

Financial Intermediation and  
the Macroeconomy of the United States:  
Quantitative Assessments

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of  
Doctor of Philosophy in the Department of Economics  
in the Graduate School of Duke University  
2012

ABSTRACT

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# Abstract

This dissertation presents a quantitative study on the relationship between financial intermediation and the macroeconomy of the United States. It consists of two major chapters, with the first chapter studying adverse shocks to interbank market lending, and with the second chapter studying a theoretical model where aggregate balance sheets of the financial and non-financial sectors play a key role in financial intermediation frictions.

In the first chapter, I empirically investigate a novel macroeconomic shock: the funding liquidity shock. Funding liquidity is defined as the ability of a (financial) institution to raise cash at short notice, with interbank market loans being a very common source of short-term external funding. Using the “TED spread” as a proxy of aggregate funding liquidity for the period from 1971M1 to 2009M9, I first discover that, by using the vector-autoregression approach, an unanticipated adverse TED shock brings significant recessionary effects: industrial production and prices fall, and the unemployment rate rises. The contraction lasts for about twenty months. I also recover the conventional monetary policy shock, the macro impact of which is in line with the results of Christiano et al. (1998) and Christiano et al. (2005). I then follow the factor model approach and find that the excess returns of small-firm portfolios are more negatively impacted by an adverse funding liquidity shock. I also present evidence that this shock as a “risk factor” is priced in the cross-section of equity returns. Moreover, a proposed factor model which includes the structural

funding liquidity and monetary policy shocks as factors is able to explain the cross-sectional returns of portfolios sorted on size and book-to-market ratio as well as the Fama and French (1993) three-factor model does. Lastly, I present empirical evidence that funding liquidity and market liquidity mutually affect each other.

I start the second chapter by showing that, in U.S. data, the balance sheet health of the financial sector, as measured by its equity capital and debt level, is a leading indicator of the balance sheet health of the nonfinancial sector. This fact, and the apparent role of the financial sector in the recent global financial crisis, motivate a general equilibrium macroeconomic model featuring the balance sheets of both sectors. I estimate and study a model within the “loanable funds” framework of Holmstrom and Tirole (1997), which introduces a double moral hazard problem in the financial intermediation process. I find that financial frictions modeled within this framework give rise to a shock transmission mechanism quantitatively different from the one that arises with the conventional modeling assumption, in New Keynesian business cycle models, of convex investment adjustment costs. Financial equity capital plays an important role in determining the depth and persistence of declines in output and investment due to negative shocks to the economy. Moreover, I find that shocks to the financial intermediation process cause persistent recessions, and that these shocks explain a significant portion of the variation in investment. The estimated model is also able to replicate some aspects of the cross-correlation structure of the balance sheet variables of the two sectors.

To my family.

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# 1

## Introduction

The recent financial crisis highlights the importance of financial frictions and financial shocks. Macroeconomics, which traditionally emphasizes the importance of real sector of economy, has not stressed too much on financial intermediation in research. Since the crisis set in, macroeconomists have shifted their attention to study the importance of financial shocks and the propagation of *real* shocks through financial frictions.

The crash of the housing market in the early 2007 exposed to the world the complicated shadow banking system and the obscure financial products in the United States. The sharp fall in housing prices, which led to waves of foreclosures from households experiencing negative home equity, directly hit financial institutions which packaged subprime mortgages into securities because the value of mortgage-related securities collapsed. The complexity of mortgage products rendered investors unsure of which financial firms would incur losses brought by the collapsing values of mortgage-related securities. A run on the shadow banking system took place when financial firms and investors pulled funds away from firms whom they regarded as vulnerable to these losses.



Lending activities of the interbank market, where financial institutions acquire short-term external funding, were seriously interrupted because providers of short-term credit were anxious about the repaying ability of the borrowing party. The *TED spread*, a financial indicator reflecting the (perceived) riskiness of interbank loans, climbed as high as 450 basis points at the zenith of the crisis. More details about this liquidity crunch can be found at Brunnermeier (2009).

## 1.1 Funding Liquidity, Business Cycles and Asset Prices

Chapter 2 of this dissertation investigates the quantitative relationship between interbank market activities and the macroeconomy in the United States. I use the TED spread as the proxy for the state of the interbank market. Since the literature defines funding liquidity as the ability of an institution to raise cash at short notice, “either via the sale of an asset or access to external funding”, whereas interbank loans are a very common source for financial institutions to acquire external finance, I also call the TED spread as a proxy for funding liquidity. The very first step is to recover the structural funding liquidity shock (*TED* shock), which is orthogonal to the interest rate shock and other demand or supply shocks.

To this end, I estimate a baseline structural vector-autoregression (VAR) model with the usual real macro-variables, the federal funds rate and the TED spread. I adopt the recursiveness assumption in the shock identification process: this assumption reflects that the TED spread can respond contemporaneously to all of the real and price variables as well as the federal funds rate but not the other way round. To confirm my results I consider various robustness checks. I also investigate if the recovered structural funding liquidity shocks are leading indicators of other financial indicators such as the implied stock market volatility index and the default spread.

I then take the structural *TED* shock as a risk factor, and follow the factor model approach in the empirical finance literature to investigate how the excess

returns of firms are impacted by funding liquidity shocks. I consider excess returns of portfolios sorted by firm size. Since the theoretical literature predicts that small firms face higher agency costs for external finance, implying that they are hit worse by deteriorating credit conditions, I should expect that excess returns of small firms are more vulnerable to *TED* shocks. In order to see if the funding liquidity shock as a “risk factor” is priced, I move on the next step to investigate the cross-section of equity returns.

In the literature, a theoretical model has been proposed that a trader’s funding liquidity and market liquidity (the condition of trading a large amount of stock quickly at a low cost) can reinforce each other. To pursue empirical evidence for this theory I adopt a market liquidity measure and first compute the dynamic correlations with the TED spread. I then augment my baseline VAR model with the market liquidity measure and study how adverse funding liquidity shocks impact market liquidity.

## 1.2 Aggregate Balance Sheets of Financial and Non-financial Sectors

The recent financial crisis also reveals a structural problem in the financial intermediation process: financial institutions borrow too much but own too little equity capital, resulting in over-leveraging. As a matter of fact, the balance sheet condition of the banking sector came into spotlight when the crisis spread within the financial sector.

Chapter 3 of this dissertation aims to complement the branch of macroeconomic research which incorporates balance sheet conditions in a dynamic stochastic general equilibrium model setting. In the data I find that the health of the financial sector is a leading indicator of the health of the nonfinancial sector. This empirical result implies potentially interesting interactions between the balance sheets of both sectors. Therefore I assess the quantitative importance of financial intermediation frictions in

a framework where the aggregate balance sheets of both the financial and nonfinancial sectors play a role.

To build a model with both aggregate financial and nonfinancial balance sheets, I require the existence of three groups of agents, namely households (who save), bankers (who receive deposits from households and make loans to firms) and firms (also called entrepreneurs, who are endowed with investment projects but need external financing). I also require two layers of financial frictions, one between households and bankers, and the other between bankers and firms. In other words, bankers and firms cannot borrow as freely as they want, hence they need to accumulate their own net worth (equity capital) in order to finance their own assets.

I adopt a general equilibrium model featuring a double moral hazard “loanable funds” framework à la Holmstrom and Tirole (1997), Meh and Moran (2010) and Christensen et al. (2011). In this model, entrepreneurs can choose to work hard or not, and thereby influence the probability of success of investment projects. Entrepreneurs always opt to shirk because they enjoy “private benefits,” which can be interpreted as the extra leisure they obtain when they shirk. Bankers have the expertise to monitor entrepreneurs, but the monitoring is imperfect. The second layer of moral hazard is on the bankers side: monitoring entrepreneurs is privately costly. Households never know if bankers perform the monitoring tasks as agreed. The model makes clear predictions about the balance sheets of both bankers and entrepreneurs because these two types of agents require both internal and external financing.

I then turn to the quantitative assessment of my model. I estimate the model with Bayesian likelihood methods, using the usual macroeconomic aggregates and the equity capital data described above. I specifically study:

1. the impact of financial intermediation shocks on the economy, in particular

- shocks to equity capital in both sectors;
2. the importance of financial intermediation shocks in explaining real variables;
  3. changes in the shock propagation mechanism in the presence of financial frictions featuring a double moral hazard;
  4. the theoretical correlations between the balance sheet variables in the two sectors.

To study (1), I compute impulse response functions after financial intermediation shocks hit the estimated model economy. I pay special attention to the duration, the depth, and the shape of real variables such as real output and real investment. To investigate (2), I conduct forecast error forecast decomposition analysis to study how different types of shocks explain variations in real variables. Point (3) is addressed by comparing the transmission mechanism of my estimated model with an estimated standard New Keynesian model with investment frictions (convex investment adjustment costs) but not financial frictions. Finally, I compute the implied theoretical correlations of the estimated model to study the lead-lag relationship of net worths and debts between the two sectors to provide answers for (4).

# Funding Liquidity and Monetary Policy in the United States: Business Cycles and Asset Pricing Implications

## 2.1 Chapter Introduction

This chapter presents an empirical investigation of the relationship between the funding liquidity and the economy in the United States. As my results show, an unanticipated, adverse shock to funding liquidity has important macroeconomic and asset pricing implications. First, an adverse funding liquidity shock generates persistent recessionary effects; industrial production, personal consumption and prices fall whereas the unemployment rate rises. Second, this shock negatively affects equity returns, with smaller firms being impacted more. The funding liquidity shock as a risk factor is also priced. A proposed factor model which includes the funding liquidity shock does a reasonably good job at explaining the cross-sectional returns of portfolios sorted on size and book-to-market ratio. Finally, my results suggest that funding liquidity and market liquidity are dynamically correlated, and structural shocks to one type of liquidity significantly negatively impacts the other.

Following Borio (2000), I define funding liquidity as the ability of an institution to raise cash at short notice, “either via the sale of an asset or access to external funding”, which “underpins the institution’s capacity to meet its contractual obligations”<sup>12</sup>. In this chapter I focus on *studying empirically the economic impact associated with unanticipated interruptions to a bank’s access to one of its sources of external funding*: **interbank market borrowing**, where the loans involved are short-term and uncollateralized.

Most of the current *theoretical* macroeconomic literature focuses on financial frictions between lenders and non-financial borrowers, whereas the financial intermediary is assumed to be able to raise funds frictionlessly. Notable papers in this literature include Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Bernanke et al. (1999) (BGG), who stress the problem of asymmetric information between households and firms. BGG in particular emphasizes the financial accelerator mechanism and how credit spreads arise. Gilchrist et al. (2009) provides an empirical investigation on corporate credit spreads. However, this line of literature is largely silent on the issue of funding liquidity, in particular on the scenarios where financial intermediaries are not always able to raise funds frictionlessly in the interbank market.

A major feature of the financial crisis in 2007-2008 was an unusual jump in interbank interest rate spreads. Taylor and Williams (2009) is among the first papers to document the development of the spreads within this period. A popular proxy for funding liquidity conditions in the US is the *TED spread*, which is defined as the difference between the three-month Eurodollar interest rate and the three-month Treasury Bill rate. As interbank loans are uncollateralized, the TED spread has

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<sup>1</sup> Brunnermeier and Pedersen (2009) adopt a similar definition of funding liquidity, although they do not define it explicitly.

<sup>2</sup> Drehmann and Nikolaou (2009) distinguish between funding liquidity and funding liquidity risk; they argue that the common definition mixes up the two distinct concepts. In this chapter I avoid this complication by adopting the most commonly used definition of funding liquidity.

generally been regarded as a measure of the average credit risk for interbank lending<sup>3</sup>.

Indeed, theoretical researchers have recently started emphasizing frictions between financial intermediaries and borrowers, with papers including Holmstrom and Tirole (1997), Brunnermeier and Pedersen (2009) and Gertler and Kiyotaki (2010)<sup>4</sup>. Brunnermeier and Pedersen (2009) explicitly models liquidity spirals involving funding liquidity. This chapter is among the first to provide *empirical evidence* that funding liquidity is important. Using the TED spread, I show that frictions in interbank market borrowing (or an unexpected dry-up in the funding liquidity of banks) can generate recessions and have more negative consequences on the equity returns for small firms than for large firms.<sup>5</sup>

I first establish the macroeconomic impact of an unanticipated change in the TED spread by estimating a vector-autoregression (VAR) model. Adopting a recursiveness assumption (the Choleski decomposition) as the identification scheme for structural shocks, a one percentage-point (p.p) adverse *TED* shock leads to contractionary effects lasting for over twenty months. Impulse responses of industrial production, personal consumption and the federal funds rate (which fall) and the unemployment rate (which rises) are all hump-shaped. At the recessionary trough, industrial production contracts by 1.5 percent, consumption falls by 0.3 percent, the unemployment rate rises by 0.3 percentage points, and the federal funds rate drops by 0.6 percentage points. Interestingly, the structural *TED* shock is correlated with the leads (not the lags) of common financial variables, an example being that the

<sup>3</sup> Some argue that the TED spread reflects the problem of flight-to-liquidity too. Traditionally the Treasury bill is regarded as a safe asset. If the market is filled with uncertainty the investor may opt to buy more Treasury bills, driving up the Treasury bill price and hence lowering the interest rate; thus the TED spread goes up.

<sup>4</sup> Gurley and Shaw (1955) may perhaps be one of the earliest papers which theoretically discuss the role the financial intermediary has in the intermediation of loans between lenders and borrowers.

<sup>5</sup> Another line of literature provides theoretical models on why a bank run occurs, how an interbank market works, and how a contagion can spread, as pioneered by Diamond and Dybvig (1983) and Bhattacharya and Gale (1987), among others. My empirical results complement their theoretical findings as well.

structural *TED* shock is correlated with the leads of the implied volatility index (*VXO*) of the stock market for at least five months. I have also recovered the conventional monetary policy shock, the macro impact of which is in line with the results of Christiano et al. (1998) and Christiano et al. (2005).

I then take the structural *TED* shock as a factor, and follow the factor model approach in the empirical finance literature to investigate how the excess returns of firms are impacted by funding liquidity shocks. The major result is that the returns of portfolios composed of small firms (or “small caps”) are more negatively impacted relative to those of large firms. This is in line with predictions from the theoretical literature that small firms face higher agency costs for external finance, implying that they are hit worse by deteriorating credit conditions. Moreover, in the cross-section of equity returns I find evidence that the funding liquidity shock as a “risk factor” is priced. I go on to propose a new factor model, which includes the structural funding liquidity and monetary policy shocks as well as the market factor. Interestingly this proposed model performs comparably to the Fama and French (1993) three-factor model in explaining the cross-section of average returns of portfolios sorted on size and book-to-market ratio.

Last but not the least, I investigate the empirical relationship between funding and market liquidity. Adopting the market liquidity measure introduced by Pastor and Stambaugh (2003), I find that market and funding liquidity are contemporaneously and dynamically correlated. By augmenting my baseline VAR model with the market liquidity measure, I find that an adverse funding liquidity shock negatively impacts market liquidity for eight months, whereas an adverse market liquidity shock reduces funding liquidity for two months. The results are indeed consistent with the prediction of the liquidity spiral model proposed in Brunnermeier and Pedersen (2009).

This chapter is also closely related to Adrian and Shin (2009) and Adrian and



Etula (2010). Section 4 of Adrian and Shin (2009) document the evidence that the growth rate of financial intermediary assets (in particular the growth rate of broker-dealers' assets) in lagged periods explains current output growth. Since Adrian and Shin (2010b) report that broker-dealers manage their balance sheets in an unusually aggressive way to take advantage of changes in funding conditions, the results in Adrian and Shin (2009) can be interpreted as how changes in the funding conditions affect the macroeconomy. Adrian and Etula (2010) build an intertemporal asset pricing framework and use broker-dealers' capital-equity ratio to explain stock return anomalies.

The outline of this chapter is as follows. I will first provide a brief description of the TED spread. I will then recover the structural funding liquidity shock using the vector-autoregression (VAR) method and study its macro impact. I will also investigate how portfolio returns are impacted by the funding liquidity shock. After that I will provide empirical evidence on the correlation between funding and market liquidity. Conclusion of the chapter follows.

## 2.2 The TED Spread

The TED spread is defined as the difference between the three-month Eurodollar (ED) interest rate and the three-month Treasury Bill interest rate<sup>6</sup>. Eurodollars are deposits denominated in USD at banks outside the United States, and they play a major role in the international capital market. For a history of the development of the Eurodollar market, see Schenk (1998).

A spike in the TED spread is usually interpreted as tight interbank market lending. Figure (2.1) plots the monthly *TED* series between 1971 and 2009, with the

<sup>6</sup> Nowadays the three-month London Interbank Offer Rate (LIBOR) is more commonly used when computing the TED spread. However, LIBOR only dates back to 1986, the time span of which is too short for macroeconomic analyses. For comparative purposes, I construct two TED spread series using the ED and the LIBOR series separately for the period between 1986 and 2009, and both series are highly correlated (they have a contemporaneous correlation of 0.95).

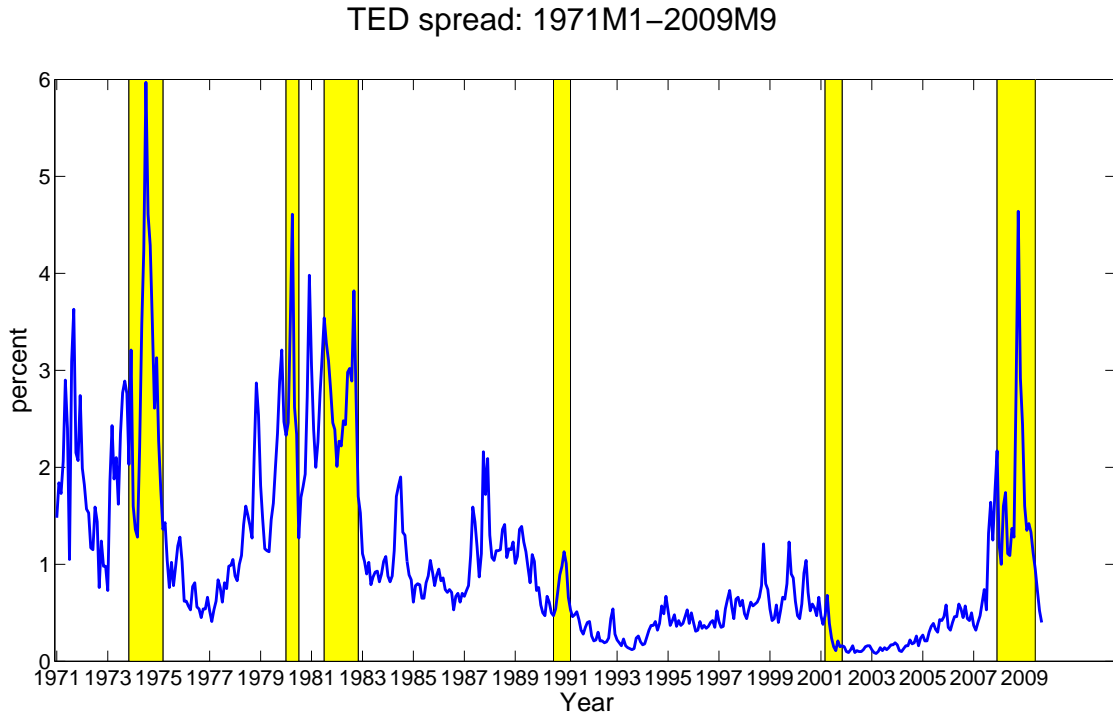


FIGURE 2.1: Plot of the monthly TED spread between 1971M1 and 2009M9. *TED* is defined as the difference between three-month Eurodollar rate and three-month Treasury-bill rate. Data source: The Federal Reserve Board.

Table 2.1: Summary statistics of the TED spread

	mean	std. deviation	skewness	kurtosis
<i>percent</i>	1.05	0.92	1.69	6.27

yellow bars indicating NBER recession dates. I see that four out of five NBER recessions were characterized by a spike in the TED spread. Table (2.1) shows some basic statistics of the TED spread.

Table (2.2) lists notable events associated with some of the spikes. While I am not claiming any causality between the spikes and the events, a spike in the TED spread usually coincides with the occurrence of domestic or foreign financial crises.

Table 2.2: A selection of spikes in the TED spread and the corresponding events

Date	Event
Aug 1971	Nixon shock—closed the gold window—end of Bretton Woods
Oct 1973	First oil crisis
Oct 1974	Collapse of Franklin National Bank
Jan 1979	Second oil crisis
1980 - 1982	Volcker disinflation program
Jun 1982	Mexican debt crisis
July 1984	Collapse of Continental Illinois bank
Oct 1987	Stock crash (Black Monday)
Aug 1990	Gulf War
Oct 1998	LTCM crisis following Russian and Asian crises
Aug 2007	Ongoing financial crisis

## 2.3 Vector Autoregression (VAR) Analysis

### 2.3.1 Baseline VAR

In this section I proceed to study the macroeconomic implications of the TED spread.

I consider the following structural VAR:

$$A_0 Y_t = A(L) Y_{t-1} + \varepsilon_t \quad (2.1)$$

where  $\varepsilon_t$  represents a vector of orthogonal structural shocks, with  $\varepsilon \sim iid(0, I)$  and  $I$  being the identity matrix.

I include the following variables: industrial production ( $IP$ ), real personal consumption ( $CONS$ ), the unemployment rate ( $UNRATE$ ), consumer price index ( $CPI$ ), commodity prices ( $PCOM$ ), the federal funds rate ( $FF$ ), and the TED spread ( $TED$ ).

Following Christiano et al. (1998) and Christiano et al. (2005) (CEE), I adopt the recursiveness assumption for identification purposes. It implies that the matrix  $A_0$  is lower triangular. I estimate the model with two lags<sup>7</sup>. The ordering of the variables is as follows:

<sup>7</sup> The lag length is determined by the Bayesian Information Criterion.

$$Y_t = [IP_t \text{ } CONS_t \text{ } UNRATE_t \text{ } CPI_t \text{ } PCOM_t \text{ } FF_t \text{ } TED_t]'$$

The rationale for this ordering is as follows. Since the federal funds rate is present in the VAR, I follow CEE's way of identifying its structural shock: the real and the price variables are pre-determined when  $FF$  is determined. Equivalently, these real and price variables will react to a  $FF$  shock with a lag. Moreover, I order  $TED$  after  $FF$ . It is reasonable to believe that any movement in  $TED$  reflects a continuous update of any important news or events in the economy. Moreover, the spread itself is a function of treasury bill rate, which is closely associated with the federal funds rate. Therefore it can be reasonably assumed that  $TED$  responds to all of the other variables contemporaneously, including  $FF$ <sup>8</sup>. I will consider robustness checks later.

### 2.3.2 Data

The sample period is from January 1971 to September 2009. The series  $IP$ ,  $CONS$ ,  $CPI$  and  $PCOM$  are expressed in logarithm, whereas  $UNRATE$ ,  $FF$  and  $TED$  are expressed in level<sup>9</sup>.

The series  $IP$ ,  $UNRATE$ ,  $CPI$  and  $FF$  are taken from the database of the Federal Reserve Bank of St. Louis.  $CONS$  is taken from the Bureau of Economic Analysis,  $TED$  is computed using data on the Eurodollar and the Treasury Bill rate available from the Federal Reserve Board.

$PCOM$ , known as the "Spot market price index:  $BLS$  &  $CRB$  (all commodities)", is taken from the Global Financial Database (ticker:CMCRBSPD).<sup>10</sup>

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<sup>8</sup> In other words, I assume that  $FF$  responds to  $TED$  with a lag.

<sup>9</sup> Each of the data series is filtered with a linear time trend before the VAR is implemented.

<sup>10</sup> The spot price index is constructed by the Commodity Research Bureau. It is a measure of price movements of various commodities whose markets are presumed to be among the first to be influenced by changes in economic conditions. Items such as metals, textiles and fibers, livestock, and fats and oils are included in this index. Please see <http://www.crbtrader.com> for details.

### 2.3.3 Impulse responses

#### Structural TED shock

Figure (2.2) displays the impulse responses of each variable to a 1 percentage point (p.p) unanticipated positive *TED* shock<sup>11</sup>. Recessionary effects takes place within twenty months after the shock.

I see that *IP* experiences a significant drop between 3 and 20 months after the shock, with the largest contraction of 1.5% in the tenth month. *CONS* falls by 0.3% after eight months of the shock. *UNRATE* rises by 0.3 p.p at the recessionary peak. There is a short-lived negative impact on *PCOM* as well. All of these variables display hump-shaped responses.

Interestingly, an adverse *TED* shock leads to a fall in *FF* within 20 months, with a drop of 0.7 p.p at the trough. A possible explanation for this response is that the Federal Reserve intends to ease the exogenous deterioration in the credit market condition by lowering the federal funds rate.<sup>12</sup>

#### Structural FF shock

Figure (2.3) displays the impulse responses of each variable to a 1 percentage point (p.p.) unanticipated positive *FF* shock<sup>13</sup>.

Contractionary effects last for 30-40 months: *IP* drops by 1% and *CONS* drops

<sup>11</sup> This corresponds to a shock of the size of three standard deviations ( $\sigma_{TED} = 32$  basis points).

<sup>12</sup> *TED* shock separately contributes up to 15% and 16% of the forecast variance of *IP* and *UNRATE*, as reflected by the following table:

Percent of k months ahead of forecast error variance due to <i>TED</i> shock							
k=	0	10	20	30	50	100	300
<i>IP</i> <sub>t</sub>	0.00	12.64	14.79	12.53	8.95	7.35	8.40
<i>CONS</i> <sub>t</sub>	0.00	3.39	2.76	1.95	1.41	2.17	5.32
<i>UNRATE</i> <sub>t</sub>	0.00	13.75	15.88	13.25	8.97	6.86	8.33
<i>CPI</i> <sub>t</sub>	0.00	1.70	3.70	5.06	5.81	4.93	4.40
<i>PCOM</i> <sub>t</sub>	0.00	2.94	3.02	2.58	2.71	4.99	7.12

<sup>13</sup> This corresponds to a shock of the size of two standard deviations ( $\sigma_{FF} = 51$  basis points).

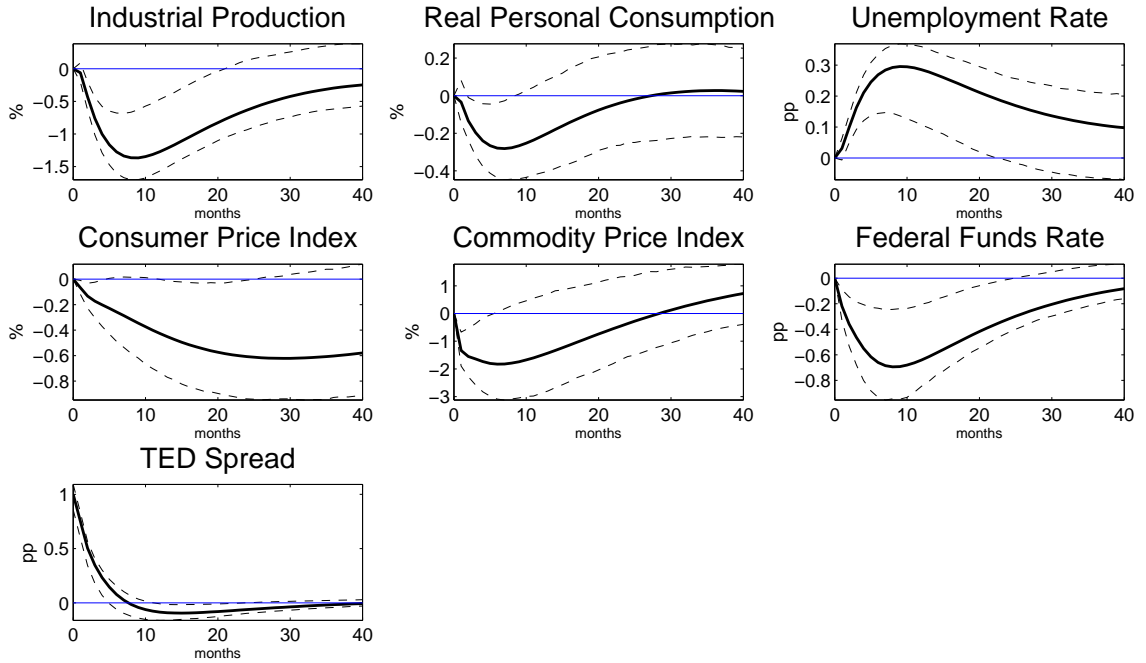


FIGURE 2.2: Impulse responses to a 1 p.p. adverse  $TED$  shock under the baseline model. The error bands show the 90% confidence interval and are constructed by bootstrapping VAR residuals.

by 0.4% at the trough, whereas  $UNRATE$  rises by 0.3 p.p. at the peak. These results are consistent with Christiano et al. (1998) and Christiano et al. (2005).

Interestingly, upon an adverse  $FF$  shock  $TED$  jumps up on impact, reaches a peak of 1.3 p.p. in the second month, and remains significantly positive for 10 months.<sup>14</sup>

<sup>14</sup>  $FF$  shock accounts for about 20% of the forecast variance of  $IP$  and  $CONS$ , and more than 30% of the forecast variance of  $UNRATE$ , as displayed by the following table. Again, these numbers are consistent with the results in CEE (1999).

Percent of k months ahead of forecast error variance due to $FF$ shock							
k =	0	10	20	30	50	100	300
$IP_t$	0.00	6.21	17.02	21.63	21.46	18.01	11.80
$CONS_t$	0.00	9.96	17.42	18.23	15.83	13.42	10.11
$UNRATE_t$	0.00	11.78	26.94	33.63	33.08	24.84	12.16
$CPI_t$	0.00	3.79	3.82	3.02	2.10	2.66	8.46
$PCOM_t$	0.00	0.07	0.11	0.36	1.84	7.42	6.06

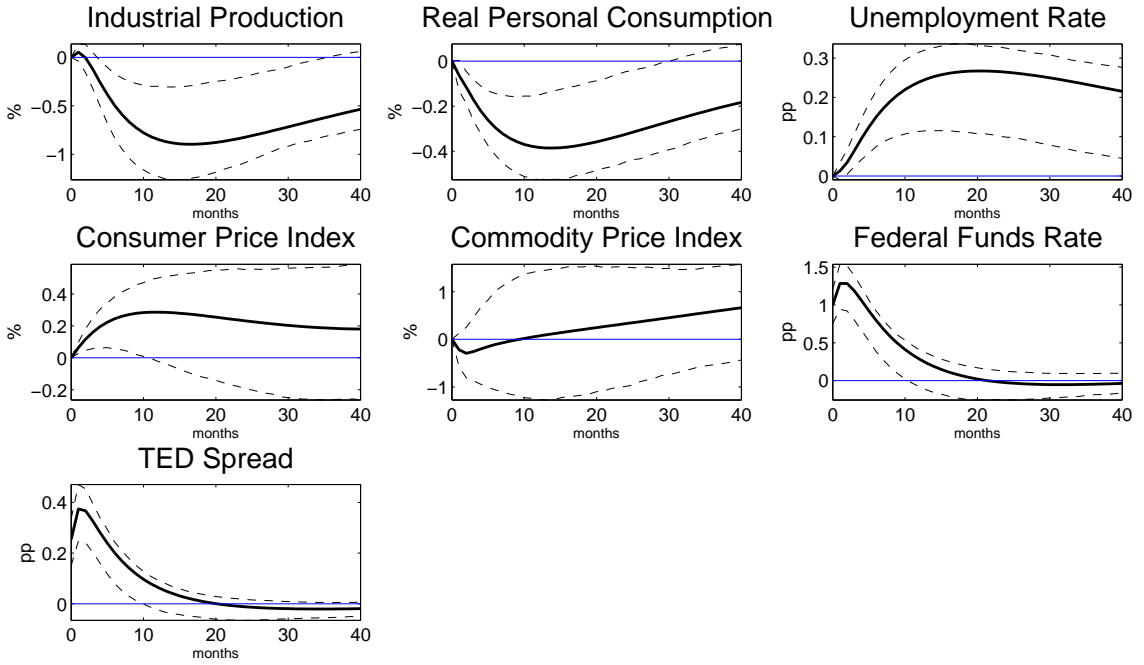


FIGURE 2.3: Impulse responses to a 1 p.p. adverse  $FF$  shock under the baseline model. The error bands show the 90% confidence interval and are constructed by bootstrapping VAR residuals.

### 2.3.4 Robustness checks

#### *Ordering of $FF$ and $TED$*

In the baseline VAR model I assume that  $TED$  responds to  $FF$  within the same period, but  $FF$  responds to  $TED$  with a lag. As a robustness check I reverse the ordering of  $TED$  and  $FF$ , implying that I assume  $FF$  can respond to  $TED$  contemporaneously but not the other way around. The impulse responses of the various macro variables are qualitatively similar except for the impulse response of  $FF$  on impact: an adverse  $TED$  shock leads to a rise in  $FF$  by 0.5 p.p (significantly positive) on impact (the plot is not shown to conserve space).  $FF$  then displays a drop significantly different from zero starting at the 10<sup>th</sup> month and the impact lasts until the 25<sup>th</sup> month. The largest fall takes place in the 20<sup>th</sup> month with a magnitude

of 0.5 p.p.

Why do we see different responses of  $FF$  when I reverse the ordering of  $FF$  and  $TED$ ? One explanation is that the  $FF$  and  $TED$  series show very high unconditional correlation, both contemporaneously and in the lags<sup>15</sup>. Just as in the baseline model (where  $FF$  is ordered before  $TED$ ) in which  $TED$  jumps up on impact when an adverse  $FF$  shock hits, if I switch the order of these two variables (i.e. ordering  $TED$  before  $FF$ ) and shock  $TED$ ,  $FF$  jumps up on impact.

I also conduct a bivariate VAR using *daily* series of  $TED$  and  $FF$  to check if I will obtain similar results using data of higher frequency. Again, I introduce a 1 p.p. adverse  $TED$  shock to the bivariate VAR system. Table (2.3) documents the response of  $FF$  (up to approximately eight months after the  $TED$  shock hits) under two possible ordering of the variables:  $[FF\ TED]'$  and  $[TED\ FF]'$ . I still adopt the Choleski decomposition as the identification scheme, and the model is estimated with 350 lags.

The left panel of Table (2.3) corresponds to the ordering  $[FF\ TED]'$ , where  $TED$  responds to  $FF$  contemporaneously, but *not* the other way around. Responses of  $FF$  are negative throughout, and are continuously, significantly negative after 30 days of the  $TED$  shock. The right panel shows the ordering  $[TED\ FF]'$ , where  $FF$  responds to  $TED$  contemporaneously, but not the other way around. Significantly positive responses of  $FF$  are observed up to 14 days after the shock. Continuously negative responses of  $FF$  come after the 43<sup>rd</sup> day of the  $TED$  shock. These results are not inconsistent with the ones from our monthly baseline VAR.

It is also interesting to note the trough value of the responses of  $FF$  in both cases:

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<sup>15</sup> The following table lists the dynamic correlation  $corr(TED_{t+j}, FF_t)$ :

$j$	-10	-5	0	5	10
$corr(TED_{t+j}, FF_t)$	0.51	0.53	0.65	0.58	0.52
error band	$\pm 0.106$	$\pm 0.110$	$\pm 0.107$	$\pm 0.113$	$\pm 0.122$



Table 2.3: Response of  $FF$  with respect to a 1 p.p. adverse  $TED$  shock, using Choleski decomposition with two different orderings

Impulse response of  $FF$  with respect to  $TED$  (1 p.p.)  
(all coefficients are significant at 5% level)

ordering: $[FF\ TED]'$		ordering: $[TED\ FF]'$	
lags (days)	IR of $FF$ (pp)	lags (days)	IR of $FF$ (pp)
0	0	0	0.203
1	-0.158	4	0.077
2	-0.120	13	0.124
3	-0.129	14	0.108
16	-0.105	31	-0.121
19	-0.103	32	-0.194
26	-0.113	36	-0.144
30	-0.207	43	-0.186
31	-0.212	44	-0.180
32	-0.292	45	-0.228
233	-0.577	233	-0.508
234	-0.601	234	-0.533
235	-0.647	235	-0.579
236	-0.640	236	-0.573
237	-0.631	237	-0.561

the largest fall in  $FF$  sets in on the 235<sup>th</sup> day, which corresponds to the eighth month after the shock, with a magnitude of  $-0.647$  p.p and  $-0.579$  p.p., respectively. These magnitudes are similar to the trough values we observe in the monthly VARs.

In short, the ordering of the  $FF$  and  $TED$  does not matter for the responses of the real variables. Despite the difference in the response of  $FF$  to  $TED$  shock *on impact*, the conclusion that the unanticipated  $TED$  shock drives down  $FF$  significantly after some time lag is robust.

*Alternative identification scheme: Extended Sims and Zha (1998)*

*Review on Sims-Zha identification* Sims and Zha (SZ) provides another way to identify monetary policy shocks<sup>16</sup>. The 7-by-7 submatrix on the upper left of Table (2.4)

<sup>16</sup> This amounts to putting zeros in different entries of the matrix  $A_0$  in the structural VAR model (2.1).

describes their identification procedures. SZ argue for a major role of the commodity price  $PCOM$ , which they consider reflects the active crude material market being able to update itself with market information every day. Therefore in their identification scheme they assume that the  $PCOM$  responds to all of the other variables contemporaneously (i.e. all the coefficients in the first row of the submatrix are non-zero).

SZ also adds a money equation (according to the “quantity theory of money”), in which they restrict the coefficient of GNP (to be proxied by  $IP$  below) and the coefficient of the GNP deflator (to be proxied by  $CPI$ ) to be **negative** of that of  $M2$  (the second row of the submatrix). They identify  $FF$  shock by assuming that it responds to  $PCOM$  and  $M2$  contemporaneously (the third row of the submatrix).

Moreover, all real and price variables ( $CPI$ ,  $U$ ,  $CONS$  and  $IP$ ) do not respond to contemporaneous  $FF$ ; the argument is that owing to inherent inertia and planning delays, most of the real economic activities respond to a lag of financial signals. But these variables *do* respond to  $PCOM$  within the same period on the assumption that commodity prices can affect these variables through the markup rules for prices. Notice that the block including these four variables is assumed to be upper triangular for identification purposes<sup>17</sup>.

*Extended Sims-Zha identification* I augment the matrix in Table (2.4) by introducing  $TED$ . I allow  $PCOM$  to react to  $TED$  within the same period ( $a_{18} \neq 0$ ), and assume that  $TED$  is a function of contemporaneous  $PCOM$  and  $FF$  ( $a_{81}, a_{83} \neq 0$ ).<sup>18</sup>

The economic intuition behind this identification scheme is straightforward. Since

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<sup>17</sup> SZ also includes wage, intermediate good price and bankruptcy rates together with GNP and CPI, all of which responds to  $PCOM$  contemporaneously and they form an upper triangular block. I am omitting those variables here in order to limit the size of our VAR system. But note that I preserve *all* the essential features of the SZ identification scheme.

<sup>18</sup> I cannot assume that  $TED$  responds to all other variables as I do in the baseline VAR model, for this assumption will result in unidentification of  $TED$  with  $PCOM$ .

Table 2.4: Sims-Zha identification scheme with TED spread

$$\left( \begin{array}{c|cccccccc} & \mathbf{PCOM}_t & \mathbf{M2}_t & \mathbf{FF}_t & \mathbf{CPI}_t & \mathbf{UNRATE}_t & \mathbf{CONS}_t & \mathbf{IP}_t & \mathbf{TED}_t \\ \hline \mathbf{PCOM}_t & a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} & a_{18} \\ \mathbf{M2}_t & 0 & a_{22} & a_{23} & -a_{22} & 0 & 0 & -a_{22} & 0 \\ \mathbf{FF}_t & a_{31} & a_{32} & a_{33} & 0 & 0 & 0 & 0 & 0 \\ \mathbf{CPI}_t & a_{41} & 0 & 0 & a_{44} & a_{45} & a_{46} & a_{47} & 0 \\ \mathbf{UNRATE}_t & a_{51} & 0 & 0 & 0 & a_{55} & a_{56} & a_{57} & 0 \\ \mathbf{CONS}_t & a_{61} & 0 & 0 & 0 & 0 & a_{66} & a_{67} & 0 \\ \mathbf{IP}_t & a_{71} & 0 & 0 & 0 & 0 & 0 & a_{77} & 0 \\ \hline \mathbf{TED}_t & a_{81} & 0 & a_{83} & 0 & 0 & 0 & 0 & a_{88} \end{array} \right)$$

I preserve the assumption that  $PCOM$  can continuously update itself with market information, it can respond to *all* of the variables contemporaneously, including  $TED$ . To stay in line with the SZ assumption that real variables react to financial signals with delays,  $IP$ ,  $CONS$ ,  $UNRATE$  and  $CPI$  do not respond to  $TED$  and  $FF$  contemporaneously.

I assume that  $TED$  reacts to  $PCOM$  contemporaneously on the grounds that  $PCOM$  contains updated information which can affect  $TED$  within the same period. I also assume that  $TED$  will respond to concurrent  $FF$  because  $TED$  is computed from the Eurodollar rate and the Treasury bill rate, both of which in turn are functions of the federal funds rate.

*Impulse responses* Figure (2.4) shows the impulse responses with respect to a 1 p.p. adverse  $TED$  shock. The impulse responses to the real variables such as  $IP$ ,  $UNRATE$ ,  $CPI$ , as well as the federal funds rate  $FF$ , are qualitatively similar to those in the baseline model<sup>19</sup>. I observe that  $PCOM$  falls on impact — this is due to our assumption that  $PCOM$  reacts to  $TED$  contemporaneously (i.e.  $a_{18} \neq 0$ ). Therefore I conclude that the results from the baseline model are robust under the

<sup>19</sup> For comparative purposes I have also introduced  $M2$  to our baseline model based on CEE(2005) (results not shown here). Here is my specification:

$$Y_t = [IP_t \text{ } CONS_t \text{ } UNRATE_t \text{ } CPI_t \text{ } PCOM_t \text{ } FF_t \text{ } M2_t \text{ } TED_t]$$

The addition of  $M2$  does not change the qualitative conclusion of the macro effect of the  $TED$  shock.

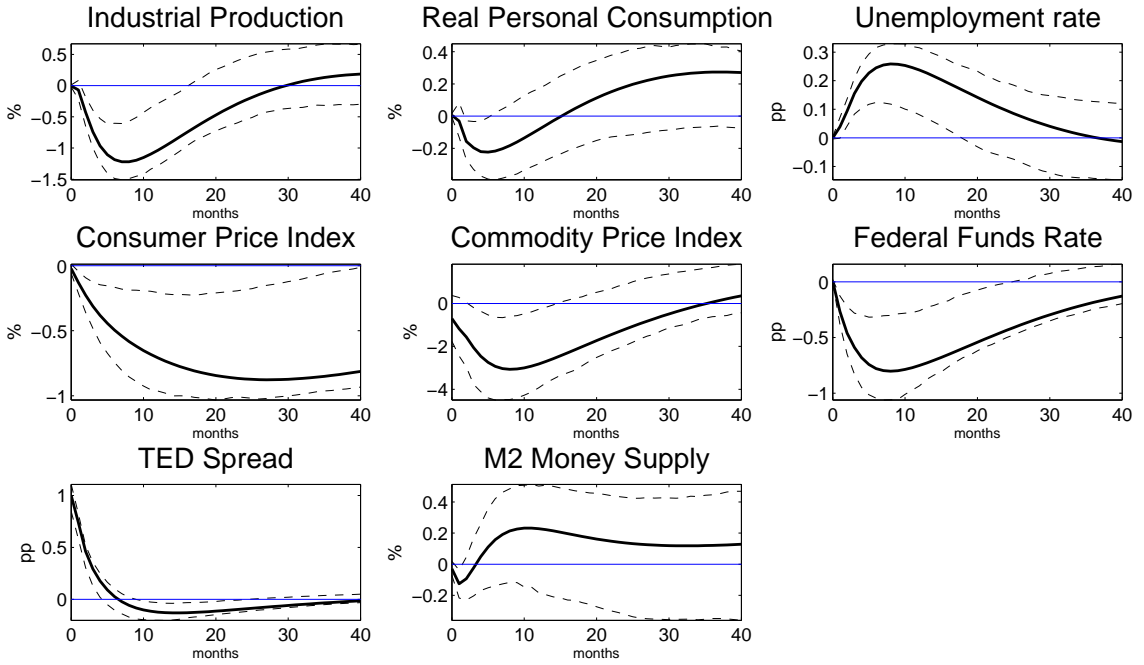


FIGURE 2.4: Impulse responses to a 1 p.p. adverse *TED* shock under the extended Sims-Zha identification. The error bands show the 90% confidence interval and are constructed by bootstrapping VAR residuals.

extended Sims-Zha identification scheme.

Moreover, the above results are robust to different variants of the SZ identification scheme, which includes

1. treating *TED* as part of the upper triangular system (i.e. *TED* responds to *CPI*, *U*, *CON*, *IP* contemporaneously);
2. switching the role of *PCOM* and *TED* while preserving the other identification features, as in Table (2.4);
3. as in (2) above and treating *PCOM* as part of the upper triangular system (i.e. *PCOM* responds to *CPI*, *U*, *CON*, *IP* contemporaneously).

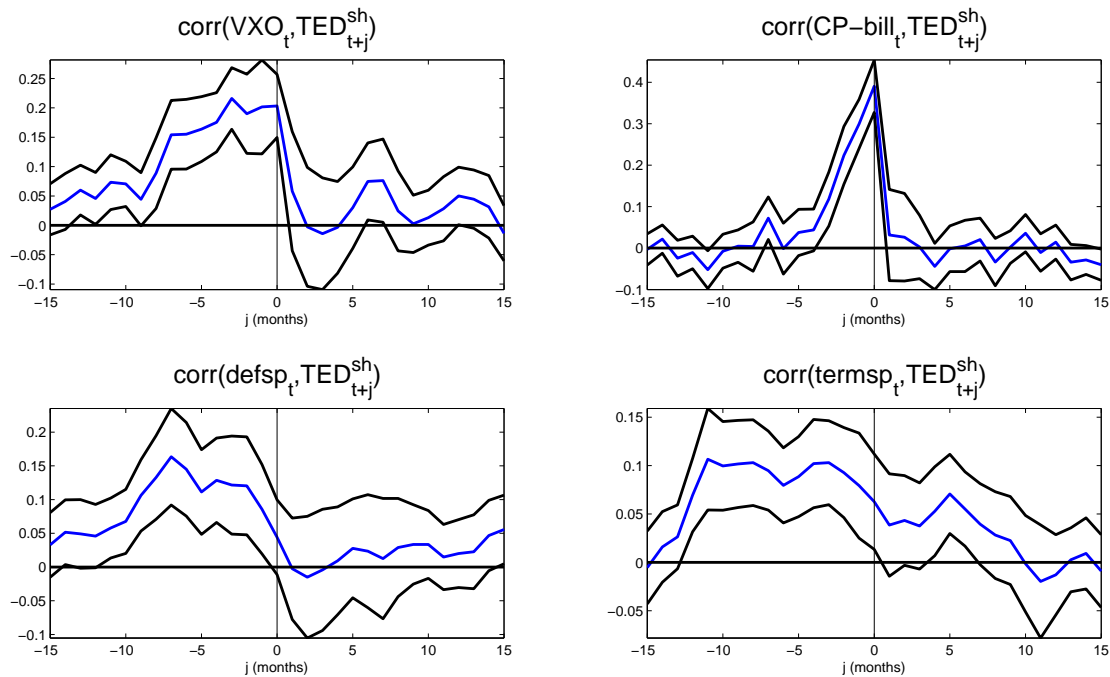


FIGURE 2.5: Plots of dynamic correlations (with GMM standard error bands) between the structural  $TED$  shock and  $VXO$ ,  $CP - bill$ , default spread and term spread. Sample period: 1971M1-2009M9.

### 2.3.5 Structural $TED$ shocks and other financial variables

Interestingly, lags of structural  $TED$  shocks are correlated with various financial variables. Figure (2.5) plots the dynamic correlations of the structural  $TED$  shock with four other common financial variables:

- $VXO$  index. A measure of implied volatility, calculated using the 30-day S&P 100 index. Also known as the “fear index”, a high value of  $VXO$  corresponds to a more volatile stock market.<sup>20</sup> Structural  $TED$  shocks have a contemporaneous correlation of 0.2 with  $VXO$ . Moreover, the lags of  $TED$  shocks are correlated with the current  $VXO$ . In other words the structural  $TED$  shocks “lead” the implied volatility of the stock market;

<sup>20</sup> Although the  $VXO$  index didn’t start until 1986, Bloom (2006) describes a way to construct a corresponding  $VXO$  series for the pre-1986 period.

- *CP – bill* spread. Defined as the difference between a three-month commercial paper rate and the three-month treasury bill rate. This spread was once a widely studied leading indicator. Structural *TED* shocks have a rather high contemporaneous correlation of 0.35 with the *CP – bill* spread. They also “lead” the *CP – bill* spread for up to five months;
- Default spread and term spread, respectively defined as the difference between Moody’s seasoned *BAA* and *AAA* corporate bond yields, and the difference between 10-year and 1-year Treasury constant maturity rate. I see that structural *TED* shocks lead the default spread. A similar story can be told for the term spread as well.<sup>21</sup>

### 2.3.6 Stylized facts on the structural *TED* shocks on macro variables

In this section I performed a range of VAR analyses to study the macro effect of the *TED* spread. The results are robust to the ordering of the variables under the recursiveness assumption as well as the extended Sims-Zha identification. To sum up, an unanticipated adverse *TED* shock brings contractionary effects for up to 20 months, with the variables *IP*, *CONS*, *UNRATE* and *FF* displaying hump-shaped responses. Interestingly, structural *TED* shocks lead some of the important financial variables, especially the implied volatility of the stock market (*VXO*).

## 2.4 Asset pricing implications of the structural *TED* shock

### 2.4.1 Motivation

It is natural to ask if asset prices are affected by structural funding liquidity shocks. The current imperfect capital market theories, including Bernanke and Gertler (1989), Gertler and Gilchrist (1994), and Kiyotaki and Moore (1997), predict that small

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<sup>21</sup> Interestingly, I do not find conspicuous correlations between monetary policy shocks (as recovered by our *baseline* VAR model) with these financial variables with the exception of the term spread.

firms, arguably having less collateral when borrowing in the credit markets, face higher agency costs in the face of information asymmetry. Hence they are more adversely affected by a deterioration of credit (including but not limited to funding liquidity) conditions. Thus, their equity returns are hit harder as well.

To motivate this section I augment my baseline VAR model (2.1) with the following series separately: value-weighted excess returns of the stock market, and equally-weighted excess returns of the stock market<sup>22</sup>.

Both the stock market returns and the risk-free interest rate are obtained from the CRSP database. I separately put these two variables after the variable  $TED$  in the VAR model (2.1), as I assume that stock market returns can respond to current changes of  $TED$  (as well as all other variables) within the same period. Figure (2.6) display the impulse responses of each of the series with respect to a 1 p.p. adverse  $TED$  shock.

Both of the excess returns are indeed significantly impacted by funding liquidity shocks, although the impact is short-lived. Moreover, the equally-weighted stock market returns decrease relatively more than their value-weighted counterpart. Since the equally-weighted returns are tilted towards smaller firms, this gives us a hint that the excess returns of smaller firms are affected more by funding liquidity shocks.

#### 2.4.2 Data and variables

I now proceed to investigate in detail the asset pricing implications of funding liquidity shocks. The structural funding liquidity shock ( $TED^{sh}$ ) comes from the *baseline* VAR model in the previous section<sup>23</sup>. Data on equity returns are obtained from

<sup>22</sup> By definition, the excess returns of value-weighted portfolios are weighted by the market capitalization of the included firms, whereas in equally-weighted portfolio the excess returns are weighted equally.

<sup>23</sup> Recall that I adopt the recursiveness assumption and order  $TED$  as the last variable, reflecting our assumption that  $TED$  responds contemporaneously to all the real and price variables, including the federal funds rate  $FF$  (but  $FF$  does not respond to  $TED$  contemporaneously).

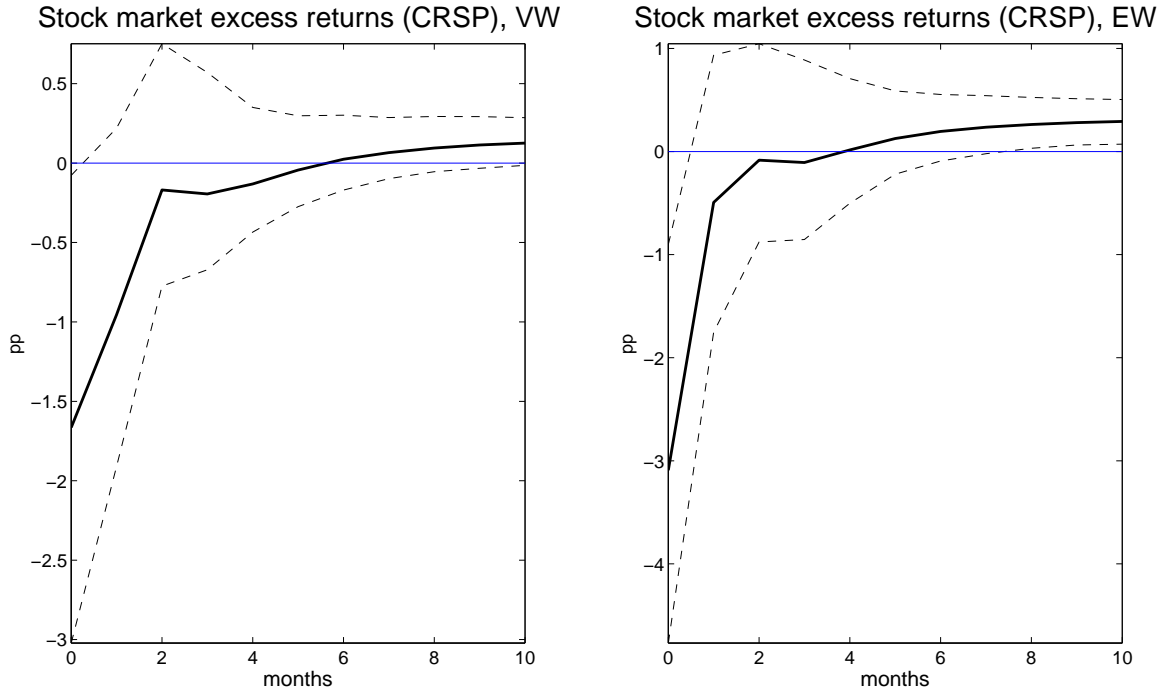


FIGURE 2.6: Impulse responses of the value-weighted (VW) and equally-weighted (EW) stock market excess returns with respect to a 1 p.p. adverse  $TED$  shock, computed from the augmented baseline VAR model. Sample period: 1971M1: 2009M9. Bootstrapped error bands show the 90% confidence interval.

Kenneth French’s website<sup>24</sup>. Returns of stocks are sorted *from lowest to highest* into ten deciles by the following two statistics: (i) size (market capitalization, or “market cap”; denoted  $ME$ ); and (ii) book-to-market ratio (the ratio of book value to market capitalization; denoted  $BEME$ ). Returns of each decile can be either value-weighted (VW) or equally-weighted (EW). The sample period is from 1971M1 to 2009M9.

To compute the excess returns, I obtain the one-month Treasury bill rate  $(R_t^f)$  taken from the same website. Denoting  $R_t$  as the simple net return from the portfolio, one-period excess return between dates  $t - 1$  and  $t$  is computed as  $r_t^i = \ln(1 + R_t) - \ln(1 + R_t^f)$ . Figure (2.7) plots the mean excess return across the ten deciles, which are separately sorted on size and book-to-market ratio. I observe that: (i) in the

<sup>24</sup> [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).



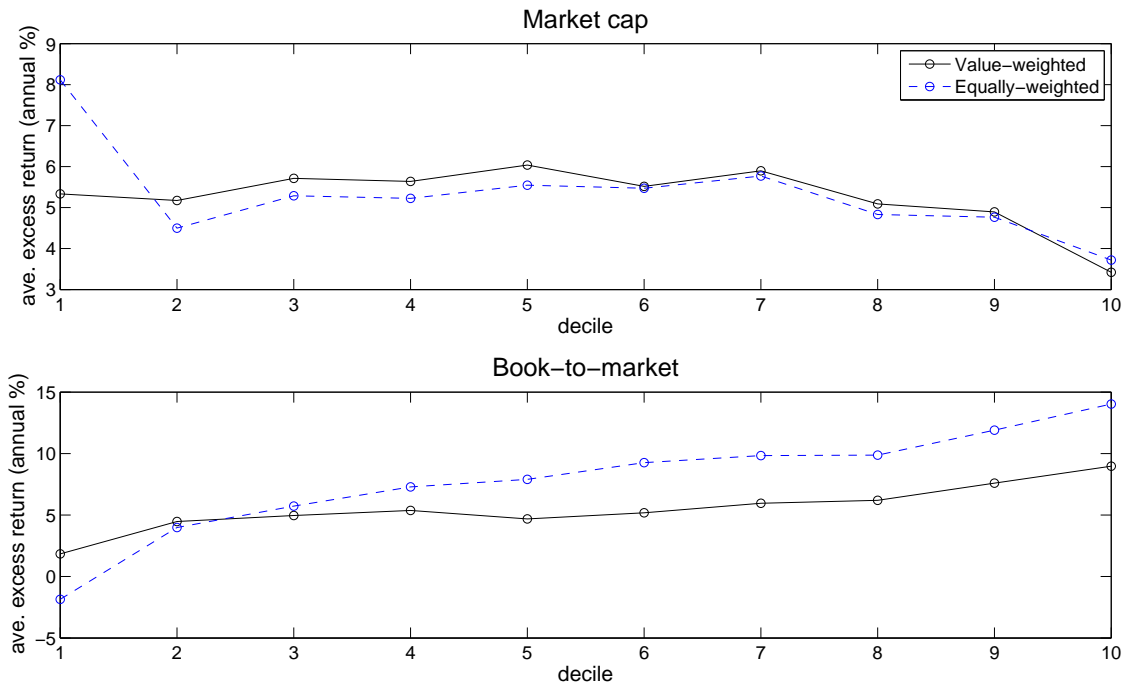


FIGURE 2.7: Average excess returns across ten deciles when returns are separately sorted on size (“market cap”) and book-to-market ratio. Sample period: 1971M1: 2009M9.

upper panel where returns are sorted by size, the average equally-weighted return is substantially higher than the value-weighted one in the first decile but not the others, implying that small firms earn much higher excess returns on average; (ii) in the lower panel where returns are sorted by book-to-market ratio, value firms (deciles with large numbers) earn higher average returns than growth firms (deciles with smaller numbers).

### 2.4.3 How are equity returns affected by funding liquidity shocks contemporaneously?

#### Estimation and results

I estimate the following equation:

$$r_t^i = \alpha^i + \beta_{TED^{sh}}^i TED_t^{sh} + \varepsilon_t^i \quad (2.2)$$

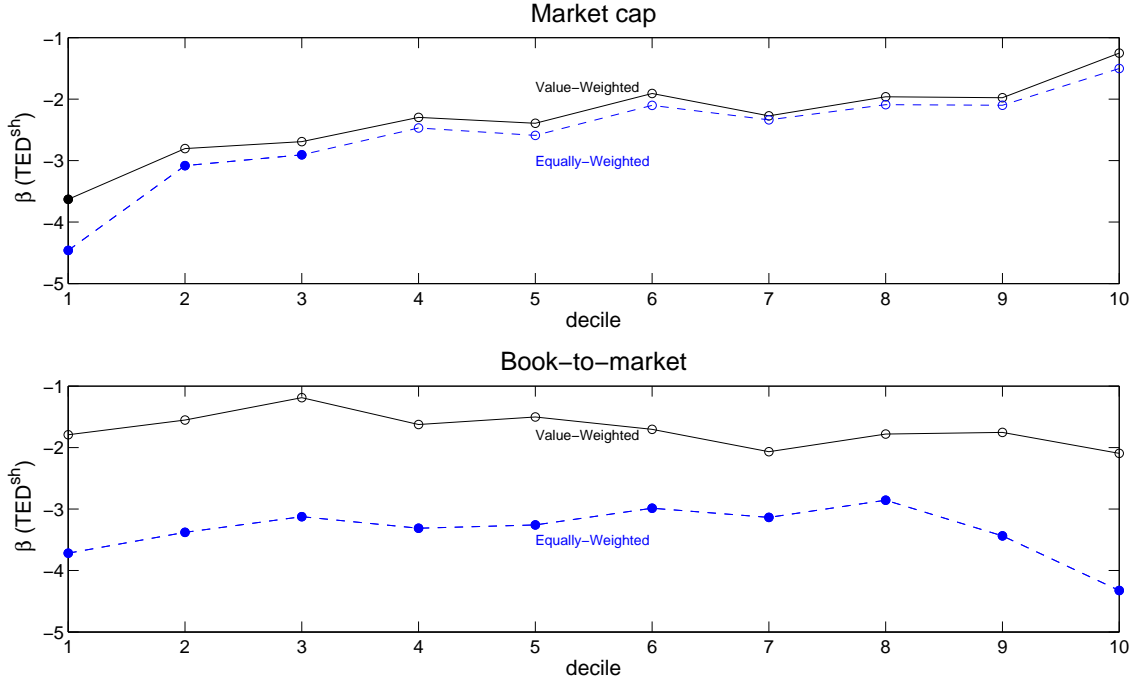


FIGURE 2.8: Plots of  $\beta_{TED^{sh}}$  for returns separately sorted on size (“market cap”) and book-to-market ratio. A solid circle means that  $\beta_{TED^{sh}}$  of the particular decile is statistically significant from zero, whereas an empty circle means it is not.

where  $r_t^i$  denotes the excess return of the  $i^{th}$  decile, and the  $\varepsilon$ 's represent the components of decile returns not explained by funding liquidity shocks. I am interested in studying the estimate of  $\beta_{TED^{sh}}^i$ , which can be interpreted as how sensitive the excess returns of the  $i^{th}$  decile are with respect to funding liquidity shocks.

Figure (2.8) shows the corresponding plot of betas across deciles. To enhance readability the decile with a statistically significant beta is characterized by a solid circle. Eyeballing gives us the following observations. First, the betas are negative across all deciles, meaning that the excess returns are negatively impacted by a positive  $TED$  shock (i.e. an unanticipated worsening of funding liquidity). Second, the betas of equally-weighted portfolios are uniformly lower than the value-weighted counterparts. Since equally-weighted returns are tilted towards smaller firms, the results show that smaller firms suffer a greater fall in returns given the same funding

liquidity shock.

Table (2.5) displays the numerical estimates as well as the  $t$ -statistics of  $\beta_{TEDsh}$  shown in Figure (2.8).

*Portfolios sorted on size* Panels A1 and A2 of Table (2.5) display the beta coefficients as well as the corresponding  $t$ -statistics corrected for autocorrelation and heteroskedasticity by using the Newey-West estimator (Newey and West (1987))<sup>25</sup>. I see that only the beta of the lowest decile for value-weighted returns as well as the lowest three deciles for equally-weighted ones are statistically significant at the 5% level. Indeed, the returns of smaller firms are harder hit by funding liquidity shocks.

*Portfolios sorted on book-to-market ratio*<sup>26</sup> Panels B1 and B2 of Table (2.5) display the beta coefficients as well as the corresponding  $t$ -statistics. The betas are in general not significant at the 5% level in the value-weighted returns, but all of them are significant in the equally-weighted ones. This again shows that the equity returns of small firms are hit harder by funding liquidity shocks.

One may wonder why, for equally-weighted returns, only the betas of the first three deciles display significance when returns are sorted on size, but all of the ten deciles show significant betas when returns are sorted on book-to-market ratio. The reason is that small firms are present in *all* of the deciles when returns are sorted by book-to-market ratio. Since these small firms receive more weight in the equally-weighted returns, the betas in each of the decile sorted on the book-to-market ratio are more likely to turn statistically significant. In fact, these results are in line with Fama and French (1988), who find that equally-weighted returns are more sensitive

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<sup>25</sup> I use five lags for the estimation of the Newey-West estimator (Newey and West (1987) and Newey and West (1994)). Such lag length is determined by the integer portion of  $4 \left(\frac{T}{100}\right)^{2/9}$ , where  $T$  is the number of observations.

<sup>26</sup> I find similar results for portfolios sorted on other fundamental-to-price variables, including cashflow-to-price and earnings-to-price.

to variations in dividend yields, term premia and default premia compared with value-weighted ones.

*Robustness check with pre-whitened TED spread ( $TED^{innov}$ )*

In the empirical finance literature it is a common practice to treat a pre-whitened financial variable as a factor in asset pricing. As a robustness check I repeat the above exercise replacing  $TED^{sh}$  with the pre-whitened TED spread. Having first fitted  $TED$  with an AR(1) process (which is chosen by the Bayesian Information Criterion), we take the “innovation” of the process ( $TED^{innov}$ ) as a factor and run the following regression:

$$r_t^i = \alpha^i + \beta_{TED^{innov}}^i TED_t^{innov} + \varepsilon_t^i \quad (2.3)$$

The results are reported in Table (2.6). Betas are negative across all deciles and the betas of equally-weighted returns are more negative. These results are consistent with our previous results with  $TED^{sh}$ . However, a major difference emerges: all of the beta coefficients in the value-weighted returns (along with those in equally-weighted ones) are statistically significant when I use  $TED^{innov}$  as a factor, whereas the betas for value-weighted returns are hardly significant when I use  $TED^{sh}$  as a factor (see Table (2.5)). There are two possible explanations for the difference: (i)  $TED^{sh}$  and  $TED^{innov}$  are computed using different lag information structures; (ii)  $TED^{innov}$  contains other contemporaneous shocks, especially the monetary policy shock  $FF^{sh}$ .

In order to determine if it is the different lag information structures which make the difference, I regress  $TED^{innov}$  on two lags of the variables used in the *baseline* VAR and obtain the residuals. I then run a similar regression as specified by (2.3) except that I use the residuals as the factor. In this way, I control for the difference in the lag information structures. The resulting significance of betas across deciles

for value-weighted returns is still qualitatively similar to that displayed in Table (2.6) (results are not shown here to conserve space). Hence I rule out the different lag information structures as the explanation. The difference in the pattern of the statistical significance of the betas between tables (2.5) and (2.6) is plausibly attributable to the existence of some other contemporaneous shocks in  $TED^{innov}$ .

#### 2.4.4 Is the funding liquidity factor priced?

*Twenty-five portfolios sorted on size and book-to-market ratio*

In this subsection<sup>27</sup> I am going to take the structural  $TED$  shock as a factor<sup>28</sup>, and then proceed to investigate if this funding liquidity factor is priced.

I first state a general asset pricing model

$$Er^i = \lambda_{RMRF}\beta_{RMRF}^i + \lambda_{SMB}\beta_{SMB}^i + \lambda_{HML}\beta_{HML}^i + \lambda_{TED^{sh}}\beta_{TED^{sh}}^i \quad (2.4)$$

for all  $i = 1, \dots, N$ , where  $Er^i$  denotes the expected excess return of the  $i^{th}$  portfolio;  $(\lambda_{RMRF}, \lambda_{SMB}, \lambda_{HML}, \lambda_{TED})$  denotes the price of risks associated with the excess return market factor ( $RMRF$ ), size premium ( $SMB$ , or “small-minus-big”), value premium ( $HML$ , or “high-minus-low”)<sup>29</sup> and the structural  $TED$  shock ( $TED^{sh}$ );  $(\beta_{RMRF}^i, \beta_{SMB}^i, \beta_{HML}^i, \beta_{TED^{sh}}^i)$  denotes the respective betas of each  $i^{th}$  portfolio. The first three factors in the model (2.4) are proposed by Fama and French (1993), and have since become the benchmark factors in the empirical finance literature. I will

<sup>27</sup> This subsection is closely linked to Adrian and Etula (2010). They use broker-dealers’ capital-equity ratio as a proxy for funding liquidity risk and they find that the funding liquidity as a risk factor can account for book-to-market, momentum and long-term reversal anomalies.

<sup>28</sup> The reason is that the structural  $TED$  shock is economically interpretable, as compared to the pre-whitened  $TED$  spread.

<sup>29</sup> To construct the factors  $SMB$  and  $HML$ , Fama and French (1993) first sort stocks into six portfolios according to size (*small* and *big*) and book-to-market (*growth*, *neutral* and *value*): *small value*, *small neutral*, *small growth*, *large value*, *large neutral* and *large growth*.  $SMB$  is formed by the difference in returns between the equally-weighted average “small” portfolios and “large” portfolios.  $HML$  is formed by the difference in returns between the equally-weighted “value” portfolios and “growth” portfolios.

first estimate the capital asset pricing model (CAPM) by imposing the restrictions of  $\lambda_{SMB} = \lambda_{HML} = \lambda_{TED^{sh}} = 0$ . After that, I will remove the restrictions one-by-one, starting with the *TED* shock. I will be able to see the relative importance of the *TED* shock in explaining equity returns in the cross-section.

To estimate the asset pricing model (2.4) I adopt the time series/cross-sectional regressions approach as presented by Cochrane (2001). I first estimate the betas by conducting the following time series regression given the  $i^{th}$  portfolio:

$$r_t^i = \delta^i + \beta_{RMRF}^i RMRF_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{TED^{sh}}^i TED_t^{sh} + \varepsilon_t^i$$

for all  $t = 1, \dots, T$ .

The asset pricing relationship described in (2.4) is then estimated by the following OLS cross-sectional regression:

$$\bar{r}^i = \lambda_{RMRF} \beta_{RMRF}^i + \lambda_{SMB} \beta_{SMB}^i + \lambda_{HML} \beta_{HML}^i + \lambda_{TED^{sh}} \beta_{TED^{sh}}^i + \alpha^i$$

for all  $i = 1, \dots, N$ , where  $\bar{r}^i = \frac{1}{T} \sum_{t=1}^T r_t^i$  denotes the average return of the portfolio  $i$ , and  $\alpha^i$  is the pricing error. I also report various statistics on how well each of the models fits the data<sup>30</sup>.

Table (2.7) shows the estimation results of the model (2.4) using the returns of the equally-weighted twenty-five portfolios sorted on size and book-to-market ratio. I start with the CAPM model (column (1)), which is clearly rejected by the

<sup>30</sup> I report the following statistics: (i) root-mean-squared-error  $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N \hat{\alpha}^i{}^2}$ ; (ii) R-squared  $R^2 = 1 - \frac{\hat{\alpha}' \hat{\alpha}}{\bar{r}' \bar{r}}$  where  $\bar{r}$  denotes  $N \times 1$  demeaned average excess returns; and (iii) adjusted R-squared  $\bar{R}^2 = 1 - (1 - R^2) \left( \frac{N-1}{N-K} \right)$ .

To check if the model in question is perfectly specified, I can test the null hypothesis that the  $N$  pricing errors are jointly equal to zero by

$$\hat{\alpha}' cov(\hat{\alpha})^{-1} \hat{\alpha} \sim \chi^2(N - K)$$

where  $K$  denotes the number of factors,  $\hat{\alpha}$  is the  $N \times 1$  vector of price errors. The covariance matrix  $cov(\hat{\alpha})$  is estimated following Shanken (1992).

data (this can be seen by the zero p-value in the bottom row of the table. The p-value is associated with the test statistic, which tests the null hypothesis that the model in question is correctly specified). As I move on to include  $TED^{sh}$  and  $SMB$  successively (column (2) and (3)),  $\lambda_{TED^{sh}}$  increases in significance. This supplies preliminary evidence that the funding liquidity shock is priced. Notice that  $\lambda_{TED^{sh}}$  is negative, which means that the more negative  $\beta_{TED^{sh}}$  is (i.e. the higher the sensitivity of a portfolio return with respect to funding liquidity shocks), the higher the average return that is earned by that portfolio. Column (4) shows that the  $HML$  factor outperforms the structural  $TED$  shock (which becomes insignificant) when it is added on top of the factors  $RMRF$ ,  $SMB$  and  $TED^{sh}$ . This provides an interesting result: value premium *per se* generates betas which better explain cross-sectional returns than funding liquidity risk alone does.

*Twenty-five portfolios sorted on size and momentum /short-term reversal*

Columns (1a), (1b), (2a) and (2b) of tables (2.8) and (2.9) respectively present the  $\lambda$  estimates for portfolios sorted on size and momentum (with size and momentum as the two main factors), and for portfolios sorted on size and short-term reversal (with size and short-term reversal as the two main factors). Structural funding liquidity shocks are indeed priced when they are included on top of the market factor as well as the two main factors in each case. A potential explanation is that these structural shocks represent unanticipated changes in credit conditions in the economy, which are not necessarily explained by the momentum or the short-term reversal factor.

*Proposing a factor model with structural funding liquidity shocks and monetary policy shocks*

To further explore the possibility of using economically-interpretable factors to explain cross-sectional returns, I include the structural  $FF$  shock from the *baseline* VAR as another factor. Specifically I want to study the following proposed factor

model:

$$Er_t^i = \lambda_{RMRF} \beta_{RMRF}^i + \lambda_{TED^{sh}} \beta_{TED^{sh}}^i + \lambda_{FF^{sh}} \beta_{FF^{sh}}^i \quad (2.5)$$

where  $\beta_{FF^{sh}}^i$  denotes the beta of portfolio  $i$  with respect to the structural  $FF$  shock, and  $\lambda_{FF^{sh}}$  is the price of the federal funds shock risk. In other words, I want to use model (2.5) to study if the funding liquidity risk and federal funds rate risk can explain the excess returns in the cross-section<sup>3132</sup>.

Table (2.10) presents the estimation results using the value-weighted and equally-weighted *twenty-five portfolios sorted on size and book-to-market ratio*, whereas columns (1d) and (2d) of tables (2.8) and (2.9) present the results using the twenty-five portfolios respectively sorted on size and momentum/ short-term reversal.

*Portfolios sorted on size and book-to-market ratio* I want to emphasize the following three findings:

1.  $FF^{sh}$  as a risk factor is significantly priced, but  $TED^{sh}$  is not;
2. comparing column (1b) with (1c), and column (2b) with (2c), I see that the proposed model (2.5) performs comparably to the Fama-French three-factor model in terms of adjusted R-squared ( $\bar{R}^2$ ) and root-mean-squared errors ( $RMSE$ ).

The size and value premium, which has been assigned an interpretation of “de-

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<sup>31</sup> Column (5) of table (2.7), and columns(1c), (2c) of tables (2.8) and (2.9) present the price estimates of  $FF^{sh}$  being a risk factor. Similar to the results of  $TED^{sh}$ ,  $FF^{sh}$  is priced in portfolios sorted on momentum and short-term reversal but not on book-to-market ratio.

<sup>32</sup> The significance of “federal funds rate innovation” as a factor to explain stock returns has been extensively documented in the previous literature, including Thorbecke (1997), Bernanke and Kuttner (2005), and most recently by Maio and Tavares (2007), among others. With the exception of Thorbecke (1997), none of the previous measures of the “federal funds rate innovation” carries a structural economic interpretation, as the structural  $FF$  shock does in this chapter. The difference between Thorbecke (1997) and this chapter is that Thorbecke (1997) only studies the responses of stock returns with respect to a monetary policy shock in a VAR, whereas I take the recovered monetary policy shocks from a VAR as a risk factor in a factor model.



fault risk” by Vassalou and Xing (2004) , may be attributable to interest rate and funding liquidity risks;

3. comparing column (2a) with (2b), the fit of the model improves substantially when I introduce the structural *TED* shock as a factor in the equally-weighted portfolios. However, I do not see such results in the value-weighted portfolios (columns (1a) and (1b)). Since small firms receive relatively more weight in the equally-weighted portfolios, this result serves as another piece of evidence that the funding liquidity risk matters for small firms.

*Portfolios sorted on size and momentum / short-term reversal* Our proposed model (2.5) does not do as well for portfolios sorted on size and momentum / short-term reversal, as can be seen from columns (1d) and (2d) of tables (2.8) and (2.9). Our structural shocks can hardly explain the return anomalies generated by momentum and short-term reversal, but they can explain the return anomalies generated by the book-to-market ratio as I have discussed. This again provides support that value premium may represent risks attributable to interest rate and funding liquidity risks.

#### *2.4.5 Stylized facts on the structural TED shocks on asset pricing*

In this section I document that equity returns of portfolios sorted on different characteristics are indeed sensitive to funding liquidity shocks. In particular, returns of small firms are particularly worse hit by funding liquidity shocks. I have also found evidence that the funding liquidity risk is priced.

Interestingly, our proposed factor model (which includes the structural funding liquidity and monetary policy shocks as well as the market factor) performs comparably to the Fama and French (1993) model in explaining the cross-sectional returns which are sorted on size and book-to-market ratio.

## 2.5 Funding liquidity and market liquidity

Brunnermeier and Pedersen (2009) proposes a model in which a trader's funding liquidity and market liquidity<sup>33</sup> are mutually reinforcing, ultimately causing liquidity spirals. They describe how market liquidity is sensitive to changes in funding conditions when markets are illiquid: (i) a "margin spiral" emerges when a reduction in investor wealth lowers market liquidity, leading to higher margins and tightening the investor's funding constraint; (ii) a "loss spiral" arises if investors hold a large initial position which is negatively correlated with consumers' demand shock. An adverse funding shock will actually raise market illiquidity, causing losses on investor's initial position and forcing him to sell more, which in turn leads to a further price drop.

Drehmann and Nikolaou (2009) argues that a downward liquidity spiral can start with a bank or broker who is short of liquidity and cannot obtain it from the interbank market. In this section I am going to study the relationship between the two types of liquidity. I will take *TED* as the proxy for a bank's (and a trader's<sup>34</sup>) funding liquidity. As an aggregate proxy for the market liquidity(denoted as *ML*) I use the liquidity factor constructed by Pastor and Stambaugh (2003)<sup>35</sup>. They construct this index based on the idea that the "order flow" of a stock should be accompanied by a return that one expects to be partially reversed in the future if the stock is not perfectly liquid. The greater the expected reversal, the lower the stock's market liquidity.

I first examine the contemporaneous correlation between the *TED* spread and *ML*. I run a simple regression of *ML* on *TED*:

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<sup>33</sup> Market liquidity is generally used to describe the condition of trading a large amount of stock quickly at a low cost without affecting the stock price.

<sup>34</sup> There is evidence that traders depend on the interbank market to raise funds. Therefore *TED* is a reasonable proxy for traders' funding liquidity.

<sup>35</sup> The liquidity factor is downloaded from [http://faculty.chicagobooth.edu/lubos.pastor/research/liq\\_data\\_1962\\_2008.txt](http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2008.txt).

$$\widehat{ML}_t = -0.014 - 1.837 TED_t \quad R^2 = 0.068$$

(-3.076)	(-5.774)
[-2.532]	[-4.228]

where the numbers in parentheses show the  $t$ -statistics computed with the ordinary-least-square (OLS) asymptotic variance, whereas those in square brackets display  $t$ -statistics computed with the variance adjusted for heteroskedasticity and autocorrelation. Figure (2.9) displays the scatterplot of the two series. The black line in the plot shows the predicted line from the regression.

I see that  $ML$  is significantly negatively correlated with the TED spread. In other words, higher market liquidity is associated with a lower TED spread (i.e. higher funding liquidity). Hence, market liquidity and funding liquidity are contemporaneously correlated, and this result is also in line with the findings of Drehmann and Nikolaou (2009).

I also consider the correlation of the market liquidity with the leads and lags of funding liquidity, which is displayed in Figure (2.10). Apart from the fact that  $ML$  and  $ML$  is negatively correlated contemporaneously with the coefficient of  $-0.25$  (which is consistent with the regression results above),  $ML$  is also significantly negatively correlated with the lags and leads of  $ML$  for up to fifteen months. In other words, funding liquidity and market liquidity are indeed dynamically correlated.

I go one step further and study the impulse responses of funding liquidity and market liquidity shocks. I augment our baseline VAR model (2.1) with the  $ML$  series. I put both liquidity series *after* the real and price variables as well as the federal funds rate, as I assume that these two liquidity series can respond to all of the other variables contemporaneously. I do not have a stance on which liquidity reacts to the other one with a lag, so I try both orderings: (i) by ordering  $ML$  before  $ML$  I assume that market liquidity reacts to funding liquidity contemporaneously but not the other way around; (ii) by ordering  $ML$  before  $ML$  I assume the opposite. The

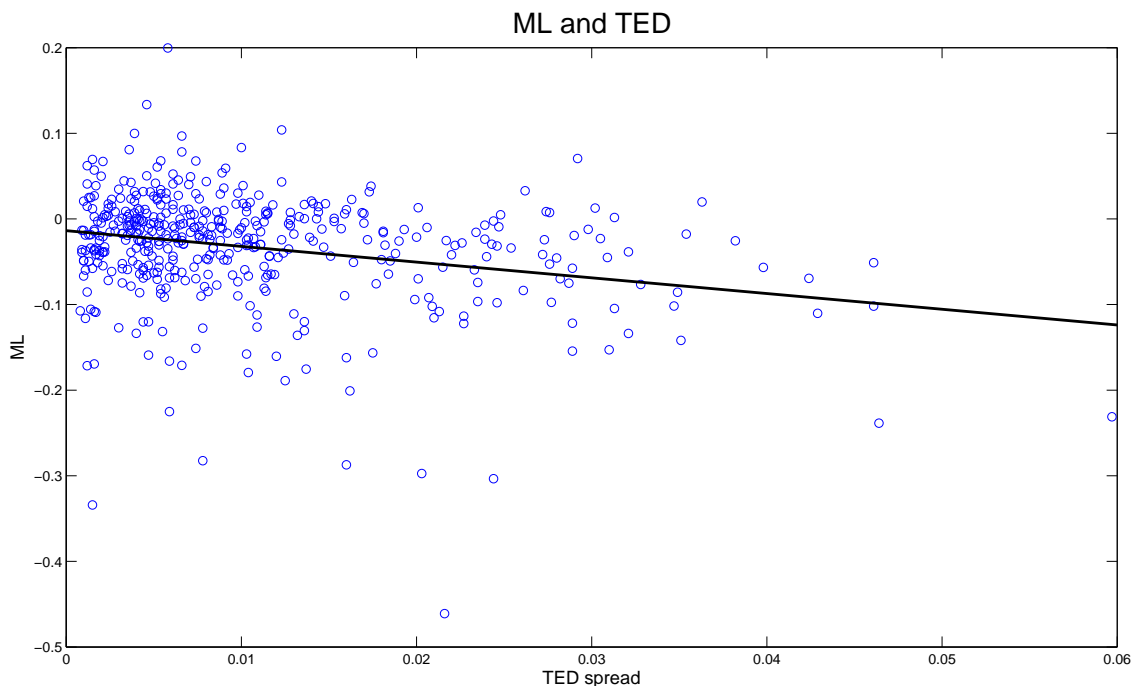


FIGURE 2.9: Funding liquidity (denoted by TED spread) versus market liquidity (denoted by  $ML$  from Pastor and Stambaugh (2003)). Sample period: 1971M1 to 2008M12.

two plots in the upper panel of Figure (2.11) respectively display, when assuming (i), the response of  $ML$  with respect to an adverse  $TED$  shock, and the response of  $TED$  with respect to an adverse  $ML$  shock. The lower panel displays the corresponding responses when assuming (ii).

It is clear that an adverse shock to one type of liquidity impacts the other negatively. An unanticipated dry-up in funding liquidity leads to a quite persistent drop in market liquidity for up to eight months (the left plots of both panels). Given an adverse market liquidity shock, funding liquidity is negatively affected ( $TED$  goes up, see the right plots of both panels), although the impact is rather short-lived.

To sum up, I have presented evidence that funding liquidity and market liquidity are indeed correlated, and that adverse shocks to one type of liquidity significantly negatively impact the other. These results are completely consistent with the pre-

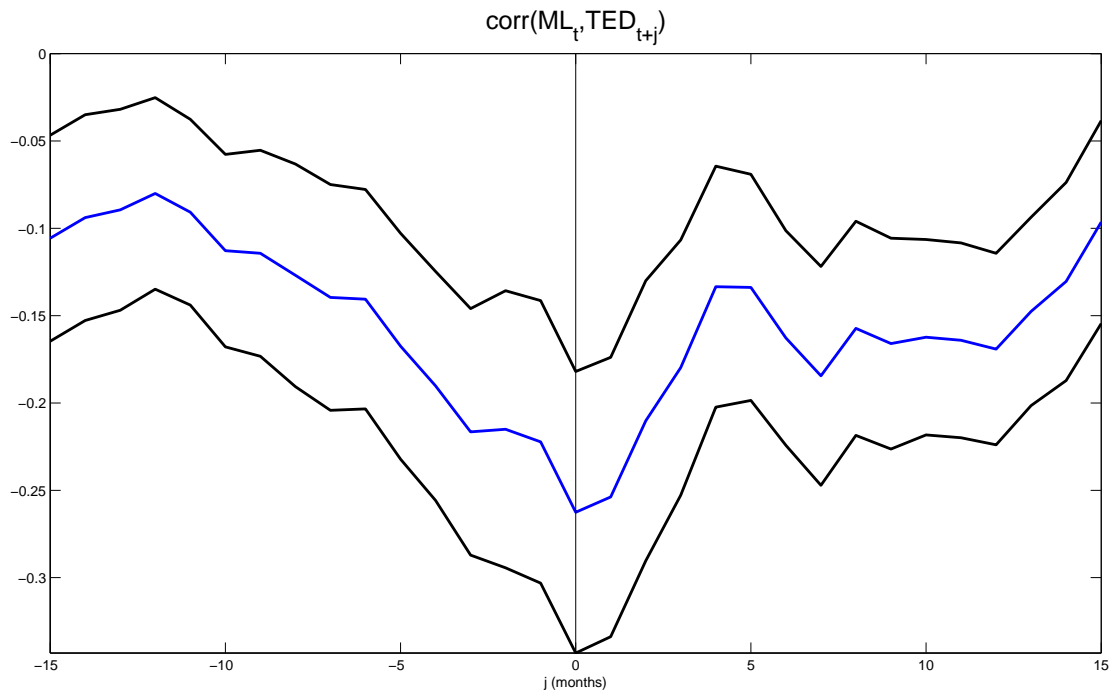


FIGURE 2.10: Dynamic correlation between TED spread and  $ML$  from Pastor and Stambaugh (2003). Sample period: 1971M1 to 2008M12.

diction of the liquidity spiral model proposed by Brunnermeier and Pedersen (2009).

## 2.6 Chapter Conclusion

This chapter presents an empirical investigation of the relationship between funding liquidity and the economy in the United States. An unanticipated, adverse shock to funding liquidity has important macroeconomic and asset pricing implications. First, an adverse funding liquidity shock generates quite persistent recessionary effects: industrial production, personal consumption and prices fall, whereas the unemployment rate rises. Second, this shock negatively impacts equity returns, with smaller firms being hit much harder. The funding liquidity shock as a risk factor is also priced. A proposed factor model which includes the funding liquidity shock does a reasonably good job in explaining the cross-sectional returns of portfolios sorted

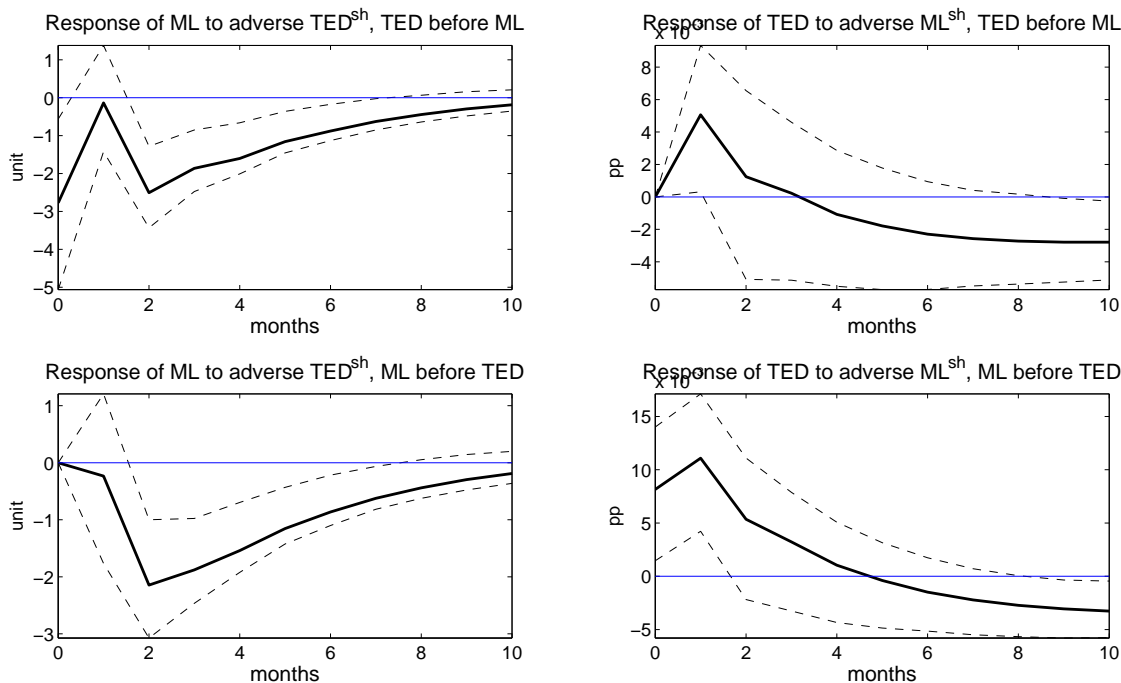


FIGURE 2.11: **Upper panel: ordering  $TED$  before  $ML$  in the augmented baseline VAR with Choleski decomposition.** (i) Left: Response of  $ML$  to an adverse  $TED$  shock; (ii) Right: Response of  $TED$  to an adverse  $ML$  shock. **Lower panel: ordering  $ML$  before  $TED$  in the augmented baseline VAR with Choleski decomposition.** (i) Left: Response of  $ML$  to an adverse  $TED$  shock; (ii) Right: Response of  $TED$  to an adverse  $ML$  shock. The error bands show the 90% confidence interval, and are constructed by bootstrapping VAR residuals. Sample period: 1971M1:2008M12.

on size and book-to-market ratio. Finally, funding liquidity and market liquidity are dynamically correlated, and structural shocks to one type of liquidity significantly negatively impact the other.

New directions of research are opened up by this chapter. My empirical results show that macroeconomists should not ignore funding liquidity shocks; introducing them in the otherwise standard dynamic stochastic general equilibrium (DSGE) model is an important task. Gertler and Kiyotaki (2010) provides a good starting point in building such a model. An interesting follow-up research question will be to investigate the importance of funding liquidity shocks relative to other types of finan-

cial friction (say the financial accelerator mechanism due to Bernanke et al. (1999)) by estimating the model. It will also be interesting to provide a model explaining how the small firms are more impacted by funding liquidity shocks than are other firms.

Table 2.5: Contemporaneous effects of  $TED_t^{sh}$  ( $\beta_{TED^{sh}}$ ) on portfolio returns separately sorted on size and book-to-market.

Value-weighted portfolios										
Panel A1 (size)										
decile	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
$\beta$	-3.631	-2.805	-2.691	-2.298	-2.393	-1.908	-2.272	-1.963	-1.977	-1.252
$t(\beta)$	<b>(-2.538)</b>	<i>(-1.95)</i>	<i>(-1.896)</i>	<i>(-1.689)</i>	<i>(-1.772)</i>	<i>(-1.363)</i>	<i>(-1.571)</i>	<i>(-1.394)</i>	<i>(-1.494)</i>	<i>(-1.167)</i>
Panel B1 (Book-to-market)										
decile	BM1	BM2	BM3	BM4	BM5	BM6	BM7	BM8	BM9	BM10
$\beta$	-1.792	-1.552	-1.189	-1.625	-1.503	-1.703	-2.068	-1.78	-1.753	-2.095
$t(\beta)$	<i>(-1.448)</i>	<i>(-1.2)</i>	<i>(-1.026)</i>	<i>(-1.244)</i>	<i>(-1.396)</i>	<i>(-1.505)</i>	<i>(-1.863)</i>	<i>(-1.633)</i>	<i>(-1.369)</i>	<i>(-1.28)</i>
Equally-weighted portfolios										
Panel A2 (size)										
decile	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
$\beta$	-4.462	-3.082	-2.906	-2.469	-2.591	-2.103	-2.338	-2.091	-2.1	-1.502
$t(\beta)$	<b>(-2.978)</b>	<b>(-2.073)</b>	<b>(-1.979)</b>	<i>(-1.757)</i>	<i>(-1.843)</i>	<i>(-1.452)</i>	<i>(-1.594)</i>	<i>(-1.463)</i>	<i>(-1.508)</i>	<i>(-1.229)</i>
Panel B2 (Book-to-market)										
decile	BM1	BM2	BM3	BM4	BM5	BM6	BM7	BM8	BM9	BM10
$\beta$	-3.719	-3.379	-3.124	-3.312	-3.258	-2.986	-3.136	-2.857	-3.436	-4.326
$t(\beta)$	<b>(-2.172)</b>	<b>(-2.189)</b>	<b>(-2.054)</b>	<b>(-2.29)</b>	<b>(-2.369)</b>	<b>(-2.356)</b>	<b>(-2.4)</b>	<b>(-2.21)</b>	<b>(-2.504)</b>	<b>(-2.635)</b>

This table presents  $\beta_{TED^{sh}}$ , the contemporaneous effect of  $TED_t^{sh}$  on portfolio returns separately sorted on size and book-to-market ratio.  $TED_t^{sh}$  is the structural funding liquidity shock recovered from the *baseline* vector-autoregression model. The sample period is 1971M1:2009M9. The model is  $r_t^i = \alpha + \beta_{TED^{sh}}^i TED_t^{sh} + \varepsilon_t^i$ , where  $r_t^i$  denotes excess returns of the  $i^{th}$  decile. Numbers in parentheses are the  $t$ -statistics computed using Newey and West (1987) correction with 5 lags. Italic and bold numbers denote significance at the level of 0.1 and 0.05 respectively.



Table 2.6: Contemporaneous effects of  $TED_t^{innov}$  ( $\beta_{TED^{innov}}$ ) on portfolio returns separately sorted on size and book-to-market.

Value-weighted portfolios										
Panel A1 (size)										
decile	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
$\beta$	-4.25	-3.635	-3.55	-3.27	-3.264	-2.939	-3.196	-2.888	-2.661	-1.847
$t(\beta)$	<b>(-3.636)</b>	<b>(-3.146)</b>	<b>(-3.149)</b>	<b>(-3.035)</b>	<b>(-3.122)</b>	<b>(-2.704)</b>	<b>(-2.907)</b>	<b>(-2.778)</b>	<b>(-2.731)</b>	<b>(-2.407)</b>
Panel B1 (Book-to-market)										
decile	BM1	BM2	BM3	BM4	BM5	BM6	BM7	BM8	BM9	BM10
$\beta$	-2.31	-2.272	-2.119	-2.304	-2.236	-2.151	-2.689	-2.216	-2.462	-3.185
$t(\beta)$	<b>(-2.531)</b>	<b>(-2.356)</b>	<b>(-2.336)</b>	<b>(-2.424)</b>	<b>(-2.808)</b>	<b>(-2.641)</b>	<b>(-3.363)</b>	<b>(-2.625)</b>	<b>(-2.493)</b>	<b>(-2.431)</b>
Equally-weighted portfolios										
Panel A2 (size)										
decile	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
$\beta$	-4.934	-3.925	-3.832	-3.473	-3.491	-3.153	-3.276	-2.999	-2.798	-2.134
$t(\beta)$	<b>(-4.088)</b>	<b>(-3.311)</b>	<b>(-3.32)</b>	<b>(-3.165)</b>	<b>(-3.242)</b>	<b>(-2.838)</b>	<b>(-2.968)</b>	<b>(-2.874)</b>	<b>(-2.762)</b>	<b>(-2.433)</b>
Panel B2 (Book-to-market)										
decile	BM1	BM2	BM3	BM4	BM5	BM6	BM7	BM8	BM9	BM10
$\beta$	-4.313	-4.026	-3.86	-3.937	-3.887	-3.694	-3.825	-3.503	-4.096	-4.957
$t(\beta)$	<b>(-3.186)</b>	<b>(-3.346)</b>	<b>(-3.24)</b>	<b>(-3.524)</b>	<b>(-3.727)</b>	<b>(-3.684)</b>	<b>(-3.751)</b>	<b>(-3.38)</b>	<b>(-3.659)</b>	<b>(-3.829)</b>

This table presents  $\beta_{TED^{innov}}$ , the contemporaneous effect of  $TED_t^{innov}$  on portfolio returns separately sorted on size and book-to-market ratio.  $TED_t^{innov}$  is computed by pre-whitening  $TED$ . The sample period is 1971M1:2009M9. The model is  $r_t^i = \alpha + \beta_{TED^{innov}}^i TED_t^{innov} + \varepsilon_t^i$ , where  $r_t^i$  denotes excess returns of the  $i^{th}$  decile. Numbers in parentheses are the  $t$ -statistics computed using Newey and West (1987) correction with 5 lags. Italic and bold numbers denote significance at the level of 0.1 and 0.05 respectively.

Table 2.7: Fama-French factors, structural  $TED$  shock and 25 portfolios formed on size and book-to-market.

<b>25 Portfolios sorted on size and book-to-market ratio (Equally-weighted)</b>						
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RMRF</i>	0.44 <i>(1.897)</i>	0.34 <i>(1.500)</i>	0.42 <i>(1.762)</i>	0.21 <i>(0.932)</i>	0.22 <i>(0.963)</i>	0.2 <i>(0.897)</i>
<i>SMB</i>			-0.12 <i>(-0.648)</i>	0.11 <i>(0.659)</i>	0.18 <i>(1.060)</i>	0.16 <i>(0.958)</i>
<i>HML</i>				0.61 <b>(3.991)</b>	0.62 <b>(4.031)</b>	0.62 <b>(4.041)</b>
<i>TED<sup>sh</sup></i>		-0.13 <i>(-1.755)</i>	-0.28 <b>(-3.475)</b>	-0.09 <i>(-1.545)</i>		
<i>FF<sup>sh</sup></i>					-0.16 <i>(-0.681)</i>	
$R^2$	-0.461	-0.309	-0.083	0.636	0.615	0.611
$\overline{R}^2$	-0.525	-0.428	-0.238	0.563	0.537	0.555
<i>RMSE</i> (%)	0.33	0.31	0.29	0.17	0.17	0.17
$\chi^2$	143.04	120.23	78.98	109.01	107.15	116.41
<i>p - value</i>	0.00	0.00	0.00	0.00	0.00	0.00

This table presents the  $\lambda$  estimates (multiplied by a factor of 100) from the two-pass regressions using equally-weighted returns of 25 portfolios sorted on size and book-to-market ratio for the sample period of 1971M1:2009M9. Numbers in parentheses are the  $t$ -statistics computed using Shanken (1992) correction. Italic and bold numbers denote significance at the level of 0.1 and 0.05 respectively. Refer to footnote (30) for explanation on notations.

Table 2.8: Price estimates of risk factors using 25 portfolios formed on size and momentum.

	25 Portfolios sorted on size and momentum							
	Value-weighted			Equally-weighted				
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
<i>RMRF</i>	0.44	0.45	0.45	0.46	0.40	0.44	0.39	0.36
	<b>(1.983)</b>	<b>(2.020)</b>	<b>(1.977)</b>	<i>(1.866)</i>	<i>(1.784)</i>	<i>(1.928)</i>	<i>(1.673)</i>	<i>(1.526)</i>
<i>SMB</i>	0.17	0.11	0.07		0.35	0.18	0.32	
	<i>(1.032)</i>	<i>(0.706)</i>	<i>(0.380)</i>		<b>(1.981)</b>	<i>(1.049)</i>	<i>(1.573)</i>	
<i>MOM</i>	0.917	0.900	0.928		0.849	0.842	0.864	
	<b>(4.163)</b>	<b>(4.075)</b>	<b>(4.070)</b>		<b>(3.822)</b>	<b>(3.748)</b>	<b>(3.754)</b>	
<i>TED<sup>sh</sup></i>		-0.17		0.19		-0.21		-0.05
		<i>(-1.910)</i>		<i>(0.999)</i>		<b>(-2.869)</b>		<i>(-0.531)</i>
<i>FF<sup>sh</sup></i>			-0.69	-1.03			-0.58	-0.58
			<b>(-2.501)</b>	<b>(-2.397)</b>			<b>(-2.240)</b>	<b>(-2.066)</b>
$R^2$	0.694	0.728	0.804	0.125	0.693	0.804	0.777	-0.111
$\bar{R}^2$	0.650	0.674	0.765	-0.000	0.649	0.765	0.732	-0.270
<i>RMSE</i> (%)	0.22	0.2	0.17	0.37	0.21	0.16	0.18	0.39
$\mathcal{R}^2$	104.41	82.51	36.25	22.65	84.65	55.72	36.44	43.56
<i>p - value</i>	0.00	0.00	0.02	0.42	0.00	0.00	0.02	0.4

This table presents the  $\lambda$  estimates (multiplied by a factor of 100) from the two-pass regressions using value-weighted and equally-weighted returns of 25 portfolios sorted on size and momentum for the sample period of 1971M1:2009M9. Numbers in parentheses are the *t*-statistics computed using Shanken (1992) correction. Italic and bold numbers denote significance at the level of 0.1 and 0.05 respectively. Refer to footnote (30) for explanation on notations.

Table 2.9: Price estimates of risk factors using 25 portfolios formed on size and short-term reversal.

	25 Portfolios sorted on size and short-term reversal							
	Value-weighted			Equally-weighted				
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
<i>RMRF</i>	0.34 (1.560)	0.36 (1.652)	0.38 (1.694)	0.37 (1.647)	0.34 (1.524)	0.37 (1.66)	0.36 (1.550)	0.38 (1.611)
<i>SMB</i>	-0.02 (-0.106)	-0.11 (-0.693)	-0.1 (-0.533)		0.05 (0.251)	-0.08 (-0.501)	0.00 (0.020)	
<i>STR</i>	0.492 (3.045)	0.487 (2.992)	0.588 (3.463)		0.625 (3.808)	0.586 (3.547)	0.737 (4.128)	
<i>TED<sup>sh</sup></i>		-0.17 (-2.124)		-0.03 (-0.235)		-0.13 (-1.899)		-0.09 (-0.846)
<i>FF<sup>sh</sup></i>			-0.58 (-2.538)	-0.49 (-2.280)			-0.66 (-2.569)	-0.57 (-2.267)
$R^2$	0.476	0.557	0.624	0.187	0.472	0.526	0.578	0.196
$\bar{R}^2$	0.402	0.468	0.549	0.071	0.397	0.431	0.494	0.08
<i>RMSE</i> (%)	0.19	0.17	0.16	0.23	0.23	0.22	0.21	0.29
$\chi^2$	112.29	82.87	50.42	63.77	256.18	209.9	92.88	109.42
<i>p</i> - <i>value</i>	0.00	0.00	0.00	0.00	0	0	0.00	0.00

This table presents the  $\lambda$  estimates (multiplied by a factor of 100) from the two-pass regressions using value-weighted and equally-weighted returns of 25 portfolios sorted on size and short-term reversal for the sample period of 1971M1:2009M9. Numbers in parentheses are the *t*-statistics computed using Shanken (1992) correction. Italic and bold numbers denote significance at the level of 0.1 and 0.05 respectively. Refer to footnote (30) for explanation on notations.

Table 2.10: Price estimates of risk factors using 25 portfolios formed on size and book-to-market.

<b>25 Portfolios sorted on size and book-to-market ratio</b>						
	Value-weighted			Equally-weighted		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
<i>RMRF</i>	0.41 <i>(1.650)</i>	0.37 <i>(1.623)</i>	0.25 <i>(1.159)</i>	0.46 <i>(1.810)</i>	0.33 <i>(1.364)</i>	0.2 <i>(0.897)</i>
<i>SMB</i>			0.08 <i>(0.503)</i>			0.16 <i>(0.958)</i>
<i>HML</i>			0.56 <b>(3.793)</b>			0.62 <b>(4.041)</b>
<i>TED<sup>sh</sup></i>		-0.07 <i>(-0.488)</i>			-0.16 <i>(-1.439)</i>	
<i>FF<sup>sh</sup></i>	-0.61 <b>(-2.792)</b>	-0.6 <b>(-2.674)</b>		-0.64 <b>(-2.457)</b>	-0.68 <b>(-2.438)</b>	
$R^2$	0.663	0.684	0.627	0.394	0.651	0.611
$\bar{R}^2$	0.632	0.639	0.573	0.338	0.602	0.555
<i>RMSE</i> (%)	0.15	0.14	0.16	0.21	0.16	0.17
$\chi^2$	39.6	38.66	95.84	50.98	42.13	116.41
<i>p</i> - value	0.017	0.015	0.00	0.00	0.01	0.00

This table presents the  $\lambda$  estimates (multiplied by a factor of 100) from the two-pass regressions using value-weighted and equally-weighted returns of 25 portfolios sorted on size and book-to-market ratio for the sample period of 1971M1:2009M9. Numbers in parentheses are the  $t$ -statistics computed using Shanken (1992) correction. Italic and bold numbers denote significance at the level of 0.1 and 0.05 respectively. Refer to footnote (30) for explanation on notations.

# A Quantitative Assessment of Loanable Funds in Business Cycles Fluctuations

## 3.1 Chapter Introduction

A firm's balance sheet, which summarizes financial balances at a specific point in time, provides information about the firm's "financial health". The literature has long emphasized the importance of balance sheet conditions in the nonfinancial sector for the real economy.<sup>1</sup> In this chapter I assess the quantitative importance of financial intermediation frictions in a framework where the aggregate balance sheets of both the financial and nonfinancial sectors play a role.

I begin by demonstrating the empirical fact that the health of the financial sector is a leading indicator of the health of the nonfinancial sector. Specifically, a "stronger" financial sector with more equity capital (or "net worth") and less debt similarly predicts a "stronger" nonfinancial sector, that is, a nonfinancial sector with higher net worth and less debt. This empirical fact illustrates the importance of

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<sup>1</sup> There is an extensive literature in finance and economics studying how nonfinancial (or corporate) balance sheets affect the real economy. Whited (1992), Hoshi et al. (1991) present evidence that corporate cash flows, leverage and other balance sheet variables influence investment spending. Hubbard et al. (1995) discuss internal finance and firm investment.

financial balance sheets, and a potential important interaction between financial and nonfinancial balance sheets. The recent global financial crisis also suggests that the balance sheet of the financial sector plays an important role in economic activity<sup>2</sup>. With the interaction of the financial and nonfinancial sectors in mind, I explore a model in which there is a dual layer of financial frictions, and both the financial and nonfinancial sector balance sheets play a role. With this model, I ask two key questions:

- Does a simple model share the property that the balance sheet variables of the financial sector are leading indicators of the balance sheet variables of the nonfinancial sector?
- Are the dual financial frictions in this model an important source of business cycle fluctuations, and do they play an important role in propagating shocks that originate in other parts of the economy?

To build a model with both aggregate financial and nonfinancial balance sheets, I require the existence of three groups of agents, namely households (who save), bankers (who receive deposits from households and make loans to firms) and firms (also called entrepreneurs, who are endowed with investment projects but need external financing). I also require two layers of financial frictions, one between households and bankers, and the other between bankers and firms. In other words, bankers and firms cannot borrow as freely as they want, hence they need to accumulate their own net worth (equity capital) in order to finance their own assets. In this respect, my model differs from Bernanke et al. (1999) (who emphasize firms' balance sheets), as

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<sup>2</sup> Adrian and Shin (2010a) and Adrian and Shin (2010b) were among the first papers to discuss that the net worth of financial intermediaries is very sensitive to asset prices, and that the role of financial intermediaries is changing with the development of securitization of assets and the integration of banking with capital market developments.

well as Gertler and Karadi (2011) and Gertler and Kiyotaki (2010) (who emphasize banks' balance sheets).

I adopt a general equilibrium model featuring a double moral hazard “loanable funds” framework à la Holmstrom and Tirole (1997), Meh and Moran (2010) and Christensen et al. (2011). In this model, entrepreneurs can choose to work hard or not, and thereby influence the probability of success of investment projects. Entrepreneurs always opt to shirk because they enjoy “private benefits,” which can be interpreted as the extra leisure they obtain when they shirk. Bankers have the expertise to monitor entrepreneurs, but the monitoring is imperfect. Therefore, bank monitoring alleviates, but does not eliminate, the first layer of moral hazard. The second layer of moral hazard is on the bankers side: monitoring entrepreneurs is privately costly. Households never know if bankers perform the monitoring tasks as agreed. The model makes clear predictions about the balance sheets of both bankers and entrepreneurs because these two types of agents require both internal and external financing.

Another rationale for adopting a double moral hazard model is that it captures the idea of bank-firm relationships, which have long been a research focus in the banking literature. Diamond (1984) provides a theoretical framework in which an intermediary delegated to monitor loan contracts written by firms can lower total monitoring costs and alleviate financial frictions. Dass and Massa (2011) empirically find that a stronger bank-firm relationship, measured in terms of the bank's proximity to the firm and the significance of the loan to the firm (loan-to-asset ratio), leads to better monitoring and reduces moral hazard concerns. Embedding these sorts of bank-firm relationships in a dynamic stochastic general equilibrium (DSGE) model helps us understand how such relationships change with and influence business cycles.

My model, which is largely based on Christensen et al. (2011), embeds Holmstrom and Tirole's double moral hazard feature in a dynamic stochastic general equilibrium



environment, and is naturally suited to a quantitative investigation using real world data. It differs from the empirically implemented model in Christiano et al. (2010), which includes a financial accelerator and an aggregate financial balance sheet, in that the latter model does not feature aggregate financial capital. The model does not feature financial frictions between banks and households so there is no need for banks to accumulate their own net worth to finance loans. My model also differs from Rampini and Viswanathan (2011). They provide a theory in which banks are more specialized in collateralization than households are, and analyze the dynamics of net worth and investment, but they do so in a deterministic environment. This chapter also belongs to a group of other papers which estimate dynamic stochastic general equilibrium models featuring financial frictions. Liu et al. (2011) estimate the role of land price dynamics in macroeconomic fluctuations. Jermann and Quadrini (2012) estimate a macro model which explains the decision of debt borrowing and equity issuance of firms.

To demonstrate the empirical facts concerning balance sheets, I construct the aggregate debt and net worth of both the financial and nonfinancial sectors using the Flows of Funds Accounts released by the Federal Reserve Board. I consider the sample period from 1952Q1 to 2010Q4. After obtaining the business cycle components of these series with the Hodrick-Prescott (HP) filter, I compute the cross-correlations of aggregate debt (and net worth) between the two sectors. I find that financial-sector net worth and nonfinancial-sector net worth are weakly positively correlated, contemporaneously, while the debt levels of the two sectors are strongly positively correlated, contemporaneously. The correlation between net worths is stronger when financial-sector net worth is lagged, and is roughly zero when nonfinancial-sector net worth is lagged. The correlation between debt levels is positive at all leads and lags, but is stronger when financial-sector debt is lagged than the other way around. In other words, a “stronger” financial sector predicts a similarly “stronger” nonfinancial

sector.

I then turn to the quantitative assessment of my model. I estimate the model with Bayesian likelihood methods, using the usual macroeconomic aggregates and the equity capital data described above. I specifically study (i) the impact of financial intermediation shocks on the economy, in particular shocks to equity capital in both sectors; (ii) the importance of financial shocks in explaining real variables; (iii) changes in the shock propagation mechanism in the presence of financial frictions featuring a double moral hazard; and (iv) the theoretical correlations between the balance sheet variables in the two sectors.

First, I show that financial intermediation shocks create persistent recessions. A one-percent drop in bank equity capital leads to a maximum fall of 0.2 percent in investment and 0.02 percent fall in GDP, whereas the same drop in firm equity capital leads to a maximum decline of 0.5 percent in investment and 0.1 percent in GDP. On the other hand, a one-percent drop in returns to investment projects (which is interpreted as a negative shock to the productivity of capital goods) generates a much deeper recession: investment falls 5 percent and GDP falls 0.7 percent at the trough.

Investment displays hump-shaped declines to all of these shocks, consistent with the discussion in Meh and Moran (2010). The hump-shape is shared by, and reflects, the dynamics of both financial and nonfinancial equity capital, highlighting the importance of balance sheets in the transmission of financial shocks.

Second, I show that, in the long run, financial intermediation shocks explain little of the variation in GDP, a modest amount of the variation (20 percent) in investment, and more than 50 percent of the variation in debt levels. Moreover, the explanatory power of financial shocks for variation in investment is fairly constant across horizons. Interestingly, financial shocks have increasing explanatory power for the variation in inflation as the forecasting horizon lengthens, and explain about 40 percent of the

variation in the long run.

Third, I find that financial frictions, modeled using the loanable funds framework, give rise to a shock transmission mechanism quantitatively different from the conventional dynamics that arise in DSGE models with convex investment adjustment costs. To see this, I compare the transmission mechanism of my estimated model with an estimated standard New Keynesian model with investment frictions but not financial frictions. In particular, I study the class of New Keynesian models that assume convex investment adjustment costs (for example, Smets and Wouters (2007)). I consider a one-percent negative total factor productivity shock in both models. The maximum decline in investment in my estimated model is 50 percent deeper than the maximum decline in the model with investment adjustment costs. Moreover, it takes a much shorter time for investment to climb half the way back to its steady state value from its trough value. GDP displays a similar response. To sum up, my estimated model delivers deeper but somewhat less persistent declines in investment and GDP than conventional models. Such a response is closely associated with the response of the aggregate financial equity capital, the evolution of which is governed by the decline of banks retained earnings, which are in turn determined by other factors including a “looser” bank-firm relationship induced by the negative productivity shock. A fall in bank earnings depresses bank equity capital, which in turn accelerates the decline in real investment. This is the “bank capital channel” discussed in Meh and Moran (2010), and it is quantitatively significant in the current context.

Finally, I find that the model is able to replicate the lead-lag relationship of net worths between the two sectors. The model predicts the strong contemporaneous correlation of debt levels, but does not generate the slight asymmetry in the lead-lag relationship in the dynamic correlations of debt levels.

The chapter is organized as follows. I first describe the construction of balance

sheet data and the empirical correlations of the balance sheet variables of the financial and nonfinancial sectors. Then I describe the DSGE model, with a double moral hazard framework in the intermediation process and other standard New Keynesian features. After that I discuss parameter estimation and present a quantitative analysis of the estimated model. Lastly I conclude.

## 3.2 Empirical Investigation

### 3.2.1 *The Flow of Funds Accounts*

The dataset I study is the Flow of Funds (FoF) Accounts. FoF is an **aggregate** dataset published by the Federal Reserve Board. It keeps track of data on borrowing, lending and investment throughout sectors like households, businesses and farms<sup>3</sup>. In the following, I use quarterly data to do the analysis.

I consider the following two aggregate variables: aggregate debt and aggregate net worth (defined as the difference between total assets and total debt)<sup>4</sup>.

#### *Data*

*Nonfinancial sector* Following Levin et al. (2004), I include both *non-farm and farm businesses* in this sector. To measure aggregate debt, I use the data item “credit market instruments”, which include commercial paper, municipal securities, corporate bonds and mortgages, among other loans.

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<sup>3</sup> Flows of Funds can be regarded as the counterpart of the National Income and Product Account (NIPA). FoF accounts relate transactions in financial markets to non-financial activities in the economy by showing the uses to which saving is applied and the means by which tangible investment is financed.

In theory, these accounts encompass all net changes in financial claims or liabilities resulting from: (1) current transactions in the economy; (2) the allocation of savings between investment in physical capital and investment in financial capital; and (3) decisions to change the composition of financial assets and liabilities. Thus FoF includes financial flows among various sectors of the economy that arise from transfers of existing physical assets as well as from shifts in the composition of financial portfolios that may be unrelated to, or indirectly related to, current production.

<sup>4</sup> The terms “net worth” and “(book-value) equity capital” are used interchangeably in this chapter.

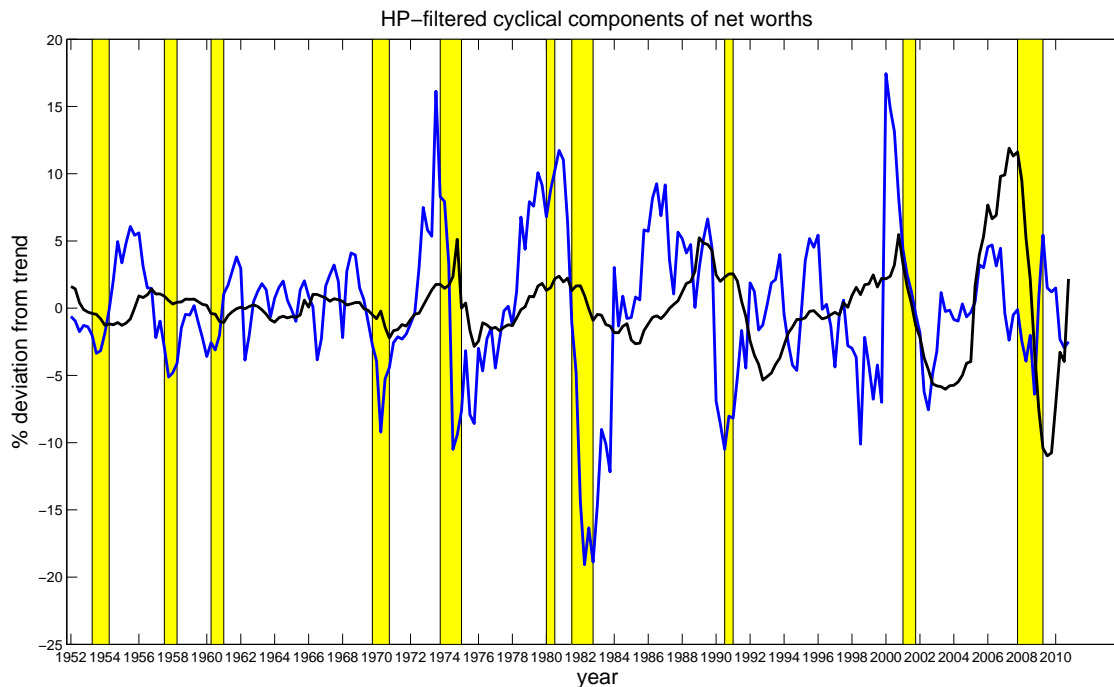


FIGURE 3.1: HP-filtered cyclical components of aggregate financial net worth (blue line) and aggregate non-financial net worth (black line) between 1952 and 2010. Data source: Flow of Funds Accounts, Federal Reserve Board.

*Financial sector* Adrian et al. (2010) document the growing importance of the shadow banking system as well as security brokers and dealers since the mid-1980s. To construct data series for the financial sector, I include depository institutions (US-chartered commercial banks, savings institutions, credit unions), security brokers and dealers, shadow banks (asset-backed securities issuers, finance companies and funding corporations) as well as insurance companies. As noted by Mimir (2010), these sectors make up 90 percent of the total financial assets.

To measure aggregate debt, I use data on deposits, federal funds and security repurchase agreements, net interbank transactions, and credit market instruments whenever they are available for each type of institution. The appendix records the data series that are used for each institution type.

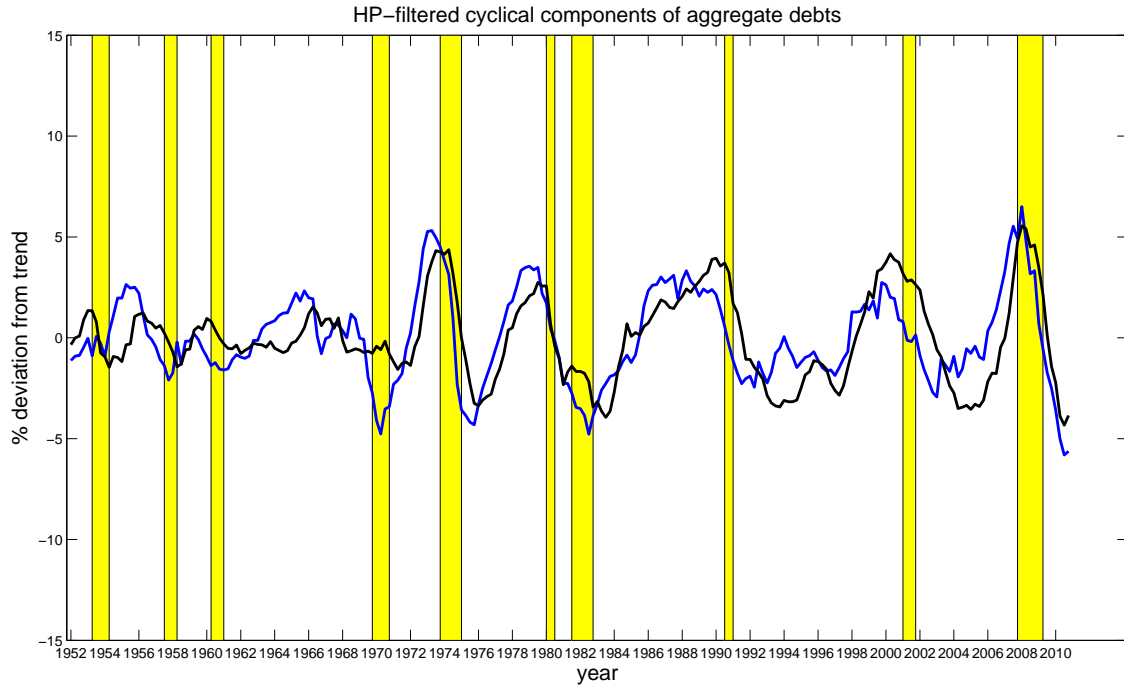


FIGURE 3.2: HP-filtered cyclical components of aggregate financial debt (blue line) and aggregate non-financial debt (black line) between 1952 and 2010. Data source: Flow of Funds Accounts, Federal Reserve Board.

*Data processing* I first seasonally adjust the raw series. Following Jermann and Quadrini (2010), I deflate aggregate debts and the aggregate net worths with the Price Index for Gross Value Added in the Business Sector<sup>5</sup>. All series are in logarithm before being HP-filtered. Figures (3.1) and (3.2) plot the HP-filtered cyclical components of aggregate debts and net worths of both financial and nonfinancial sectors between 1952 and 2010.

### 3.2.2 Empirical Results

#### *Financial net worth mildly leads nonfinancial net worth*

Figure (3.3) plots the cross-correlations of net worths, and table (3.1) reports the numerical figures. There is a small contemporaneous correlation (coefficient equals

<sup>5</sup> This series is taken from Table 1.3.4 of the National Income and Product Account.

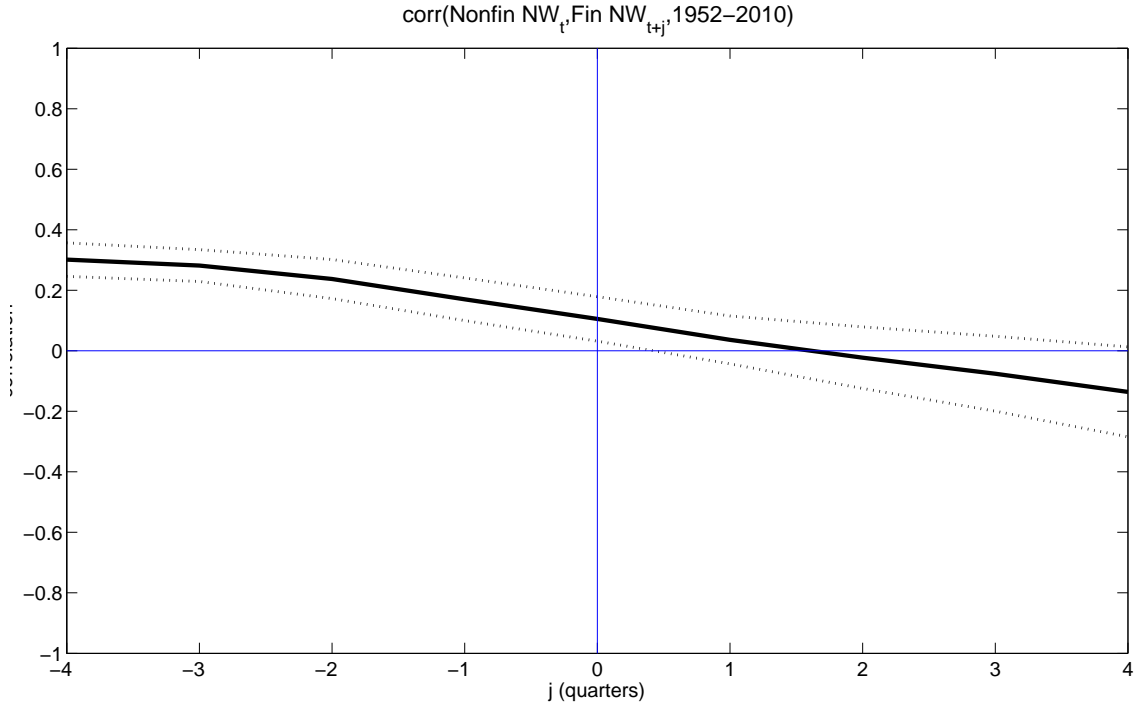


FIGURE 3.3: HP-correlations of aggregate non-financial net worth with leads and lags of aggregate financial net worth. The dotted blue lines represent the empirical error bands at 95% confidence intervals. Period: 1952-2010. Data source: Flow of Funds Accounts, Federal Reserve Board.

0.1) between each type of net worth. Instead, higher financial net worth mildly leads to higher nonfinancial net worth, with a correlation of 0.3 at the fourth quarter lead. Interestingly, nonfinancial net worth does not lead financial net worth significantly.

An interpretation of this result is that an erosion of financial net worth (or capital) predicts the erosion of nonfinancial net worth. In other words, to maintain the health of financial intermediation, we may need to build up enough capital for the financial sector such that the capital for the nonfinancial sector may also increase.<sup>6</sup>

<sup>6</sup> I also consider the series of “market-value equity” of the “financial business sector” in FoF. I find that the aggregate market-value equity of both sectors are highly contemporaneously correlated, with a coefficient of 0.7. Moreover, there is no clear lead-lag relationship. This is probably driven by the highly correlated share prices of the financial and non-financial sectors. For the rest of this chapter, I will use book-value equity as the benchmark series, because it is relatively less volatile and there is a natural correspondence between this series and the variable “bank capital” in my model.

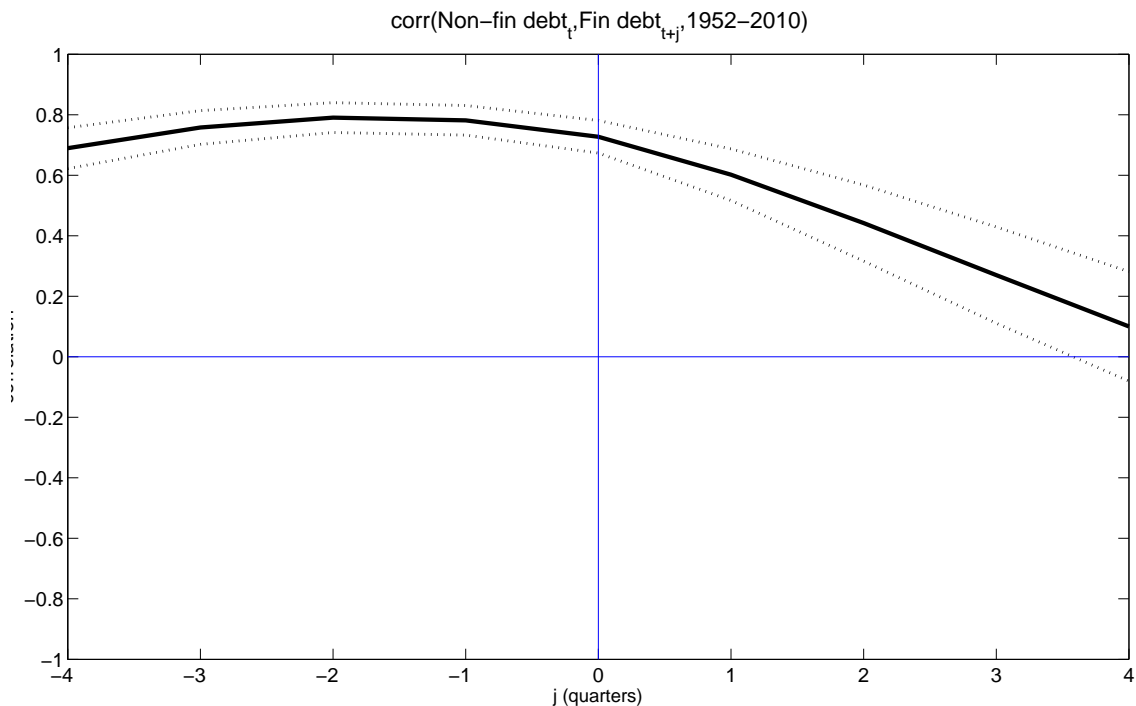


FIGURE 3.4: HP-correlations of aggregate non-financial debt with leads and lags of aggregate financial debt. The dotted blue lines represent the empirical error bands at 95% confidence intervals. Period: 1952-2010. Data source: Flow of Funds Accounts, Federal Reserve Board.

*Debts are highly correlated and financial debt positively leads nonfinancial debt*

Figure (3.4) plots the cross-correlations of debt levels, and table (3.1) reports the numerical figures. Financial and nonfinancial debts have a high contemporaneous correlation of 0.73. Although higher financial debt predicts higher nonfinancial debt and vice versa, there is more evidence that financial debt leads nonfinancial debt.

The significance of this result is that both financial and nonfinancial sectors borrow more at the same time. It also appears that if we would like to keep nonfinancial borrowing under control, we probably want to monitor financial borrowing first.



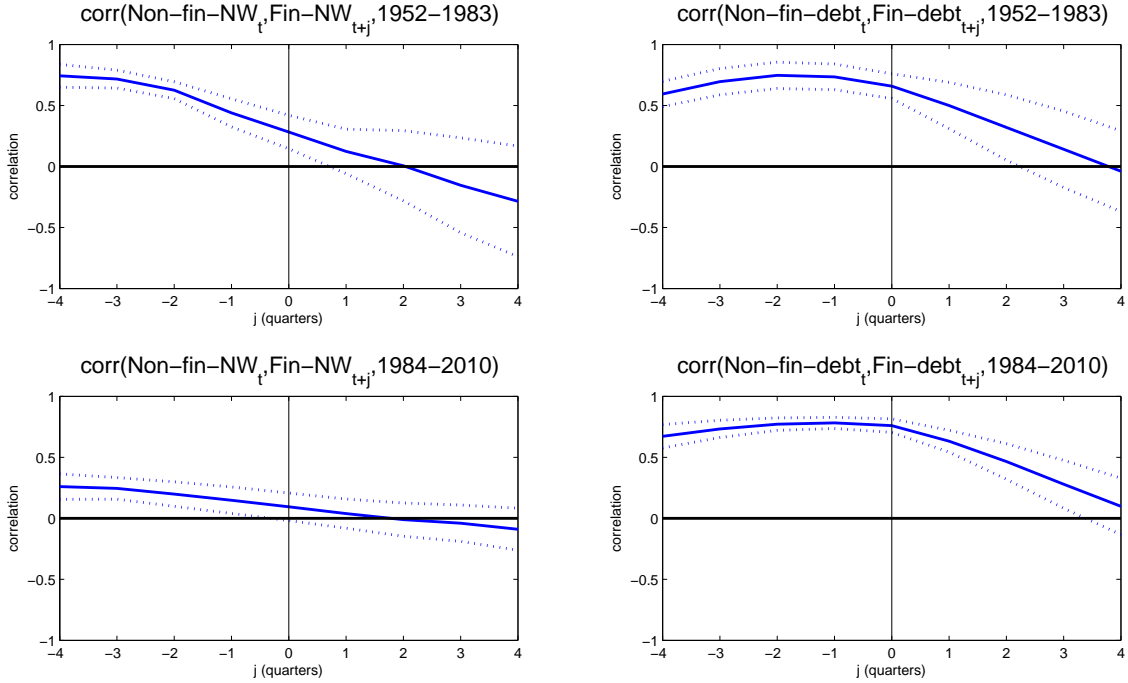


FIGURE 3.5: HP-correlations of (i) aggregate non-financial and financial net worths (left panel) and (ii) aggregate non-financial and financial debt (right panel). Subsample periods: 1952-1983 (upper panel) and 1984-2010 (lower panel). The dotted blue lines represent the empirical error bands at 95% confidence intervals. Data source: Flow of Funds Accounts, Federal Reserve Board.

*The first two results are robust across the two sub-sample periods*

I also study the correlations of aggregate net worths and debts under two different subsamples: 1952-1983 and 1984-2010, as shown in figure (3.5). The results for aggregate debts are quantitatively similar. As for aggregate net worths, I still see that financial net worth leads nonfinancial net worth, but the lead is stronger in the first subsample period. So I conclude that the correlation patterns are robust across the two sub-sample periods. The numerical figures are also reported in table (3.1).

### 3.2.3 Summary

By constructing aggregate data series on debts and net worths for both financial and nonfinancial sectors, I find that: (i) financial net worth mildly leads nonfinancial net worth; and (ii) debts are highly correlated but financial debt positively leads nonfinancial debt. The implication of these results is that a “stronger” financial sector (more capital and less borrowing) predicts a stronger nonfinancial sector. Thus, the balance sheet of the financial sector should not be left out in the modeling of financial process.

## 3.3 The Model

In this section I describe a dynamic stochastic general equilibrium (DSGE) model with an aggregate financial and nonfinancial sector. This model features the double moral hazard feature following Holmstrom and Tirole (1997) and Christensen et al. (2011), as well as standard New Keynesian business cycle components as in Smets and Wouters (2007) and Christiano et al. (2005).

### 3.3.1 Final goods producers

The final good  $Y_t$  is made up of a continuum of intermediate goods  $Y_{jt}$ , where  $j \in (0, 1)$ . The final goods producer buys intermediate goods and package them into final goods which are to be sold in a perfectly competitive market. The final goods producers maximize

$$\max_{Y_t, Y_{jt}} P_t Y_t - \int_0^1 P_{jt} Y_{jt} dj$$

subject to

$$Y_t = \left( \int_0^1 Y_{jt}^{\frac{\epsilon_t^p - 1}{\epsilon_t^p}} dj \right)^{\frac{\epsilon_t^p}{\epsilon_t^p - 1}}$$

where  $P_t$  and  $P_{jt}$  are the price of final goods and intermediate goods, respectively. The term  $\epsilon_t^p$  denotes the elasticity of substitution between intermediate goods. This elasticity is subject to a “mark-up” shock. To capture the high-frequency movement, I follow Smets and Wouters (2007) in modeling it to be an ARMA process:

$$\ln \epsilon_t^p = (1 - \rho_p) \ln \epsilon^p + \rho_p \ln \epsilon_{t-1}^p - \theta_p \eta_{t-1}^p + \eta_t^p$$

where  $\eta_t^p \sim N(0, \sigma_p)$ .

The first order condition gives

$$Y_{jt} = \left( \frac{P_{jt}}{P_t} \right)^{-\epsilon_t^p} Y_t$$

Imposing the zero-order condition leads to the usual definition of a final good price index.

$$P_t = \left( \int_0^1 P_{jt}^{1-\epsilon_t^p} di \right)^{\frac{1}{1-\epsilon_t^p}}$$

### 3.3.2 Intermediate goods producers

Firms producing intermediate goods operate under monopolistic competition and nominal rigidities in price- setting. The firm producing good  $j$  operates the technology

$$y_{jt} = \begin{cases} \varepsilon_t^a K_{jt}^\alpha (H_{jt}^h)^{1-\alpha-\theta_e-\theta_b} (H_{jt}^e)^{\theta_e} (H_{jt}^b)^{\theta_b} - \Theta & \text{if } A_t K_{jt}^\alpha (H_{jt}^h)^{1-\alpha-\theta_e-\theta_b} (H_{jt}^e)^{\theta_e} (H_{jt}^b)^{\theta_b} \geq \Theta \\ 0 & \text{otherwise} \end{cases}$$

where  $K_{jt}$ ,  $H_{jt}^h$ ,  $H_{jt}^e$  and  $H_{jt}^b$  respectively represent the amount of capital services, labor services from household, entrepreneurs and bankers.  $\Theta > 0$  denotes the fixed cost of production and  $\varepsilon_t^a$  is an aggregate technology shock that follows an AR(1) process:

$$\ln(\varepsilon_t^a) = \rho_a \ln(\varepsilon_{t-1}^a) + \eta_t^a$$

where  $\rho_a \in (0, 1)$  and  $\eta_t^a \sim N(0, \sigma_a)$ .

Minimizing production costs for a given demand solves the problem

$$\min_{K_{jt}, H_{jt}^h, H_{jt}^e, H_{jt}^b} r_t^k K_{jt} + w_t H_{jt}^h + w_t^e H_{jt}^e + w_t^b H_{jt}^b$$

with respect to the production function. The real rental rate of capital services is  $r_t^k$ , while  $w_t$ ,  $w_t^b$  and  $w_t^e$  denote real wage for households, entrepreneurs and bankers, respectively. The first order conditions are:

$$r_t^k = \alpha A_t MC_t k_t^\alpha H_{jt}^{1-\alpha-\theta_e-\theta_h} (H_{jt}^e)^{\theta_e} (H_{jt}^b)^{\theta_h} \quad (3.1)$$

$$w_t = (1 - \alpha - \theta_e - \theta_h) A_t MC_t k_t^\alpha H_{jt}^{1-\alpha-\theta_e-\theta_h} (H_{jt}^e)^{\theta_e} (H_{jt}^b)^{\theta_h} \quad (3.2)$$

$$w_t^b = \theta_h A_t MC_t k_t^\alpha H_{jt}^{1-\alpha-\theta_e-\theta_h} (H_{jt}^e)^{\theta_e-1} (H_{jt}^b)^{\theta_h} \quad (3.3)$$

$$w_t^e = \theta_e A_t MC_t k_t^\alpha H_{jt}^{1-\alpha-\theta_e-\theta_h} (H_{jt}^e)^{\theta_e} (H_{jt}^b)^{\theta_h-1} \quad (3.4)$$

where  $MC_t$  (real marginal cost) is the Lagrangian multiplier to the production function.

Under Calvo (1983) pricing with partial indexation, the optimal price set by a firm ( $\tilde{P}_{jt}$ ) that is allowed to re-optimize results from the following problem:

$$\max_{\tilde{P}_{jt}} E_t \left\{ \sum_{s=0}^{\infty} \xi_p^s \frac{\beta^s \Lambda_{t+s}}{\Lambda_t} [(P_{jt} \Pi_{t,t+s} - MC_t) Y_{jt+s}] \right\}$$

subject to

$$Y_{jt+s} = \left( \frac{P_{jt+s} \Pi_{t,t+s}}{P_{t+s}} \right)^{-\epsilon_t^p} Y_{t+s}$$

where

$$\Pi_{t,t+s} \equiv \prod_{k=1}^s \pi_{t+k-1}^{\iota_p} \pi_*^{1-\iota_p}$$

$\Lambda_t$  denotes the marginal utility of a household's consumption.  $\xi_p$  represents the Calvo parameter which dictates the fraction of firms not able to re-optimize prices,  $\pi_*$  is the steady state inflation rate, and  $\iota_p$  denotes the weight on which the non-optimized price is adjusted to previous inflation. In other words, for firms which are not allowed to adjust price, prices are set according to

$$P_{jt} = P_{jt-1} \pi_{t-1}^{\iota_p} \pi_*^{1-\iota_p}$$

The first order condition reads

$$0 = E_t \left\{ \sum_{s=0}^{\infty} \xi_p^s \beta^s \Lambda_{t+s} \tilde{Y}_{t+s} \left[ \tilde{P}_t \Pi_{t,t+s} - \frac{\epsilon_t^p}{\epsilon_t^p - 1} MC_{t+s} \right] \right\} \quad (3.5)$$

where  $\tilde{P}_t$  is the optimally chosen price (which is the same for all firms due to identical marginal cost) and  $\tilde{Y}_{t+s}$  is the aggregate demand they face at  $t + s$ .

The aggregate price index is

$$P_t = \left[ (1 - \xi_p) \tilde{P}_t^{\epsilon_t^p - 1} + \xi_p \left( \pi_{t-1}^{\iota_p} \pi_*^{1-\iota_p} P_{t-1} \right)^{\epsilon_t^p - 1} \right]^{\frac{1}{\epsilon_t^p - 1}}$$

### 3.3.3 Households

There exists a continuum of household  $i \in (0, \omega^h)$ . Households consume, make deposits, supply specialized labor, choose a capital utilization rate, and purchase capital goods.

The wage-setting set-up (which will be described later) implies that different households will provide different labor hours and hence different labor earnings. We assume the *existence of state-contingent securities*, as in Erceg et al. (2000), which makes households *homogeneous in terms of consumption and saving decisions*. The following maximization problem has taken into account the equilibrium effect because of this assumption: consumption, deposits and capital stock are the same across all household types.

Household  $i$  chooses consumption  $C_t^h$ , hours  $H_{it}^h$ , investment  $i_t^h$ , deposits  $D_t$ , and capital utilization  $Z_t$  by maximizing

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \psi \left[ \log (C_t^h - \lambda C_{t-1}^h) - \varphi \frac{(H_{it}^h)^{1+\nu}}{1+\nu} \right]$$

subject to

$$C_t^h + q_t i_t^h + D_{t+1} - T_t = \frac{W_{it} H_{it}^h}{P_t} + \frac{R_{t-1}^d D_t}{P_t} + \frac{r_t^k Z_t K_t^h}{P_t} - a(Z_t) K_t^h + \frac{Div_t}{P_t}$$

and

$$K_{t+1}^h = (1 - \delta) K_t^h + i_t^h$$

where  $q_t$  is the price of investment goods,  $R_t^d \equiv 1 + r_t^d$  is the gross risk-free rate,  $W_{it}$  is the wage received by the individual household,  $r_t^k$  is the marginal product of labor,  $a(Z_t) \equiv \frac{Z_t^{1+\tilde{\psi}} - 1}{1+\tilde{\psi}}$ , where  $\tilde{\psi} = \frac{\psi}{1-\psi}$  and  $\psi \in (0, 1)$  is a convex function

describing the utilization cost for each unit of capital,  $T_t$  is the nominal lump-sum tax (or transfer) and  $Div_t$  are the dividends distributed by the intermediate goods producers.

Household also chooses the utilization rate of capital. The amount of effective capital that households can rent to firms is

$$K_t^s = Z_t K_{t-1}$$

where renting capital services is  $r_t^k Z_t K_t^h$  and the cost of changing capital utilization is  $P_t a(Z_t) K_t^h$ .

Defining the inflation rate as  $\pi_{t+1} \equiv \frac{P_{t+1}}{P_t}$  and  $\Lambda_t$  as the Lagrangian multiplier to the budget constraint, the first-order conditions with respect to  $C_t^h, D_t, K_{t+1}^h, i_t^h$  and  $Z_t$  are as follows:

$$\Lambda_t = \frac{\psi}{C_t^h - \lambda C_{t-1}^h} - \lambda \beta E_t \frac{\psi}{C_{t+1}^h - \lambda C_t^h} \quad (3.6)$$

$$\Lambda_t = \beta R_t^d E_t \frac{\Lambda_{t+1}}{\pi_{t+1}} \quad (3.7)$$

$$\Lambda_t q_t = \beta E_t \Lambda_{t+1} [Z_{t+1} r_{t+1}^k - a(Z_{t+1}) + (1 - \delta) q_{t+1}] \quad (3.8)$$

$$r_t^k = a'(Z_t) \quad (3.9)$$

#### 3.3.4 Specialized labor and labor aggregators

I follow Erceg et al. (2000) and assume that each household supplies a specialized labor  $H_{it}^h$ , while competitive labor aggregators assemble all types of labor into one composite using the Dixit-Stiglitz aggregator:

$$H_t \equiv \left( \int_0^{\omega^h} (H_{it}^h)^{\frac{\epsilon_t^w - 1}{\epsilon_t^w}} di \right)^{\frac{\epsilon_t^w}{\epsilon_t^w - 1}}$$

The demand for each labor type is

$$L_{it} = \left( \frac{W_{it}}{W_t} \right)^{-\epsilon_t^w} H_t$$

where  $W_t$  is the aggregate wage, which can be found by imposing the zero-profit condition on the perfectly competitive labor aggregators

$$W_t = \left( \int_0^{\omega^h} W_{it}^{1-\epsilon_t^w} di \right)^{\frac{1}{1-\epsilon_t^w}}$$

Note that the exogenous wage mark-up follows an ARMA process:

$$\ln \epsilon_t^w = (1 - \rho_w) \ln \epsilon^w + \rho_w \ln \epsilon_{t-1}^w - \theta_w \eta_{t-1}^w + \eta_t^w$$

where  $\eta_t^w \sim N(0, \sigma_w)$ .

Household wages are set in a manner similar to the price-setting setup according to Calvo (1983). Each period, household  $i$  can reoptimize wage ( $\widetilde{W}_{it}$ ) with the probability of  $1 - \xi_w$ . They maximize

$$\max_{\widetilde{W}_{it}} E_t \left\{ \sum_{s=0}^{\infty} \xi_w^s \beta^s \left[ -\psi \frac{(H_{it+s}^h)^{1+\nu}}{1+\nu} + \Lambda_{t+s} \widetilde{W}_{it} L_{it+s} \right] \right\}$$

subject to

$$L_{it+s} = \left( \frac{\widetilde{W}_{it} \Pi_{t,s}^w}{W_{t+s}} \right)^{-\epsilon_t^w} H_{t+s}$$



where  $\Pi_{t,s}^w = \prod_{l=1}^s \pi_{t+l-1}^{\iota_w} \pi_*^{1-\iota_w}$ , and  $\iota_w$  denotes the weight on which the non-optimized wage is adjusted to previous inflation.

For those who cannot set wages, they follow the indexation rule

$$W_{it} = W_{it-1} \pi_{t-1}^{\iota_w} \pi_*^{1-\iota_w}$$

The first order conditions reads

$$0 = E_t \left\{ \sum_{s=0}^{\infty} \xi_p^s \beta^s \Lambda_{t+s} \tilde{L}_{t+s} \left[ \tilde{W}_t \Pi_{t,t+s}^w - \frac{\epsilon_t^w}{\epsilon_t^w - 1} \psi \frac{\tilde{L}_{t+s}^\nu}{\Lambda_{t+s}} \right] \right\} \quad (3.10)$$

The aggregate wage evolves as

$$W_t = \left[ (1 - \xi_w) \tilde{W}_t^{\epsilon_t^w - 1} + \xi_w \left( \pi_{t-1}^{\iota_p} \pi_*^{1-\iota_p} P_{t-1} \right)^{\epsilon_t^w - 1} \right]^{\frac{1}{\epsilon_t^w - 1}}$$

### 3.3.5 Capital goods production

Following Holmstrom and Tirole (1997) and Christensen et al. (2011) (CMM), I adopt the framework of the double moral hazard problem. There is a continuum of entrepreneurs and bankers of mass  $\omega^e$  and  $\omega^b = 1 - \omega^h - \omega^e$ , respectively. Each entrepreneur has access to a technology producing capital goods. An investment of  $i_t$  units of final goods returns  $\tilde{R}_t i_t$  ( $\tilde{R}_t > 1$ ) units of capital (publicly observable) if the project succeeds, and zero if it fails. Note that  $\tilde{R}_t = \varepsilon_t^q \tilde{R}_{ss}$ , where  $\varepsilon_t^q$  is the aggregate shock to “steady-state investment return” (*widetildeR<sub>ss</sub>*) (which can be interpreted as the exogenous change to the “productivity” of turning final goods to capital goods) and follows an AR(1) process:

$$\ln(\varepsilon_t^q) = \rho_q \ln(\varepsilon_{t-1}^q) + \eta_t^q$$

The first moral hazard problem occurs as entrepreneurs can choose to shirk their responsibilities: they can enjoy “private benefits” but the investment project succeeds with lower probability. Specifically, entrepreneurs are assumed to choose from two classes of projects: (i) a no-private benefit project that involves a high probability of success (denoted by  $\alpha^g$ ) and zero private benefits; or (ii) a continuum of projects with different private benefits but with a common, lower probability of success  $\alpha^g - \Delta\alpha$ . The private benefit is denoted by  $b i_t$ , where  $i_t$  is the size of the project and  $b \in [\underline{B}, \overline{B}]$ . Note that this private benefit  $b(\mu_t)$  does not reduce the input to the investment project (which is  $i_t$ ), nor does it decrease the return to the investment project (which is  $\tilde{R}_t i_t$ ) if the project succeeds. This is meant to be a reduced-form way of modeling “extra” leisure to the entrepreneur as a result of his shirking behavior<sup>7</sup>. An entrepreneur will prefer the project with the highest private benefit  $b$  possible, as they all produce the same low probability of success<sup>8</sup>.

Bank monitoring reduces the private benefits associated with projects. CMM interprets bank monitoring as the inspection of cash flows and balance sheets, or the verification that firms conform with loan covenants. A bank monitoring at intensity  $\mu_t$  limits the private benefit an entrepreneur can take to  $b(\mu_t)$ , where  $b(0) = \overline{B}$ ,  $b(\infty) = \underline{B}$ ,  $b'(\cdot) < 0$  and  $b''(\cdot) > 0$ . The specific functional form follows that of CMM:

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<sup>7</sup> Later I will only consider an equilibrium in which entrepreneurs will be hardworking and enjoy zero private benefit.

<sup>8</sup> Following CMM, I also assume that only the project with no private benefit is economically productive:

$$q_t \alpha \tilde{R}_t i_t - R_t^d i_t > 0 > q_t (\alpha^g - \Delta\alpha) \tilde{R}_t i_t - R_t^d i_t + \overline{B} i_t$$

where  $q_t$  is the price of capital goods produced by the entrepreneur’s technology and  $R_t^d \equiv 1 + r_t^d$  is the opportunity cost of funds engaging in projects. A sufficient condition is  $\overline{B} \leq \Delta\alpha \tilde{R}_t$ . In other words, the biggest private benefit generated by the second class of projects is smaller than the decrease in the probability of success it imposes.

$$b(\mu_t) = \underline{B} + \overline{B}(1 + \chi\mu_t)^{-\varepsilon^b} \quad (3.11)$$

A higher monitoring intensity, which can be interpreted as a tighter bank-entrepreneur relationship, produces more information about the entrepreneur and thus reduces his ability to enjoy private benefit. By contrast, a lower monitoring intensity generates less information, implying a more severe moral hazard on the entrepreneur's side.

Bank monitoring is imperfect; even when monitored by his bank at intensity  $\mu_t$ , an entrepreneur may still choose to run a project with private benefit  $b(\mu_t)$ <sup>9</sup>. A key component of the financial project discussed below ensures that the entrepreneur will have the incentive to choose the no-private benefit project.

As shown in the next section, the banker's project return depends on his monitoring intensity, hence he prefers to monitor more. However, bank monitoring is costly; monitoring an entrepreneur at intensity  $\mu_t$  entails a real cost equal to  $z\mu_t i_t$ , where  $z > 0$ . Moreover, monitoring is not publicly observable. The second moral hazard problem thus emerges between banks and households. A bank investing its own equity capital in entrepreneurial projects alleviates the problem because the bank now has a stake in the project. Following CMM, I also assume that returns in the projects funded by each bank are perfectly correlated, which improves the model's tractability.

### *Financial contract*

*Set-up* An entrepreneur with net worth  $n_t^e$  investing in a project of size  $i_t > n_t^e$  needs external finance in the amount of  $i_t - n_t^e$ . The banker provides this loan with investor investment  $d_t$  and his own net worth  $n_t^b$  net of monitoring costs, i.e. the bank lends  $n_t^b + d_t - z\mu_t i_t$ .

---

<sup>9</sup> If bank monitoring is perfect, then the layer of friction between entrepreneur and banker will vanish, implying that entrepreneurial capital is not important any more. This will not give us an interesting non-financial sector balance sheet to study.

As in CMM, I only focus on the financial contract that *leads all entrepreneurs to undertake the project with no private benefit, and that  $\alpha^g$  is the probability of success*. Inter-period anonymity is assumed, and I restrict the analysis to one-period projects.

The financial contract is set in real terms. It determines an investment size  $i_t$ , investment from the banker's net worth  $n_t^b$ , and investment from the household  $d_t$ , as well as the share of returns  $\tilde{R}_t^e$ ,  $\tilde{R}_t^b$ , and  $\tilde{R}_t^h$ , respectively, to the entrepreneur, banker, and household if the project succeeds. It also specifies the intensity  $\mu_t$  at which the bank agrees to monitor. Limited liability is assumed.

Given  $\{q_t, n_t^e, R_t^{nb}, R_t^d\}$ , where  $q_t$  is the price of physical capital,  $R_t^{nb}$  is the market-based return to bank equity capital, and  $R_t^d$  is the nominal risk-free rate, the contract maximizes the entrepreneur's expected payoff  $\alpha q_t \tilde{R}_t^e i_t$  subject to six constraints:

$$\max_{\{i_t, \tilde{R}_t^e, \tilde{R}_t^b, \tilde{R}_t^h, n_t^b, d_t, \mu_t\}} \alpha^g q_t \tilde{R}_t^e i_t$$

subject to

$$\tilde{R}_t = \tilde{R}_t^e + \tilde{R}_t^b + \tilde{R}_t^h \quad (3.12)$$

$$q_t \alpha^g \tilde{R}_t^b i_t - z \mu_t i_t \geq q_t (\alpha^g - \Delta \alpha) \tilde{R}_t^b i_t \quad (3.13)$$

$$q_t \alpha^g \tilde{R}_t^e i_t \geq q_t (\alpha^g - \Delta \alpha) \tilde{R}_t^e i_t + q_t b (\mu_t) i_t \quad (3.14)$$

$$q_t \alpha^g \tilde{R}_t^b i_t \geq R_t^{nb} n_t^b \quad (3.15)$$

$$q_t \alpha^g \tilde{R}_t^h i_t \geq R_t^d d_t \quad (3.16)$$

$$n_t^b + d_t - z\mu_t i_t \geq i_t - n_t^e \quad (3.17)$$

Equation (3.12) says that the shares of the returns  $(\tilde{R}_t^e, \tilde{R}_t^b, \tilde{R}_t^h)$  to the three parties must add up to the total return  $(\tilde{R}_t)$ . Equation (3.13) denotes the incentive compatibility constraint for bankers. It states that the expected payoff to the banker, net of the monitoring costs, must be at least as high as the expected payoff if no monitoring occurs. Equation (3.14) is the incentive compatibility constraint for entrepreneurs. Given that bankers monitor at intensity  $\mu_t$ , entrepreneurs can at most choose projects that give them private benefit  $b(\mu_t)$  per unit of investment<sup>10</sup>. This constraint therefore gives them enough incentive to choose the project with no-private benefits and with high probability of success. Equation (3.15) represents the participation constraints of the banker; the expected payoff from investing in the project must be at least as large as the (market-determined) return to bank equity capital. Equation (3.16), in turn, is the participation constraint of the household investors. The expected payoff to the project has to be at least large as the nominal rate the investment can earn as risk-free deposits. Lastly, equation (3.17) is the resource constraint; the loanable funds available to a banker, net of monitoring costs, are sufficient to cover the loan given to the entrepreneur.

*Solution* In equilibrium, (3.12), (3.13) and (3.14) bind, implying:

$$\tilde{R}_t^e = \frac{b(\mu_t)}{\Delta\alpha} \quad (3.18)$$

$$\tilde{R}_t^b = \frac{z\mu_t}{q_t\Delta\alpha} \quad (3.19)$$

---

<sup>10</sup> Note that the private benefit  $b(\mu_t) i_t$  is expressed in terms of capital goods, hence the total return in terms of final goods is expressed as  $q_t b(\mu_t) i_t$ , as shown in (3.14).

$$\tilde{R}_t^h = \tilde{R}_t - \frac{b(\mu_t)}{\Delta\alpha} - \frac{z\mu_t}{q_t\Delta\alpha} \quad (3.20)$$

More intense bank monitoring (a higher  $\mu_t$ ) reduces the project share allocated to entrepreneurs. However, more intense monitoring exacerbates the moral hazard problem on the bank's side, as banks promise to privately allocate more costly resources to monitoring, resulting in a higher banker's share of return.

Introducing (3.20) in the participation constraint of households (3.16) holding with equality leads to

$$d_t = \frac{\alpha q_t}{R_t^d} \left( \tilde{R}_t - \frac{b(\mu_t)}{\Delta\alpha} - \frac{z\mu_t}{q_t\Delta\alpha} \right) i_t \quad (3.21)$$

Combining (3.19) and (3.15) yields

$$n_t^b = \frac{z\alpha^g \mu_t}{R_t^{nb} \Delta\alpha} i_t \quad (3.22)$$

which states that for a given  $i_t$ , more intense monitoring of entrepreneurs requires banks investing more capital in the project (because it induces more moral hazard from bank's side). It also implies that an increase in the rate of return on bank equity reduces the amount of capital banks will invest in a given-size project.

Using the resource constraint (3.17) to eliminate  $d_t$  in (3.21) yields

$$[(1 + z\mu_t) i_t - n_t^b - n_t^e] = \frac{\alpha^g q_t}{R_t^d} \left( \tilde{R}_t - \frac{b(\mu_t)}{\Delta\alpha} - \frac{z\mu_t}{q_t\Delta\alpha} \right) i_t$$

and using (3.22) to substitute away  $n_t^b$  enables us to characterize the project size as a function of entrepreneurial net worth  $n_t^e$ :

$$i_t = \frac{n_t^e}{\Gamma_t} \quad (3.23)$$

where  $\Gamma_t \equiv 1 + z\mu_t - \frac{\alpha^g z\mu_t}{\Delta\alpha R_t^{nb}} - \frac{\alpha^g q_t}{R_t^d} \left( \tilde{R}_t - \frac{b(\mu_t)}{\Delta\alpha} - \frac{z\mu_t}{q_t\Delta\alpha} \right)$ .

Finally, the solution for  $\mu_t$  can be obtained by rewriting the objective function with (3.18) and (3.23):

$$\max_{\mu_t} \alpha q_t \tilde{R}_t^e i_t = \alpha q_t \frac{b(\mu_t)}{\Delta\alpha} \frac{n_t^e}{\Gamma_t}$$

Since the parameters and the price of capital ( $q_t$ ) are taken as given, the problem reduces to choosing  $\mu_t$  to maximize the ratio  $\frac{b(\mu_t)}{\Gamma_t}$ . The first-order condition reads

$$b'(\mu_t) \Gamma_t = \Gamma_t' b(\mu_t)$$

or

$$\mu_t = \frac{1}{z} \frac{\epsilon_t^\mu}{\epsilon_t^\mu + 1} \frac{q_t \alpha^g \tilde{R}_t - R_t^d}{R_t^d + \frac{\alpha^g}{\Delta\alpha} \frac{R_t^{nb} - R_t^d}{R_t^{nb}}}$$

$$\text{where } \epsilon_t^\mu \equiv -\frac{-\mu_t \bar{B} \varepsilon^b \chi (1 + \chi \mu_t)^{-\varepsilon^b - 1}}{b(\mu_t)}.$$

### *Entrepreneurs and bankers*

There exists a continuum of risk neutral entrepreneurs and bankers. A fraction of  $1 - \tau^e$  of entrepreneurs and  $1 - \tau^b$  of bankers exit the economy at the end of the period. At the beginning of each period, new bankers and entrepreneurs are born such that the number of bankers and entrepreneurs remains constant. The newborn bankers and entrepreneurs possess zero assets. I assume that all bankers and entrepreneurs supply labor (respectively  $H_t^b$  and  $H_t^e$ ) and earn wages so that they have start-up funds.

Entrepreneurs and bankers solve similar optimization problems. In the first part of each period, they accumulate net worth, which they invest in entrepreneurial

projects later in that period. Exiting agents consume accumulated wealth while surviving agents with successful projects save.

An entrepreneur starts at period  $t$  with holdings  $k_t^e$  in capital goods, which are rented to intermediate goods producers. I assume that the value of these retained earnings are affected by a “valuation” shock  $\varepsilon_t^{ne}$ , which is assumed to follow an AR(1) process:

$$\ln \varepsilon_t^{ne} = \rho_{ne} \ln \varepsilon_{t-1}^{ne} + \eta_t^{ne}$$

where  $\eta_t^{ne} \sim N(0, \sigma_{ne})$ . An adverse shock is interpreted as a sudden loss in a firm’s net worth caused by loan losses and asset writedowns. The corresponding rental income, combined with the value of undepreciated capital and the wage received from intermediate goods producers, makes up their net worth  $n_t^e$

$$n_t^e = \varepsilon_t^{ne} [r_t^k + q_t(1 - \delta)] k_t^e + w_t^e \quad (3.24)$$

Each entrepreneur then undertakes a capital-good producing project and invests his net worth in the project. As described above, an entrepreneur whose project is successful receives a payment of  $\tilde{R}_t^e i_t$  units of capital, whereas unsuccessful projects produce zero returns. At the end of the period, entrepreneurs associated with successful projects but who received the signal to exit the economy consume their net worth. Surviving successful entrepreneurs will save their entire return to buy capital stock, i.e.

$$k_{t+1}^e = \begin{cases} \tilde{R}_t^e i_t & \text{if surviving and successful} \\ 0 & \text{otherwise} \end{cases}$$

where  $k_{t+1}^e$  denotes the capital stock of an entrepreneur in the next period. Unsuccessful surviving entrepreneurs neither consume nor save.



Similarly, a typical banker starts period  $t$  with holdings  $k_t^b$  in capital goods and rents capital services to firms producing intermediate goods. Similarly, I assume that the value of these retained earnings is affected by a “valuation” shock  $\varepsilon_t^{nb}$  which follows an AR(1) process:

$$\ln \varepsilon_t^{nb} = \rho_{nb} \ln \varepsilon_{t-1}^{nb} + \eta_t^{nb}$$

where  $\eta_t^{nb} \sim N(0, \sigma_{nb})$ . An adverse shock is interpreted as a sudden loss in a bank’s net worth caused by loan losses and asset writedowns. Thus, a banker’s net worth  $n_t^b$  reads:

$$n_t^b = \varepsilon_t^{nb} (r_t^k + q_t(1 - \delta)) k_t^b + w_t^b \quad (3.25)$$

A banker also invests his own net worth  $n_t^b$  in the projects of entrepreneurs (together with the loanable funds raised from the investors). A banker with a successful project but receiving the signal to exit the economy consumes his net worth, whereas the successful surviving banks retain all their earnings and buy physical capital:

$$k_{t+1}^b = \begin{cases} \tilde{R}_t^b i_t & \text{if surviving and successful} \\ 0 & \text{otherwise} \end{cases}$$

Similarly, unsuccessful surviving bankers neither consume nor save.

### 3.3.6 Defining Gross Domestic Product

Following Justiniano et al. (2010) and Christiano et al. (2010), I define  $x_t$ , the gross domestic product (GDP) of the model economy, in the following way:

$$x_t = C_t + C_t^E + C_t^B + I_t + G_t \quad (3.26)$$

### 3.3.7 Government policy

#### Monetary policy

The monetary authority sets  $r_t^d$ , the short-term nominal interest rate, according to the Taylor rule:

$$r_t^d = (1 - \rho_r) r^d + \rho_r r_{t-1}^d + (1 - \rho_r) [\rho_\pi \hat{\pi}_t + \rho_y \hat{x}_t] + \varepsilon_t^r \quad (3.27)$$

where  $r^d$  is the steady-state rate,  $\hat{\pi}_t$  is the inflation deviations from the steady state,  $\hat{x}_t$  is the GDP deviations from the steady state,  $\varepsilon_t^r$  is the monetary policy shock following an AR(1) process:

$$\ln \varepsilon_t^r = \rho_r \ln \varepsilon_{t-1}^r + \eta_t^r$$

where  $\eta_t^r \sim N(0, \sigma_r)$ .

#### Fiscal policy

The government budget constraint is of the form

$$P_t G_t = T_t$$

Government spending expressed relative to steady state output path  $\varepsilon_t^g = \frac{G_t}{Y}$  follows the process:

$$\ln \varepsilon_t^g = (1 - \rho_g) \ln \varepsilon^g + \rho_g \ln \varepsilon_{t-1}^g + \eta_t^g$$

where  $\eta_t^g \sim N(0, \sigma_g)$ .

### 3.3.8 Aggregation

One important implication of the assumption of constant-return-to-scale capital goods technology is that the monitoring intensity  $\mu_t$  is independent of the distri-

bution of the net worth of bankers and entrepreneurs. Therefore it is easy to study the aggregate behavior of balance sheet variables.

Aggregation of (3.23) gives

$$I_t = \frac{N_t^e}{\Gamma_t}$$

where  $I_t$  is aggregate investment and  $N_t^e$  is aggregate entrepreneurial net worth. Both aggregate bank and entrepreneurial net worth are found respectively by summing (3.25) and (3.24) across bankers and entrepreneurs:

$$N_t^b = \varepsilon_t^{nb} (r_t^k + q_t(1 - \delta)) K_t^b + \omega^b w_t^b \quad (3.28)$$

$$N_t^e = \varepsilon_t^{ne} (r_t^k + q_t(1 - \delta)) K_t^e + \omega^e w_t^e \quad (3.29)$$

where  $K_t^b = \omega^b k_t^b$ ,  $K_t^e = \omega^e k_t^e$ ,  $\omega^e$  and  $\omega^b$  denote the masses of entrepreneurs and bankers.

As described above, bankers and entrepreneurs survive to the next period with probability  $\tau^b$  and  $\tau^e$ , respectively. Surviving agents save all their wealth because of risk-neutral preferences and the high return on internal funds. Aggregate wealth at the beginning of the period at  $t + 1$  is thus

$$K_{t+1}^b = \tau^b \alpha^g \tilde{R}_t^b I_t \quad (3.30)$$

$$K_{t+1}^e = \tau^e \alpha^g \tilde{R}_t^e I_t \quad (3.31)$$

Combining (3.28) with (3.30), and (3.29) with (3.31) yields the law of motion

$$N_t^b = \varepsilon_t^{nb} (r_t^k + q_t(1 - \delta)) \tau^b \alpha^g \tilde{R}_{t-1}^b \frac{N_{t-1}^e}{\Gamma_{t-1}} + \omega^b w_t^b \quad (3.32)$$

$$N_t^e = \varepsilon_t^{ne} (r_t^k + q_t (1 - \delta)) \tau^e \alpha^g \tilde{R}_{t-1}^e \frac{N_{t-1}^e}{\Gamma_{t-1}} + \omega^e w_t^e \quad (3.33)$$

Exiting banks and entrepreneurs consume the value of their available wealth. Hence the aggregate consumption of banks ( $C_t^b$ ) and entrepreneurs ( $C_t^e$ ) are

$$C_t^e = (1 - \tau^e) q_t \alpha^g \tilde{R}_t^e I_t \quad (3.34)$$

$$C_t^b = (1 - \tau^b) q_t \alpha^g \tilde{R}_t^b I_t \quad (3.35)$$

Moreover, the aggregate equilibrium return on bank net worth reads:

$$R_t^{nb} = \frac{q_t \alpha^g \tilde{R}_t^b I_t}{N_t^b}$$

### 3.3.9 Market clearing

The market for physical capital, capital services, labor services, investment goods and final goods have to clear in equilibrium:

$$K_t = K_t^h + K_t^e + K_t^b \quad (3.36)$$

$$z_t K_t^h + K_t^e + K_t^b = \int_0^1 K_{jt} dj \quad (3.37)$$

$$H_t^h = \int_0^1 H_{jt}^h dj \quad (3.38)$$

$$K_{t+1} = (1 - \delta) K_t + \alpha \tilde{R}_t I_t \quad (3.39)$$

$$C_t + C_t^E + C_t^B + (1 + \mu_t) I_t + G_t + a(Z_t) K_t = Y_t \quad (3.40)$$

Equation (3.36) defines the total capital stock held by households, entrepreneurs and banks. Equation (3.37) shows that total capital services equate total demand from intermediate good producers. Equation (3.38) shows that the total supply of the composite labor equals total demand from intermediate good producers, whereas equation (3.39) displays the evolution of aggregate stock in the economy. Finally, equation (3.40) describes the overall resources constraint given by integrating the budget constraint across households, entrepreneurs and bankers, and the expression for the dividends of intermediate goods producers and labor unions.

### 3.3.10 *Competitive Equilibrium*

Given the exogenous shocks  $\{\eta_t^a, \eta_t^g, \eta_t^r, \eta_t^q, \eta_t^{nb}, \eta_t^{ne}, \eta_t^p, \eta_t^w\}_{t=0}^\infty$  and exogenous processes  $\{\varepsilon_t^a, \varepsilon_t^g, \varepsilon_t^r, \varepsilon_t^q, \varepsilon_t^{nb}, \varepsilon_t^{ne}, \varepsilon_t^p, \varepsilon_t^w\}_{t=0}^\infty$ , a competitive equilibrium consists of (i) decision rules  $\{C_t^h, i_t^h, K_{t+1}^h, W_{it}, Z_t, D_t\}_{t=0}^\infty$  that solve the maximization problem of the household; (ii) decision rules for  $\{p_{jt}\}_{t=0}^\infty$  as well as input demands  $\{K_{jt}^h, H_{jt}^h, H_{jt}^e, H_{jt}^b\}_{t=0}^\infty$  that solve for the profit maximization problem of firms producing intermediate goods; (iii) decision rules for  $\{i_t, R_t^e, R_t^b, R_t^h, d_t, n_t^b, \mu_t\}_{t=0}^\infty$  that solve for the maximization problem associated with the financial contract; (iv) saving and consumption decision rules for entrepreneurs and banks, and (v) the market-clearing conditions (3.36), (3.37), (3.38), (3.39) and (3.40).

Table (3.2) shows the timeline of the model economy. The model is solved by log-linearizing the equilibrium conditions about the steady state.

## 3.4 Parameter estimates

### 3.4.1 Data

The model is estimated with eight macroeconomic aggregates: real gross domestic product (GDP), real consumption, real investment, real wages, inflation, the short-term nominal interest rate, and financial and nonfinancial capital. The time period is 1952-2010.

Following Smets and Wouters (2007), I adopt real GDP, consumption and investment series from the Bureau of Economic Analysis. Real GDP is in billions of chained 2005 dollars. I deflate nominal personal consumption expenditures and fixed private domestic investment with the GDP deflator. Inflation is the first difference of the logarithm of the GDP price deflator. To construct the real wage series, I first get the “compensation for the non-farm business sector” from the Bureau of Labor Statistics, then deflate it with the GDP price deflator. The construction of financial and nonfinancial capital data is described earlier in this chapter.

I divide all aggregate real variables by the population over 16 years of age so that the variables are expressed in per capita. The short-term interest rate is the federal funds rate. All series are seasonally adjusted. With the exception of interest rate and inflation, all data are first-differenced and de-meanned. Inflation and the interest rate are de-meanned by their respective steady state values.

### 3.4.2 Prior distribution of the parameters

Parameters are divided into a group of fixed parameters and another group of the parameters being estimated. Parameters being calibrated include the depreciation rate  $\delta$  (at 0.02 on a quarterly basis), the exogenous spending-GDP ratio (at 18 percent), and elasticities of substitution of intermediate goods and specialized labor (both at 6). Following CMM, I set the share of labor  $\theta_e$  and  $\theta_b$  to be 0.00005. I also

fix the Calvo parameters for prices ( $\xi_p$ ) and wages ( $\xi_w$ ) at 0.65 and 0.7, respectively, implying that the average duration of price and wage contracts are not longer than 4 quarters. These values are in line with the values found in the literature.

I adopt the following strategy in solving for the steady state of the model with regard to the financial intermediation process<sup>11</sup>. In order to take advantage of the constructed data, I calibrate the steady state value of aggregate nonfinancial and financial leverage (defined as the ratio of aggregate debt to aggregate net worth) to be 0.34 and 9.35, which are respectively the average values of the two aggregate data series. The entrepreneurial success rate  $\alpha^g$  is set at a quarterly rate of 0.99 (which follows Carlstrom and Fuerst (1997) who calibrate the quarterly rate of failure of entrepreneurs to be one percent). I calibrate  $\tilde{R}_{ss}$ , the gross return of successful investment project, to be 1.05, which is in line with the calibration value in CMM. I also set 0.05 to be the ratio of steady state monitoring costs relative to successful investment project returns. I normalize the parameter  $\varepsilon^b$  in (3.11) to be unity such that I will focus on the estimation of the parameter  $\chi$ . The rest of the parameters are determined endogenously at steady state<sup>12</sup>.

For the prior distribution of estimates outside of the financial intermediation process, I follow Smets and Wouters (2007)<sup>13</sup>. For parameters which govern the exogenous processes of financial shocks, I still adopt the same prior distribution as the other similar parameters. Finally, I adopt a normal prior distribution of mean 0.15 and standard deviation of 0.02 for  $\frac{b_{ss}}{\tilde{R}_{ss}}$ , the ratio of firm private benefits to project return at steady state. I use a normal prior distribution of mean 10 and standard

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<sup>11</sup> My way of solving for the steady state values is different from the one used in CMM. Therefore, a subset of the parameters which I am going to calibrate is different from theirs.

<sup>12</sup> These parameters include  $\Delta\alpha$  (the decline in success probability of projects when firms shirk),  $\tau^b$  (probability that bankers survive to next period),  $\tau^e$  (probability that entrepreneurs survive to next period), and  $z$  (the scaling factor in the real cost  $z\mu_t i_t$ ).

<sup>13</sup> Please refer to Smets and Wouters (2007) for the rationale for defining the prior distribution of those parameters.

deviation of 1 for  $\chi$ , the monitoring intensity factor in (3.11).

### 3.4.3 Posterior estimates of the parameters

Table (3.3) shows the posterior distribution of the parameters obtained by the Metropolis-Hastings algorithm.<sup>14</sup>

The data seems to be quite informative on the stochastic processes for the exogenous disturbances. The productivity, government spending, bank capital and investment return shock shocks are very persistent, with an AR(1) coefficient above 0.9. The share of capital in the production function is estimated to be 0.17, a number similar to Smets and Wouters (2007). The persistence of consumption habits (0.46) is also lower than the literature value (0.6-0.7). The ratio of firm private benefits to project return at steady state is estimated to be 0.14, very similar to the prior mean, whereas the estimate of the monitoring intensity factor is about 10.

## 3.5 Theoretical Analyses

In this section I present my theoretical results. I will first present impulse responses to financial intermediation shocks. Then I will explain my findings on the importance of financial shocks. I will also discuss the quantitative differences in macro shock transmission mechanisms in my estimated model, compared with a standard New Keynesian model with investment frictions but not financial frictions. Finally, I will discuss how well my estimated model explains the empirical correlations of the debt level and equity capital between financial and nonfinancial sectors.

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<sup>14</sup> The convergence of Markov Chain Monte Carlo (MCMC) chains are monitored according to Brooks and Gelman (1998). The idea is to compute within-chain and across-chain moments (first, second, or beyond). Convergence can be monitored by estimating the factor between the two moments, which should converge to zero as sample size increases.



### 3.5.1 *Financial intermediation shocks*

I am going to study three financial intermediation shocks: shocks to bank equity capital ( $\varepsilon_t^{nb}$ ), shocks to firm equity capital ( $\varepsilon_t^{ne}$ ), and investment return shock ( $\varepsilon_t^q$ ).

#### *Negative bank capital shocks*

Figure (3.6) displays the impulse responses of various variables given a one-percent fall in bank equity capital.

The shock creates persistent recessions which last for 40 quarters, but the depth of recession is shallow. At the trough, GDP falls by 0.02 percent and investment falls by 0.2 percent. The price of capital goods rises slightly, which is consistent with the discussion in Meh and Moran (2010).

A sudden drop in bank capital reduces banks' lending capacity to firms. As a result, fewer projects are financed and aggregate investment falls on impact. Moreover, banks now have to economize on the use of bank capital, resulting in a fall in monitoring intensity on firms. According to the equilibrium shares of project return to firms and banks as indicated by equations (3.18) and (3.19), a decrease in monitoring intensity reduces shares of project return to bankers but raises shares of return to firms. Banks suffer a continuous fall in retained earnings, leading to a further erosion of bank capital. This adds to the second-round effect, where bank loans contract even more. Although firm equity capital rises slightly, the fall in bank equity capital dominates and hence reduces aggregate investment further. Consistent with the discussion in Meh and Moran (2010), investment displays a hump-shaped decline.

On the whole, a negative bank capital shock leads to a very persistent drop in bank equity capital. Such shocks also create persistent recessions, although the degree of contraction is relatively small.

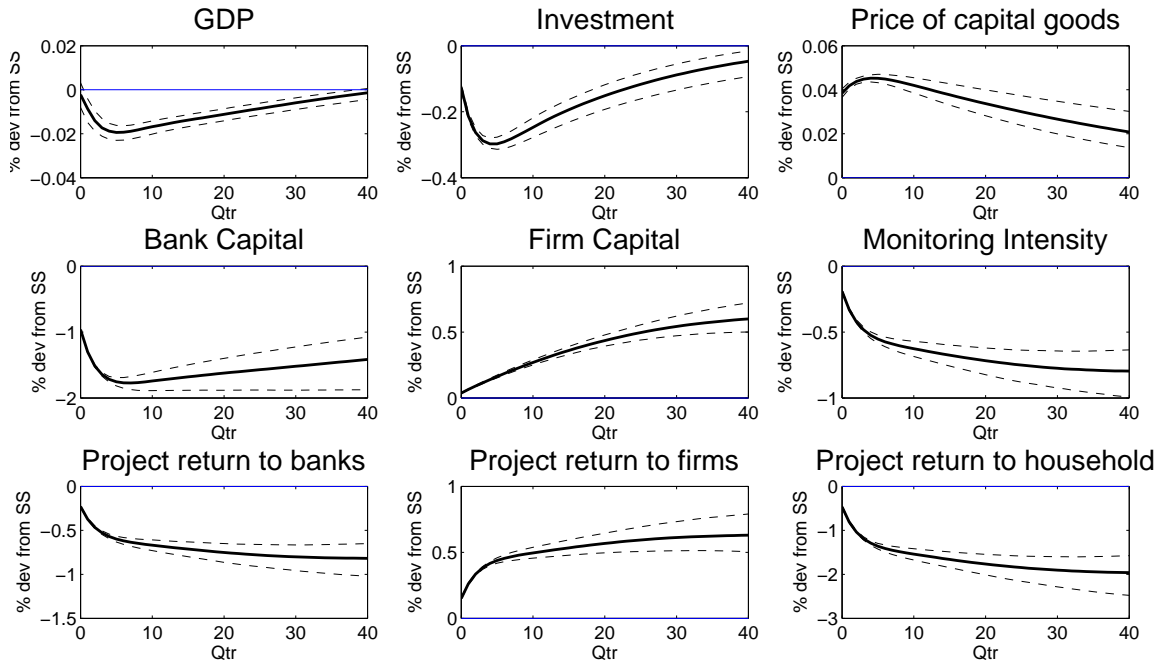


FIGURE 3.6: Impulse response functions to a **one-percent drop in bank capital**. The solid line is the mean impulse response; the dotted lines are the 10% and 90% posterior intervals.

### *Negative firm capital shocks*

Figure (3.7) displays the responses of the economy when a one percent drop in aggregate firm equity capital hits.

The shock creates a very persistent recession, lasting for more than 40 quarters. Moreover, a relatively deeper recession results: GDP reduces by 0.1 percent at the trough, where investment also falls by 0.5 percent.

An unanticipated fall in firm capital reduces a firm's internal finance available, thus directly affecting its own capacity to invest in projects. Therefore aggregate investment falls on impact. Since entrepreneurs have less internal funds to start with, the problem of moral hazard between banks and firms worsens: firms are prone to shirk more as they have less stake in invested projects. As a result, banks

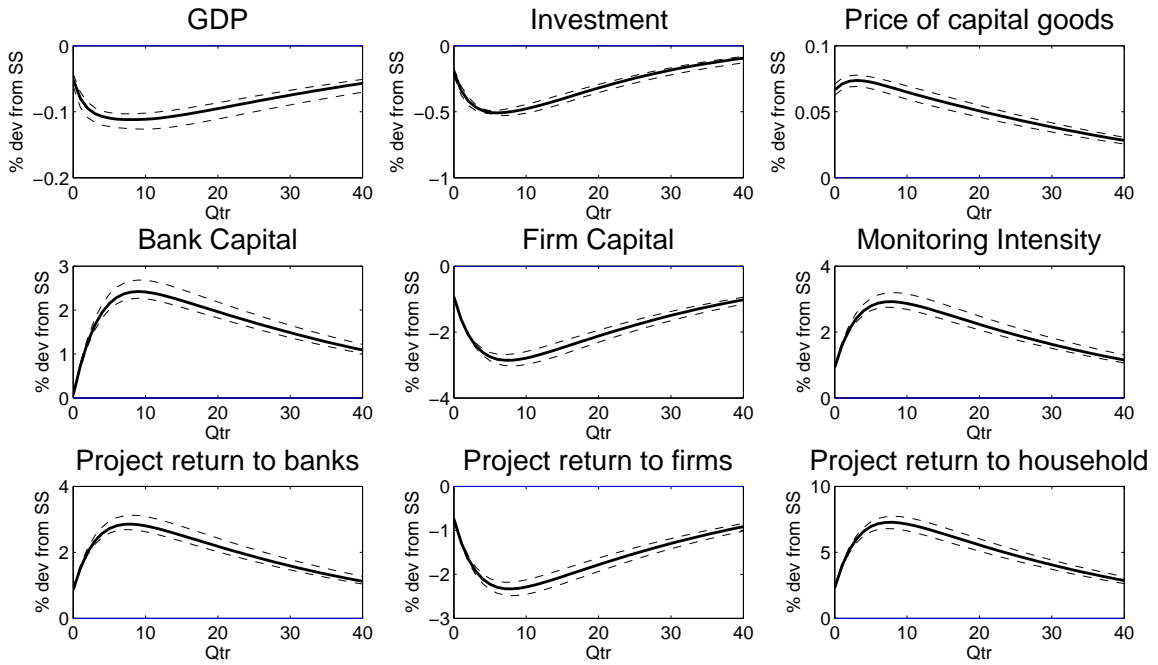


FIGURE 3.7: Impulse response functions to a **one-percent drop in firm capital**. The solid line is the mean impulse response; the dotted lines are the 10% and 90% posterior intervals.

need to raise monitoring intensity, thus lowering the project return to entrepreneurs. Retained earnings to firms fall further, adding to a second-round effect to the fall in firm equity capital, which in turn lowers aggregate investment further and deepens the recession.

The hump shape decline in investment comes from the persistent decline in firm equity capital, which dominates the rise in bank equity as a result of rising banks' share of project return due to an increase in monitoring. GDP also follows a hump shaped decline.

### *Negative shocks to investment return*

Figure (3.8) shows a one-percent drop in investment return<sup>15</sup>. It creates the deepest recession among the three types of financial intermediation shocks. At the trough, GDP falls by 0.7 percent and investment falls by almost 5 percent.

The initial decrease in investment is due to a drop in investment demand, as investment projects are less attractive. However, the equilibrium price of capital goods goes up, which is attributable to a larger fall in the supply of capital goods relative to the decrease in demand for investment.

An interesting point to note is that with the rise of price of capital goods, the gross return to capital goods<sup>16</sup> increases *given* investment. As a matter of fact, both types of equity capital rise slightly on impact. Equilibrium monitoring intensity increases.

After one quarter, bank capital takes a great hit and falls about 5 percent. This was driven by the huge fall in banks' retained earnings attributable to the fall in the number of projects they invest in and the drop in project return because of the decrease in monitoring intensity. Lending to firms drops further, therefore driving down investment to create the hump-shaped response.

Firm equity capital also takes a toll after the first quarter. Cushioned by the initial rise in its share of project return, the fall in firm equity capital is milder. After a while, aggregate firm capital falls below the steady state level and bank monitoring soon rises above the steady state level. Overall, the decline in bank capital is not too persistent; it only lasts for fifteen quarters. The shape of the response of investment closely follows the shape of bank equity capital, reflecting the importance of bank

<sup>15</sup> Since the steady state gross return to investment ( $\tilde{R}$ ) is calibrated as 1.05, a one-percent fall in investment return amounts to an approximate one *percentage point* drop in investment return.

<sup>16</sup> Recall that the gross return to physical capital is  $r_t^k + q_t(1 - \delta)$ , which includes rental income from the intermediate goods producers and the value of the undepreciated capital.

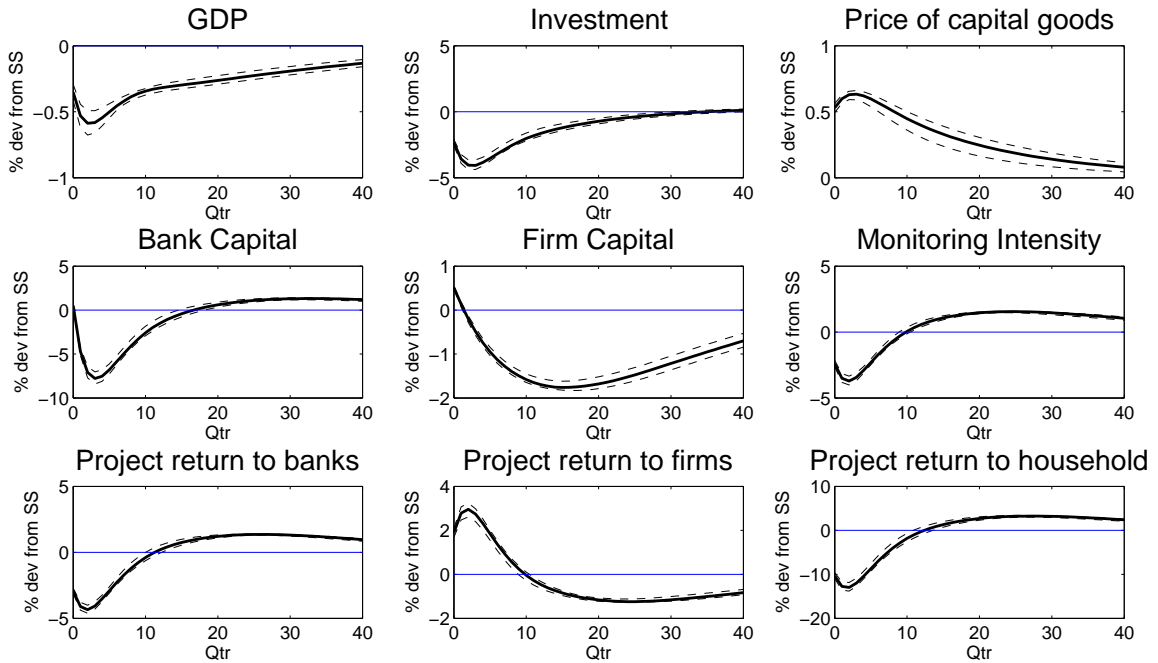


FIGURE 3.8: Impulse response functions to a **one-percent drop in investment return**. The solid line is the mean impulse response; the dotted lines are the 10% and 90% posterior intervals.

equity capital in transmitting financial shocks.

### 3.5.2 How important are financial shocks?

#### *Conditional variance decomposition*

Figure (3.9) shows the conditional (forecast error) variance decomposition of GDP, investment, inflation, and firm debt level. A few observations are in order.

First, equity capital shocks to banks and firms play virtually no role in explaining all of these variables except debt levels. Second, shocks to investment return play a bigger role; they explain twenty percent of variations in investment, and only about five percent of variations in GDP. The low explanatory power of financial shocks in explaining variability of GDP is different from the results shown in Christiano et al. (2010) and Jermann and Quadrini (2012). Both of these papers find that financial

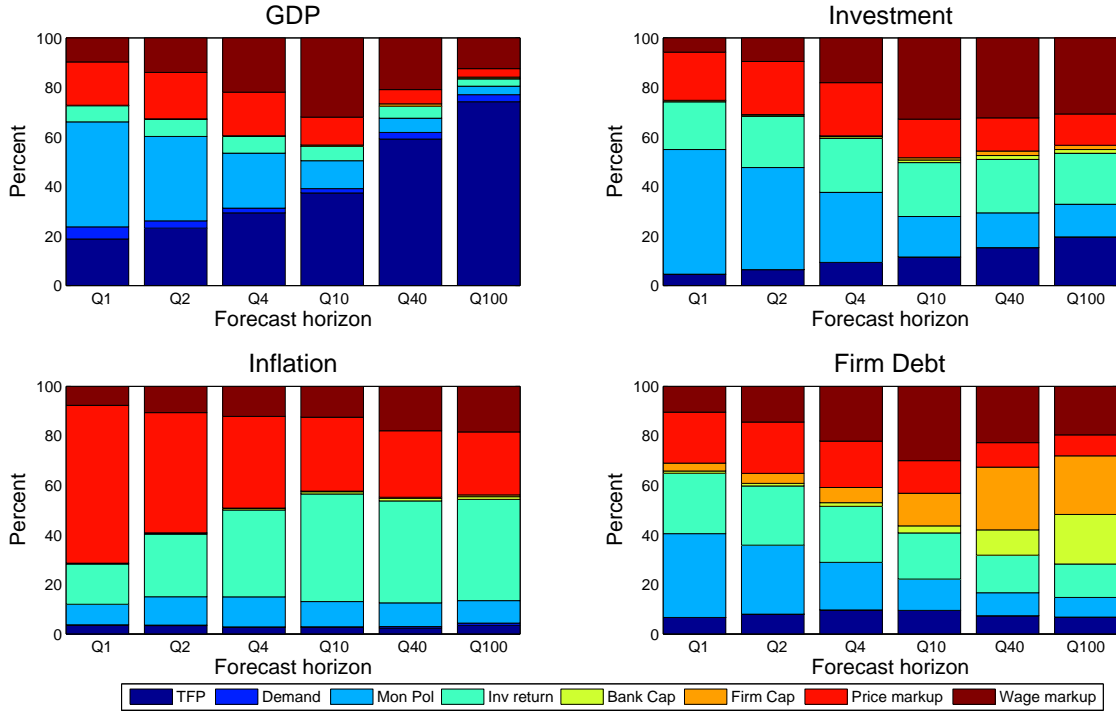


FIGURE 3.9: Conditional (forecast error) variance decomposition for GDP, investment, inflation and firm debt. For each panel, the bottom-most bar belongs to TFP shocks.

shocks explain about one-third of the variations in GDP.

One interesting result is that financial shocks (especially investment return shocks) have increasing explanatory power on inflation. They explain only ten percent of the variations in the first horizon, but they explain about forty percent in the long run. One explanation for this is that investment return shocks generate a persistent change in marginal costs in the estimated model, which in turn affects inflation persistently.

Another notable result is that the aggregate firm debt is explained by an interesting mix of shocks (aggregate bank debt displays very similar results). In the short horizon, financial shocks explain roughly thirty percent of variations. But the share of explanation increases to almost sixty percent in the long run. Markup shocks also explain thirty percent. The rest is explained by monetary policy shocks and TFP shocks.

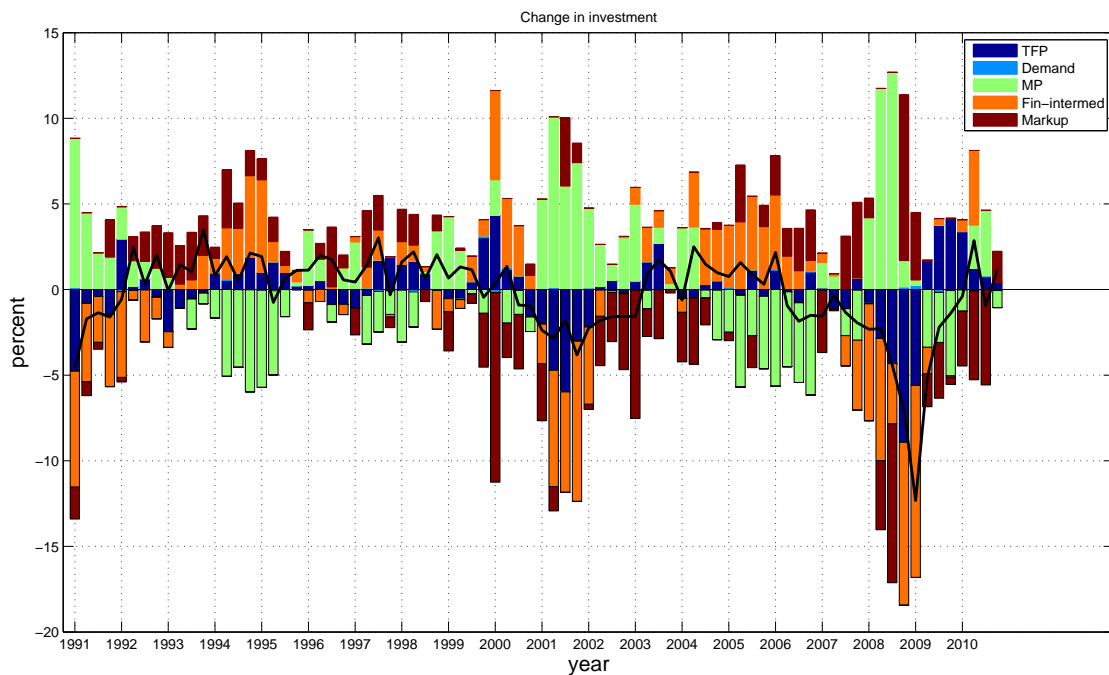


FIGURE 3.10: Historical decomposition of the **growth rate of investment** from 1991 to 2010. “TFP” refers to total factor productivity shocks. “Demand” refers to government spending shocks. “MP” refers to monetary policy shocks. “Fin-intermed” refers to financial intermediation shocks which include bank equity capital shocks, firm equity capital shocks and investment return shocks. “Mark-up” refers to price and wage mark-up shocks

To sum up, financial shocks only play a modest role in explaining variations in real variables. They are better at explaining inflation and debt levels.

*Historical decomposition for the growth rate of investment*

Figure (3.10) shows the historical decomposition of the quarterly change in investment accounted for by five major groups of shocks: total factor productivity (“TFP”), government spending (“demand”), monetary policy (“MP”), financial intermediation (“Fin-intermed”, including shocks to bank equity capital, firm equity capital and investment return) and mark-up (“Mark-up, including price and wage mark-up shocks). For brevity and clarity I only show the results between 1991 and

2010.

It is interesting to observe that financial intermediation shocks (orange bars) and productivity shocks (deep blue bars) play a big role in reducing aggregate investment in 1991, 2001 and 2008 recessions. Financial intermediation shocks also have a role in explaining the boom of investment from 1993 to 1995 and from 2004 to 2006.

It is also interesting to see how monetary policy shocks (light green bars) affect investment: the expansionary effect on investment is particularly conspicuous during recessions, during which the Federal Reserve was trying to loosen the federal funds rate to lift the economy.

### *3.5.3 Shock transmission mechanism under the loanable funds framework*

In this subsection, I study the hump-shaped responses of investment and GDP by comparing my estimated model with another estimated model: a New Keynesian business cycle model without financial frictions but with convex adjustment costs<sup>17</sup>. This alternate model follows closely that of Smets and Wouters (2007) and is widely used in assessing central bank policies.

As discussed in Meh and Moran (2010), the hump-shaped response of investment is driven by the dynamics of bank and firm net worths in my current model. I am interested in studying how the implied shock transmission mechanism in the current model differs from that in the alternate model when both models are taken to the data.

#### *Negative total factor productivity shocks*

I first consider a one percent drop in total factor productivity (TFP) as displayed in figure (3.11), which overlaps the responses of my estimated model (black lines) and the responses of a standard New Keynesian model (red lines). Two observations are

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<sup>17</sup> I estimate the alternate model with the same dataset except the equity capital series of financial and non-financial sectors.



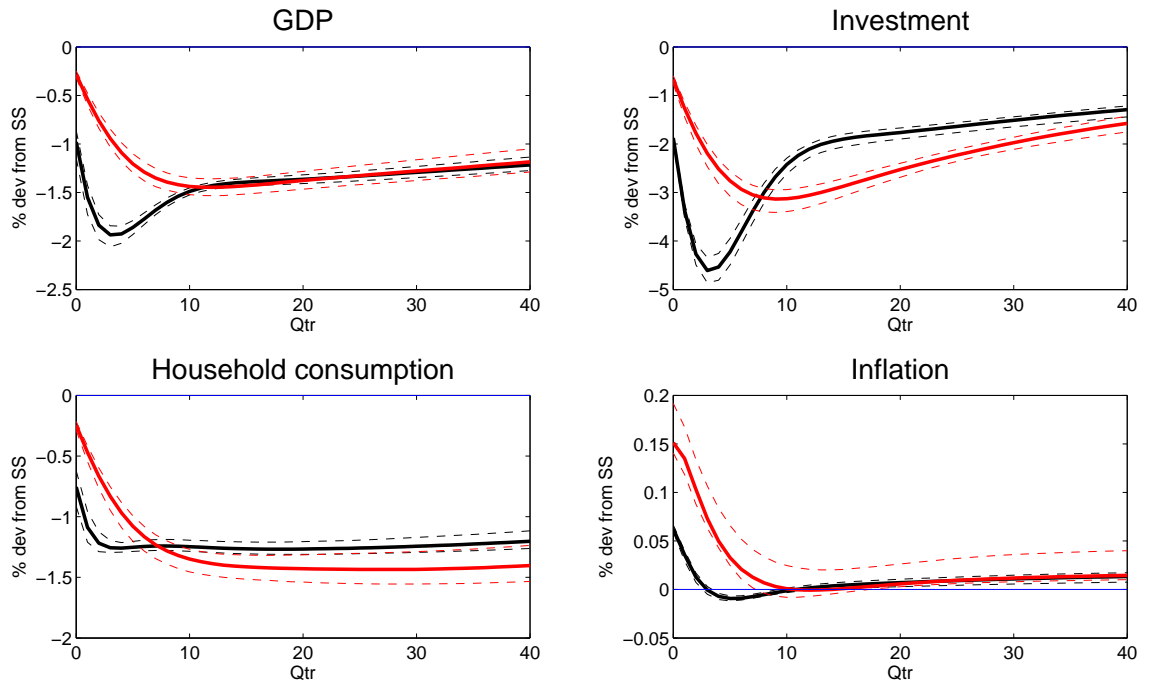


FIGURE 3.11: Comparison of the impulse responses when a **one-percent drop in total factor productivity** hits my estimated model (black lines) and an estimated New Keynesian model with no financial frictions but with convex investment adjustment costs à la Smets and Wouters (2007) (red lines). Solid lines represent the median responses; dotted lines are the 10% and 90% posterior intervals.

in order for the responses of investment. First, the immediate decline in investment (two percent) is larger in my estimated model and so is the maximum decline (4.5 percent) at the trough, whereas the alternate model gives respectively a one-percent and three-percent decline. Second, investment in my estimated model quickly climbs from the trough to half of the trough value (2.75 percent) before the tenth quarter, and the subsequent decline in investment is smaller than that of the alternate model afterwards. However, investment in the alternate model displays a smooth decline, reaches its trough at the tenth quarter, and slowly returns to the steady state.

I see that GDP experiences a deeper fall on impact for my estimated model, attributable to the larger initial fall in investment and consumption. Then it displays

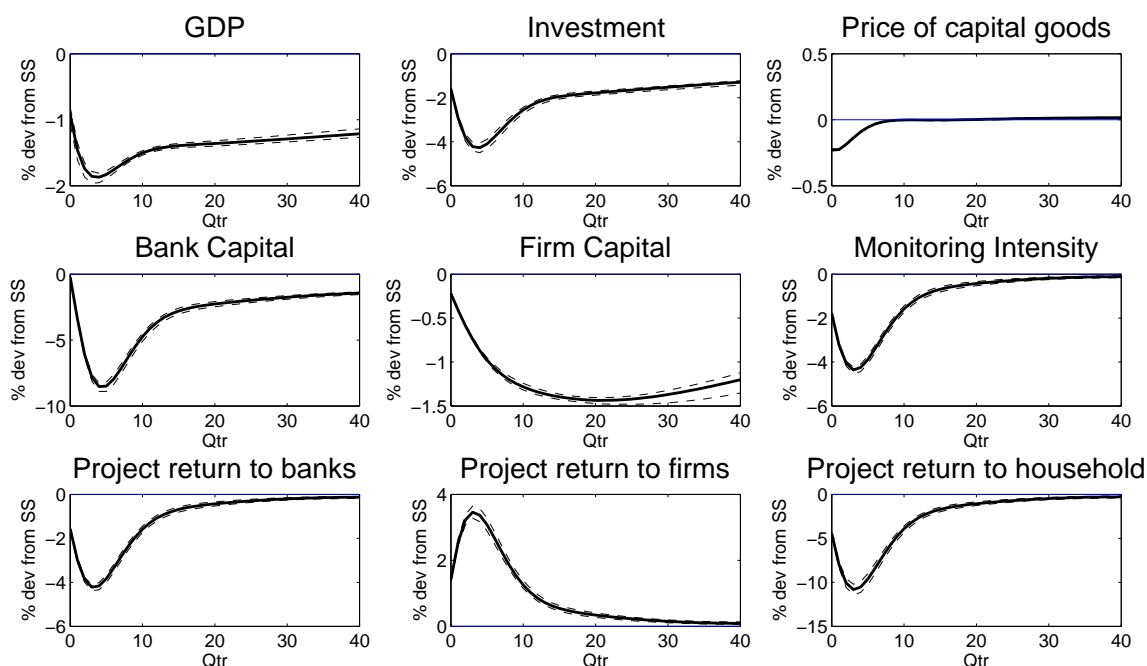


FIGURE 3.12: Impulse response to a **one-percent drop in total factor productivity** in my estimated model. The solid line represents the median response; dotted lines are the 10% and 90% posterior intervals.

the hump shape similar to the one for investment: GDP contracts by a maximum of two percent at the fourth quarter. Unsurprisingly, the alternate model delivers a very smooth decline in GDP with the trough happening at the tenth quarter.

Figure (3.12) explains the transmission of the TFP shock in my estimated model. As a negative TFP shock hits, the current and expected rental income for physical capital falls. This reduces the demand for investment on impact, hence driving down the price of capital goods.

Aggregate bank and firm capital drops slightly on impact, as a result of the fall in the price of capital goods. The equilibrium monitoring intensity falls by two percent. According to the incentive compatibility constraints, the share of project return to firms increases but the share to banks decreases. Coupled with a large fall in investment, this seriously depresses earnings for banks, resulting in a big fall in

bank equity capital in the subsequent quarters. The reduction in bank equity capital curtails the amount of bank loans made to firms, further deepening the fall in the aggregate investment level for a few more quarters.

It can be seen that the shape of the investment response is closely associated with that of aggregate bank equity capital, which in turn is determined by the monitoring intensity. The firm-bank relationship in this model influences the evolution of bank equity capital, which then drives business cycles. These results show that the “bank capital channel” is quantitatively significant in the transmission of productivity shocks.

#### *Negative price mark-up shocks*

I then consider a 0.2 percent (approximately a one-standard-deviation) positive price mark-up shock. Figure (3.13) displays the comparison of the responses of the major variables in my estimated current model as well as the estimated alternate model.

Similarly, investment experiences a greater drop in the first few quarters and the recessionary effect is short-lived. In particular, investment suffers a deep fall (3.5 percent) on impact, reaches the trough (5.8 percent) at the third quarter, and quickly reverts to zero at the tenth quarter. GDP follows closely the movement of investment, and displays a deep fall for the first three quarters and reverts back to the steady state level after the tenth quarter.

The transmission mechanism of the price mark-up shock is reported in figure (3.14). A positive price mark-up shock decreases the desired level of capital given marginal product of capital, hence reducing aggregate investment on impact, which drives down the price of capital goods. The rest of the story is similar to that of TFP shock: both equity capital of banks and firms drop on impact; the equilibrium monitoring intensity decreases on impact as well. Retained earnings for banks fall, as a result of a drop in investment and share of project return to banks. Loans to firms

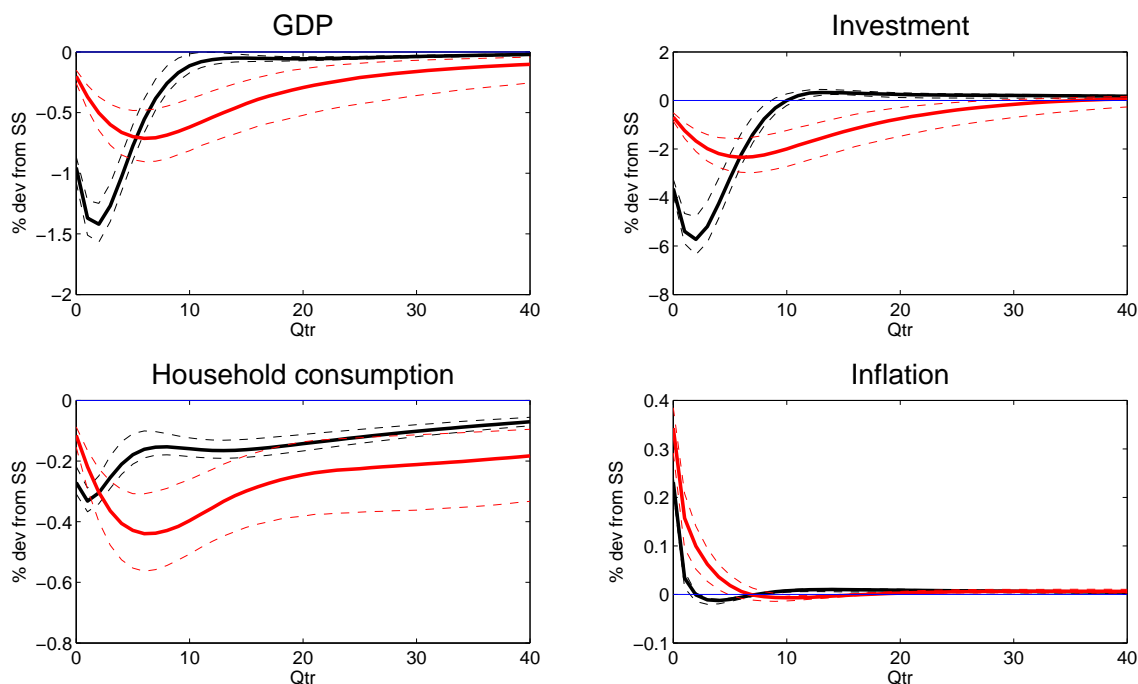


FIGURE 3.13: Comparison of the impulse responses when a **0.2 percent positive shock in price mark-up** hits my estimated model (black lines) and an estimated New Keynesian model with no financial frictions but with convex investment adjustment costs à la Smets and Wouters (2007) (red lines). Solid lines represent the median responses; dotted lines are the 10% and 90% posterior intervals.

are curtailed, further reducing investment for a few quarters. This gives investment the hump-shaped response. However, the drop in investment is rather short-lived; banks are able to reverse the deep fall in the equity capital and starts lending again, helping the recovery of investment.

The shape of the response of investment closely follows that of bank equity capital, reflecting the important role financial equity plays in transmitting macro shocks.

#### 3.5.4 Theoretical cross-correlations of balance sheet variables

Lastly, it will be useful to check the corresponding cross-correlations of aggregate capital and debt between financial and nonfinancial sectors in the model. To that end, I compute the HP-filtered theoretical dynamic correlations following Burnside

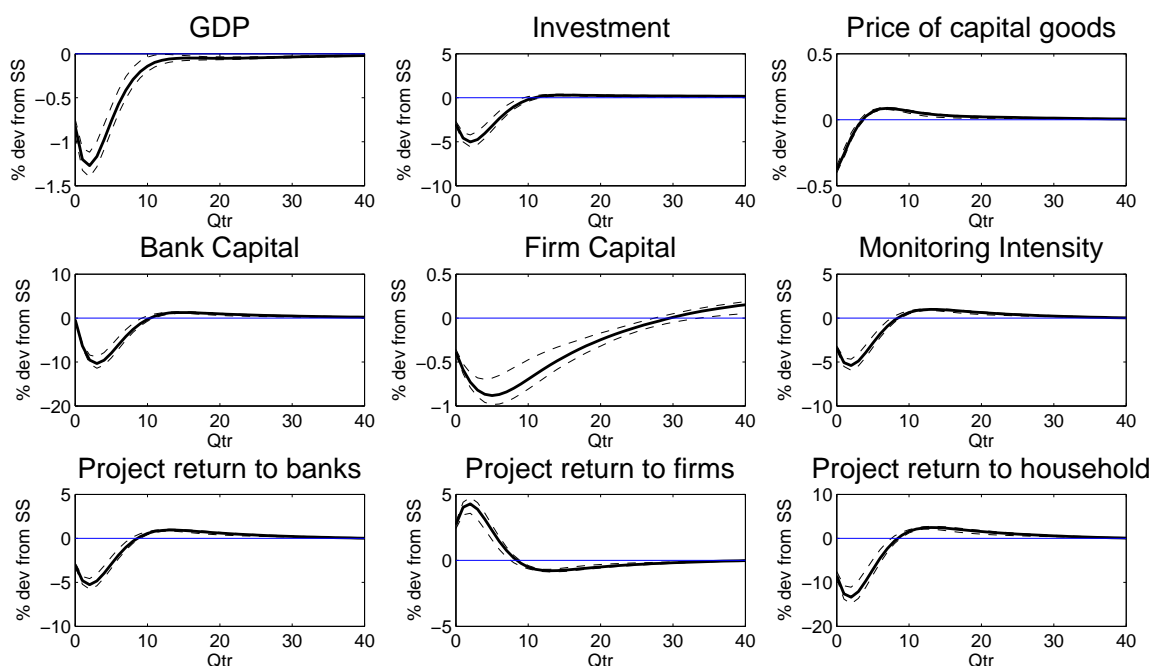


FIGURE 3.14: Impulse response to a **0.2 percent positive shock in price mark-up** in my estimated model. Solid line represents the median response; dotted lines are the 10% and 90% posterior intervals.

(1999). Figure (3.15) displays the theoretical (red lines) and empirical (blue lines) cross-correlations of net worths and debts between the two sectors.

The model does a good job of explaining the lead-lag relationship of net worths. In particular, the model can replicate the fact that financial capital mildly leads nonfinancial capital, as well as the mild contemporaneous correlation between the two sectors.

With regard to debt levels, the model can replicate the high contemporaneous correlations of debt (which is almost one). However, the theoretical cross-correlations do not display a lead-lag relationship between the debts, which can be seen by the rather symmetric shape of the correlation functions. The model needs a specific mechanism to generate the leading relationship of financial debt to nonfinancial debt.

On the whole, the model can reasonably replicate the empirical correlations of

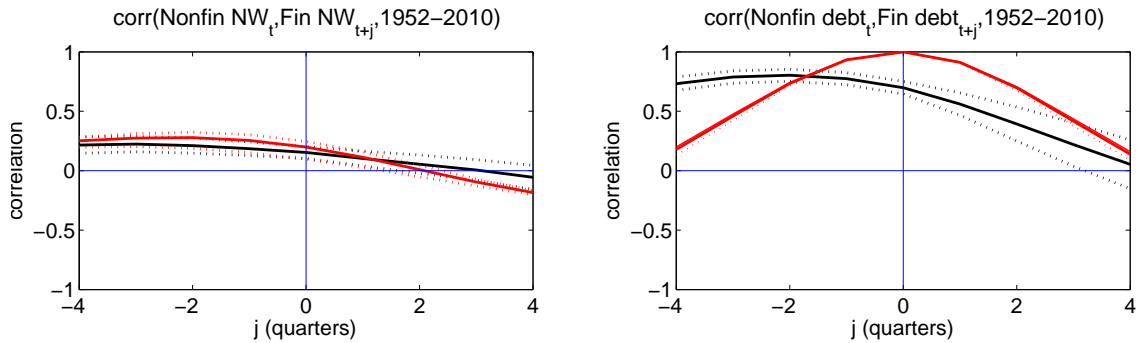


FIGURE 3.15: Empirical (*black lines*) and theoretical (*red lines*) cross-correlations of (i) aggregate net worths (equity capital) (left panel) and (ii) aggregate debts (right panel) of financial and non-financial sectors. The empirical results, computed with aggregate balance sheet data between 1952 and 2010, are the same as those reported in this chapter. The solid red line is the mean theoretical correlations implied by the parameter estimates of the model. The dotted blue lines are the 10% and 90% posterior intervals.

the net worth and debt between financial and nonfinancial sectors.

### 3.6 Chapter Conclusion

In this chapter, I empirically show that a financial sector with more equity capital and less debt predicts a nonfinancial sector with the same features in the United States. Motivated by this empirical fact, I investigate a macro general equilibrium model featuring aggregate balance sheets which have clear implications for the debt level and equity capital of *both* sectors. In particular, I estimate and study a macro model with “loanable funds” framework which introduces a double moral hazard problem in the financial intermediation process. I have three major results. First, I find that financial frictions modeled under this framework give rise to a shock transmission mechanism quantitatively different from the conventional modeling assumption of convex investment adjustment costs. Specifically, financial equity capital plays an important role in determining the depth of declines and the speed of rebound from

the troughs for real variables such as investment and GDP. Second, I find that shocks to the financial intermediation process create persistent recessions, and that these shocks explain a modest amount of the variation in investment. Last but not least, the model is also able to replicate many of the empirical cross-correlations of the equity capital and debt level between the two sectors.

An extension of this chapter is to modify the current lending mechanism of banks so as to make the model explain the empirical correlations better. It also will be interesting to estimate the model taking into account the change in regulations in the financial markets since the 1980s. I will leave both proposals for future research.

Table 3.1: Cross-correlations of the aggregate net worth (equity capital) and the aggregate debt of financial and non-financial sectors

j =	-4	-3	-2	-1	0	+1	+2	+3	+4
	Time period: 1952Q1: 2010Q4								
corr(Non-fin NW <sub>t</sub> , Fin NW <sub>t+j</sub> )	<b>0.30</b>	<b>0.28</b>	<b>0.24</b>	<b>0.17</b>	<b>0.10</b>	0.03	-0.03	-0.08	-0.14
corr(Non-fin debt <sub>t</sub> , Fin debt <sub>t+j</sub> )	<b>0.69</b>	<b>0.76</b>	<b>0.79</b>	<b>0.78</b>	<b>0.73</b>	<b>0.60</b>	<b>0.44</b>	<b>0.27</b>	0.10
	Time period: 1952Q1: 1983Q4								
corr(Non-fin NW <sub>t</sub> , Fin NW <sub>t+j</sub> )	<b>0.74</b>	<b>0.72</b>	<b>0.63</b>	<b>0.44</b>	<b>0.28</b>	0.12	0.01	-0.16	-0.29
corr(Non-fin debt <sub>t</sub> , Fin debt <sub>t+j</sub> )	<b>0.59</b>	<b>0.70</b>	<b>0.75</b>	<b>0.73</b>	<b>0.66</b>	<b>0.50</b>	<b>0.32</b>	0.14	-0.04
	Time period: 1984Q1: 2010Q4								
corr(Non-fin NW <sub>t</sub> , Fin NW <sub>t+j</sub> )	<b>0.26</b>	<b>0.25</b>	<b>0.20</b>	<b>0.15</b>	0.09	0.04	-0.01	-0.04	-0.09
corr(Non-fin debt <sub>t</sub> , Fin debt <sub>t+j</sub> )	<b>0.67</b>	<b>0.73</b>	<b>0.77</b>	<b>0.78</b>	<b>0.76</b>	<b>0.63</b>	<b>0.47</b>	0.28	0.10

Notes:

- Each data series is seasonally-adjusted, and is expressed in logarithm and in real term before the HP-filter is applied. Numbers in **bold** type reflect significance at five percent level.
- Data source: Flow of Funds Accounts, Federal Reserve Board.
- Notation: Fin NW = financial net worth; Non-fin NW = nonfinancial net worth; Fin debt = financial debt; Non-fin debt = nonfinancial debt



Table 3.2: Timeline of the model economy

1. Aggregate macro shocks are realized
2. Intermediate goods are produced with capital and labor services as inputs; final goods are produced with intermediate goods
3. Household deposit savings in banks, who use these funds as well as their own net worth to financial entrepreneurial projects
4. Entrepreneurs choose to be hardworking or not; bankers choose their intensity of monitoring on entrepreneurs
5. Successful projects return  $\tilde{R}_t i_t$  units of new capital, shared between the three agents according to terms of financial contract; failed projects return nothing
6. Exiting agents consumer their net worth, surviving agents with successful projects save their return by buying physical capital
7. All markets close

Table 3.3: Prior and posterior distribution of structural parameters

Estimated Parameter		Prior distribution			Posterior distribution		
		Distr.	Mean	St. Dev	Mean	5%	95%
$\alpha$	Capital share in production fn	Normal	0.3	0.05	0.17	0.15	0.20
$100 \left( \frac{1}{\beta} - 1 \right)$	Discount factor	Gamma	0.25	0.1	0.62	0.59	0.66
$\nu$	Power utility for leisure	Normal	2	0.75	1.42	1.37	1.46
$\psi$	Elasticity of capital utilization adj cost	Beta	0.5	0.15	0.49	0.46	0.52
$\phi_p$	1 + ratio of fixed costs to SS output	Normal	1.25	0.125	1.57	1.54	1.59
$\iota_p$	Price indexation	Beta	0.5	0.15	0.09	0.06	0.13
$\iota_w$	Wage indexation	Beta	0.5	0.15	0.15	0.12	0.19
$\lambda$	Consumption habits	Beta	0.7	0.15	0.46	0.42	0.54
$100 (\pi_{ss} - 1)$	Steady state inflation rate	Gamma	0.625	0.1	0.51	0.44	0.55
$\frac{b_{ss}}{\tilde{R}_{ss}}$	SS firm private benefit/SS project return	Normal	0.15	0.02	0.14	0.12	0.17
$\chi$	Monitoring intensity factor	Normal	10	1	9.99	9.96	10.01
$\rho_r$	Interest rate smoothing	Beta	0.75	0.1	0.60	0.57	0.62
$\rho_y$	Response to output dev	Normal	0.12	0.05	0.00	0.00	0.00
$\rho_\pi$	Response to inflation dev	Normal	1.5	0.25	1.43	1.36	1.51
$\rho_a$	Persistence of TFP shock	Beta	0.5	0.2	0.99	0.98	0.99
$\rho_g$	Persistence of demand shock	Beta	0.5	0.2	0.99	0.98	0.99
$\rho_q$	Persistence of inv. return shock	Beta	0.5	0.2	0.93	0.92	0.94
$\rho_r$	Persistence of mon. pol shock	Beta	0.5	0.2	0.02	0.01	0.03
$\rho_{nb}$	Persistence of bank capital shock	Beta	0.5	0.2	0.98	0.97	0.99
$\rho_{ne}$	Persistence of firm capital shock	Beta	0.5	0.2	0.74	0.72	0.76
$\rho_p$	Persistence of price markup shock	Beta	0.5	0.2	0.82	0.78	0.84
$\rho_w$	Persistence of wage markup shock	Beta	0.5	0.2	0.87	0.84	0.90
$\theta_p$	M.A. process of price markup	Beta	0.5	0.2	0.62	0.56	0.65
$\theta_w$	M.A. process of wage markup	Beta	0.5	0.2	0.44	0.39	0.51
$\sigma_a$	Volatility of TFP shock	IG	0.5	2	0.98	0.92	1.04
$\sigma_g$	Volatility of demand shock	IG	0.5	2	0.61	0.54	0.64
$\sigma_q$	Volatility of inv. return shock	IG	0.5	2	1.26	1.21	1.30
$\sigma_r$	Volatility of mon. pol shock	IG	0.5	2	0.31	0.29	0.32
$\sigma_{nb}$	Volatility of bank capital shock	IG	0.5	2	4.51	4.44	4.57
$\sigma_{ne}$	Volatility of firm capital shock	IG	0.5	2	2.10	2.06	2.15
$\sigma_p$	Volatility of price markup shock	IG	0.5	2	0.22	0.20	0.24
$\sigma_w$	Volatility of wage markup shock	IG	0.5	2	0.22	0.20	0.24

# 4

## Conclusion

Motivated by the recent financial crisis which highlights the importance of financial intermediation, I focus on studying the quantitative relationship between business cycles and financial intermediation shocks. Financial intermediation is indeed important to the real economy: shocks to the intermediation process can create persistent and deep recessions, and the intermediation process implies a significantly different transmission mechanism of traditional macroeconomic shocks.

### 4.1 Quantitative importance of funding liquidity shocks

The vector-autoregression (VAR) results in chapter 2 reveal that funding liquidity shocks are important in generating business cycles. A one percentage-point (p.p) adverse *TED* shock leads to contractionary effects lasting for over twenty months. Impulse responses of industrial production, personal consumption and the federal funds rate (which fall) and the unemployment rate (which rises) are all hump-shaped. At the recessionary trough, industrial production contracts by 1.5 percent, consumption falls by 0.3 percent, the unemployment rate rises by 0.3 percentage points, and the federal funds rate drops by 0.6 percentage points. Interestingly, the structural *TED*

shock is a leading indicator of common financial variables, an example being that the structural *TED* shock is correlated with the leads of the implied volatility index (*VXO*) of the stock market for at least five months.

Following the factor model approach in the empirical finance literature, I also show that the excess returns of firms are impacted by funding liquidity shocks. The major result is that the returns of portfolios composed of small firms (or “small caps”) are more negatively impacted relative to those of large firms. This is in line with predictions from the theoretical literature that small firms face higher agency costs for external finance, implying that they are hit worse by deteriorating credit conditions. There is also evidence that funding liquidity shock as a “risk factor” is priced in the cross-section of equity returns.

There is also a quantitatively important relationship between funding and market liquidity. Adopting the market liquidity measure introduced by Pastor and Stambaugh (2003), I find that market and funding liquidity are contemporaneously and dynamically correlated. By augmenting my baseline VAR model with the market liquidity measure, I find that an adverse funding liquidity shock negatively impacts market liquidity for eight months, whereas an adverse market liquidity shock reduces funding liquidity for two months. The results are indeed consistent with the prediction of the liquidity spiral model proposed in Brunnermeier and Pedersen (2009).

## 4.2 Quantitative importance of balance sheet frictions and shocks

In chapter 3, I first demonstrate the empirical fact that the health of the financial sector is a leading indicator of the health of the nonfinancial sector. Specifically, a “stronger” financial sector with more equity capital (or “net worth”) and less debt similarly predicts a “stronger” nonfinancial sector, that is, a nonfinancial sector with higher net worth and less debt. This empirical fact illustrates the importance of financial balance sheets, and a potential important interaction between financial and

nonfinancial balance sheets.

I go on to build a general equilibrium macro model with a double moral hazard framework following Holmstrom and Tirole (1997), Meh and Moran (2010) and Christensen et al. (2011) and quantitatively assess this model. Here is the summary of results:

1. Financial intermediation shocks create persistent recessions. A one-percent drop in bank equity capital leads to a maximum fall of 0.2 percent in investment and 0.02 percent fall in GDP, whereas the same drop in firm equity capital leads to a maximum decline of 0.5 percent in investment and 0.1 percent in GDP. A one-percent drop in returns to investment projects (which is interpreted as a negative shock to the productivity of capital goods) generates a much deeper recession: investment falls 5 percent and GDP falls 0.7 percent at the trough. Investment and output display hump-shaped declines to all of these shocks, where the hump-shape reflects the dynamics of both financial and nonfinancial equity capital, highlighting the importance of balance sheets in the transmission of financial shocks.
2. In the long run, financial intermediation shocks explain little of the variation in GDP, a modest amount of the variation (20 percent) in investment, and more than 50 percent of the variation in debt levels. Moreover, the explanatory power of financial shocks for variation in investment is fairly constant across horizons. Interestingly, financial shocks have increasing explanatory power for the variation in inflation as the forecasting horizon lengthens, and explain about 40 percent of the variation in the long run.
3. Financial frictions modeled using the loanable funds framework give rise to a shock transmission mechanism quantitatively different from the conventional

dynamics that arise in DSGE models with convex investment adjustment costs. I consider a one-percent negative total factor productivity shock in both models. My estimated model delivers deeper but somewhat less persistent declines in investment and GDP than conventional models. Such a response is closely associated with the response of the aggregate financial equity capital, the evolution of which is governed by the decline of banks retained earnings, which are in turn determined by other factors including a “looser” bank-firm relationship induced by the negative productivity shock. The “bank capital channel” is quantitatively significant in the current context.

4. The model is able to replicate the lead-lag relationship of net worths between the two sectors. The model predicts the strong contemporaneous correlation of debt levels, but does not generate the slight asymmetry in the lead-lag relationship in the dynamic correlations of debt levels.

### 4.3 Future research

More future research can be carried out to study the importance of financial frictions and financial shocks. Here I list two possible directions.

1. Firm size, balance sheet and funding liquidity

An interesting future research is to study financial data at the firm level. It is interesting to establish quantitative relationships between firms which are vulnerable to credit conditions and their corresponding balance sheet characteristics, including size, leverage, cash-flow and other variables. Moreover, data analysis at the micro level needs to be done to improve our understanding on the interactive dynamics of the balance sheet of banks and the balance sheet of firms.

## 2. Loanable funds model, shock transmission and policy response

The loanable funds framework adopted in chapter 3 is useful to study problems associated with balance sheet frictions. First, it is interesting to compare standard shock transmission mechanism between various modeling assumptions, including the financial accelerator model in Bernanke et al. (1999), the bank's balance sheet model in Gertler and Karadi (2011), and the current loanable funds model. It will also be interesting to use the loanable funds model to distinguish which of the two moral hazard problem is more important in the economy. Moreover, the loanable funds set-up is useful to study optimal policy response, with Christensen et al. (2011) pioneering in this area.

This dissertation has hopefully furthered our understanding in the quantitative relationship between financial intermediation shocks and the economy in the United States. Obviously, macroeconomists need to do more work to gain deeper understanding in our increasingly complex financial system and to devise better policies to alleviate the impact of future financial crises.

# Appendix A

## Appendix to Chapter 2

### Items used to construct “aggregate debt” of each financial institution from the Flow of Funds Accounts

1. US-chartered commercial banks

Federal funds and security repurchase agreements (net), net interbank transactions, credit market instruments, checkable deposits, small time and savings deposits, large time deposits

2. Savings institutions

Federal funds and security repurchase agreements (net), total deposits, credit market instruments

3. Credit Unions

Total shares/ deposits, FHLB advances

4. Funding corporations

Credit market instruments

5. Life insurance companies

Federal funds and security repurchase agreements (net)

6. Security brokers and dealers

Federal funds and security repurchase agreements (net), security credit, credit market instruments

7. Finance companies

Credit market instruments

8. Issuers of asset-backed securities

Credit market instruments



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# Biography

Ching-Wai (Jeremy) Chiu was born in Hong Kong in 1981. He received his B.A. in Translation (first class of honors) from the Chinese University of Hong Kong in 2005, and his M.A. in Economics from the University of British Columbia in 2006. He also earned an M.A. in Economics from Duke University in 2008. He is expected to obtain his Ph.D. in Economics from Duke University in May 2012.

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