate or pay down high credit card balance, suggesting that borrowed funds maybe used for real outlays (i.e. consumption or home improvement).

on their borrowing as a positive function of their leverage i.e. higher firm leverage leads to a higher premium on external funds. The demand side comprises of heterogeneous households following Iacoviello (2005) differing in their degree of impatience. Consumption and housing enter households' utility and housing can also be used as collateral for loans. In equilibrium, patient households are lenders providing funds to impatient households and firms. Impatient households borrow a proportion of their expected value of housing stock. The joint production of non-housing and housing sector produces interesting dynamics vis-a-vis residential and nonresidential investment. Furthermore, changes in house prices significantly affect the borrowing capacity of impatient households affecting the dynamics of both firm and household behavior.

We use quarterly data for the U.S for the period 1970 - 2006 on six key macroeconomic variables (consumption, non-residential investment, residential investment, house prices, hours worked in the consumption sector and hours worked in the housing sector to estimate the model using Bayesian techniques. We find that although the non-housing technology shock is the most important driving force for variation in GDP and consumption, housing preference and housing technology shock together account for more than 50 percent of the variation in housing investment and housing prices. Investment and risk shocks are an important determinant of the cyclical variation in macroeconomic aggregates, particularly business investment. Further, we find that housing prices and housing investment are strongly procyclical as observed in the data.

We document a clear evidence of an existing financial accelerator at both firm and household level. As compared to financial accelerator at only firm or household level, inclusion of both types of financial frictions further amplifies the response of GDP, consumption and investment (both residential and non-residential) to exogenous shocks. This implies that a model containing both firm and household frictions incorporates additional channels in which demand side frictions impact business cycle dynamics and macroeconomic volatility. Further in our model, firm and household financing constraints interact in two important ways. First, higher financing frictions for households reduce their demand for loans. This, through the loan market equilibrium condition decreases the interest rate and causes a downward pressure on the external financing costs for firms. Second, a fall in house prices and housing demand (that is amplified in the model with household collateral constraints), reduces the demand for housing capital, which further deteriorates capital price and therefore the net worth of firms. This increases the external finance premium facing firms. The two effects work in opposite direction. Overall the second effect dominates and worse household financing conditions tend to tighten firm financing constraints.

The rest of the paper is structured at follows. We first give an overview of the existing literature in the following section. Section 1.3 discusses the model with household and firm leverage following the existing work by BGG (1999) and Iacoviello (2010). Section 1.4 describes the data and estimation technique. In section 1.5, we present the results from bayesian estimation and finally conclude in section 1.6.

1.2 Literature: Theory and Evidence

Early line of literature relating to financial market frictions, attempts at deriving credit constraints from microeconomic considerations in a partial equilibrium framework. Some of these contributions toward a theory of credit constraints based on first principles are by Jaffee and Russell (1976) and Stiglitz and Weiss (1981). These contributions are based on the impossibility to enforce debt contracts (i.e. the existence of incentives to default) and adverse selection or moral hazard phenomena, respectively.

A more recent and growing body of literature in this area has investigated the role of financial market imperfections using models where agents are allowed to select the best contractual arrangements. These papers rely on either costly state verification/agency costs or limited commitment/collateral obligations to introduce financial frictions in a fully-fledged general equilibrium model. In Bernanke and Gertler (1989), entrepreneurs undertake a costly screening activity to assess the characteristic of a project. Since these characteristics are privately observed, lenders face an adverse selection problem in financing entrepreneurs' project. Following this paper, various authors have employed costly state verification in dynamic models in which financial frictions on firm side may amplify output fluctuations in response to exogenous shocks. Examples include Carlstorm and Fruest (1997) and BGG (1999). BGG (1999) present a model of financial accelerator in a quantitative general equilibrium framework with price stickiness and investment lags. They allow for heterogeneity among firms to capture the fact that borrowers have differential access to capital markets. Firms are ex-ante similar but differ in the ex-post realization of the idiosyncratic shock. The financial contract between an intermediary and a risk-neutral entrepreneur in this framework implicitly results in a risk premium, which is an increasing function of the leverage of the firm. Under reasonable parametrisations of the model, they find that the financial accelerator works to amplify and propagate shocks to the macroeconomy and has a significant influence on business cycle dynamics. Following this, there have been attempts to estimate the BGG model for various economies, most notably the U.S and Euro area. Christiano, Motto and Rostagno (2003, 2008) estimate a DSGE model with financial accelerator by calibrating parameters related to financial frictions and get a significant impact of credit market on the economy. Christensen and Dib (2008) estimate the BGG model for the U.S using maximum likelihood and find evidence in favor of the financial accelerator model. Gilchrist, Ortiz, and Zakrajsek (2009) incorporate a high information-content credit spread constructed directly from the secondary-market prices of outstanding corporate bonds into the Bayesian ML estimation. This credit spread serves as a proxy for the unobservable external finance premium. Using the U.S data for 1973-2008, they find that increases in the external finance premium causes significant and protracted declines in investment and output. Virginia Queijo von Heideken (2009) modified the DSGE financial accelerator model developed by BGG (1999) by adding frictions such as price indexation to past inflation, sticky wages, consumption habits and variable capital utilization. Using Bayesian methods to estimate the model for the US and euro area, he finds that financial frictions are relevant in both cases.

An alternative way to explain credit constraints and financial propagators is via limited commitment and unenforceability of contracts. When studying optimal (individually rational) contracts with limited commitment, the existence of collateralisable assets may play a very important role. This is because a high value of collateralisable asset increases borrower's net worth, which plays an important role in enhancing his debt capacity and financial propagation. The latter may be especially strong since the value of a collateral is typically low in situations of financial distress. Kiyotaki and Moore (1997) include collateralisable asset in the form of land in their model. The role of land is twofold, not only is it a factor of production, but it also serves as collateral for loans. They show that small, temporary shocks to technology or income distribution can generate large, persistent fluctuations in output and asset prices.

Traditionally the literature on credit markets has focused on financial frictions at the firm level. There have been some empirical studies documenting the importance of financial constraints at the household level, for e.g.. Zeldes (1989), Jappelli and Pagano (1989), Campbell and Mankiw (1989), and Carroll and Dunn (1997). However, the focus has hardly been to study the business cycle dynamics of these frictions. More recently, Iacoviello and Neri (2010), Mian and Sufi (2009, 2011, 2012), Favara and Imbs (2015) and Justiniano, Primiceri and Tambalotti (2013) have studied the evolution of household debt, housing market spillovers and the credit boom and bust of 2000s. These papers however focus entirely on the housing leveraging and deleveraging ignoring frictions at the firm level. We add to the existing literature by providing a joint analysis of financing constraints on both household and entrepreneur side. Earlier work with financial frictions at both household and firm level include Iacoviello (2005) and Gerali et. al. (2010). They rely on quantity borrowing constraints tied to the value of collateral for both household and firms, however they do not examine the dynamics of modeling both types of financial frictions as opposed to just one. Solomon (2010) is the only other study that provides a model of interaction of consumer and household debt over the business cycle. However, he does not explicitly model the quantity and price side of housing sector. We construct a model with heterogeneous production sector comprising separate housing and non-housing production such that both housing quantity and prices are endogenous. Unlike in Solomon (2010) we are able to capture two salient features of housing and firm financial friction as documented in empirical literature. First, we find that inclusion of both household and firm financial constraints amplifies the response of

GDP, consumption and investment as opposed to having only firm or household frictions. In contrast, Solomon (2010) find that adding household financial frictions to an environment with firm financing frictions dampens the overall effect of shocks on aggregate variables, which is at odds with the data and empirical evidence. Secondly, in our model residential and non-residential investment generally tends to co-move in the same direction however Solomon (2010) finds a strong negative counterfactual comovement between residential and nonresidential investment.

1.3 The Model

The Economy consists of two types of households and of entrepreneurs. Households consume, work and accumulate housing. The two households differ in the degree of their impatience i.e they discount future utility at differing rates. We call the ones with a higher discount factor as the patient household and the others as impatient (following Iacoviello (2005)). Patient and impatient households are both available in unit mass each. In equilibrium patient households are lenders and impatient ones are borrowers who borrow against the value of housing stock as collateral. On the supply side, firms operate the housing and non-housing sector. The non-housing sector uses labour supplied from households and capital to produce wholesale consumption and intermediate business goods. The housing sector produces new homes using capital, labour, intermediate business good and land. Entrepreneurs provide physical capital to firms that is used in the production of consumption good and housing.

The output produced by firms is used up in consumption, investment (housing and non-housing goods), goods used up in capital utilization and in bank monitoring. Capital producers combine investment goods with used capital purchased from entrepreneurs to produce new capital. This new capital is then purchased by entrepreneurs. Entrepreneurs make these purchases using their own resources — net worth, or equity, which they accrue by compounding the net proceeds of their activity from one time to the next — as well as bank loans. Heterogeneity among entrepreneurs exists in the form of a different idiosyncratic shock faced by each one of them (thus ex-ante each entrepreneur is same). This arrangement is similar to that in BGG (1999). There exists a financial intermediary, which channels the savings of the patient households to impatient household and entrepreneurs. Two types of one-period financial instruments are provided by the bank - deposits and loans. The patient households purchase a positive amount of deposits and do not borrow while the impatient households borrow a positive amount of loan (tied to housing collateral). For firms, following BGG (1999), we have a financial contract, which minimizes the expected agency costs of the borrowers arising from idiosyncratic shocks.

1.3.1 Patient Households (P)

There is a continuum of measure 1 of agents in each of the two groups (patient and impatient). A representative patient household maximizes the expected utility:

$$\max_{c_{p,t},h_{p,t},d_{p,t},k_{b,t},p_{la,t},l_{pc,t},l_{ph,t}} E_0\sum_{t=0}^{\infty}\beta_p^t z_t \left[\log(c_{p,t}) + J_{h,t}\log h_{p,t} - \frac{\varsigma_t}{(1+\phi_p)}(l_{pc,t}^{1+\eta_p} + l_{ph,t}^{1+\eta_p})^{\frac{(1+\phi_p)}{(1+\eta_p)}}\right] \tag{1.1}$$

The expected utility depends on the current individual consumption $c_{p,t}$, housing services $h_{p,t}$ and hours worked in the non-housing, $l_{pc,t}$ and the housing sector, $l_{ph,t}$[2]. Traditionally, productivity shocks are hailed as the prominent driver of fluctuations in real business cycle models. We add additional shocks to the model to see their relative contribution in driving business cycle fluctuations. Three such shocks are listed below. First, movements in z_t captures shock to inter-temporal preferences that governs how households weigh current utility relative to future utility. Several recent papers have used time preference shocks to explain business cycle dynamics (Hall (2013), Christiano, Eichenbaum and Rebelo (2011), Iacoviello and Neri (2010), Christensen and Dib (2008), Smets and Wouters (2003)) as well as asset pricing puzzle (Albuquerque, Eichenbaum and Rebelo (2012)). Second, movements in ς_t captures shock to intratemporal preference - it affects how agents value utility from consumption or housing relative to utility from leisure. Many recent quantitative

[2]See appendix 1.5 for a complete list of model variables and parameters.

macroeconomic models allow for such intratemporal preference shocks. An unobserved demand shock plays an important role in explaining aggregate fluctuations in Rotemberg and Woodford (1997). They interpret the shock as a combination of a labour preference shock and a shock to government spending. Erceg et al. (2000) and Smets and Wouters (2003) also have a quantitatively important labour preference shock in their models of monetary policy. More recently, Galí and Rabanal (2004) find that a labour preference shock explains fifty-seven percent of the variance of output and seventy percent of the variance of hours in their estimated dynamic stochastic general equilibrium model. We assume that both z_t and ς_t follow mean zero AR(1)s in the log.

$$log z_t = \rho_z log z_{t-1} + \varepsilon_{z,t};$$

$$log \varsigma_t = \rho_\varsigma log \varsigma_{t-1} + \varepsilon_{\varsigma,t},$$

where $\varepsilon_{x,t}$ is i.i.d $N(0, \sigma_x^2)$; for $x \in (z, \varsigma)$.

Few things to point out: First, z_t does not show up in the labour supply equilibrium condition; higher z_t increases the marginal utility of both consumption and the marginal disutility of labour, but these cancel out. Second, since z_t is mean reverting, when z_t is high we will have a relatively low value of $E_t z_{t+1}$. This means that an increase in z_t is isomorphic to a temporary reduction in β_p, i.e. you are relatively more impatient. Third, ς_t shows up in the labour supply equilibrium condition in a way analogous to a distortionary tax rate on labour income.

Finally, movements in $J_{h,t}$ can be viewed as a housing preference shock. This shock is included to study the business cycle dynamics in response to shifts in housing demand. Iacoviello and Neri (2010) provide two possible interpretation of this shock. "One interpretation is that the shock captures, in a reduced form way, cyclical variations in the availability of resources needed to purchase housing relative to other goods or other social and institutional changes that shift preferences toward housing. Another interpretation is that fluctuations in $J_{h,t}$ could proxy for random changes in the factor mix required to produce home services from a given housing stock." The U.S housing market, and particularly the housing finance market, has undergone several institutional changes in the past decades. These factors, including the rise in mortgage finance and home ownership rates[3] has affected households' demand for housing and are possible sources of household demand shocks. In addition, the preference shock could also capture shifters of housing demand not explicitly included in our stylized model, for instance the changing demographic profile of the U.S population. $J_{h,t}$ denotes the weight attached to housing in the utility function, which also has an AR(1) representation with i.i.d normal innovations.

$$logJ_{h,t} = \rho_h logJ_{h,t-1} + (1-\rho_h)log\overline{J_h} + \varepsilon_{h,t},$$

where $\varepsilon_{h,t}$ is i.i.d $N(0,\sigma_h^2)$. $\overline{J_h} > 0$ denotes the weight attached to housing in the steady state.

The log-log specification of preferences for consumption and housing is borrowed from the literature (Davis and Heathcote (2005), Fisher (2007) and Iacoviello and Neri (2010)). The specification of the disutility of labour ($\phi_p, \eta_p \geq 0$) follows Horvath (2000) and Iacoviello and Neri (2010). This allows for less than perfect labour mobility across sectors, wherein $\eta_p = 0$ would imply that hours in the two sectors are perfect substitutes. ϕ_p is the inverse of Frisch wage elasticity of labour supply.

Patient households maximize their utility subject to the budget constraint (in real terms):

$$c_{p,t} + q_{h,t}(h_{p,t} - (1-\delta_h)h_{p,t-1}) + d_{p,t} + p_{la,t}la_t + k_{b,t} \leq w_{pc,t}l_{pc,t} + w_{ph,t}l_{ph,t} + R_{t-1}d_{p,t-1}$$
$$+p_{b,t}k_{b,t} + (p_{la,t} + R_{la,t})la_{t-1} + lump_t \qquad (1.2)$$

[3]Home ownership rates in the United States were constant around 64/65 percent between 1970 and 1995, and rose at a constant pace up to 69 percent at the peak of the housing boom in 2005. Rising home ownership can by 'keeping up with the joneses' hypothesis affect consumers demand for housing.

Thus, patient household chooses consumption $c_{p,t}$, housing stock $h_{p,t}$ priced at $q_{h,t}$, deposits $d_{p,t}$, intermediate business input $k_{b,t}$ priced at $p_{b,t}$, land la_t priced at $p_{la,t}$ and hours worked $l_{pc,t}$ and $l_{ph,t}$ in the non-housing and housing sector respectively. δ_h is the housing depreciation rate, R_{t-1} is the gross real return on the deposits between period $t-1$ and t, $w_{pc,t}$ and $w_{ph,t}$ the real wages earned in non-housing and housing sector respectively. $lump_t$ are transfers from entrepreneurs (discussed later).

1.3.2 Impatient Households (I)

Impatient households neither hold deposits nor own retail firms. They have the same intra-period preferences over housing, consumption and leisure as the patient households and are subject to the same preference shocks, but they have a lower discount factor than the lenders (patient households) i.e $\beta_p > \beta_i$. A representative impatient household maximizes the expected utility:

$$\max_{c_{i,t},h_{i,t},l_{ic,t},l_{ih,t},b_{i,t}} E_0 \sum_{t=0}^{\infty} \beta_i^t z_t \left[\log(c_{i,t}) + J_{h,t} \log h_{i,t} - \frac{\varsigma_t}{(1+\phi_i)} (l_{ic,t}^{1+\eta_i} + l_{ih,t}^{1+\eta_i})^{\frac{(1+\phi_i)}{(1+\eta_i)}} \right] \tag{1.3}$$

The expected utility again depends on consumption, housing and hours worked. The budget constraint now is:

$$c_{i,t} + q_{h,t}(h_{i,t} - (1-\delta_h)h_{i,t-1}) + R_{t-1}b_{i,t-1} \leq w_{ic,t}l_{ic,t} + w_{ih,t}l_{ih,t} + b_{i,t} \tag{1.4}$$

Therefore, for impatient households, resources spent on consumption, accumulation of housing stock and reimbursement of past borrowing have to be financed with wage income and new borrowing ($b_{i,t}$). They further face a borrowing constraint[4]:

[4]The assumption $\beta_p > \beta_i$ implies that the borrowing constraint faced by impatient borrowers is binding for small shocks near the steady state.

$$b_{i,t} \leq \overline{m} E_t \frac{q_{h,t+1} h_{i,t}}{R_t} \tag{1.5}$$

This means that the borrowers cannot borrow more than the net present expected value of the collateralisable housing stock. Thus, $\overline{m}$ reflects the amount of loans given by the intermediary against a given amount of housing stock. A high value of $\overline{m}$ means loose credit constraints for impatient households. At this stage we do not include defaults explicitly in the case of household loans. However, implicitly if we assume that the price (or value) of houses does not fall below the amount borrowed i.e $\overline{m} E_t \frac{q_{h,t+1} h_{I,t}}{R_{t+1}}$, lenders can simply usurp the collateral and are effectively protected from default.

1.3.3 Entrepreneurs

Entrepreneurs are assumed to be risk-neutral and have finite horizons. Specifically, we assume that each entrepreneur has a constant probability γ of surviving to the next period (implying an expected lifetime of $1/(1-\gamma)$). We assume the birth rate of entrepreneurs to be such that the number of entrepreneurs is constant. In each period t, entrepreneurs acquire physical capital, which is used in the production of consumption goods and housing. Entrepreneurs that die in period t are not allowed to purchase capital. A fraction Θ of their total net worth is consumed upon exit, and the remaining fraction of their net worth is transferred as a lump-sum payment to patient households. New entrepreneurs entering in period $t+1$ receive a 'start-up' transfer of net worth, W^e.

Each entrepreneur is indexed by j. Each period, entrepreneurs purchase physical capital, $K_{t,j}$, at the real price, $Q_{k,t}$, which is financed by entrepreneurial wealth, or net worth, $N_{t,j}$ and borrowing, $B_{t,j} = Q_{k,t} K_{t,j} - N_{t,j}$. At this point, the state of an entrepreneur is summarized by its net worth, $N_{t,j}$. The purchased capital, $K_{t,j}$ is transformed into $\omega K_{t,j}$, where ω is a log-normally distributed random variable across all entrepreneurs with a cumulative distribution function denoted by $F_t(\omega)$. The assumption about ω implies that entrepreneurial investments in capital are risky.

The mean and standard deviation of logω are μ_{ϖ} and σ_t respectively. The random variable, ω, is observed by the entrepreneur, but can only be observed by the bank if it pays a monitoring cost. The standard deviation, σ_t, is the realization of a stochastic process, which we refer to below as the risk shock. This shock captures the notion that the riskiness of entrepreneurs varies over time and follows a stationary AR(1) process.

$$log\sigma_t = \rho_\sigma log\sigma_{t-1} + (1-\rho_\sigma)log\sigma + \varepsilon_{\sigma,t},$$

where σ is the steady state standard deviation and $\varepsilon_{\sigma,t}$ is i.i.d $N(0, \sigma_r^2)$.

The total payoff in period $t+1$ to an entrepreneur with idiosyncratic productivity shock, ω, can be written as $R_{k,t+1}Q_{k,t}\omega_{t+1}K_{t,j}$ where,

$$R_{k,t+1} = \frac{r_{k,t+1} + (1-\delta_k)Q_{k,t+1}}{Q_{k,t}},$$

where $r_{k,t+1}$ is marginal productivity of capital at $t+1$ and the expression also incorporates capital gain on holding a unit of capital from period t to $t+1$ where δ_k is capital depreciation rate.

As in BGG, entrepreneurs can self finance only a fraction of the capital stock. They need external finance to complement their net worth as a source of funding. Entrepreneurs obtain external finance from the bank in the form of bank loans. The standard debt contract that they enter foresees that entrepreneurs above an endogenously determined cut off value, $\bar{\omega}_{t+1}$ pay gross interest, on their bank loan.

$$\bar{\omega}_{t+1}R_{k,t+1}Q_{k,t}K_{t,j} = R_{F,t}B_{t,j} \tag{1.6}$$

Where $R_{F,t}$ is contractual gross interest rate on the loan taken from the bank in period t. Therefore, we can write the threshold value of idiosyncratic shock, $\bar{\omega}_{t+1}$, above which the entrepreneur can repay its loan as:

$$\bar{\omega}_{t+1} = \frac{R_{F,t}B_{t,j}}{Q_{k,t}K_{t,j}}.\frac{1}{R_{k,t+1}}$$

We define $x_t = \frac{Q_{k,t}K_{t,j}}{N_{t,j}}$ as the entrepreneurial leverage, defined as the ratio of entrepreneurs' purchase to net worth at t. We have left off the indexing j on x_t, $\bar{\omega}_{t+1}$, and $R_{F,t}$. This is to minimize notation and is a reflection of the fact (see below) that the equilibrium value of these objects is independent of the state variable ($N_{t,j}$). When entrepreneurs defaults on their loan, following the CSV approach, we assume that the lender must pay a cost if s/he wishes to observe the borrower's realized return on capital, which it then seizes. This auditing cost is interpretable as the cost of bankruptcy (including for example auditing, accounting, and legal costs, as well as losses associated with asset liquidation and interruption of business). The monitoring cost is assumed to equal a proportion μ_e of the realized gross payoff to the firm's capital, i.e., the monitoring cost equals $\mu_e R_{k,t+1} Q_{k,t} \omega_{t+1} K_{t,j}$. Thus, under certain realizations of the idiosyncratic shocks, entrepreneurs will go bankrupt, especially when their ex-ante leverage x_t is high.

We follow BGG notation for the division of return from entrepreneurial investment between entrepreneurs and banks. The share of gross return (gross of verification costs) accruing to the bank is:

$$\Gamma(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega_{t+1} f(\omega_{t+1}) d\omega_{t+1} + \bar{\omega}_{t+1} \int_{\bar{\omega}_{t+1}}^{\infty} f(\omega_{t+1}) d\omega_{t+1} \tag{1.7}$$

The part of these returns that comes from defaulted loans is:

$$\mathrm{G}(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega_{t+1} f(\omega_{t+1}) d\omega_{t+1} \tag{1.8}$$

Therefore, the share of returns accruing to entrepreneurs can be written as $1 - \Gamma(\bar{\omega}_{t+1})$. The share (net of verification costs) that the bank appropriates can be written as $\Gamma(\bar{\omega}_{t+1}) - \mu_e G(\bar{\omega}_{t+1})$.

Entrepreneurs maximize their expected return subject to a participation constraint for the bank. In particular, they choose the leverage, x_t, and default threshold $\bar{\omega}_{t+1}$ to maximize:

$$\max_{x_t, \bar{\omega}_{t+1}} \; E_t \; [(1 - \Gamma(\bar{\omega}_{t+1})) R_{k,t+1} x_t N_{t,j}]$$

Subject to banks' participation constraint:

$$E_t[(\Gamma(\bar{\omega}_{t+1}) - \mu_e G(\bar{\omega}_{t+1}))]R_{k,t+1}Q_{k,t}K_{t,j} = R_t(Q_{k,t}K_{t,j} - N_{t,j}),$$

which states that the return to banks should cover their cost of raising funds. The object on the left is the return received by banks from lending to entrepreneurs. Using the definition of leverage, $x_t = \frac{Q_{k,t}K_{t,j}}{N_{t,j}}$, we can rewrite the participation constraint as:

$$E_t[(\Gamma(\bar{\omega}_{t+1}) - \mu_e G(\bar{\omega}_{t+1}))]R_{k,t+1}x_t = R_t(x_t - 1) \tag{1.9}$$

The $(x_t, \bar{\omega}_{t+1})$ combinations which satisfy (1.9) define a menu of state (t + 1)-contingent standard debt contracts offered to entrepreneurs. Entrepreneurs select the contract that maximizes their objective. Since $N_{t,j}$ does not appear in the constraint and appears only as a constant of proportionality in the objective, it follows that all entrepreneurs select the same $(x_t, \bar{\omega}_{t+1})$ regardless of their net worth. As mentioned earlier, a fraction γ of the entrepreneurs die at the end of each period and are replaced by the same amount of new entrepreneurs. New entrepreneurs entering in period $t+1$ receive a 'start-up' transfer of net worth, W^e. Entrepreneurs who die consume a constant fraction, Θ, of their net worth and transfer the rest to patient households.

Aggregation - The quantity of raw capital purchased by entrepreneurs in period t is given by summing the capital across all entrepreneurs. Market clearing in the capital services require that supply of capital, K_t must equal firms' demand for capital (discussed later).

$$K_t = \sum K_{t,j}$$

The aggregate entrepreneurial net worth at the end of period t can be written as $(1 - \Gamma(\bar{\omega}_{t+1}))R_{k,t+1}Q_{k,t}K_t$. Once a fraction $(1-\gamma)$ of the entrepreneurs exit the scene and the newly entering entrepreneur receive lump sum payments W^e, the law of motion of entrepreneurial net worth, N_{t+1} can be written as:

$$N_{t+1} = \gamma(1 - \Gamma(\bar{\omega}_{t+1})R_{k,t+1}Q_{k,t}K_t + W^e,$$

where W^e is the 'start-up' transfer of net worth received by new entering entrepreneurs in period t+1. The aggregate net worth can be further written as:

$$N_{t+1} = \gamma\{R_{k,t+1}Q_{k,t}K_t - [R_t + \mu_e \frac{\int_0^{\bar{\omega}_{t+1}} \omega_{t+1}f(\omega_{t+1})d\omega_{t+1}Q_{k,t}K_t}{Q_{k,t}K_t - N_t}](Q_{k,t}K_t - N_t)\} + W^e \tag{1.10}$$

The object in braces in (1.10) represents receipts by entrepreneurs active in period t+1 minus their payments to banks. The object in square brackets is the gross rate of return paid by entrepreneurs to banks. The external finance premium on loans between period t and t+1 can therefore be defined as:

$$efp_{t+1} = \mu_e \frac{\int_0^{\bar{\omega}_{t+1}} \omega_{t+1}f(\omega_{t+1})d\omega_{t+1}Q_{k,t}K_t}{Q_{k,t}K_t - N_t} \tag{1.11}$$

The remaining two financial variables to determine are the aggregate quantity of debt extended to entrepreneurs in period t, B_t, and their state-contingent interest rate, $R_{F,t}$. The aggregate borrowing is given by the sum of borrowing of all entrepreneurs.

$$B_t = \sum B_{t,j} = Q_{k,t}K_t - N_t$$

Finally, the interest rate takes the form (aggregating equation 1.6 and solving):

$$R_{F,t} = \bar{\omega}_{t+1}R_{k,t+1}(\frac{x_t}{x_t - 1})$$

The entrepreneurs that exit the economy in t+1 consume a fraction Θ of their net worth. Therefore, their aggregate consumption is given by:

$$c_{e,t+1} = \Theta\frac{(1-\gamma)}{\gamma}(N_{t+1} - W^e) \tag{1.12}$$

Where $\frac{(N_{t+1}-W^e)}{\gamma}$ is the average net worth held by an entrepreneur who exits the economy at the end of the current period and $(1-\gamma)$ is the share of exiting entrepreneurs. Finally, the lump sum transfers, $lump_t$, made to patient households is $(1-\Theta)\frac{(1-\gamma)}{\gamma}(N_{t+1}-W^e)$.

1.3.4 Firms

Firms produce wholesale consumption goods and housing using two CRS production technologies. They hire labour from households, rent capital from entrepreneurs, purchase intermediate business goods, $k_{b,t}$, at price, $p_{b,t}$ and use capital for the production of wholesale goods Y_t and new housing IH_t. They undertake the following static optimization:

$$\max_{K_{c,t-1},K_{h,t-1},l_{ic,t},l_{pc,t},l_{ih,t},l_{ph,t},k_{b,t},la_{t-1}} Y_t+q_{h,t}IH_t-\{\sum_{s=c,h} w_{ps,t}l_{ps,t}+\sum_{s=c,h} w_{is,t}l_{is,t}+r_{kc,t}K_{c,t-1}+ \tag{1.13}$$

$$r_{kh,t}K_{h,t-1}+R_{la,t}la_{t-1}+p_{b,t}k_{b,t}\}$$

Where $K_t = K_{c,t}+K_{h,t}$; $K_{c,t}$ is the business capital and $K_{h,t}$ is the housing capital and $r_{kc,t}$ and $r_{kh,t}$ are marginal productivity of capital in the two sectors.[5] The production technology for non-housing and housing are respectively:

$$Y_t = A_{c,t}K_{c,t-1}^{\alpha}(l_{ic,t}^{\mu}l_{pc,t}^{1-\mu})^{1-\alpha} \tag{1.14}$$

$$IH_t = A_{h,t}(l_{ih,t}^{\mu}l_{ph,t}^{1-\mu})^{1-\beta-\theta-\tau}K_{h,t-1}^{\beta}k_{b,t}^{\theta}la_{t-1}^{\tau} \tag{1.15}$$

Where $A_{c,t}$ and $A_{h,t}$ is non-housing and housing sector specific aggregate technology that follows a stationary AR(1) process of the form:

[5] Since capital is homogeneous (there is no difference between non-housing and housing capital), in equilibrium the return on capital is equalized $r_{kc,t}=r_{kh,t}=r_{k,t}$.

$$\ln A_{c,t} = \rho_{ac} \ln A_{c,t-1} + \varepsilon_{ac,t};$$

and

$$\ln A_{h,t} = \rho_{ah} \ln A_{h,t-1} + \varepsilon_{ah,t}$$

$\varepsilon_{ac,t}$ and $\varepsilon_{ah,t}$ are normally distributed with zero mean and standard deviation σ_{ac} and σ_{ah} respectively.

1.3.5 Capital Goods Producer

At the beginning of each period, capital good producer buys final goods and the stock of undepreciated capital from the firms. We introduce convex investment costs whereby I_t units of output is converted into $\eta_{k,t}(1 - S(G_t))I_t$ units of new capital (sold at real price $Q_{k,t}$).

Where $\eta_{k,t}$ is the investment shock, $G_t = I_t/I_{t-1}$ and the function $S(G_t) = \varphi_x(G_t - 1)^2$ satisfies $S', S'' \geq 0$. Also in steady state $S(.) = S'(.) = 0$.

The capital goods producer maximize expected discounted profits:

$$\max_{I_t} E_t \sum_{k=0}^{\infty} D_{t,t+k}[Q_{k,t+k}.\eta_{k,t}(1 - S(\frac{I_{t+k}}{I_{t+k-1}}))I_{t+k} - I_{t+k}],$$

where $D_{t,t+k} = \beta_p \frac{MU_{c,t+k}}{MU_{c,t}}$ is the real stochastic discount factor, $MU_{c,t}$ is the marginal utility of consumption. Capital evolves according to the following relation:

$$K_{t+1} = (1 - \delta_k)K_t + \eta_{k,t}(1 - S(G_t))I_t \tag{1.16}$$

The investment shock is a source of exogenous variation in the efficiency with which the final good can be transformed into physical capital, and thus into tomorrow's capital input. Justiniano, Primiceri, and Tambalotti (2011) show that this variation might stem from technological factors specific to the production of investment goods, as in Greenwood, Hercowitz, and Krusell (1997), but also from disturbances to the process by which these investment goods are turned into productive capital. Here, as in Justiniano, Primiceri and Tambaloti (2010), we ignore that distinction and maintain an agnostic stance on the ultimate source of these disturbances. The investment shock follows a stochastic process:

$$log\ \eta_{k,t} = \rho_\eta log\ \eta_{k,t-1} + \varepsilon_{\eta,t},$$

where $\varepsilon_{\eta,t}$ is i.i.d $N(0, \sigma_\eta^2)$.

1.3.6 Market Clearing and Competitive Equilibrium

Patient households and impatient households are each present in unit mass. Therefore, their aggregate consumption is the sum of consumption of representative patient and impatient household. The aggregation for entrepreneurs, including their aggregate consumption, is discussed in 1.3.3. Combining the budget constraints of the model's agents gives us the resource constraint of the economy.

$$Y_t = C_t + I_t + k_{b,t} + \mu_e G(\bar{\omega}_t) R_{k,t} Q_{k,t-1} K_{t-1} \tag{1.17}$$

Where $C_t = c_{p,t} + c_{i,t} + c_{e,t}$. The goods market equilibrium governs that the non-housing output is either consumed, invested, used as a factor in housing production or lost in monitoring services. Where, $\mu G(\bar{\omega}_t) R_{k,t} Q_{k,t-1} K_{t-1}$ is the aggregate output used up in monitoring costs. Investment is already net of adjustment costs described in the earlier section.

Housing production is equal to the change in housing stock net of depreciation.

$$IH_t = H_t - (1 - \delta_h) H_{t-1} \tag{1.18}$$

Where $H_t = h_{p,t} + h_{i,t}$ is the aggregate housing stock. Equilibrium in the housing market requires that the supply of housing is equal to the demand from patient and impatient households. Furthermore, loan market equilibrium implies:

$$d_{p,t} = b_{i,t} + B_t \tag{1.19}$$

Equilibrium in capital market requires that the supply from entrepreneurs is equal to the capital demanded by firms. The labour market is in equilibrium when firms' demand for labour equals supply at the competitive wage level. Finally, GDP (net of monitoring costs) is defined as the value added of the two sectors:

$$GDP_t = Y_t - k_{b,t} + \overline{q}IH_t \tag{1.20}$$

A competitive equilibrium consists of a set of prices and interest rates $\{p_{b,t}, p_{la,t}, q_{h,t}, q_{k,t}, R_{la,t}, R_t, r_{k,t}, w_{ic,t}, w_{ih,t}, w_{pc,t}, w_{ph,t}\}$ for all possible states and for all $t \geq 0$ such that all markets clear when all agents i.e. patient households, impatient households, entrepreneurs, firms and capital goods producer solve their maximization problems while taking these prices and interest rates as given.

1.4 Understanding the effects of financing constraints in the model

Before going into estimation of the model, in this section we discuss some theoretical insights on how financial frictions affect dynamics of the model. We first look at households and entrepreneur in partial equilibrium and then discuss how their financing constraints interact with each other.

1.4.1 Impatient Households

Impatient households first order conditions for the choice of consumption and housing is given by:

$$\frac{z_t}{c_{i,t}} = E_t(\frac{z_{t+1}\beta_i R_t}{c_{i,t+1}}) + \lambda_t R_t$$

$$\frac{z_t}{c_{i,t}} - E_t(\lambda_t \bar{m}\frac{q_{h,t+1}}{q_{h,t}}) = E_t(\frac{\beta_i z_{t+1} q_{h,t+1}(1-\delta_h)}{q_{h,t} c_{i,t+1}}) + \frac{z_t J_{h,t}}{q_{h,t} h_{i,t}}$$

Finally, the borrowing constraint is given by:

$$R_t b_{i,t} \leq \overline{m} E_t q_{h,t+1} h_{i,t}$$

The marginal utility from consumption is affected by an additional term, $\lambda_t R_t$, where λ_t is the lagrange multiplier on the borrowing constraint and equals the increase in lifetime utility that would stem from borrowing R_t today, consuming the proceeds, and reducing consumption by the appropriate amount next period. Since agents are constrained from borrowing more, but not from saving more, λ_t enters the equation with a positive sign. Therefore, at the constrained optimum, the marginal utility from consuming one unit today is always greater than or equal to the marginal utility from waiting until tomorrow to consume the extra amount.

Next, we look at how the borrowing constraint affects the first order condition for choice of housing by impatient household. If the borrowing constraint never binds, i.e. $\lambda_t = 0$, then the purchasing cost of housing - the marginal cost of current resources or the marginal utility from consumption- is equated to the marginal utility of housing and its discounted resale value (as is the case for patient households, see appendix 1.2). However, when the borrowing constraint is binding, the purchasing cost of housing is lower because it can be used as collateral. Thus, borrowing constraint affects the inter-temporal allocation of resources as well as the within period one, since housing is both a good and collateral.

Any shock that increases house price increases the borrowing capacity of impatient households on impact. The effect of the shock in future periods depends on how borrowers adjust loan demand and housing in response to the shock. The impatient household behaves like the consumption smoothing patient household with a bias towards debt financed consumption instead of saving. For a given amount of desired housing, a consumption smoothing borrower reacts to an increase in wealth by increasing savings. This increase in saving can be accomplished through a combination of reduced borrowing and increased accumulation of collateral in the form of housing. At the same time, an increase in the value of collateral encourages higher borrowing. Impatient household increase their demand for housing as the purchasing cost of housing is lower with higher collateral values. Furthermore, their consumption of non durable good also increases since the marginal utility from consuming one extra unit today is greater than the utility from waiting until tomorrow when the borrowing constraint is binding.

1.4.2 Entrepreneurs

The external finance premium faced by entrepreneurs is given by equation 1.11 in section 1.3.3.

$$efp_{t+1} = \mu_e \frac{\int_0^{\bar{\omega}_{t+1}} \omega_{t+1} f(\omega_{t+1}) d\omega_{t+1} Q_{k,t} K_t}{Q_{k,t} K_t - N_t}$$

Therefore $\frac{\partial efp_{t+1}}{\partial Q_{k,t}} < 0$ i.e. the external finance premium is decreasing in the price of capital in a neighbourhood of the steady state. Any shock that increases the price of capital will tend to reduce the external finance premium thereby increasing investment.

1.4.3 Interaction of households and firm credit constraints

Here, we highlight two channels by which firm and household financial frictions interact with each other. First is through the loan market equilibrium condition.

$$d_{p,t}(R_t, *) = b_{i,t}(R_t, q_{h,t+1}, *) + B_t(R_t, Q_{k,t}, *)$$

A rise in house price increases households demand for loans for any given risk free interest rate. This puts an upward pressure on the risk-free interest rate. From the bank loan participation constraint above, this increases financing cost for entrepreneurs. Therefore, loosening of households borrowing constraint in this case would lead to higher financing cost for entrepreneurs i.e. a negative interaction between household and firm financial frictions.

The second channel operates through impact of house prices on the demand for capital. An increase in house price raises the marginal product of capital, $\frac{\beta q_{h,t} IH_t}{K_{h,t-1}}$, in housing production. This increases the demand for capital in housing production and consequently housing investment. There is a shift of resources from production of consumption good to housing i.e. the use of capital in consumption good falls while more capital is diverted to production of housing good. The impact on total capital depends on which effect dominates. If total capital increases, the price of capital and therefore entrepreneurs net worth rises as well. This leads to a decline in entrepreneurs financing spread i.e. a positive interaction between household and firm financial frictions.

1.5 Estimation

1.5.1 Methodology and Data

A second order approximation of the model is used, which is computed using Dyane version 4.3.3. The solution takes form of a state-space model that is used to compute the likelihood function. We use Bayesian approach, whereby we specify the prior distribution for parameters and their posterior distribution is computed by Metropolis-Hastings algorithm. We use six observables: real consumption, real business investment, real housing investment, real house prices, hours worked in the consumption sector and hours worked in the housing sector. The sample period runs from 1970:1 to 2006:4. To make the data in accordance with the variables in our model, we remove the trend from consumption, business non-residential investment, residential investment and house prices using the HP filter. Also, we demean the data series for hours worked in the consumption and housing sector[6].

[6] Details on data series transformation along with their sources are presented in appendix 1.1.

Table 1 – Calibrated Parameters

Parameter	Description	Value
β_p	Patient household discount factor	0.99
β_i	Impatient household discount factor	0.97
δ_k	Capital depreciation rate	0.025
δ_h	Housing depreciation rate	0.015
α	Share of capital in non-housing production	0.33
β	Share of capital in housing production	0.10
τ	Share of land in housing production	0.10
θ	Share of intermediate goods in housing production	0.10
$\overline{J_h}$	Steady state share of housing in the utility function	0.15
$\overline{m}$	LTV ratio	0.80
μ_e	Fraction of realized profits lost in bankruptcy	0.30
$Var(log\omega)$	Variance of log of idiosyncratic productivity	0.25
Θ	Fraction of net worth consumed by entrepreneurs upon exit	0.10
W^e	Transfer from households to entering entrepreneurs	0.009
γ	Survival rate of entrepreneurs	0.97

1.5.2 Calibrated Parameters and Prior Distribution

We calibrate some of the model's parameters to get reasonable values for key steady-state values and ratios, while the rest of the parameters are estimated. Table 1 reports the calibrated values. The patient households discount factor is set to 0.99 to get the steady state real interest rate close to 4 percent. For impatient households, we set the discount factor to be slightly lower at 0.97 to ensure that the borrowing constraints bind for them. $\overline{J_h}$, the weight attached to housing in the utility function is set to have a value of 0.15. This together with the depreciation rate for housing, δ_h, pins down the ratio of residential investment to total output at about 6 percent as observed in the data.

The capital share of production in the non-housing sector, α, and the capital depreciation rate, δ_k, is set to get reasonable value of the steady state I/GDP ratio. In the housing sector, we choose a capital share of $\beta = 0.10$ and a land share of $\tau = 0.10$ following Davis and Heathcote (2005) and Iacoviello and Neri (2010).

Finally the share of intermediate business goods, θ, is set at 0.10 following Iacoviello and Neri (2010).

Next we turn to parameters relating to financial frictions. The first parameter is the loan to value ratio $\overline{m}$. This parameter reflects the typical LTV for credit constrained households who would borrow maximum against their housing stock. Following Iacoviello and Neri (2010), we set this value at 80%. The values of the parameters that control firm financial frictions (e.g.. γ, μ_e, $F(\bar{\omega})$ and $Var(log(\omega))$ are primarily determined to match, $R_F - R$, leverage ratio and the rate of return on capital. Following popular literature (BGG (1999) and Christensen and Dib (2008)), we use a value of 0.97 for the survival rate of entrepreneurs, γ, implying an expected working life for entrepreneurs of 36 years. Bankruptcy cost parameter, μ_e, is set at 0.3 that is within the range of 0.20 - 0.36 that Carlstrom and Freust (1997) defend as empirically relevant. $F(\bar{\omega})$ is set at 0.75 quarterly percent value implying an annual bankruptcy rate of 3 percent (as in BGG). There is considerable uncertainty about the spread between the cost of external finance, R_F and the return on households deposits, R. BGG (1999) measure the external finance premium as approximately the historical average spread between the prime lending rate and the six- month Treasury bill rate, which amounts to 200 basis points. Levin, Natalucci and Zakrajsek (2004) report a spread of 227 basis points for the median firm included in their sample. De Fiore and Uhlig (2005) report that the spread between the prime rate on bank loans to business and the commercial paper is 298 basis points over the period 1997-2003. Carlstrom and Fuerst (1997) report a somewhat lower spread of 187 basis points. Our calibrations produce a spread of 210 basis points. Finally, the calibrated values of fraction of net worth consumed by entrepreneurs upon exit, Θ, and the transfer from households to entering entrepreneurs, W^e, are borrowed from Christiano, Motto and Rostagno (CMR, 2014).

Table 2 reports the key steady state steady state ratios. Consumption share of GDP is 75% and the business investment share is 18.5%. Housing investment is close to 6% percent of GDP. Furthermore, the chosen calibrated values imply a ratio of business capital to GDP of about 1.51 and housing wealth to GDP of about 1.1 and the ratio of business loans to GDP of 1.4. The rate of return on capital at 11.5

Table 2 – Key Steady State Results

Annual real interest rate	$4 \times R - 1$	4.1%
Consumption share	C/GDP	75%
Business investment share	I/GDP	18.5%
Housing investment share	$q_h IH/GDP$	6.5%
Housing wealth	$q_h H/GDP$	4.34
Business capital in non-housing sector	k_c/GDP	6.05
Business capital in housing sector	k_h/GDP	0.11
leverage ratio	K/N	1.29
Rate of return of Capital	R_k	11.5%
Cost of external finance	R_F	6.2%
Firm borrowing/GDP	B/GDP	1.40

percent is slightly higher than in the data (10.32 percent) as documented in Verona et. al. (2014). Finally, the leverage ratio at 1.29 is very close to the value in Verona et. al (2014) who document a range of 1.21 - 1.77 based on US data over the sample 1998:Q4 to 2003:Q4.

The priors used in the study are presented in Tables 3 and 4. The choice of priors for the estimated parameters is usually determined by the theoretical implications of the model and evidence from previous studies. For the standard deviation of the shocks we use an inverse gamma distribution. For the parameters reflecting persistence of the shocks, we use a beta distribution with a prior mean of 0.8 and a standard error of 0.1. The inverse of labour supply elasticity for patient and impatient households, ϕ_p and ϕ_i have a gamma prior with 0.5 mean and 0.1 standard deviation. This implies an elasticity of hours aggregator of 2. For parameters reflecting the inverse elasticity of substitution across hours in the two sectors, η_p and η_i, we set a normal prior with a mean of 1, as estimated by Horvath (2000) and Iacoviello and Neri (2010). Finally, the prior mean of the labour income share of the collateral constrained households, μ, is set to 0.35, with a standard error of 0.05. This is close to Iacoviello (2005) estimate of the wage share of collateral constrained agents of around 36%, using a limited information approach.

Table 3 – Prior and Posterior Distribution of the Structural Parameters

	Prior distribution			Posterior distribution			
Parameter	Distribution	Mean	SD	Mean	2.5%	Median	97.5%
ϕ_p	Gamma	0.5	0.1	1.0961	0.7467	1.0890	1.4250
ϕ_i	Gamma	0.5	0.1	0.3953	1.2585	0.3885	0.5252
η_p	Normal	1	0.1	1.0947	0.9701	1.0935	1.2177
η_i	Normal	1	0.1	1.0251	0.8634	1.0256	1.1841
μ	Beta	0.35	0.05	0.1873	0.1486	0.1866	0.2259
φ_x	Gamma	5	2.5	16.88	14.12	16.82	19.56

1.5.3 Posterior Distributions

Table 3 and 4 gives the posterior values for the parameters. The posterior estimates of labour supply elasticity, ϕ_p and ϕ_i are 1.09 and 0.39. The estimated mean of η_p and η_i showing substitution between hours in the two sectors is close to 1 implying relatively low preference for mobility across sectors. The value of μ, the labour income share of credit constrained households in non-housing sector is around 19 percent, which is lower than the prior mean however close to the value estimated by Iacoviello and Neri (2010). The estimated adjustment cost parameter is about 17, which is in the range found in other estimated models with financial frictions - from around 6 in De Graeve (2008) to around 30 in CMR (2014). Finally with regards to the shocks, all shocks are fairly persistent.

1.6 Results

1.6.1 Model Comparison

We estimate several alternative versions of the model to see the impact of household and firm financial frictions and the interaction between them. The baseline model above is compared with (i) Only housing frictions - a model without firm financial frictions i.e. restricting the value to $Var(log\omega)$ to zero. This ensures that firms' probability of default is zero and hence lending to entrepreneurs is risk-less. The spread between the prime lending rate and risk-less rate in this case is fixed at

Table 4 – Prior and Posterior Distribution of the Shock Parameters

	Prior distribution			Posterior distribution			
Parameter	Distribution	Mean	SD	Mean	2.5%	Median	97.5%
ρ_{ac}	Inv. gamma	0.8	0.1	0.7967	0.7500	0.7975	0.8437
ρ_{ah}	Inv. gamma	0.8	0.1	0.8641	0.8216	0.8652	0.9091
ρ_h	Inv. gamma	0.8	0.1	0.9125	0.8596	0.9168	0.9712
ρ_z	Inv. gamma	0.8	0.1	0.8182	0.6714	0.8290	0.9657
ρ_ς	Inv. gamma	0.8	0.1	0.9951	0.9910	0.9956	0.9992
ρ_η	Inv. gamma	0.8	0.1	0.8281	0.8002	0.8365	0.8563
ρ_σ	Inv. gamma	0.8	0.1	0.6054	0.5490	0.6066	0.6446
σ_{ac}	Inv. gamma	0.01	0.05	0.0449	0.0404	0.0448	0.0493
σ_{ah}	Inv. gamma	0.01	0.05	0.0403	0.0364	0.0402	0.0443
σ_h	Inv. gamma	0.01	0.05	0.0784	0.0385	0.08	0.1327
σ_z	Inv. gamma	0.01	0.05	0.0085	0.0021	0.0062	0.0170
σ_ς	Inv. gamma	0.01	0.05	0.0442	0.0394	0.0441	0.0490
σ_r	Inv. gamma	0.01	0.05	0.9927	0.8794	0.9889	1.0809
σ_η	Inv. gamma	0.01	0.05	0.5044	0.4407	0.5026	0.5696

Table 5 – Model Comparison: Results from estimation

Marginal density/Model	Baseline	Only house frictions	Only firm frictions	No credit frictions
Modified Harmonic Mean	1655.03	1360.34	1544.11	1385.23
Laplace Approximation	1655.38	1360.65	1545.09	1385.95

the steady state obtained from the baseline model. Therefore, the usual net worth dynamics and financial accelerator effects in response to shocks is missing from this model; (ii) Only firm frictions - a model without household leverage constraint i.e. restricting the share of impatient households in the economy ($\mu = 0$); and (iii) No credit frictions - in this model both firm and households are not credit constrained ($Var(log\omega) = 0$, $\mu = 0$). The four models are estimated using data from 1970Q1 to 2006Q4 and the marginal likelihood (see Table 5) suggests that the data favors our baseline model with both household and firm financial frictions.

1.6.2 Posterior Impulse Response Analysis

The impulse response functions are based on averaging 1000 simulated series for each variable. Dynare generates IRFs using the approximate policy functions as follows: (i) It draws a series of all the exogenous shocks for a number of 100 + T periods, where T is the number of periods shown in the IRF graphs, here T = 40, (ii) It performs a simulation H1 of all the variables of interest using this realization of the shocks, (iii) It changes the sequence of exogenous shocks, by adding a one-standard deviation of the shock, to the realization of period 101, (iv) It performs a new simulation H2 of all variables based on the new sequence of shocks, and (v) It calculates the IRF from H2-H1. These steps are then repeated a number of times (we choose 1000 replications) and the produced IRFs are averages of the series from these 1000 experiments.

Non housing technology shock The response of aggregate variables to technology shock is plotted in figure 1. A positive technology shock leads to an increase in output and its components – consumption and investment, both residential and non-residential. An estimated one standard deviation (0.04 percent) increase in aggregate productivity increases GDP and consumption by 0.04 and 0.05 percent respectively in the baseline model. Business investment increases by 0.02 percent while housing investment increases by 0.002 percent. The firm financial accelerator works in its well understood way. A positive technology shock leads to an increase in the price of capital and hence firms' net worth. This improves firms' cost of funding, in particular, driving down the external finance premium leading to an increase in business investment and output. We notice that the amplification of output, consumption and business investment is maximum in the presence of both types of frictions. The response of GDP and consumption in the presence of both household and firm friction is more than twice as compared to the frictionless economy. The amplification in business investment is even more pronounced with firm financing frictions accounting for most of it.

We now turn to households. A positive technology shock drives up both residential investment and house prices. The interaction between firm and household frictions operates in different way for different variables. The effect is in the same direction (more amplification) for output, consumption and business investment. This is driven by the increase in the price of capital and housing, which is maximum in the model with both frictions. The price of capital increases by 0.06 percent in the baseline model while the increase is only about 0.02 percent in a frictionless setup. Similarly, housing price increases by over 0.04 percent in baseline model and only 0.02 percent in frictionless economy. However, household financial frictions dampen the response of housing investment in the initial periods after a shock. This result stems from the consumption and labour supply decisions of the patient and impatient households. A positive technology shock increases the wealth (by an increase in house prices) and income (an increase in wages). Both patient and impatient households increase their consumption of production good in response to rising house prices thereby displaying the importance of wealth effects. Patient household respond to higher wealth and income by consuming more consumption good, selling housing stock and increasing their supply of labour to both housing and non-housing production. Impatient household increase their demand for housing in response to loosening borrowing constraint. They further also reduce their labour supply (to both consumption and housing production) leading to an overall reduction of labour in the housing sector. In contrast, in models without impatient households labour supply to housing production increases, translating into a higher housing investment.

The increase in house prices and housing investment leads to a higher demand of housing capital, thus amplifying the demand for total capital boosting capital price and non-residential investment. The peak response of total capital at 0.008 percent in the baseline model is more than three times than in frictionless economy. The increase in capital price and firm's net worth is most pronounced in the model with both firm and household financial accelerator. Therefore, while allowing for household financial frictions leads to lower residential investment, it amplifies the response of business investment to technology shocks. We see a similar amplification at play for output and consumption, suggesting a positive interaction between financial accelerators driven by firm and household financing constraints.

Housing demand shock (housing preference shock) We analyze the impact of an estimated one standard deviation (0.1 percent) housing preference shock in figure 2. In response to the shock, house prices rise by 0.02 percent in the baseline model thereby leading to an increase in housing investment (also by 0.02 percent). As the collateral value increases with increasing house prices, borrowing capacity of impatient households increase. This raises both the borrowing and consumption of impatient households. On the other side of the ledger, lenders need to mobilize the extra resources consumed by the borrowers. They do so in response to a higher interest rate, which induces them to consume less, sell part of their housing stock, and work harder. The effect of lenders dominate and overall consumption falls however the fall is lower in the model with household collateral constraints reflecting the importance of wealth effects due to higher house prices.

Overall total housing demand is higher in the model with collateral effects, driven primarily by the demand from impatient households. Their demand for housing increase by over 0.05 percent in the baseline model in contrast to 0.04 percent in a model with only housing frictions. Higher demand translates into a higher increase in housing investment in the baseline (0.02 percent) as compared to the frictionless model (0.015 percent), reflecting the role played by collateral effects in the amplification process. The elasticity of residential investment to house prices in this model is less than that found by Iacoviello and Neri (2010). They note that, the combination of flexible housing prices and sticky wages in construction is required to have a high sensitivity of residential investment to changes in demand conditions.

We next turn to the impact on firms. Given the loan market equilibrium ($d_{p,t} = b_{i,t} + B_t$), an increase in impatient household borrowing puts an upward pressure on interest rate. This therefore raises the cost of funding for entrepreneurs. The overall impact on real business investment however is a cumulative effect of two forces. On the one hand, capital in the housing sector K_h increases, with the increase being amplified under collateral constraints. Housing capital increases by 0.04 percent in the baseline model in contrast to 0.03 in frictionless economy. At the same time, business capital declines with the fall being more under the presence of housing financing shocks (as interest rates rise more). As mentioned earlier, the overall impact depends on which effect dominates and whether the total capital stock rises or falls. The highest increase in business investment is in the model with only collateral constraints with a shift of resources (capital) from non-housing to housing sector. The model with both frictions generates slightly positive business investment after the first few quarters. While housing constraints play a major role in transfer of resources from consumption to housing sector, the overall impact of this shock on business investment is only marginal in the baseline model.

Housing technology shock A positive housing technology shock (plotted in figure 3) leads to a rise in housing investment and a fall in house prices (driven by a fall in construction costs). A one standard deviation (0.05 percent) increase in housing technology raises housing investment by 0.1 percent and reduces housing price by 0.01 percent in the baseline model. Once again the responses are amplified under the presence of housing credit frictions. For instance, the increase in housing investment in the baseline model is more than twice the impact in frictionless setting. With regards to housing v/s non-housing capital, there is a shift of resources from non housing to housing, which is further amplified in the presence of household financial frictions. Therefore, there is an increase in housing capital K_h, which increases by 0.1 percent in baseline model, nearly twice the size of increase in frictionless case. However, non-housing capital K_c falls. Overall, these opposing forces nearly cancel each other with the effect on business investment being small. While the change in total capital is negligible in the case of no credit frictions, it moves in opposite directions in the model with only firm and household friction respectively. In a model with both firm and household frictions, the increase in housing capital is higher than the fall in non-housing capital, leading to positive effect on net worth and capital price. This acts as an amplification mechanism and increases business investment. Thus, while looking at housing frictions in isolation would result in a negative comovement between business and housing investment, treating them together in a model leads to an increase in both in response to a positive housing technology shock.

A fall in house prices reduces the borrowing capacity and therefore the demand for housing and consumption by impatient households. Patient households buy more houses to maintain equilibrium in the housing market and reduce their consumption of nondurable goods. Overall, there is a fall in consumption, with the fall mostly driven by the presence of household financial frictions. Furthermore, housing technology shocks also creates a tradeoff between wholesale production in non-housing and housing sector. With a fall in consumption and business investment (in some cases), there is a fall in economic activity in non-housing production. However, overall GDP increases driven by an increase in housing production.

Investment shock A positive shock to marginal productivity of investment (Figure 4) increases real interest rate, giving households an incentive to save more and postpone consumption. With lower consumption, the marginal utility of income increases, shifting labour supply to the right - an inter-temporal substitution effect. Along an unchanged labour demand schedule, this supply shift raises hours and output. The investment shock leads to an increase in capital and a fall in capital price depressing net worth. This causes investment to gradually fall back to its steady state. The increase in capital and therefore business investment in higher in the model with firm financing frictions. A one standard deviation (0.5 percent) positive investment shock increases business investment by 0.05 percent in the baseline model (more than twice the increase (0.02 percent) in frictionless setup). As the capital and housing price decrease, impatient households hit their borrowing constraint - forcing them to reduce consumption of both final consumption good and housing. The consumption therefore falls more in the model with housing constraints. Overall, firm and household credit constraints do not seem to have any important interaction in response to an investment shock.

Other shocks The other three shocks included in the model are - risk shock, preference shock and labour supply shock. A one standard deviation (0.99 percentage point) risk shock decreases output and consumption by close to 0.3% (figure 5). Business investment falls by 0.08% while housing investment falls by over 0.15% on impact. An increase in entrepreneur's idiosyncratic risk leads to higher default.

This causes a decline in their net worth and a fall in capital price and investment. While risk shocks have quantitatively large effects, housing collateral constraints do not play an important role in driving the response to this shock. As for the responses of aggregate variables to preference and labour supply shock, our findings resemble those of estimated DSGE models that do not include a housing sector (Smets and Wouters (2003), Christensen and Dib (2008)). Figure 6 shows the impulse responses to a one standard deviation (0.009%) positive preference shock, which raises the marginal utility of consumption and therefore the opportunity cost of holding deposits (savings). As households divert deposits towards consumption, the return on deposits (the risk-free real interest rate) rises. The responses of output and consumption are almost identical in the models with and without financial frictions. Finally, figure 7 shows the effects of a negative labour supply shock. The qualitative effects of this supply shock on GDP, consumption and investment are very similar to those of a negative productivity shock. The main qualitative differences are that employment also falls in line with output. Again the results are not affected by adding housing constraints to the model.

1.6.3 Comparison of results from first and second order approximation

In this section, we compare impulse responses generated from first order v/s second order approximation of the model around the steady state. Figure 8 and 9 show responses of key variables to the seven shocks described above. In figure 8, responses to housing preference, housing technology and nonhousing technology shocks are unchanged under first v/s second order approximation of the model. A similar trend is seen in figure 9 where responses to preference shock, labour supply shock and investment shock are mostly invariant to the order of approximation. Therefore, the response of key macroeconomic variables to these shocks does not exhibit significant non-linearities. The only exception is risk shock (figure 9) where non-linearities play a big role - GDP and consumption under second order approximation fall about six times more than under first order approximation. A one standard deviation (0.99

percentage point) increase in the risk reduces GDP by 0.05% and 0.3% under first and second order approximation, respectively. It is important to note that second order approximation may still not capture the non-linearities well as it is approximation within the neighbourhood of the deterministic steady state. To be able to characterize the non-linearities in the model, we would require a global solution to the model. Although this would certainly be a fruitful avenue for future research, it is beyond the scope of this paper.

1.6.4 Robustness: Prior sensitivity

To check whether the results are robust to prior selection, we estimate the baseline model again with same prior means but double the standard deviation. The results are presented in table 6. The posterior median is largely robust to increasing standard deviation of the prior distribution.

1.6.5 Variance Decomposition

The results from variance decomposition are presented in table 7. Non-housing technology shock explains nearly half of the variation in GDP, about 40 percent variation in consumption and 18 percent variation in nonresidential investment. However, its contribution towards explaining variation in other aggregate variables, particularly relevant to housing market is low suggesting that other shocks are important in our model too. Housing demand (housing preference) and supply (housing technology) shocks together account for more than 70 percent of the variation in housing investment and about 50 percent of the variation in house prices. Investment shock also plays an important role, explaining about 50 percent of the variance of non-housing investment and 10 percent of the variance of housing investment. It also explains close to 20 percent of the variation in consumption and house prices and 15 percent of the variation in output. Finally, risk shock explains more than 20 percent of the variation in output, consumption and non-housing investment. Thus, total factor productivity shock together with investment and risk shocks explain majority of the variation in GDP, consumption and nonresidential investment at business cycle fre-

Table 6 – Posterior median of baseline model: Prior sensitivity

Baseline				Sensitivity w.r.t prior std. dev		
Structural Parameters				Structural Parameters		
Parameter	Mean	Std. dev	Median	Mean	Std. dev	Median
ϕ_p	0.5	0.1	1.0890	0.5	0.2	1.6235
ϕ_i	0.5	0.1	0.3885	0.5	0.2	0.3236
η_p	1	0.1	1.0935	1	0.2	1.1756
η_i	1	0.1	1.0256	1	0.2	1.0247
μ	0.35	0.05	0.1866	0.35	0.1	0.1506
φ_x	5	2.5	16.82	5	5	16.05
Shock Parameters				Shock Parameters		
ρ_{ac}	0.8	0.1	0.7975	0.8	0.2	0.7894
ρ_{ah}	0.8	0.1	0.8652	0.8	0.2	0.8435
ρ_h	0.8	0.1	0.9168	0.8	0.2	0.9533
ρ_z	0.8	0.1	0.8290	0.8	0.2	0.8728
ρ_ς	0.8	0.1	0.9956	0.8	0.2	0.9976
ρ_η	0.8	0.1	0.8365	0.8	0.2	0.8299
ρ_σ	0.8	0.1	0.6066	0.8	0.2	0.6108
σ_{ac}	0.01	0.05	0.0448	0.01	0.1	0.0450
σ_{ah}	0.01	0.05	0.0402	0.01	0.1	0.0435
σ_h	0.01	0.05	0.08	0.01	0.1	0.0614
σ_z	0.01	0.05	0.0062	0.01	0.1	0.0062
σ_ς	0.01	0.05	0.0441	0.01	0.1	0.0410
σ_r	0.01	0.05	0.9889	0.01	0.1	0.9723
σ_η	0.01	0.05	0.5026	0.01	0.1	0.5031

quency. However, dynamics of the housing market are predominantly explained by housing demand and supply shocks.

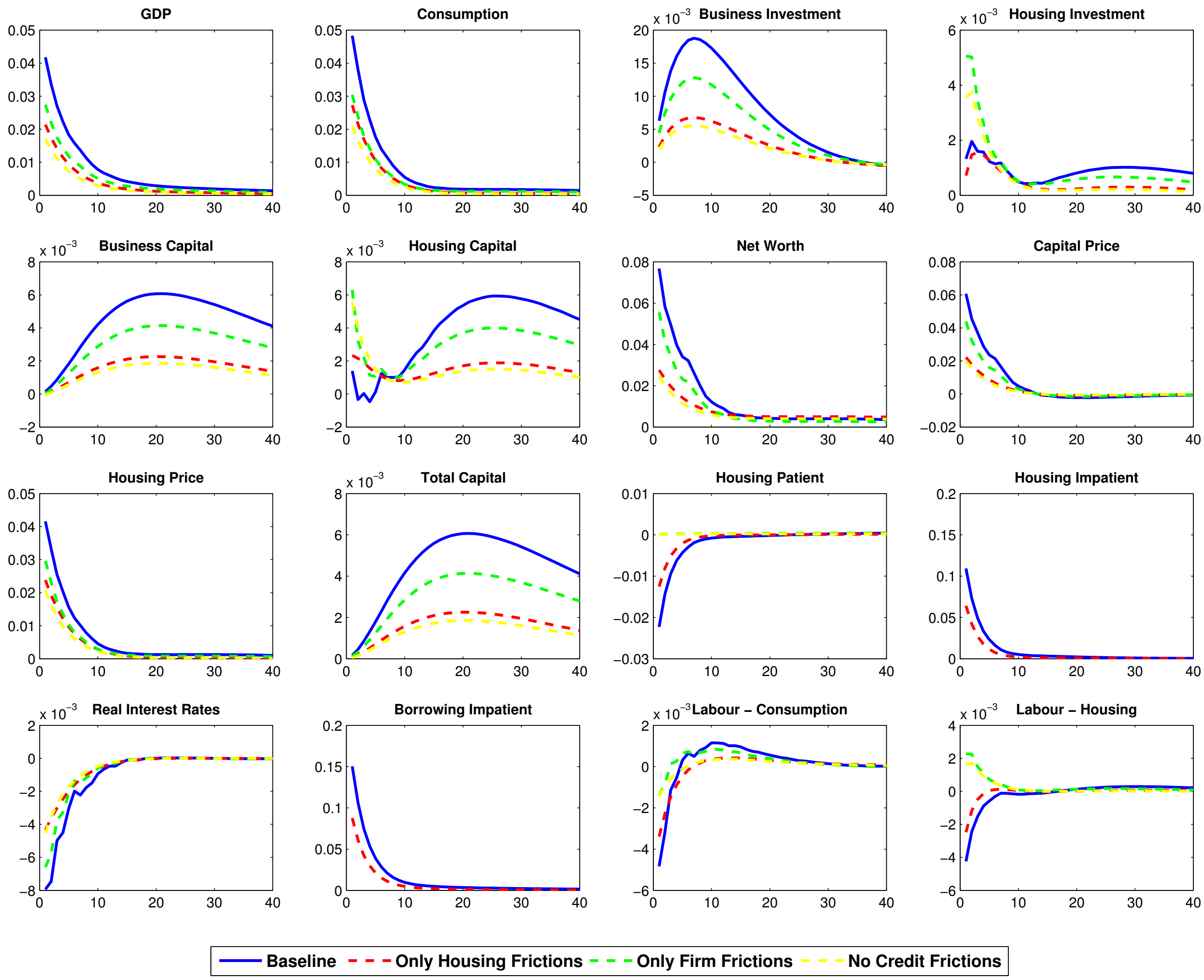
1.7 Concluding Remarks

In this paper, we develop and estimate a dynamic stochastic general equilibrium model of firm and household leverage. We introduce a multi sector production economy with housing and non-housing goods. The demand side of the model embodies financial frictions for both household and firms. Financial frictions for households appear in the form of borrowing based on collateralisable asset (housing). For firms, our model generates an endogenous external finance premium as a function of firm's leverage. The fluctuations of the asset prices (housing and capital) affect the value of the collateral and hence, the borrowing capacities of these agents. We see that the presence of these financial frictions amplifies the impact of shocks that originate elsewhere in the economy. We observe a strong financial accelerator mechanism in operation, wherein inclusion of both housing and firm financial frictions amplify the shocks hitting the economy as opposed to just one. There are two important ways in which firm and household financial frictions interact with each other. First is via the loan market equilibrium condition, a tighter credit constraint on households encourage them to reduce their demand for loans and increase their labour supply. This reduces the financing costs faced by firms. Secondly, an increase in housing demand and investment (that is amplified with collateral constraints) increases the demand for housing capital thereby boosting capital price. An increase in capital price improves the net worth position of firms and therefore reduces the external finance premium they face.

We also notice interesting dynamics with regards to resources being devoted to housing v/s non-housing production. Shocks related to housing market that increase the demand and price of housing cause capital to be diverted from non-housing to housing production. There is an increase in housing capital K_h and a fall in capital in the consumption sector, K_c, with the overall effect on business investment depending on which effect dominates. We further find the effect of housing market frictions to be predominantly concentrated on consumption and housing investment. There is a substantial spillover effect of house prices on non-housing consumption pointing towards the importance of wealth effects on household consumption.

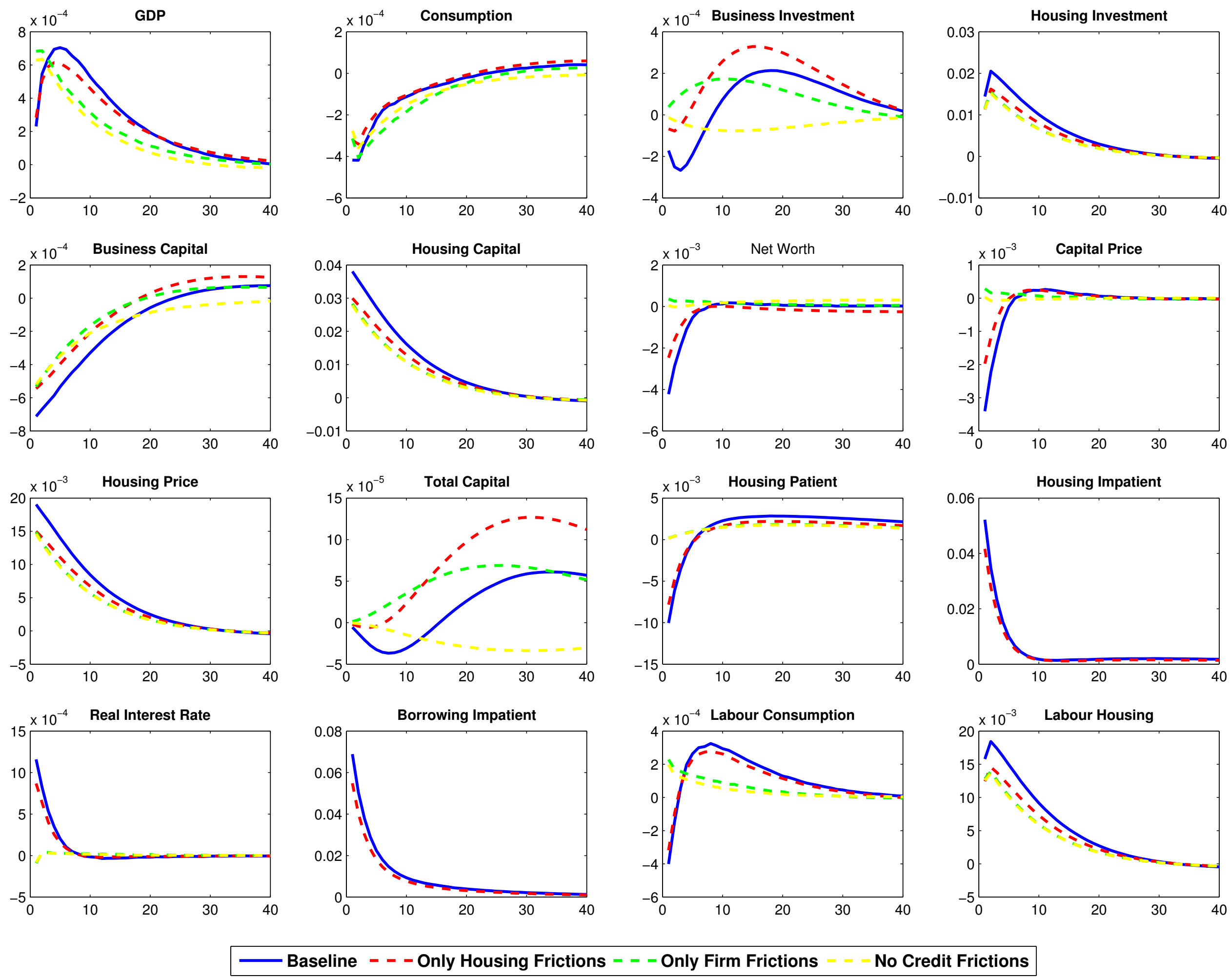
At cyclical frequencies, we observe that both housing prices and housing investment are strongly procyclical as in the literature (Iacoviello and Neri (2010)). Further, business and housing investment tend to co-move. Finally, we find that non-housing technology shocks are most important in explaining variations in GDP, consumption and business investment. However housing demand and supply shocks account for more than 50% of the cyclical volatility of housing investment and housing prices.

Figure 1 – Impulse responses to the estimated non-housing technology shock



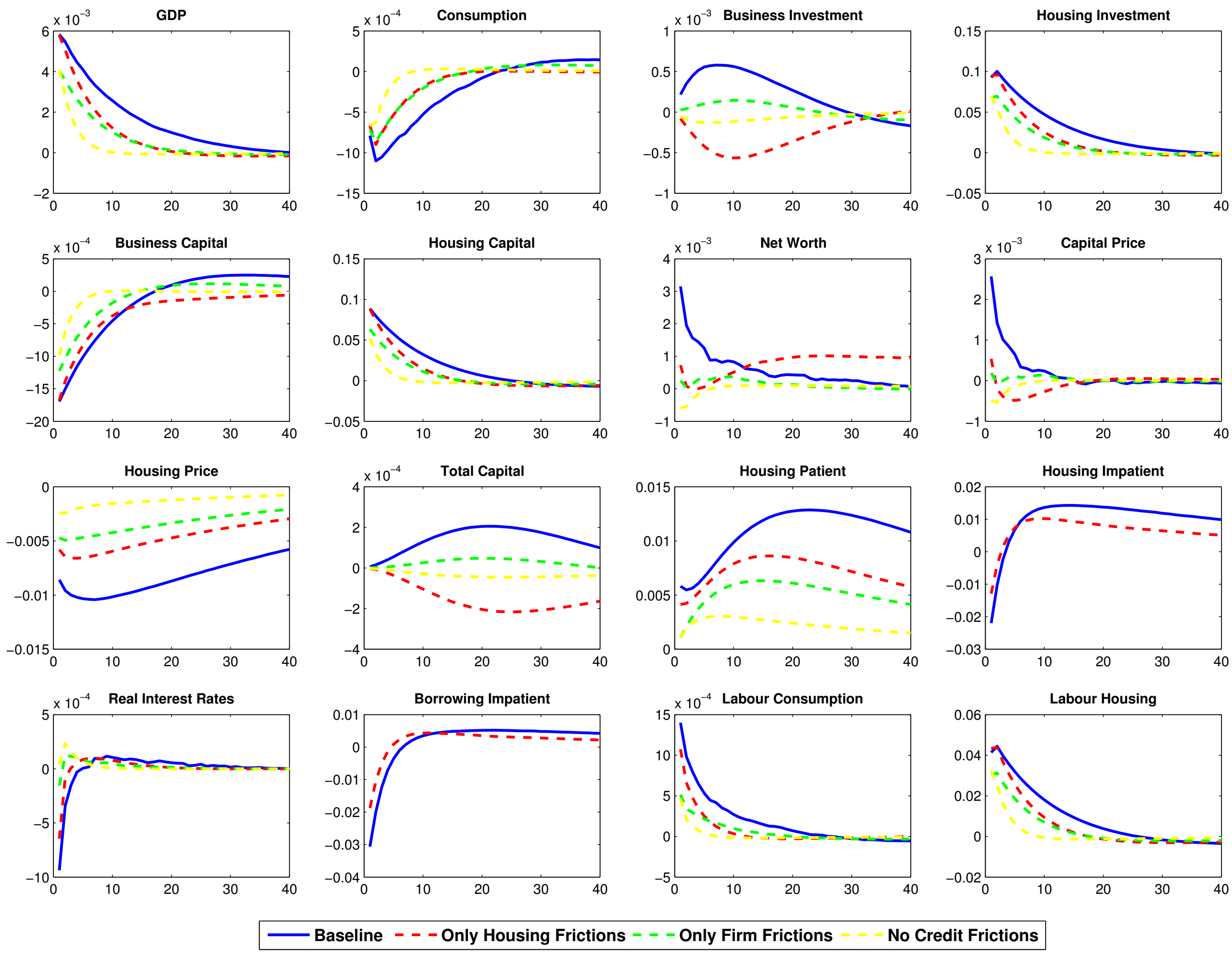
Note: IRFs to the estimated one standard deviation (0.04%) non-housing technology shock. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.04% increase in non-housing technology increases GDP by 0.04% in the baseline model. X-axis is time in quarters.

Figure 2 – Impulse responses to the estimated housing preference shock



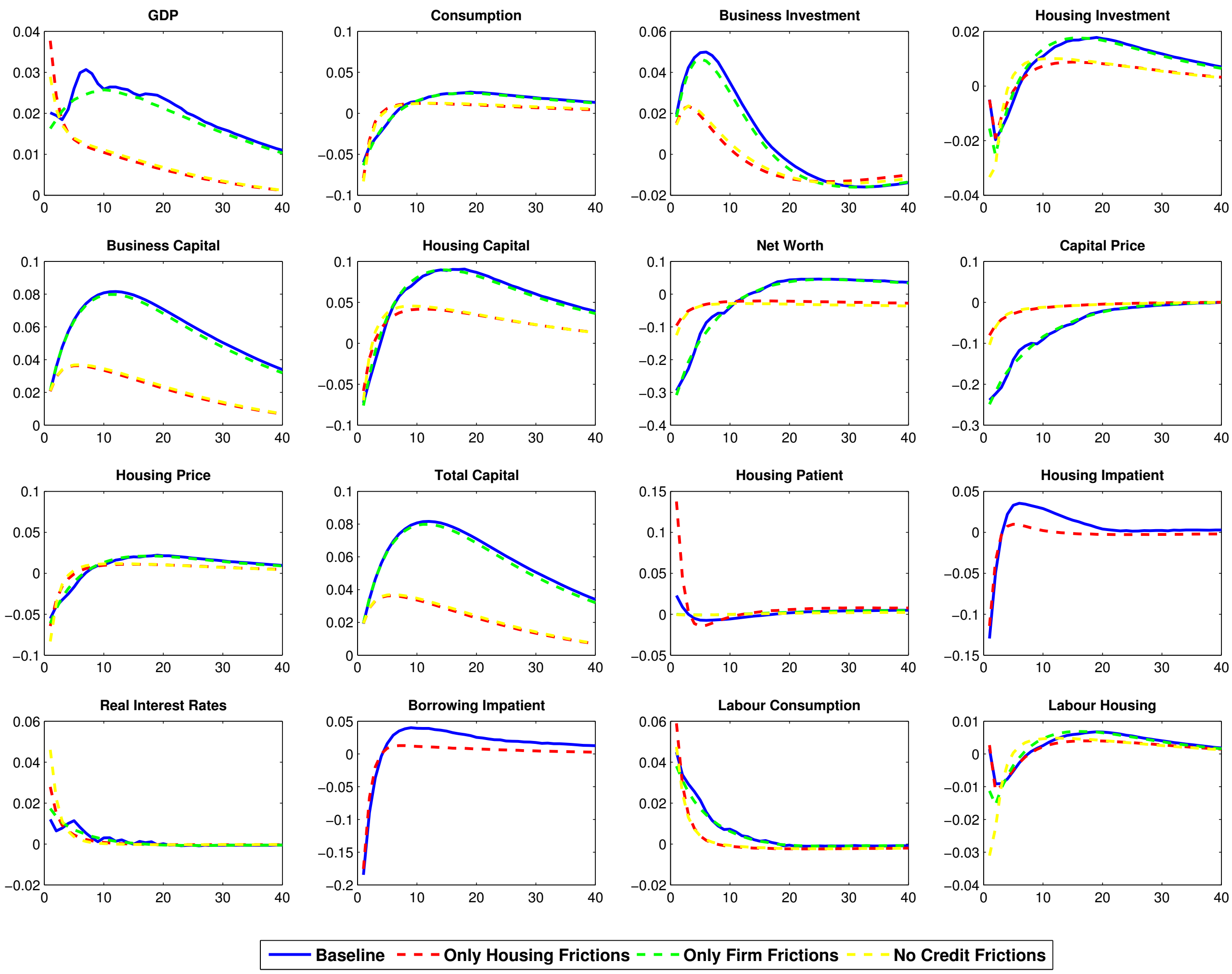
Note: IRFs to the estimated one standard deviation (0.1%) housing preference shock. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.1% increase in demand for housing increases GDP by 0.0007% in the baseline model. X-axis is time in quarters.

Figure 3 – Impulse responses to the estimated housing technology shock



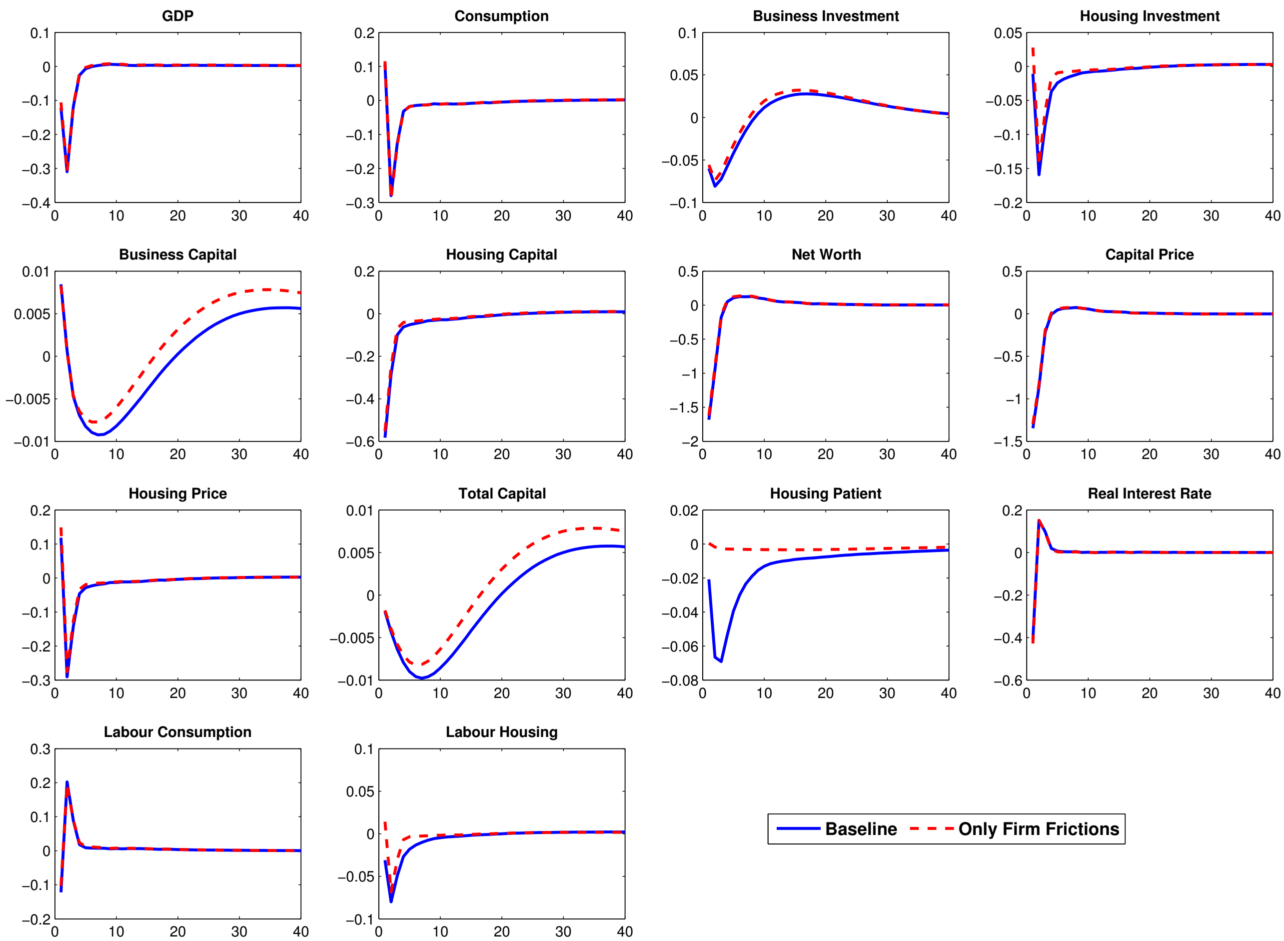
Note: IRFs to the estimated one standard deviation (0.05%) housing technology shock. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.05% increase in housing technology increases GDP by 0.006% in the baseline model. X-axis is time in quarters.

Figure 4 – Impulse responses to the estimated investment shock



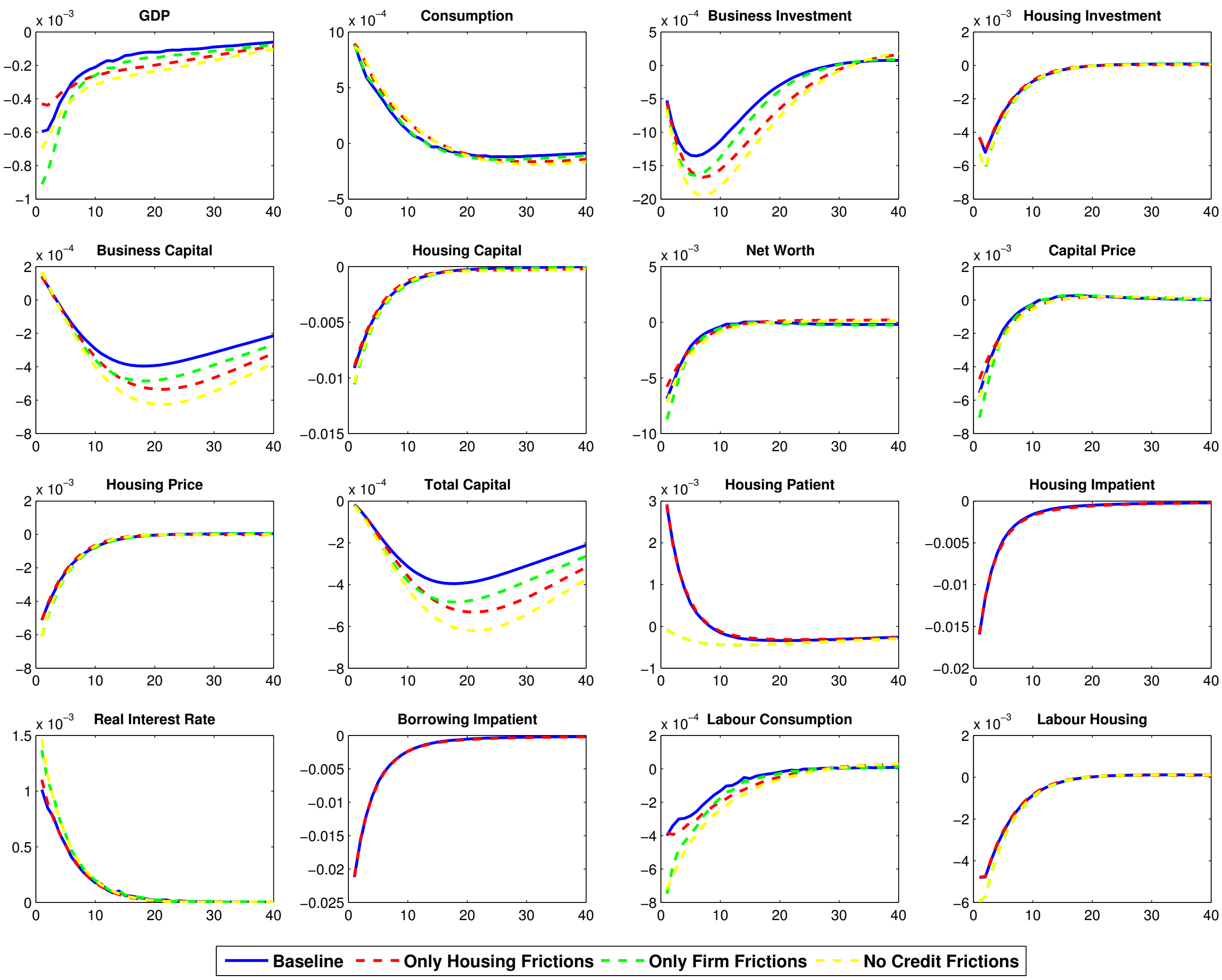
Note: IRFs to the estimated one standard deviation (0.5%) investment shock. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.5% increase in the efficiency with which final good is converted into capital, increases GDP by 0.03% in the baseline model. X-axis is time in quarters.

Figure 5 – Impulse responses to the estimated risk shock



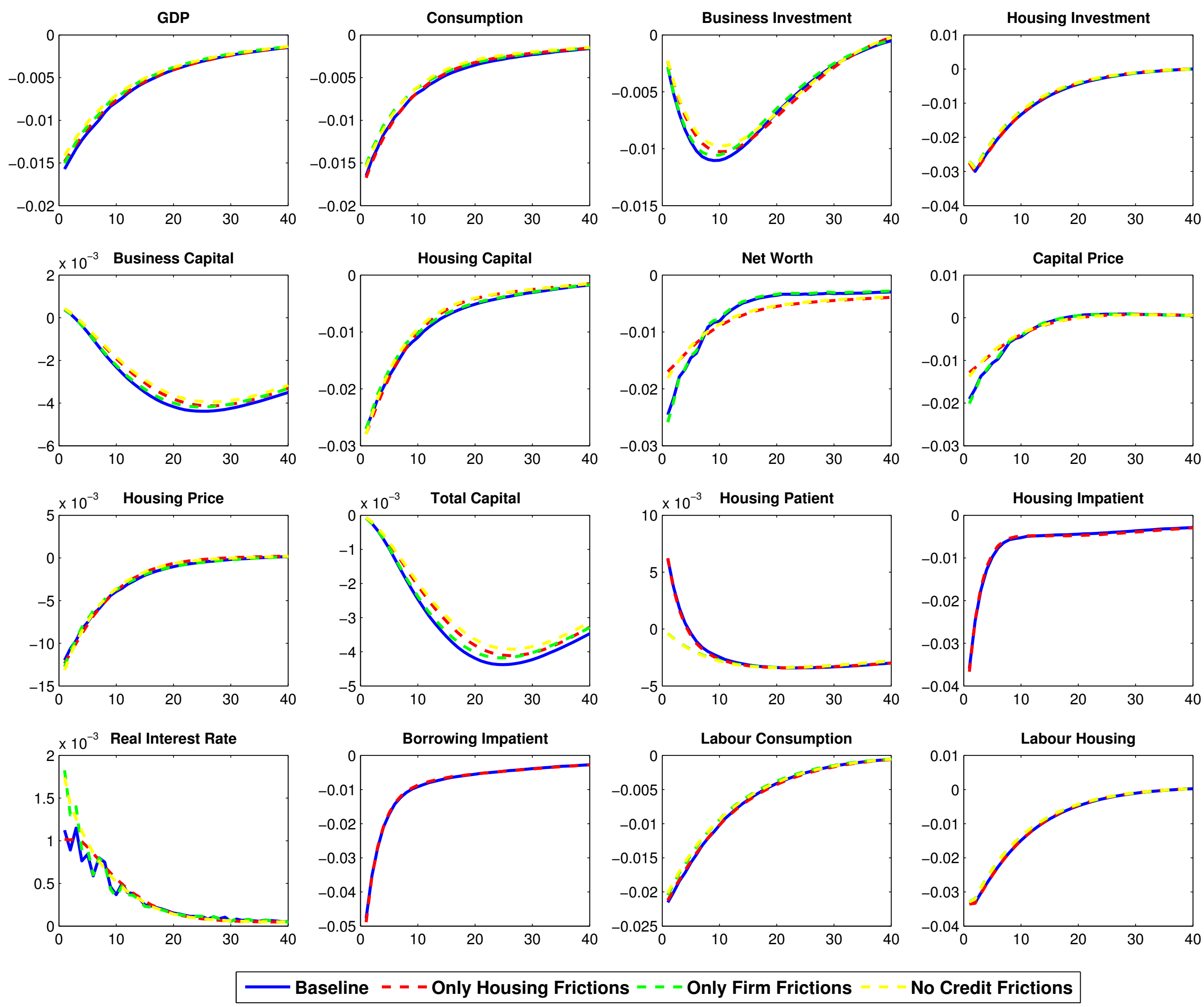
Note: IRFs to the estimated one standard deviation (0.99 percentage point) risk shock. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.99 percentage point increase in the standard deviation of firms' idiosyncratic shock reduces GDP by 0.3% in the baseline model. X-axis is time in quarters.

Figure 6 – Impulse responses to the estimated preference shock



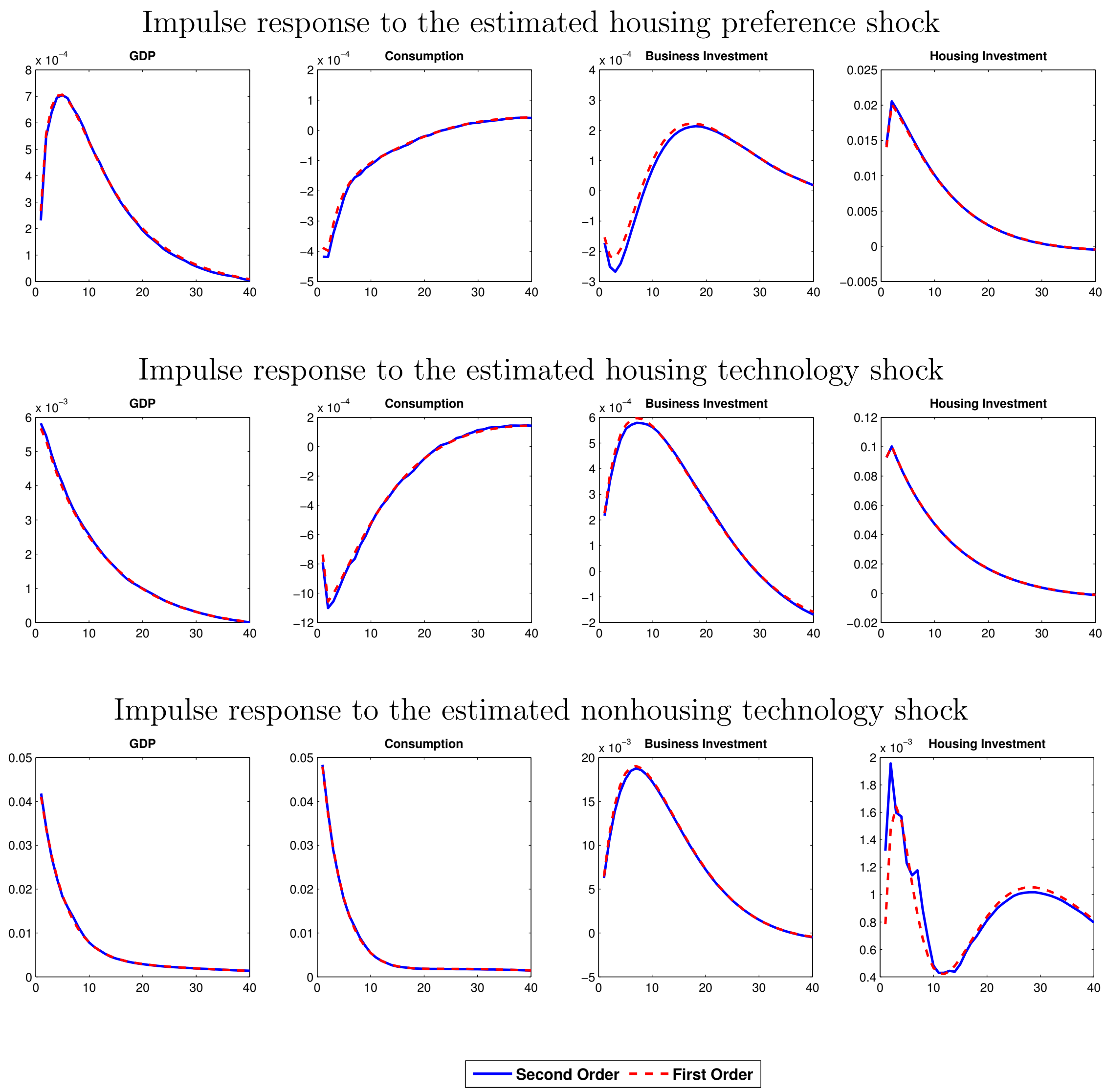
Note: IRFs to the estimated one standard deviation (0.009%) preference shock. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a positive 0.009% preference shock reduces GDP by 0.0006%. X-axis is time in quarters.

Figure 7 – Impulse responses to the estimated labour supply shock



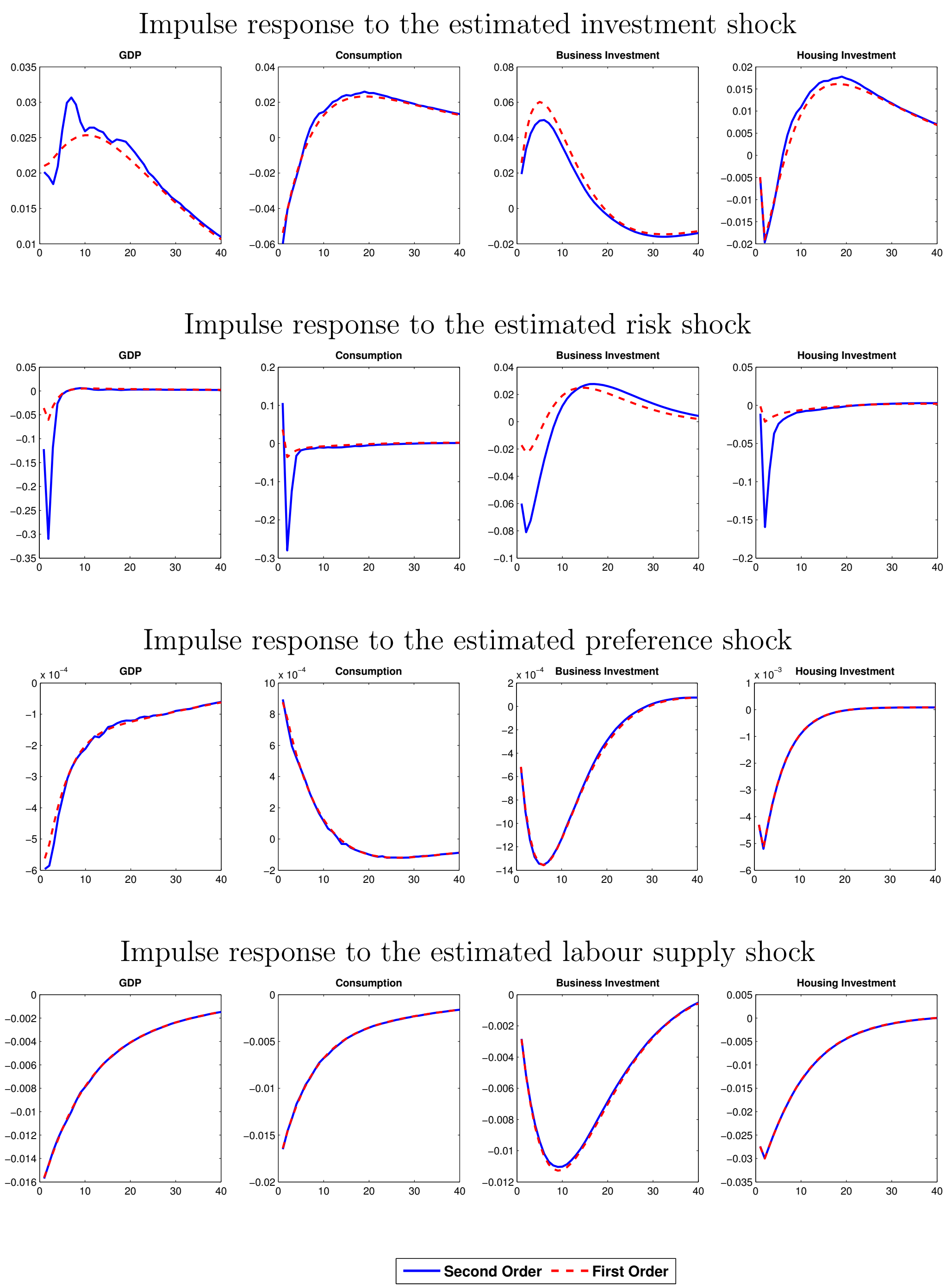
Note: IRFs to the estimated one standard deviation (0.04%) negative labour supply shock. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a negative 0.04% labour supply shock reduces GDP by 0.015%. X-axis is time in quarters.

Figure 8 – Impulse response functions under first order v/s second order approximation



Note: IRFs to the estimated one standard deviation shock based on first and second order approximation (averaging one thousand simulation) of the model around the steady state. X-axis is time in quarters.

Figure 9 – Impulse response functions under first order v/s second order approximation (cont.)



Note: IRFs to the estimated one standard deviation shock based on first and second order approximation (averaging one thousand simulation) of the model around the steady state. X-axis is time in quarters.

Table 7 – Variance Decomposition (in percent)

Variable/Shock	ε_{ac}	ε_{ah}	ε_{h}	ε_{z}	ε_{ς}	ε_{η}	ε_{σ}
GDP	44.50	3.29	4.28	1.96	10.51	15.26	20.2
C	42.24	1.94	0.85	1.40	6.73	21.14	25.7
I	18.37	0.01	0.26	4.11	7.42	47.35	22.48
IH	0.78	48.79	28.73	3.56	2.02	9.88	6.24
q_h	14.55	30.32	21.99	3.16	2.19	19.28	8.51

Appendix 1.1: Data and Sources

Aggregate Consumption: Real personal consumption expenditure (seasonally adjusted, billions of chained 2009 dollars), divided by the civilian non-institutional population (CNP16OV). Source: Bureau of Economic Analysis (BEA).

Business Investment: Real private fixed investment - Nonresidential (seasonally adjusted, billions of chained 2009 dollars), divided by the civilian non-institutional population (CNP16OV). Source: Bureau of Economic Analysis (BEA).

Residential Investment: Real private fixed investment - Residential (seasonally adjusted, billions of chained 2009 dollars), divided by the civilian non-institutional population (CNP16OV). Source: Bureau of Economic Analysis (BEA).

Real House Prices: Census Bureau house price index deflated with the implicit price deflator for the non-farm business sector.

Source: Census Bureau, http://www.census.gov/const/price_sold_cust.xls.

Hours worked in Consumption-good Sector: Total Non-farm Payrolls (Series ID: PAYEMS in Saint Louis Fed - FRED) less all employees in the construction sector (Series ID: USCONS), times average weekly hours of production workers (Series ID: CES0500000005), divided by CNP16OV. Demeaned. Source: BLS.

Hours worked in Housing Sector: All employees in the construction sector (Series ID: USCONS in Saint Louis Fed - FRED), times average weekly hours of construction workers (Series ID: CES2000000005), divided by CNP16OV. Demeaned. Source: BLS.

Appendix 1.2: Model Equations

Here, we summarize the equations describing the equilibrium of the model. The competitive equilibrium of our model is a set of endogenous variables B_t, $c_{p,t}$, $c_{i,t}$, $c_{e,t}$, $d_{p,t}$, efp_t, GDP_t, $h_{i,t}$, $h_{p,t}$, H_t, I_t, IH_t, K_t, $k_{b,t}$, $k_{c,t}$, $k_{h,t}$, λ_t, la_t, x_t, $l_{ic,t}$, $l_{ih,t}$, $l_{pc,t}$, $l_{ph,t}$, N_t, $\bar{\omega}_t$, $p_{b,t}$, $p_{la,t}$, $q_{h,t}$, $q_{k,t}$, $r_{k,t}$, $r_{kc,t}$, $r_{kh,t}$, $R_{la,t}$, R_t, $R_{F,t}$, $R_{k,t}$, $w_{ic,t}$, $w_{ih,t}$,$w_{pc,t}$, $w_{ph,t}$, $\zeta_{e,t}$, Y_t satisfying the relations (1.21) to (1.62), given the exogenous stochastic processes $A_{c,t}$, $A_{h,t}$, z_t, ς_t, $J_{h,t}$, $\eta_{k,t}$, σ_t and the initial conditions $b_{i.t-1}$, $d_{p,t-1}$, $h_{i,t-1}$, $h_{p,t-1}$, H_{t-1}, K_{t-1}, $k_{c,t-1}$, $k_{h,t-1}$, la_{t-1}, N_{t-1}, r_{t-1}, I_{t-1}, $q_{k,t-1}$. The endogenous variables jointly satisfy the following equations that include first-order conditions for patient households, impatient households, entrepreneurs, firms, capital goods producers, and the market clearing conditions.

A competitive equilibrium consists of a set of prices and interest rates $\{p_{b,t}, p_{la,t}, q_{h,t}, q_{k,t}, R_{la,t}, R_t, r_{k,t}, w_{ic,t}, w_{ih,t}, w_{pc,t}, w_{ph,t}\}$ for all possible states and for all $t \geq 0$ such that all markets clear when all agents i.e. patient households, impatient households, entrepreneurs, firms and capital goods producer solve their maximization problems while taking these prices and interest rates as given.

Patient Households

The budget constraint of patient households is:

$$c_{p,t} + q_{h,t}(h_{p,t} - (1-\delta_h)h_{p,t-1}) + d_{p,t} + p_{la,t}la_t + k_{b,t} \leq w_{pc,t}l_{pc,t} + w_{ph,t}l_{ph,t} + R_{t-1}d_{p,t-1}$$

$$+p_{b,t}k_{b,t} + (p_{la,t} + R_{la,t})la_{t-1} \tag{1.21}$$

The first order conditions faced by the patient household can be summarized by:

$$\frac{z_t}{c_{p,t}} = E_t(\frac{\beta_p z_{t+1} R_t}{c_{p,t+1}}) \tag{1.22}$$

$$\frac{z_t q_{h,t}}{c_{p,t}} = \frac{z_t J_{h,t}}{h_{p,t}} + \beta_p E_t(\frac{z_{t+1} q_{h,t+1}(1-\delta_h)}{c_{p,t+1}}) \tag{1.23}$$

$$\frac{p_{b,t}-1}{c_{p,t}} = 0 \tag{1.24}$$

$$\frac{z_t p_{la,t}}{c_{p,t}} = E_t(\frac{\beta_p z_{t+1}}{c_{p,t+1}}(p_{la,t+1} + R_{la,t+1})) \tag{1.25}$$

$$\frac{w_{pc,t}}{c_{p,t}} = \varsigma_t l_{pc,t}^{\eta_p}(l_{pc,t}^{1+\eta_p} + l_{ph,t}^{1+\eta_p})^{\frac{(\phi_p-\eta_p)}{(1+\eta_p)}} \tag{1.26}$$

$$\frac{w_{ph,t}}{c_{p,t}} = \varsigma_t l_{ph,t}^{\eta_p}(l_{pc,t}^{1+\eta_p} + l_{ph,t}^{1+\eta_p})^{\frac{(\phi_p-\eta_p)}{(1+\eta_p)}} \tag{1.27}$$

Impatient Households

The budget constraint of the impatient households is:

$$c_{i,t} + q_{h,t}(h_{i,t} - (1-\delta_h)h_{i,t-1}) + R_{t-1}b_{i,t-1} \leq w_{ic,t}l_{ic,t} + w_{ih,t}l_{ih,t} + b_{i,t} \tag{1.28}$$

The first order conditions for impatient households are as follows[7]:

$$\frac{z_t}{c_{i,t}} = E_t(\frac{z_{t+1}\beta_i R_t}{c_{i,t+1}}) + \lambda_t R_t \tag{1.29}$$

$$\frac{z_t q_{h,t}}{c_{i,t}} = E_t(\frac{\beta_i z_{t+1} q_{h,t+1}(1-\delta_h)}{c_{i,t+1}} + \lambda_t \bar{m} q_{h,t+1}) + \frac{z_t J_{h,t}}{h_{i,t}} \tag{1.30}$$

$$\frac{w_{ic,t}}{c_{i,t}} = \varsigma_t l_{ic,t}^{\eta_i}(l_{ic,t}^{1+\eta_i} + l_{ih,t}^{1+\eta_i})^{\frac{(\phi_i-\eta_i)}{(1+\eta_i)}} \tag{1.31}$$

[7] λ_t is the Lagrange multiplier on the borrowing constraint faced by impatient households.

$$\frac{w_{ih,t}}{c_{i,t}} = \varsigma_t l_{ih,t}^{\eta_i} (l_{ic,t}^{1+\eta_i} + l_{ih,t}^{1+\eta_i})^{\frac{(\phi_i - \eta_i)}{(1+\eta_i)}} \tag{1.32}$$

$$b_{i,t} = \frac{\bar{m} q_{h,t+1} h_{i,t}}{R_t} \tag{1.33}$$

Entrepreneurs

The law of motion of aggregate entrepreneurial net worth[8] is:

$$N_{t+1} = \gamma\{R_{k,t+1} Q_{k,t} K_t - [R_t + \mu_e \frac{\int_0^{\bar{\omega}_{t+1}} \omega_{t+1} f(\omega_{t+1}) d\omega_{t+1} Q_{k,t} K_t}{Q_{k,t} K_t - N_t}](Q_{k,t} K_t - N_t)\} + W^e \tag{1.34}$$

Their aggregate borrowing is:

$$B_t = Q_{k,t} K_t - N_t \tag{1.35}$$

The first order conditions for entrepreneur yields:

$$-\Gamma^{'}(\bar{\omega}_{t+1})) + \zeta_{e,t}(\Gamma^{'}(\bar{\omega}_{t+1}) - \mu_e G^{'}(\bar{\omega}_{t+1})) = 0 \tag{1.36}$$

$$(1 - \Gamma(\bar{\omega}_{t+1})) R_{k,t+1} + \zeta_{e,t}[(\Gamma(\bar{\omega}_{t+1}) - \mu_e G(\bar{\omega}_{t+1})) R_{k,t+1} - R_t] = 0 \tag{1.37}$$

Where $\zeta_{e,t}$ is the Lagrange multiplier associated with the participation constraint:

$$E_t[(\Gamma(\bar{\omega}_{t+1}) - \mu_e G(\bar{\omega}_{t+1}))] R_{k,t+1} x_t = R_t (x_t - 1) \tag{1.38}$$

The aggregate consumption of entrepreneurs that exit the economy in t+1 is given by:

[8] The aggregation of net worth, capital and borrowing is discussed in section 1.3.3.

$$c_{e,t+1} = \Theta\frac{(1-\gamma)}{\gamma}(N_{t+1} - W^e) \tag{1.39}$$

The external finance premium for loans between period t and t+1 is:

$$efp_{t+1} = \mu_e \frac{\int_0^{\bar{\omega}_{t+1}} \omega_{t+1} f(\omega_{t+1}) d\omega_{t+1} Q_{k,t} K_t}{Q_{k,t} K_t - N_t} \tag{1.40}$$

The state contingent interest rate, $R_{F,t}$ is given by:

$$R_{F,t} = \bar{\omega}_{t+1} R_{k,t+1} . (\frac{x_t}{x_t - 1}) \tag{1.41}$$

and

$$R_{k,t+1} = \frac{r_{k,t+1} + (1-\delta_k) Q_{k,t+1}}{Q_{k,t}} \tag{1.42}$$

Firms

The production technology for non-housing and housing are respectively:

$$Y_t = A_{c,t} K_{c,t-1}^{\alpha} (l_{ic,t}^{\mu} l_{pc,t}^{1-\mu})^{1-\alpha} \tag{1.43}$$

$$IH_t = A_{h,t} (l_{ih,t}^{\mu} l_{ph,t}^{1-\mu})^{1-\beta-\theta-\tau} K_{h,t-1}^{\beta} k_{b,t}^{\theta} la_{t-1}^{\tau} \tag{1.44}$$

The first order conditions are:

$$w_{ic,t} = \frac{\mu(1-\alpha)Y_t}{l_{ic,t}} \tag{1.45}$$

$$w_{pc,t} = \frac{(1-\mu)(1-\alpha)Y_t}{l_{pc,t}} \tag{1.46}$$

$$r_{kc,t} = \frac{\alpha Y_t}{K_{c,t-1}} \tag{1.47}$$

$$w_{ih,t} = \frac{\mu(1-\beta-\theta-\tau)q_{h,t}IH_t}{l_{ih,t}} \tag{1.48}$$

$$w_{ph,t} = \frac{(1-\mu)(1-\beta-\theta-\tau)q_{h,t}IH_t}{l_{ph,t}} \tag{1.49}$$

$$r_{kh,t} = \frac{\beta q_{h,t}IH_t}{K_{h,t-1}} \tag{1.50}$$

$$R_{la,t} = \frac{\tau q_{h,t}IH_t}{la_{t-1}} \tag{1.51}$$

$$p_{b,t} = \frac{\theta q_{h,t}IH_t}{k_{b,t}} \tag{1.52}$$

Capital goods producer

The evolution of capital stock is given by:

$$K_{t+1} = (1-\delta_k)K_t + \eta_{k,t}(1-S(G_t))I_t \tag{1.53}$$

and the inter-temporal profit maximization with respect to I_t yields:

$$Q_{k,t}(1-S(G_t)-X_tS'(G_t)) + E_t[D_{t,t+1}Q_{k,t}S'(G_{t+1})\frac{I_{t+1}^2}{I_t^2}] = \frac{1}{\eta_{k,t}} \tag{1.54}$$

Market clearing

Patient and impatient households are available in unit mass each. Housing investment in the economy is given by:

$$IH_t = H_t - (1-\delta_h)H_{t-1} \tag{1.55}$$

$$H_t = h_{p,t} + h_{i,t} \tag{1.56}$$

Equilibrium in the housing market implies that the housing stock (undepreciated old stock and the new housing investment) is equal to the sum of demand for housing from patient and impatient household.

Resource constraint (goods market equilibrium) is obtained by adding budget constraints for all agents.

$$Y_t = C_t + I_t + k_{b,t} + \mu_e G(\bar{\omega}_t) R_{k,t} Q_{k,t-1} K_{t-1} \tag{1.57}$$

Loan market equilibrium is:

$$d_{p,t} = b_{i,t} + B_t \tag{1.58}$$

Total land is normalized to unity.

$$la_t = 1 \tag{1.59}$$

Total capital is the sum of capital in non-housing and housing sector whereby equilibrium in capital services market requires that the supply from entrepreneurs is equal to the capital demanded by firms.

$$K_t = K_{c,t} + K_{h,t} \tag{1.60}$$

GDP (net of monitoring costs) is defined as the value added of the two sectors.

$$GDP_t = Y_t - k_{b,t} + \overline{q} IH_t \tag{1.61}$$

Equilibrium in the labor market requires that labor demanded by firms is equal to the labor supplied by households (both patient and impatient) at their respective competitive real wage. Finally, equilibrium in the market for capital requires that the marginal product is same across both the sectors, i.e.

$$r_{k,t} = r_{kc,t} = r_{kh,t} \tag{1.62}$$

Appendix 1.3: Steady State

Entrepreneurs and Net Worth

In equilibrium, optimization by capital goods producers implies capital price of one.

$$q_k = 1$$

Following popular studies BGG(1999), Christensen and Dib (2008), we pin down the steady state capital to net-worth K/N ratio. This together with the entrepreneurs loan contract gives the values of $\bar{\omega}$ and $R_{K,t}$. Therefore:

$$r_k = R_k - (1 - \delta_k)$$

Furthermore, in equilibrium marginal return of capital in the consumption and housing good production is equalized.

$$r_{kc} = r_{kh} = r_k$$

The Euler equations for the demand of capital from non-housing and housing sector can then be used to derive the following ratios:

$$S_0 = \frac{K_c}{Y} = \frac{\alpha}{(R_k - (1 - \delta_k))}$$

$$S_1 = \frac{K_h}{q_h IH} = \frac{\beta}{R_k - (1 - \delta_k)}$$

Finally, setting land $la = 1$, we have

$$R_{la} = \tau q_h IH$$

Households

Marginal utility of consumption and housing are equal to $1/c$ and $\overline{J_h}/h$ respectively. This gives the steady state level of real interest rate as

$$R = \frac{1}{\beta_p}$$

The Euler equation of h_p yields

$$S_2 = \frac{q_h h_p}{c_p} = \frac{\overline{J_h}}{(1 - \beta_p(1 - \delta_h))}$$

Euler equation for h_i and b_i

$$S_3 = \frac{q_h h_i}{c_i} = \frac{\overline{J_h}}{1 - \beta_i(1 - \delta_h) - \overline{m}(\beta_p - \beta_i)}$$

$$\lambda = \frac{(\beta_p - \beta_i)}{c_i}$$

From the above ratios, we have:

$$K_c = S_0 Y$$

$$K_h = S_1 q_h IH$$

$$q_h h_p = S_2 c_p$$

$$q_h h_i = S_3 c_i$$

From housing market clearing condition, we get:

$$\delta_h(q_h h_p + q_h h_i) = q_h IH$$

The loan market equilibrium yields:

$$d_p = \beta_p \overline{m} q_h h_i + (K - N)$$

Using $K = K_c + K_h$, we get

$$S_4 = \frac{K}{Y} = S_0 + S_1\delta_h(S_2\frac{c_p}{Y} + S_3\frac{c_i}{Y})$$

The budget constraints of the two types of households solve:

$$c_p + \delta_h q_h h_p = \sum wl + \tau q_h IH + d_p(R-1)$$

$$c_i + \delta_h q_h h_i = \sum wl + \overline{m} q_h h_i(\beta_p - 1)$$

Eliminating h_p and h_i, we get:

$$\delta_h(S_2 c_p + S_3 c_i) = q_h IH$$

$$c_p + \delta_h S_2 c_p = \sum wl + \tau q_h IH + (\beta_p \overline{m} S_3 c_i + S_4 Y(1-n_k))(R-1)$$

$$c_i + \delta_h S_3 c_i = \sum wl + \overline{m} S_3 c_i(\beta_p - 1)$$

The Euler equations for labour demand provide following steady state relations:

$$w_{ic} = \frac{\mu(1-\alpha)Y}{l_{ic}}$$

$$w_{pc} = \frac{(1-\mu)(1-\alpha)Y}{l_{pc}}$$

$$w_{ih} = \frac{\mu(1-\beta-\theta-\tau)q_h IH}{l_{ih}}$$

$$w_{ph} = \frac{(1-\mu)(1-\beta-\theta-\tau)q_h IH}{l_{ph}}$$

Further, we saw above that we need the total wage bill earned by each group to compute the steady state:

$$w_{pc}l_{pc} + w_{ph}l_{ph} = (1-\mu)((1-\alpha)Y + (1-\beta-\theta-\tau)q_h IH)$$

$$w_{ic}l_{ic} + w_{ih}l_{ih} = \mu((1-\alpha)Y + (1-\beta-\theta-\tau)q_h IH)$$

$$\delta_h(S_2c_p + S_3c_i) = q_h IH$$

$$c_p + \delta_h S_2 c_p = (1-\mu)((1-\alpha)Y + (1-\beta-\theta-\tau)q_h IH) + \tau q_h IH + (\beta_p \overline{m} S_3 c_i + S_4 Y(1-n_k))(R-1)$$

$$c_i + \delta_h S_3 c_i = \mu((1-\alpha)Y + (1-\beta-\theta-\tau)q_h IH) + \overline{m} S_3 c_i(\beta_p - 1)$$

Using the formula for $q_h IH$, we have:

$$c_p + \delta_h S_2 c_p = (1-\mu)((1-\alpha)Y + (1-\beta-\theta-\tau)\delta_h(S_2c_p + S_3c_i)) + \tau\delta_h(S_2c_p + S_3c_i) +$$

$$(\beta_p \overline{m} S_3 c_i + (S_0 Y + S_1\delta_h(S_2c_p + S_3c_i))(1-n_k))(R-1)$$

$$c_i + \delta_h S_3 c_i = \mu((1-\alpha)Y + (1-\beta-\theta-\tau)\delta_h(S_2c_p + S_3c_i)) + \overline{m} S_3 c_i(\beta_p - 1)$$

These two equations can be used to derive consumption/output rations:

$$c_p(1 + \delta_h S_2 - (1-\mu)(1-\beta-\theta-\tau)\delta_h S_2 - \tau\delta_h S_2 - S_1\delta_h S_2(1-n_k)(R-1)) - c_i((1-\mu)(1-\beta-\theta-\tau)\delta_h S_3 + \tau\delta_h S_3$$

$$+(\beta_p \overline{m} S_3 + S_1\delta_h S_3(1-n_k))(R-1)) = (1-\mu)((1-\alpha)Y + S_0 Y(1-n_k)(R-1)$$

$$c_i(1+\delta_h S_3-\mu(1-\beta-\theta-\tau)\delta_h S_3-\overline{m}S_3(\beta_p-1))-c_p(\mu(1-\beta-\theta-\tau)\delta_h S_2)=\mu(1-\alpha)Y$$

Solving for $c_p/Y, c_i/Y$ and $q_h IH/Y$, we get:

$$\frac{c_p}{Y}=\frac{\Upsilon_2\Upsilon_6+\Upsilon_3\Upsilon_4}{\Upsilon_1\Upsilon_4-\Upsilon_2\Upsilon_5}$$

$$\frac{c_i}{Y}=\frac{\Upsilon_1\Upsilon_6+\Upsilon_3\Upsilon_5}{\Upsilon_1\Upsilon_4-\Upsilon_2\Upsilon_5}$$

$$\frac{q_h IH}{Y}=\delta_h(S_2\frac{c_p}{Y}+S_3\frac{c_i}{Y})$$

Where

$$\Upsilon_1=1+\delta_h S_2-(1-\mu)(1-\beta-\theta-\tau)\delta_h S_2-\tau\delta_h S_2-S_1\delta_h S_2(1-n_k)(R-1)$$

$$\Upsilon_2=(1-\mu)(1-\beta-\theta-\tau)\delta_h S_3+\tau\delta_h S_3+(\beta_p\overline{m}S_3+S_1\delta_h S_3(1-n_k))(R-1)$$

$$\Upsilon_3=(1-\mu)((1-\alpha)+S_0(1-n_k)(R-1)$$

$$\Upsilon_4=1+\delta_h S_3-\mu(1-\beta-\theta-\tau)\delta_h S_3-\overline{m}S_3(\beta_p-1)$$

$$\Upsilon_5=\mu(1-\beta-\theta-\tau)\delta_h S_2$$

$$\Upsilon_6=\mu(1-\alpha)Y$$

Next we derive the levels of the variables starting with the hours worked. We use the equilibrium in the labour market equating labour demanded to labour supply:

$$(1-\mu)(1-\alpha)Y=c_p l_{pc}^{1+\eta_p}(l_{pc}^{1+\eta_p}+l_{ph}^{1+\eta_p})^{\frac{(\phi_p-\eta_p)}{(1+\eta_p)}}$$

$$(1-\mu)(1-\beta-\theta-\tau)q_h IH=c_p l_{ph}^{1+\eta_p}(l_{pc}^{1+\eta_p}+l_{ph}^{1+\eta_p})^{\frac{(\phi_p-\eta_p)}{(1+\eta_p)}}$$

This gives:

$$\frac{l_{ph}}{l_{pc}} = \left\{ \frac{(1-\beta-\theta-\tau)q_h IH}{(1-\alpha)Y} \right\}^{\frac{1}{1+\eta_p}}$$

Substituting this in the first equation yields:

$$\frac{(1-\mu)(1-\alpha)Y}{c_p} = \left\{ 1 + \frac{(1-\beta-\theta-\tau)q_h IH}{(1-\alpha)Y} \right\}^{\frac{(\phi_p-\eta_p)}{(1+\eta_p)}} l_{ph}^{1+\phi_p}$$

We can now substitute for $\frac{c_p}{Y}$ and $\frac{q_h IH}{Y}$ to get the level of l_{ph}.

$$l_{ph} = \left\{ \frac{\frac{(1-\mu)(1-\alpha)Y}{c_p}}{[1 + \frac{(1-\beta-\theta-\tau)q_h IH}{(1-\alpha)Y}]^{\frac{(\phi_p-\eta_p)}{(1+\eta_p)}}} \right\}^{\frac{1}{1+\phi_p}}$$

We can now use this to get l_{pc}.

$$l_{pc} = \frac{l_{ph}}{\left\{ \frac{(1-\beta-\theta-\tau)q_h IH}{(1-\alpha)Y} \right\}^{\frac{1}{1+\eta_p}}}$$

l_{ih} and l_{ic} can be similarly derived. Once we have the levels of hours worked we can find non-housing output as follows:

$$Y = \left(\frac{K_c}{Y} \right)^{\frac{\alpha}{1-\alpha}} l_{ic}^{\mu} l_{pc}^{1-\mu} = (S_0)^{\frac{\alpha}{1-\alpha}} l_{ic}^{\mu} l_{pc}^{1-\mu}$$

We get the value of $q_h IH$ using:

$$q_h IH = \frac{q_h IH}{Y}.Y$$

Subsequently we find K_h and k_b using:

$$K_h = \frac{\beta q_h IH}{R_k - (1-\delta_k)}$$

$$k_b = \theta q_h IH$$

We can now compute housing production:

$$IH = (l_{ih}^{\mu} l_{ph}^{1-\mu})^{1-\beta-\theta-\tau} K_{h,}^{\beta} k_b^{\theta}$$

Also, the price of housing can be computed:

$$q_h = \frac{q_h IH}{IH}$$

Finally, the levels of consumption of the two types of households:

$$c_p = \{\frac{\Upsilon_2\Upsilon_6 + \Upsilon_3\Upsilon_4}{\Upsilon_1\Upsilon_4 - \Upsilon_2\Upsilon_5}\}.Y;$$

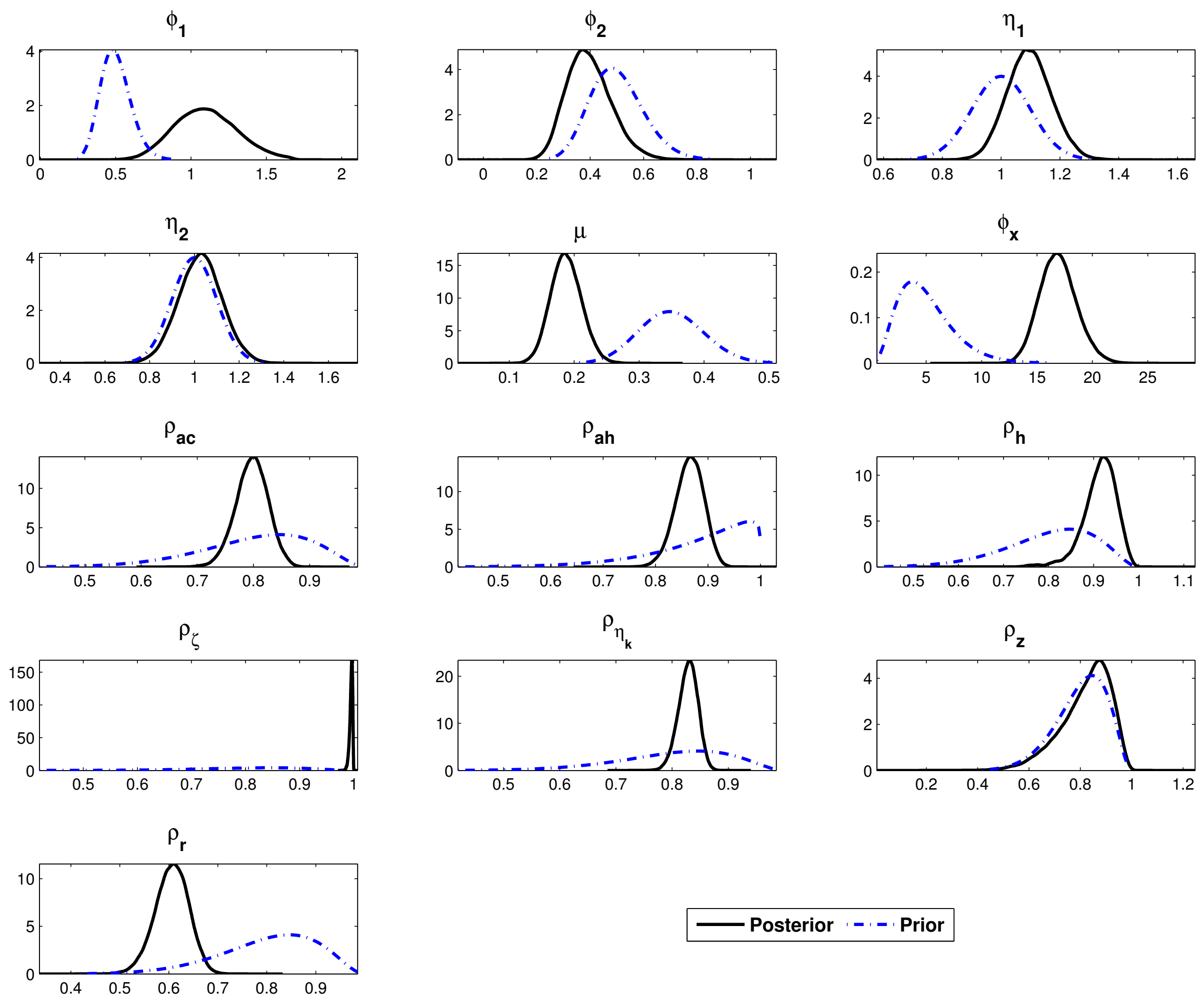
$$c_i = \{\frac{\Upsilon_1\Upsilon_6 + \Upsilon_3\Upsilon_5}{\Upsilon_1\Upsilon_4 - \Upsilon_2\Upsilon_5}\}.Y,$$

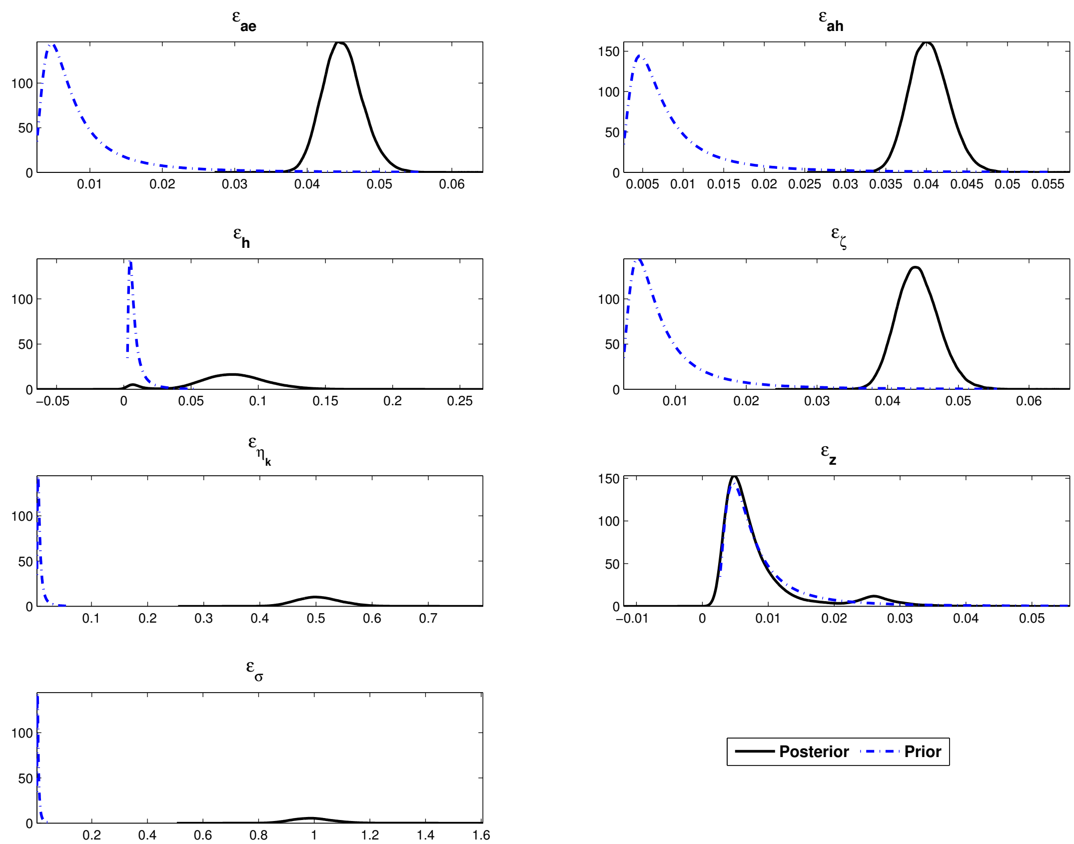
and their housing stock:

$$h_p = S_2 \frac{c_p}{q_h}$$

$$h_i = S_3 \frac{c_i}{q_h}$$

Appendix 1.4: Prior and Posterior




ε_ae
ε_ah
ε_h
ε_ζ
ε_η_k
ε_z
ε_σ
Posterior
Prior

Appendix 1.5: Model Variables and Parameters

Variable	Notation
Patient household consumption	c_p
Impatient household consumption	c_i
Patient household housing	h_p
Impatient household housing	h_i
Weight of housing in the utility function	J_h
Patient household labour; consumption good	l_{pc}
Patient household labour; housing	l_{ph}
Impatient household labour; consumption good	l_{ic}
Impatient household labour; housing	l_{ih}
Deposits; patient households	d_p
Intermediate business input	k_b
Price of intermediate input	p_b
Land	la
Price of land	p_{la}
Return on land	R_{la}
Patient household real wage rate; consumption good sector	w_{pc}
Patient household real wage rate; housing	w_{ph}
Impatient household real wage rate; consumption good sector	w_{ic}
Impatient household real wage rate; housing	w_{ih}
Impatient household borrowing	b_i
Deposit return	R
House prices	q_h
Entrepreneurs' profit diverted to households	$Lump$
Entrepreneur j's net worth	N_j

Entrepreneur j's purchase of capital	K_j
Entrepreneur j's bank loan	B_j
Aggregate Net worth	N
Aggregate capital	K
Aggregate loans	B
Capital price	Q_k
Return on capital	R_k
Marginal product of capital	r_k
Entrepreneurs' idiosyncratic shock	ω^e
Threshold value of idiosyncratic shock (for entrepreneurs survival)	$\bar{\omega}^e$
Contractual gross return on bank loan	R_F
Entrepreneurial leverage	x
Bank's share of gross return on entrepreneurial investment	$\Gamma^e(.)$
Share of return from defaulted loans	$G^e(.)$
Startup transfer of net worth to new entrepreneurs	W^e
External finance premium	efp
Entrepreneurs' consumption	c_e
Consumption good	Y
Non housing productivity	A_c
Housing productivity	A_h
Housing investment	IH
Investment	I
Business capital	K_c
Housing capital	K_h
Total housing stock	H
Total consumption	C

Convex investment costs	$S(.)$

Parameter	Notation
Patient household discount factor	β_p
Impatient household discount factor	β_i
Degree of labour substitution between sectors; patient households	η_p
Degree of labour substitution between sectors; impatient households	η_i
Inverse labour supply elasticity, patient household	ϕ_p
Inverse labour supply elasticity, impatient household	ϕ_i
Survival probability of firms	γ
Entrepreneur bankruptcy cost	μ_e
Proportion of net worth consumed by exiting entrepreneurs	Θ
Investment adjustment cost parameter	φ_x
Capital depreciation rate	δ_k
Housing depreciation rate	δ_h
Share of capital in non-housing production	α
Share of capital in housing production	β
Share of land in housing production	τ
Share of intermediate goods in housing production	θ
LTV ratio	$\bar{m}$
labour income share of impatient households	μ
Non housing technology shock; persistence	ρ_{ac}
Housing technology shock; persistence	ρ_{ah}
Housing preference shock; persistence	ρ_h
Time preference shock; persistence	ρ_z
labour supply shock; persistence	ρ_ς

Investment shock; persistence	ρ_η
Risk shock, persistence	ρ_σ
Non housing technology shock; standard deviation	σ_{ac}
Housing technology shock; standard deviation	σ_{ah}
Housing preference shock; standard deviation	σ_h
Time preference shock; standard deviation	σ_z
labour supply shock; standard deviation	σ_ς
Investment shock; standard deviation	σ_η
Risk shock, standard deviation	σ_r

2 Securitization, Shadow Banking and Regulation

We construct a dynamic stochastic general equilibrium model with an active shadow banking system to study the interaction between traditional and shadow banking. Securitization is motivated by incentives for commercial banks to shift loans from on to off balance sheet entities for regulatory arbitrage. Bank equity is costly, therefore commercial banks cover part of their funding needs by selling loans in the secondary market. These loans are then bundled together to provide marketable liquid deposit like securities. Commercial banks' return is subject to their monitoring effort. Their incentives to monitor reduces as a larger share of loans is sold in the secondary market. Thus, bank monitoring is subject to a moral hazard that limits loan sale in the secondary market. We find that while securitization enhances the resilience to productivity shocks, it exposes the economy to additional vulnerabilities emanating from financial shocks. Government via its credit intermediation policy can play a significant role in containing the impact of financial shocks. Finally, we also look at the macroeconomic and financial impact of capital regulation. In particular, we compare fixed (Basel I) with procyclical (Basel II) capital requirement. In response to a negative technology shock, commercial banks transfer a higher proportion of loans from on to off balance sheet i.e. from regulated commercial to unregulated shadow banking sector under Basel II. Furthermore, bank monitoring falls leading to a decline in overall return on bank portfolio.

2.1 Introduction

Decades prior to the global financial crisis were marked by a changing financial landscape with a shift from traditional commercial banking towards securitized banking. Commercial banking facilitated credit, maturity and liquidity transformation by issuing short-term deposits to provide long-term loans. However, growth in innovation, financial technology, regulation and competition led to an evolutionary change in the whole financial services industry (see e.g. Pozsar (2008), Rosen (2009) and Blair (2010)). A series of regulatory changes and innovations eroded competitive advantage of banks and led to the growth of shadow banking[9]. Shadow banking system undertook securitized banking by issuance of tradable securities against collateral of an underlying pool of assets, including mortgages and business loans. As shadow banking and securitization grew in prominence, it exposed the economy to financial vulnerabilities leading up to systemic instability culminating in credit crunch and global financial crisis. This paper provides a theoretical framework for understanding the role and operations of shadow banking, associated risks, and key regulatory and broader policy implications.

Securitization is one of the most important financial innovations that occurred in the last part of the century. Several reasons have been put forward by academic studies for the growth of securitization. For example, a liquidity hypothesis suggests that securitization allows banks to transform illiquid financial claims into tradable ones via a pooling and pass-through mechanism (Greenbaum (1986), DeMarzo and Duffie (1999), DeMarzo (2003) and Martin-Oliver et. al. (2007)). With the new funds raised, they can increase lending. In this setup, soon after the loan is granted, it is packaged into a bundle of other mortgages, given a risk assessment by a rating agency and sold out through asset backed securities (ABS). According to a hypothesis of regulatory arbitrage, securitization allows banks to shift loans off balance sheet and thus reduces the costly bank capital required as per minimum regulatory capital ratios (Greenbaum and Thankor (1987), Pennacchi (1998)). Calomiris and Mason (2004) and Ambrose, Lacour-Little and Sanders (2005) show that securitization of credit cards and mortgages, respectively, respond to regulatory capital arbitrage. Similarly, Thomas (2001) finds that securitization alleviates the regulatory burden. A specialization hypothesis argues that securitization facilitates separation of loan

[9]The term shadow banking was coined by McCulley (2007) and the Financial Stability Board (FSB, 2011) defines shadow banking broadly as "credit intermediation involving entities and activities outside the regular banking system". Other authors give complementary definitions that emphasize different aspects of shadow banking for example Adrian and Ashcraft (2012) say it is "a web of specialized financial institutions that channel funding from savers to investors through a range of securitization and secured funding techniques". Pozsar, Adrian, Ashcraft and Boesky (2013) emphasize that "shadow banks [unlike] traditional banks lack access to public sources of liquidity such as the Federal Reserve's discount window, or public sources of insurance such as Federal Deposit Insurance".

origination, servicing, and bond/ABS administration and thus capitalizes on specialization in each step of intermediation (Greenbaum (1986) and Hess and Smith (1988)). Finally, as security issuers may possess private asymmetric information regarding asset returns, they can use pooling and tranching to diversify risk (DeMarzo 2005).

The main purpose of this paper is to provide a model with securitization that deepens our understanding of the interaction between traditional banking and shadow banking. In our model, the first three hypotheses listed above are main drivers of securitization. Commercial banks cannot compete with shadow banks that are not subject to tight capital constraints as the former. Thus, the presence of regulatory arbitrage leads to a shift from traditional loan issuance and funding (originate-to-hold) to a originate-to-distribute model. Instead of holding loans on the balance sheet, the originator could easily sell and transfer them off balance sheet. This creates space for a new financial entity - shadow banks - where these loans are transferred.[10] As per the specialization hypothesis, these shadow banks act as the workhouse of securitization where issued loans are underwritten and sold as rated asset backed securities (ABS) linked to the loan portfolio. Unlike the illiquid loans, which cannot be resold (other than to the shadow banks), the ABS underwritten by the shadow banks are viewed as liquid securities as per the liquidity hypothesis.

Thus, the model by adding shadow banks and ABS issuance to a canonical business cycle model, allows for a non-trivial role for credit intermediation in the economy. Traditional banks finance their lending to entrepreneurs by issuing deposits, equity and via loan sales. Since these banks are subject to regulatory capital requirement, loan sales allow them to finance loans less expensively than costly equity issuance. However, the extent of banks' loan sale is limited by a moral-hazard problem, as shown in Pennacchi (1998) that arises from the diminished incentive by banks to efficiently monitor and service loans after they have been sold. This defines the size of shadow banking system in the economy.

The second main contribution of the paper is to encompass the most relevant

[10]To provide regulatory relief, an explicit sale of the loans is required from the commercial bank balance sheet to shadow banks' balance sheet.

aspects of the macroprudential concern in a single model. Regulation is at the heart of our model setup, which provides incentives for loan sale in the secondary market and growth of shadow banking. The model allows for a study of the most relevant interlinkages between the real and the financial sectors and thereby facilitates the interaction between financial and macroeconomic stability. The construction of this DSGE model is very distant from the typical models in use prior to 2007, which were seen as ignoring the relevance of financial intermediation and financial stability. The model therefore provides analytical tools to properly consider the impact of prudential policies on macroeconomic performance and financial stability. Furthermore, the model provides for an interaction between asset quality and leverage where the moral hazard problem faced by the banks in monitoring links off balance sheet finance and the quality of bank loan portfolio.

We find that securitization dampens the response of the economy to negative total factor productivity shocks by improving the resilience of the financial system however shocks emerging within the financial system expose the economy to sustained vulnerabilities. An increase in bank risk leads to transfer of higher proportion of loans to the secondary market. This increases the moral hazard problem facing commercial banks who respond by reducing the monitoring effort thereby lowering the effective return on bank portfolio. We find that government via its credit intermediation policy, in form of direct loan purchase, can play a positive role in containing the impact of such shocks in the economy. Such policies are discussed elsewhere in the literature including Gertler and Karadi (2011) and Meeks et. al. (2014) who find similar positive effects. Finally, we also look at the macroeconomic and financial impact of capital regulation. We find that there is a transfer of loans from on to off balance sheet i.e. from regulated commercial to unregulated shadow banking sector under Basel II rules with procyclical capital requirement.

The notion of shadow banking encompasses a wide universe of financial activities and entities, not all of which are captured in this paper. In particular, we take a stylized approach wherein shadow banks are the sole workhouse of securitization. The simplification aligns well with our aim of looking at the securitization dynamics arising from regulatory arbitrage. Furthermore, we do not model any type of risk transfer motive behind shadow banking, or the sponsorship relationship between traditional banks and shadow banks[11]. The modeling of these phenomena is beyond the scope of this paper. Instead, we focus on shadow banking emerging from regulatory arbitrage and the interaction between securitization, shadow banking and macroeconomic instability.

The remainder of the paper is structured as follows. We begin with a brief overview of the literature in next section. In section three, we will analyze the development of specific institutions of the shadow banking system. Furthermore, we will examine instruments and transaction used by shadow banking institutions, e.g. ABS issuance. Thereafter, section four describes the general equilibrium model including households, entrepreneurs, firms and the financial system. Section five present model calibration and section six explains results from simulations and policy experiments. Finally, we conclude in section seven.

2.2 Related Literature

This paper draws from different strands of literature related to supply side dynamics of credit growth, bank capital channel and the recently growing work on shadow banking.

The borrower or demand side mechanisms relating to credit growth and business cycle have been extensively studied starting from the financial accelerator mechanism of Bernanke, Gertler, and Gilchrist (1999). The recent financial crisis however brought to light the important role played by the financial system in credit generation and growth. Following that, there has been a surge in papers attempting to model the supply side dynamics of credit growth. Some notable examples include Gerali et. al. (2010), Dib (2010), Meh and Moran (2010), Gertler and karadi (2011), and Gertler et. al. (2012). Gerali et. al. model an imperfectly competitive banking sector subject to exogenous bank capital requirement for the euro area and find that the shocks to the banking sector explain the major part of fall in output in

[11] For risk transfer see, for example, Hobijn and Ravenna (2010). For sponsorship relationship and specific models on special purpose vehicles see, for example, Parlatore (2016).

2008. Dib (2010) embed an active banking sector with interbank market and bank capital into a standard financial accelerator model. Meh and Moran (2010) analyze the bank capital channel of transmission by introducing a moral hazard problem between banks and investors which can be mitigated by banks investing their own capital in entrepreneurial projects. In a similar vein, Gertler and Karadi (2011) introduce an agency problem between banks and depositors that imposes an endogenous constraint on intermediary's leverage ratio and thereby linking overall credit flows to bank equity capital. Gertler et. al. (2012) go a step further and allow banks to raise outside equity as an alternative to short term debt (deposits) to provide loans. One common feature of all these studies is the inclusion of bank capital either in the form of exogenous capital requirements or endogenous bank leverage ratios. This paper is similar to the extent that we also look at the supply side dynamics of financial intermediation and bank capital requirements. However, all these papers take banks to represent the entire financial system. This paper allows for heterogeneity, namely in the form of a stylized shadow banking sector that focuses on securitization, thereby generating an additional source of dynamics.

The financial stability issues around shadow banking, and securitization in particular, have by now been widely discussed (Adrian and Shin, 2008). Rosen (2009) sketches the evolution of the U.S. financial system from traditional banking to shadow banking. Furthermore, the author focuses on the role of shadow banking and describes the crisis as a logical outcome of increasing interconnectedness and leverage of financial intermediaries, overconfident investors and rapid growth in structured finance. Pozsar et al. (2013) and Pozsar (2008) provide a detail catalogue of the types of shadow banks. They map and describe shadow banking as a daisy chain of financial intermediaries that conduct credit intermediation. Stein (2010) provides a short overview of the securitization process, how it developed in the event of the crisis and how it is conducted within the shadow banking system. Furthermore, the article also explains the fragility of the securitization market during the crisis and yields some regulatory approaches of securitization and suggests implications for future regulation. Poschmann (2012) explores the nexus between traditional and shadow banking and provides a stylized descriptive framework of a banking sector with NBFI (Non

Bank Financial Institutions) in a macroeconomic context. Claessens et. al. (2012) focus on securitization and collateral intermediation function of the shadow banking system in a descriptive set up. In particular, they posit that the securitization function of shadow banking provides the wholesale/institutional investors with deposit like safe investments[12]. At the same time it also gives banks an access to highly liquid (high rated) securitized debt, which can be used for repo funding and to increase leverage. The securitization process also provides banks with an opportunity to bypass regulatory capital constraints by shifting loans to off balance sheet entities (shadow banks); (Poschmann (2012) and Stein (2010)).

The existing literature concentrates on descriptive analysis: how the system developed before and within the crisis and what are the important aspects that led to the growth of certain parts of the financial system. Until now, few papers have attempted to model shadow banking in a macroeconomic context. We aim to fill this gap in the literature by embedding a traditional and shadow banking sector in an otherwise standard business cycle model.

Verona, Martins, and Drumond (2014) introduce shadow banks as a distinct class of financial intermediaries into a DSGE model. In their model, shadow banking differentiates bond financing from bank finance with the former done by shadow banks and latter by commercial banks. The model however, does not feature securitization, and shadow banks have no direct interaction with the commercial banking system. Goodhart, Kashyap, Tsomocos, and Vardoulakis (2012) study a two period general equilibrium model with heterogeneous households, banks and shadow banks. The authors generate a role for shadow banking by assuming lower risk aversion amongst non-banks than amongst banks. They find that when borrowers default the shadow banks pass losses back to the rest of the financial system and kick off a fire sale dynamic that further tightens the financial constraints. Hobijn and Ravenna (2010), introduce an adverse selection problem into a New Keynesian monetary policy model.

[12]Global corporate short-term savings grew from less than \$50 billion in 1990 to more than \$750 billion in 2007 and over \$1.2 trillion by the end of 2010 (Pozsar et. al. (2013)). Together, corporate and asset management ("institutional") cash pools have grown over the past decade by a factor of 30 to equal almost half of traditional deposits (Claessens et. al. (2012)).

The asymmetric information held by borrowers leads to an endogenous sorting of loans into those directly held by originators, and those sold into securitization pools of differing qualities[13]. Meeks et al. (2014) introduce in the framework of Gertler and Karadi (2011) a shadow banking sector that funds itself from traditional banks, and assume that traditional banks have a weaker friction when investing in shadow bank liabilities. They show that endogenous constraints on shadow bank's net worth can amplify the shocks due to limited ability of commercial banks to securitize. Ferrante (2015) consider a model with traditional and shadow banking intermediation where banks can finance risky projects and affect their quality by exerting costly screening effort. They find that while shadow banking enhances credit intermediation, it also makes the economy more fragile. None of these studies approach the growth of shadow banking from regulation perspective, a gap that we fill in this paper.

This paper builds on the work of Christiano et. al. (2014). They extend the framework of BGG (1999) with costly state verification in the market for entrepreneurial loans. The returns from entrepreneurial investment are subject to an idiosyncratic variable whose cross-sectional standard deviation is regarded as risk. They model this risk to be time varying. They find that when risk is high, the credit spread is high, and credit extended to entrepreneurs is low. Furthermore, risk shocks are found as the most important driver of business cycles. While the focus of their paper is to study the importance of entrepreneurial risk shocks in driving business cycle fluctuations, we augment their framework with a heterogeneous banking sector to study the propagation of financial shocks, in particular, risk shock in the banking system. We build on their model in following important ways 1.) Since the focus of this paper is to study the regulatory arbitrage motive behind shadow banking, we develop a banking sector that is subject to a regulatory capital constraint. Capital regulation and macroprudential policies have an economically important role as they arise to tackle two key distortions. First distortion stems from banks' limited liabil-

[13] We refrain from any endogenous sorting of loans due to adverse selection however that would further exacerbate the situation. In our model, commercial bank transfer a representative pool of loans into off balance sheet rather than a sorting based on quality. Therefore, securitization in this model is motivated by a desire to receive regulatory relief rather than to transfer risky loans off balance sheet.

ity and the existence of deposit insurance. Deposit insurance provides incentives for banks to take on risk at the expense of the deposit insurance agency. The second distortion arises from the assumption that depositors suffer some transaction costs in the event of a bank failure despite the presence of deposit insurance. Clerc et al. (2015) study macroprudential policies in a macroeconomic model with default in a similar setting. 2.) We introduce shadow banks in the model to facilitate loan sale in the secondary market, which are then securitized. Traditional banks are subject to capital requirements and therefore find it profitable to shift some of the loans to shadow banks, which are not regulated. The size of these loan sales is based on a moral-hazard problem similar to Pennacchi (1988). Traditional banks undertake costly monitoring that affects the return on its investment. This loan monitoring is unobservable to loan buyers in secondary market, which creates diminished incentive for banks to efficiently monitor and service loans after they have been sold. This limits the amount of loans sold in the secondary market and therefore the size of the shadow banking sector. 3.) Finally, shadow banks finance their operations by underwriting asset backed securities. The underwriting services are usually provided by investment banks, much as a corporation would use an investment bank to underwrite the sale of bonds or stocks[14]. The market for loan purchase and underwriting securities by shadow banks is assumed to be monopolistically competitive. This is consistent with empirical evidence for the U.S for bond underwriting. Fang (2005) shows that the largest five investment banks underwrite more than 60 percent of all deals, and the largest fifteen banks account for roughly 95 percent of all deals. We expect a similar pattern for ABS underwriting as well.

Our model belongs to the class of DSGE models and we solve it with standard methods, i.e. perturbation methods. This is different from a relatively recent body of work, which uses a continuous time methodology to solve full dynamics of models with financial frictions. For example, Brunnermeier and Sannikov (2012) build on

[14]Typically, a shadow bank would hire an investment bank to sell its securities. The investment bank (the underwriter) acts as an intermediary between the issuing entity and the ultimate investors. See Ellis, Michaely, and O'Hara (2000) for an in-depth analysis of the underwriting process in bond finance.

the BGG model in a continuous time frame. The model has two types of agents - productive experts and less productive households. Because of financial frictions, the wealth of experts is important for their ability to buy physical capital and use it productively. They find that the systems reaction to shocks is highly nonlinear. While the system is resilient to most shocks near the steady state, unusually large shocks are strongly amplified. Furthermore. most of the effects are asymmetric and only arise in a downturn.

2.3 Institution, Entities and Instruments

This section provides a brief overview of the institutions and financial instruments that constitute the shadow banking system with an emphasis on mapping the financial structures to the stylized set up of the model. Following Pozsar (2008) and Poschmann (2012) we classify entities and instruments as those involved in the issuance of loans (risk originators), creation of securities (loan warehousing and ABS issuance) and institutions that invest in these instruments (risk bearers).

Risk originators comprise of depository institutions like the commercial banks, investment banks and broker-dealers. In this paper, we only focus on depository institutions, in particular, on the commercial banks which accounts for 80 to 90% of the total assets of depository institutions in the United States. Deposits dominate the liability side of depository institutions, however they are also required to hold a minimum regulatory capital in accordance with the Basel rules.

As regards to the shadow banks, we take a narrow view and concentrate on the securitization process involving ABS issuance. Securitization denotes a financing process where illiquid assets from the risk originators are pooled and transformed into liquid financial instruments. The securitization process is conducted by shadow banks. They are thinly capitalized and loan sale involves a true sale of assets from risk originators to shadow banks. This transaction allows the originator to free capital and therefore, reduce capital requirements. Shadow banks then issue ABS to fund purchase of loans in the secondary market. ABS is a collective term and encompasses traditional ABS, mortgage backed securities (MBS), Collateralized debt obligations (CDO) and asset backed commercial papers (ABCP) depending on the underlying pool of assets. Traditional ABS mostly consists of trade and credit card receivables, consumer credits and lease contracts. MBS, a large part of ABS, are ordinarily based on a pool of residential and commercial mortgages. CDOs are securitized loan and bond portfolios, including CLO - collateralized loan obligations and CBO - collateralized bond obligations.

Finally, we have the risk bearers who invest in the securitized products and serve as wholesale or shadow bank depositors. Traditionally, these are the institutional investors comprising mostly of mutual funds and money market funds. These institutional investors raise money from individuals, households and businesses, through the sale of fund shares, which is then invested in mainly short term high credit quality and liquid debt instruments like ABS. To simplify the analysis and avoid introducing too many new agents in the model, we treat household as final buyers of these securities[15].

2.4 The Model

The Economy consists of seven types of agents: households, entrepreneurs, commercial banks, shadow banks, consumption good producer, capital good producer and deposit insurance agency. The economic modeling of households, entrepreneurs, consumption good producer and capital goods producer parallels that in Christiano et. al (2014) wherein inspite of some differences in modeling assumptions, the dynamics are similar[16].

[15]Alternatively, the model can also be closed by adding a new class of agent i.e. the wholesale depositors. They would be the depositors in shadow banking system by purchasing ABS securities. Wholesale depositors on the other hand, would issue mutual fund shares to households to raise money.

[16]In particular, there are following differences in modeling assumption for these agents. In Christiano et. al. (2014), households are assumed to build raw capital (subject to convex adjustment costs) in the economy instead of competitive capital good producer. The is done to limit the number of agents in the economy and does not alter the dynamics. Entrepreneurs have the same dynamics as in Christiano et. al (2014). However, since we work with a real business cycle model, nominal

Households. Households are risk averse and infinitely lived and derive utility from a storable consumption good. They provide labour to firms and funding in the form of deposits, bank equity and securities, to the financial sector. The consumption good acts as a numeraire in our economy and its price is normalized to one.

Entrepreneurs. Entrepreneurs are risk neutral agents specialized in owning and maintaining the stock of physical capital, which they rent in each period to the firms involved in the production of the consumption good. At the beginning of each period, entrepreneurs buy capital using their net worth and borrowed loans from the commercial banks as in BGG. These loans are subject to limited liability and default risk, and recovering residual returns from bankrupt entrepreneurs requires banks to pay verification costs.

Consumption good producer. There is a perfectly competitive consumption good producing sector which combines rented capital from entrepreneurs and labour from households to produce consumption good using a standard cobb-douglas production sector.

Capital goods producers. Capital goods producer are perfectly competitive and owned by the households. These firms optimize intertemporally in response to changes in the price of capital and are subject to investment adjustment costs in conversion of consumption goods into capital. This sector is not directly affected by financial frictions.

The rest of the agents in the economy relating to the financial system i.e. commercial banks and shadow banks are specific to our model and are described below.

Commercial banks. Commercial banks are perfectly competitive and risk neutral in the credit markets when providing loans to the firms. We differ from BGG and Christiano et. al. by introducing macroprudential regulation on bank balance sheet. Bank funding in our model comprise of debt in the form of deposits from households, equity by issuing bank capital shares and loan sales. Banks are subject to regulatory capital requirement that provides incentives for loan sales to minimize costs arising from costly bank capital. However, the extent of banks' loan sale is limited by a

frictions - both in production of final good and supply of labour - are not included.

moral-hazard problem, as shown in Pennacchi (1998) that arises from the diminished incentive by banks to efficiently monitor and service loans after they have been sold. In addition, banks are faced by an idiosyncratic risk, which in equilibrium implies that some banks cannot service their deposit payments and thus are subject to defaults.

Shadow banks. Shadow banks are not subject to regulation, are thinly capitalized and are buyers of loans in the secondary market. They are funded by underwriting ABS against loan pools. Unlike commercial banks which specialize in credit intermediation i.e. providing loans to final borrowers (firms), shadow banks specialize in securitization and cannot directly provide loans to the final borrowers.

Deposit insurance agency. Deposit insurance agency recoups earnings from failed banks (net of monitoring costs) and service household deposits. It is assumed to ex-post balance its budget by imposing lump sum taxes on households.

2.4.1 Households

The households derive utility from consumption C_t, and leisure, $1 - L_t$, where L_t is the hours worked[17]. A representative household maximizes the following utility function.

$$\max_{C_t, L_t, D_t, ABS_t, Z_t} E_t \sum_{t=0}^{\infty} \beta^t (\log C_t + \frac{\eta}{(1+\varphi)}(1 - L_t)^{(1+\varphi)}) \tag{2.1}$$

The parameter $0 < \beta < 1$ is the discount factor, $\eta > 0$ is the weight attached to leisure in the utility function and $\varphi > 0$ is the inverse of Frisch wage elasticity of labour supply. Households can either save in the form of one-period deposits D_t with retail bank that pays a non-contingent risk-less rate $\widetilde{R}_t$, invest in bank shares Z_t, or buy asset backed securities, ABS_t, from shadow banks with return rate $R_{m,t}$. A representative household enters period t with D_{t-1} units of deposits, Z_{t-1} units of bank shares and ABS_{t-1} units of shadow bank deposits, which pays a gross real return of $\widetilde{R}_t$, $R_{z,t}$, and $R_{m,t}$, respectively between periods $t-1$ and t.

[17]See appendix 2.2 for a complete list of model variables and parameters.

Every period t, households provide labour to firms in return for real wage income $w_t L_t; w_t$ is the economy wide real wage. In addition, they also receive lump sum transfers, $Lump_{e,t}$ from exiting entrepreneurs, as well as profits from shadow banks $(\Pi_{I,t})$. The overall household income is allocated to consumption, commercial and shadow bank deposits.

The household budget constraint can be written as:

$$C_t + D_t + ABS_t + Z_t \leq w_t L_t + \widetilde{R}_t D_{t-1} + R_{m,t} ABS_{t-1} + R_{z,t} Z_{t-1} + \Pi_{I,t} + Lump_{e,t} - \Theta_z \frac{Z_t^2}{2} - TD_t \tag{2.2}$$

Where

$$\widetilde{R}_t = R_{t-1}(1 - \Omega PD_t) \tag{2.3}$$

The term, $\Theta_z \frac{Z^2}{2}$, represents costs associated with equity transactions, with $\Theta_z > 0$ denoting an adjustment cost parameter. R_{t-1} is the fixed (gross) interest rate received at t on savings deposited at banks in t-1. The principal and interest of bank deposits are fully guaranteed by a deposit insurance agency (DIA) that, for simplicity, is assumed to ex post balance its budget by imposing a lump sum tax TD_t on households. However, in case a bank fails, households incur a linear transaction cost Ω in recovery of the funds. PD_t is the fraction of deposits in banks that fail in period t. This transaction cost introduces a link between banks' probability of default and their funding cost via deposits. Following Clerc et. al. (2015), it is modeled in a way that does not affect the incentives of individual banks to take excessive risks at the expense of the DIA.

A representative household chooses consumption (C_t), labour (L_t), deposits (D_t), bank share (Z_t) and securities (ABS_t) to maximize the lifetime utility function subject to individual period budget constraint.

2.4.2 Entrepreneurs

Entrepreneurs are assumed to be risk-neutral and have finite horizons: Specifically, we assume that each entrepreneur has a constant probability γ of surviving to the next period (implying an expected lifetime of $1/(1-\gamma)$). The assumption of finite horizons for entrepreneurs is intended to capture the phenomenon of ongoing births and deaths of firms, as well as to preclude the possibility that the entrepreneurial sector will ultimately accumulate enough wealth to be fully self-financing. A fraction Θ of the total net worth owned by those entrepreneurs who close business is consumed upon exit, and the remaining fraction of their net worth is transferred as a lump-sum payment to households. We assume the birth rate of entrepreneurs to be such that the fraction of agents who are entrepreneurs is constant. New entrepreneurs entering in period $t+1$ receive a 'start-up' transfer of net worth, W^e[18].

There is a large number of entrepreneurs, each indexed by j. An entrepreneur's state in period t is its level of net worth, $N_{t,j}$. In each period, an entrepreneur combines its net worth, $N_{t,j}$, with a bank loan, $B_{t,j}$ to purchase new, installed physical capital, $K_{t,j}$ from the capital producer ($B_{t,j} + N_{t,j} = Q_{k,t}K_{t,j}$), where $Q_{k,t}$ is the price of capital. The entrepreneur then experiences an idiosyncratic shock, ω^e, to its stock of capital. The purchased capital, $K_{t,j}$ is transformed into $\omega^e K_{t,j}$ where ω^e is a log-normally distributed random variable which is independently and identically distributed across entrepreneurs with an expected value of one, and density and cumulative distribution function denoted by $f(.)$ and $F(.)$, respectively. The shock therefore is a simple way to generate a non-trivial default rate on entrepreneurial loans. The setup for entrepreneurs is similar to as studied in the previous chapter.

The gross return per unit of capital obtained in period t+1 out of capital owned in period t is:

$$R_{k,t+1} = \frac{r_{k,t+1} + (1-\delta)Q_{k,t+1}}{Q_{k,t}} \tag{2.4}$$

[18]In BGG (1999), newly entering entrepreneurs have positive net worth by supplying a unit of labour inelastically to be used in the production of consumption good. We follow later papers, for example Christiano, Motto and Rostagno (2014) who assume lump-sum transfer of start-up capital for newly entering entrepreneurs.

Where δ is the depreciation rate of capital and r_k is the marginal return on capital.

Let $R_{F,t}$ be the contractual gross interest rate on the loan taken from the bank in period t. Then the total contracted repayments due to banks at period t+1 is $R_{F,t}B_{t,j}$. The gross return that an entrepreneur obtains on the capital investment undertaken in the previous period is $R_{k,t+1}Q_{k,t}\omega^e_{t+1}K_{t,j}$. We assume limited liability for entrepreneurs whereby they cannot be held liable for any contracted repayments above the gross return, in which case they default on their bank loans. In particular, the entrepreneur will repay loan at $t+1$ when

$$R_{k,t+1}Q_{k,t}\omega^e_{t+1}K_{t,j} \geq R_{F,t}B_{t,j}$$

Which provides the threshold value of idiosyncratic shock, $\bar{\omega}^e_{t+1}$, above which the entrepreneur can repay its loan.

$$\bar{\omega}^e_{t+1} = \frac{R_{F,t}B_{t,j}}{Q_{k,t}K_{t,j}}.\frac{1}{R_{k,t+1}} \tag{2.5}$$

We define $x_t = \frac{Q_{k,t}K_{t,j}}{N_{t,j}}$ as the entrepreneurial leverage, defined as the ratio of entrepreneurs' purchase to net worth at t. We have left off the indexing j on x_t, $\bar{\omega}_{t+1}$, and $R_{F,t}$. This is to minimize notation and is a reflection of the fact (see below) that the equilibrium value of these objects is independent of the state variable ($N_{t,j}$). When an entrepreneur defaults on its loan, following the Costly State Verification (CSV) approach, we assume that the lender must pay a cost if he or she wishes to observe the borrower's realized return on capital, which it then seizes. This auditing cost is interpretable as the cost of bankruptcy (including for example auditing, accounting, and legal costs, as well as losses associated with asset liquidation and interruption of business). The monitoring cost is assumed to equal a proportion μ_e of the realized gross payoff to the firm's capital, i.e., the monitoring cost equals $\mu_e R_{k,t+1}Q_{k,t}\omega^e_{t+1}K_{t,j}$. Thus, under certain realizations of the idiosyncratic shocks, entrepreneurs will go bankrupt, especially when their ex-ante leverage x_t is high.

We follow BGG notation for the division of return from entrepreneurial investment between entrepreneurs and banks. The share of gross return (gross of verification costs) accruing to the bank is:

$$\Gamma^e(\bar{\omega}^e_{t+1}) = \int_0^{\bar{\omega}^e_{t+1}} \omega^e_{t+1} f^e(\omega^e_{t+1}) d\omega^e_{t+1} + \bar{\omega}^e_{t+1} \int_{\bar{\omega}^e_{t+1}}^{\infty} f^e(\omega^e_{t+1}) d\omega^e_{t+1} \tag{2.6}$$

The part of these returns that comes from defaulted loans is:

$$\mathrm{G}^e(\bar{\omega}^e_{t+1}) = \int_0^{\bar{\omega}^e_{t+1}} \omega^e_{t+1} f^e(\omega^e_{t+1}) d\omega^e_{t+1} \tag{2.7}$$

Therefore, the share of returns accruing to entrepreneurs can be written as $1 - \Gamma^e(\bar{\omega}^e_{t+1})$. The share (net of verification costs) that the bank appropriates can be written as $\Gamma^e(\bar{\omega}^e_{t+1}) - \mu_e G^e(\bar{\omega}^e_{t+1})$.

Entrepreneurs maximize their expected return subject to participation constraint for the bank. In particular, they choose the leverage, x_t, and default threshold $\bar{\omega}^e_{t+1}$ to maximize:

$$\max_{x_t, \bar{\omega}^e_{t+1}} \; E_t \; [(1 - \Gamma^e(\bar{\omega}^e_{t+1})) R_{k,t+1} x_t N_{t,j}]$$

Subject to banks' participation constraint:

$$E_t[(\Gamma^e(\bar{\omega}^e_{t+1}) - \mu_e G^e(\bar{\omega}^e_{t+1}))] R_{k,t+1} x_t = \widetilde{R}_{F,t+1}(x_t - 1) \tag{2.8}$$

Where $\widetilde{R}_{F,t+1}$ is the return on a well diversified portfolio of bank loans and will be discussed in detail in the next section. The main difference from chapter one is that the cost of raising funds for commercial banks is no longer the risk free rate. The participation constraint captures the fact that banks would provide loans to entrepreneurs only if the return is sufficient to cover their cost of raising funding.

Aggregation - The quantity of raw capital purchased by entrepreneurs in period t is given by summing the capital across all entrepreneurs. Market clearing in the capital services require that supply of capital, K_t must equal firms' demand for capital (discussed later).

$$K_t = \sum K_{t,j}$$

The aggregate entrepreneurial net worth at the end of period t can be written as $(1 - \Gamma(\bar{\omega}_{t+1}))R_{k,t+1}Q_{k,t}K_t$. Once a fraction $(1 - \gamma)$ of the entrepreneurs exit the scene and the newly entering entrepreneur receive lump sum payments W^e. The law of motion of entrepreneurial net worth, N_{t+1} can be written as:

$$N_{t+1} = \gamma(1 - \Gamma(\bar{\omega}_{t+1})R_{k,t+1}Q_{k,t}K_t + W^e,$$

where W^e is the 'start-up' transfer of net worth received by new entering entrepreneurs in period t+1. The aggregate net worth can be further written as:

$$N_{t+1} = \gamma\{R_{k,t+1}Q_{k,t}K_t - [R_t + \mu_e \frac{\int_0^{\bar{\omega}_{t+1}} \omega_{t+1} f(\omega_{t+1}) d\omega_{t+1} Q_{k,t}K_t}{Q_{k,t}K_t - N_t}](Q_{k,t}K_t - N_t)\} + W^e \tag{2.9}$$

The object in braces in (2.9) represents receipts by entrepreneurs active in period t+1 minus their payments to banks. The object in square brackets is the gross rate of return paid by entrepreneurs to banks. The external finance premium on loans between period t and t+1 can therefore be defined as:

$$efp_{t+1} = \mu_e \frac{\int_0^{\bar{\omega}^e_{t+1}} \omega^e_{t+1} f^e(\omega^e_{t+1}) d\omega^e_t Q_{k,t}K_t}{Q_{k,t}K_t - N_t}$$

The remaining two financial variables to determine are the aggregate quantity of debt extended to entrepreneurs in period t, B_t, and their state-contingent interest rate, $R_{F,t}$. The aggregate borrowing is given by the sum of borrowing of all entrepreneurs.

$$B_t = \sum B_{t,j} = Q_{k,t}K_t - N_t$$

Finally, the interest rate takes the form (aggregating equation 2.5 and solving) :

$$R_{F,t} = \bar{\omega}^e_{t+1} R_{k,t+1} (\frac{x_t}{x_t - 1})$$

The entrepreneurs that exit the economy in t+1 consume a fraction Θ of their net worth. Therefore, their aggregate consumption is given by:

$$C_{e,t+1} = \Theta \frac{(1-\gamma)}{\gamma} (N_{t+1} - W^e) \tag{2.10}$$

Where $\frac{(N_{t+1} - W^e)}{\gamma}$ is the average net worth held by an entrepreneur who exits the economy at the end of the current period and $(1-\gamma)$ is the share of exiting entrepreneurs. Finally, the lump sum transfers made to patient households is $(1 - \Theta)\frac{(1-\gamma)}{\gamma}(N_{t+1} - W^e)$.

2.4.3 Commercial Banks

Commercial banks are risk neutral and perfectly competitive in the credit market. They collect deposits, D_t, from households and also raise funds in the form of bank capital, Z_t. To provide loans B_t to the final borrowers (entrepreneurs), banks must fulfill a certain regulatory capital requirement. This capital requirement is defined as the ratio of bank capital to bank assets. However, in practice banks hold more capital than the minimum requirement, which is motivated by the presence of gains associated with bank capital buffer. To gain relief from the regulatory constraint, banks can shift a part of the loan, $B_{s,t}$, away from their balance sheet to the shadow banks. Therefore, commercial banks not only originate loans for the primary borrowers, but also sell loans in the secondary market[19]. We assume that banks sell a portion, b_t, of the return on all loans, retaining the portion $(1 - b_t)$. Thus, a representative bundle of loan is sold in the secondary market. Bundling is important as it helps banks to overcome an adverse selection problem when they come to sell loans. If private information about individual loan cannot be credibly communicated to the seller, no creditor in the secondary market would be willing to buy an individual

[19]For details on bank funding via loan sales see, for example, Pennacchi (1988), Berger and Udell (1993) and Gorton and Pennacchi (1995).

loan under the fear of being sold the worst class of loans. Bundling of loans destroys private information and thereby ensures that a fair mix of loans is transferred and not just lemons[20]. Therefore, the shift of loans off balance sheet is motivated by regulatory reasons rather than the desire to remove the worst loans from commercial banks' balance sheet.

Furthermore, banks' effective return on its portfolio is subject to its monitoring. One way of thinking of this is that bank managers can divert a part of return for their own personal benefit. In such a case, monitoring of bank managers would be beneficial in increasing the final return to the bank equity holders. Alternatively, one could also think of a possibility where the manager of bank may shirk since the final return is accrued to shareholders. In such a case, an inefficiency would arise where a part of return would be lost. Banks may then undertake costly effort to increase the final return. This could be in the form of effort (e) exerted in screening or monitoring[21]. We adopt the standard assumption that the level of bank credit services is unobservable so that the bank and loan buyers cannot write contracts that are contingent on the level of these services. Therefore, loan sales involve a moral hazard problem, namely, that the bank may not exert the monitoring effort at the most efficient level. Importantly, monitoring is costly, since it entails a non-pecuniary convex cost $c(e_t) = \frac{\tau_1}{2}(e_t^2 + \tau_2 e_t)$, where τ_2 is allowed to be negative, meaning that there could be some benefits from screening. However, we consider calibrations where $c'(e_t) > 0$, meaning that it is costly for financial intermediaries to

[20]The idea that the purpose of bundling is to destroy private information is also found in DeMarzo (2005). In general, private information may exist on either the side of the market. DeMarzo considers the case of sellers who specialize in originating and marketing assets, but do not have a comparative advantage in valuing or holding them. Pooling of these assets reduces the information asymmetry as it prevents sophisticated buyers, such as specialist brokers, from cherry-picking assets.

[21]A monitoring role for intermediaries is modeled in Gorton and Haubrich (1990), and Gorton and Kahn (1994). Further, Campbell and Kracaw (1980) and Boyd and Prescott (1986) explain the existence of financial intermediaries as providing efficient credit evaluation services. We assume that monitoring is required to ensure bank managers do not shirk/divert return for their own gain/operate inefficiently. Alternatively, monitoring could be introduced to ensure that banks perform credit evaluation on borrowers i.e. entrepreneurs to ensure they undertake projects with high returns. This would however require that different projects are available to entrepreneurs and without proper incentives, entrepreneurs may deliberately choose a project with a lower ex post return (see Holmstrom and Tirole (1997), Chen (2001), Meh and Moran (2010)).

increase their screening effort.

Commercial bank's balance sheet at any time t can be represented as below:

Balance Sheet: Commercial Bank

Assets	Liabilities
Loans (B_t)	Deposits (D_t)
	Bank capital (equity) (Z_t)
	Loans (sold to shadow banks) ($B_{s,t}$)

The bank's objective is to maximize the return on shareholders' equity, which is given by the positive part of the difference between returns from its on balance sheet loans and the repayments due to its deposits and payment for monitoring. Let $e\widetilde{R}_{F,t+1}$ denote the realized return on a well diversified portfolio of loans. The return is assumed to be a simple linear function of the monitoring effort (i.e. a fraction (1 - e) is either diverted or lost in inefficiency costs). Similar to the entrepreneurs, banks are also subject to an idiosyncratic risk. The idiosyncratic portfolio return shock ω^b, which can be interpreted as a shock to each individual banks' ability to extract payoffs from its loans, is i.i.d across banks and is assumed to have log-normal distribution with a mean of 1 and a distribution function $F(\omega^b)$. The mean and standard deviation of $log\omega^b$ are μ_{ϖ^b} and σ_t respectively. The standard deviation, σ_t, is the realization of a stochastic process, which we refer to below as the risk shock. This shock captures the notion that the riskiness of banks varies over time and follows a stationary AR(1) process.

$$log\sigma_t = \rho_\sigma log\sigma_{t-1} + (1 - \rho_\sigma)log\sigma + \varepsilon_{\sigma,t},$$

where σ is the steady state standard deviation and $\varepsilon_{\sigma,t}$ is i.i.d $N(0, \sigma_r^2)$.

Thus, individual bank return $\omega^b_{t+1}e_t\widetilde{R}_{F,t+1}$ (and therefore bank default) depends on monitoring effort, aggregate loan return $\widetilde{R}_{F,t+1}$ (itself driven by firms' default rates) and the bank-idiosyncratic shock ω^b_{t+1}. The monitoring effort therefore plays an important role as the effective return on bank loans (and therefore the cost of bank funding in a competitive environment where banks are risk neutral) is directly related to monitoring. For a given effective return, a fall in bank monitoring would lead to an increase in $\widetilde{R}_{F,t+1}$. This implies a higher cost of funding for the final borrowers i.e. entrepreneurs since $\widetilde{R}_{F,t+1}$ enters banks participation constraint in equation (2.8) in entrepreneurs optimization problem.

When a bank fails, its equity is written down to zero and its deposits are taken over by a deposit insurance fund that pays out all deposits in full. The presence of deposit insurance ensures that the gross interest rate paid on the deposits, R_t is uniform across all banks. The deposit insurance fund replenishes itself by taking over failed banks' loan portfolio minus resolution costs, which are assumed to be a fraction, μ_b, of the total bank assets (net of screening costs).

Commercial bank is also subject to a regulatory constraint such that:

$$Z_t = \kappa_t B_t(1 - b_t) \geq \bar{\kappa} B_t(1 - b_t) \tag{2.11}$$

Where k_t is the bank capital ratio and $\bar{\kappa}$ is the regulatory minimum capital requirement. In reality, banks often keep higher capital as it reflects a healthy banking sector and thus reduces the cost of issuing equity. It also captures the view that maintaining a positive capital buffer generates some benefits—it represents a signal that the bank's financial position is strong and reduces the intensity of regulatory scrutiny. This, in turn, reduces the pecuniary cost associated with the preparation of data and documents required by the supervision authority[22]. The gain associated with banks being more capitalized i.e ($\kappa_t > \overline{\kappa}$) is modeled in a reduced form way as $\tau_z(\frac{\kappa_t - \overline{\kappa}}{\overline{\kappa}})^{0.5}$, where $\tau_z > 0$. We assume the gain to be concave, which implies that the benefits from capital buffers diminish over time.

We begin by analyzing the impact of fixed capital requirement, as in Basel I. In section 2.6.5, implications of procyclical Basel II are also discussed. The capital requirement here plays a role to counteract the effect of limited liability in the banking

[22]See for example, Ayuso et al. (2004), in which capital buffers reduce the probability of not complying with capital requirements.

sector. As in Clerc et. al. (2015), the presence of deposit insurance provides an implicit subsidy to the defaulting banks, which can lead to perverse incentives for banks to take excessive risks. A higher capital requirement reduces leverage, forcing banks to get funded with a larger share of equity, which is more costly. It also reduces the probability of bank default and hence the subsidy implied by the deposit insurance, leading to a higher lending rate and more restricted access to credit for entrepreneurs.

Unlike in Clerc et. al., we also allow banks to fund themselves by selling loans in the secondary market. This helps the bank to relax the capital requirement constraint to an extent. This is reflected by the factor $(1-b_t)$ in equation (2.11). However, the extent of loan sales is limited by the moral-hazard problem described earlier, since loan monitoring is not observable by loan buyers. The gains from monitoring are assumed to be linear however the cost of monitoring is convex implying a decreasing marginal profit from monitoring.

Let $\bar{\omega}^b_{t+1}$ denote the threshold realization of ω^b_{t+1} below which the bank fails because the realized return on its loan portfolio is lower than the deposit repayment obligation:

$$(1-b_t)\bar{\omega}^b_{t+1} e_t \widetilde{R}_{F,t+1} B_t = R_t D_t \tag{2.12}$$

The left hand side shows the return on on-balance sheet loans net of the screening costs. Since a portion b_t of the loan is sold to shadow banks in the secondary market (i.e. $B_{s,t} = b_t B_t$), only a fraction $(1-b_t)$ is available to service debt and equity repayments. The balance sheet of the commercial bank reads as:

$$B_t + \frac{\tau_1}{2}(e_t^2 + \tau_2 e_t)B_t = D_t + Z_t + P_{s,t} b_t B_t \tag{2.13}$$

Where the term $\frac{\tau_1}{2}(e_t^2 + \tau_2 e_t)B_t$ is the funds used in costly monitoring services. Therefore, the resources required to fund and monitor the loan can come from either deposits, equity finance or via sale of loans in the secondary market. $P_{s,t}$ is the price of loans in the secondary market. The balance sheet constraint can be simplified as

$D_t = B_t(1 + \frac{\tau_1}{2}(e_t^2 + \tau_2 e_t) - \kappa_t(1 - b_t) - P_{s,t}b_t)$. Therefore:

$$\bar{\omega}^b_{t+1} = \frac{R_t}{e_t \widetilde{R}_{F,t+1}(1 - b_t)}(1 + \frac{\tau_1}{2}(e_t^2 + \tau_2 e_t) - \kappa_t(1 - b_t) - P_{s,t}b_t) \tag{2.14}$$

Thus, the threshold below which the bank fails is decreasing in bank capital ratio, κ_t, and the average bank return (on a well diversified portfolio), $\widetilde{R}_{F,t}$. A higher capital ratio and higher average return therefore implies lower bank default. The threshold is increasing in the fraction of bank loans diverted to secondary loan market, b_t, the return on bank deposits, R_t, and the screening cost per unit of loan.

The profit function of commercial banks can be written as:

$$\pi_{z,t+1} = (1-b_t)e_t\widetilde{R}_{F,t+1}B_t \int_{\bar{\omega}^b_{t+1}}^{\infty} \omega^b_{t+1} f^b(\omega^b_{t+1}) d\omega^b_{t+1} - \int_{\bar{\omega}^b_{t+1}}^{\infty} f^b(\omega^b_{t+1}) d\omega^b_{t+1} R_t D_t - R_{z,t+1}Z_t + \tau_z(\frac{\kappa_t - \overline{\kappa}}{\overline{\kappa}})^{0.5}$$

The first term is the return from banks' on-balance sheet loans that do not default. The second term is the payment for return on deposits. This is multiplied with the probability of bank survival i.e. $\int_{\bar{\omega}^b_{t+1}}^{\infty} f^b(\omega^b_{t+1}) d\omega^b_{t+1}$. The third term is the required return on bank capital and the fourth term denotes concave gains from keeping capital buffers. Using equation (2.12), the profit function can be simplified to:

$$\pi_{z,t+1} = (1-b_t)e_t\widetilde{R}_{F,t+1}B_t[\int_{\bar{\omega}^b_{t+1}}^{\infty} \omega^b_{t+1} f^b(\omega^b_{t+1}) d\omega^b_{t+1} - \bar{\omega}^b_{t+1} \int_{\bar{\omega}^b_{t+1}}^{\infty} f^b(\omega^b_{t+1}) d\omega^b_{t+1}] - R_{z,t+1}Z_t + \tau_z(\frac{\kappa_t - \overline{\kappa}}{\overline{\kappa}})^{0.5}$$

Following BGG , we can again define:

$$\Gamma^b(\bar{\omega}^b_{t+1}) = \int_0^{\bar{\omega}^b_{t+1}} \omega^b_{t+1} f^b(\omega^b_{t+1}) d\omega^b_{t+1} + \bar{\omega}^b_{t+1} \int_{\bar{\omega}^b_{t+1}}^{\infty} f^b(\omega^b_{t+1}) d\omega^b_{t+1}$$

$$\mathrm{G}^b(\bar{\omega}^b_{t+1}) = \int_0^{\bar{\omega}^b_{t+1}} \omega^b_{t+1} f^b(\omega^b_{t+1}) d\omega^b_{t+1}$$

$G^b(\bar{\omega}^b_{t+1})$ denotes the share of total bank assets that belong to banks which end up in default. Thus, $\mu_b G^b(\bar{\omega}^b_{t+1})$ is the total cost of bank default expressed as a fraction of total bank assets where μ_b is the fraction of assets lost in bankruptcy.

Banks choose total bank loans, B_t, the fraction of bank loans diverted to OBSE, b_t, efficient level of bank capital ratio, κ_t, and the monitoring effort, e_t to maximize the following profit function subject to equation (2.11) and (2.14):

$$\max_{B_t, b_t, \kappa_t, e_t} E_t\,(1-b_t)e_t\widetilde{R}_{F,t+1}B_t(1-\Gamma^b(\bar{\omega}^b_{t+1})) - R_{z,t+1}Z_t + \tau_z(\frac{\kappa_t - \overline{\kappa}}{\overline{\kappa}})^{0.5} \qquad (2.15)$$

Finally, the probability of bank default, which also enters the households' budget constraint is given by:

$$PD_t = \int_0^{\bar{\omega}^b_{t+1}} f^b(\omega^b_{t+1})d\omega^b_{t+1} \qquad (2.16)$$

2.4.4 Shadow Banks

Shadow banks solely serve the purpose of securitization and to provide regulatory relief to commercial banks. In reality shadow banks comprise of myriad range of institutions and instruments. However, here we characterize the system as special off balance sheet entities that purchase a part of loan portfolio of commercial banks and refinance these loans through underwriting of structured debt instruments (ABCP, ABS etc.). We assume a continuum of shadow banks of measure one. Unlike commercial banks, they are not subject to regulatory capital requirement. Their balance sheet can be represented as:

Balance Sheet: Shadow Bank

Assets	Liabilities
$B_{s,t}$	ABS_t

Where $B_{s,t}$ is the amount of loan sold to the shadow bank. These loans are then underwritten into marketable asset backed securities, ABS_t. According to literature, the competition in underwriting industry in the U.S can be described as monopolistic competition (see for example, Fang (2005)).

Loan sale in secondary market There is a continuum of shadow banks, indexed by $z \in [0, 1]$, and they have some market power when conducting their services. A commercial bank seeking to raise an amount of borrowing, $P_{s,t}BS_t$, through loan sale would allocate it among different shadow banks, $P_{s,t}(z)BS_t(z)$, so as to maximize the total proceeds. In period t, commercial banks choose how much loan to sell to shadow bank z, $BS_t(z)$ by solving the following problem:

$$max_{BS_t(z)} \int_0^1 P_{s,t}(z)BS_t(z)dz,$$

subject to a Dixit-Stiglitz aggregator:

$$BS_t = \{\int_0^1 (BS_t(z))^{\frac{\varepsilon_s - 1}{\varepsilon_s}} dz\}^{\frac{\varepsilon_s}{\varepsilon_s - 1}},$$

where $P_{s,t}(z)$ is the price paid by the zth shadow bank and $\varepsilon_s > 1$ is the elasticity of the demand for funds. The first order condition yields the following commercial bank's demand for funds:

$$BS_t(z) = (\frac{P_{s,t}(z)}{P_{s,t}})^{-\varepsilon_s} BS_t,$$

where $P_{s,t}$ is the average sale price of loans in the secondary market, defined as:

$$P_{s,t} = \{\int_0^1 (P_{s,t}(z))^{1-\varepsilon_s} dz\}^{\frac{1}{1-\varepsilon_s}}$$

Therefore, when the price paid by the z-th shadow bank falls relative to the average price, the commercial bank wishes to sell less loans to that shadow bank.

Shadow bank profit maximization The loan sale in previous section is financed by underwriting of asset backed securities. Households are the ultimate investors in these securities[23]. To keep the analysis as simple as possible, we follow the recent DSGE banking literature and assume perfect competition in the market for households' funding (see e.g. Kobayashi, 2008). At the end of period t, the z-th shadow bank thus chooses the price $P_{s,t}(z)$ to solve the following profit maximization problem:

$$\max_{P_{s,t}(z)} \; e_t\widetilde{R}_{F,t+1}BS_t(z) - R_{m,t+1}P_{s,t}(z)BS_t(z),$$

subject to

$$BS_t(z) = (\frac{P_{s,t}(z)}{P_{s,t}})^{-\varepsilon_s,}BS_t$$

Deriving the first order conditions and imposing symmetric equilibrium yields:

$$e_t\widetilde{R}_{F,t+1} = \frac{\varepsilon_s}{\varepsilon_s - 1}P_{s,t}R_{m,t+1} \tag{2.17}$$

As mentioned before, loans purchased by shadow banks are financed by underwriting marketable liquid ABS[24] wherein, $ABS_t = P_{s,t}BS_t$. The average return on ABS underwritten by shadow banks, $R_{s,t+1}$ is therefore:

$$R_{s,t+1} = \frac{e_t\widetilde{R}_{F,t+1}BS_t}{P_{s,t}BS_t},$$

[23]The process of securitization whets the appetite of institutional investors for liquid deposit like safe investments. To avoid introducing too many agents in the model, we allow households to be the ultimate investors in ABS. Alternatively, another agent institutional investors can be added to the model who would mobilize resources from households in return of mutual fund shares. These funds can then be used by institutional investors to buy ABS. This would however not alter the dynamics of the model.

[24]The shadow bank (the underwriter) acts as an intermediary between the ultimate borrower and the ultimate investors. In bond finance, the most common type of underwriting arrangement is the firm commitment underwriting, according to which the underwriter buys the entire stock of bonds from the firm and resells it to investors at a higher price (i.e., at a lower interest rate). This spread represents the shadow bank's profits. We use a similar setup for ABS underwriting. See Ellis et al. (2000) for an in-depth analysis of the underwriting process.

where numerator is the return on loan purchases and denominator is the price paid by shadow banks for these loans[25]. Therefore, equation (2.17) can be written as:

$$R_{s,t+1} = \frac{\varepsilon_s}{\varepsilon_s - 1} R_{m,t+1}$$

Households' maximization problem suggests that the return on shadow bank deposits, $R_{m,t}$ is equal to the return on deposits (i.e. $R_{m,t+1} = \widetilde{R}_{t+1}$). Thus, the cost of issuing ABS is a markup, $\frac{\varepsilon_s}{\varepsilon_s - 1}$, over the deposit rate. The profits of the shadow banks in period t+1 is given by:

$$\Pi_{I,t+1} = (R_{s,t+1} - \widetilde{R}_{t+1})ABS_t$$

2.4.5 Consumption good producer

Consumption good producer uses capital K_t rented from entrepreneurs and labour L_t hired from households to produce output Y_t with the following constant returns to scale production function:

$$Y_t = A_t K_{t-1}^{\alpha} L_t^{1-\alpha}; \quad 0 < \alpha < 1$$

The aggregate technology parameter, A_t evolves as:

$$\ln(A_t) = \rho_a \ln(A_{t-1}) + \varepsilon_{a,t}; \quad \rho_a < 1,$$

$\varepsilon_{a,t}$ is normally distributed with zero mean and standard deviation σ_a.

[25] Since we assume that shadow banks receive a fraction of loan from all banks, they can perfectly diversify all the risk and are thus guaranteed a risk-less return in aggregate (still subject to monitoring effort of the commercial bank). Therefore, the value added of shadow bank is to allow regulatory arbitrage in the model, which has been hailed in the literature as one of the key factors for the growth of securitization and shadow banking.

2.4.6 Capital good producer

At the beginning of each period, capital good producer buys final good and the stock of undepreciated capital from the firms. We introduce convex investment costs, therefore at time t, I_t units of output is converted into $(1 - S(X_t))I_t$ units of new capital[26]. $X_t = I_t/I_{t-1}$ and the function $S(.)$ satisfies $S', S'' \geq 0$. Also in steady state $S(.) = S'(.) = 0$.

$$S(X_t) = \varphi_x(X_t - 1)^2$$

The capital goods producer maximizes expected discounted profits:

$$\max_{I_t} E_t \sum_{k=0}^{\infty} D_{t,t+k}[Q_{t+k}(1 - S(\frac{I_{t+k}}{I_{t+k-1}}))I_{t+k} - I_{t+k}],$$

where $D_{t,t+k}$ is the real stochastic discount factor. Capital therefore evolves according to the following relation:

$$K_{t+1} = (1 - \delta)K_t + (1 - S(X_t))I_t$$

2.4.7 Deposit insurance agency

Deposit insurance agency absorbs the costs of servicing the deposit payments of banks that default. This is in turn covered by imposing lump-sum taxes, TD_t, on households where

$$TD_t = [\bar{\omega}_t^b - \Gamma^b(\bar{\omega}_t^b) + \mu^b G^b(\bar{\omega}_t^b)]e_{t-1}\widetilde{R}_{F,t}(Q_{k,t-1}K_{t-1} - N_{t-1})(1 - b_{t-1})$$

[26]In the absence of investment adjustment costs, the capital price Q_t is constant and equals 1. Investment adjustment costs generate capital price variability, which contributes to the volatility of entrepreneurs' net worth.

2.4.8 Competitive Equilibrium

Households are present in unit mass therefore aggregate household consumption is equal to consumption of a representative household. Aggregation across entrepreneurs' (described in section 2.4.2) yields aggregate entrepreneurial consumption ($C_{e,t}$). Further, aggregate resources lost in entrepreneurial bankruptcy are given by $\mu_e G^e(\bar{\omega}_t^e) R_{k,t} Q_{k,t-1} K_{t-1}$.

Combining the budget constraints of the model's agents gives us the resource constraint of the economy:

$$Y_t = C_t + I_t + C_{e,t} + \mu_e G^e(\bar{\omega}_t^e) R_{k,t} Q_{k,t-1} K_{t-1} + \Omega P D_t R_{t-1} D_{t-1} \tag{2.18}$$

$$+\mu_b G^b(\bar{\omega}_t^b) e_{t-1} \widetilde{R}_{F,t} (Q_{k,t-1} K_{t-1} - N_{t-1}) + (1 - e_{t-1}) \widetilde{R}_{F,t} B_{t-1} (1 - \Gamma^b(\bar{\omega}_t^b))$$

Total output Y_t, is equal to the aggregate consumption demand of households, C_t, plus the resources absorbed in the production of new capital, I_t, plus aggregate consumption of entrepreneurs who exit in period t, plus the resources lost in the recovery by commercial banks of the proceeds associated with defaulted bank loans, in transaction costs by depositors at failed banks and by the deposit insurance agency in the recovery of assets from banks that default plus the loss in effective bank return due to diversion/inefficiency by bank managers.

In addition labour market equilibrium requires that labour demand from firms is equal to household's labour supply at the competitive real wage rate. Loan market equilibrium implies that amount borrowed by entrepreneurs is equal to loan supply from banks that is financed by deposits, bank capital or sale of loan in the secondary market. Market for capital services require that supply from entrepreneurs is equal to the capital demanded by firms. Finally, equilibrium in the ABS market requires that ABS issued by shadow banks is equal to the demand for securities by households.

A competitive equilibrium consists of a set of prices and interest rates $\{Q_{k,t}, R_t, R_{m,t}, R_{k,t}, w_t\}$ for all possible states and for all $t \geq 0$ such that all markets clear when the agents in the model i.e. households, entrepreneurs, commercial banks, shadow banks, consumption good producer and capital goods producer solve their maximization problems while taking these prices and interest rates as given.

2.5 Baseline Parameterization

The model is calibrated to replicate key features of the US economy and the parameter values are given in table 9. The parameters fall into two broad categories. The first consists of the standard, more widely understood and estimated macroeconomic parameters, for which values are borrowed from previous studies. The second are the parameter values more specific to the financial system presented in this model and deserve special mention. We consider two model, one is the case of securitization in which financial sector of the model imitates features of the U.S. in the decade prior to the financial crisis. The other case is that of no-securitization. In an absence of any counterfactual, we draw out inferences from the features of the U.S. financial system of the early 1990's as in Meeks et. al. (when there was some securitization, but lending was predominantly done by banks).

As regards the macroeconomic parameters, household's discount factor, β, is set to 0.99 to match the historical average of risk free interest rate, R_t. Parameter ϕ, the inverse labour supply elasticity is set to 0.5, as is common in the literature. The share of capital in production, α and its depreciation rate, δ is set at 0.33 and 0.025 respectively, which is standard in the literature. The calibrated values for these parameters are same as those used in chapter 1. The probability of survival of firms to next period, γ, is set at 0.97 (as in BGG(1999) and Christensen and Dib (2008)), which implies an expected working life for entrepreneurs of 36 years. The values of other parameters controlling firm financial frictions (e.g.. μ_e, $F(\varpi)$, and σ_e) are determined to match, $R_F - R$, leverage ratio and the rate of return on capital. Bankruptcy cost parameter, μ_e, is set at 0.3 that is within the range of 0.20 - 0.36 that Carlstrom and Freust (1997) defend as empirically relevant. $F(\bar{\omega})$ is set at 0.75

quarterly percent value implying an annual bankruptcy rate of 3 percent (as in BGG). The variance of the entrepreneurial risk shock, σ_e^2, is set at 0.26 following Christiano, Motto, Rostagno (2014). There is considerable uncertainty about the spread between the cost of external finance, R_F and the return on households deposits. BGG (1999) measure the external finance premium as approximately the historical average spread between the prime lending rate and the six- month Treasury bill rate, which amounts to 200 basis points. Levin, Natalucci and Zakrajsek (2004) report a spread of 227 basis points for the median firm included in their sample. De Fiore and Uhlig (2011) report that the spread between the prime rate on bank loans to businesses and the commercial paper is 298 basis points over the period 1997-2003. Our calibrations produce a spread of 300 basis points. Finally, the calibrated values of fraction of net worth consumed by entrepreneurs upon exit, Θ, and the transfer from households to entering entrepreneurs, W^e, is borrowed from Christiano, Motto and Rostagno (2014).

Capital requirements are set at a benchmark level of 8 percent for corporate loans (compatible with the full weight level of Basel I and the treatment of non-rated corporate loans in Basel II and III). Parameter determining the probability of default of banks is chosen so as to make their baseline steady-state values equivalent to annual rates of 2 percent for banks. The bankruptcy cost parameters imply losses of 10 percent of face value of deposits for depositors at failed banks and of 30 percent of asset value for creditors repossessing assets from defaulting borrowers (Clerc et. al. (2015)). Parameters τ_1, τ_2 and τ_z are set to hit the following targets - a steady state bank capital ratio of 10 percent i.e. higher than the regulatory constraint, share of bank loans sold and securitized, b_t, at 0.3 following Meeks et. al. (2014) who find that the share of securitized asset based on call report data on bank asset sold and securitized at 30 percent and an annualized return on bank equity of 15 percent, matching the evidence reported by Berger (2003). Adjustment cost parameter associated with household purchase of bank equity, Θ_z, is calibrated at 0.36 to ensure that household demand for bank equity is in accordance with banks' steady state capital ratio. Finally, the steady state value of the elasticity of funds in the secondary loans market, ε_s is calibrated to ensure a risk spread of 50 basis point (above the deposit return) in the ABS market, as in Meeks et. al. (2014)[27].

2.6 Results

In this section, we compare two versions of our model economy - with and without securitization. In particular, the no securitization economy is characterized by the share of loans sold in the secondary market, $b_t = 0$. Furthermore, since banks do not sell loans in the secondary market they have a higher incentive to monitor resulting in a higher steady state monitoring effort as compared to the baseline model. There is a range of evidence from various markets that borrowing rates fell amongst assets that could be sold and securitized. For example, in the market for corporate loans, Nadauld and Weisbach (2012) cite a reduction in the yield of 15 basis points. The steady state lending rate in the no-securitization model is therefore targeted at an annualized 20 basis point higher than in the baseline model. The results presented below are based on second order approximation of the model and are computed using Dyane 4.3.3. The impulse response functions are based on averaging 1000 simulated series for each variable. Dynare generates IRFs using the approximate policy functions as follows: (i) It draws a series of all the exogenous shocks for a number of 100 + T periods, where T is the number of periods shown in the IRF graphs, (ii) It performs a simulation H1 of all the variables of interest using this realization of the shocks, (iii) It changes the sequence of exogenous shocks, by adding a one-standard deviation of the shock, to the realization of period 101, (iv) It performs a new simulation H2 of all variables based on the new sequence of shocks, and (v) It calculates the IRF from H2-H1. These steps are then repeated a number of times (we choose 1000 replications) and the produced IRFs are averages of the series from these 1000 experiments. We begin our analysis by looking at the response of the model economy to (i) a standard productivity shock; and (ii) shocks emerging in the

[27]The 2000–2007 average ABS spread over comparable swap rates for high-quality securitizations varied from around 7 basis points for credit card and auto receivables, to 25 basis points for large equipment and 70 basis points for non-conforming mortgages. Meeks et. al. (2014) adopt a rough mid-point of 50 basis points for the steady state ABS spread in their model.

financial system - a risk shock, which increases the volatility of banks' idiosyncratic risk.

2.6.1 Total factor productivity shock: shock to the aggregate productivity

Figure (10) reports the effect of a one percent decline in total factor productivity. We compare the results from our baseline model to a model with no shadow banking. A decline in aggregate productivity results in a drop in capital return in both models. This adversely affects capital price and net worth of the banks in both cases. However, the impact is muted under the baseline model. While capital price and net worth falls by about 2 percent in no shadow banking model, the fall is less than half of that in a model with shadow banking. Similarly, fall in investment is lower in the baseline model. The dynamics of the two models differ due to differing response of monitoring effort and the ability to sell loans in the baseline model. In response to a negative productivity shock, the return on deposits increase. This increases the cost of funding for shadow banks thereby decreasing their overall issuance of ABS, resulting in a lower proportion of loans sold in the secondary market. As a larger share of commercial bank loans is now kept on balance sheet, they have greater incentives to monitor reflected by an increase in bank monitoring of about 0.5 percent. Therefore, the initial increase of interest rate on bank loans is reversed more quickly in the baseline model. The existence of shadow banking has a dampening effect on the fall in investment and overall credit intermediation.

2.6.2 Bank risk shock: shock to the volatility of banks' idiosyncratic risk

Next, we look at the impact of a financial shock. Figure (11) shows the dynamic effects of a 0.1 percentage point increase in the standard deviation of the idiosyncratic shock to banks' performance (with a high persistence of 0.9), which we interpret as a shock to bank risk. The size of the shock is chosen such that it causes the loan interest rate to increase by about 0.25 basis point (100 basis point increase of the annualized interest rate). Later, we also check robustness with a lower persistence and larger size of the shock. The effects of the shock are amplified in the economy with shadow banking (baseline model). An increase in bank risk implies a higher probability of bank default. In a model without shadow banking, banks resort to higher monitoring to increase the effective return on their portfolio. This significantly contains the impact of risk shock on loan interest rate and consequently investment and loan supply. However, in a model with shadow banking, banks respond to a greater risk by shifting loans to the secondary market as can be seen by an increase of nearly 6 percent in the loan share sold. Lower proportion of on-balance sheet loan leads to reduced monitoring (a fall in monitoring of over 1 percent) effectively downgrading the quality of bank portfolio. A fall in monitoring increases interest rate charged on loans (to ensure the effective return can cover the cost of funding for banks) as described in section 2.4.3. Finally, this results in an amplified and prolonged fall in output, investment, capital price and banks' net worth vis-a-vis a model with only commercial banks. Overall credit intermediation in the baseline model falls about tenfold than in the no shadow banking economy. The peak decline in loans in the baseline model is over 5 percent in contrast to about 0.5 percent in a model without shadow banking. We see similar dynamics for capital, capital price and investment. Capital in the baseline model falls by just under 2 percent, while investment falls by about 5 percent. In contrast, the impact on these variables in the economy without shadow banking is negligible in relative terms. Output in no-shadow banking economy falls by just over 0.5 percent, primarily driven by the fall in consumption. Furthermore, the impact is short-lived and output goes back to steady state in about 10 quarters. In the baseline model, not only is the peak impact magnified (output declines by 1 percent) but it's also more persistent. Finally, as the quality of loan portfolio falls, loan price in secondary market falls by nearly 1 percent. This also leads to a fall in the ABS return. Therefore, as commercial banks' risk increases a larger portion of loans is sold into the secondary market increasing the fragility of the system. It also significantly constrains the credit intermediation process consequently causing an amplified decline in investment and output.

Next, we look at the impact of risk shock under different shock size and persistence. The baseline scenario (shock of 0.1 percentage point increase, 0.9 persistence) is compared with three additional scenarios in figure (12). Additional scenarios include (i) scenario 1: shock size of 0.2 percentage point, 0.9 persistence; (ii) scenario 2: shock size of 0.1 percentage point, 0.5 persistence; and (iii) scenario 3: shock size of 0.2 percentage point, 0.5 persistence. Comparing baseline model and scenario 1 shows that the impact of risk shock is highly non-linear. Doubling the size of shock from 0.1 to 0.2 percentage point leads to larger than three-fold decrease in key variables - output, investment, loans, capital, capital price and net worth - as compared to the baseline scenario. The persistence of shock has an important role to play as well. The impact of baseline model and scenario 3 are very similar. Baseline has a smaller risk shock that scenario 3, however that is counterbalanced by a lower persistence in scenario 3. Overall, the impact is amplified as the size or the persistence of shock increases. A large enough risk shock augmented with high persistence is therefore capable to create a crisis like scenario (scenario 2). In such a scenario, credit intermediation is seriously hampered reflected in a decline of loans by 20 percent. Capital price falls by about 8 percent and entrepreneurs net worth falls by 10 percent. A large part of loan portfolio is sold in the secondary loan market at low prices as the overall quality of loan portfolio falls with declining monitoring effort. Finally, investment falls by over 15 percent and peak impact on output is a decline of 4 percent.

Second v/s first order approximation The results presented above are based on a second order approximation of the economy around the steady state. Under first order approximation, unconditional expectations of the endogenous variables are equal to their non- stochastic steady state values. Therefore, risk or uncertainty shock - in essence shock to the variance of the shock do not affect the dynamics of the model. Figure 12 shows that responses to risk shocks are highly non-linear.

To further assess the non-linearity of the system, figure 13 compares impulse responses under first and second order approximation of the model around the deterministic steady state. In the top panel, responses to one percent technology shocks are larger under second order approximation. The amplification is most pronounced for monitoring effort and loan sale in secondary market, which consequently leads to larger decline in capital and loans for second order approximation of the model. In particular, peak decline in capital and investment under second order approximation is nearly twice of that seen under first order approximation. The lower panel, which reports impulse responses to risk shocks, shows a similar pattern however the non-linearities are even more pronounced here. The response under second order is significantly larger, so much so that results under first order approximation appear negligible in comparison. In general, the impact under second order approximation is about tenfold of the responses under first order. For example, while for first order approximation output falls by less than 0.1 percent in response to risk shock (of 0.1 percentage point), the decline is nearly 1 percent when second order approximation of the model is used. Similarly, peak decline in investment is over 4 percent when the model is solved using second order in comparison to about 0.4 percent when first order approximation is used. Again the amplification, under second order approximation, is driven by significantly larger decline in bank monitoring and higher share of bank loans sold in secondary market.

2.6.3 Robustness Checks

In section 2.6.2 (figure 11 and 12), we documented the response of key variables to bank risk shock. Figure 12 shows that the magnitude of variation in economic variables in response to the shock depends to a large extent on the size and persistence of the shock. In this section, we assess the robustness of our results to the choice of calibrated parameters. The baseline calibration is guided by (i) standard parameters for which there is agreement in the literature; and (ii) parameters which are specific to the model and are calibrated to match certain steady state values. The solution under the baseline parameterization is stable and unique i.e. the Blanchard-Kahn condition is satisfied (the number of eigenvalues larger than one in modulus is equal to the number of forward looking variables). Further, in response to temporary shocks the system converges back to the steady state. For robustness, we take the standard parameters as given and increase the calibrated values of parameters specific to the model by 10 percent. In particular, for this robustness exercise we increase by 10 percent the parameters related to the financial system $(\sigma_e, \sigma_b, \mu_e, \mu_b, \Omega, \tau_1, \tau_2, \tau_z, \varepsilon_s)$. Figure 14 shows the response of model economy to aggregate productivity shock under the baseline and robustness scenario. The results are largely robust to the change in calibrated parameters. Further, the solution is again unique and stable (Blanchard-Kahn conditions are satisfied). Similarly, impulse responses to risk shock are also robust to the measured change in calibrated parameters (see figure 15).

2.6.4 Government credit policy

The problems experienced in credit and interbank markets at the onset of the sub-prime crisis in August 2007 were swiftly followed by policy actions from the central bank and government, including cuts in official interest rates and enhanced provision of liquidity. Overtime as the crisis intensified, policy makers have taken recourse to various unconventional monetary and fiscal policy tools. In the United States, official backstops for the banking system have been a prominent component of the policy response (Pozsar et al., 2010). These have included a policy of providing long-term liquidity through the TALF[28], and outright purchases of Agency MBS and debt funded by central bank reserves. In this section, we describe the operation and impact of government backstop programs.

Credit Policy We have previously characterized the credit intermediation process via lending by both the traditional retail banks and the shadow banks. We now suppose that the central bank is willing to facilitate lending. It can do this by lending directly to firms i.e. loan purchase. Therefore, overall credit intermediated can be written as the sum of private $(B_{p,t})$ and government $(B_{g,t})$ assisted intermediation.

[28]Under TALF, the Federal Reserve Bank of New York (NY Fed) lent up to $1 trillion (originally planned to be $200 billion) on a non-recourse basis to holders of certain AAA-rated ABS backed by newly and recently originated consumer and small business loans. In the United Kingdom, the SLS (Special Liquidity Scheme) was also aimed at long-term liquidity provision. It allowed banks to undertake swaps of securitized assets for Treasury bills, which could then be used as collateral to obtain secured funding in wholesale markets.

$$B_t = B_{p,t} + B_{g,t} \quad (2.19)$$

To conduct credit policy, the central bank issues government debt to households that pays the risk-less rate R_t and then lends the funds to non-financial firms. The return from these loans is assumed to be equal to the return on a well diversified portfolio, $\widetilde{R}_{F,t+1}$. Thus for households, government debt is a substitute for bank deposits. We suppose that government intermediation involves efficiency costs: in particular, the central bank credit involves an efficiency cost of τ_g per unit supplied. This deadweight loss could reflect the costs of raising funds via government debt. It might also reflect costs to the central bank of identifying preferred private sector investments. On the other hand, the government always honors its debt: thus, unlike the case with private financial institutions there is no agency conflict that inhibits the government from obtaining funds from households. Put differently, unlike private financial intermediation, government intermediation is not balance sheet constrained.

The overall government intermediation costs therefore are:

$$G_t = \tau_g * B_{g,t} \quad (2.20)$$

If we define T_t as government transfers and assume that at every period the government is going to fund its asset purchases through risk-free bonds then:

$$\tau_g * B_{g,t} = T_t + (\widetilde{R}_{F,t+1} - R_t) B_{g,t}$$

Government intermediation policy takes the form of buying a proportion φ_i of the steady state value of loans. In particular, we suppose that at the onset of a crisis, which we define loosely to mean a period where credit spreads rise sharply, the central bank injects credit in response to movements in credit spreads, according to the following feedback rules:

$$\varphi_{l,t} = \varphi_l + \nu_l E_t[(\widetilde{R}_{F,t+1} - R_t) - (\tilde{R}_F - R)] \quad (2.21)$$

Where φ_l is the steady state fraction of publicly intermediated assets and $\tilde{R}_F - R$ is the steady state premia. In addition, the feedback parameter ν_i is positive. According to this rule, the central bank expands credit as the spread increases relative to its steady state value.

Risk shock with credit policy We now look at the response to risk shock (as in figure 11) with and without government credit policy. The results from this exercise are presented in figure 16. As mentioned before, risk shock leads to a decline in investment, output and capital price, which is amplified by the usual financial accelerator channel. Total credit intermediation in the economy falls with loans falling by about 6 percent in the baseline economy. An increase in banks' probability of default reduces bank monitoring effort leading to higher proportion of loans sold and securitized. The effective return on the portfolio of banks falls further leading to a reduction in credit intermediation and consequently investment and output. At its peak investment falls by over 4 percent and output by 1 percent in the baseline economy.

We evaluate the impact of central bank backstop programs in forms of direct loan purchase. Loan purchases go a long way in ameliorating the impact of this shock on the economy. We calibrate the steady state fraction of publicly intermediated assets φ_i at 2.5 percent and the feedback parameter is set to ensure that government intermediation as a proportion of total capital in the economy increases to around 5 percent. Direct loan purchases stabilize the economy through various channel. First, since the loan sold to government does not suffer from monitoring inefficiency, overall effective return on loans does not fall as much as in the baseline economy. This translates to a damped response of loan interest rate to the shock preventing the interest rate spread from soaring. While in the baseline economy loan spread increases by about 150 basis point (annualized), the impact is muted with credit policy (less than 100 basis point increase in the risk spread). Second, government intervention helps in stabilizing the capital price in the economy and thus limits the amplification process. Capital price declines by 2 percent in baseline model and only about 1 percent with an active credit policy. This significantly dampens the response of firms' net worth and consequently output and investment in the economy with active credit policy. It also limits the maximum fall in total credit intermediated from 6 percent to about 3 percent. The fall in output and investment is also reduced by half when credit policy is in place. Furthermore, government through its credit policy can also significantly shorten the duration of the impact of risk shocks on key macro economic variables. While with no policy response the impact of risk shock is long lived, active credit policy significantly lowers the number of periods (here quarters) it takes for the economy to return to equilibirum.

2.6.5 Capital Regulation

The financial crisis has reinforced interest in macroprudential tools and policies that might be applied by policymakers to reduce the risks of financial boom and bust cycles and thereby lead to a more stable path of real economic growth. In addition to the attention on the role of financial intermediaries brought forward by the financial crisis, the introduction of more risk-sensitive capital requirements (i.e., the Basel II capital adequacy framework) has reinforced the concerns that financial intermediation by itself might have substantial feedback effects on the real economy. In this section, we aim to analyze the impact of capital regulation on macroeconomic dynamics. In particular, we look at the procyclicality of the economy under Basel II.

Procyclical Impact of Capital Regulation In this section, we compare the impulse responses for 2 alternative scenario which we call Basel I and Basel II. Next we describe the form of minimum capital constraints in these two alternative regimes. The capital requirement used in the paper until now is in accordance with Basel I accord. We assumed that minimum tier 1 regulatory capital was fixed at 8% of the risk weighted assets and used that to compute the constraints on commercial bank leverage. Basel II however calls for a procyclical capital regime. Therefore, we can redefine the minimum capital requirement as:

$$Cap_t = C_0 A_t^{c_1} (C_0 > 0)$$

For Basel I $c_1 = 0, C_0 = 0.08$.

Let us first discuss the calibration of capital requirement ratio. Under the pro-cyclical regulation regime, the capital requirement ratio increases (decreases) when the economy is in a downturn (boom), implying that $c_1 < 0$. We calibrate C_0 and c_1 by using Basel II risk-weight formula[29]. Note that Basel II requires banks to calculate the risk weight for each loan based on the formula. We follow Covas et. al. (2010) and calibrate $c_1 = -8$.[30].

The response of the economy to one percent negative productivity shock under the two alternative regulation regimes is shown in figure 17. In response to a negative productivity shock, minimum capital requirement under Basel II increases i.e. the capital buffer reduces. This leads to a higher increase in the lending rate under Basel II regime. Overtime bank capital increases and lending rate falls. Bank capital ratio and required return on bank equity are not significantly affected in the Basel I regime. A higher increase in lending rate leads to a much higher fall in loans under Basel II than in Basel I, which due to the financial accelerator mechanism leads to a higher fall in capital price, net worth of entrepreneurs and investment. Overall loans fall by 7 percent under basel II as opposed to about 1 percent under Basel I. Similarly, capital price and net worth decline by over 2 percent under Basel II while the fall in case of Basel I is under 1 percent. Investment decline of about 6 percent under Basel II is sixfold of the decline under basel I. Finally, output reduction is also amplified under Basel II regime. Following a fall in total loans both on and off balance sheet

[29] The internal ratings based (IRB) approach uses the probability of default (PD), the loss given default (LGD), the exposure at default, and maturity for each exposure (M) to calculate the bank's capital requirement for each loan (see Basel Committee on Banking Supervision (2004)). The capital requirement ratio is derived from the formula: $Capital_t = LGD[N(\frac{N^{-1}(PD_t)+\sqrt{C_t}\times N^{-1}(0.999)}{\sqrt{1-C_t}}) - PD_t] \times (\frac{1+(M-2.5)\times b_t}{1-1.5\times b_t})$,
where $N(.)$ is the standard normal distribution function and C the correlation factor.

[30] Covas et. al. (2010) calculate the average risk weight (i.e., the average capital requirement ratio) by using average values for PD, LGD and M. LGD is taken to be 40%. and they use the Moody's default rate series for PD.

loans decline in fixed capital requirement case. However in the basel II model, an increase in capital requirement leads to a higher share of securitization and shift of loans from on to off balance sheets as can be seen from the loan share sold in the secondary market. Furthermore, there is also a reduction in bank monitoring which has similar effects as described earlier. Therefore, there are two perverse effects in response to a negative productivity shock under Basel II with procyclical capital constraints. First, there is a greater tendency to move to the unregulated shadow banking sector and second, banks face higher incentives to reduce monitoring effort thereby lowering the effective return on their portfolio.

2.7 Concluding Remarks

The financial crisis that started in 2007 exposed a number of flaws in the financial system. Many of these were associated with financial instruments that were issued by the shadow banking system. The growth of the shadow banking system as an alternative to traditional banking had been going on for a number of years, but accelerated rapidly with the expansion of securitization in recent years. Even though the crisis brought forward the ills of the shadow banking system, securitization is still significant and important in the credit intermediation process. Keeping that in mind, regulatory authorities are now seeking to reform the financial system and shadow banking in particular. This paper provides guidance on the interaction between traditional and shadow banking in the economy. We analyze both the credit intermediation process as well as the impact of current regulatory regimes.

In particular we build a Dynamic Stochastic General Equilibrium model with an active role for bank capital and regulation. In addition we also embed features of the shadow banking system. For ease of exposition, we only focus on off balance sheet entities as the shadow banks, which are specialized financial institutions designed to transfer a part of loans from banks balance sheet to offer regulatory capital relief. Shadow banks bundle these loans to offer liquid securities.

Our analysis highlights that originate to distribute model makes the economy vulnerable to financial market shocks. An increase in bank risk leads to a sale of larger share of loans in the secondary market in the presence of shadow banks. This generates perverse incentives for banks to lower their monitoring effort, reducing the effective return on their portfolio. The overall impact is a substantial fall in credit intermediation, investment and output in contrast to an economy without shadow banking. Government intervention in the form of direct loan purchase proves to be an effective measure in containing the impact of a negative shock emanating within the financial system.

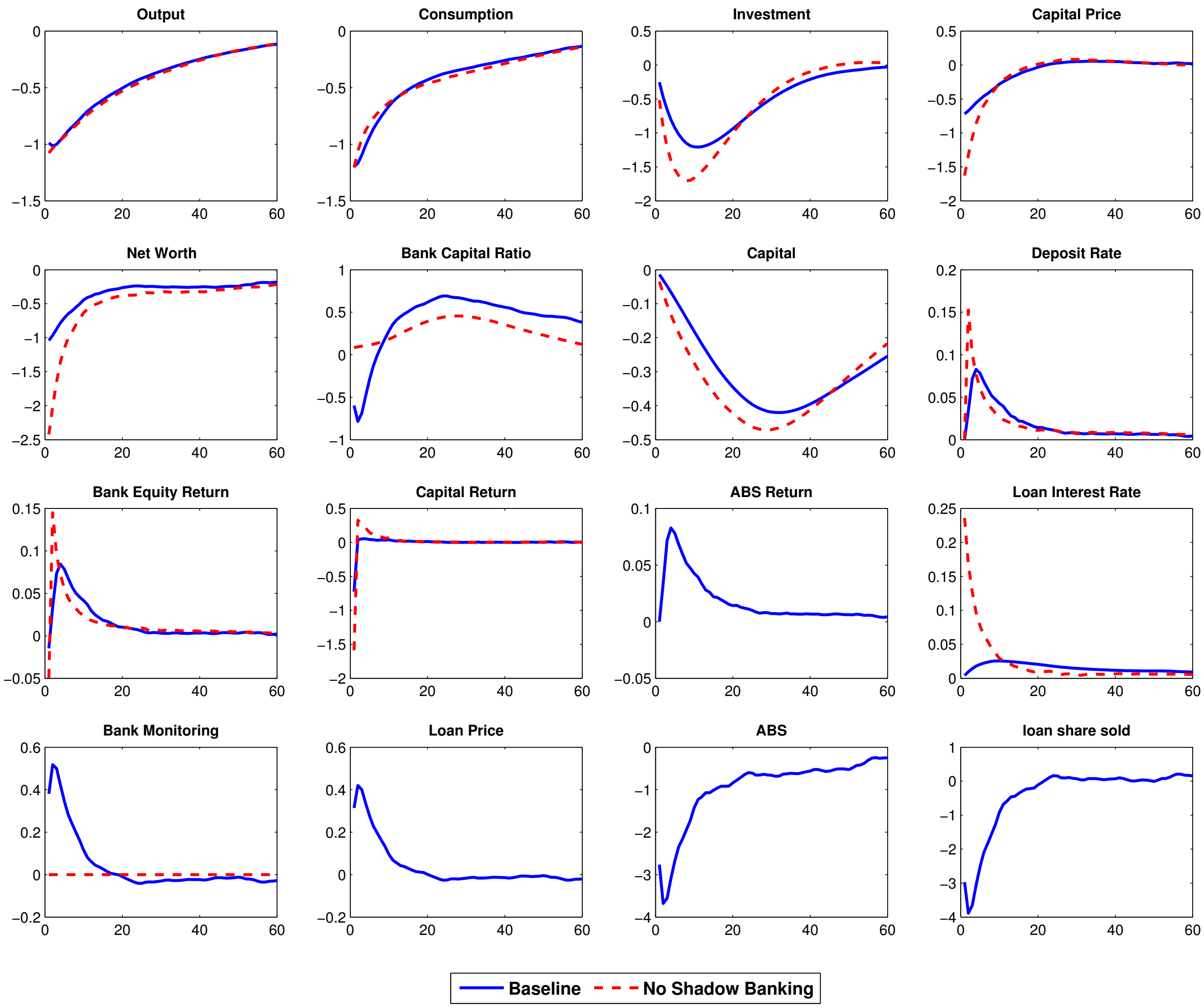
We also study the role of bank capital regulation. Higher capital provides gain in the form of lower borrowing costs as it signals a healthy banking system. We analyze the behavior of the economy under two alternative regulatory regimes, Basel I with fixed capital requirement and Basel II with procyclical capital constraints. In response to a negative productivity shock, we see a fall in economic activity, which is amplified under Basel II. Furthermore, under Basel II a negative technology shock leads to a shift in the economic activity from regulated traditional banking to the unregulated shadow banking sector. Therefore, there is a need to investigate counter cyclical capital requirement as being implemented under Basel III accord.

Finally, while this paper provides a model of shadow banking in the presence of regulatory arbitrage it does not provide micro-foundations for the shadow banking system - including pricing of risk in the shadow banking, and a possible run on the shadow banks. It is difficult to pin down multiple and complex determinants of ABS finance in a DSGE model – we therefore defer that task to more stylized models of finance.

Table 10 – Calibrated Parameters

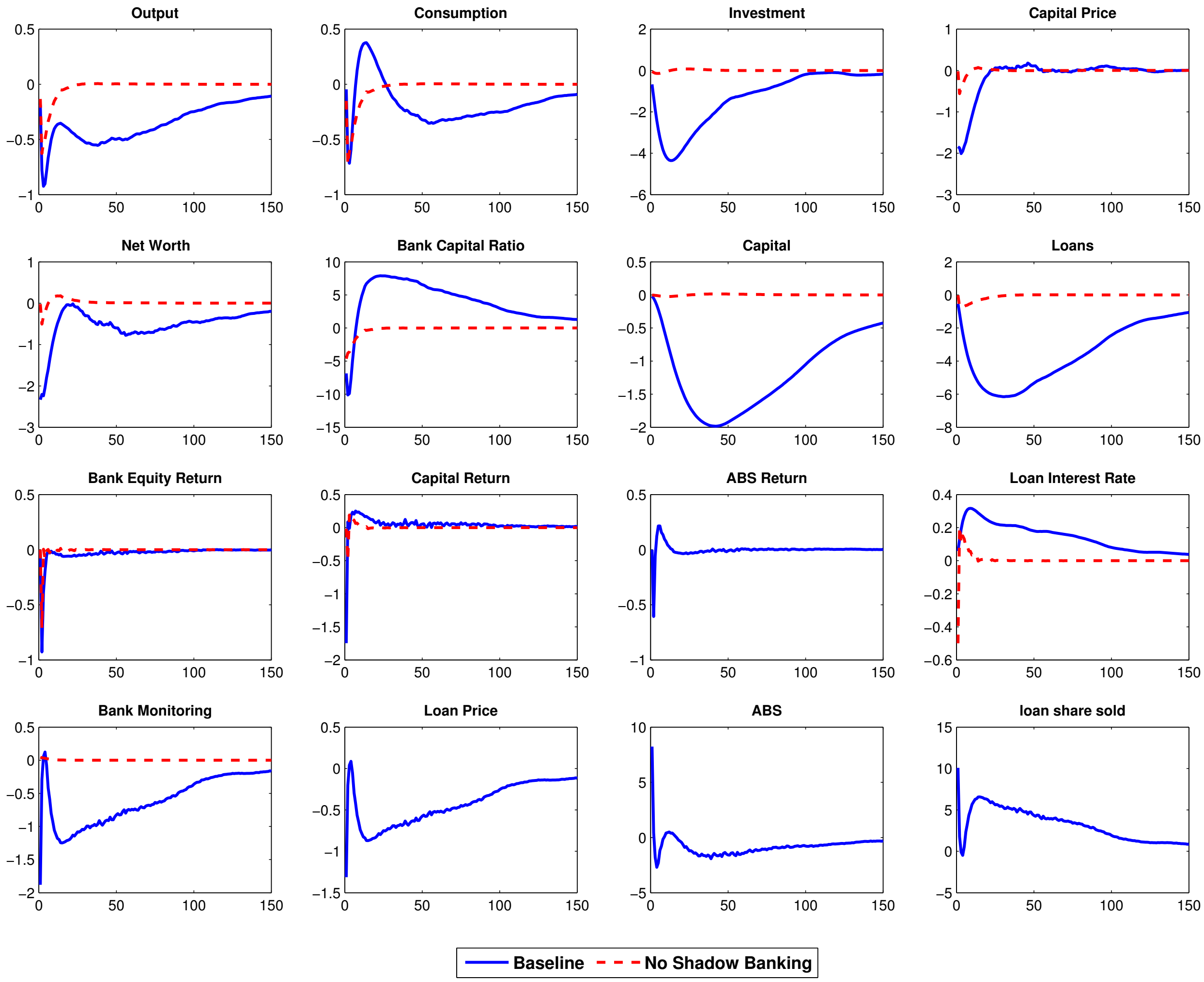
Parameter	Description	Value
Households		
β	Household discount factor	0.99
φ	Inverse labour supply elasticity	0.5
Θ_z	adjustment cost parameter, bank equity transactions	0.36
η	weight attached to leisure in utility function	9.06
Production		
δ	Capital depreciation rate	0.025
α	Share of capital in production	0.33
γ	Survival probability of firms	0.97
φ_x	Investment adjustment cost parameter	12
Entrepreneurs		
σ_e^2	Variance of entrepreneurial idiosyncratic shock	0.255
μ_e	Entrepreneur bankruptcy cost	0.3
Θ	Proportion of net worth consumed by exiting entrepreneurs	0.10
W^e	Transfer from households to entering entrepreneurs	0.009
Financial System		
$\overline{\kappa}$	Capital requirement	0.08
σ_b^2	Variance of banks' idiosyncratic shock	0.046
μ_b	Banks' bankruptcy cost	0.3
Ω	Depositor cost of bank default	0.1
τ_1	Monitoring cost parameter	1.41
τ_2	Monitoring cost parameter	-0.997
τ_z	Coefficient on bank capital buffer	0.0022
ε_s	Elasticity of funds in ABS market	298.2
Shocks		
ρ_a, ρ_σ	Baseline persistence of technology and risk shock	0.9

Figure 10 – TFP shock: One percent drop in TFP



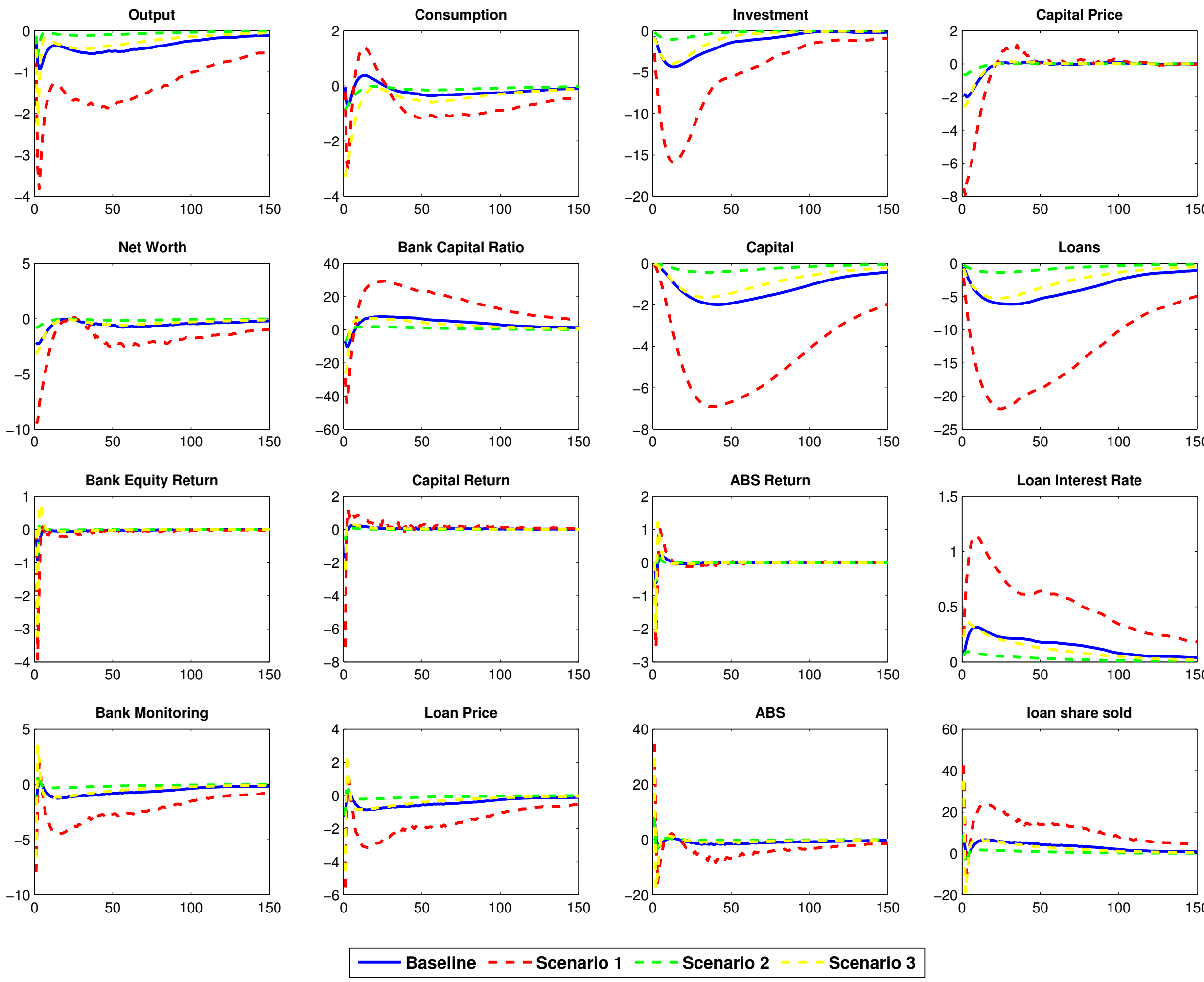
Note: IRFs to one percent decrease in total factor productivity (TFP). Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a one percent drop in TFP decreases output by one percent in the baseline model. X-axis is time in quarters.

Figure 11 – Bank risk shock: 0.1 percentage point increase in the volatility of bank's idiosyncratic risk



Note: IRFs to 0.1 percentage point increase in the standard deviation of banks' idiosyncratic risk. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.1 percentage point increase in bank risk decreases output by one percent in the baseline model. X-axis is time in quarters.

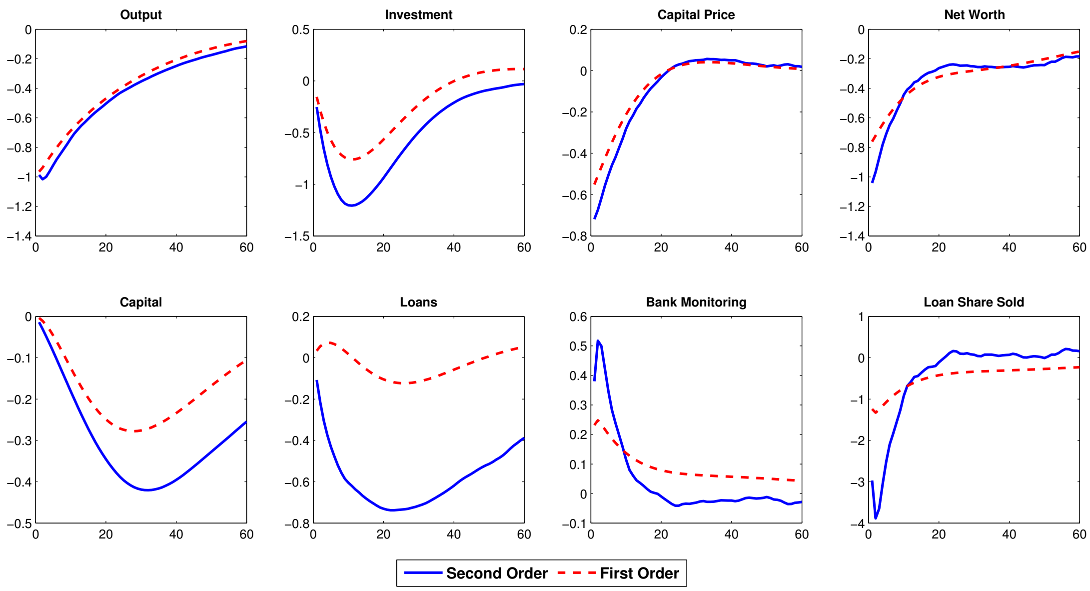
Figure 12 – Bank risk shock: Comparison with different size and persistence of shock



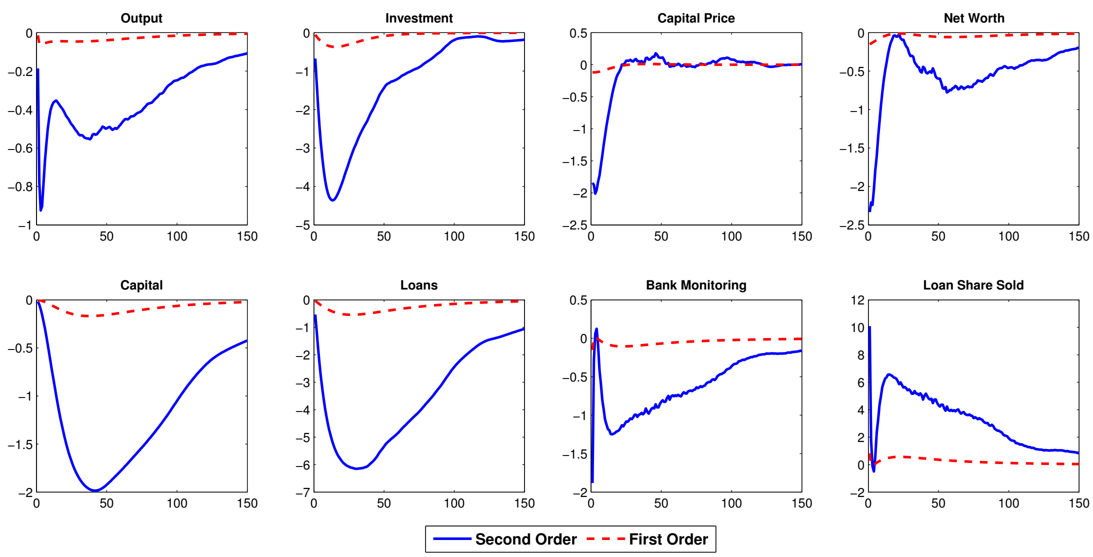
Note: IRFs to bank risk shock under different scenarios. Baseline: persistence 0.9, shock size 0.1 percentage point; Scenario 1: persistence 0.9, shock size 0.2; Scenario 2: persistence 0.5, shock size 0.1; Scenario 3: persistence 0.5, shock size 0.2. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.1 percentage point increase in bank risk decreases output by one percent in the baseline model. X-axis is time in quarters.

Figure 13 – First v/s second order approximation

Impulse response to one percent drop in aggregate productivity

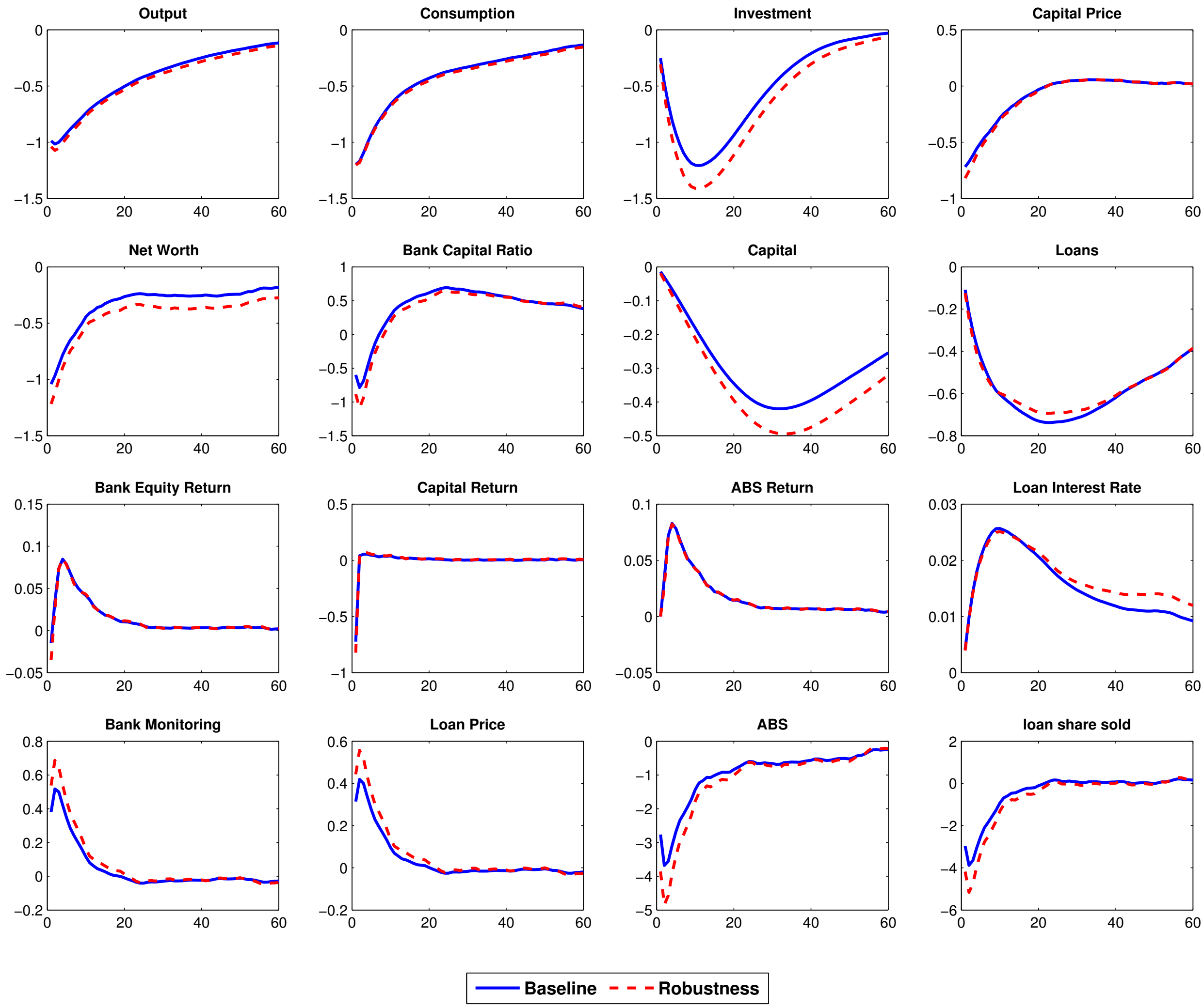


Impulse response to 0.1 percentage point increase in volatility of bank's idiosyncratic risk



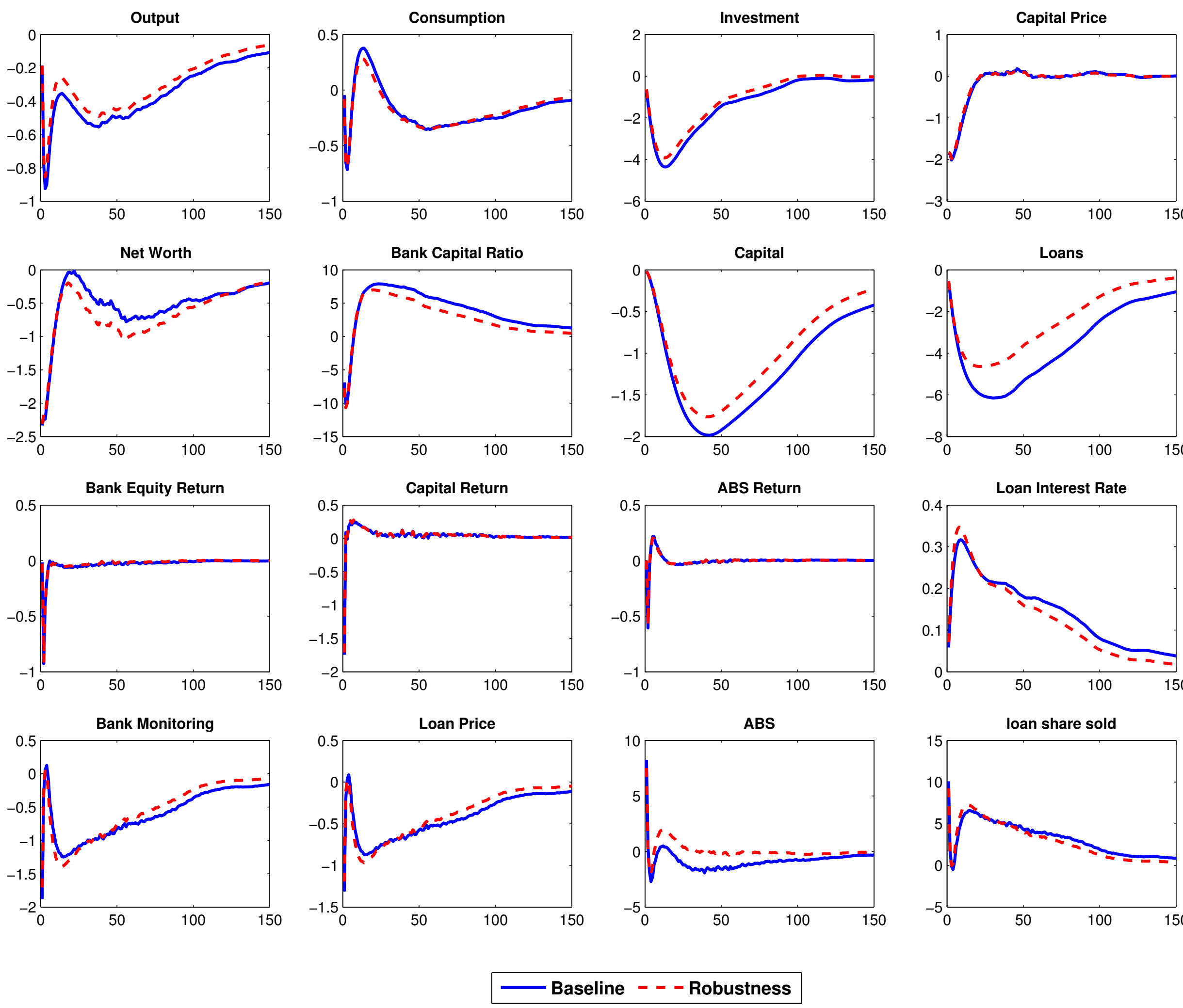
Note: IRFs to one percent decrease in total factor productivity (TFP) and 0.1 percentage point increase in bank risk based on first and second order approximation (averaging one thousand simulations) of the model around the steady state. X-axis is time in quarters.

Figure 14 – TFP shock: Baseline and Robustness scenario



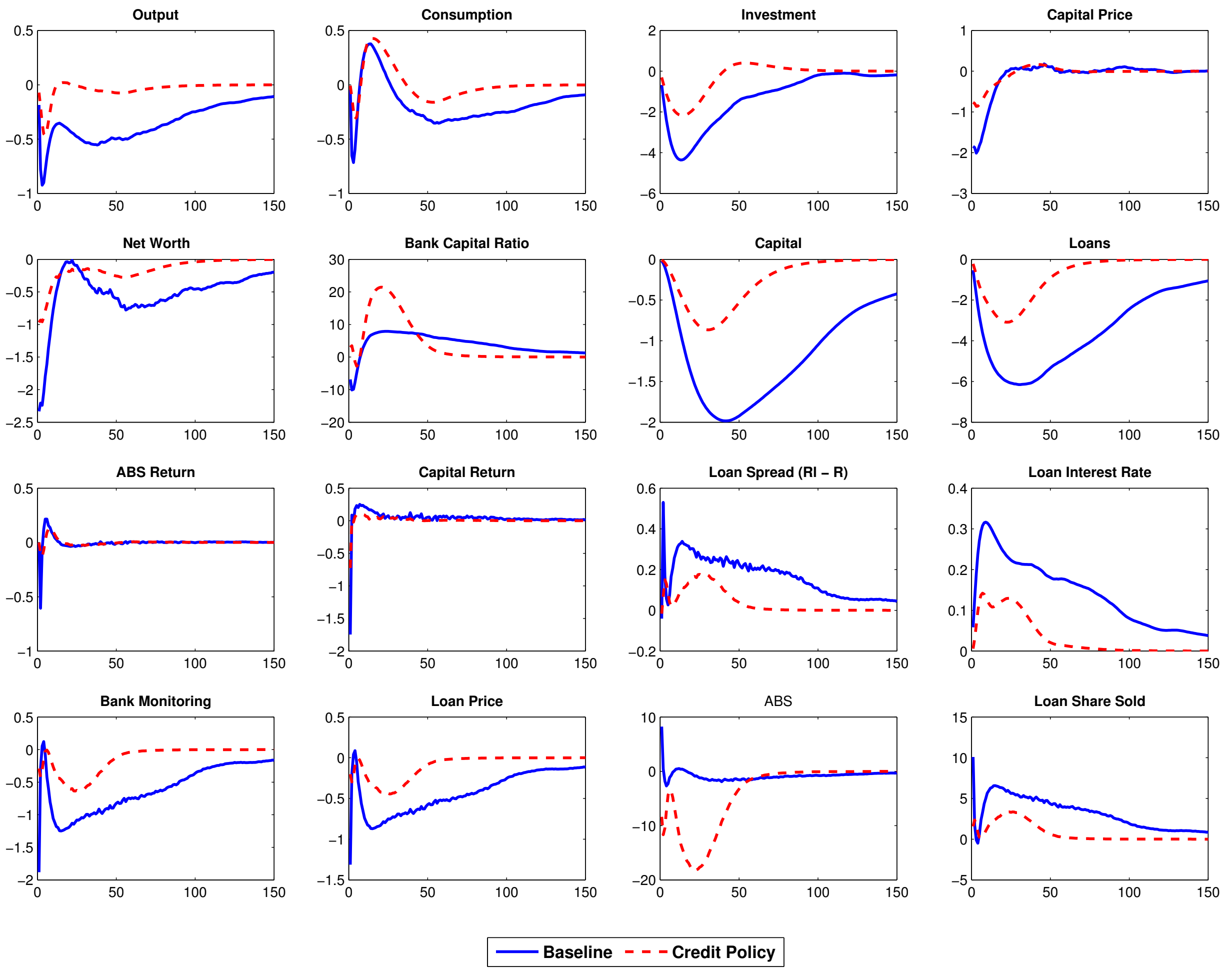
Note: IRFs to one percent decrease in total factor productivity (TFP) under baseline and robustness scenario. Robustness scenario involves increasing financial sector calibrated parameters $(\sigma_e, \sigma_b, \mu_e, \mu_b, \Omega, \tau_1, \tau_2, \tau_z, \varepsilon_s)$ by 10 percent each. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a one percent drop in TFP decreases output by one percent in the baseline model. X-axis is time in quarters.

Figure 15 – Risk shock: Baseline and Robustness scenario



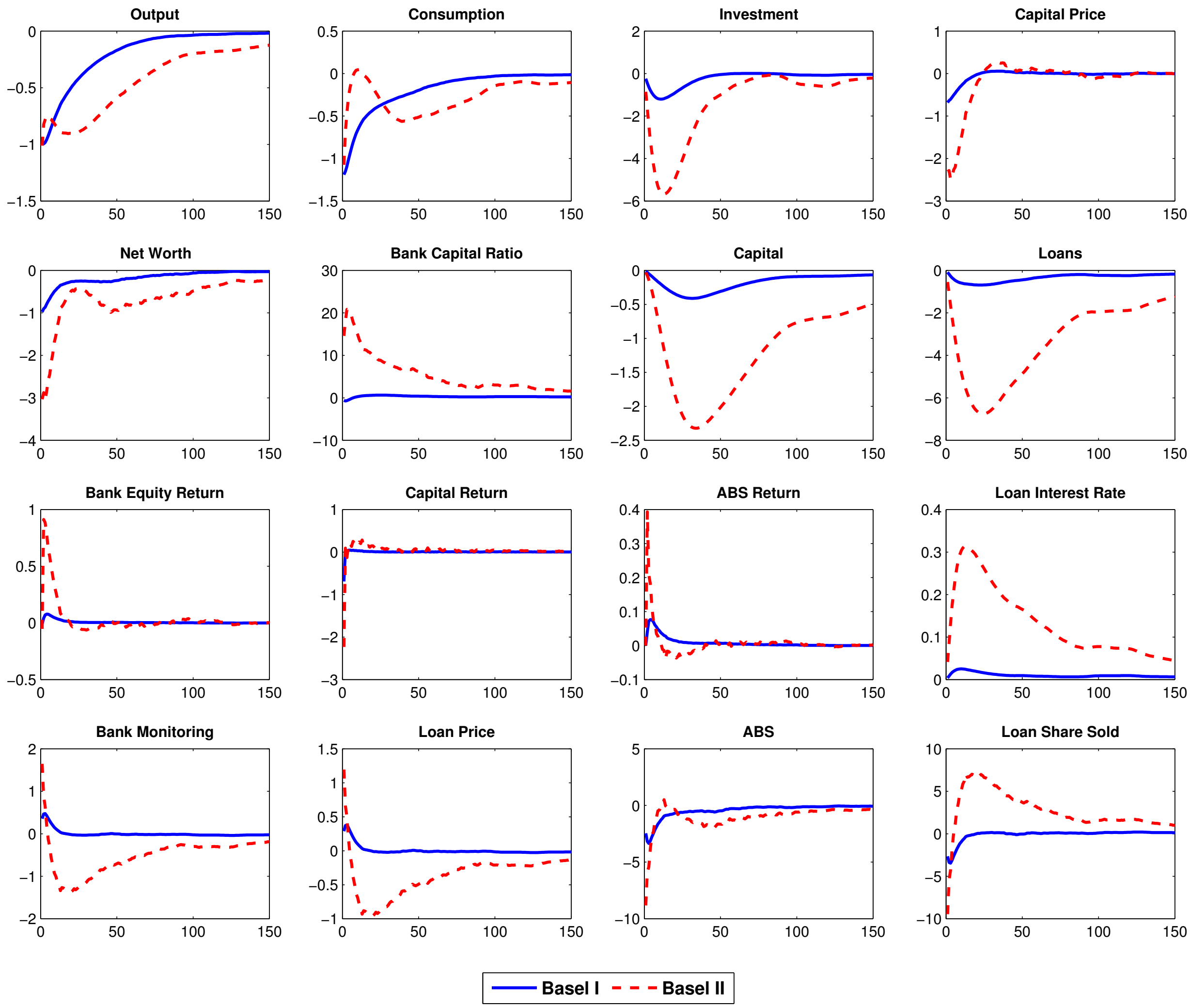
Note: IRFs to 0.1 percentage point increase in the standard deviation of banks' idiosyncratic risk under baseline and robustness scenario. Robustness scenario involves increasing financial sector calibrated parameters $(\sigma_e, \sigma_b, \mu_e, \mu_b, \Omega, \tau_1, \tau_2, \tau_z, \varepsilon_s)$ by 10 percent each. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.1 percentage point increase in bank risk decreases output by one percent in the baseline model. X-axis is time in quarters.

Figure 16 – Risk shock: Response under baseline and active credit policy



Note: IRFs to 0.1 percentage point increase in the standard deviation of banks' idiosyncratic risk under baseline and active credit policy. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a 0.1 percentage point increase in bank risk decreases output by one percent in the baseline model. X-axis is time in quarters.

Figure 17 – Procyclical capital requirement: Response to a negative productivity shock under Basel I and Basel II



Note: IRFs to one percent decrease in total factor productivity (TFP) under fixed and procyclical capital requirement. Based on averaging one thousand simulation of a second-order approximation of the model around the steady state. Y-axis denotes percentage deviation from the steady state i.e. a one percent drop in TFP decreases output by one percent in the baseline model. X-axis is time in quarters.

Appendix 2.1: Model Equations and Competitive Equilibrium

Here, we summarize the equations describing the equilibrium of the model. The competitive equilibrium of our model is a system of endogenous variables ABS_t, B_t, C_t, $C_{e,t}$, D_t, e_t, efp_t, I_t, K_t, κ_t, L_t, b_t, x_t, N_t, $\bar{\omega}_t^e$, $\bar{\omega}_t^b$, PD_t, $P_{s,t}$, $Q_{k,t}$, R_t, $R_{F,t}$, $R_{m,t}$, $R_{k,t}$, $R_{s,t}$, $\widetilde{R}_{F,t}$, $\widetilde{R}_t$, $R_{z,t}$, TD_t, Z_t, w_t, Y_t, GDP_t and $\zeta_{e,t}$, satisfying the relations (2.22) to (2.54), given exogenous stochastic processes A_t,σ_t^b and the initial conditions B_{t-1}, D_{t-1}, e_{t-1}, F_{t-1}, I_{t-1}, K_{t-1}, κ_{t-1}, b_{t-1}, x_{t-1}, N_{t-1}, PD_{t-1}, $P_{s,t-1}$, $Q_{k,t-1}$, R_{t-1}, Z_{t-1}. The endogenous variables jointly satisfy the following equations that include first-order conditions for households, entrepreneurs, commercial banks, shadow banks, firms, capital goods producers, and the resource constraint.

The goods market equilibrium is given by the aggregate resource constraint. Loan market equilibrium requires that the amount borrowed by entrepreneurs is equal to loan supply from banks that is financed by deposits, bank capital or sale of loan in the secondary market. Market for capital services require that the supply from entrepreneurs is equal to the capital demanded by firms. Labour market is equilibrated at the competitive wage when labour supplied by households is equal to firms' labour demand. Finally, equilibrium in the ABS market requires that ABS issued by shadow banks - which in turn depends on the loan sale in secondary market - is equal to the demand for securities from households. A competitive equilibrium consists of a set of prices and interest rates $\{Q_{k,t}, R_t, R_{m,t}, R_{k,t}, w_t\}$ for all possible states and for all $t \geq 0$ such that all markets clear when the agents in the model i.e. households, entrepreneurs, commercial banks, shadow banks, consumer goods producer and capital goods producer solve their maximization problems while taking these prices and interest rates as given.

Households:

Households maximize their present value of utility by choosing D_t, ABS_t , Z_t and L_t The first order conditions are:

$$\beta C_t = E_t(\frac{C_{t+1}}{\widetilde{R}_{t+1}}) \tag{2.22}$$

$$\beta C_t = E_t(\frac{C_{t+1}}{R_{m,t+1}}) \tag{2.23}$$

$$w_t = \eta C_t (L_t)^{\varphi} \tag{2.24}$$

$$\beta C_t = (1 + \Theta_z Z_t).E_t(\frac{C_{t+1}}{R_{z,t+1}}) \tag{2.25}$$

$$\widetilde{R}_t = R_{t-1}(1 - \Omega PD_t) \tag{2.26}$$

Entrepreneurs:

The law of motion of aggregate entrepreneurial net worth is:

$$N_{t+1} = \gamma\{R_{k,t+1}Q_{k,t}K_t - [\widetilde{R}_{F,t+1} + \mu_e \frac{\int_0^{\bar{\omega}^e_{t+1}} \omega^e_{t+1} f^e(\omega^e_{t+1}) d\omega^e_t Q_{k,t}K_t}{Q_{k,t}K_t - N_t}](Q_{k,t}K_t - N_t)\} + W^e \tag{2.27}$$

Their aggregate borrowing is:

$$B_t = Q_{k,t}K_t - N_t \tag{2.28}$$

The first order conditions for entrepreneur yields:

$$-\Gamma^{e'}(\bar{\omega}^e_{t+1})) + \zeta_{e,t}(\Gamma^{e'}(\bar{\omega}^e_{t+1}) - \mu_e G^{e'}(\bar{\omega}^e_{t+1})) = 0 \tag{2.29}$$

$$(1 - \Gamma^e(\bar{\omega}^e_{t+1}))R_{k,t+1} + \zeta_{e,t}[(\Gamma^e(\bar{\omega}^e_{t+1}) - \mu_e G^e(\bar{\omega}^e_{t+1}))R_{k,t+1} - \widetilde{R}_{F,t+1}] = 0 \tag{2.30}$$

Where $\zeta_{e,t}$ is the Lagrange multiplier associated with the participation constraint.

$$E_t[(\Gamma^e(\bar{\omega}^e_{t+1}) - \mu_e G^e(\bar{\omega}^e_{t+1}))]R_{k,t+1}x_t = \widetilde{R}_{F,t+1}(x_t - 1) \tag{2.31}$$

The consumption of entrepreneurs that exit the economy is given by:

$$C_{e,t} = \Theta\frac{(1-\gamma)}{\gamma}(N_t - W^e) \tag{2.32}$$

The state contingent interest rate, $R_{F,t}$ is given by:

$$R_{F,t} = \bar{\omega}^e_{t+1}R_{k,t+1}.(\frac{x_t}{x_t - 1}) \tag{2.33}$$

and

$$R_{k,t+1} = \frac{r_{k,t+1} + (1-\delta)Q_{k,t+1}}{Q_{k,t}} \tag{2.34}$$

The external finance premium on loans between period t and t+1 therefore can be defined as:

$$efp_{t+1} = \mu_e\frac{\int_0^{\bar{\omega}^e_{t+1}} \omega^e_{t+1}f^e(\omega^e_{t+1})d\omega^e_t Q_{k,t}K_t}{Q_{k,t}K_t - N_t} \tag{2.35}$$

Commercial Banks:

Banks' default threshold is given by:

$$\bar{\omega}^b_{t+1} = \frac{R_tD_t}{e_t\widetilde{R}_{F,t+1}B_t(1-b_t)} \tag{2.36}$$

The first order conditions of commercial banks' maximization problem are:

$$R_{z,t+1} = \frac{e_t\widetilde{R}_{F,t+1}(1-\Gamma^b(\bar{\omega}^b_{t+1}))}{\kappa_t} \tag{2.37}$$

$$-e_t\widetilde{R}_{F,t+1}(1-\Gamma^b(\bar{\omega}^b_{t+1}))-\Gamma^{b'}(\bar{\omega}^b_{t+1}).e_t\widetilde{R}_{F,t+1}(\bar{\omega}^b_{t+1}+\frac{R_t}{(1-b_t)}(\kappa_t-P_{s,t})+R_{z,t+1}\kappa_t=0 \tag{2.38}$$

$$R_{z,t+1}(1-b_t)B_t-\Gamma^{b'}(\bar{\omega}^b_{t+1})(1-b_t)R_tB_t=\frac{\tau_z}{2}(\frac{\kappa_t-\overline{\kappa}}{\overline{\kappa}})^{-0.5}.\frac{1}{\overline{\kappa}} \tag{2.39}$$

$$[(1-\Gamma^b(\bar{\omega}^b_{t+1}))+\Gamma^{b'}(\bar{\omega}^b_{t+1}).\bar{\omega}^b_{t+1}]\widetilde{R}_{F,t+1}=\Gamma^{b'}(\bar{\omega}^b_{t+1})R_t[\frac{\tau_1}{2}\frac{(2e_t+\tau_2)}{(1-b_t)}] \tag{2.40}$$

The probability of bank default, which also enters the households' budget constraint is given by:

$$PD_t=\int_0^{\bar{\omega}^b_{t+1}} f^b(\omega^b_{t+1})d\omega^b_{t+1} \tag{2.41}$$

and the total bank equity is given by:

$$Z_t=\kappa_tB_t(1-b_t) \tag{2.42}$$

Finally, the commercial banks' balance sheet states:

$$B_t+\frac{\tau_1}{2}(e_t^2+\tau_2e_t)B_t=D_t+Z_t+P_{s,t}b_tB_t \tag{2.43}$$

Shadow banks:

The average return on ABS sold by shadow banks is:

$$R_{s,t+1}=\frac{e_t\widetilde{R}_{F,t+1}}{P_{s,t}} \tag{2.44}$$

The supply of ABS based on loan sale in secondary market is:

$$P_{s,t}B_{s,t} = P_{s,t}b_tB_t = ABS_t \tag{2.45}$$

and their profit maximization condition yields:

$$R_{s,t+1} = \frac{\varepsilon_s}{\varepsilon_s - 1}R_{m,t+1} \tag{2.46}$$

Consumption Good Producer:

The production function of consumption good producer is:

$$Y_t = A_tK_{t-1}^{\alpha}L_t^{1-\alpha} \tag{2.47}$$

The firms maximize their profits subject to the production function which gives the following first order conditions:

$$r_{k,t} = \alpha\frac{Y_t}{K_{t-1}} \tag{2.48}$$

$$w_t = (1-\alpha)\frac{Y_t}{L_t} \tag{2.49}$$

Capital Good Producer:

The evolution of capital stock is given by:

$$K_{t+1} = (1-\delta_k)K_t + (1-S(G_t))I_t \tag{2.50}$$

and the inter-temporal profit maximization with respect to I_t yields:

$$Q_{k,t}(1 - S(G_t) - X_tS'(G_t)) + E_t[D_{t,t+1}Q_{k,t}S'(G_{t+1})\frac{I_{t+1}^2}{I_t^2}] = 1 \tag{2.51}$$

where $D_{t,t+1}$ is the real stochastic discount rate.

Deposit Insurance Agency:

The total costs to the deposit insurance agency are given by:

$$TD_t = [\bar{\omega}_t^b - \Gamma^b(\bar{\omega}_t^b)) + \mu_b G^b(\bar{\omega}_t^b)]e_{t-1}\widetilde{R}_{F,t}(Q_{k,t-1}K_{t-1} - N_{t-1})(1 - b_{t-1}) \tag{2.52}$$

Resource Constraint:

$$Y_t = C_t + I_t + C_{e,t} + \mu_e G^e(\bar{\omega}_t^e)R_{k,t}Q_{k,t-1}K_{t-1} + \Omega PD_t R_{t-1}D_{t-1} \tag{2.53}$$

$$+\mu_e G^b(\bar{\omega}_t^b)e_{t-1}\widetilde{R}_{F,t}(Q_{k,t-1}K_{t-1} - N_{t-1}) + (1 - e_{t-1})\widetilde{R}_{F,t}B_{t-1}(1 - \Gamma^b(\bar{\omega}_t^b))$$

Finally, we define GDP as net of bankruptcy costs due to default.

$$GDP_t = C_t + I_t + C_{e,t} \tag{2.54}$$

Appendix 2.2: Model Variables and Parameters

Variable	Notation
Household Consumption	C
labour	L
Deposits	D
Asset backed securities/shadow bank deposits	ABS
Bank shares	Z
Real wage rate	w
Riskless return	R
Commercial bank deposit return	$\widetilde{R}$
Shadow bank deposit return	R_m
Shadoe banks' return on asset backed securities	R_s
Bank share return	R_z
Shadow bank profit diverted to households	Π_I
Entrepreneurs' profit diverted to households	$Lump_e$
Lump sum tax on households	TD
Fraction of deposits that default	PD
Entrepreneur j's net worth	N_j
Entrepreneur j's purchase of capital	K_j
Entrepreneur j's bank loan	B_j
Aggregate Net worth	N
Aggregate capital	K
Aggregate loans	B
Capital price	Q_k
Return on capital	R_k
Marginal product of capital	r_k

Entrepreneurs' idiosyncratic shock	ω^e
Variance of entrepreneurial idiosyncratic shock	σ_e^2
Threshold value of idiosyncratic shock (for entrepreneurs survival)	$\bar{\omega}^e$
Contractual gross return on bank loan	R_F
Entrepreneurial leverage	x
Bank's share of gross return on entrepreneurial investment	$\Gamma^e(.)$
Share of return from defaulted loans	$G^e(.)$
Startup transfer of net worth to new entrepreneurs	W^e
External finance premium	efp
Entrepreneurs' consumption	C_e
Off balance sheet loan	B_s
Share of loans sold in secondary market	b
Bank manager's monitoring effort	e
Convex monitoring cost	$c(e)$
Bank return on a well diversified portfolio	$\widetilde{R_F}$
Banks' idiosyncratic shock	ω^b
Variance of banks' idiosyncratic shock	σ_b^2
Threshold value of idiosyncratic shock (for bank survival)	$\bar{\omega}^b$
Bank capital ratio	κ
Loan price in secondary market	P_s
Bank's profit	π_z
Depositors share of gross return on loans	$\Gamma^b(.)$
Share of bank assets of defaulted banks	$G^b(.)$
Loan price paid by zth shadow bank in secondary market	$P_s(z)$
Loan sold to zth shadow bank in secondary market	$BS(z)$
Return on household funding to shadow banks	R_m

Output	Y
Total factor productivity	A
Investment	I
Convex investment costs	$S(.)$
Government lending; credit policy	B_g
Private lending; credit policy	B_p
Government intermediation costs; credit policy	G
Government transfers; credit policy	T
Minimum capital requirement; Basel II	Cap

Parameter	Notation
Household discount factor	β
Weight attached to leisure in the utility function	η
Inverse labour supply elasticity	φ
Adjustment cost parameter, bank equity transactions	Θ_z
Depositor cost of bank default	Ω
Survival probability of firms	γ
Entrepreneur bankruptcy cost	μ_e
Proportion of net worth consumed by exiting entrepreneurs	Θ
Monitoring cost parameter; bank effort	τ_1
Share of capital in production	α
Monitoring cost parameter; bank effort	τ_2
Banks' bankruptcy cost	μ_b
Capital requirement	$\bar{\kappa}$
Coefficient on bank capital buffer	τ_z
Elasticity of funds in secondary loan sale market	ε_s

Investment adjustment cost parameter	φ_x
Capital depreciation rate	δ
Technology shock; persistence	ρ_a
Risk shock; persistence	ρ_σ
Technology shock; std. deviation	σ_a
Risk shock; std. deviation	σ_r

3 Can Low interest rates be harmful: An assessment of bank risk taking channel in Asia-Pacific

Events surrounding the global financial crisis have brought to light the potential role of monetary policy in precipitating the crisis. Numerous studies on advanced economies have documented a significant negative relationship between interest rates and bank risk-taking. This paper also finds the presence of the risk-taking channel based on a panel of publicly listed bank data in Asia. Using both annual and quarterly data, "too low" interest rates are found to lead to an increase in bank risk-taking.[31]

3.1 Introduction

Of the many causes of the global financial crisis, one that strikes a particular discord among central bankers is the notion that an accommodative monetary policy can be harmful to the economy. For many, it is unsettling to realize that the role of monetary policy, which has long been considered a stabilizer or stimulant of short-term business cycles—the solution—could in fact be the problem. Still, the literature that implicates the role of monetary policy is not completely new or unknown. Fisher (1933), Hayek (1939), and Kindleberger (1978) are some studies that highlight easy monetary conditions as classical ingredients in boom-bust business fluctuations. Hayek (1939) of the Austrian business cycle theory fame espouses that excessive credit expansion accommodated by lax monetary policy precedes and lays the groundwork for recessions. Meanwhile, Minsky's (1992) financial instability hypothesis posits that during periods of high economic growth, the income-debt arrangements of economic units shifts from hedge finance (completely hedged debt) toward speculative and Ponzi finance (highly unstable leverage and higher risk). This tendency is heightened by protracted low interest rates when a growing number of investors seek higher yields

[31] This chapter was started during my short stint at the Asian Development Bank (ADB) under the guidance of Dr. Hsiao Chink Tang and Dr. Arief Ramayandi. However, all analytical work, estimations and analysis of results was done by me. I continued to work on the chapter even after I left ADB. Dr. Hsiao Chink Tang provided useful comments and suggestions.

despite increasing risk. Thus, loose monetary and credit policy play an important role in the evolution from financial stability to crisis.

This paper focuses exclusively on the risk-taking behavior of financial intermediaries in response to loose monetary conditions. A prolonged period of relatively low interest rates can induce financial imbalances by reducing risk aversion of banks and other investors. In the context of the global financial crisis, it is said to have contributed to the credit boom, asset price increases, a decline in risk spreads, and a search-for-yield that eventually saw the bust in the US subprime and housing markets, the collapse of major financial institutions, and ultimately, the Great Recession (Hume and Sentance 2009; Taylor 2009; Diamond and Rajan 2009). This, until recently, missing link in the monetary policy transmission mechanism—known as the risk-taking channel (Borio and Zhu 2012; Rajan 2006)—relates to how changes in interest rates affect either risk perceptions or risk-tolerance of financial intermediaries.

As a relatively recent issue of monetary transmission mechanism, risk-taking channel does not have a specific definition, but indeed, it is a common term used for various mechanisms at work, which are all mutually inclusive. While this new monetary policy channel has its gray areas at the time being, it deserves close exploration for a fuller understanding the link between the monetary policy and financial stability and to draw clearcut policy conclusions. The findings regarding the risk-taking channel have potentially important implications for the conduct and design of monetary policy, as a better understanding of risk taking channel may provide an insight for monetary authorities to adjust their policies in order to mitigate the adverse consequences of their polices on bank risk-taking and in turn, avoid the buildup of risks in the financial system. If policymakers understand banks' risk-taking incentives and focus on the potential impact of their polices on bank risk, they may find answers to when and how to be more cautious and what factors they should take into account in their policy design. Furthermore, understanding the risk-taking channel would provide us comprehension regarding the macroeconomic implications of bank supervision and regulation as well.

Empirical literature on the risk-taking channel has thus far focused mostly on the

US and the euro area. This study therefore fills an important void in examining the impact of low interest rates in 10 Asian economies (the People's Republic of China (PRC); Hong Kong, China; India; Indonesia; the Republic of Korea; Malaysia; the Philippines; Singapore; Taipei,China; and Thailand) from 2000 to 2011. Since a meaningful study of bank risk taking would require sufficiently large and relatively well developed banking sector, we restrict our focus to developed and emerging market economies in Asia. The study also sheds light on the bank specific characteristics which may have an impact on bank risk. Furthermore, in our computation of bank risk instead of relying on one particular risk measure as done by most studies on the risk-taking channel, we employ alternative risk measures to cover different risk-taking behavior. In particular, both market based and accounting based indicators of bank-risk are considered. We control for a number of factors that may have an impact on banks' risk such as macroeconomic performance, financial deepening, stock market returns, regulatory environment as well as bank specific characteristics, namely size, capitalization and profitability of banks. Based on both quarterly and annual data, we find the presence of the risk-taking channel in Asia. In addition, we find more nuanced results using the quarterly data. In particular, we find contemporaneous impact of low interest rates reduces bank riskiness mostly likely in lowering the default probability of existing loans. Yet over time, banks become more aggressive and tend to lend less to creditworthy borrowers. As a result, the overall risk level of banks rises.

There are some important caveats in our study that should be be asserted before going into details of the analysis. First, we do not make any inferences on the optimality of risk choices of banks, as from a theoretical viewpoint, it may be optimal for a bank to engage in riskier projects when interest rates are low and further, it may also be the socially optimal outcome of monetary policy during recession periods as well. Thus, the results from the study should be interpreted as changes in the risk appetite/tolerance of banks in response to interest rates being lower than some benchmark level. Second, and more important there is a part of literature suggesting that risk-taking principally refers to new risk i.e. new loans. In effect, the focus then is on the incentives of banks to undertake risky projects ex-ante.

It is therefore important to distinguish between realized and new risk to draw an accurate inference regarding the relationships between monetary policy and bank risk taking. Such a comprehensive analysis requires the use of detailed data on individual bank loans from credit registers, which provides information on lending standards, loan performance etc, which is missing for the case of Asia. Furthermore, data on individual loan borrower characteristics is confidential in most cases and available for very few countries that maintain a credit register. This is reflected in the handful of studies that make use of such detailed data to study the relationship between monetary policy and bank risk-taking (Jimenez et al. (2014); Ioannidou et al. (2015) and Lopez et al. (2011)). Finally, the paper does not explicitly take into account the issue of implicit government support. There has been significant debate about the role of implicit guarantees in exacerbating moral hazard and undue risk-taking. The effect of implicit government support would be more pervasive under an extended period of lower-than-usual interest rates. Capturing this effect would require detailed data to proxy the expectation of external government support, which to our knowledge is not available for Asia.

The rest of this paper is organized as follows. Section two reviews the theoretical and empirical literature on the bank risk-taking channel. Section three discusses the model specification of the bank risk-taking channel with a focus to delineate it from other channels of monetary policy transmission mechanism. Section four delves on data and estimation issues. Results are presented in section five, while section six concludes.

3.2 Literature: Theory and Evidence

The relatively new concept of the risk-taking channel of monetary policy transmission mechanism is reflected in the scarcity of its theoretical contributions. Some elements of the theory of risk-taking channel can be traced in the theoretical propositions of some previous work such as Keeley (1990); Allen and Gale (2000); Dell' Ariccia and Marquez (2006); and Rajan (2006). Although some of the mechanisms have been discussed previously, the term 'risk-taking channel' of monetary policy was coined by Borio and Zhu (2012) in which they point to the potential of low interest rates to increase bank risk-taking.

More specifically, low interest rates can lead banks to take on more risk in several ways. First, low interest rates boost prices and collateral values of assets on banks' balance sheets, which in turn modify banks' estimates of probabilities of default, losses in the case of default, and overall volatility of bank returns[32]. Measured volatility tends to decrease in rising markets[33], which relaxes banks' budgetary constraints and leads to even more risk-taking (Borio and Zhu 2012). According to Adrian and Shin (2009), low short-term rates may lead to more risk-taking because they improve banks' profitability and relax their budgetary constraints.

Second, low interest rates may influence banks to search-for-yield (Rajan 2006). In a low interest rate environment, the incentives of asset managers to engage in more risky projects rise for a number of reasons. Primarily, this mechanism predominantly works through the relationship between the low levels of short-term interest rates and sticky target rate of returns. Financial institutions often enter into long-term contracts committing them to produce high nominal rates of return. In a period of low interest rates, these contractual rates may exceed the yields available on safe assets. To earn higher returns, banks therefore will have to search for higher yields from the more risky assets. Moreover, a similar mechanism could be in place whenever managerial compensation is linked to absolute yields. In a low interest rate environment, lower yields on safe assets imply a lower compensation for managers that choose to invest in safe assets, giving managers higher incentives to invest in more risky assets. In all cases, the effect of the channel becomes stronger as the resulting gap between the market and target rates becomes larger.

[32] This is in close spirit to the familiar financial accelerator mechanism, which argues that increases in collateral values reduce borrowing constraints (Bernanke et al. 1996). Adrian and Shin (2009) claim that the risk-taking channel is distinct but complementary to the financial accelerator because it focuses on amplification mechanisms due to financing frictions in the lending sector

[33] The literature suggests that short-term volatility is directional, that is, it tends to fall in rising markets and rise in falling markets. For instance, for equity returns, see Schwert (1989) and, for bonds, Borio and McCauley (1996).

Third way through which the risk taking channel operates is through the effect of communication policies and the reaction function of the central bank (Borio and Zhu (2012). In this process, capability of central banks for managing short term inflation expectations and inflation rate is especially important. In this context, transparency and predictability of monetary policies decrease both the uncertainty related to the variation in inflation and short and long term interest rates and accordingly in financial market prices. Fourth, banks' perception that the central bank will ease monetary policy in bad economic times can also lower the expectations of large downside risks—the moral hazard problem. This implies that changes in interest rates can have an asymmetric impact on risk-taking, that is, reductions encourage risk-taking by more than the equivalent increases in discouraging risk-taking. This expectation became more important in the recent period. When banks expose to a shock threatened the stability of the financial system, and they expect from central bank to lower the interest rate aggressively, they will incline to undertake higher risk. Accordingly, essential reason of the formation of moral hazard is the commitment stating interest rates will be implicitly kept low instead of having low interest rates (De Nicolo et al, 2010). Fifth, Dell'Ariccia and Marquez (2006) point out that low interest rates reduce adverse selection in credit markets, which decrease banks' incentives for screening loan application. Finally, Akerlof and Shiller (2009), in turn, suggest that, due to money illusion in periods of low interest rates, investors take higher risks to increase returns.

All of the above mentioned mechanisms are the candidate driving forces behind the risk-taking channel. Although being diverse, they may tend to work at the same time as well. Furthermore, it should be noted that none of these proposed explanations is more important than the other, as there is no conclusive evidence regarding the relative importance of them. In part, this is due to the lack of theoretical models, which reveal the details of either potential mechanism and allows the precise understanding of their characteristics. The risk-taking channel is a relatively recent area of monetary economics; hence the theoretical literature is still being developed and is rather limited for the time being. There are only a handful studies that present formal models where several mechanisms of the risk-taking channel act together. We summarize some of these theoretical studies here. However, since our main focus is on the empirical analysis of risk-taking channel we list the empirical contributions in greater detail. Dubecq et al. (2015) provide a model with risk-shifting where the level of interest rates affects the risk perception of some investors and risk exposure by others. They argue that situation of uncertainty with respect to regulatory constraints may cause market participants to form wrong inferences on risks. Dell' Ariccia et al. (2010) use a static model to assess the impact of prolonged easy monetary policy on bank risk-taking. In their model, banks' risk appetite increase in prolonged periods of lax monetary conditions, however the net effect of monetary policy depends on the balance of the interest rate pass-through, risk shifting and capital structure. Giavazzi and Giovannini (2010) model the interactions between monetary policy and liquidity transformation. They claim that optimal monetary policy consists of a modified Taylor rule, which takes into account the possibility of liquidity crises and thus adjusts to changes in risk-taking. Diamond and Rajan (2012) present a model where the fiscal authority is able to affect real interest rates, arguing that ex ante regulation may not be effective if the extent of ex ante promises are hard to observe. They suggest raising real interest rates in normal times to prevent banks from making excessive liquidity promises. Cao and Illing (2015) model how financial intermediaries' incentives for liquidity transformation are affected by the central bank's reaction to financial crisis. They demonstrate that interest rate policy as financial stabilizer is dynamically inconsistent, and imposing ex ante liquidity requirements can increase efficiency.

Although the risk-taking channel of monetary transmission is still not well-understood, an increasing number of empirical studies have been produced to analyze whether there is a relationship between low interest rates and bank risk-taking and attempt to clarify characteristics of the risk-taking channel. Most single or multiple-country empirical studies have tended to find the presence of risk-taking channel. There are two broad types of studies: those using macro data that try to capture the link between monetary policy and risk behavior, and others using micro data to provide micro-level panel evidence for the impact of interest rate changes on individual bank' risk-taking behavior[34]. The list of papers that use micro data to study bank behavior has been increasing rapidly in the recent past. Our work belongs to this line of research and the remaining part of this section summarizes these studies. The first empirical investigation on bank risk taking behavior in response to monetary policy conditions belongs to Jimenez et al. (2014) who examined the case of Spanish banks before the introduction of the euro. Using a variety of duration models and time to default as a measure of risk, they find that low interest rates affect the risk of bank loan portfolio in two opposing ways. In the short-term, low interest rates reduce the probability of default of the outstanding loans; in the medium term, however, banks act more aggressively, that is, they lend to borrowers with a worse credit history and grant more loans with a higher probability of default. In the same vein, Gaggl and Valderrama (2010) look at Austrian banks and find that the expected default rates of banks' business loans increased during the period of low refinancing rates from 2003 to 2005.

On the other hand, Ioannidou et al. (2015) take a slightly different approach by examining the quantity and quality of loans, as well as the price of loans. Based on data from 1999 to 2003, they find that when the federal funds rate was reduced, Bolivian banks not only increased the number of risky loans, they also reduced the rates they charged to risky borrowers relative to the rates for less risky ones[35]. Using a similar methodology, in addition to the loan and bank specific characteristics as per Ioannidou et al. (2015), Paligorova and Santos (2017) also control for borrower specific characteristics and find over the period of 1990 to 2010, when the US federal funds rates were low, banks demanded relatively lower spreads on their loans to riskier borrowers than to safer ones.

Tabak et al. (2010) uses individual bank- level data for commercial banks operating in Brazil over the period from 2003 to 2009 in order to analyze the risk-taking

[34]Studies using macro data include, for instance, Angeloni et al. (2015); Eickmeier and Hoffman (2013) and Bekaert et al. (2013). These papers employ vector autoregression (VAR) to provide time series evidence on the risk taking channel. Another group of studies utilize both macro and micro level data in their analysis, for example De Graeve et al. (2008); De Nicolo et al. (2010).

[35]Bolivia is a highly dollarized economy with the exchange rate pegged to the US dollar. Hence, the US federal funds rate was used in their study.

channel of monetary policy transmission. Their results indicate that lower interest rates lead to an increase in banks' credit risk exposure, supporting the existence of the risk-taking channel. Furthermore, liquidity and bank size are found to have a positive relation with risk. Lopez et al. (2011) employs a dataset from the Credit Register from Colombia over the period 2000-2008. This paper finds a statistically significant link between interest rates and banks' risk taking. Lower interest rates increase the probability of default on new loans and reduce that on outstanding loans. They find that small and highly leveraged banks are more willing to take risks. Using 53 quarterly bank level data for Turkey over the period 2002-2012, Özsuca and Akbostancı (2016) find evidence that low levels of interest rates have a positive impact on banks' risk-taking behavior. Specifically, low short term interest rates reduce the risk of outstanding loans; however short term interest rates below a benchmark level increase risk-taking of banks. Delis et al. (2011) examine the impact of US monetary policy on bank risk-taking by using two alternative micro datasets: quarterly balance sheet data from Call Reports and data on new loans from the syndicated loan market. They present empirical evidence that low interest rates tend to decrease loan portfolio risk of a bank in the short-run, but increase it in the long-run.

In terms of multi-country studies, Maddaloni and Peydro (2011) use credit standards surveys and find periods of low short-term rates are associated with softening of lending standards by banks in the euro area and the US. Altunbas et al. (2014) also find low interest rates over protracted periods lead to an increase in bank risk as captured by banks' expected default frequencies. They use publicly available quarterly information of 600 banks from 1999 to 2008, of which about two-thirds are US listed entities, the rest, European. Using a database of listed banks from the European Union and United States developed by Altunbaş et al. (2014), Gambacorta (2009) states that when interest rates are low for an extended period banks' EDFs tend to increase. The results confirm the existence of a risk-taking channel. All other things being equal, liquid and well capitalized banks are found to be less risky. This result differs from Jimenez et al. (2014) and Ioannidou et al. (2015). Delis and Kouretas (2011) use a similar panel generalized method of moment (GMM) methodology but with annual euro bank data from 2001 to 2008 and find substantive evidence of bank risk-taking.

In general, there is enough international evidence to suggest the presence of an operational risk-taking channel. Notably, most of the existing empirical literature on the risk-taking channel provide evidence for the U.S and Euro area, whereas very few studies have investigated the role of monetary policy in emerging market economies. Specifically, these include Ioannidou et al. (2015) for Bolivia, Tabak et al. (2010) for Brazil, Lopez et al. (2011) for Colombia and Özsuca and Akbostancı (2016) for Turkey and all of them present empirical evidence on the existence of such a channel. So far there has not been any study examining the risk-taking channel in Asia, a gap we intend to fill. Our paper is closest to Altunbas et al. (2014), but with the major exception of being Asian focused. In addition to using quarterly data as per Altunbas et al. (2014), which helps provide a more nuanced analysis of the dynamics of bank risk-taking, we also use annual data as they present a longer time-series and larger cross-sectional dimension. Unlike Altunbas et al. (2014), however, we explicitly derived our bank risk dependent variable, whereas their main bank risk indicator is obtained from a proprietary data provider.

For many emerging economies, it is instructive to note that low interest rates abroad especially in advanced economies can also translate to lower than appropriate interest rates in the domestic economy (Bank for International Settlements (BIS) 2012; Taylor 2012). The centrality of the US dollar in the world trading system means that many emerging economies tend to peg their currencies to the US dollar (McKinnon 2013; McKinnon and Schnabl 2004). With capital mobility, this implies that their monetary policies will typically track the monetary policy of the US. A particular problem arises when the emerging economies' business cycles do not synchronize with the US business cycle. BIS (2012) highlights a specific scenario during the global financial crisis, when despite the decline in world interest rates, persistent interest rate differentials remained between the relatively higher interest rates in the emerging economies and that of the advanced economies. The search-for-yield in this case led to a surge in capital flows into the emerging economies buoying domestic economic and financial conditions. The appropriate stabilization strategy would be to tighten policy (let interest rates rise), yet this was seldom done in order to discourage further capital inflows and hold the exchange rate relatively steady.

3.3 Model Specification

This paper follows the modeling spirits of Altunbas et al. (2014) and Delis and Kouretas (2011), which is based on the literature of the determinants of bank risk and monetary policy transmission mechanism. In essence, besides the interest rate variables of focus, the model also includes a set of bank specific controls, and a set of structural, macro, and regulatory controls pertinent to a particular country. These controls are aimed to better delineate the impact of bank risk-taking channel from other monetary policy transmission channels.

The model with annual data is:

$$br_{i,j,t} = \alpha br_{i,j,t-1} + \beta ir_{j,t} + \gamma ig_{j,t} + \delta gr_{j,t} + \theta yc_{j,t} + \rho cg_{j,t} + \tau er_{j,t} + \upsilon sm_{j,t} + \phi_1 sz_{i,j,t} + \phi_2 cp_{i,j,t-1} + \phi_3 lq_{i,j,t-1} + \phi_4 pr_{i,j,t-1} + \mu_1 sp_{j,t} + \mu_2 md_{j,t} + \mu_3 cs_{j,t} + \zeta ce_{i,t} + \varepsilon_{i,t}$$

On the other hand, the quarterly model is:

$$br_{i,j,t} = \alpha br_{i,j,t-1} + \sum_{k=0}^{1} \beta_k ir_{j,t-k} + \sum_{k=0}^{1} \gamma_k ig_{j,t-k} + \sum_{k=0}^{1} \delta_k gr_{j,t-k} + \sum_{k=0}^{1} \theta_k yc_{j,t-k} + \sum_{k=0}^{1} \rho_k cg_{j,t-k} + \sum_{k=0}^{1} \tau_k er_{j,t-k} + \sum_{k=0}^{1} \upsilon_k sm_{j,t-k} + \phi_1 sz_{i,j,t} + \phi_2 cp_{i,j,t-1} + \phi_3 lq_{i,j,t-1} + \mu_1 sp_{j,t} + \mu_2 md_{j,t} + \mu_3 cs_{j,t} + \zeta ce_{i,t} + \varepsilon_{i,t}$$

$br_{i,j,t}$ is a measure of bank risk of bank i in country j at time t. For the annual model, we use four measures of bank risk: (1) the idiosyncratic risk of a simple capital asset pricing model (CAPM), br_1; (2) the ratio of non-performing loans to total loans, br_2; (3) the z-score, br_3 ; and (4) the standard deviation of the return on assets, br_4. For the quarterly model, due to data constraints, we only use the idiosyncratic risk[36].

$ir_{j,t}$, is the change in short-term interest rates that proxy for the change in the monetary policy stance. $ig_{j,t}$ is the interest rate gap that measures the difference between the policy rate and a benchmark rate. It is the variable of main interest

[36]Derivations of these measures will be discussed later. See also the appendix 3.1 and Table 9 for summary statistics of variables used.

that captures the bank risk-taking channel, specifically the phenomenon of search-for-yields as discussed in Section 3.2. Since a drop in interest may not necessarily imply excessive low rates, a benchmark would provide a measure for how low is actually low. If the bank risk-taking channel is operational, we expect γ to be negative, meaning higher interest rates (above some benchmark) reduce bank risk-taking or, conversely, lower interest rates increase bank risk-taking. We follow Altunbas et al. (2014) in using this indicator as a measure of the bank risk-taking channel[37]. In addition, as per Altunbas et al. (2014), we use both the change in interest rates and the interest rate gap in the estimations. The latter is a sharper measure of bank risk-taking channel as it better captures the phenomenon of search-for-yield, while the former is a coarse measure that also incorporates the financial accelerator effect or the balance sheet channel. Specifically, any change in interest rates will affect borrower's collateral value (the balance sheet effect), and in turn the riskiness of bank loans portfolio[38].

The Taylor benchmark rates are consistently higher than the natural rates (or more accurately the trend rates) in all economies. The interest rates in most of the economies, although higher than the rates in developed countries, are still low against the background of their trend output growth rates over the past several years. This reinforces BIS (2012) which argues that policy rates in emerging market economies, particularly in Asia, appeared unusually accommodative by the end of 2011. Following the global financial crisis of 2007, there was a downward movement in the interest rates in line with the near zero-interest rate policy in the developed world with some signs of reversal post 2010. Output and inflation also followed a

[37]Delis and Kouretas (2011) use levels of interest rates in their main estimations, and changes in interest rates as a robustness check. They acknowledge that the changes in interest rates are a measure of the bank risk-taking channel.

[38]It is important to distinguish the risk-taking channel from more widely understood channels relating to credit market, namely, the financial accelerator or the balance sheet and bank lending channels, which together constitute the broad credit channel. The risk-taking channel goes beyond the change in the net worth of both lenders and borrowers (which is incorporated in the broad credit channel). It focuses on "the impact of changes in policy rates on either risk perceptions or risk-tolerance and hence on the degree of risk in the portfolios, on the pricing of assets, and on the price and non-price terms of the extension of funding" (Borio and Zhu 2012). In other words, it accounts for the amount of uncertainty a lender is willing to hold in its portfolio.

downward trend, most notably between 2008 and 2009, followed by a quick recovery thereafter. This is also reflected in the rising Taylor benchmark rates post 2009.

$gr_{j,t}$ is the real GDP growth rate of country j. $yc_{j,t}$ measures the slope of the yield curve of country j. Both these variables are included to capture the effects of the expectations channel of the transmission mechanism. As a priori, the coefficient of gr is expected to be negative—better economic conditions raise the profitability of a larger number of projects in accordance with the expected net present value, which reduces the overall credit risk to banks (Kashyap et al. 1993, Altunbas et al. 2014). Similarly, the coefficient of yc should be negative—the steeper the slope of the yield curve, the higher the bank profits (Viale et al. 2009; Entrop et al. 2012) and the lower the bank risk.

$cg_{j,t}$ is bank credit to GDP of country j (Delis and Kouretas 2011; Mannasoo and Mayes 2009). Previous studies have found mixed signs. For example, Gonzalez-Hermosillo et al. (1997), Mannasoo and Mayes (2009), and Delis and Kouretas (2011) find that financial deepening increases the vulnerability of the banking sector—a positive relationship. This lends support to evidence from the global financial crisis particularly in the developed economies where excessive finance was found to have harmed the economy (Taylor 2009; Diamond and Rajan 2009; Turner 2012). On the other hand, other studies consider financial deepening as a sign of economic maturity and therefore expect a negative coefficient (Hutchison and Mc-Dill 1999).

$er_{j,t}$ measures exchange rate volatility of country j to account for the exchange rate channel. As the countries studied in this paper are mostly small and open economies, they tend to be susceptible to volatile capital flows. Hence, the more volatile the economic environment, the more volatile is the exchange rate and the higher is the bank risk.

$sm_{j,t}$ measures changes in the broad stock market index of country j that captures the wealth channel. We expect the coefficient to be negative. An increase in the asset prices would increase the collateral value, thereby reducing bank risk.

$sz_{i,j,t}$ size; , capitalization; $cp_{i,j,t-1}$ and $pr_{i,j,t-1}$, profitability; are the bank specific variables of bank i in country j included to control for the bank lending channel effects.

The bank lending channel focuses on the financial frictions derived from the balance sheet situation of banks[39]. Based on empirical evidence, the signs on these variables are expected to be negative as bigger, more capitalized, highly liquid and more profitable banks would be as less risky. Bank specific characteristics, except size, which is considered as a predetermined variable, are lagged to deal with endogeneity (Delis and Kouretas 2011).

$cs_{j,t}$, capital stringency index; $sp_{j,t}$, supervisory power index; and $md_{j,t}$, market discipline index; represent the regulatory indexes of country j (Barth et al. 2013)[40]. They are included as per Delis and Kouretas (2011) to avoid the problem of omitted variable bias, that is, to account for the bank regulatory environment. The higher the value of each index, the greater the capital stringency, the stronger the supervisory power, and the greater the market disclosure faced by banks. As such, we expect these indices to have a negative impact on bank risk.

$ce_{i,t}$ is individual country effects to account for unobserved cross-country differences. Time dummies are also included which vary according to the frequency of the data. This is to account for technological change that occurs over time, which may influence bank risk-taking behavior.

Both equations (1) and (2) are a dynamic model that includes the lagged bank-risk variable as an explanatory variable. This can be justified on several grounds (Delis and Kouretas, 2011). First, the persistence may reflect the existence of intense competition, which tends to alleviate bank risk-taking. Second, the importance and prevalence of relationship-banking with customers means bank risk is likely to persist. Third, given that bank risk is likely to follow business cycles, we may find a persistent bank risk behavior in line with the dynamics of business cycle. Hence, if

[39] The bank lending channel contends that a monetary policy tightening can affect the supply of bank loans due to a decline in their total reservable deposits. This can be offset by raising non-reservable funding. However, the cost of non-reservable funding would be higher for smaller and low-capitalized banks if the market perceives them as riskier. Similarly, illiquid banks will be more adversely affected by a monetary tightening due to a lower possibility of being able to liquidate their assets. See Bernanke and Blinder (1988), Kashyap and Stein (1995), Kishan and Opiela (2000), among others, for a good analysis of the specific effects of the variables on the bank lending channel.

[40] See the appendix for detailed definition of each index.

risk is persistent, a static model would be biased, and a dynamic model is preferred[41].

The main difference between the annual model and the quarter model is the inclusion of persistence or one-period lagged macroeconomic variables in the latter (Altunbas et al. 2014). In addition, the quarterly model excludes bank profitability because of the unavailability of quarterly profitability data. Treatment of stock variables (bank specific characteristics and regulatory indices) remains unchanged in the two specifications.

3.4 Data Sample and Estimation Issues

Existing work on risk-taking channel of monetary policy has focused exclusively on the U.S and Europe. This paper in contrast aims to fill this gap in the empirical literature by studying the bank risk pattern in Asia. Given the linkages of emerging market economies with the advanced economies, they continue to grapple with spillovers of monetary policy from advanced to emerging economies. External factors, prominently concerns about exchange rate and capital flow volatility, therefore play a significant role in these economies' monetary policy conduct. Monetary policy may be eased in the absence of overheating in order to reduce the incentive for further inflows. But if capital flows result in inflationary pressures and credit booms, then the policy interest rate may need to be tightened to ensure stability of the domestic economy. This is however seldom done due to the fear of causing further capital inflows. According to the BIS (2012) monetary policy stance in emerging market economies, particularly Asia, as measured by real (inflation-adjusted) policy rates and Taylor rule rates has been very accommodative. The risk taking channel of monetary policy posits that this overly accommodative monetary policy stance can translate into bank risk taking. Since a meaningful study of interaction between bank risk behavior and monetary policy would require the banking sector to be both

[41] The coefficient of the lagged bank risk may be viewed as the speed of convergence to equilibrium. A statistically significant value of zero implies that bank risk is characterized by a high speed of adjustment; while a value of one means that the adjustment is very slow. Values between 0 and 1 suggest that risk persists, but will eventually return to its mean.

sizable and relatively well developed, in this study we focus on a group of emerging market economies in Asia. This restricts our sample to ten economies, namely, the PRC; Hong Kong, China; India; Indonesia; the Republic of Korea; Malaysia; the Philippines; Singapore; Taipei,China; and Thailand. The panel is unbalanced due to different data availability for the chosen countries. The largest panel for annual data runs from 2000 to 2011. For quarterly data, the longest period is from 2003Q1 to 2011Q4. There are no quarterly data available for Hong Kong, China and India, therefore they are not included in the quarterly model.

The choice of measures accounting for banks' risk is of particular importance for our empirical analysis. Measuring risk is a complicated issue and there is no specific proxy for bank risk-taking. A priori, bank risk refers to the amount of uncertainty a lender is willing to hold in his portfolio. Previous literature have used accounting or market based measures to quantify the extent of bank risk tolerance. In the absence of a well established bank risk proxy, this paper uses four measures of bank risk, namely the idiosyncratic bank risk, z-score, ratio of non-performing loans to total loans and the standard deviation of return on assets[42]. These indicators are considered to reveal different type of risk related information and reflect diverse aspects of risk-taking, hence each has its own advantages and disadvantages as measures of bank-risk taking. In other words, neither of them is more accurate or superior to another, but rather complementary to each other in capturing the main dimension of bank risk.

The first bank risk measure used in this paper is the idiosyncratic bank risk, $br1_i$. This indicator is derived from stock market information. As the variable name suggests, this indicator measures the risk specific to a bank after accounting for the broad market effects by decomposing risk into idiosyncratic (individual) and systemic (market wide) elements. Thus it allows us to ascertain whether monetary policy influences each individual bank's risk position on top of systemic considerations. The computation of this measure is based on a simple Capital Asset Pricing Model (CAPM). The CAPM model is based on the following equation: $R_{i,j,t} = \beta_{i,t} R_{m,j,t} + \varepsilon_{i,t}$ where $R_{i,j,t}$ are the daily stock market logarithmic abnormal returns from each

[42]See appendix 3.1 for detailed derivations of the bank risk variables and sources of data.

bank i in country j. $R_{m,j,t}$ are the daily stock market abnormal returns from the broad stock market index m from country j. The term $\varepsilon_{i,t}$ is the bank specific residual. Specific beta coefficients, $\beta_{i,t}$, are calculated for each bank in the sample by running separate regressions on daily data for every year (annual model) and quarter (quarterly model). The idiosyncratic bank risk, $br1_i$ is therefore given by:

$$br1_i = \sum_{t=1}^{m} \frac{\varepsilon_{i,t}^2}{m}$$

where m is the number of daily trading days in a year (for the annual model) or quarter (for the quarterly model). Daily individual bank return index and daily stock market return index for each country used in the CAPM estimation are obtained from Datastream.

The other three indicators are accounting based constructed using data obtained from Bankscope. The second indicator is the ratio of non-performing loans to total loans, $br2_i$, which is taken as a proxy of credit risk in a bank's portfolio. Since some proportion of non-performing loans will result in losses for a bank, a higher ratio indicates a higher level of bank risk. Unlike the other measures for bank risk such as z-score or standard deviation of return on assets, which reflect insolvency risk, this measure directly refers to credit risk. However, it is instructive to note that this measure of bank risk is backward looking.

The third indicator which is also based on accounting information from banks' balance sheet is the z-score, which is a universal measure of individual bank fragility. The index measures bank soundness in terms of insolvency risk or distance to default and is often used as a measure of financial soundness or risk-taking (De Nicolo et al. (2003), Demirgüç-Kunt et al. (2006); Maechler et al. 2007, Angkinand and Wihlborg (2008), Berger et al. (2009), Tabak et al. (2010), Delis et al. (2011)). Z-index combines in a single measure the profitability, leverage and return volatility. It is given by the ratio:

$$br3_{i,t} = \frac{ra_{i,t} + ek_{i,t}}{\sigma(ra_{i,t})}$$

where $ra_{i,t}$ is the return on asset and $ek_{i,t}$ the ratio of equity capital to total assets for bank i and $\sigma(ra_{i,t})$ is the standard deviation of return on assets of bank i. In essence, the z-score measures the lower bound in which expected returns need to drop in order to exhaust the bank's equity. In other words, it represents the probability of a negative shock to profits that forces bank to default (Yeyati and Micco, 2003). While z-index increases with higher profitability and capitalization levels, it decreases with unstable earnings captured by the standard deviation of return on assets. So a higher level of z-score corresponds to a greater distance to equity depletion and therefore greater bank stability.

The data to compute z-score index, namely, the return on assets and equity to total asset ratio is available from Bankscope. We use a three-year rolling time window for calculating standard deviation of returns on assets $\sigma(ra_{i,t})$, following Cihak et al. (2009). Furthermore, given that z-score is highly skewed, we use natural logarithm of z-index, which is normally distributed, following Leaven and Levine (2009) and Özsuca and Akbostancı (2016).

Finally, standard deviation of asset returns, $br4_i$, which measures the volatility of return on bank assets is used as the fourth proxy for banks' risk exposure. Again, we use a three-year rolling time window to compute the standard deviation.

In terms of interest rate gaps, we use two measures as per Altunbas et al. (2014) in calculating the deviation of policy rate from some benchmark levels[43]. The first known as the Taylor gap (ig_1) is the difference between the actual nominal interest rates and that generated from a Taylor-type equation[44]. For data comprehensiveness, we use the 3-month money market or interbank rate from the International Monetary Fund's International Financial Statistics (IFS) as a proxy of the policy rate. (The change in interest rates, ir_j, included in the specification is therefore the first difference of this series). The second measure, for simplicity, called the natural gap (ig_2) is the difference between the real short-term interest rates and the natural

[43]See appendix 3.1 for detailed estimations of the interest rate gaps.

[44]The Taylor equation is estimated as $ig1 = c + 1.5(\pi - \pi^*) + 0.5y$, where π measures the inflation rate, π^* measures the average inflation rate from 2000Q1, y measures the output gap, and c is the sum of the average inflation and real GDP growth since 2000Q1. See appendix 3.1 for more details.

interest rates calculated using the Hodrick-Prescott filter. The first measure is more of an ad-hoc rule. And since not all central banks of the sampled countries follow the Taylor type rule, we also rely on the estimates that generate natural rates, which remove the long-run trend of the interest rate series.

Raw data for the macro variables—growth rate (gr); yield curve (yc); exchange rate volatility (er); changes in stock market index (sm); and bank credit to GDP (cg)—are obtained from the IFS, Datastream, Bloomberg, and CEIC, depending on countries and availability. Growth rate is obtained directly from the IFS as period-on-period change in the GDP volume index. Yield curve measures the difference between the 10-year government bond yield and the 3-month treasury bill rate. Changes in stock market index are the first differences in the natural log of the index. Exchange rate volatility is calculated as the standard deviation of the first differences of the daily natural log exchange rate. Bank credit to GDP is the ratio of bank lending to the private sector over nominal GDP.

For the bank specific variables: size, sz_i, is the log of total assets (Kashyap and Stein 1995, 2000); liquidity, lq_i, is the liquidity to-total asset ratio; capitalization, cp_i, is the capital to asset ratio (Kishan and Opiela 2000; Van den Heuvel 2002). In the annual model, profitability, pr_i, as measured by the return on equity is also included. These are data obtained directly from Bankscope (for the annual model), and Bloomberg (for quarterly model), except the variable, lq in the quarterly model, where it is calculated based on the raw data obtained from Bloomberg.

Table 9 provides descriptive statistics for the variables used. Note the sample shows a large variability as measured by bank size, which implies that the sample includes both large and small banks that reduce the potential of selection bias. Table 10 provides the descriptive statistics of the data sorted by country. The average size of bank (as measured by total assets) is largest in the PRC and lowest in the Philippines. Overall, the distribution of average bank size is homogeneous reflecting that no single country has a dominant role in driving the results. In general, the banks included in the sample cover roughly the top 85% of the banking sector (publicly listed) in each of the countries[45]. Table 11 presents correlation matrix of the variables included in estimation. The four measures of bank risk are positively (and significantly) correlated with each other. Furthermore the two measures of the stance of monetary policy, $ig1$ and $ig2$, are also positively and significantly correlated to each other.

This paper uses the dynamic general method of moments (GMM) to estimate model equations (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998). The dynamic modeling approach has been used in various studies, such as, measuring economic growth convergence (Caselli, Esquivel, and Lefort 1996), estimating labour demand (Blundell and Bond 1998), estimating the relationship between financial intermediary development and economic growth (Beck, Levine, and Loayza 2000), and more recently in the literature dealing with bank risk-taking channel (Altunbas et al. 2014; Delis and Kouretas 2011).

One possible identification challenge of testing whether monetary policy affects bank risk is that there could be, in principle, a two-way relationship between monetary policy and bank risk. If financial stability is an important goal of monetary policy, then interest rate setting is also affected by overall changes in financial fragility and bank risk. Ioannidou et al. (2015) and Jimenez et al. (2014), using data for Bolivian and Spanish banks, respectively, find that bank risk-taking and interest rates are endogenous in the countries. That said, for the countries studied in this paper, the objective of monetary policy is generally focused on achieving stable prices or the dual mandate of stable prices and sustainable growth. We are unaware that maintaining low bank risk is an explicit monetary policy objective in any of the countries. However, in accordance with theory and following earlier empirical work we treat interest rates as endogenous in the estimation methodology described below to avoid any simultaneity bias.

Another possible source of endogeneity is unobserved heterogeneity, whereby there are factors unobservable to researchers that can affect both bank risk and the explanatory variables. Econometrically, unobservable heterogeneity exists in the baseline equation if $E\left(\eta_i | X_{i,t}\right) \neq 0$, where η_i is the individual bank specific fixed ef-

[45]According to Datastream, the stock market data typically cover the top 85% of firms in each industry group.

fect, and $X_{i,t}$ is the vector of explanatory variables. Given the greater co-movements of macroeconomic data, the problem of unobservable heterogeneity is likely going to be an issue, which means that the OLS estimators are both biased and inconsistent. To address this and given the availability of panel data, fixed-effects estimation is the solution. Still, fixed-effects estimation is biased if past values of the dependent variable are used as an explanatory variable—if there is dynamic endogeneity, where past values of the dependent variable are correlated with the current values of other explanatory variables[46].

Therefore, to obtain consistent and unbiased estimates in the presence of unobserved and dynamic endogeneity, a dynamic GMM panel estimator is used. This method uses the dynamic endogeneity inherent in the explanatory variables, that is, lags of endogenous variables as instruments. In the difference GMM estimator, lagged levels of endogenous variables are used as instruments for the difference equation. Arellano and Bover (1995) and Blundell and Bond (1998) show that the difference GMM estimator can be improved by also including equations in levels in the estimation procedure or what is known as the system GMM estimator. System GMM estimator is an improvement over the difference estimator in two main ways. First, Beck, Levine, and Loayza (2000) note that if the original model is conceptually in levels, differencing may attenuate the signal-to-noise ratio and reduce the power of statistical inferences. Second, Arellano and Bover (1995) suggest that variables in levels may be weak instruments for first-differenced equations. Thus, in system GMM estimation, difference equations are complimented with equations in levels, wherein lagged levels of endogenous variables as well as lags of first-differenced variables are used as instruments for difference and level equations, respectively.

In the estimations, besides the interest rate variables (ir and ig), we treat as endogenous the following variables: yield curve (yc), lagged bank return on equity (pr), lagged bank liquidity (lq), and lagged bank capitalization (cp). For annual model, therefore, the second to fifth lags of these variables are used as instruments[47].

[46] See Wooldridge (2001) for more details on the nature of the bias.

[47] The lags used refer to both the difference and levels equations. Given the limited number of observations, especially in the annual model, we restrict the number of instruments to avoid falling

All the regulatory indices and bank size are treated as predetermined variables (Delis and Kouretas 2011). This implies that banks already have information on the size and regulatory environment before making their decisions. This suggests that the first to fifth lags of these variables are included as instruments. For the quarterly model, since first lag of endogenous variables is included in the estimation, we employ as instruments third to fifth lags of endogenous variable and second to fifth lags of predetermined variables.

The GMM estimator ensures efficiency and consistency, provided that the dynamic regression model is not subject to second-order serial correlation and that the instruments used are valid. The p-value of AR(2) should be large accepting the null hypothesis of no serial correlation of order two in first differences of the errors. This is important as higher order autocorrelation would imply that lags of the dependent variable is not actually endogenous and, hence bad instruments. Furthermore, the validity of the instruments is checked by using Sargan test for overidentifying restrictions.

3.5 Results

3.5.1 Annual Model

Table 12 and 13 present the results of the annual model with the two measures of interest rate gaps, the Taylor gap ($ig1$) and the natural gap ($ig2$), respectively. The different columns indicate the different bank risk variables: idiosyncratic bank risk ($br1$); ratio of non-performing loans to total loans ($br2$); z-score ($br3$); and volatility of return on assets ($br4$).

Several key results can be gleaned from Table 12. First, the significant lagged dependent variables show that bank risk is highly persistent (first four rows). This result also lends support to the choice of a dynamic model. Given that the coefficient is less than one, this implies that the risk, while it persists, eventually returns to its

into the trap of "too many instruments" as pointed out by Roodman (2009).

equilibrium[48].

Second, changes in short-term interest rates (ir) do not have a significant impact on most measures of bank risk, except in the case of idiosyncratic bank risk ($br1$), where the coefficient is positive. A positive coefficient is expected for the market determined risk measure, as lower interest rate are supposed to decrease bank risk on the outstanding loans.This is likely to capture the effects from the balance sheet channel—lower interest rates increase the creditworthiness of borrowers, and via valuation effects reduce the riskiness of existing banks' loans. This is consistent with the findings of Jimenez et al. (2014) and Altunbas et al. (2014) that lower rates make loan repayment easier by reducing the interest burden of borrowers, which in turn, makes loan less risky.

Third, the coefficient of the main variable of interest, the Taylor gap ($ig1$) is significant and has the expected negative sign in all bank risk variables. (Since the z-score as a measure of bank risk is interpreted as the opposite of other measures, the correct a priori sign is positive). This means that higher interest rates above the Taylor-rule benchmark decreases bank risk or, conversely, lower interest rates below the benchmark increases bank risk—supporting the phenomenon that "too low interest rates" can be harmful[49]. In terms of magnitude, if interest rates are 100-basis point lower than the benchmark, the short (1 year) and long term effect on bank risk (in percent) as measured by different indicators is given below:

Bank risk variable	Short term (%)	Long term (%)
Idiosyncratic bank risk	0.04	0.07
Non-performing loans	0.07	0.2
Z-score	0.03	0.07
Volatility of return on assets	0.01	0.02

[48] We also included higher lags of the bank risk variables, but found no evidence of persistence beyond the first year.

[49] Taken together with the preceding result, it is clear that the interest gap variable is a better measure of risk-taking channel. Take for instance the current situation where interest rates in emerging economies are not close zero-bound (unlike the case in many advanced economies); in this environment, a fall in the interest rates does not necessarily lead to more risk-taking. Yet, if interest rates are "too low" (lower than a benchmark), we find a significant evidence of more risk-taking by banks which is robust to different measures of bank-risk.

The increase in bank risk in response to lax monetary policy is lower in the case of Asia as compared to advanced economies like the US and euro area, for instance Altunbas (2014) find that if the interest rate is 100 basis point below the value given by taylor rule, the average probability for a bank to go into default increases by 0.6% after a quarter and 0.8% in the long run. The estimates in our study however are closer to findings in some other emerging market economies. For instance, Özsuca and Akbostancı (2016) find that in Turkish banks, the average probability of loan default increases by 0.09 percent after a quarter and 0.2 in the long run in response to interest rate being 100 basis point below the benchmark rate.

Thus, the impact on bank risk varies depending on the risk measure utilized. As mentioned earlier, a priori, no one measure is better than the other and therefore these results should be viewed as complementary in understanding the impact of low interest rates on bank risk taking.

Fourth, of the four bank specific variables, only profitability (pr) as measured by return on equity is statistically significant and correctly negatively signed in two measures of bank risk—idiosyncratic risk ($br1$) and volatility of the return on assets ($br4$). This implies that more profitable banks have a lower riskiness measure. On the other hand, both bank size (sz) and bank liquidity (lq) are appropriately negatively signed in each case of idiosyncratic bank risk measure ($br1$) and ratio of non-performing loans to total loans ($br2$), respectively. However non-performing loans are positively related to bank size bank size (sz). One reason why large large banks may undertake higher levels of risky assets is that they are more capable in managing risk and have an easier access to external funds when needed.

Fifth, in terms of accounting for the expectations channel, the output growth rate (gr) is statistically significant and correctly signed in all four measures of bank risk. Better economic conditions increase the profitability or net present values of projects, which reduce the overall credit risk of banks (Kashyap et al. 1993; Altunbas et. al. 2014). This result is consistent with the findings of Gambacorta (2009) and Altunbas et al. (2014). The steepness of the yield curve (yc), however, has a significant negative impact only for idiosyncratic bank risk ($br1$).

Sixth, there is some evidence to suggest that financial deepening reduces bank risk. Bank credit to GDP (*cg*) is statistically significant and appropriately signed in the case of *br*3 and *br*4.

Seventh, exchange rate volatility and stock market performance does not seem to effect bank risk taking in Asia. Both exchange rate volatility (*er*) and changes in broad stock market index (*sm*) are statistically insignificant for all bank risk measures.

Eighth, there is also some evidence to suggest that regulatory environment ameliorates bank risk-taking. Greater capital stringency is statistically significant and reduces bank risk in the case of *br*1. Similarly, supervisory power has a negative effect on non-performing loans, *br*2.

The validity and consistency of the results is confirmed by the tests for the second-order serial correlation and instrument exogeneity (the Hansen test). The null hypothesis of no second-order serial correlation cannot be rejected in each of the bank risk specification. Similarly, the null of instrument exogeneity cannot be rejected implying that the instruments used are valid. Time and country dummies are also jointly significant in most specifications.

As robustness checks, we also use an alternate measure of interest rate gap based on the natural real interest rates (Table 13). By and large, the results are consistent with the findings in Table 12. There is strong evidence to support the specification of a dynamic model—the lagged dependent variable is always statistically significant. "Too low" interest rates (*ig*2) contribute to greater risk-taking in all measures of bank risk (see table below), not lower interest rates per se (*ir*)[50]. If interest rates are 100 basis point lower than the benchmark, as measured by the natural rate, the short (1 year) and long term effect on bank risk (in percent) is:

[50] As in Table 12, changes in interest rates (ir) are only statistically significant when bank risk is measured as idiosyncratic bank risk (br1).

Bank risk variable	Short run (%)	long run (%)
Idiosyncratic bank risk	0.03	0.05
Non-performing loans	0.11	0.33
Z-score	0.04	0.08
Volatility of return on assets	0.02	0.04

Bank profitability (*pr*) seems to be a more important bank specific variable that affects bank risk-taking compared to liquidity and size. Likewise, growth rate (*gr*) rather than slope of the yield curve (*yc*) is a more important determinant of economic activity or indirectly profitability of projects that affects credit risk of banks and hence bank risk-taking. Similarly, regulatory environment, particularly capital stringency and supervisory power appears to be significant in some risk specification. One result that differs slightly between the two measures of interest rate gap, is the more mixed evidence of financial deepening in reducing bank risk using the natural gap measure. Finally, the specification tests on the absence of second-order serial correlation and instrument exogeneity are passed, implying that the parameter estimates are consistent and valid.

Further robustness checks are employed to ensure that the model does not suffer from multi-collinearity problem. There are two interest rate variables included in the model, namely *ir* and *ig*. Table 14 and 15 present results of the model with only *ig* i.e. the main variable of interest. The coefficient is still significant and of expected negative sign. Furthermore, the magnitudes of the effect are also similar to the baseline models confirming that the two variables capture separate effects. The impact of other macroeconomic and bank specific controls are also similar as in the baseline model.

The sample used in the paper consists of countries where interest rates are not the main policy instrument and in some cases where interest rates are not necessarily market determined. This may affect the computation of interest rate gap variable. Furthermore, China is a peculiar case wherein the credit boom following the government stimulus efforts in the aftermath of the global financial crisis may distort any relation between interest rates and bank risk taking. Therefore, table 16 and

17 present results without China, Hong Kong and Singapore (where interest rates are not the main policy instruments), to further assess the robustness of the findings. The results from the models are qualitatively unchanged. In particular, the coefficient on both the taylor rate and natural rate gap is significant and appropriately negatively signed suggesting that inclusion of these countries, especially China, does not bias the findings. Furthermore, quantitatively the effect of low interest rate (below a benchmark) on bank risk taking is similar to that reported above.

3.5.2 Quarterly Model

The effects of short-term interest rate on bank's risk tolerance can be very brisk, and hence the use of annual data to study the risk-taking channel has been contested by Altunbas et al. (2014). Furthermore, Jimenez et al. (2014) find interest rates could affect bank risk in two opposing ways. In the short term, low interest rates, by reducing the probability of default on existing loans, leads to a fall in the risk of bank's portfolio. Over time, however, banks start to undertake more risky operations and lending to projects with a higher probability of default. To further investigate this relationship and to distinguish between any likely short- and longer-term effects that might be missing in the annual specification, this paper also estimates a model with quarterly data. In the quarterly model, idiosyncratic risk is the only bank risk used because of lack of data availability.

Indeed, the quarterly model provides more nuanced results (Table 18, Column 1). The contemporaneous Taylor gap ($ig1$) is statistically significant and positive, meaning if interest rates are higher than benchmark, bank risk increases, or conversely, if interest rates are lower than benchmark, bank risk decreases. This runs contrary to what is expected of an operating risk-taking channel. That said, lagged $ig1$ has the a priori sign that supports the risk-taking channel (as in the annual model). In fact, the combined magnitude of the contemporaneous and lagged $ig1$ is still negative, implying overall the risk-taking channel is still operating and the effects of "too low" interest rates is likely to dominate. The long run impact of low interest rate on bank risk is 0.05 and 0.1 percent respectively in the quarterly model.

The coefficient of exchange rate volatility, which captures market risk, is positive and significant, implying that countries with more volatility in the exchange rate tend to have a more risky banking sector. The other result that is statistically significant is the adverse impact of financial deepening on bank risk—the contemporaneous coefficient of credit to GDP is positive. Again as a robustness check, the other measure of interest rate gap ($ig2$) is used (Column 2). The results are likewise similar to that of the Taylor gap.

3.6 Conclusion

Recent studies have found a significant negative relationship between interest rates and bank risk-taking in the US and the euro area. This paper explores the impact of low interest rates on bank risk-taking in selected Asian economies with a relatively developed banking sector. Using a recent line of empirical and theoretical literature, and a panel dataset of publicly listed banks, we find evidence of an operational bank risk-taking channel. In particular, we find that when interest rates are "too low"—lower than a benchmark—bank risk increases. This result is robust to other factors, which might have influenced banks' risk-taking behavior, namely, general economic conditions, bank specific characteristics, country specific market risk, and the regulatory environment.

The results of this paper point to three main policy considerations. First, the conduct of monetary policy, in particular, the setting of interest rates does not seem neutral to the financial stability goal. It is therefore encouraging to see work done to incorporate financial stability considerations into macroeconomic models, especially in the context of monetary policy formulation (Agur and Demertzis 2010; Curdia and Woodford 2011). Second, more importantly, this suggests a greater role of macroprudential policy focusing on possible excesses in finance and its related areas, even during periods of benign inflation rate when interest rates are usually kept low. In particular, the capital stringency requirement seems to pose a limiting check on bank risk. Finally, as the Asian economies are not well insulated from the loose monetary policy of the advanced economies, it is important for policy makers to allow the exchange rates to move more flexibly, especially in level terms. There will be periods when policy makers—by allowing interest rates to fall too low—not only fuel the risk-taking channel, but may also interfere with the pursuit of domestic stabilization goals.

Table 13 – Summary Statistics of the Variables used in Annual Regression, 2000-2011

Variable	No of obs.	Mean	Std. Deviation	Min	Max
Idiosyncratic risk, *br1*	824	0.1240	0.7250	0.00004	12.2978
Non-performing loans to total loans, *br2*	768	0.0533	0.0563	0.0013	0.2904
Z-score, *br3*	734	3.7791	1.2864	-2.0381	7.8179
Volatility of returns on asset, *br4*	731	0.4093	0.8872	0.0116	11.0302
Changes in short-term interest rate, *ir*	826	-0.2056	2.2732	-13.2634	7.4900
Taylor gap, *ig1*	826	-5.7417	4.8519	-23.5854	10.5615
Natural gap, *ig2*	826	0.1140	2.3175	-7.9591	7.6715
Growth rate, *gr*	813	5.7603	3.2587	-7.2370	14.7630
Yield curve, *yc*	805	1.8120	1.2050	-0.6431	6.7590
Credit to GDP, *cg*	800	0.7519	0.3990	0.1816	2.0212
Exchange rate volatility, *er*	826	0.0014	0.0011	0.0000	0.0075
Change in stock market index, *sm*	826	0.0347	0.1239	-0.3915	0.4770
Bank size, *sz*	815	10.2053	1.3598	6.8954	14.7142
Profitability, *pr*	818	12.8695	10.7146	-70.4210	44.8120
Liquidity, *lq*	824	22.2159	11.3602	2.1370	80.7420
Bank capitalization, *cp*	790	8.1472	3.1576	0.1600	23.7900
Supervisor index, *sp*	826	11.5387	1.3327	7.0000	14.0000
Market discipline index, *md*	826	6.8535	0.8408	5.0000	9.0000
Capital stringency index, *cs*	826	5.2143	1.5386	3.0000	8.0000

Note: See the appendix for details of each variable. The variables in index are index numbers, while idiosyncratic risk, z-score, volatility of returns on asset, and exchange rate volatility are unit-free. All the other variables are in percent, except bank size which is the natural log of US million.
Source: Authors' calculations.

Table 14 – Descriptive Statistics by Country (mean values), 2000 - 2011

Variable	PRC	HK	IND	INO	KOR	MAL	PHI	SIN	TAP	THA
br1	0.0047	0.0094	0.0094	0.2234	0.0413	0.0185	0.0628	0.0103	0.0592	0.2667
br2	0.0150	0.0129	0.0313	0.0581	0.0164	0.0852	0.0990	0.0409	0.0124	0.1068
br3	4.3097	4.2498	4.2620	2.9952	3.0652	4.0856	4.1526	4.2024	3.4799	2.8399
br4	0.1104	0.2009	0.1420	0.8701	0.4187	0.3845	0.2858	0.1872	0.2983	1.0297
ir	0.0192	-0.4222	0.1823	-1.3363	-0.1549	-0.0311	-0.4441	-0.1432	-0.0017	0.0584
ig1	-11.6494	-4.0297	-8.7797	-5.7888	-4.1938	-4.5033	-2.4541	-6.9155	-3.0482	-4.3433
ig2	-0.1012	-0.1711	0.7403	-0.6128	0.0874	0.0458	0.3676	0.0186	-0.0615	0.1700
gr	10.9097	4.5150	7.7555	5.4174	4.2668	5.0121	4.7129	5.9411	4.2113	3.9494
yc	1.5117	2.2253	1.3069	1.9677	1.1235	1.4977	3.5072	1.7385	0.8975	2.2589
cg	1.1847	1.5315	0.4452	0.2441	0.9406	1.1073	0.3097	1.0013	0.5378	0.9858
er	0.0004	0.0001	0.0015	0.0027	0.0029	0.0009	0.0017	0.0014	0.0012	0.0014
sm	0.0355	0.0199	0.0009	0.0775	0.0411	0.0282	0.0744	0.0153	0.0203	0.0336
sz	12.0988	10.7471	10.1456	9.2576	11.6287	9.8637	8.5764	11.5259	10.7194	9.6430
pr	18.4509	16.4763	17.2230	17.8226	10.8787	11.0267	9.9985	10.4788	6.3182	6.6352
lq	27.3887	29.8162	10.2021	28.6074	13.8684	29.7413	29.9321	29.9521	14.9926	16.4083
cp	5.5872	8.6296	6.4593	10.5523	6.0612	8.7753	11.4927	9.6669	6.5575	7.7838
sp	10.3377	9.8261	12.2109	12.5652	10.3654	11.3448	11.3636	12.5000	13.1233	10.7273
md	6.4545	7.0000	6.7891	6.3913	7.6154	7.3362	7.0000	7.8333	6.8767	6.0455
cs	3.4416	4.6522	7.0000	5.8913	4.3462	4.0345	5.1515	5.8333	5.2192	5.2500
Number of banks	14	4	16	9	5	10	9	3	8	8
Weight of country i	16.28	4.65	18.60	10.47	5.81	11.63	10.47	3.49	9.30	9.30

Note: PRC=the People's Republic of China; HKG=Hong Kong, China; IND=India; INO=Indonesia; KOR=the Republic of Korea; MAL=Malaysia; PHI=the Philippines; SIN=Singapore; TAP=Taipei,China; and THA=Thailand. br1=idiosyncratic risk, br2=non-performing loans to total loans, br3=z-score, br4=volatility of returns on asset, ir =changes in short-term interest rate, ig1=Taylor gap, ig2=natural gap, gr =growth rate, yc =yield curve, cg =credit to GDP, er =exchange rate volatility, sm=change in stock market index, sz =bank size, pr =profitability, lq =liquidity, cp =bank capitalization, sp =supervisor index, md =market discipline index, and cs =capital stringency index. Number of banks=number of banks included from each country. Weight of country i = number of banks (country i)/total number of banks.
Source: Authors' calculations.

Table 15 – Correlation Matrix

	br1	*br2*	*br3*	*br4*	*ir*	*ig1*	*ig2*	*cg*	*gr*	*yc*	*sm*	*sz*	*lq*	*cp*	*pr*	*er*	*sp*	*md*	*cs*
br1	1.000																		
br2	0.116	1.000																	
br3	-0.211	-0.319	1.000																
br4	0.129	0.314	-0.659	1.000															
ir	-0.025	-0.098	0.139	0.024	1.000														
ig1	0.029	0.288	-0.152	0.103	0.015	1.000													
ig2	-0.014	-0.026	0.052	-0.020	0.308	0.620	1.000												
cg	0.004	-0.032	0.082	-0.082	0.037	-0.067	-0.011	1.000											
gr	-0.136	-0.165	0.145	-0.122	0.182	-0.381	-0.046	-0.032	1.000										
yc	0.067	0.297	-0.063	0.131	-0.115	0.010	-0.222	-0.124	-0.085	1.000									
sm	-0.032	0.029	0.063	-0.052	0.089	-0.043	-0.094	-0.110	0.324	-0.010	1.000								
sz	-0.136	-0.483	0.191	-0.224	0.102	-0.331	0.004	0.445	0.193	-0.325	-0.061	1.000							
lq	-0.043	0.201	0.083	0.019	-0.116	0.105	-0.052	0.196	-0.053	0.197	0.086	-0.092	1.000						
cp	-0.063	0.258	0.201	-0.024	-0.068	0.219	-0.011	-0.177	-0.168	0.295	0.107	-0.439	0.402	1.000					
pr	-0.091	-0.309	0.297	-0.181	0.010	-0.217	-0.025	-0.055	0.181	-0.069	0.102	0.171	0.048	0.000	1.000				
er	0.035	-0.027	-0.233	0.175	-0.099	-0.053	-0.098	-0.407	-0.202	0.062	-0.128	-0.118	-0.105	0.066	-0.052	1.000			
sp	-0.078	-0.209	0.063	-0.067	-0.063	-0.019	-0.045	-0.529	-0.016	-0.192	0.048	-0.105	-0.134	0.032	0.032	0.172	1.000		
md	-0.167	-0.128	0.238	-0.213	0.144	0.117	0.092	0.118	-0.039	-0.123	0.084	0.168	0.078	0.110	0.008	-0.102	-0.035	1.000	
cs	0.036	-0.255	0.151	-0.115	0.074	-0.076	0.119	-0.500	0.007	-0.113	-0.008	-0.077	-0.264	-0.002	0.122	0.221	0.428	0.066	1.000

Table 16 – Results: Annual Model with Taylor Interest Rate Gap (ig1) and Different Bank Risk Measures

Variables	Idiosyncratic risk, *br1*	Non-performing loans, *br2*	Z-score, *br3*	Volatility of Return on Assets, *br4*
L.*br1*	0.386***			
	(0.0398)			
L.*br2*		0.659***		
		(0.0749)		
L.*br3*			0.546***	
			(0.0694)	
L.*br4*				0.506***
				(0.0610)
ir	0.0436**	0.000732	-0.000613	-0.0178
	(0.0187)	(0.000497)	(0.0353)	(0.0191)
ig1	-0.0221**	-0.000847**	0.0305**	-0.0114*
	(0.0106)	(0.000359)	(0.0141)	(0.00644)
cg	0.434	0.0193	1.221***	-0.481**
	(0.347)	(0.0123)	(0.455)	(0.213)
gr	-0.0255**	-0.000853**	0.0270**	-0.0111*
	(0.0117)	(0.000334)	(0.0131)	(0.00629)
yc	-0.0874*	-0.000779	0.0820	0.0228
	(0.0490)	(0.00209)	(0.0765)	(0.0326)
sm	0.00450	-0.0115	-0.337	-0.218
	(0.187)	(0.00916)	(0.411)	(0.155)
sz	-0.600*	0.0135**	-0.0532	-0.0490
	(0.312)	(0.00637)	(0.339)	(0.188)
L.*lq*	0.0125	-0.000624**	-0.00492	-0.000533
	(0.00965)	(0.000281)	(0.0112)	(0.00677)
L.*cp*	-0.0440	7.01e-05	0.00556	-0.00617
	(0.0318)	(0.000911)	(0.0492)	(0.0234)
L.*pr*	-0.0330***	-9.25e-05	0.0153	-0.0152*
	(0.00410)	(0.000281)	(0.0114)	(0.00840)
er	-78.62	1.829	-33.70	-22.59
	(47.86)	(1.325)	(78.33)	(32.24)
sp	-0.0688	-0.00334***	0.0705	-0.0145
	(0.0481)	(0.000905)	(0.0558)	(0.0218)
md	-0.112	0.00171	-0.0808	0.00921
	(0.0783)	(0.00162)	(0.0643)	(0.0465)
cs	-0.0511*	-0.000319	0.0429	-0.000106
	(0.0285)	(0.00123)	(0.0606)	(0.0362)
Observations	684	646	624	623
F-statistic	72.86***	262.25***	37.58***	53.11***
AR(2)	0.581	0.636	0.918	0.150
Hansen	0.220	0.266	0.0920	0.267
Wald test for country and time effects	1.38	3.46***	3.56***	3.15***

Note: br1=idiosyncratic risk, br2=non-performing loans to total loans, br3=z-score, br4=volatility of returns on asset, ir =changes in short-term interest rate, ig1=Taylor gap, ig2=natural gap, gr =growth rate, yc =yield curve, cg=credit to GDP, er =exchange rate volatility, sm=change in stock market index, sz =bank size, pr =profitability, lq =liquidity, cp =bank capitalization, sp =supervisor index, md =market discipline index, and cs =capital stringency index. L refers to one-period lag. F-stat and its p-value is the goodness of fit of the regression, AR(2) is the test for second-order serial correlation and Hansen is the test for over-identifying restrictions. Wald test is the test for joint significance of country and time dummies. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.
Source: Authors' estimations.

Table 17 – Results: Annual Model with Natural Interest Rate Gap (ig2) and Different Bank Risk Measures

Variables	Idiosyncratic risk, *br1*	Non-performing loans, *br2*	Z-score, *br3*	Volatility of Return on Assets, *br4*
L.*br1*	0.414***			
	(0.0291)			
L.*br2*		0.649***		
		(0.0791)		
L.*br3*			0.512***	
			(0.0731)	
L.*br4*				0.518***
				(0.0659)
ir	0.0284*	0.000376	-0.00477	-0.00988
	(0.0151)	(0.000440)	(0.0282)	(0.0137)
ig2	-0.0258**	-0.00114**	0.0393**	-0.0211**
	(0.0108)	(0.000568)	(0.0194)	(0.0104)
cg	0.537*	0.0270**	1.188**	-0.382**
	(0.313)	(0.0122)	(0.492)	(0.186)
gr	-0.0209**	-0.000774**	0.0300**	-0.0120*
	(0.0101)	(0.000336)	(0.0133)	(0.00641)
yc	-0.0721*	-5.84e-05	0.0433	0.0121
	(0.0386)	(0.00194)	(0.0664)	(0.0343)
sm	-0.0111	-0.0118	-0.269	-0.221
	(0.197)	(0.00878)	(0.405)	(0.166)
sz	-0.509**	0.0108*	-0.434	-0.0867
	(0.249)	(0.00616)	(0.320)	(0.257)
L.*lq*	0.0133	-0.000555**	-0.00727	0.00113
	(0.0128)	(0.000270)	(0.0119)	(0.00703)
L.*cp*	-0.0353	-9.65e-05	-0.00865	-0.0101
	(0.0259)	(0.000889)	(0.0572)	(0.0247)
L.*pr*	-0.0303***	-0.000193	0.0143	-0.0151*
	(0.00400)	(0.000269)	(0.0108)	(0.00787)
er	-72.48*	1.763	-64.65	-30.18
	(41.82)	(1.278)	(82.78)	(35.72)
sp	-0.0816	-0.00365***	0.0608	-0.0241
	(0.0498)	(0.000984)	(0.0579)	(0.0260)
md	-0.0931	0.00243	-0.0764	0.00857
	(0.0731)	(0.00159)	(0.0634)	(0.0432)
cs	-0.0505**	-0.00129	0.0451	-0.0109
	(0.0239)	(0.00128)	(0.0597)	(0.0414)
Observations	684	646	624	623
F-statistic	75.92***	265.02***	18.23***	63.08***
AR(2)	0.400	0.696	0.992	0.156
Hansen	0.204	0.227	0.107	0.168
Wald test for country and time effects	1.68*	3.31***	1.85**	1.98**

Note: br1=idiosyncratic risk, br2=non-performing loans to total loans, br3=z-score, br4=volatility of returns on asset, ir =changes in short-term interest rate, ig1=Taylor gap, ig2=natural gap, gr =growth rate, yc =yield curve, cg=credit to GDP, er =exchange rate volatility, sm=change in stock market index, sz =bank size, pr =profitability, lq =liquidity, cp =bank capitalization, sp =supervisor index, md =market discipline index, and cs =capital stringency index. L refers to one-period lag. F-stat and its p-value is the goodness of fit of the regression, AR(2) is the test for second-order serial correlation and Hansen is the test for over-identifying restrictions. Wald test is the test for joint significance of country and time dummies. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.
Source: Authors' estimations.

Table 18 – Results: Annual Model with Taylor Interest Rate Gap (ig1) - without ir

Variables	Idiosyncratic risk, *br1*	Non-performing loans, *br2*	Z-score, *br3*	Volatility of Return on Assets, *br4*
L.*br1*	0.382***			
	(0.0421)			
L.*br2*		0.676***		
		(0.0711)		
L.*br3*			0.538***	
			(0.0653)	
L.*br4*				0.490***
				(0.0671)
ig1	-0.0171*	-0.000798**	0.0298**	-0.0128*
	(0.00973)	(0.000371)	(0.0139)	(0.00660)
cg	0.488	0.0192	1.258***	-0.464**
	(0.349)	(0.0125)	(0.459)	(0.195)
gr	-0.0202*	-0.000756**	0.0267**	-0.0135**
	(0.0109)	(0.000336)	(0.0133)	(0.00623)
yc	-0.0501	-0.000104	0.0833	0.00927
	(0.0337)	(0.00197)	(0.0739)	(0.0294)
sm	-0.00998	-0.0120	-0.315	-0.202
	(0.179)	(0.00909)	(0.412)	(0.154)
sz	-0.619*	0.0147**	-0.0788	-0.0760
	(0.332)	(0.00640)	(0.332)	(0.166)
L.*lq*	0.0104	-0.000624**	-0.00939	0.00295
	(0.0112)	(0.000281)	(0.00992)	(0.00615)
L.*cp*	-0.0561*	0.000215	-0.00187	-0.00212
	(0.0309)	(0.000913)	(0.0476)	(0.0226)
L.*pr*	-0.0320***	-2.46e-05	0.0141	-0.0200***
	(0.00431)	(0.000272)	(0.0100)	(0.00675)
er	-67.05	2.104	-46.99	-29.87
	(45.50)	(1.312)	(80.22)	(32.55)
sp	-0.0798*	-0.00339***	0.0651	-0.0102
	(0.0475)	(0.000901)	(0.0546)	(0.0202)
md	-0.0740	0.00214	-0.0747	-0.00872
	(0.0696)	(0.00155)	(0.0630)	(0.0354)
cs	-0.0541*	-0.000168	0.0387	-0.00525
	(0.0296)	(0.00127)	(0.0605)	(0.0295)
Observations	684	647	625	624
F-statistic	62.55***	250.74***	38.78***	53.28***
AR(2)	0.472	0.577	0.522	0.147
Hansen	0.593	0.341	0.142	0.233
Wald test for country and time effects	1.64*	3.67***	3.45***	2.96***

Note: br1=idiosyncratic risk, br2=non-performing loans to total loans, br3=z-score, br4=volatility of returns on asset, ir =changes in short-term interest rate, ig1=Taylor gap, ig2=natural gap, gr =growth rate, yc =yield curve, cg=credit to GDP, er =exchange rate volatility, sm=change in stock market index, sz =bank size, pr =profitability, lq =liquidity, cp =bank capitalization, sp =supervisor index, md =market discipline index, and cs =capital stringency index. L refers to one-period lag. F-stat and its p-value is the goodness of fit of the regression, AR(2) is the test for second-order serial correlation and Hansen is the test for over-identifying restrictions. Wald test is the test for joint significance of country and time dummies. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.
Source: Authors' estimations.

Table 19 – Results: Annual Model with Natural Interest Rate Gap (ig2) - without ir

Variables	Idiosyncratic Bank risk, *br1*	Non-performing loans, *br2*	Z-score, *br3*	Volatility of Return on Assets, *br4*
L.*br1*	0.376***			
	(0.0395)			
L.*br2*		0.666***		
		(0.0750)		
L.*br3*			0.506***	
			(0.0734)	
L.*br4*				0.504***
				(0.0709)
ig2	-0.0275**	-0.00105*	0.0381*	-0.0245**
	(0.0135)	(0.000577)	(0.0194)	(0.0110)
cg	0.570	0.0263**	1.249**	-0.351*
	(0.352)	(0.0121)	(0.520)	(0.180)
gr	-0.0200*	-0.000704**	0.0293**	-0.0143**
	(0.0107)	(0.000341)	(0.0132)	(0.00670)
yc	-0.0561	0.000347	0.0390	0.00279
	(0.0362)	(0.00187)	(0.0671)	(0.0326)
sm	-0.00875	-0.0119	-0.240	-0.211
	(0.191)	(0.00872)	(0.406)	(0.167)
sz	-0.619*	0.0119*	-0.498	-0.112
	(0.352)	(0.00605)	(0.338)	(0.242)
L.*lq*	0.0113	-0.000555**	-0.0120	0.00484
	(0.0114)	(0.000269)	(0.0103)	(0.00662)
L.*cp*	-0.0581*	-2.75e-05	-0.0197	-0.00639
	(0.0314)	(0.000889)	(0.0547)	(0.0234)
L.*pr*	-0.0315***	-8.97e-05	0.0121	-0.0202***
	(0.00438)	(0.000253)	(0.00975)	(0.00689)
er	-65.51	1.963	-84.27	-34.00
	(44.89)	(1.188)	(83.60)	(35.70)
sp	-0.0835*	-0.00363***	0.0539	-0.0212
	(0.0496)	(0.000967)	(0.0559)	(0.0227)
md	-0.0690	0.00257	-0.0740	-0.00149
	(0.0710)	(0.00155)	(0.0649)	(0.0368)
cs	-0.0670*	-0.00112	0.0384	-0.0192
	(0.0359)	(0.00131)	(0.0592)	(0.0362)
Observations	684	647	625	624
F-statistic	55.01***	253.31***	18.56***	59.93***
AR(2)	0.386	0.612	0.592	0.150
Hansen	0.518	0.217	0.156	0.229
Wald test for country and time effects	1.78**	3.50***	2.32***	2.77***

Note: br1=idiosyncratic risk, br2=non-performing loans to total loans, br3=z-score, br4=volatility of returns on asset, ir =changes in short-term interest rate, ig1=Taylor gap, ig2=natural gap, gr =growth rate, yc =yield curve, cg=credit to GDP, er =exchange rate volatility, sm=change in stock market index, sz =bank size, pr =profitability, lq =liquidity, cp =bank capitalization, sp =supervisor index, md =market discipline index, and cs =capital stringency index. L refers to one-period lag. F-stat and its p-value is the goodness of fit of the regression, AR(2) is the test for second-order serial correlation and Hansen is the test for over-identifying restrictions. Wald test is the test for joint significance of country and time dummies. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.
Source: Authors' estimations.

Table 20 – Results: Annual Model with Taylor Interest Rate Gap (ig1) - restricted sample

Variables	Idiosyncratic risk, *br1*	Non-performing loans, *br2*	Z-score, *br3*	Volatility of Return on Assets, *br4*
L.*br1*	0.389***			
	(0.0405)			
L.*br2*		0.743***		
		(0.144)		
L.*br3*			0.610***	
			(0.0634)	
L.*br4*				0.562***
				(0.112)
ir	0.0473**	0.00117*	0.0102	-0.0223
	(0.0184)	(0.000646)	(0.0327)	(0.0188)
ig1	-0.0121*	-0.000887**	0.0263**	-0.0106*
	(0.00640)	(0.000445)	(0.0130)	(0.00587)
cg	1.169	0.0877***	1.721*	-1.781**
	(0.846)	(0.0326)	(0.972)	(0.715)
gr	-0.0332**	-0.000727**	0.0333*	-0.0115
	(0.0145)	(0.000338)	(0.0172)	(0.0103)
yc	-0.0820	-0.000245	0.0863	0.0429
	(0.0520)	(0.00263)	(0.0754)	(0.0309)
sm	-0.0631	-0.0299	-0.258	-0.224
	(0.178)	(0.0191)	(0.416)	(0.186)
sz	-0.235	-0.00352	-0.185	-0.216
	(0.296)	(0.00575)	(0.285)	(0.212)
L.*lq*	0.0138	-0.000713**	-0.0170	-0.00556
	(0.0147)	(0.000353)	(0.0121)	(0.00651)
L.*cp*	-0.0104	-0.00191**	-0.00120	0.00301
	(0.0290)	(0.000932)	(0.0470)	(0.0232)
L.*pr*	-0.0304***	-0.000273*	0.00307	-0.00590*
	(0.00572)	(0.000159)	(0.00554)	(0.00317)
er	-109.9	3.951*	-111.6	7.185
	(68.39)	(2.035)	(87.38)	(31.30)
sp	-0.0776	-0.00183	0.0586	-0.0310
	(0.0499)	(0.00185)	(0.0617)	(0.0271)
md	-0.186*	0.00257	-0.104	0.0899
	(0.102)	(0.00256)	(0.0897)	(0.0833)
cs	-0.0229	0.000719	0.0145	-0.0146
	(0.0325)	(0.00140)	(0.0804)	(0.0541)
Observations	568	552	511	516
F-statistic	196.57***	147.99***	33.53***	40.83***
AR(2)	0.392	0.347	0.923	0.265
Hansen	0.419	0.283	0.515	0.229
Wald test for country and time effects	2.60***	3.54***	2.20**	1.86**

Note: br1=idiosyncratic risk, br2=non-performing loans to total loans, br3=z-score, br4=volatility of returns on asset, ir =changes in short-term interest rate, ig1=Taylor gap, ig2=natural gap, gr =growth rate, yc =yield curve, cg=credit to GDP, er =exchange rate volatility, sm=change in stock market index, sz =bank size, pr =profitability, lq =liquidity, cp =bank capitalization, sp =supervisor index, md =market discipline index, and cs =capital stringency index. L refers to one-period lag. F-stat and its p-value is the goodness of fit of the regression, AR(2) is the test for second-order serial correlation and Hansen is the test for over-identifying restrictions. Wald test is the test for joint significance of country and time dummies. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.
Source: Authors' estimations.

Table 21 – Results: Annual Model with Natural Interest Rate Gap (ig2) - restricted sample

Variables	Idiosyncratic risk, *br1*	Non-performing loans, *br2*	Z-score, *br3*	Volatility of Return on Assets, *br4*
L.*br1*	0.384***			
	(0.0360)			
L.*br2*		0.719***		
		(0.142)		
L.*br3*			0.596***	
			(0.0689)	
L.*br4*				0.558***
				(0.116)
ir	0.0388**	0.000816	0.00584	-0.0237
	(0.0185)	(0.000617)	(0.0313)	(0.0172)
ig2	-0.0241*	-0.00143**	0.0443**	-0.0144*
	(0.0143)	(0.000703)	(0.0221)	(0.00839)
cg	1.278	0.108***	1.606	-1.662**
	(0.902)	(0.0320)	(1.043)	(0.627)
gr	-0.0347**	-0.000604*	0.0356**	-0.0104
	(0.0157)	(0.000320)	(0.0176)	(0.0108)
yc	-0.0875*	-0.000943	0.123	0.0322
	(0.0521)	(0.00314)	(0.0784)	(0.0214)
sm	-0.00359	-0.0235	-0.285	-0.201
	(0.186)	(0.0177)	(0.431)	(0.175)
sz	-0.186	-0.00260	-0.222	-0.197
	(0.319)	(0.00758)	(0.321)	(0.266)
L.*lq*	0.0152	-0.000430	-0.0197	-0.00381
	(0.0147)	(0.000343)	(0.0146)	(0.00699)
L.*cp*	-0.0162	-0.00375***	-0.00954	0.000230
	(0.0321)	(0.00109)	(0.0482)	(0.0277)
L.*pr*	-0.0305***	-0.000196	0.00309	-0.00577*
	(0.00560)	(0.000175)	(0.00586)	(0.00328)
er	-94.89	3.445*	-119.8	10.41
	(70.65)	(1.904)	(88.18)	(34.30)
sp	-0.0842	-0.00286*	0.0706	-0.0361
	(0.0519)	(0.00159)	(0.0668)	(0.0296)
md	-0.174*	0.00401	-0.0930	0.0856
	(0.101)	(0.00280)	(0.106)	(0.0831)
cs	-0.0247	9.65e-05	0.0331	-0.0176
	(0.0349)	(0.00196)	(0.0830)	(0.0577)
Observations	568	552	511	516
F-statistic	134.73***	112.32***	29.85***	43.78***
AR(2)	0.372	0.281	0.955	0.257
Hansen	0.448	0.212	0.524	0.240
Wald test for country and time effects	3.89***	4.79***	2.37***	2.07**

Note: br1=idiosyncratic risk, br2=non-performing loans to total loans, br3=z-score, br4=volatility of returns on asset, ir =changes in short-term interest rate, ig1=Taylor gap, ig2=natural gap, gr =growth rate, yc =yield curve, cg=credit to GDP, er =exchange rate volatility, sm=change in stock market index, sz =bank size, pr =profitability, lq =liquidity, cp =bank capitalization, sp =supervisor index, md =market discipline index, and cs =capital stringency index. L refers to one-period lag. F-stat and its p-value is the goodness of fit of the regression, AR(2) is the test for second-order serial correlation and Hansen is the test for over-identifying restrictions. Wald test is the test for joint significance of country and time dummies. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.
Source: Authors' estimations.

Table 22 – Results: Quarterly Model with Idiosyncratic Bank Risk (br1)

Variable	Equation 1	Equation2
br1(t-1)	0.895***	0.907***
	(0.1420)	(0.1440)
ir	-0.0705	-0.0473
	(0.0888)	(0.0750)
ir(t-1)	-0.0145	-0.016
	(0.0535)	(0.0527)
ig1	0.0158*	
	(0.0090)	
ig1(t-1)	-0.0209**	
	(0.0095)	
ig2		0.0233*
		(0.0138)
ig2(t-1)		-0.0367*
		(0.0185)
gr	0.0245	0.024
	(0.0215)	(0.0210)
gr(t-1)	-0.0288	-0.029
	(0.0191)	(0.0193)
yc	-0.212	-0.213
	(0.1700)	(0.1750)
yc(t-1)	0.185	0.184
	(0.1190)	(0.1200)
cg	0.0779*	0.0771*
	(0.0423)	(0.0410)
cg(t-1)	-0.0651	-0.0641
	(0.0436)	(0.0469)
er	46.76**	47.92***
	(17.96)	(17.70)
er(t-1)	-16.78	-14.89
	(22.43)	(24.41)
sm	-0.312	-0.331
	(0.2710)	(0.2910)
sm(t-1)	0.0615	0.0414
	(0.1460)	(0.1570)
sz	-0.0339	-0.0476
	(0.0564)	(0.0641)
cp(t-1)	0.00157	0.00221
	(0.0026)	(0.0026)
lq(t-1)	0.00394	0.00346
	(0.0049)	(0.0049)
sp	-0.0316	-0.0303
	(0.0227)	(0.0220)

md	0.0271	0.0304
	(0.0299)	(0.0311)
cs	-0.0643	-0.0623
	(0.0510)	(0.0497)
Observations	1,616	1,615
F-statistics	397.59 ***	409.10***
AR(2)	0.276	0.276
Hansen	0.438	0.36
Wald test for Country and seasonal effects	1.79*	1.81*

Note: br1=idiosyncratic risk, ir =changes in short-term interest rate, ig1=Taylor gap, ig2=natural gap, gr =growth rate, yc =yield curve, cg=credit to GDP, er =exchange rate volatility, sm=change in stock market index, sz =bank size, lq =liquidity, cp =bank capitalization, sp =supervisor index, md =market discipline index, and cs =capital stringency index. L refers to one-period lag. F-stat and its p-value is the goodness of fit of the regression, AR(2) is the test for second-order serial correlation and Hansen is the test for over-identifying restrictions. Wald test is the test for joint significance of country and time dummies. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, and * p<0.1.

Source: Authors' estimations.

Appendix 3.1: Data, Sources and Transformation

Variable	Data, Source and Period	Transformation/Remarks
Bank risk		
Idiosyncratic risk, $br1$	Daily total return index of bank i; index number. Source: Datastream Daily total market return index of country j, index number. Source: Datastream, TOTMK...(RI). Period (annual model):* 2000 to 2011, except the People's Republic of China (PRC) from 2004; and India and Taipei,China from 2002.	Idiosyncratic risk is calculated as: $br1_i = \sum_{t=1}^{m} \frac{\varepsilon_{i,t}^2}{m}$, where m is the number of trading days in a year or a quarter depending on the model used, and is the residual of the following estimated capital asset pricing model: $r_{i,j,t} - \bar{r_{i,J}} = \beta_{i,t}(r_{m,j,t} - \bar{r_{m,J}}) + \varepsilon_{i,t}$ where $r_{i,j,t}$ is the daily return of stock price index of bank i at time t, $\bar{r_{i,J}}$is the average historical daily return of stock price index of bank i, $r_{m,j,t}$ is the daily return of stock market price index of country j, and $\bar{r_{m,J}}$ is the average historical daily return of the stock market price index of country j. Note, all daily returns are first transformed into natural log before estimation.
Non-performing loans to total loans, $br2$ (%)	Non-performing loans to total loans, %. Source: Consolidated bank balance sheet, universal bank model, Bankscope. Period: 2000 to 2011, except the PRC from 2004; the Republic of Korea from 2001; and India and Taipei,China from 2002.	

Z-score, $br3$	Equity capital to total assets of bank i, %. Source: Consolidated bank balance sheet, universal bank model, Bankscope. Return on assets of bank i , %. Source: Consolidated bank balance sheet, universal bank model, Bankscope.	The z-score is calculated as: $br3_{i,t} = z_{i,t} = \frac{ra_{i,t}+ek_{i,t}}{\sigma(ra_{i,t})}$ where $ra_{i,t}$ is the return on asset and $ek_{i,t}$ the ratio of equity capital to total assets for bank i.
	Period: 2000 to 2011, except the PRC and Taipei,China from 2004; and India from 2003.	$\sigma(ra_{i,t})$ is the standard deviation of $ra_{i,t}$ computed using data for period t, $t-1$ and $t-2$, that is, a three-year rolling window.
Volatility of return on assets, $br4$	Return on assets of bank i , %. Source: Consolidated bank balance sheet, universal bank model, Bankscope. Period: 2000 to 2011, except the PRC from 2004; Indonesia, Malaysia, the Philippines, Thailand from 2001; and India and Taipei,China from 2002.	Standard deviation of the return on assets, computed over a three year rolling window (over time period t, $t-1$ and $t-2$).
Interest rate variables		

Change in short-term interest rate, ir_t, (%)	3-month money market rate or 3-month interbank deposit rate; end of period, %. Source: IFS, 60B..ZF For India: Call money rate (%) Source: Reserve Bank of India For Taipei,China: Policy rate: discount rate (%). Source: CEIC, 45972101 (WMAD) Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	Change in short-term interest rate is simply: $ir_t = i_t - i_{t-1}$, where i is the 3-month money market or interbank rate. For the annual model, i_t is an average of monthly rates.
Taylor rule gap, $ig1$ (%)	3-month money market rate/3-month interbank deposit rate; end of period, %. Source: IFS, 60B..ZF Annual CPI % change (quarterly frequency, %. Source: IFS, 64..XZF GDP volume index, 2005=100. Source: IFS, 99BVPZF For Taipei,China: Inflation: Consumer price index, year-on-year % change. Source: CEIC, 249101701 (WIGEBAAA)	Quarterly Model: ig1 is computed as the difference between the actual nominal interest rate at end-period and that generated by a Taylor-rule as follows: $ig1 = c + 1.5(\pi - \pi^*) + 0.5y$, where π is the quarter-on-quarter inflation rate, and y is the measure of output gap created using HP filter (with a smoothing parameter $\lambda = 1600$). The constant c is defined as the sum of the average inflation and real GDP growth since 2000Q1. $\pi^*$is computed as the average level of the inflation rate since 2000Q1.

	Gross domestic product, 2006p, national currency. Source: CEIC, 261788101 (WARKAA) GDP deflator, index number. Source: CEIC, 261820301 (WARRAA) GDP volume index = Nominal GDP/GDP deflator (adjusted to ensure that 2005 is base year). Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	Annual Model: $ig1$ for the annual model is calculated as the average of quarterly $ig1$.
Natural rate gap, $ig2$ (%)	3-month money market rate/3 month interbank deposit rate; end of period, %. Source: IFS, 60B..ZF. Annual CPI % change, quarterly frequency, %. Source: IFS, 64..XZF. Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	Quarterly Model: Real interest rate is computed using the Fisher equation: $r_t = i_t - \pi_t$ where r_t is the real interest rate, i_t the nominal interest rate and π_t is annual inflation rate (quarter–on-quarter). $ig2$ is computed as the difference between the above real interest rates and the natural rate calculated using the Hodrick-Prescott filter (with a smoothing parameter $\lambda = 1600$). Annual model: $ig2$ for the annual model is calculated as the average of quarterly $ig2$.

Real GDP growth rate, gr (%)	Quarter: GDP volume index, quarter-on- quarter % change. (%) Source: IFS, 99BPXZF. Annual: GDP volume index, year-on-year % change. (%) Source: IFS, 99BPXZF For Taipei,China: Real GDP, y-o-y % change, quarterly series. Source: CEIC, 261981801 (WARKAB).	
	Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	

Yield curve, *yc* (%)	Malaysia, the Philippines, Thailand, Singapore: 3 month T-bill rate, end-period, %. Source: IFS, 60C..ZF The People's Republic of China: Central Bank Bill, middle-rate, end-period, %. Source: Datastream, CHBNK3M. Hong Kong, China: Exchange fund bills (3 months), end-period, %. Source: Datastream, HKEFB3M. India: 91-day T-bill rate, end-period, %. Source: Datastream, INTB91D. Indonesia: SBI 90-day middle rate, end-period, %. Source: Datastream, IDSB90. The Republic of Korea: Yield on CD-91-day, end-period, %. Source: Datastream, KOCD91D. Taipei, China: T-bill rate 91-day, end-period, %. Source: CEIC, 45984701 (WMPGA). India, the Republic of Korea, Malaysia, the Philippines, Singapore, Thailand: 10-year government bond yield, end-period, %. Source: IFS, 61…ZF. The People's Republic of China: 10-year government bond yield, end-period, %. Source: Bloomberg, GCNY10YR. Hong Kong, China: HK Exchange Fund note, 10-year, end-period, %. Source: Datastream, HKEFN10.	Quarterly Model: yc is the difference between the 10 year government bond yield and the 3-month T-bill rate. Annual Model: The average of quarterly yield curve is used as a measure of the steepness of yield curve for the annual model.

	Indonesia: 10-year government bond yield, end-period, %. Source: Bloomberg, GIDN10YR. Taipei,China: Government bond yield, 10-year, end-period, %. Source: CEIC, 45985701 (WMUAE). Period (annual model): From 2000 to 2011, except the PRC from 2005; India and Taipei,China from 2002; and Indonesia from 2003.	

Bank credit to GDP ratio, *cg* (%)	For all countries: Bank's claim on private sector, national currency, billion. Source: IFS, 22D..ZF. GDP, national currency, billion. Source: IFS, 99B..ZF The PRC: GDP, national currency, billion. Source: Datastream, CHGDP...A. Taipei,China: Bank Credit: Loans and investments of financial institutions, national currency, billion. Source: Datastream, TWBANKLPA. GDP, national currency, billion. Source: Datastream, TWGDP...B. Period (annual model): 2000 to 2011, except the PRC from 2004; India and Taipei,China from 2002; and Indonesia, Malaysia, Philippines and Thailand from 2001.	Ratio of bank credit to GDP using quarterly credit and quarterly GDP, and annual credit and annual GDP for the quarterly and annual model, respectively.

Exchange rate volatility, er	Daily nominal exchange rate, daily average (USD/national currency). Source: Bloomberg Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	er is calculated as the standard deviation of the first difference in the natural log of the daily exchange rate: $er = lne_t - lne_{t-1}$, where e is the daily exchange rate. Quarterly exchange rate volatility is therefore calculated based on the daily rate in each quarter; and annual volatility, daily rate in each year.
Change in broad stock market index, sm	Share price: end period, index. Source: IFS, 62.EPZF Taipei,China: Equity Market Index: TAIEX Capitalization Weighted, end-month, index number. Source: CEIC, 46107601 (WZJA). Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	Calculated as (annual/quarterly) changes in the natural log of the broad stock market index.
Bank specific variables		

Total assets (log), *sz* (Millions USD)	Annual: Total Assets, USD million. Source: Consolidated bank balance sheets, universal bank model, Bankscope. Quarter: Total Assets, USD million. Source: Consolidated bank balance sheets, Bloomberg. Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	In cases where accounting standard had changed from local Generally Accepted Accounting Principles (GAAP) to International Financial Reporting Standards (IFRS), information from both C* (local GAAP) and C2 (IFRS) accounts was used to obtain historical series.
Profitability (return on equity), *pr* (%)	Annual: Return on Average Equity (ROAE), %. Source: Consolidated bank balance sheets, universal bank model, Bankscope. Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	As above

Liquidity (% of total assets), lq (%)	Annual: Liquid assets/short-term funding, % Source: Consolidated bank balance sheets, universal bank model, Bankscope. Quarter, USD million: Cash and bank balance. Interbank assets. Short-term investment. Total Assets. Source: Bloomberg Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	For annual data, when accounting standards had changed from local GAAP to IFRS, information from both C* (local GAAP) and C2 (IFRS) accounts was used to obtain historical series. For quarterly model: Liquidity = (Cash and bank balance + interbank assets + short term investments)/Total Assets
Capitalization (% of total assets), cp (%)	Equity capital as a percentage of total assets Annual: Equity/total assets, %. Source: Consolidated bank balance sheets, universal bank model, Bankscope. Quarter: Total capital ratio. (%) Source: Bloomberg Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	Capitalization is the ratio of equity capital to total assets. For annual data, when accounting standards had changed from local GAAP to IFRS, information from both C* (local GAAP) and C2 (IFRS) accounts was used to obtain historical series. For quarterly data, total capital ratio is the ratio of total capital to total assets.
Regulatory Indexes		

Supervisory Power, *sp*	Source: Barth et al. (2013) Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	Supervisory power, reflects the powers invested with the supervisory agencies to take specific actions against bank management and directors, shareholders, and bank auditors. The supervisory power index can take values between 0 and 14, with higher values denoting higher supervisory power. This variable is determined by the answers to14 survey questions. This index like the other two regulatory indexes is an annual series.
		To obtain the quarterly series, the value for each year is used as the value of each quarter in that particular year.
Market Discipline, *md*	Source: Barth et al. (2013) Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	Market discipline reflects the degree of transparency and disclosure of accurate information to the public that the banks are forced to undertake. This index can take values between 1 and 7 (depending on answers to 7 survey questions), again with higher values denoting higher market discipline.

Capital Stringency, *cs*	Source: Barth et. al. (2013) Period (annual model): 2000 to 2011, except the PRC from 2004; and India and Taipei,China from 2002.	Capital stringency shows the extent of both initial and overall capital stringency. Initial capital stringency refers to the constraints on the sources of funds counted as regulatory capital, as well as whether the regulatory or supervisory authorities verify these sources. Overall capital stringency indicates whether or not provisions are made for market risk and value losses while calculating the regulatory capital. Theoretically, the capital stringency index can take values between 0 and 8 (depending on answers to 8 survey questions), with higher values indicating more stringent capital requirements.

Note: * All quarterly data for the PRC, Indonesia, Malaysia, Philippines, the Republic of Korea, and Singapore are from 2004:1 to 2011:4, except the yield curve of the PRC from 2005:1. All quarterly data from Thailand and Taipei,China are from 2003:1 to 2011:4.

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