Uncertainty and the Shadow Banking Crisis: A Structural Estimation

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Abstract

Shadow banks play an important role in the modern financial system and are arguably the source of key vulnerabilities leading to the 2007-2009 financial crisis. In this paper, I develop a quantitative framework with endogenous bank default and aggregate uncertainty fluctuation to study the dynamics of shadow banking. I argue that the increase in asset return uncertainty during the crisis results in the spread spike, making it more costly for shadow banks to roll over their debt in the short-term debt market. As a result, these banks are forced to deleverage, leading to a decrease in the credit supply. The model is estimated using a bank-level dataset of shadow banks in the United States. The findings show that uncertainty shocks are able to generate statistics and pathways of leverage, spread, and assets which closely match those observed in the data. Maturity mismatch and asset firesales amplify the impact of the uncertainty shocks. First moment shocks alone can not reproduce the large interbank spread spike, dramatic deleveraging and contraction of the US shadow banking sector during the crisis. The model also allows for policy experiments. I analyze how unconventional monetary policies can help to counter the rise in the interbank spread, thus stabilizing the credit supply. Taking into consideration of bank moral hazard, I find that government bailout might be counterproductive as it might result in more aggressive risk-taking of shadow banks.

Keywords: Shadow banking, uncertainty, maturity mismatch, fire-sale, unconventional monetary policy, moral hazard

JEL Classification: D81, E32, E44, E50, G18, G20

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1 Introduction

The 2007-2009 financial crisis is distinguished from previous crises by the role played by the shadow banking sector. Shadow banks are financial intermediaries that conduct maturity, credit, and liquidity transformation without explicit access to central bank liquidity or public sector credit guarantees. They play a major role in global finance and are arguably the source of key vulnerabilities leading to the crisis. Different from traditional banks whose funding mainly depends on customer deposits, shadow banks finance their asset purchases primarily by means of collateralized debt with very short maturity, such as repurchase agreements (repo) or asset-backed commercial papers (ABCP). The markets for these financial instruments are typically highly liquid. However, during the recent financial crisis, the initial loss suffered by some of the assets (mainly subprime mortgage-backed security) which serve as collateral in the repo or ABCP transactions, together with the uncertainty surrounding individual exposures to such assets, led financial institutions to largely stop exchanging liquidities in these markets. Interbank spread spiked up and market liquidity shrank dramatically, forcing the shadow banks to deleverage and ultimately resulting in a contraction in the credit supply to the real economy.

This paper explains the increase of interbank spread and the contraction of shadow banking credit supply during the recent recession using a model with endogenous bank default and aggregate uncertainty fluctuation. The increase in bank asset return uncertainty raises the bank default probability, leading to an increase in the interbank market spread[1]. Facing a higher cost of financing, banks are forced to deleverage, thus decreasing the credit supply. Using this framework, I also analyze how unconventional monetary policy (debt guarantees and the Trouble Asset Relief Program) can help to reduce the interbank spread and stimulate supply of credit. Assuming bailout probability is an increasing function of bank sizes, I also show that bank bailouts might worsen moral hazard. Bigger banks might think they are "too big to fail" and would be bailed out by the government with higher probability. Thus they would take excessive risk and act less responsibly.

The contribution of this paper is both empirical and theoretical. Using a comprehensive bank-

[1] Since the major participants in the short-term collateralized debt market are financial institutions, in this paper, I use the term "interbank market" and "short-term collateralized debt market" interchangeably. See Pozsar, Adrian, Ashcraft, and Boesky (2013) for an in-depth analysis about shadow banking and short-term collateralized debt markets.

level dataset, I find that during the 2007-2009 financial crisis, the asset return uncertainty of shadow banks increased by 147%; they deleveraged much more than traditional banks and shrank their asset size by 21%. Moreover, I analyze the change of aggregate leverage of shadow banks from both the "intensive margin" and "extensive margin", where the intensive margin is the leverage change resulting from banks on all asset quantiles take lower leverage. Extensive margin stands for leverage change resulting from the change of bank asset distribution. I find that the "extensive margin" contributed more to the aggregate leverage changes of shadow banks than the "intensive margin". I also find shadow banks depend heavily on short-term funding and tend to choose riskier asset portfolios compared with traditional banks. Surprisingly, to the best of my knowledge, this is the first paper in the literature which document these stylized facts of the U.S. shadow banking industry using a micro-level dataset.

On the theoretical front, I first present a tractable two period framework illustrating the impact of uncertainty on the financing and leverage decisions of shadow banks. I then extend the framework to an infinite horizon model with endogenous bank default and aggregate uncertainty fluctuation. In the model, shadow banks borrow from the interbank market in the form of short-term risky debt and invest in a long-term risky loan. In each period, every bank receives an idiosyncratic shock to its asset return. Depending on the realization of asset return and debt due, each bank decides whether to default, how much new debt to issue and new loans to invest in, and how much long-term asset to firesale (if necessary) to pay its debts due. I assume the idiosyncratic asset return shock is drawn from a log-normal distribution. When the standard deviation of the distribution increases, the bank's asset return becomes riskier and its expected default probability would increase; thus it would be charged a higher interest rate when it borrows from the interbank market. Facing a higher cost of financing and higher probability of costly asset firesales, shadow banks reduce their leverages and decrease their asset sizes.

Using simulated method of moments (SMM), the model parameters are chosen to best fit a wide-ranging set of facts on the U.S. shadow banking industry, such as moments from the distribution of leverage, asset growth, default probability, and dividend payouts. Using the estimated parameters, I document the model's implications for shadow banking dynamics by conducting an event study about the 2007-2009 financial crisis and several counterfactual experiments in the spirit of recent microeconometric analyses. These out-of-sample tests reveal that uncertainty shocks are able to generates statistics and leverage, interest rate spread, and asset pathways that closely match my empirical observations about the U.S. shadow banking industry. In particular, when running the same regressions on the model-generated data, the coefficients estimates for the impact of the asset return uncertainty on shadow bank leverages are quantitatively similar to their empirical counterpart even though they are not targeted in the estimation. I also find that high maturity mismatch and firesale costs amplify the impact of uncertainty shocks. Alternative models with only pure first-moment shocks, without asset firesale costs, or without maturity mismatch, can not rationalize the large spike in the interbank spread, dramatic deleveraging, or contraction in the U.S. shadow banking industry in the recent financial crisis.

This paper contributes to the large literature on the shadow banking crisis. Following Gorton and Metrick (2012), who argue that the panic of 2007-2008 was a run on the short-term collateralized debt market, various studies have emphasized the role played by shadow banking sector in the origin and propagation of the financial turmoil. Pozsar et al. (2013) maintain that the shadow banking sector played a major role in the 2007-2009 financial crisis. Adrian and Shin (2010) argue that due to the limited liability of the short debt contracts of shadow banks, during the crisis, creditors in the interbank market are less willing to roll over their lending, resulting in the procyclicality of financial intermediaries' leverage and credit supply. Chodorow-Reich (2014) argues that the contraction of the credit supply matters more for the decline in output compared with the decrease of credit demand, and interbank market disruption played a crucial role in the decrease in the credit supply. The shocks in these papers are all first-order moment shocks (TFP shocks or Investment quality shocks). Different from these papers, I focus on the impact of uncertainty shock on the financing and leverage decisions of financial intermediaries. Nuno and Thomas (2014) also build a model to analyze the impact of uncertainty shocks on banks' leverage choices. They use log-linear approximations to study how financial frictions amplify shocks near the steady state of the economic system. This would only work if the economy is not knocked too far away from the steady state. Compared with their work, my model characterizes the financial intermediary dynamics in a fully nonlinear manner. Such nonlinearities can generate rich and interesting dynamics. Also, in their model, bank default decisions are not endogenously determined, whereas my model allows for such a possibility.

This paper is complementary to the growing literature on the impact of uncertainty on the real economy, such as Arellano, Bai, and Kehoe (2012a),Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), Christiano, Motto, and Rostagno (2014) and Gilchrist, Sim, and Zakrajsek (2013). All these papers focus on the impact of uncertainty on non-financial firms' choice about investment or employment, whereas I focus on the decisions of financial intermediaries. In these papers, the marginal rate of substitution of financial intermediaries is often implicitly assumed to be equal to that of households or firms. Thus financial intermediaries always act on behalf of the households or firms and their decisions are often not modelled. However, one of the key features of the recent crisis is the disruption of financial intermediation. Without explicitly modelling the behavior of financial institutions, we might not be able to fully understand the cause of this crisis.

Lastly, this paper is also related to the literature concerning interbank markets and unconventional monetary policy, such as Gertler and Kiyotaki (2010). Different from Gertler and Kiyotaki (2010), in my model, the bank's debt is risky and default occurs in equilibrium, whereas in Gertler and Kiyotaki (2010), interbank loans are fully collateralized and there is no default risk in the equilibrium. Moreover, in this strand of literature, crises are often driven by first-order moment shocks such as investment quality shock, while I argue that even if the expected level of asset return shock remains unchanged, an increase in the uncertainty of asset return can result in the freeze of interbank market and the reduction in the supply of credit. Furthermore, I take into account moral hazard behavior of banks by endogenizing the bailout probability as a function of the bank size. Researchers have typically analyzed how credit policy can mitigate a credit crunch ex-post, or investigated the moral hazard of government bailout theoretically. This paper contributes to fill in this gap by developing a quantitative model to assess the interaction between ex-post interventions and the build-up of risk ex-ante in a tractable unified framework.

The paper is organized as follows. In Section 2, I document several stylized facts of the U.S. shadow banking industry. In Section 3, I illustrate the impact of uncertainty on the leverage and financing decisions of shadow banks using a two-period model, laying the theoretical groundwork for further quantitative exploration. In Section 4 and 5, I analyze the shadow banking industry dynamics using an infinite horizon model with endogenous bank default and aggregate uncertainty fluctuation. Concluding remarks are given in Section 6.

2 Empirical Analysis

2.1 Data Source

In this section, I document several stylized facts about the U.S. banking industry. Since Gorton and Metrick (2012), there has been an outpouring of theoretical work on the shadow banking sector but the empirical work is only slowly catching up. I obtain yearly bank-level panel data from the Bankscope database. Bankscope contains comprehensive information on banks across the globe. I choose real estate and mortgage banks, investment banks, micro-financing institutions, securities firms, private banking and asset management companies, investment and trust corporations, finance companies, clearing and custody institutions, and group finance companies in the U.S. as representatives of shadow banks. I also choose commercial banks, savings banks, cooperative banks, and bank holding companies as representatives of traditional banks. Complemented with bank-level data from WorldScope database, the final panel data sample contains 281 shadow banks and 9554 traditional banks for the 1998 to 2013 period, covering 49 states in the U.S. As a robustness check, I also take quarterly aggregated data from the U.S. Flow of Funds Database. The sample periods are from 1990:Q1 to 2013:Q4. [2]

2.2 Stylized Facts

Stylized Fact 1: The Shadow banking sector asset return uncertainty increased in the 2007-2009 recession.

The left panel of Figure 1 illustrates the kernel density of return on asset (ROA)[3] for shadow banks during non-crisis periods and crisis periods. [4] The standard deviation of shadow banks' ROA

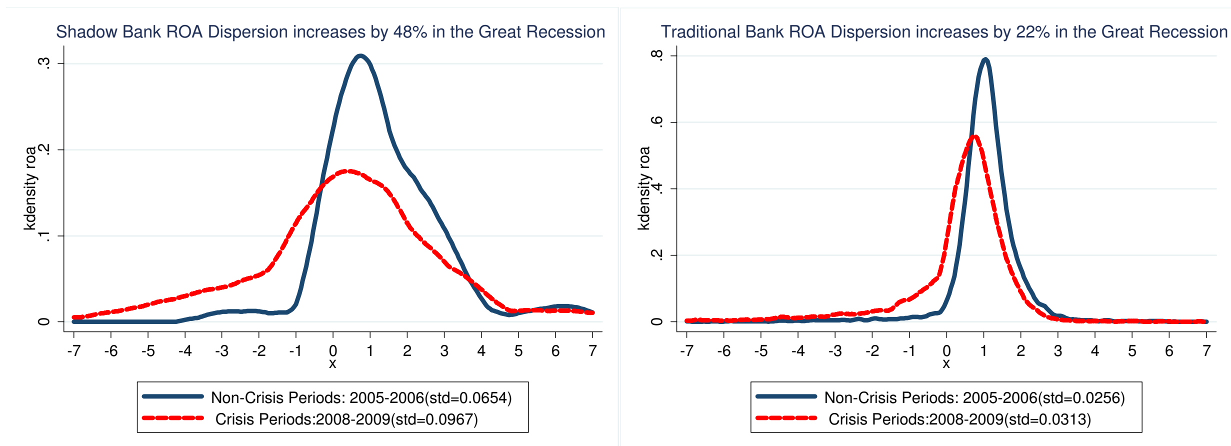
[2]U.S. Flow of Funds only provides aggregated data of different categories of financial institutions. As shown below, one of the disadvantages of aggregate data is that the pattern of the data might be driven by banks in certain asset quantiles in the sample. From a regulatory point of view, the policy prescription will differ if aggregate leverage is driven by large banks rather than a large number of small or mid-size banks.

[3]ROA is bank's return on assets. ROA is often defined as net income divided by total asset. I add interest expense back into net income when performing this calculation.

[4]Following Bloom et al. (2012), non-crisis periods are defined as from the year 2005 to year 2006, whereas crisis periods are defined as from year 2008 to year 2009. According to the NBER the recession began in 12/2007, so 2007 is not a clean "before" or "during" recession year.

increases by 48% during the crisis. To have a clearer idea about the magnitude of the change, I also show the standard deviation change of traditional banks for reference. By comparison, the ROA standard deviation of traditional banks increases by only 22% , less than one-half of that of shadow banks. Explaining the difference between shadow banks and commercial banks is beyond the scope of this paper. All the empirical analyses for traditional banks are only shown for comparison and to provide a better understanding of shadow banks.

Figure 1: ROA Dispersion of Banks



Notes: Shadow banks are defined as real estate and mortgage banks, investment banks, micro-financing institutions, securities firms, private banking and asset management companies, investment and trust corporations, finance companies, clearing and custody institutions, and group finance companies. Traditional banks are defined as commercial banks, savings banks, cooperative banks and bank holding companies. The whole sample contains 281 shadow banks and 9554 traditional banks for the 1998 to 2013 period, covering 49 states in the U.S. ROA is the bank's return on assets and is defined as net income divided by total assets. Interest expense is added back into net income when performing this calculation. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009. According to the NBER, the recession began in 12/2007, so 2007 is not a clean "before" or "during" recession year.

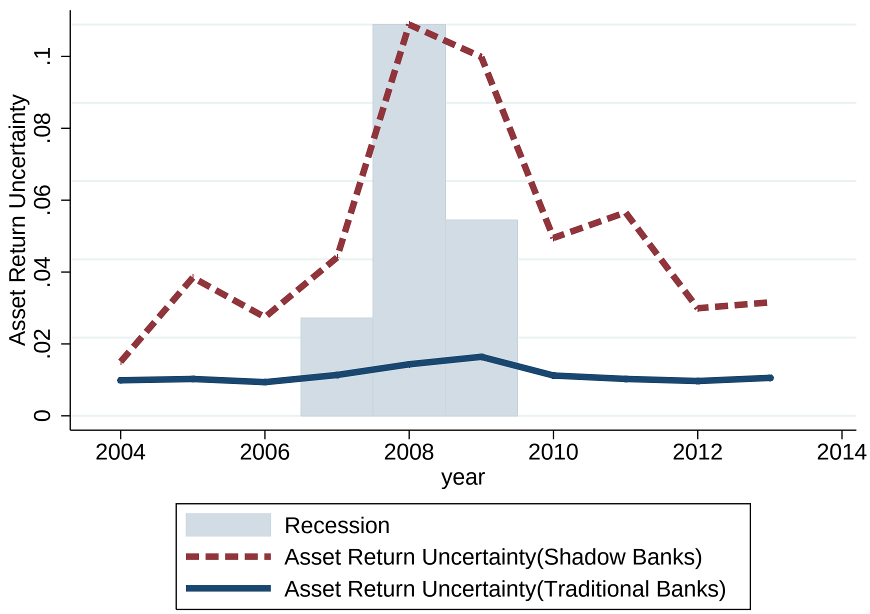
To measure the uncertainty of banks' ROA, I follow a standard approach as Foster, Haltiwanger, and Krizan (2001). I assume the bank gross return on asset follows an AR(1) process. To ease notation, I define the bank gross asset return rate $groa_{it} = 1 + ROA_{it}$. I then fit the data $\{log(groa_{it})\}_{i=1,...,N,\, t=1998,...,2013}$ [5] into an AR(1) process, controlling for time and bank-level fixed effects:

$$log\left(groa_{it}\right) = \rho log\left(groa_{it-1}\right) + \lambda_t + \mu_i + X_{it} + \epsilon_{it}, \tag{1}$$

where λ_t is the year fixed effect (controlling for cyclical shocks), μ_i is bank-level fixed effect

[5] N is the number of banks in our dataset

Figure 2: Bank Return on Asset Uncertainty



Notes: Return on asset uncertainty is defined as the standard deviation of the residual term after fitting the panel data of individual bank gross ROA into into an AR(1) process, controlling for time and bank level fixed effects and other bank level heterogeneity. The classification of shadow banks and traditional banks is shown in the appendix. The grey bar is the NBER recession. Since we only have yearly data, the recession periods are plotted such that the length of grey bar represent how much fraction of any particular year is defined as recession period according to NBER. One quarter of 2007 is in recession, the whole 2008 and two quarters of 2009 are in recession.

(controlling for bank-level differences). X_{it} are other control variables including bank size, asset riskiness, etc. The uncertainty on bank asset return σ_t is then defined as the cross-sectional dispersion of the residual ϵ_{it}. The evolution of σ_t is then shown in the Figure 2. The figure shows that the shadow bank return uncertainty increases from 0.044 to 0.109 during the 2007-2009 recessions. The percentage change is 147%, much higher than that of the traditional bank asset return uncertainty, which is only 56%[6].

Stylized Fact 2: Interbank market spreads spiked up during the 2007-2009 financial crisis.

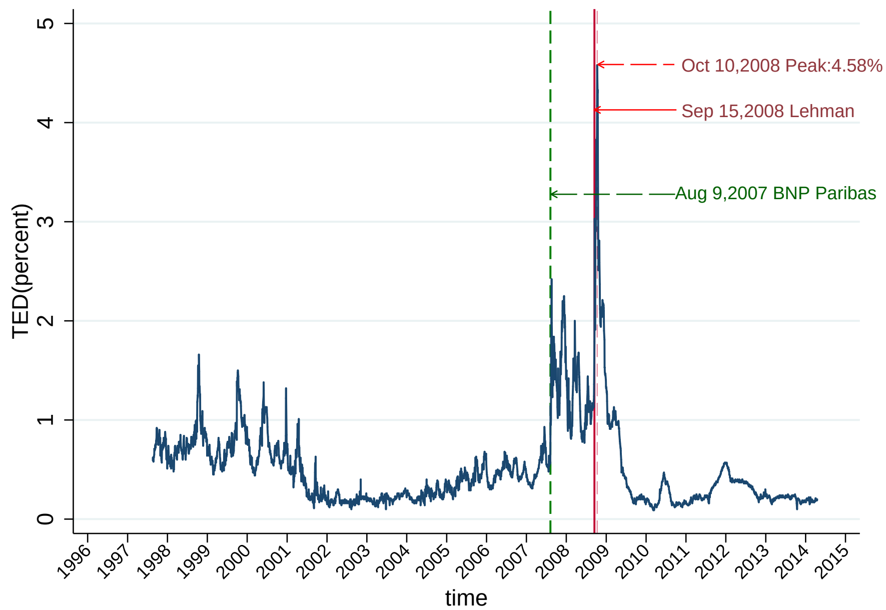
I use the TED spread as the indicator of the interbank market spread. The TED spread is the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"). It is a commonly used indicator of perceived credit risk in the economy. An increase in the TED spread is a sign that lenders believe the risk of default on interbank loans (also known as counterparty risk) is increasing and thus they charge a higher interest rate when lending in the interbank market. I obtain the daily TED spread data from the FRED database and plot it in Figure 3. The average TED spread was approximately 0.6% from the fourth quarter of 2001 until August of 2007 when BNP Paribas's suspended the valuation of three of its hedge funds related to the U.S. asset-backed securities. The market uncertainty increased dramatically and the average interbank credit spread increased sharply to 2.5%. The TED spread continued to increase following Lehman Brothers' bankruptcy on September 15, 2008 and reached its peak of 4.58% on October 10, 2008, 25 days after the bankruptcy of Lehman.

Stylized Fact 3: The shadow banking sector asset size shrank by 21% during the 2007-2009 financial crisis.

I obtain the bank-level data from the Bankscope database and WorldScope database and calculate the total assets for the U.S. shadow banking sector. The dashed line in Figure 4 depicts the total

[6] One explanation for this is illustrated in stylized fact 4: traditional banks and shadow banks has very different asset composition and funding structure. The exposure to risky asset is much higher for shadow banks. And therefore their asset return uncertainty is much more volatile compared with traditional banks.

Figure 3: TED Spread



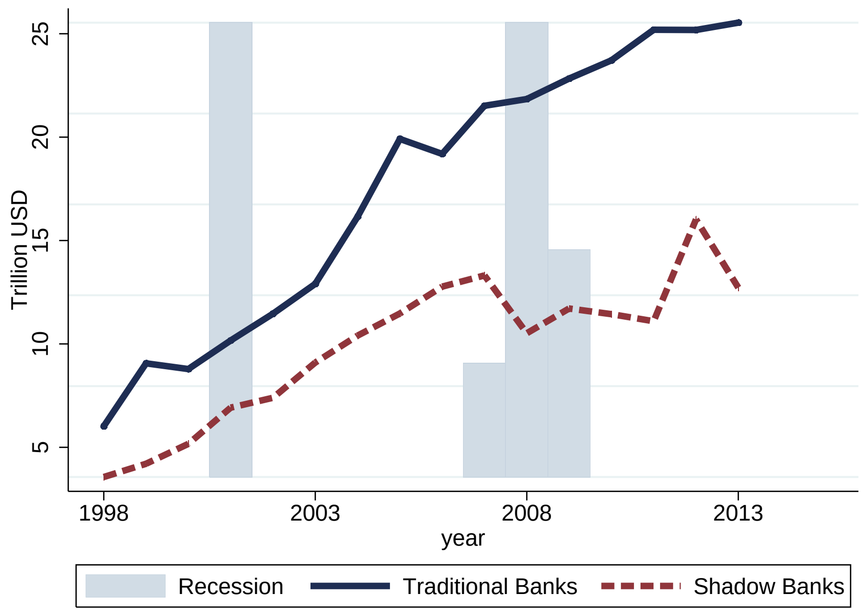
Notes: This figure depicts the change of interbank market spread based on daily TED spread data obtained from the FRED Database. TED spread is the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"). It is a commonly used indicator of perceived credit risk in the economy.

asset of shadow banks. [7] The units of the Y-axis are trillions of 2005 US dollars. Figure 4 shows that the shadow banking sector has a positive trend in assets. During the 2007-2009 recession, the shadow banking sector asset size shrank by 21%. By comparison, traditional banking sector asset size increased during 2007-2009 crisis, although with a lower growth rate.

Since assets and liabilities of different financial institutions are not netted out during the aggregation. Simply adding up the assets and liabilities of different banks might lead to double counting of asset cross positions. To mitigate this concern, I further check the aggregate asset data from the US Flow of Funds. I take commercial banks and credit unions as the representative of traditional banks, security brokers and dealers, and finance companies as representative of shadow banks. The results are shown in Figure 5. The shaded area is the NBER recession. The units of the Y-axis are Trillions of 2005 US dollars. Similar to Figure 4, shadow banks are much negatively affected: Security brokers and dealers' asset size alone shrank by over 2 trillions, larger than total shrinkage of commercial banks and credit unions combined. From Figure 4 and Figure 5, we can

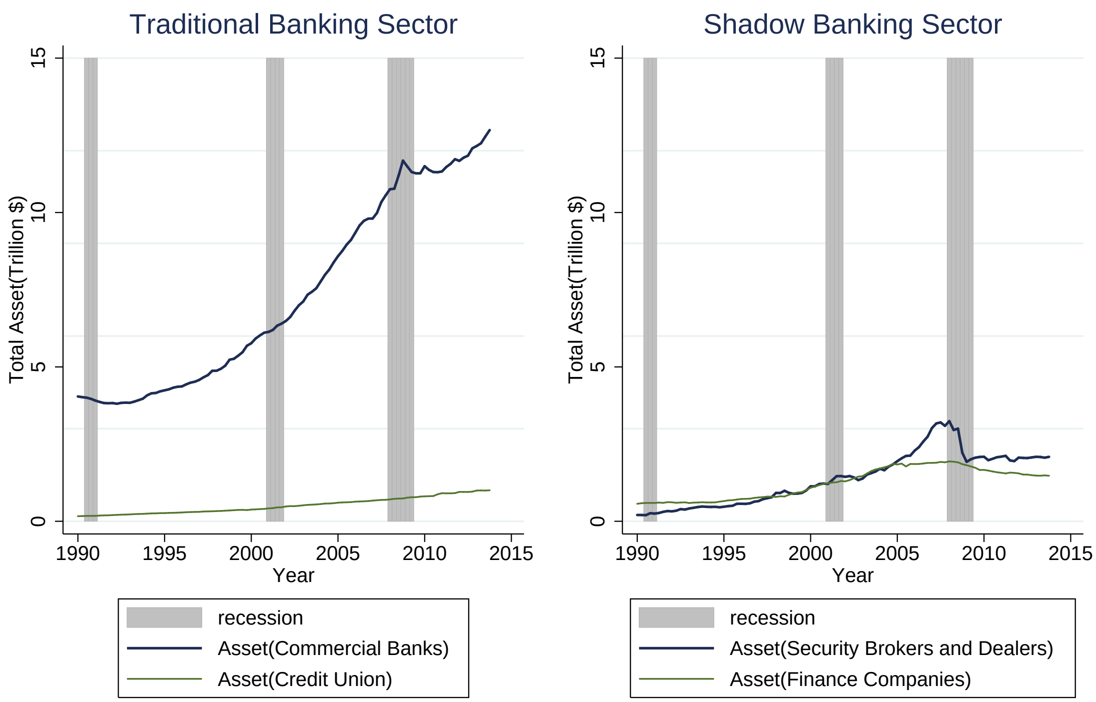
[7] Traditional Banks also engage in shadow banking activities. They set up conduits and the activity of these conduit are not recorded on their balance sheet. In the empirical analysis of this paper, I only focus on the shadow banking activities observable in the data.

Figure 4: Total Asset of Banks(BankScope and WorldScope Micro-level Data)



Notes: This figure depicts the change in total asset size of the U.S. traditional and shadow banking sector respectively using bank-level dataset from BankScope and WorldScope database. The classification of shadow banks and traditional banks is shown in the appendix. The data is winsorized at 2 percent level. The grey bar is the NBER recession. Since we only have yearly data, the recession periods are plotted such that the length of grey bar represent how much fraction of any particular year is defined as recession period according to NBER.

Figure 5: Total Asset(US Flow of Fund Aggregate Data)



Notes: This figure depicts the change in total asset size of the U.S. traditional and shadow banking sector respectively using the U.S Flow of Funds quarterly aggregate data. Here I take commercial banks and credit unions as the representative of traditional banks, security brokers and dealers and finance companies as representative of shadow banks. The grey area are quarters in recession.

reach the conclusion that the assets of the shadow banking sector shrank during the 2007-2009 recession and the total banking credit shrinkage mainly comes from the contraction of the shadow banking sector.

Stylized Fact 4: The leverage of shadow banks decreased during the 2007-2009 financial crisis. The extensive margin contributed more than the intensive margin to the aggregate leverage change of shadow banks. Bigger banks tend to have higher leverage.

I calculate the aggregate leverage for shadow banks and traditional banks in non-crisis periods and crisis periods, respectively. The leverage is defined as total liabilities divided by total assets. The results are shown in Table 1. The leverage of shadow banks decreased by 0.074. Traditional bank leverage decreased by merely 0.005. To get a clearer idea about the contributing factor of the aggregate leverage change, I decompose aggregated leverage change into the intensive margin and extensive margin. I divide the bank asset size into 10 asset quantiles. At each asset quantile i, banks have a mean asset size k_i. Denote b_{it} as the mean debt held by banks at asset quantile i at period t, and ω_{it} as the measure of banks within asset quantile i at period t. B_t and K_t are aggregated liabilities and assets, respectively. Then the change in aggregate leverage $\triangle L_t \equiv \triangle \frac{B_t}{K_t} = \frac{B_t}{K_t} - \frac{B_{t-1}}{K_{t-1}} = \frac{\sum \omega_{it} b_{it}}{\sum \omega_{it} k_i} - \frac{\sum \omega_{it-1} b_{it-1}}{\sum \omega_{it-1} k_i}$. I denote the total assets of banks within asset quantile i as a fraction of aggregated assets as $\alpha_{it} \equiv \frac{\omega_{it} k_i}{\sum \omega_{it} k_i} = \frac{\omega_{it} k_i}{K_{it}}$, and the leverage of banks at asset quantile i at time t as $l_{it} \equiv \frac{b_{it}}{k_i}$. Then $\triangle L_t = \sum \alpha_{it} l_{it} - \sum \alpha_{it-1} l_{it-1} = \sum (l_{it} - l_{it-1}) \alpha_{it-1} + \sum (\alpha_{it} - \alpha_{it-1}) l_{it}$. The first term of the equation captures the intensive margin leverage change: the change in aggregate leverage resulting from bank of all asset quantiles take a lower leverage, given a fixed asset distribution. The second term captures the extensive margin: the change of aggregate leverage resulting from the change of bank's asset distribution. The contribution of each margin is reported in Table 1. The extensive and intensive margins contribute to 61% and 39% of the aggregate leverage change of shadow banks respectively. By comparison, the change of aggregate leverage change of traditional banks almost exclusively comes from the intensive margin.

Figure 6 illustrates the leverage for different asset quantiles of banks using the bank-level dataset. Shadow banks of different asset sizes on average choose a lower leverage during the crisis. This captures the intensive margin. Figure 6 also shows that bigger banks tend to have higher leverage;

this positive correlation is robust for both type of banks. This result is consistent with Adrian and Shin (2010). As Adrian and Shin (2010) argued, if banks target a leverage ratio, the optimal leverage will not increase with asset values. But if banks target a level of risk exposure, leverage will be positively correlated with assets values. My finding supports the conjecture that banks target a certain level of risk exposure.

Figure 7 depicts the change of bank asset distribution. Shadow banks choose smaller asset size and the whole asset distribution becomes more skewed toward the lower asset level region. This captures the extensive margin in the sense that banks jump across their asset quantile bins[8].

Table 1: Leverage Change Decomposition

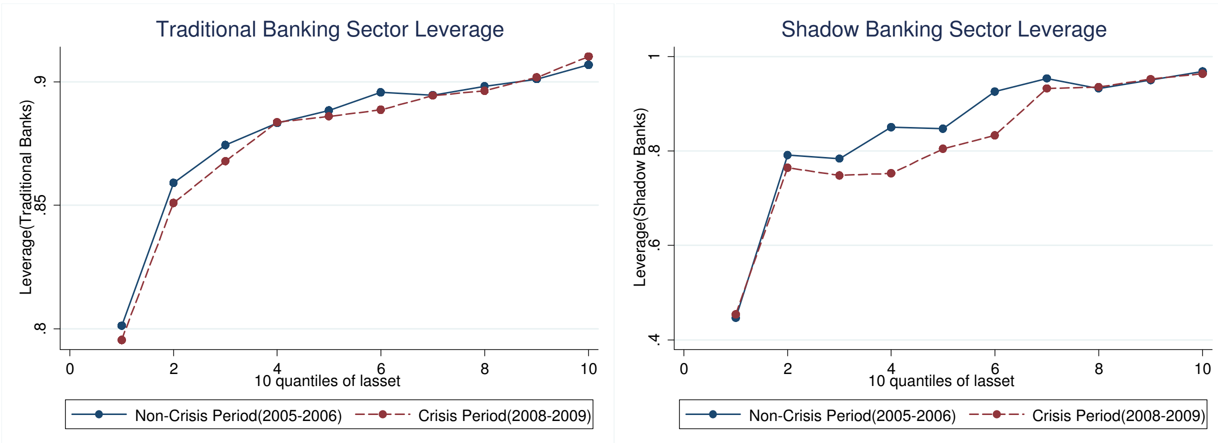
Shadow Banks	non-crisis periods	crisis periods	leverage change
Average leverage	0.969	0.895	-0.074
Extensive margin		61%	
Intensive margin		39%	
Traditional Banks	non-crisis periods	crisis periods	leverage change
Average leverage	0.896	0.891	-0.005
Extensive margin		7%	
Intensive margin		93%	

Notes: The extensive margin is defined as the change of aggregate leverage resulting from change of bank's asset distribution. The intensive margin is defined as the change of aggregate leverage resulting from bank across all asset quantiles choose a different leverage ratio, given a fixed asset distribution. The data is winsorized at 2 percent level. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009.

To further analyze the relationship between asset return uncertainty and bank leverage, I also report the regression of leverage on the uncertainty of the bank asset return, controlling for bank asset size, profitability (gross asset return rate), and risky asset exposure (i.e., fraction of derivative and other securities in total assets) for both types of banks in Tables 2 and 3. To mitigate the concern about reverse causality, I lag all explanatory variables by one year. In 2004, the Securities and Exchange Commission (SEC) deregulated the minimum capital requirement for investment banks, freeing leverage ratios from direct regulatory constraint. I therefore include an interaction term between the explanatory variable and an indicator variable that takes the value of one for the observations after 2004 to see whether the leverage choices of shadow banks after 2004 is

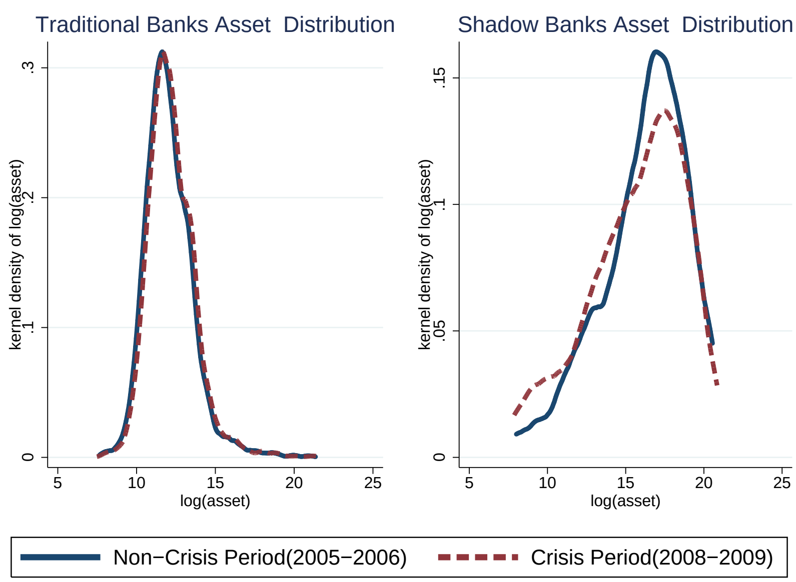
[8]There is actually another extensive margin of deleveraging resulting from the banks which exit the market. Yet I find that this margin's contribution is too small to be relevant for the fluctuation in aggregate leverage. The major contraction of credit supply results from the fact that banks remaining on the market provided less credit, not because a few banks such as Lehman Brothers went bankruptcy.

Figure 6: Leverage over Asset Quantiles



Notes: This figure depicts the change of leverage ratio of shadow banks and traditional banks over ten asset quantiles. Leverage ratio is defined as total debt to total asset ratio within each asset quantile. The data is winsorized at 2 percent level. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009.

Figure 7: Asset Distribution



Notes: This figure depicts the change of asset distribution of shadow banks and traditional banks. The measure of small and medium size shadow banks increases during the recession whereas the distribution of traditional banks barely changes. The data is winsorized at 2 percent level. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009.

significantly different from those in earlier years. The first four regressions control for both bank-level fixed effects and time fixed effects, while regression 5 to 8 include asset uncertainty. Since the measure of asset uncertainty only has time-variation and no cross-sectional variation, I drop the time fixed effect in these regressions to avoid multicollinearity. The regression results show that asset size always has a positive impact on the leverage choices of shadow banks. One explanation for this is equity issuance is much more costly than debt issuance. As documented in Adrian and Shin (2010), equity issuance is very sticky. Banks expand their assets mainly through debt issuance. Hence asset size and leverage generically change simultaneously in the same direction. The second takeaway from the regression is that the uncertainty of bank asset return has a negative impact on leverage after 2004. As shown in regressions 6 and 8, the coefficients on asset return uncertainty are both significantly negative for both types of banks. I also find that the profitability of banks has a significantly negative impact on a bank's leverage. This is consistent with the findings of Kalemli-Ozcan, Sorensen, and Yesiltas (2011). As profitability is a source of internal financing, higher profitability means a lower need for external debt financing. I also include the interaction term between uncertainty and asset level to check whether the impact of uncertainty on leverage is different over banks of different asset sizes. Since the coefficients of the interaction term are insignificant. For brevity, I do not report them here.

Stylized Fact 5: Shadow banks are very different in terms of both funding structure and exposure to risky assets compared with traditional banks. Shadow banks heavily depend on short-term funding, while traditional banks mainly depend on customer deposits. Shadow banks typically invest more than 60% of their assets on risky financial products, whereas traditional banks invest less than 30% of their assets on such products on average.

Figure 8 illustrates the funding structures of shadow banks and traditional banks. The unit is 2005 trillion USD. Traditional banks highly depend on customer deposits which account for over 60% of traditional banks liability for almost all years in the sample. By comparison, shadow banks highly depend on funds provided by the short-term collateralized debt market. Before 2008, short-term funding accounts for over 70% of the funding for shadow banks. And since 2007, the funding provided by the short-term collateralized market has declined, and shadow banks gradually switched to rely more on long-term funding after 2011. Customer deposit has always been an almost

Table 2: Regression: Leverage Decision of Shadow Banks

VARIABLES	(1) $leverage_{it}$	(2) $leverage_{it}$	(3) $leverage_{it}$	(4) $leverage_{it}$	(5) $leverage_{it}$	(6) $leverage_{it}$	(7) $leverage_{it}$	(8) $leverage_{it}$
$log(asset_{it-1})$	0.0450***	0.0511***	0.0288***	0.0376***	0.0236***	0.0312***	0.0174***	0.0266***
	(0.0037)	(0.0038)	(0.0055)	(0.0054)	(0.0046)	(0.0053)	(0.0043)	(0.0051)
$log(asset_{it-1}) * 1_{(year>2004)}$		-0.0099***		-0.0129***		-0.0044***		-0.0039***
		(0.0016)		(0.0019)		(0.0011)		(0.0011)
$log(gross\ asset\ return_{it-1})$			-0.1173***	0.0045	-0.1081***	0.0478	-0.0993***	0.0245
			(0.0294)	(0.0460)	(0.0292)	(0.0471)	(0.0276)	(0.0430)
$log(gross\ asset\ return_{it-1}) * 1_{(year>2004)}$				-0.2281***		-0.2780***		-0.2430***
				(0.0595)		(0.0604)		(0.0589)
$log(asset\ return\ uncertainty_{t-1})$					-0.0021	0.0053	0.0004	0.0056
					(0.0035)	(0.0040)	(0.0032)	(0.0038)
$log(asset\ return\ uncertainty_{t-1}) * 1_{(year>2004)}$						-0.0230***		-0.0174***
						(0.0061)		(0.0058)
$log(asset\ riskiness_{it-1})$							0.0005	0.0036
							(0.0029)	(0.0039)
$log(asset\ riskiness_{it-1}) * 1_{(year>2004)}$								-0.0034
								(0.0038)
Constant	0.0897	0.1531**	0.3480***	0.4169***	0.4366***	0.3391***	0.5442***	0.4223***
	(0.0607)	(0.0608)	(0.0879)	(0.0865)	(0.0727)	(0.0817)	(0.0691)	(0.0789)
Bank Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes				
Observations	1916	1916	1306	1306	1259	1259	1172	1172
R^2	0.1132	0.1146	0.1521	0.0988	0.1247	0.2621	0.2261	0.2744
Number of id	281	281	215	215	214	214	202	202

Notes: Robust asymptotic standard errors reported in parentheses are double-clustered in the bank and time dimension, according to Cameron, Gelbach, and Miller (2011). Shadow banks are defined as all the U.S. real estate and mortgage banks, investment banks, micro-financing institutions, securities firms, private banking and asset management companies, investment and trust corporations, finance companies, clearing and custody institutions, and group finance companies in the BankScope and WorldScope database. The sample period is from 1998 to 2013 at annual frequency. The sample is winsorized at 2% level. The dependent variable is the leverage ratio, which is defined as the total debt over asset ratio of each individual bank. The explanatory variables are the one-period lagged bank asset size, profitability (gross asset return rate), and risky asset exposure(fraction of derivative and other securities in total asset). $***p < 0.01, **p < 0.05, *p < 0.1$.

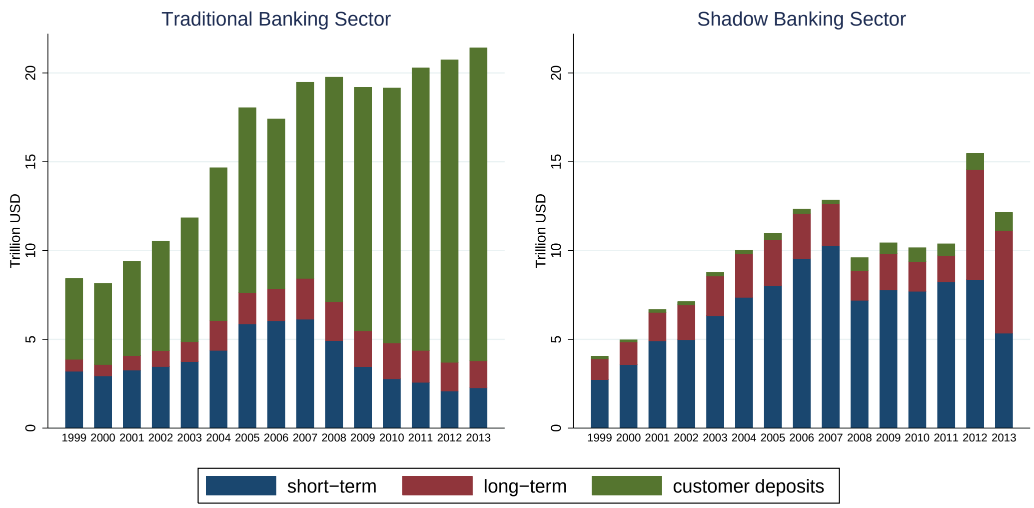
Table 3: Regression: Leverage Decision of Traditional Banks

VARIABLES	(1) $leverage_{it}$	(2) $leverage_{it}$	(3) $leverage_{it}$	(4) $leverage_{it}$	(5) $leverage_{it}$	(6) $leverage_{it}$	(7) $leverage_{it}$	(8) $leverage_{it}$
$log(asset_{it-1})$	0.0248***	0.0275***	0.0251***	0.0278***	0.0140***	0.0233***	0.0111***	0.0203***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
$log(asset_{it-1}) * 1_{(year>2004)}$		-0.0033***		-0.0033***		-0.0017***		-0.0016***
		(0.0001)		(0.0001)		(0.0001)		(0.0001)
$log(gross\ asset\ return_{it-1})$			-0.0377***	0.0200***	-0.0064	0.0303***	-0.0213***	-0.0133*
			(0.0055)	(0.0069)	(0.0055)	(0.0069)	(0.0054)	(0.0069)
$log(gross\ asset\ return_{it-1}) * 1_{(year>2004)}$				-0.1551***		-0.1560***		-0.0973***
				(0.0089)		(0.0089)		(0.0092)
$log(asset\ return\ uncertainty_{t-1})$					-0.0013***	-0.0021***	-0.0011***	-0.0019***
					(0.0003)	(0.0003)	(0.0003)	(0.0003)
$log(asset\ return\ uncertainty_{t-1}) * 1_{(year>2004)}$						-0.0021***		-0.00302***
						(0.0003)		(0.0003)
$log(asset\ riskiness_{it-1})$							-0.0012***	-0.0042***
							(0.0002)	(0.0002)
$log(asset\ riskiness_{it-1}) * 1_{(year>2004)}$								0.0028***
								(0.0002)
Constant	0.6159***	0.5807***	0.6132***	0.5765***	0.7101***	0.6010***	0.7452***	0.6331***
	(0.0036)	(0.0039)	(0.0037)	(0.0039)	(0.0033)	(0.0039)	(0.0032)	(0.0039)
Bank Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes				
Observations	110656	110656	110652	110652	110141	110141	108208	108208
R^2	0.0705	0.0760	0.0710	0.0795	0.0366	0.0648	0.0264	0.0529
Number of id	9498	9498	9497	9497	9497	9497	9456	9456

Notes: Robust asymptotic standard errors reported in parentheses are double-clustered in the bank and time dimension, according to Cameron et al. (2011). Traditional banks are defined as all the U.S commercial banks, savings banks, cooperative banks and bank holding companies in Bankscope and WorldScope database. The sample period is from 1998 to 2013 at annual frequency. The sample is winsorized at 2 percent level. The dependent variable is leverage ratio which is defined as the total debt over asset ratio of each individual bank. The explanatory variables are the one-period lagged bank asset size, profitability (gross asset return rate) and risky asset exposure(fraction of derivative and other securities in total asset). $***p < 0.01, **p < 0.05, *p < 0.1$.

negligible funding source of shadow banks. Its proportion in shadow banks' total funding is less than 10% for every year of the sample. Given this feature, when modelling the liability side of shadow banks, I abstract from the customer deposit.

Figure 8: Funding Structure



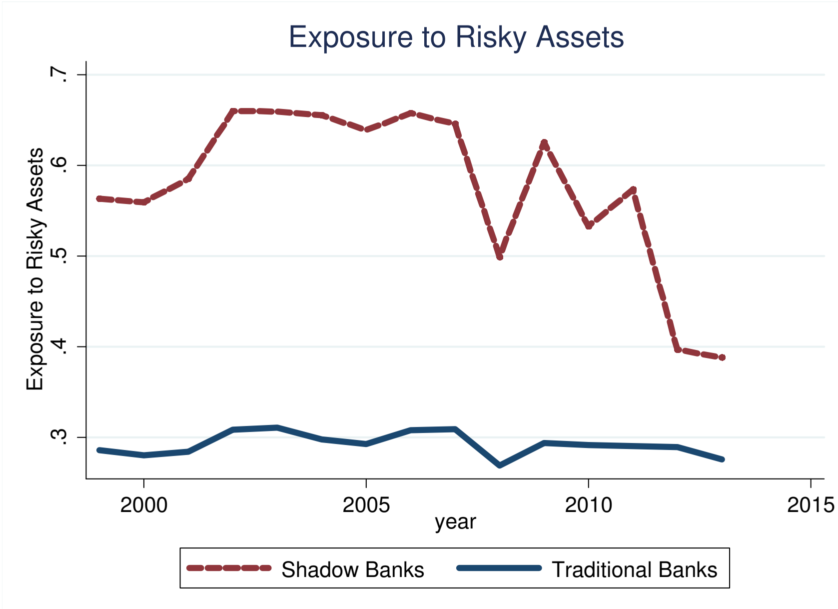
Notes: This figure depicts the change of funding structure of shadow banks and traditional banks. Short-term and long-term refers to the short-term debt and long-term debt the banks hold respectively. The classification of shadow banks and traditional banks is shown in the Appendix.

Figure 9 illustrates that shadow banks invest over 60% of their assets in risky assets (derivative and other securities), while traditional banks invest less than 30% of their assets in these risky products.

In sum, based on the first four stylized facts, I find that: shadow bank asset return uncertainty increases during the 2007-2009 crisis; interbank spread also increases, forcing shadow banks to deleverage and reduce their asset sizes. Since shadow banks contribute more to the total banking credit contraction in the recent crisis compared with traditional banks, in this paper, I focus on the shadow banks[9]. To explain the empirical findings, I build a model that provides a micro-foundation for the impact of uncertainty on the financing and leverage decisions of shadow banks. And because shadow banks have very different asset and liability composition compared with traditional banks as illustrated in Stylized Fact 5, different from conventional modelling about traditional banks, I

[9]Building a unified model including the both types of banks and explaining the difference between them is clearly desirable. I leave this for future research. Given the limited role traditional banks played in the recent recession, to keep the model as simple as possible, I focus on shadow banks in the current version of the paper.

Figure 9: Risk Exposure



Notes: This figure depicts the change in the asset risk exposure of shadow banks and traditional banks. Risk exposure is defined as the fraction of total asset invested in derivative and other securities. The classification of shadow banks and traditional banks is shown in the Appendix. The data is winsorized at 2% level.

abstract from customer deposits and assume shadow banks totally depends on short-term funding when I model the shadow banks [10].

3 A Simple Two-Period Model

In this section, I use a simple two-period model to illustrate the key mechanism of the paper. Assume there is a representative bank which finances its investment in risky loans using risky debt and equity. In the first period, the bank issues equity and debt and invests in a risky project. The bank's balance sheet can be written as : $qb + n/\chi = k$, where χ is the floatation cost of issuing equity, $\chi > 1$, q is the price of risky bond the bank issues, and n is the amount of equity issuance. [11]

[10] As will be illustrated in section 4, the funding structure and asset composition of shadow banks makes the bank's problem inherently similar to that of a firm with constant return to scale production technology. The other difference is that bank use short term debt to fund long-term project, whereas firms usually fund long-term project with long-term debt. Thus the degree of maturity mismatch of bank's asset and liability is much higher than that of a generic firm.

[11] Floatation cost is incurred by a publicly traded company when it issues new securities. It includes expenses such as underwriting fees, legal fees and registration fees.

In the second period , the bank needs to repay b. Assume the total loan return is zk, where z captures the gross loan return rate, $logz \sim N(-\frac{\sigma^2}{2}, \sigma^2)$.

When $zk < b$, the bank cannot repay its debt . Since the value of repaying is negative, smaller than the value of default, which is zero in this case, the bank would choose to default. Thus we get the default cutoff of the asset return rate $z^* = \frac{b}{k}$. Note that z^* also denotes the leverage ratio. When bank defaults, for simplicity, I assume the lender gets θ fraction of total loan return zk as recovery. $\theta < 1$, $1 - \theta$ captures the bankruptcy costs.

Then the bank's discounted expected net worth in the second period is : $\beta \int_{z^*}^{1} [zk - b] \, dF(z)$. Denote $\Psi(k, 0)$ as the quadratic adjustment cost of investment[12]. The bank's net payoff maximization problem can be written as:

$$\max_{b,k} - n - \Psi(k, 0) + \beta \int_{z^*} [zk - b] \, dF(z) \tag{2}$$

$$\begin{aligned} s.t\; n &= (k - qb)\chi && (3) \\ z^* &= \frac{b}{k} && (4) \\ qb &= \frac{1}{1+r} \left[\int_{z^*} b \, dF(z) + \int_0^{z^*} (\theta z k) \, dF(z) \right], && (5) \end{aligned}$$

Substitute b by k and z^*, the bank's problem is equivalent to:

$$\begin{aligned} \max_{k,z^*} \left\{ -k + \frac{1}{1+r} \left[z^*(1 - F(z^*))k + \int_0^{z^*} \theta z k \, dF(z) \right] \right\} \chi \quad & -\Psi(k, 0) \\ +\beta \int_{z^*}^{\infty} [k(z - z^*)] \, dF(z). & \qquad (6) \end{aligned}$$

F.O.C:

with respect to k:

[12] We need a quadratic adjustment cost on loan investment or decreasing return to loan to avoid corner solutions for the bank's problem. Without a quadratic adjustment cost, maximizing linear function of k subject to a budget set linear in k would lead to corner solutions.

$$1 + \Psi^{'}(k, 0) = \frac{\chi}{1+r}\left[\int_0^{z^*} z\theta\, dF(z) + z^*(1 - F(z^*))\right] + \beta \int_{z^*} (z - z^*) dF(z). \tag{7}$$

The left-hand side is the marginal cost of a loan, whereas the right-hand side is the marginal return of loan k.

with respect to z^*:

$$\frac{\chi}{1+r}(1-\theta)z^* f(z^*) = (\frac{\chi}{1+r} - \beta)(1 - F(z^*)). \tag{8}$$

The left-hand side is the marginal cost of leverage(the increase of expected bankruptcy cost). The right-hand side is the marginal benefit of leverage(lower flotation cost in non-default states).

From equation(8), we can get:

$$z^* = \frac{1}{1-\theta}\left[1 - \frac{\beta(1+r)}{\chi}\right]\left[\frac{f(z^*)}{1 - F(z^*)}\right]^{-1} \tag{9}$$

Denote $\pi(z^*) = \frac{f(z^*)}{1-F(z^*)}$. This is the hazard rate. As shown in the Appendix, for a wide range of value of σ and z^*, the hazard rate is an increasing function of the standard deviation of the underlying asset return distribution. We have the following four propositions.

Proposition 1: Bank's leverage z^* decreases in its discount factor β and increases in floatation cost χ . When the bank is sufficiently patient, $\beta = \frac{\chi}{1+r}$, it totally depends on internal(equity) finance (i.e., $z^* = 0$).

Proof: See Appendix.

Proposition 2: When the bank is sufficiently impatient, $\beta < \frac{\chi}{1+r}$, as long as the hazard rate is an increasing function of asset return uncertainty, i.e., $\frac{\partial \pi(z^*)}{\partial \sigma} > 0$, bank leverage is a decreasing function of the asset return uncertainty, $\frac{\partial z^*}{\partial \sigma} < 0$

Proof: See Appendix.

Proposition 3: Bank asset size is a decreasing function of the asset return uncertainty: $\frac{\partial k}{\partial \sigma} < 0$.

Proof: See Appendix.

Proposition 4: The increase in asset return uncertainty increases the interest spread the bank faces when it issues debt.

Proof: See Appendix.

I prove in the appendix that when the hazard rate is an increasing function of the standard deviation of the asset return distribution, leverage increases when volatility increases. The intuition for this is when volatility increases, the default risk increases and interest spread increases. Facing a higher financing cost, the bank has the incentive to lower default risk by reducing its leverage. I also show in the Appendix that the negative effect of a decrease in leverage on default risk typically cannot offset the direct impact of volatility on default risk. Thus the net effect is that the default risk increases and the bank still faces a higher spread when it issues debt.

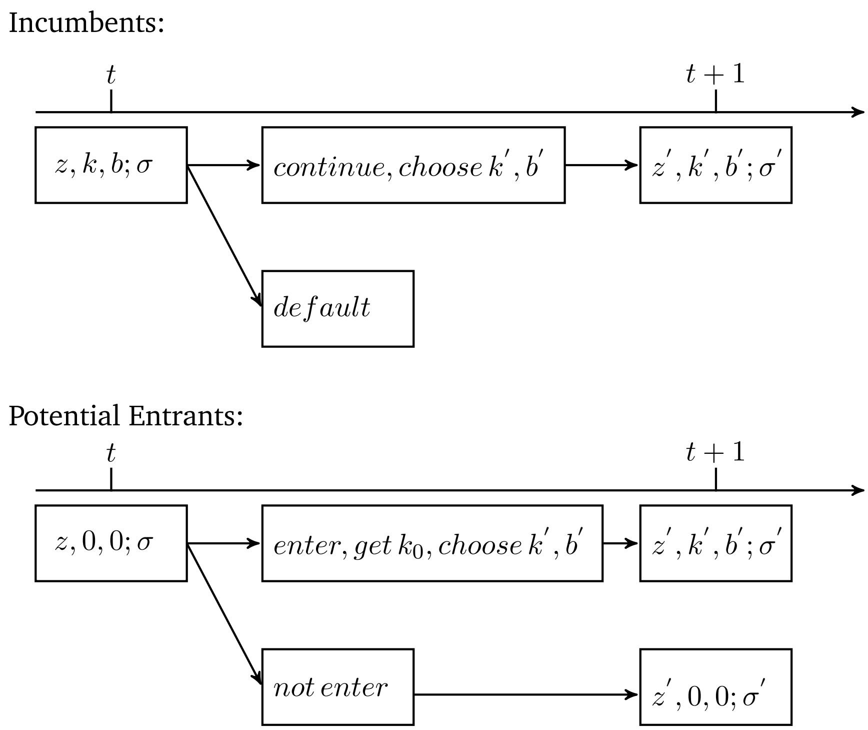
4 Full Model

In this section, I extend the model to an infinite horizon. I assume there is a continuum of banks borrowing from the interbank market in the form of risky debt. A clearing house take funds from some banks and lends to other banks. In each period, depending on the idiosyncratic shock to its asset return, a bank would choose to borrow from the clearing house or save in the clearing house. For simplicity, assume that when a bank chooses to save in the clearing house ($b < 0$), it only receives risk-free rate r as the rate of return. Each bank invests in a risky loan. The risky loan gives the bank the gross return $z_t k_t$. z_t is the idiosyncratic gross rate of return on the bank's assets[13] which captures the investment quality of the loan. Assume idiosyncratic asset return shock z_t follows a Markov process with transition function $\pi_z(z_t|z_{t-1}, \sigma_{t-1})$, where σ_{t-1} is an aggregate shock to the standard deviation of idiosyncratic asset return shocks . The aggregate shock σ_t follows a Markov process with transition function $\pi_\sigma(\sigma_t|\sigma_{t-1})$.

The timing of the model is illustrated in Figure 10. In each period, based on an idiosyncratic state variable vector $s = \{z, k, b\}$ and aggregate state variable $S = \sigma$, the incumbent bank would chooses whether to default, as well as how much to borrow from the interbank market b' and how much risky loan to initiate k'.

[13] The empirical counterpart for z_t would be bank's ROA(return on asset)+1.

Figure 10: Timeline from Time t to $t+1$



Different from a conventional one-period loan, the risky loan here is a long-term loan. In each period, only a fraction δ of the loan is matures. The rest of the loan $(1-\delta)k_t$ is rolled over to the next period. The law of motion of the loan is given by: $k' = (1-\delta)k + i$, where i is the amount of new loans that are invested at current period. As documented by a rich body of literature (see Brunnermeier, Gorton, and Krishnamurthy (2014), Farhi and Tirole (2012), Krishnamurthy (2010), etc), maturity mismatch and associated firesale cost play a very important role in amplifying the contraction of the economy. [14] Thus I include these features in the model. Introducing these features also helps us conveniently analyzing the government intervention in the next section. When the government intervenes, banks can sell a certain fraction of their assets to the government at full value, thus avoiding the cost of firesale.

The balance sheet of an incumbent bank when it needs to repay its debt is shown in Table 4. On the asset side, the total gross asset return consists of two parts: cash flow and long-term assets. In

[14] Firesale costs and maturity mismatch are inherently correlated with each other. Given a fixed investment strategy, the higher the degree of maturity mismatch, the more likely the bank would be forced to firesale its long-term assets. A direction for future research is to consider the impact of a firesale on the price of assets that are not firesaled. The firesale can result in a decrease in the value of assets that are not sold. This would lead to a vicious cycle and further amplify an economic downturn.

Table 4: Balance Sheet of Banks

Assets	Liabilities
long-term asset $(1-\delta)k_t$	Net worth n_t
cash flow$z_t k_t - (1-\delta)k_t$	Risky debt$b_t - q_t b_{t+1}$

each period, only δ fraction of the loan is due.[15] Denote the cash balance to be c, which is the cash flow minus the amount of debt due plus the new debt issued in each period: $c \equiv zk-(1-\delta)k-b+qb'$. When the cash balance become negative, the bank firesales part of its long-term assets. Assume when the bank firesales its long-term assets, it can only get ς fraction of the total value. The net worth of the bank is equal to what is remained in the asset side after paying the debt due: $n \equiv \begin{cases} c+(1-\delta)k & if\ c \geq 0 \\ (1-\delta)k + \frac{c}{\varsigma} & if\ c < 0 \end{cases}$

The incumbent bank's problem is as follows. In each period, the bank would choose to default or not to default:

$$V(z,k,b;\sigma) = \max_{d \in \{0,1\}} (1-d)V^c(z,k,b;\sigma) + dV^d(z;\sigma). \tag{10}$$

The value of continuation is determined by the following bellman equation:

$$V^c(z,k,b;\sigma) = \max_{\{b',k'\}} \Big\{(1+\gamma_e 1_{\{e<0\}} - \tau_d 1_{\{e>0\}})e + \beta EV(z',k',b';\sigma')\Big\} \tag{11}$$

$$e = \begin{cases} c+(1-\delta)k - k' - \Phi(k',k) & if\, c \geq 0 \\ (1-\delta)k + \frac{c}{\varsigma} - k' - \Phi(k',k) & if\, c < 0 \end{cases}$$

where $\Phi(k',k)$ is the quadratic asset adjustment cost.[16] d is the default decision of the bank; when $d=1$, the bank chooses to default. e is the dividend; when $e<0$, the bank has to pay an extra equity issuance cost of γ_e. When $e>0$, the bank pays a dividend; the dividend tax rate is τ_d.

[15] z is the gross return on bank assets. One way to understand this is to denote $z = 1 + r_k$, where r_k is the asset return rate. Then cash flow would equal to $(r_k+\delta)k$, in which $r_k k$ is the interest payment, δk is the fraction of principal paid in period t. $(1-\delta)$ fraction of principal is left to the next period.

[16] The microfoundation of asset size adjustment cost is that when a bank adjusts its asset size, it needs to pay a cost to examine the quality of a new loan and pay for the legal fees and possible personnel adjustment costs.

I allow for the presence of both convex and non-convex adjustment costs in asset size. As is well known in the literature, it is the presence of the non-convex adjustment costs that leads to a real options or wait-and-see effect of uncertainty shocks. One concern about uncertainty literature is that uncertainty might increase the investment level if the bank can adjust the asset size freely to take advantage of a good asset return shock while shrinking size when the asset return is low. The redistribution of assets across efficient and inefficient banks might result in an increase in the total investment level. This is the classical Oi-Hartman-Abel effect. However, this effect depends on whether a bank can adjust its asset size frequently and with very low adjustment cost. As will be shown later, in my model, both the quadratic asset size adjustment cost and firesale cost dampen the Oi-Hartman-Abel effect in the short run.

Assume the value of default is zero:

$$V^d(z;\sigma) = 0. \tag{12}$$

In each period, there are also a continuum of idle bankers deciding whether to start a new bank based on their idiosyncratic shock and aggregate shock. I call them potential entrants. A potential entrant would start a new bank if the value of entry V^e is non-negative. An entrant starts with start-up asset k_0 and decides on the optimal k' and b':

$$V^e(z,\sigma) = \max_{\{b',k'\}} \left\{(1+\gamma_e 1_{\{e<0\}} - \tau_d 1_{\{e>0\}})e + \beta EV(z',k',b';\sigma')\right\} \tag{13}$$

$$e = qb' - k' - \Phi(k',k_0). \tag{14}$$

The price schedule of risky debt offered by a clearing house can be written as:

$$\begin{aligned} q(z,k',b';\sigma) \quad = \quad & \frac{1 - \iint d(z',k',b';\sigma')f(z'|z,\sigma')g(\sigma'|\sigma)\,dzd\sigma}{1+r} \\ & + \frac{\iint d(z',k',b';\sigma')R(z',k',b')f(z'|z,\sigma')g(\sigma'|\sigma)\,dzd\sigma}{(1+r)b'} - \frac{\xi}{b'}, \end{aligned} \tag{15}$$

where $R(z, k, b)$ is the recovery of lender when the bank defaults. ξ is the fixed credit cost. [17] $f(z'|z, \sigma')$ is the probability distribution function for the gross asset return rate z and $g(\sigma'|\sigma)$ is the probability distribution function for the asset return uncertainty[18].

$$R(z, k, b) = \max\left\{0, \min\left[b, zk - (1-\varsigma)(1-\delta)k - \Phi(k, 0)\right]\right\}. \tag{16}$$

Definition 1:

An equilibrium consists of the policy function $k'(z, k, b; \sigma)$*,* $b'(z, k, b; \sigma)$*, value function of banks* $V(z, k, b; \sigma)$*,* $V^c(z, k, b; \sigma)$*,* $V^d(z, \sigma)$*, value function of new entrant* $V^e(z, \sigma)$*, bond pricing function* $q(z, k, b; \sigma)$*, recovery function* $R(z, k, b)$ *such that:*

(1) Given the bond pricing function $q(z, k, b; \sigma)$*, the policy and value function of banks solve their optimization problem;*

(2) Given recovery function $R(z, k, b)$ *and bond pricing function* $q(z, k, b; \sigma)$*, lenders in the interbank market break even.*

5 Quantitative Analysis

5.1 Estimation

There are 14 parameters in this model, as shown in Table 5. Two parameters are calibrated and the rest are jointly estimated using SMM. I assume that the bank asset return has two components: a permanent component a and an idiosyncratic component v. In particular,

$$z_{it} = a_i + v_{it}. \tag{17}$$

[17]Fixed credit cost is necessary to generate the positive correlation between asset size and leverage in this model environment. It inherently captures the legal fees and account management cost when a bank decide to borrow from the interbank market. Without fixed credit cost, small banks would depend highly on debt finance and this would make the leverage schedule over asset quantiles counterfactually downward sloping.

[18]Here I only consider partial equilibrium. Because there exists aggregate fluctuation, there is no stationary distribution. But if we keep aggregate state variable unchanged for a sufficient long time, we would obtain an ergodic distribution of assets and risky debts.

Table 5: Model Parameters and Target Moments

A.Parameter estimates

Calibrated Parameters	Value	Description
β	0.96	discount factor
τ_d	0.12	dividend tax
Estimated Parameters	**Value**	**Description**
γ_e	0.0612(0.0121)	equity issuance cost
ς	0.6149(0.0527)	firesale cost
δ	0.3274(0.0144)	degree of maturity mismatch
ξ	0.0093 (0.0083)	fixed credit cost
k_0	0.0080 (0.0014)	entrant start-up asset
ϕ	1.3336 (0.0320)	asset size adjustment cost
ρ_v	0.8042(0.0978)	persistence of asset return
ρ_σ	0.7687 (0.1547)	asset return uncertainty persistence
μ_σ	0.0345 (0.0021)	asset return uncertainty mean
φ	0.1492 (0.0439)	standard deviation of uncertainty shock
μ	3.3712(0.5741)	Pareto distribution shape
A	11.5771(2.1043)	Pareto distribution upper bound

B. Moments

Target Moments	Data	Model	t-statistics
mean of leverage	0.9541	0.9489	0.1714
Std of leverage	0.1917	0.0847	1.2516
autocorrelation of leverage	0.8514	0.6874	0.3470
mean of asset growth	0.0447	0.0378	0.4149
Std of asset growth rate	0.0035	0.0142	-0.1477
autocorrelation of asset growth rate	0.8997	0.9409	-0.2158
mean default rate	0.0110	0.0098	1.4121
mean of dividend/asset ratio	0.0214	0.0369	-0.0011
Std of dividend/asset ratio	0.0145	0.0019	1.5620
autocorrelation of dividend/asset ratio	0.7949	0.8532	-0.3314
mean entrant leverage	0.9718	0.9945	-0.6678
mean entrant growth	0.2417	0.1007	1.1788
IQR(75/25) leverage slope	1.1715	1.1954	-0.0143

Notes: Calculations are based a annual sample of shadow banks from the Bankscope and WorldScope database. The estimation is done with SMM, which chooses model parameters by matching the moments from a simulated panel of banks to the corresponding moments from the data. Panel A reports the estimated parameters, with clustered standard deviation in the parenthesis. Panel B reports the simulated and actual moments and the clustered t-statistics for the differences between the corresponding moments.

Following Midrigan and Xu (2014) and Arellano, Bai, and Zhang (2012b), I assume that the permanent component follows a pareto distribution with an upper bound A and a shape parameter μ, i.e

$$Pr(exp(a_i) \leq x) = \frac{1 - x^{-\mu}}{1 - A^{-\mu}}. \tag{18}$$

The idiosyncratic component v_{it} follows an AR(1) process,

$$log\,(v_{it}) = \rho_v log\,(v_{it-1}) + \lambda_t + \sigma_{t-1}\epsilon_{it} \tag{19}$$

$\epsilon_{it} \sim N(0,1)$. I impose $\lambda_t = -\frac{\sigma_{t-1}^2}{2}$ so as to keep the mean level of v_{it}.

The discrete process for the aggregate shocks approximates the continuous process:

$$log\,(\sigma_t) = (1 - \rho_\sigma)\, log\mu_\sigma + \rho_\sigma log\,(\sigma_{t-1}) + \nu_t, \tag{20}$$

where $\nu_t \sim N(0, \varphi^2)$. The discrete Markov chain is then discretized into two aggregate shocks [19] and five discrete sets of values for the asset return shock for each of the two aggregate shocks. These approximations follow the methods of Tauchen and Hussey (1991). The permanent productivity is discretized into five levels, which are given by the 5th, 25th, 50th, 75th, and 95th percentile of the pareto distribution.

The annual discount factor β is set to 0.96, which is a standard value for annual RBC models. The annual risk-free interest rate r is 0.03, which is calculated using my sample period of the three-month T-bill rate minus the rate of growth in the Consumer Price Index. Dividend τ_d is set to 0.12 following Hennessy and Whited (2007).

The rest of the 12 parameters include the following: the fraction of loan due each period δ, equity issuance cost γ_e , firesale cost ς , parameters governing aggregate shocks $\rho_\sigma, \mu_\sigma, \varphi$, the asset adjustment cost ϕ, the persistence of asset return ρ_v, credit fixed cost ξ, entrant start-up asset k_0, and two parameters μ and A which govern the pareto distribution of the permanent productivity. They are jointly estimated to match the following 13 moments: the mean of default rate, the mean,

[19] Assume σ can take two values: σ_l and σ_h. The transition matrix of σ is $\pi = \begin{bmatrix} p_{ll} & p_{lh} \\ p_{hl} & p_{hh} \end{bmatrix}$ .z and σ are correlated with each other. The transition matrix of z depends on the realization of σ'.

the standard deviation, and the auto-correlation of leverage, asset growth rate, and dividend to asset ratio of shadow banks, the mean leverage and growth of new entrant banks, and the slope of the leverage schedule using simulated methods of moments(SMM). The detailed estimation procedure is illustrated in the Appendix. I report actual data moments, model moments and t statistics which test whether data moments and model-generated moments are statistically significantly different. The model tightly matches the 13 data moments. No simulated moment is statistically significantly different from its actual data counterpart.

5.2 Identification

The success of SMM estimation depends on model identification, which requires that we choose moments that are sensitive to variations in the structural parameters. I now describe and rationalize the moments that I choose to match. The credit fixed cost ξ , adjustment cost ϕ, and firesale cost ς are most relevant for the bank's leverage choice. The fixed credit cost affects both the mean and standard deviation of leverage ratios. A lower ξ increases mean leverage and decreases the standard deviation of leverage. The estimation requires a positive fixed credit costs for the economy to replicate the observed pattern of leverage distribution of the U.S. shadow banking industry. The asset adjustment cost ϕ is more relevant for the standard deviation and persistence of leverage. The higher the adjustment cost ϕ, the less willing is the bank to change its asset level; the smaller the standard deviation of leverage, and the higher the autocorrelation of leverage. The smaller the firesale cost parameter ς, the larger the loss the bank would suffer during financial distress. Hence, the bank would take lower leverage. The three parameters $\rho_\sigma, \mu_\sigma, \varphi$ that govern the persistence, level and volatility of aggregate shock are most closely related to the auto-correlation, mean and standard deviation of asset growth, respectively. They would also indirectly affect the standard deviation of dividend-to-asset ratio by changing the standard deviation of the bank's asset return AR(1) processes. k_0 and γ_e mainly affect the mean leverage and the growth rate of entrants. The measure of entrants in this model is equal to the measure of defaulted banks in the ergodic distribution. Thus k_0 is also indirectly related to mean default probability. The equity issuance cost parameter γ_e directly affects the mean of dividend over asset ratio. The asset return persistence parameter ρ_v is most closely related to the persistence of the dividend-to-asset ratio. The shape parameters and upper bound of pareto distribution determine the bank's asset distribution. The smaller the shape parameter, the fatter the right tail of bank distribution[20], and the higher the concentration of market share. The upper bound of the truncated pareto distribution determines the degree of permanent technology heterogeneity across banks. The shape and upper bound of the pareto distribution would thus indirectly affect the all other moments through their impacts on the bank's distribution. They help me to match the slope of the leverage schedule. The higher the upper bound of the pareto distribution and the smaller the shape parameter, the more heterogenous the banks will be. Although the leverage schedule slope within each cohort of permanent productivity might only be slightly positive or even negative, with large enough heterogeneity in permanent productivity, the aggregate leverage schedule can be upward sloping.

5.3 Model Implications

5.3.1 Policy Rules and Interest Spread Schedule

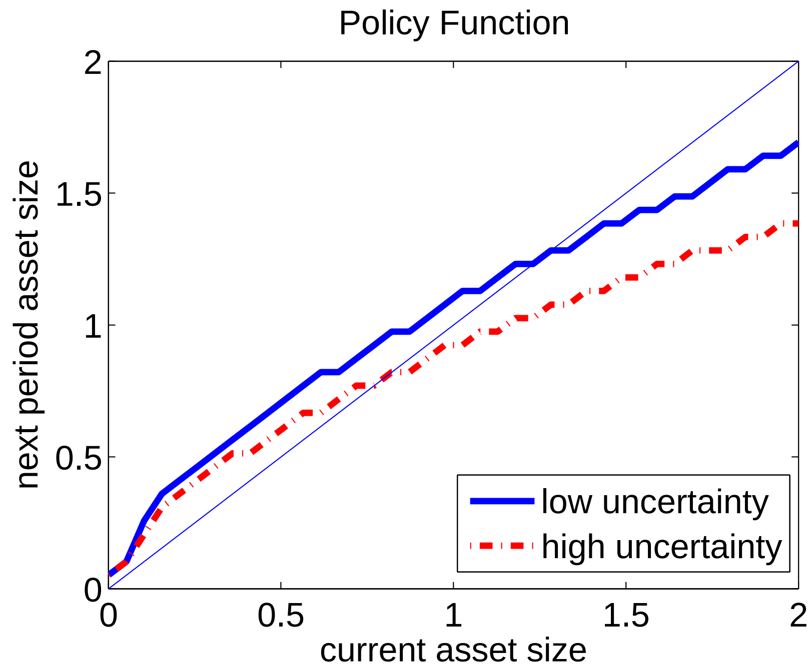
In Figure 11, I plot the optimal policy rules for the asset size. The model generates a positive correlation between the current asset size and the future asset size. Banks that have higher a asset size in the current period tend to choose a higher asset size in the next period. Moreover, banks choose a lower asset size when the uncertainty of asset return is higher.

Figure 12 illustrates the interest spread schedule of risky debt. In the figure, the spread schedule for risky debt under low and high asset return uncertainty for a bank with mean idiosyncratic productivity, mean permanent productivity and mean asset size are plotted in blue solid and red dash-dot line respectively. Under the low asset return uncertainty regime, the bank can borrow up to 1.5 times of its asset without defaulting. When the uncertainty of asset return is high, bank faces higher interbank market spread. This is consistent with what is observed in the data and also with what I proved analytically in section 3. Also, note that fixed credit costs make borrowing very costly especially for the very small loans.

The left panel of Figure 13 shows the spread schedule of risky debt for bank's with a lower asset

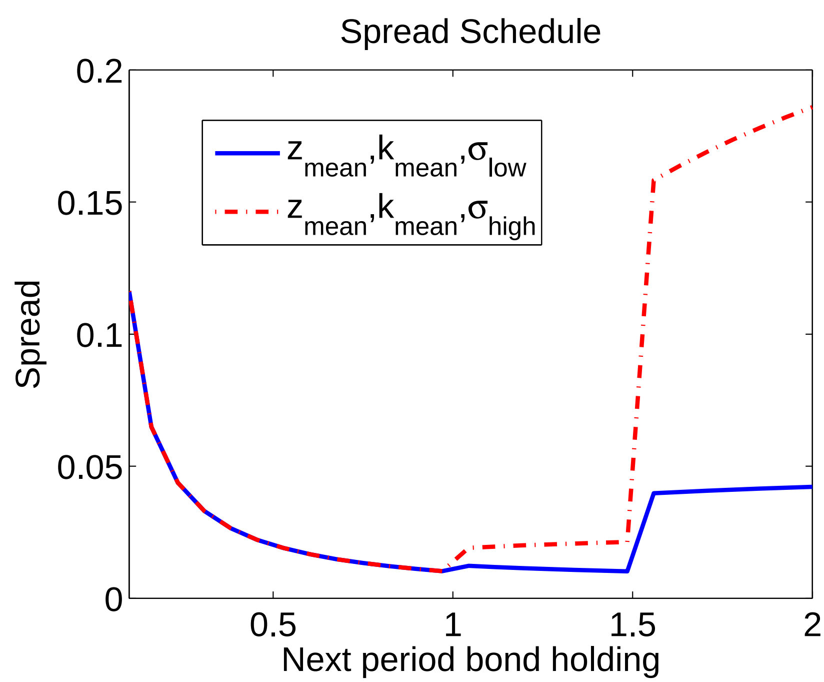
[20]Despite temporal variations, however, the general shape of the bank size distribution has been shown to be well described by a lognormal distribution with a pareto tail (see Janicki and Prescott (2006) and Benito (2008).)

Figure 11: Policy Rules



Notes: This figure plots the optimal asset size choice as a function of the previous period asset size K for a bank with mean permanent asset return component a_i^3 , stochastic shock and debt level. All values on the axis are relative to the average asset size of the a_i^3 banks

Figure 12: Interest Spread Schedule

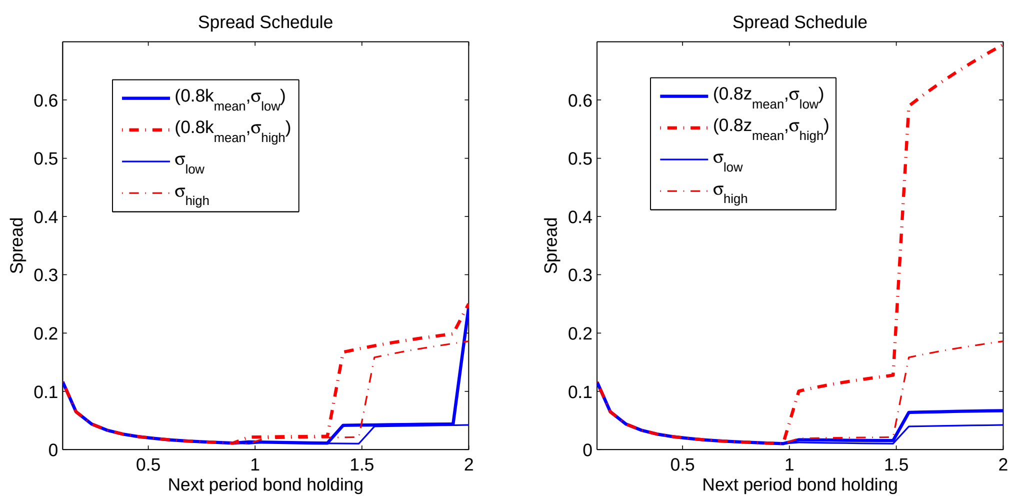


Notes: This figure shows the interbank interest spread as a function of the debt issuance for a bank with mean permanent asset return component a_i^3, stochastic shock and asset level. All values on the horizontal axis are relative to the average asset size of the a_i^3 banks.

size under low and high asset return uncertainty, respectively. Interest spread is higher for banks with asset size that is 80% of average asset size. Asset return uncertainty's impact on spread is still positive. The right panel of Figure 13 shows the spread schedule of risky debt for bank's with lower asset return under low and high asset return uncertainty. Interest spread is lower for banks with an asset return that is 80% as large as average asset return. The impact of asset return uncertainty on interest spread is still positive.

Figure 14 illustrates the default and non-default regions for bank's with different asset sizes and bond holdings. Banks with higher asset sizes have lower default probability. Bank's default probability increases when it issues more bonds. Also, bank default probability increases under higher asset uncertainty. As shown in the figure, the red default area increases when the uncertainty of asset return increases. This indicates that banks would choose to default in more cases of combination of asset sizes and bond holdings.

Figure 13: Spread Schedule Comparison

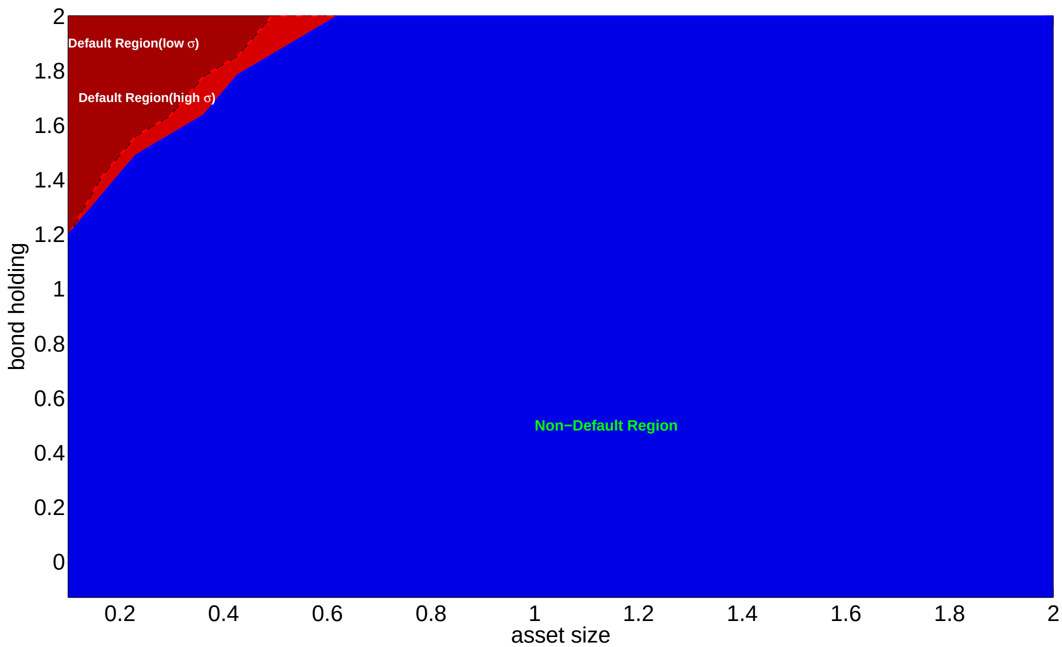


Notes: The left panel shows the interbank interest spread as a function of the debt issuance for a bank with mean permanent asset return component a_i^3 , stochastic shock and 80% of mean asset level at across the a_i^3 banks. The right panel shows the interbank interest spread as a function of the debt issuance for a bank with mean permanent asset return component a_i^3 , asset level and 80% of mean stochastic shock at across the a_i^3 banks. All values on the axis are relative to the average asset across the a_i^3 banks

5.3.2 Regression: Model vs. Data

I simulate the model for 100,000 banks for 200 periods. The model delivers a simulated bank panel. Then I draw 281 banks from this simulated panel randomly. Using the simulated bank panel data,

Figure 14: Default Region



Notes: The figure depicts the default and non-default regions of a bank with median permanent asset return component a_i^3 and stochastic shock. All values on the axis are relative to the average capital across the a_i^3 banks.

I run the same regression as I did in section 2 to check if the model implications match the data statistics. Both regressions control for bank fixed effects. The results are reported in Table 6. The regression can be viewed as an out-of-sample test of the model given that they are not targeted in the estimation. The model generates similar positive correlation between leverage and asset size, and negative correlation between asset return uncertainty and leverage. When asset return uncertainty increases by 1%, leverage decreases by 0.0177 percentage point in the data, and by 0.0224 percentage point in the model. When asset size increases by 1%, leverage increases by 0.0268 percentage point in the data, by 0.0451 percentage point in the model.

5.3.3 Event Study: Modelling the 2007-2009 Financial Crisis

The 2007-2009 financial crisis can be modelled as a decrease in asset returns, or an increase in asset return uncertainty. In this paper, I focus on the impact of an increase of bank asset return uncertainty. I fit the empirical observed asset return uncertainty to the model and resolve the model. Given a

Table 6: Regression: Model v.s Data

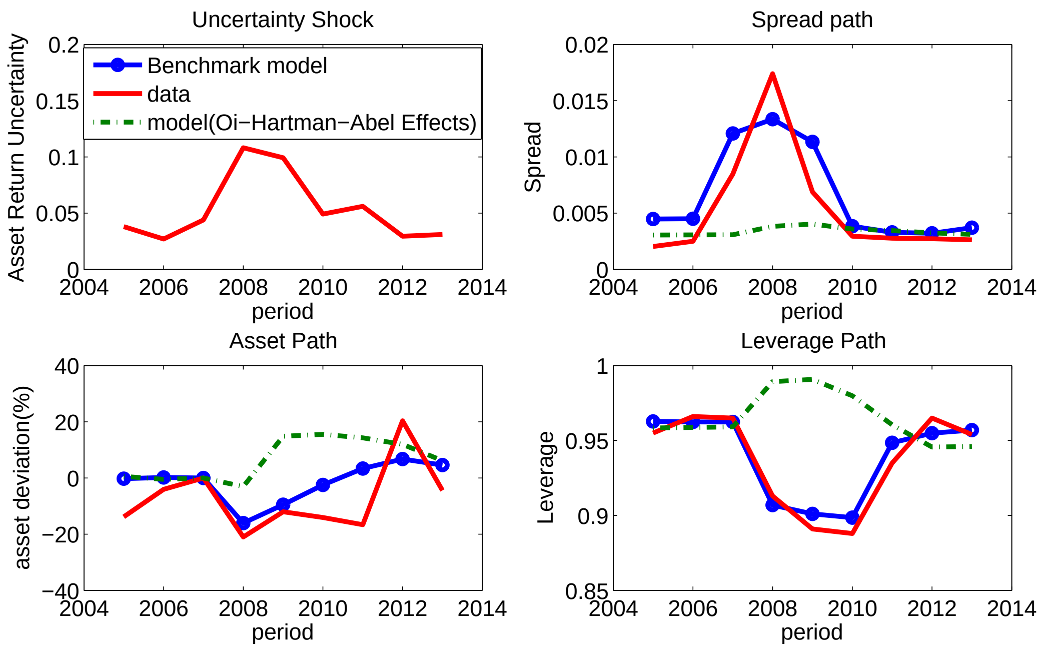
VARIABLES	Model $leverage_{it}$	Data $leverage_{it}$
$log(asset_{it-1})$	0.0414***	0.0268***
	(0.0094)	(0.0049)
$log(gross\, asset\, return_{it-1})$	-0.1120*	-0.2302***
	(0.0704)	(0.0431)
$log(gross\, asset\, return\, uncertainty_{t-1})$	-0.0161***	-0.0177***
	(0.0012)	(0.0032)
Fixed effect	$\surd$	$\surd$
R^2	0.3101	0.2621

Notes: Standard errors in parentheses. Standard errors of simulated data regression are calculated using the bootstrapping method. $***p < 0.01, **p < 0.05, *p < 0.1$.

sequence of measured asset return uncertainty shocks exactly as observed in the data, the responses of the model economy are shown in Figure 15.

In Figure 15, I normalize the total asset by calculating the percentage deviation from its base value at year 2007 when the crisis started. The data and simulated path by the benchmark model are shown in solid line and line with circle respectively. In response to the uncertainty shock, bank asset size shrinks by around 20%, similar to what is observed in the data. But bank assets in the model recover faster than that in the real data. The evolution path of leverage generated by the model tightly matches the data. Mean leverage decreases from around 0.96 to around 0.89, both in the model and in the data. The increase of uncertainty raises the external financing cost and the possibility of costly firesale, thus the banks decrease their leverage to lower their expected default probability and reduce the financing costs. I also examine the response of the economy under no quadratic asset adjustment cost or firesale cost. The result are plotted in dotted lines. When asset return uncertainty increases, the total asset actually increases. This result is related to the Oi (1961), Hartman (1972) and Abel (1983) effect. When there is no adjustment cost of any type in the economy, bank would take advantage of the uncertainty shock by adjust their sizes freely: banks with good asset return shock would increase their asset size whereas banks with low asset return shock would shrink their asset size. The redistribution might result in an increase of the aggregate asset level. By comparison, when we add quadratic adjustment cost and firesale cost of asset, the real option effect dominates in the short run and results in a decrease in the asset size and the leverage ratio.

Figure 15: Event Study: Model v.s Data



Notes: The figure depicts the simulated evolution paths of total asset, aggregate leverage ratio and mean interest spread of shadow banks in response the asset return uncertainty shocks compared with their data counterparts. Leverage is defined as total debt to total asset ratio. The data and simulated path by the benchmark model are shown in solid line and line with circle respectively. The dotted line depicts the evolution path of the asset, leverage and interest spread assuming there is no firesale cost or asset adjustment cost such that Oi-Hartman-Abel effects dominates the real option effect.

Figure 15 also shows the simulated path of the interbank spread. The spread increases when uncertainty increases, as observed in the data and proved in the Section 3. The data for interbank spread is calculated by taking the yearly average of the daily TED spread. The interbank spread spikes up by around 1.3 percent, smaller than what observed in the data. That is because in the data the spread also includes an extra risk premium that results from people's risky averse utility function, whereas in my model, shadow banks are risk neutral. Under the Oi-Hartman-Abel case, because there is no quadratic asset adjustment or firesale costs, the banks adjust their leverages and asset sizes very quickly, thus lowering their default probability. Therefore, the interbank spread barely increases.

I calculate the statistics for the non-crisis periods and crisis period. Following Bloom et al. (2012), normal periods are defined as from 2005 to 2006 and 2010 to 2013 , crisis periods are defined as from 2008 to 2009. The statistics comparison are shown in Table 7.

Table 7: Statistics: Model v.s Data

Panel A:

	normal periods		crisis periods	
	model	data	model	data
default probability	0.008	0.007	0.018	0.019
spread	0.005	0.004	0.013	0.016
leverage	0.961	0.969	0.891	0.895

Panel B:

Correlation	Model spread	data spread
default probability	0.85	0.91
leverage	-0.69	-0.42

Panel C:

	Model	data
Aggregate leverage change	0.070	0.074
Extensive margin	57%	61%
Intensive margin	43%	39%

Notes: This table shows the simulated statistics of shadow banks compared with their data counterparts. Leverage is defined as total debt over total asset ratio. Panel A shows the mean value of default probability, spread and leverage respectively. Panel B shows the correlation between expected default probability of bank. Panel C show the contribution of intensive margin and extensive margin to aggregate leverage ratio respectively. Extensive margin is defined as the change of aggregate leverage resulting from change of bank's asset distribution. Intensive margin is defined as the change of aggregate leverage resulting from bank of all asset quantiles take a lower leverage, given a fixed asset distribution.

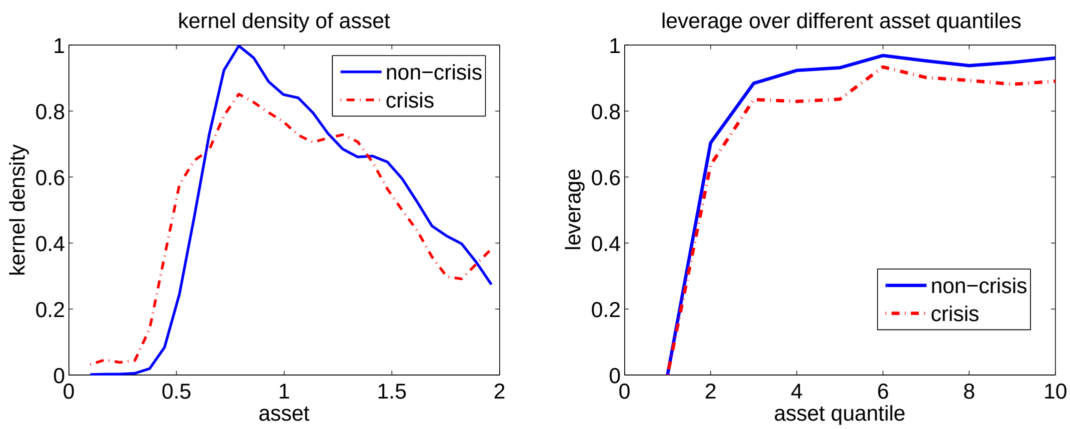
Panel A of Table 7 shows the mean value of the default probability, the spread and the leverage. The statistics generated by the model match the data closely. Panel B of Table 7 shows the correlation between expected default probability [21] and interbank spread. I find that interbank market spread is positively correlated with bank default probability and is negatively correlated with the bank leverage. The magnitudes of correlations generated by the model is close to those observed in the data. Panel C of Table 7 shows the proportion of aggregated leverage change which can be attributed to extensive margin (banks are distributed more densely at lower asset level) and intensive margin(banks on different asset quantiles employ lower leverage). In both the model and the data, a larger portion of

[21]The default probability of banks in the data is estimated by bankruptcy frequency in the dataset. The Bankscope dataset provides detailed information about the date at which a bank becomes inactive. When a bank files for Chapter 7 or Chapter 11 for bankruptcy, it is labeled as inactive. The bank default probability in a given year is calculated as the number of banks that become inactive divided by the total number of banks in that year.

aggregate leverage change can be attributed to the extensive margin. The model over-predicts the intensive margin by merely 4%.

I also find that the model can generate a similar pattern for the change of leverage schedule over different asset quantiles and asset distribution. The left panel of Figure 16 shows the asset distribution in non-crisis periods and crisis periods. Banks reduce their size such that the whole distribution of assets would skew more to the left in the crisis, similar to our empirical observation. The right panel of Figure 16 shows the change of leverages over different asset quantiles. Consistent with what is observed in the data, banks with higher asset sizes employ a higher leverage. During a crisis, banks of different asset quantiles generally take a lower leverage.

Figure 16: Asset Distribution and Leverage over different Asset Quantiles

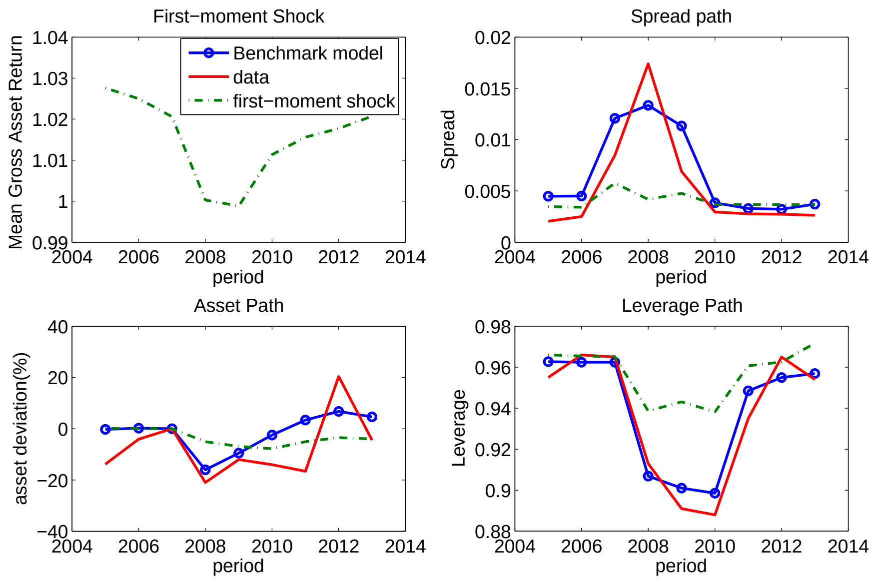


Notes: This figure depicts the simulated asset distribution and leverage schedule over different asset quantiles based on the simulated bank panel. Crisis periods are defined as the periods with high asset return uncertainty value. The rest of the periods are defined as non-crisis periods.

To further check if a purely first-moment shock can also generate a similar impact on interbank spreads, bank asset sizes and leverages, I solve an alternative model with a purely first-moment shock. I assume the risky loan gives the bank the gross return $A_t z_t k_t$. z_t is the idiosyncratic gross rate of return on the bank asset. A_t is an aggregate state variable that captures the mean asset return rate of the economy. I impose the aggregate uncertainty of the bank return constant, fit the empirical observed mean asset return to the model, and resolve the model. Given a sequence of measured mean asset return exactly as what observed in the data, the responses of the moment to a purely first moment aggregate asset return shock are shown in Figure 17.

I also reestimate the model under the following three specifications: model with purely first

Figure 17: Event Study: Model(Pure first-moment shocks) v.s Data



Notes: The figure depicts the simulated evolution paths of total asset, aggregate leverage ratio and mean interest spread of shadow banks in response the first moment (level) shocks compared with second moment (uncertainty) shocks and their data counterparts. Leverage is defined as total debt to total asset ratio. The data and simulated path by the benchmark model are shown in solid line and line with circle respectively. The dotted line depicts the evolution path of the asset, leverage and interest spread is response to a purely first moment shock.

moment shock, model without firesale cost, and model without maturity mismatch. Table 8 reports the estimation results. Models with these alternative specifications tend to underestimate the standard deviation of leverage, asset growth rate, and default probability and overestimate the mean leverage. The over-identification tests fail to reject the baseline model with a p-value of 0.6491. The simulated moments are not statistically significant different from the actual moments, hence the baseline model is valid. The tests reject the model with purely first-moment shock, the model without firesale costs, and the model without maturity mismatch at the significance level of 5%.

5.4 Policy Experiment: Debt Guarantee and TARP

In this section, I consider the effects of government intervention. In the 2007-2009 financial crisis, because the nominal interest rate dropped to zero, to stimulate the economy, the Federal Reserve took drastic unconventional monetary policies, including directly lending, Troubled Asset Relief Program (TARP) , and debt guarantee, etc. One strand of literature led by Gertler and Kiyotaki (2010) analyzed the effect of unconventional monetary policies on the real economy ex post. At the

Table 8: Moments across Alternative Model Specifications

Target Moments	Actual Moments	Baseline Model	First-moment Shock	No Firesale Cost: $\zeta = 1$	No Maturity Mismatch: $\delta = 1$
mean of leverage	0.9541	0.9489	0.9952	1.0984	1.1965
Std of leverage	0.1917	0.1312	0.0131	0.0247	0.0178
autocorrelation of leverage	0.8514	0.6874	0.6954	0.6844	0.6021
mean of asset growth	0.0447	0.0378	0.0119	0.0088	0.0767
Std of asset growth rate	0.0035	0.0142	0.0005	0.0012	0.0001
autocorrelation of asset growth rate	0.8997	0.9409	0.9788	0.8544	0.8730
mean default rate	0.0110	0.0098	0.0011	0.0028	0.0047
mean of dividend/asset ratio	0.0214	0.0369	0.0751	0.0485	0.0652
Std of dividend/asset ratio	0.0145	0.0019	0.0004	0.0027	0.0035
autocorrelation of dividend/asset ratio	0.7949	0.8532	0.9433	0.8104	0.7548
mean entrant leverage	0.9718	0.9945	0.9957	0.9844	1.0142
mean entrant growth	0.2417	0.1007	0.3014	0.2412	0.2578
IQR(75/25) leverage slope	1.1715	1.1954	1.0401	0.9215	0.9521
J-statistics		0.2070	4.3453	5.9981	6.0514
P-value		0.6491	0.0371	0.0498	0.0485

Notes: Calculations are based on an annual sample of shadow banks from the BankScope and WorldScope database. The estimation is done with SMM, which chooses model parameters by matching the moments from a simulated panel of banks to the corresponding moments from the data. J-statistics tests the over-identification constraint for the moment conditions.

same time, a growing theoretical literature investigates the moral hazard caused by the government bailout. When considering moral hazard, government intervention can be severely counterproductive. Once forming the expectation of government bailout, banks might act even more recklessly and this might even lead to a vicious cycle. In this section, I analyze the effects of two government policies: the Troubled Asset Relief Program(TARP) and debt guarantee.

Firstly, I consider the impact of TARP. The U.S. government announced Troubled Asset Relief Program(TARP) during the recent financial crisis. Under TARP, the U.S. Treasury provided capital to 736 financial institutions of all sizes across the country. The total rescue funds are around 200 billion, around 4.39% of bank's total asset. The Federal Reserve took some nonstandard procedures such as extending the range of collateral a bank could use to borrow from the central bank, and the exchange of illiquid assets by liquid assets. We model TARP in the following way: the government would purchase a certain fraction of a bank's long-term assets at full value, such that the bank can avoid part of the asset firesale costs. The balance sheet of the bank under TARP is shown in the following table.

Assets	Liabilities
long-term asset $(1-\delta)k_t - G_t$	net worth n_t
G_t cash flow$z_t k_t - (1-\delta)k_t$	risky debt $b_t - q_t b_{t+1}$

where $G_t = \xi^g(b_t - q_t b_{t+1} - z_t k_t + (1-\delta)k_t)$, ξ^g is the fraction of cash shortage replenished by the government, and ξ^g is calibrated to match the fraction of total government rescue fund in total assets.

After government intervention, the bank still need to firesale $\frac{(1-\xi^g)(b_t - q_t b_{t+1} - z_t k_t + (1-\delta)k_t)}{\zeta}$ amount of its long-term asset to pay the debt due, the total amount of long-term asset left after the firesale is $(1-\delta)k_t - G_t - \frac{(1-\xi^g)G_t}{\zeta\xi^g}$. The constraint of banks becomes:

$$e = (1-\delta)k_t - G_t - \frac{(1-\xi^g)G_t}{\zeta\xi^g} - k_{t+1}. \tag{21}$$

Second, I consider the impact of debt guarantee. During the recent financial crisis, the government also announced a debt guarantee for new short and medium term debt issued by eligible institutions in case a bank default. I examine the impact of this program by making the lender in the interbank market take into consideration of the possibility that the government will guarantee the debt of the bank in case of default. This formulation is in the same spirit as the third-party bailout in Aguiar and Gopinath(2006). [22]

Then the price schedule for risk debt can be written as follow:

$$\begin{aligned} q(z,k',b';\sigma) &= \frac{1-\iint d(z',k',b';\sigma')f(z'|z,\sigma')g(\sigma'|\sigma)\,d\theta d\sigma}{1+r} \\ &+(1-p)\,\frac{\iint d(z',k',b';\sigma')R(z',k',b')f(z'|z,\sigma')g(\sigma'|\sigma)\,dzd\sigma}{(1+r)b'} \\ &+p\,\frac{\iint d(z',k',b';\sigma')f(z'|z,\sigma')g(\sigma'|\sigma)\,dzd\sigma}{1+r} - \frac{\xi}{b'}. \end{aligned} \tag{22}$$

Since the bank could be bailed out by the government after it chooses to default, its default value is no longer zero. After taking into account of government bailout, the default value for the bank becomes

$$V^d = pV^c(z,k,0,\sigma). \tag{23}$$

I take into consideration of bank's moral hazard by modelling banks with larger asset size has higher probability of receiving debt guarantee. I assume the bailout probability is an increasing function of the bank's sizes and its asset return :$p = \varsigma z^{\chi} k^{1-\chi}$. Then I compare the leverage ratio a bank would have taken if it took into account of the endogenously determined bailout rate with the case that bailout probability is exogenously given. The expected bailout probability of these two types of bailout strategies are the same. The difference is that, under exogenous bailout probability, the government literally choose which bank to bailout by lottery, whereas in the case of an endogenous bailout probability, government bailout the banks with larger assets with higher probability.

I compare the different effects of debt guarantee and TARP on default rate, leverage, interbank

[22] In the 2007-2009 financial crisis, the U.S government bailed out some financial institutions and let others file for bankruptcy without further aid. It rescued Bear Sterns by subsidizing its merger with JP Morgan Chase&Co. It injected capital directly into 736 financial institutions, it also let over 400 financial institutions file for bankruptcy including Lehman Brothers.

Table 9: Government Policy Comparison

	No Policy	TARP	Debt Gurantee	
			exogenous bailout	endogenous bailout
mean spread	0.013	0.011	0.010	0.034
mean leverage	0.954	0.975	0.977	0.989
mean default rate	0.018	0.012	0.024	0.037
total liquidity	1.708	2.111	2.014	1.801

Notes: This table shows the simulated statistics of shadow banks using simulated bank panel under different government policy regime. TARP is modelled as the government purchases a certain fraction of bank's long-term asset at full value, such that the bank can avoid part of the costs of a firesale. Debt guarantee is modelled as the government bails out a bank with certain probability if a bank defaults. Bailout probability is the same for all banks under the exogenous bailout case and is an increasing function of bank asset size under the endogenous bailout case.

spread, and market liquidity. The results are shown in Table 9. In Table 9, two government interventions are chosen such that the total government resources used in each case are equal. Under debt guarantee, two bailout probability strategies are chosen such that the expected bailout probabilities are the same under two cases. The first column shows the statistics under no government policy. The second column corresponds to asset purchase of 5% of total bank assets under TARP. The third and fourth columns correspond to expected government bailout probability of 23% in case the bank defaults. This is obtained when I set $\varsigma = 0.395$ and $\chi = 0.4$.

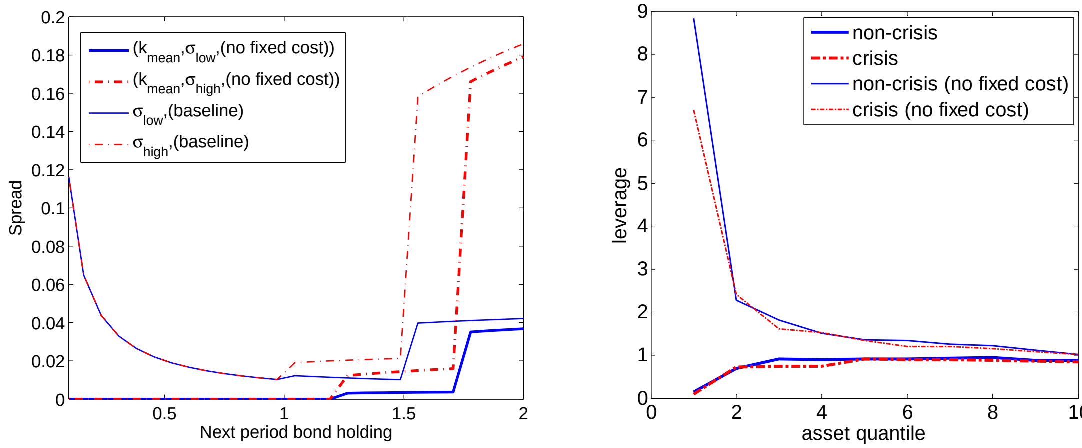
As shown in Table 9, given government intervention strategies, the banks would choose higher leverage ex ante on average. Under TARP, because banks partly avoid costly firesale, the banks' default probability is lower and the spreads they face are lower than the no policy case. However, bank would employ a slightly higher leverage compared with no policy case. Under the debt guarantee intervention, when the bailout probability is set as an increasing function of bank size , a bank would employ a higher leverage than in the exogenous bailout case. The reason is that a bank would tend to employ a higher leverage to build a bigger "empire" to take advantage of bailout probability. The implication is that it might be optimal to make uncertainty as a commitment. The uncertainty of government bailout makes the bank more cautious, avoiding to be the worst performer and exposing itself to the risk of not getting bailed out. Also, notice that under debt guarantee, although the default probability of banks is higher, because of government debt guarantee, the spread the bank faces is actually lower than no policy case. The total liquidity is calculated as the sum of assets of all non-default banks in the market, and the unit is 10^6. It inherently captures the credit shadow banks supply to the economy. Under government intervention, banks employ higher leverage and the total liquidity in the market is higher. However, since the bank default rate is higher under debt guarantee, the total liquidity of the market is lower than that under the TARP. Under the endogenous bailout case, although the total liquidity is higher than the no policy case because banks employ higher leverages, it is lower than the TARP or exogenous bailout case because banks default with higher probability.

5.5 Counterfactuals

I now examine the default, financing and investment decisions of banks provided that banks had different fundamental characteristics than those implied by the parameters estimates from Table 5. To this end, I first consider a baseline model without fixed credit cost. The interest spread schedule and the leverage schedule under no fixed credit cost are shown in Figure 18. Without fixed credit cost, banks face lower interest spreads. Banks experiencing sequence of bad asset return shocks would choose to reduce their scale to avoid costly equity issuance and increase their debt financing, climbing up their debt schedules. Thus the leverage schedule over asset would be counterfactually downward sloping. With fixed credit costs, it is much more costly for small banks to issue small amounts of debt, thus they would tend to employ lower leverages.

I also model financial innovation as the change of fixed credit cost to estimate the contribution of financial innovation to risk building of the U.S. shadow banking system before 2007-2009 financial crisis. This is in the same spirit as Quadrini (2015). I estimate the model on the subsamples of data from 1999 to 2004 and from 2007 to 2013, respectively. Then I keep other parameters unchanged, and change the fixed credit parameter to its average value during the 1999-2004 period. By doing this, I find that the aggregate leverage of the U.S. shadow banking sector would have been 0.941 in 2007 if the fixed credit cost were as high as it was during the period from 1999 to 2004. To the extent that other factors remain constant, financial innovation alone contributes to 44% of the increase of aggregate leverage in the U.S. shadow banking sector. Other factors contributes to the build up of risk, as argued in the literature, might be the change of interest rate driven by the increasing foreign demand for the U.S. risk-free assets, and the change of SEC regulations on shadow banking in 2004.

Figure 18: Interest Spread Schedule and Leverage Schedule under no fixed credit cost

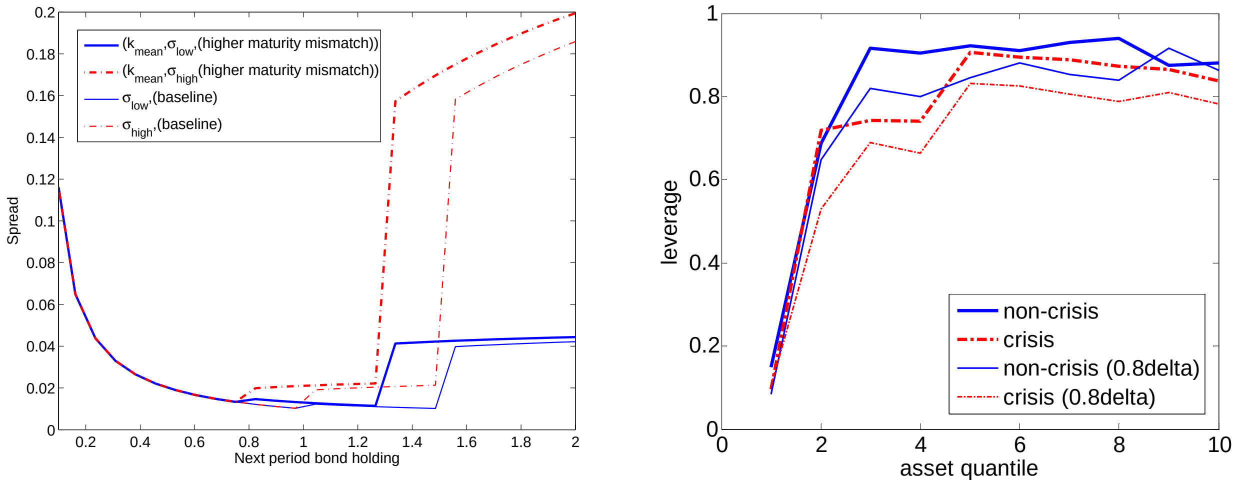


Notes: This figure depicts the counterfactual spread schedule and leverage schedule over different asset quantiles based on the bank panel data simulated assuming that there is no fixed credit cost. Crisis periods are defined as the periods with high asset return uncertainty. The rest of the periods are defined as non-crisis periods.

I then consider the impact of a higher degree of maturity mismatch. The results are shown in Figure 19. Because a higher degree of maturity mismatch would increase the probability of a costly firesale, banks would be more cautious and banks over all asset quantiles tend to use lower leverage in crisis-period compared with non-crisis periods. Higher maturity mismatch also increases the change of interest spread in the interbank market.

Finally, I show the comparative statics of the impact of changing the parameters that govern equity issuance cost, firesale cost, maturity mismatch, and asset adjustment cost on mean leverage of banks. The results are shown in Figure 20. The results of the model are robust across a wide range of parameter settings. To construct each panel, I change one parameter at a time while keeping other parameters unchanged as estimated in the benchmark model. For each panel, I solve and simulate the model 20 times, each time corresponding to different value of the parameter in question. For each of these 20 simulations, I calculate the mean leverage over the 100,000 simulated time periods. I find that the result that mean leverage is lower when the economy is in a high uncertainty state is robust across a wide range of parameter setups. When I increase the equity issuance cost, the mean leverage of the economy decreases. Banks would be more cautious, employing a lower leverage to reduce the probability of costly equity issuance. The higher the firesale cost parameter ζ, the higher the fraction of value the bank can get from the firesale of its asset. Because firesale becomes less

Figure 19: Interest Spread Schedule and Leverage Schedule under greater maturity-mismatch



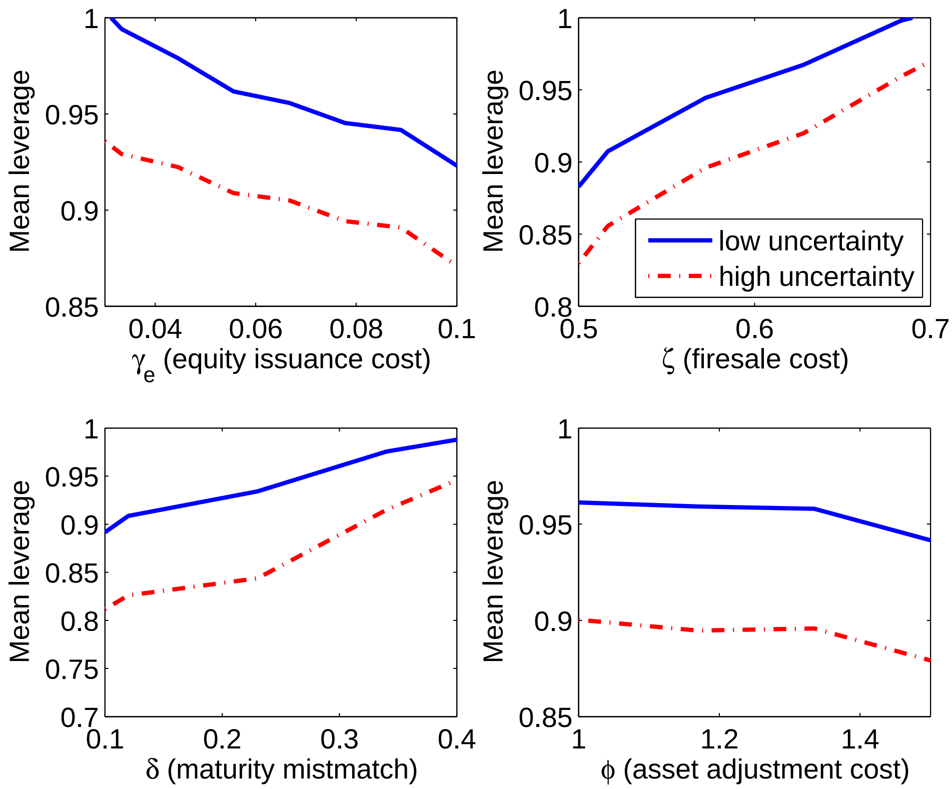
Notes: This figure depicts the counterfactual spread schedule and leverage schedule over different asset quantiles based on the bank panel simulated assuming that the degree of maturity mismatch is 80% of the estimated value. Crisis periods are defined as the periods with high asset return uncertainty. The rest of the periods are defined as non-crisis periods.

costly, banks are more willing to take higher leverage. The higher the maturity mismatch parameter, the lower the degree of the bank's asset and liability maturity mismatch. The probability of costly asset fire sale would decrease and thus banks employ higher leverages on average. Also the change of mean leverage from low to high uncertainty state would be smaller. Increasing asset adjustment costs raises the cost for banks to adjust assets when hit by unfavorable shocks. Thus, in general, banks would employ lower leverage when the adjustment cost increases.

6 Conclusion

In this paper, I examine the impact of asset return uncertainty on the financing and leverage decisions of shadow banks. I contribute to the literature by being the first in documenting several stylized facts of the U.S. shadow banking industry using a detailed micro-level dataset. On the theoretical front, I contribute to the literature by being the first in building a quantitative model with heterogeneous banks, endogenous bank default, aggregate uncertainty fluctuation and maturity mismatch to characterize the shadow banking dynamics in a full nonlinear manner. I show that when the uncertainty of bank asset return increases and interbank spread spikes up, shadow banks would

Figure 20: Mean leverage Comparative Statics



Notes: This figure depicts aggregate leverage ratio comparative statics under different parameter settings. For each panel, I solve and simulate the model 20 times, each time corresponding to a different value of the parameter in question. For each of these 20 simulations, I calculate the mean leverage over the 100,000 simulated time periods. The mean leverage under low uncertainty state and high uncertainty state are shown in solid blue line and red dotted line respectively.

employ a lower leverage to lower their default probability and reduce financing costs. This leads to a contraction in the credit supply. The findings show that uncertainty shocks are able to generate statistics and evolution paths of leverage, spread, and assets which closely match the empirical observations about the U.S shadow banking industry. High maturity mismatch and firesale costs amplify the impact of uncertainty shocks. Alternative model settings with only pure first-moment shocks, without asset firesale costs, or without maturity mismatch, can not rationalize the large spike in the interbank spread, dramatic deleveraging, and contraction of the U.S. shadow banking sector. I also analyze the impact of unconventional monetary policies. The finding suggests that unconventional monetary policies can help dampen the liquidity contraction. However, after taking into account bank moral hazard, government bailout might be counterproductive.

The paper also contributes to the literature for its strong policy implications. First, to counter the credit contraction, only maintaining the average asset return above a certain level is insufficient, certain measures[23] should be taken to cap the asset return uncertainty since it plays a more important role in affecting the size of shadow banking. Second, since maturity mismatch and firesale cost amplify the impacts of adverse shocks, to counter the rise in interbank spread and stabilize the credit supply, certain measures should be taken to restrict the degree of maturity mismatch and reduce the cost of asset firesale. Third, when carrying out unconventional monetary policies, the government should take into account the potential cost incurred by bank moral hazard.

To keep the analysis tractable, I have focused on a stylized model that abstracts from some realistic features in the actual economy. For example, I did not include firm sector and traditional banking sector in the model. Generalizing the model to incorporate firm sector and traditional banking sector is clearly desirable and is left for future research. Such generalization would make the model more empirically relevant for studying the role of financial intermediary leverage in propagating macroeconomic fluctuations, as shown by Liu, Wang, and Zha (2013) and Christiano et al. (2014). The key mechanism of the model, however, is likely to carry over to a model with more realistic features.

For my purpose, I have focused on understanding the impact of asset return uncertainty on financing and leverage decisions of shadow banks. When analyzing the impact of unconventional

[23]Potential policy remedies include stress tests on the shadow banking system ex ante to put a cap of the riskiness of the bank asset portfolio and ex post government interventions to restrict the movements of asset prices.

monetary policy, I abstracted from the direct cost of these policies. An important direction for future research is to study optimal fiscal and monetary policy interventions in the presence of bank moral hazard. The bailout probability in the model is still exogenous in the sense that the I did not explicitly model a government that chose this probability endogenously. Moreover, I did not explore what policies governments should take ex-ante to avoid bank's excessive risk-taking. A mix of ex-ante macro-prudential policy and ex-post interventions may serve the optimal purpose of banking regulation. Future research along these lines should be both promising and fruitful. My work represents a small step toward this direction.

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Appendix

A Computation Algorithm:

1. Discretize a finite state space for the four state variables: $\{z, k, b; \sigma\}$. The gross asset return rate and asset return uncertainty are discretized according the method proposed by Tauchen and Hussey (1991).

2. Take as given the risk-free interest rate, and assume an initial price function $q^0(z, k, b; \sigma)$. Use this q^0 and solve for the maximization problem of banks using value function iteration.

3. Update the price function as q^1 and solve for the bank's problem. Repeat step 2 and 3 until the distance between value function and price schedule is sufficiently close . Obtain the policy function.

4. Using the policy function, simulate a data panel of $(KN, T + 100)$,where K is a strictly positive integer denoting the number of simulated panel datasets, N is the number of banks in the actual data, T is the time dimension of the simulated data. Estimate the parameters by simulated methods of moments (SMM).

B SMM Estimation

The fraction of the loan due each period δ, equity issuance cost γ_e , firesale cost ς , parameters governing aggregate shocks $\rho_\sigma, \mu_\sigma, \varphi$, the adjustment cost ϕ, the persistence of asset return ρ_v, credit fixed cost ξ, entrant start-up asset k_0, and two more paremeters govern the pareto distribution of the permanent productivity are jointly determined to matched 13 moments: the mean of default rate, the mean, the standard deviation and the auto-correlation of leverage, asset growth rate and the dividend to asset ratio of shadow banks and the mean leverage and growth of new entrant banks and the slope of the leverge schedule using simulated methods of moments(SMM), which minimizes a distance criterion between key moments from actual data. SMM procedes in the following way: For an arbitrary value of parameter vector $\theta = \{\nu, A, \rho, \rho_\sigma, \mu_\sigma, \varphi, \phi, \xi, k_0, \gamma_e, \delta, \varsigma\}$, the dynamic problem is solved and the policy functions are generated. Then I use the policy functions to simulate a data panel of $(KN, T + 100)$, where K is a strictly positive integer denoting the number of simulated panel datasets, N is the number of banks in the actual data, and T is the time dimension of the simulated data. The first 100 periods are discarded so as to start from the ergodic distribution.

Let x_{it} be the actual data vector, $i = 1, 2, ..., N$, $t = 1, ...T$, and let $y_{itk}(b)$ be the simulated vector from simulation k,$i = 1, 2, ..., n$, $t = 1, ...T$, and $k = 1, 2, ..., K$. The simulated data vector, $y_{itk}(\theta)$, depends on a vector of structural parameters, θ. Define the moment conditions as:

$$\frac{1}{NT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left[h(x_{it}) - \frac{1}{K}\sum_{k=1}^{K}h(y_{itk}(\theta))\right] \equiv \Psi^A - \Psi^S(\theta) \tag{B.1}$$

where $h(y_{itk}(\theta))$ is a vector of simulated moments and $h(x_{it})$ is the actual data moments. $\Psi^A = \frac{1}{NT}\sum\limits_{i=1}^{n}\sum\limits_{t=1}^{T}h(x_{it})$, $\Psi^S(\theta) = \frac{1}{NTK}\sum\limits_{i=1}^{n}\sum\limits_{t=1}^{T}\sum\limits_{k=1}^{K}h(y_{itk}(\theta))$

The simulated moments estimator is defined as the solution to the minimization of:

$$\hat{\theta} = \underset{\theta}{argmin}\left[\Psi^A - \Psi^S(\theta)\right]'\hat{W}\left[\Psi^A - \Psi^S(\theta)\right] \tag{B.2}$$

in which $\hat{W}$ is a positive definite matrix that converges in probability to a deterministic positive definite matrix W. It is constructed by calculating the inverse of the variance-covariance matrix of the data moments. Define Ω as the variance covariance matrix of the data moments Ψ^A. Lee and Ingram (2010) show that under the estimating null, the variance covariance of the simulated moments $\Psi^S(\theta)$ is equal to $\frac{1}{K}\Omega$. Since $\Psi^A$and $\Psi^S(\theta)$ are independent by construction, $\hat{W} = \left[(1 + \frac{1}{K})\Omega\right]^{-1}$. Ω is calculated using influence function method following Erickson and Whited (2002).

I use a simulated annealing algorithm for minimizing the objective function. This starts with a predefined first and second guess. For the third guess onward, it takes the best prior guess and randomizes from this to generate a new set of parameter guesses. That is, it takes the best-fit parameters and randomly "jumps off" from this point for its next guess. Over time the algorithm "cools", so that the variance of the parameter jumps falls, allowing the estimator to fine-tune its parameter estimates around the global best fit. I restart the program with different initial conditions to ensure the estimator converges to the global minimum. The simulated annealing algorithm is extremely slow, which restricts the size of the parameter space that can be estimated. Nevertheless, I use this because it is robust to the presence of local minima and discontinuities in the objective function across the parameter space.

The simulated moments is asymptotically normal for fixed K. Denote $g(\theta) \equiv \Psi^A - \Psi^S(\theta)$. The asymptotic distribution of θ is given by:

$$\sqrt{n}(\theta - \hat{\theta}) \xrightarrow{d} N(0, avar(\hat{\theta})) \tag{B.3}$$

in which

$$avar(\hat{\theta}) = (1 + \frac{1}{K}) \left[\frac{\partial g}{\partial \theta} W \frac{\partial g}{\partial \theta'}\right]^{-1} \left[\frac{\partial g}{\partial \theta} W \Omega W \frac{\partial g}{\partial \theta'}\right] \left[\frac{\partial g}{\partial \theta} W \frac{\partial g}{\partial \theta'}\right] \tag{B.4}$$

in which Ω is the probability limit of a consistent estimator of the covariance matrix. I calculate the estimate of this covariance matrix using influence function of the moment vector clustered at bank level following Erickson and Whited (2002).

C Proofs

Proposition 1: Bank's leverage z^* decreases in its discount factor β and increases in floatation cost χ . When the bank is sufficiently patient: $\beta = \frac{\chi}{1+r}$, it totally depends on internal (equity) finance ($z^* = 0$).

Proof:

Denote

$$G(\beta, z^*) = z^* - \frac{1}{1-\theta}\left[1 - \frac{\beta(1+r)}{\chi}\right]\pi(z^*)^{-1} = 0,$$

Then by implicit function theorem

$$\frac{\partial z^*}{\partial \beta} = -\frac{\partial G/\partial \beta}{\partial G/\partial z^*} = -\frac{\frac{1}{1-\theta}\frac{(1+r)}{\chi}\pi(z^*)^{-1}}{1 + \frac{1}{1-\theta}\left[1 - \frac{\beta(1+r)}{\chi}\right]\pi(z^*)^{-2}\frac{\partial \pi(z^*)}{\partial z^*}}.$$

Note that:

$$\frac{\partial \pi(z^*)}{\partial z^*} = \frac{f'(z^*)\left[1 - F(z^*)\right] + f(z^*)^2}{\left[1 - F(z^*)\right]^2} > 0$$

.

Hence:

$$\frac{\partial z^*}{\partial \beta} < 0.$$

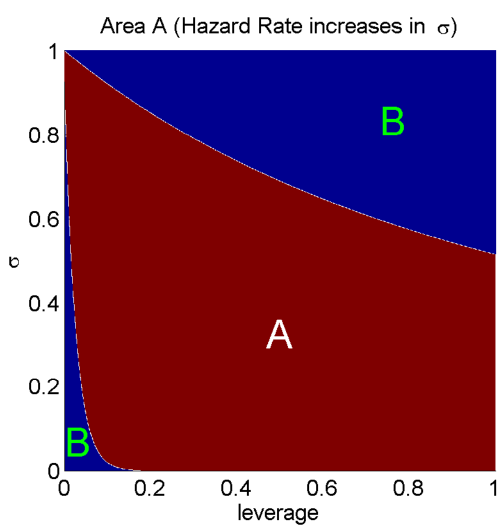
Similarly, it is trivial to show z^* increases in flotation cost χ.

Q.E.D

Proposition 2: When the bank is sufficiently impatient:$\beta < \frac{\chi}{1+r}$, as long as the hazard rate is an increasing function of asset return uncertainty, i.e., $\frac{\partial \pi(z^*)}{\partial \sigma} > 0$, leverage is a decreasing function of asset return uncertainty: $\frac{\partial z^*}{\partial \sigma} < 0$.

Proof:

Unfortunately, the hazard rate of log-normal distribution is not monotone in σ, which makes analytical solution for the range of parameters a nontrivial task. However, I find that under a wide range of parameters, $\frac{\partial \pi(z^*)}{\partial \sigma} > 0$[24]. As shown in the following graph, the hazard rate function of lognormal distribution is an increasing function of σ in Area A and a decreasing function of σ in Area B. Both the value of asset return uncertainty σ and mean leverage value z^* I estimated from the data[25] fall in Area A.



[24]Statistically, hazard rate $\pi(z^*)$ is the probability of observing an outcome within a neighborhood of z^*, conditional on the outcome being no less than z^*. For lognormal distribution, in a wide range of distribution parameters, when the volatility of the economy increases, this probability increases.

[25]See Figures 2, 6 and 7.

As long as $\frac{\partial \pi(z^*)}{\partial \sigma} > 0$ and $\frac{\beta(1+r)}{\chi} < 1$[26], it is trivial to show $\frac{\partial z^*}{\partial \sigma} < 0$.

Define:

$$H(z^*, \sigma) = z^* - \frac{1}{1-\theta}\left[1 - \frac{\beta(1+r)}{\chi}\right]\pi(z^*)^{-1},$$

Note that:

$$\frac{\partial \pi(z^*)}{\partial z^*} = \frac{f'(z^*)\left[1 - F(z^*)\right] + f(z^*)^2}{\left[1 - F(z^*)\right]^2} > 0$$

by the implicit function theorem, we have:

$$\frac{\partial z^*}{\partial \sigma} = -\frac{\partial H/\partial \sigma}{\partial H/\partial z^*} = -\frac{\frac{1}{1-\theta}\left[1 - \frac{\beta(1+r)}{\chi}\right]\frac{1}{\pi(z^*)^2}\frac{\partial \pi(z^*)}{\partial \sigma}}{1 + \frac{1}{1-\theta}\left[1 - \frac{\beta(1+r)}{\chi}\right]\frac{1}{\pi(z^*)^2}\frac{\partial \pi(z^*)}{\partial z*}} < 0$$

Q.E.D

Assumption 1: $\frac{1}{2}erfc(\sqrt{\pi}) < \frac{\theta}{2} < \frac{\beta(1+r)}{\chi} < 1, 0 < z^* < 1.$

Proposition 3: The bank asset is a decreasing function of the asset return uncertainty: $\frac{\partial k}{\partial \sigma} < 0$.

Proof:

From the first order condition with respect to k, denote

$$G(z^*, k, \sigma) \quad = \quad \frac{\chi}{1+r}\left[\int_0^{z^*} z\theta \, dF(z) + z^*(1 - F(z^*))\right] + \beta \int_{z^*} (z - z^*)dF(z) - 1 - \Psi^{'}(k, 0)$$

After some algebra, it can be shown that:

$$\frac{\partial G}{\partial \sigma} \quad = \quad a_1 \left\{ \left[2\theta + \sqrt{z^*}e^{\frac{\sigma^4 + 4[log(z^*)]^2}{8\sigma^2}} erfc(\sqrt{\pi})\right] log(z^*) - \left[2\frac{\beta(1+r)}{\chi} - \theta + \sqrt{z^*}e^{\frac{\sigma^4 + 4[log(z^*)]^2}{8\sigma^2}} erfc(\sqrt{\pi})\right]\sigma^2 \right\},$$

where $a_1 = \frac{\chi}{1+r}\frac{\sqrt{z^*}}{2\sqrt{2\pi\sigma^2}}e^{-\frac{\sigma^4 + 4[log(z^*)]^2}{8\sigma^2}} > 0$,
Where $erfc$ is the emplementary error function, $erfc(x) = \frac{2}{\sqrt{\pi}}\int_x^\infty e^{-t^2}dt, erfc(\sqrt{\pi}) = 8.9696 \times 10^{-6} > 0$,

Under assumption 1, $\frac{\partial G}{\partial \sigma} < 0$.

Also note that by F.O.C with respect to z^* (equation (8)):

$$\frac{\partial G}{\partial z^*} = (\frac{\chi}{1+r} - \beta)\left[1 - F(z^*)\right] - \frac{\chi}{1+r}\left[(1-\theta)z^* f(z^*)\right] = 0.$$

Then by total differentiating $G(z^*, k, \sigma) = 0$ with respect to σ on both sides, we get:

$$\partial k/\partial \sigma = -\frac{\frac{\partial G}{\partial \sigma} + \frac{\partial G}{\partial z^*}\frac{\partial z^*}{\partial \sigma}}{\partial G/\partial k} = \frac{\frac{\partial G}{\partial \sigma}}{\Psi''(k, 0)} < 0$$

[26]The condition $\frac{\beta(1+r)}{\chi} < 1$ requires that the bank is sufficiently impatient: its discount factor is smaller than $\frac{\chi}{1+r}$, so that the bank would choose to borrow.

[27]

Q.E.D

Proposition 4: The increase of asset return uncertainty increases the spread the bank faces when it issues debt.

Proof:

By

$$q = \frac{1}{1+r}\left[\int_{z^*} dF(z) + \int_0^{z^*} \frac{z\theta}{z^*} dF(z)\right],$$

we have:

$$\frac{dq}{d\sigma} = \frac{\partial q}{\partial z^*} \cdot \frac{\partial z^*}{\partial \sigma} + \frac{\partial q}{\partial \sigma},$$

There exist two competing forces:

On the one hand, the bank would deleverage to decrease the default rate. Volatility increase would have a negative impact on default cutoff z^*, imposing a positive impact on the bond price:

$$\because \frac{\partial q}{\partial z^*} = -\frac{1}{1+r}\left[f(z^*)(1-\theta) + \int_0^{z^*} \frac{z\theta}{z^{*2}} dF(z)\right] < 0,$$

and from Proposition 2, $\frac{\partial z^*}{\partial \sigma} < 0$,

$$\therefore \frac{\partial q}{\partial z^*} \cdot \frac{\partial z^*}{\partial \sigma} > 0.$$

On the other hand, the increase of volatility would increase the default rate for any given default cutoff, this would have a negative impact on bond price.

The sign of $\frac{dq}{d\sigma}$ depends on which force prevails. Under lognormal distribution, it can be shown that the second force prevails.

After some algebra, it can be shown that, under assumption 1, $z^* e^{-\frac{[\sigma^4 - 2log(z^*)^2]}{8\sigma^2}} erfc(\sqrt{\pi}) < erfc(\sqrt{\pi}) < \theta$, thus:

$$\frac{dq}{d\sigma} = -a_2 \left\{ \left[\theta - z^* e^{-\frac{[\sigma^4 - 2log(z^*)^2]}{8\sigma^2}} erfc(\sqrt{\pi})\right] \sigma^2 - \left[2\theta + z^* e^{-\frac{[\sigma^4 - 2log(z^*)^2]}{8\sigma^2}} erfc(\sqrt{\pi})\right] log(z^*) \right\} < 0$$

[27] Notes that since both asset size k and leverage z^* are decreasing in σ, when σ increases, the asset and leverage ratio both decreases. This prediction is consistent with the empirical observation.

where $a_2 = \frac{1}{2z^*\sqrt{2\pi\sigma^2}} e^{-\frac{[\sigma^4 - 2log(z^*)^2]}{8\sigma^2}} > 0$

Denote $spread = \frac{1}{q} - 1 - r$, then $\frac{\partial spread}{\partial \sigma} = -\frac{1}{q^2}\frac{dq}{d\sigma} > 0$

Q.E.D

D Data

I now describe in detail how I obtain the data for shadow banks. In the literature, shadow banks are often defined as financial institutions that do not have access to central bank liquidity or public sector credit guarantees. One of the difficulties for analyzing shadow banking is the lack of publicly available micro-level dataset. Another difficulty lies in the fact that the definition of shadow banks is not clear-cut. Commercial banks also engage in shadow banking activities and many shadow banking activities are not reported on the banks' balance sheets. In this paper, I obtain the yearly bank-level panel data from the BankScope database, complemented with bank-level data from WorldScope database. BankScope contains comprehensive information on banks across the globe. I choose real estate and mortgage banks, investment banks, micro-financing institutions, securities firms, private banking and asset management companies, investment and trust corporations, finance companies, clearing and custody institutions, group finance companies of U.S. as representatives of shadow banks. I also choose commercial banks, savings banks, cooperative banks, and bank holding companies as representatives of traditional banks. I drop all banks which have negative equity/asset/capital or deposits, drop all banks with faulty records such as inconsistent information on any generic variables: date of establishment/type of company etc. The names of variables I am interested in are: assets, liabilities, return on asset(ROA), long-term asset, short-term asset, deposit, equity, derivatives, other securities. The final panel data sample contains 281 shadow banks and 9554 traditional banks from 1998 to 2013, covering 49 states of the U.S.

The descriptive statistics for the data are illustrated in the following Table 1 and Table 2

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Table 1: Descriptive Statistics 1998-2013

ID	Specialization		Asset(Million USD)			Leverage		
		Number	mean	min	max	mean	min	max
1	Commercial Banks	6674	1.37	0.00	1,950.00	0.88	0.00	1.00
2	Savings Bank	708	0.88	0.00	62.90	0.86	0.02	1.00
3	Cooperative Bank	17	12.90	0.04	97.60	0.88	0.01	0.99
4	Real Estate & Mortgage Bank	19	104.00	0.51	1,990.00	0.94	0.64	1.00
5	Investment Banks	73	64.40	0.00	1,020.00	0.83	0.00	1.00
6	Other Non Banking Credit Institution	2	0.05	0.01	0.22	0.36	0.17	0.65
11	Securities Firm	51	85.70	0.01	679.00	0.80	0.00	1.00
12	Private Banking & Asset Mgt Companies	6	19.00	0.32	103.00	0.66	0.04	0.96
13	Investment & Trust Corporations	26	14.50	0.00	239.00	0.67	0.00	0.99
14	Finance Companies	93	27.70	0.00	404.00	0.82	0.05	1.00
15	Clearing Institutions & Custody	8	30.90	0.11	161.00	0.91	0.22	1.00
16	Group Finance Companies	2	46.60	0.54	138.00	0.74	0.55	0.99
17	Bank Holding & Holding Companies	2155	11.50	0.01	2,420.00	0.90	0.00	1.00
	Traditional Banks:1,2,3,17	9554	2.866	0.001	2,420.000	0.8822	0.0000	0.9999
	Shadow Banks:4,5,6,11,12,13,14,15,16	281	69.800	0.002	3,270.000	0.8219	0.0000	0.9993
	Total	9835	4.096	0.001	3270.000	0.8809	0.0000	0.9999

Table 2: Statistics for Top 10 Largest Banks(by 2013 Total Asset(Unit: Billion U.S. dollars))

		2006			2008			2010		
Ranking	Specialization	Asset	Equity	Leverage	Asset	Equity	Leverage	Asset	Equity	Leverage
Traditional Banks:										
1	JP Morgan Chase Bank, NA	1179.390	98.898	0.916	1746.242	129.796	0.926	1631.621	123.399	0.924
2	Bank of America, National Association	1196.124	111.347	0.907	1471.631	133.335	0.909	1482.278	179.814	0.879
3	Wells Fargo Bank, NA	398.671	40.331	0.899	538.958	41.805	0.922	1102.278	123.562	0.888
4	Citibank NA	1019.497	74.210	0.927	N.A	86.554	N.A	1154.293	127.960	0.889
5	US Bank National Association	217.802	22.163	0.898	261.776	22.850	0.913	302.260	30.827	0.898
6	PNC Bank, National Association	90.142	8.354	0.907	N.A	12.915	N.A	256.639	33.875	0.868
7	Bank of New York Mellon (The)	85.987	8.875	0.897	195.164	11.723	0.940	181.855	15.865	0.913
8	Capital One National Association	30.803	5.576	0.819	115.142	20.033	0.826	126.901	24.228	0.809
9	TD Bank National Association	39.582	8.869	0.776	101.632	18.292	0.820	168.749	25.842	0.847
10	HSBC Bank USA, National Association	165.673	12.258	0.926	181.620	12.673	0.930	181.118	17.603	0.903
Subtotal/Average:		4423.671	390.881	0.912	4612.165	489.976	0.894	6587.992	702.974	0.893
Total Asset of Traditional Banking System:		19189.192			21840.704			23712.785		
Top10TB/Total Asset of Tradition Banking System(%)		23.053			21.117			27.782		
Top10TB/Total Asset of Banking System(%)		13.841			14.252			18.741		
Traditional Banking/Total Banking System(%)		60.041			67.491			67.456		
Shadow Banks:										
1	Merrill Lynch & Co., Inc.	841.299	39.038	0.954	667.543	20.003	0.970	621.626	50.146	0.919
2	Goldman, Sachs & Co	509.251	4.686	0.991	476.490	7.758	0.984	527.001	9.286	0.982
3	JP Morgan Securities LLC	236.191	3.659	0.985	399.545	4.422	0.989	362.019	10.243	0.972
4	Citigroup Financial Products Inc	657.481	15.115	0.977	N.A	N.A	N.A	484.457	10.594	0.978
5	Morgan Stanley & Co LLC	583.405	5.520	0.991	297.422	5.760	0.981	372.537	9.702	0.974
6	Credit Suisse (USA), Inc.	N.A	N.A	N.A	N.A	N.A	N.A	377.487	25.444	0.933
7	Barclays Capital Inc	236.023	1.935	0.992	240.429	6.449	0.973	330.107	7.343	0.978
8	Credit Suisse Securities (USA) LLC	269.834	9.776	0.964	326.348	10.664	0.967	312.685	12.595	0.960
9	Merrill Lynch Pierce Fenner & Smith Inc	216.650	5.438	0.975	138.013	2.238	0.984	297.900	13.827	0.954
10	Citigroup Global Markets, Inc	377.951	10.833	0.971	286.825	6.383	0.978	288.409	16.020	0.944
Subtotal/Average:		3928.084	95.999	0.976	2832.615	63.676	0.978	3974.229	165.200	0.958
Total Asset of Shadow Banking System:		12771.000			10520.000			11440.000		
Top10SB/Total Asset of Shadow Banking System(%)		30.758			26.926			27.545		
Top10SB/Total Asset of Banking System(%)		12.291			8.753			11.306		
Shadow Banking/Total Banking System(%)		39.959			32.509			32.544		
Total Asset of Banking System:		31960.192			32360.704			35152.785		
Top10/Total Asset Banking System		22.005			18.994			24.026		
Notes: All non-ratio items are in billion 2005 dollars										