Online Appendices for “Uncertainty and the Shadow Banking Crisis: Estimates from a Dynamic Model”

A SMM estimation

The model has 22 parameters, as shown in Table 4. 8 parameters are calibrated externally and the rest 14 parameters are jointly estimated following a simulated method of moments approach as in Erickson and Whited (2002). The 14 parameters include the following: equity issuance cost γ_e, fire-sale cost ζ, parameters governing the value and transition matrix of aggregate uncertainty shocks $\pi^{\sigma}_{H,H}, \pi^{\sigma}_{L,L}, \sigma_H, \sigma_L$, the asset adjustment cost ϕ, persistence of asset return ρ_v, fixed operating cost ξ, entrant start-up asset k_0, entry cost f_e, Pareto distribution parameter of the entrant productivity ω, and two parameters μ and A that govern the Pareto distribution of the permanent productivity. They are jointly estimated to match the following 18 moments: the mean of leverage, the mean of default rate, the mean, standard deviation, and the auto-correlation of dividend payout/asset ratio and new asset issuance/asset ratio, the mean of equity issuance, the mean, standard deviation, auto-correlation, and skewness of asset return uncertainty, the average growth rate and relative size of new entrant banks, mean and standard deviation of interest spread, and the slope of the leverage schedule using simulated methods of moments (SMM), which minimizes a distance criterion between key moments from actual data and simulated data. SMM proceeds in the following way: For an arbitrary value of parameter vector $\theta = \{\gamma_e, \zeta, \pi^{\sigma}_{H,H}, \pi^{\sigma}_{L,L}, \sigma_H, \sigma_L, \phi, \rho_v, \xi, k_0, f_e, \omega, \mu, A\}$, the dynamic problem is solved and the policy functions are generated. Then I use the policy functions to simulate a data panel of $(KN, T+1000)$, where K is a strictly positive integer denoting the number of simulated panel data sets, N is the length of the simulated sample, and T is the time dimension of the simulated data. The first 1000 periods are discarded so as to start from the ergodic distribution.

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

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[h(x_{it}) - \frac{1}{K}\sum_{k=1}^{K}h(y_{itk}(\theta))\right] \equiv \Psi^A - \Psi^S(\theta) \tag{28}$$

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

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

$$\hat{\theta} = \underset{\theta}{argmin}\left[\Psi^A - \Psi^S(\theta)\right]' \hat{W}\left[\Psi^A - \Psi^S(\theta)\right] \tag{29}$$

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

$$\sqrt{n}(\theta - \hat{\theta}) \xrightarrow{d} N(0, avar(\hat{\theta})) \tag{30}$$

in which

$$avar(\hat{\theta}) = (1 + \frac{1}{K}) \left[\frac{\partial g}{\partial \theta} W \frac{\partial g}{\partial \theta'} \right]^{-1} \left[\frac{\partial g}{\partial \theta} W \Omega W \frac{\partial g}{\partial \theta'} \right] \left[\frac{\partial g}{\partial \theta} W \frac{\partial g}{\partial \theta'} \right]^{-1} \tag{31}$$

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).

B Empirical Appendix

B.1 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 in analyzing shadow banking is the lack of publicly available micro-level data set. In this paper, I obtain the yearly bank-level panel data from the Bankscope database, complemented with bank-level data from Worldscope database. Bankscope and Worldscope database contain comprehensive information on financial institutions across the globe. I choose real estate and mortgage banks, investment banks, securities firms, private banking and asset management companies, investment and trust corporations, finance companies and other nonbank financial institutions in the U.S. as representatives of shadow banks. My classification of shadow banks is similar to the Financial Stability Board's measure of shadow banking activity based on nonbank financial intermediaries (NBFIs) engaged in credit intermediation activities. 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, and all banks with faulty records such as inconsistent information on any generic variables: date of establishment/type of company, etc. The final panel data sample contains 281 shadow banks and 9554 traditional banks from 1998 to 2013, covering 49 states of the US.

B.2 The Measurements for Maturity Mismatch and Fire-sale Cost

There is no bank-level information available on maturity and fire-sale cost for shadow banks in my dataset. Due to the data limitation, I resort to aggregate data to obtain the estimates for maturity mismatch and fire-sale cost. Following the approach in Hanson, Shleifer, Stein, and Vishny (2015), I assemble data on the assets and liability of various types of financial intermediaries using the Federal Reserve's Financial Accounts of the United States. I use data on intermediary balance sheet. In an effort to avoid subjective judgment, following Hanson, Shleifer, Stein, and Vishny (2015), wherever possible I assign numerical values for liquidity and maturity based on the bank liquidity requirements put forth under Basel III Accord. For each instrument type, I attempt to choose values of these parameters based on the proposed calibration of Basel III's Net Stable Funding Requirement (NSFR) in Basel Committee on Banking Supervision (2010) and the final calibration of the Liquidity Coverage Ratio (LCR) in Basel Committee on Banking Supervision (2013).

Let A_{ji} and L_{ji} denote intermediary j's assets and liabilities of instrument type i. $A_j = \sum_i A_{ji} = \sum_i L_{ji}$ denotes the total assets of intermediary type j. For intermediary type j, its maturity mismatch index is the weighted average contractual maturity of its liabilities versus its assets: $MMI_j = \frac{\sum_i L_{ij} \times Maturity_i}{\sum_i A_{ji} \times Maturity_i}$. The lower is the index, the higher is the degree of maturity mismatch. The weighted value of maturity mismatch index for non-bank financial institutions is 0.0956. Therefore, the maturity mismatch parameter λ is set at the value of 0.0956, implying that the maturity of asset is around

$10.46 (= 1/0.0956)$ times that of the liability.[55]

For intermediary type j, I also construct its fire-sale cost index. The asset fire-sale cost index for intermediary type j is defined as the weighted average illiquidity of its asset holdings: $FCI_j = \frac{\sum_i A_{ij} \times Illiquidity_i}{A_j}$. The higher is the index, the higher is the fire cost. I use these fire-sale cost indices to split the whole sample into subsamples with low and high fire-sale cost in the subsample estimation.

The fire-sale cost index constructed above, however, can not directly be used to measure the fire-sale cost parameter since it has no cardinal meaning. I compare the model estimated fire-sale cost with the estimates of fire-sale cost based on the haircut estimates reported by BIS Committee on the Global Financial System.[56] The estimated fire-sale parameter implies a haircut rate of 42% in recession and 16% in normal periods. These values lie within the broad range of estimated haircut rates for nonbank financial institutions by BIS Committee on the Global Financial System.

B.3 Alternative Measurements for Asset Return Uncertainty

Since I only have annual data for ROA in 15 years, there is not enough data to construct a time-series of the idiosyncratic component of bank ROA using moving sample regression.[57] One possible estimate of uncertainty is based on the following two-step procedure proposed by Gilchrist, Sim, and Zakrajsek (2014) using stock price information of non-bank financial institutions. First, I remove the forecastable variation in daily excess returns using the standard (linear) factor model:

$$R_{it_d} - r^f_{t_d} = \alpha_i + \boldsymbol{\beta_i'} \boldsymbol{f_{t_d}} + u_{it_d} \tag{32}$$

where i index banks and t_d, $d = 1, 2, ..., D_t$ indexes trading days in quarter t. R_{it_d} denotes the daily return of bank i, $r^f_{t_d}$ is the risk-free rate, and $\boldsymbol{f_{t_d}}$ is a vector of observable risk factors. I employ a 4-factor model-namely the Fama and French (1992) 3-factor model, augmented with the momentum risk factor proposed by Carhart (1997).

In the second step, I calculate the quarterly firm-specific standard deviation of daily idiosyncratic returns, according to the following formula:

$$\sigma_{it} = \sqrt{\left[\frac{1}{D_t} \sum_{d=1}^{D_t} (\hat{u}_{it_d} - u_{it})^2 \right]} \tag{33}$$

where $\hat{u}_{it_d}$ denotes the OLS residual- the idiosyncratic return-from equation (32) and $u_{it} = \frac{1}{D_t} \sum_{d=1}^{D_t} \hat{u}_{it_d}$ is the sample mean of daily idiosyncratic returns in quarter t. σ_{it} is an estimate of time-varying equity

[55] The (weighted) average maturity of existing loans (assets) at date t , assuming the bank neither defaults nor makes any adjustments on the current investment in loans, is $\sum_{s=0}^{\infty} \frac{(s+1)\lambda k_{t+s}}{k_t} = \sum_{s=0}^{\infty} (s+1)\lambda(1-\lambda)^s = \frac{1}{\lambda}$, as the residual loan outstanding at date $t+s$, $s \geq 0$, is $k_{t+s} = k_t(1-\lambda)^s$.

[56] There are very few empirical surveys of haircuts in the repo and securities lending markets. One of the more comprehensive was conducted by the BIS Committee on the Global Financial System in 2007 and 2009.

[57] For instance, if we use rolling window of 10 years to run the regression, we can at most obtain estimates of bank idiosyncratic component in 6 years.

volatility for bank i. This measure is purged of the forecastable variation in expected returns. The cross-sectional average of σ_{it} can serve as an estimate for the uncertainty shock.

Figure B1 shows the comparison between the estimated asset return uncertainty and the one estimated using the method proposed by Gilchrist, Sim, and Zakrajsek (2014). Although the raw magnitudes are different for these two measures, they roughly follow the same pattern. The correlation between the two series is as high as 0.9846.

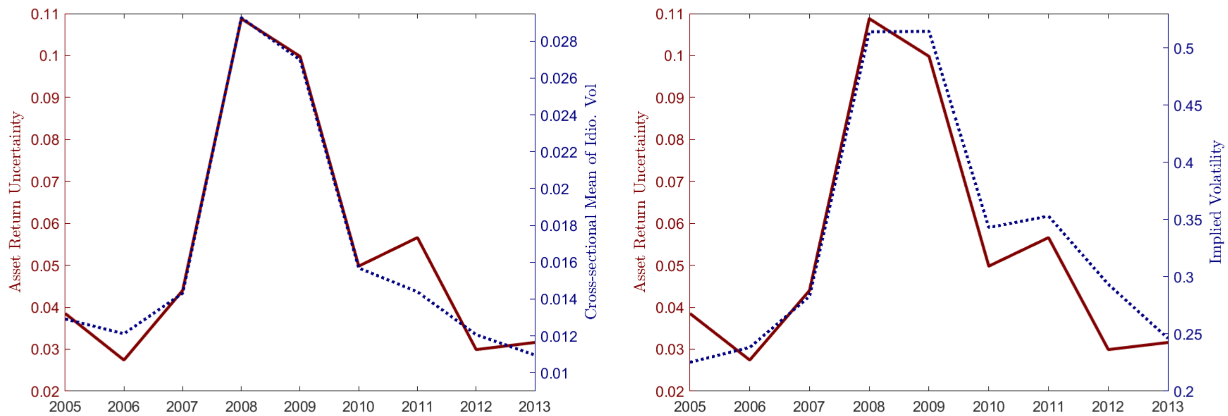

Figure B1: **Robustness Check: Alternative Measurements for Asset Return Uncertainty**. The left panel of this figure depicts the baseline measurement of asset return uncertainty (left axis) and an alternative measure of uncertainty (right axis) using the method proposed in Gilchrist, Sim, and Zakrajsek (2014), where uncertainty is measured as the cross-sectional mean of idiosyncratic volatility. The right panel of this figure depicts the baseline measurement of asset return uncertainty (left axis) and an alternative measure of uncertainty (right axis) using option prices information of non-bank financial institutions in the Option Metric database, where uncertainty is measured as the annual average of daily (365-day) implied volatility of at-the-money-forward call options following Alfaro, Bloom, and Lin (2019).

Note that I couldn't observe the daily stock price information for all banks in my sample. Thus this method is subject to sample limitation. Due to the data limitation, I choose to follow the standard approach as in Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2019) and Arellano, Bai, and Kehoe (2018) to construct the uncertainty shock measures in the paper. The other advantage of the standard approach is that it provides a very tight link between the model and the data. The gross asset return rate is assumed to follow an AR(1) process, both in the model and in the data. And asset return uncertainty is measured as the cross-sectional standard deviations of the residual terms, both in the model and in the data.[58] This tight mapping provides much cleaner identification in the parameter estimation.

I also use option prices information of non-bank financial institutions in the Option Metric database and back out the implied uncertainty using Black-Scholes formula. Uncertainty is measured as the annual average of daily (365-day) implied volatility of at-the-money-forward call options following Alfaro, Bloom, and Lin (2019). The pattern of the estimated "perceived" uncertainty are also quite similar to the "realized" uncertainty. The correlation between these two measures is 0.9668. This is unsurprising. As shown in the literature (see Baker, Bloom, and Davis (2016) among others), many

[58] In both the data and the model, I fit the measured gross asset return rate into an AR(1) process. The asset return uncertainty is measured as the cross-sectional standard deviations of the residual terms.

measures of uncertainty are highly correlated.

B.4 Write-down of Assets vs. Reduction in Asset Origination

In the section, I provide empirical evidence on the new asset issuance (investment) to explore whether the decline in banks' asset size comes from the reduction in the new asset issuance or is it just the case the banks have recognized the losses on their existing assets (asset write-down) during the crisis period.

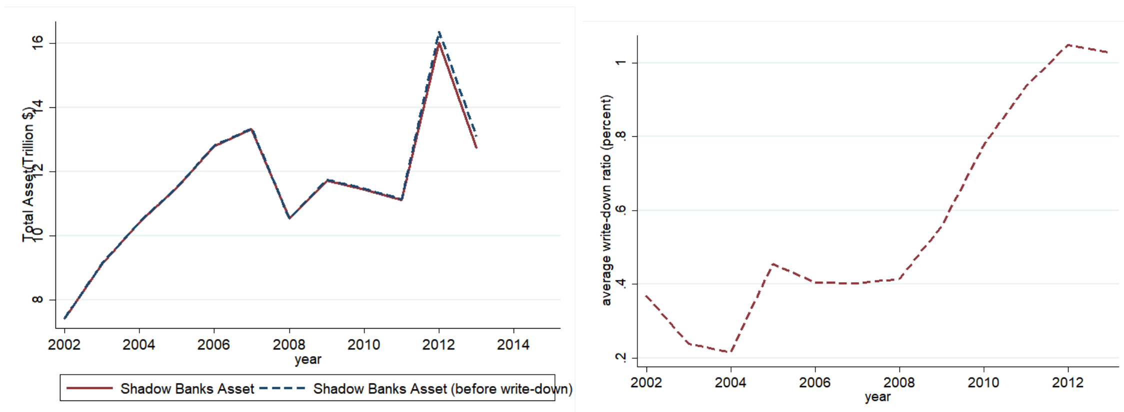

Figure B2: **Robustness Check: Taking Into Account Write-down of Assets.** The left panel illustrates the total asset value of the shadow banking industry before and after write-down. The right panel illustrates the change in write-down ratio of the shadow banking industry over time.

In the data, total assets is the book value of assets after writing down the impaired loan, and securities and other credit impairment charges: $\text{asset}_{t+1} = \text{asset}_t - \text{maturing asset}_t + \text{new asset issuance}_t - \text{writedown}_{t+1}$.[59] Thus, the changes in total assets capture both changes in new asset issuance and asset write-down. I calculate the total asset value before the write-down by adding back the value of impaired loans and securities and other credit impairment charges. The total asset value before the write-down is plotted together with the total asset after the write-down in Figure B2. The left panel of this Figure shows that total asset value before write-down is very close to its value after write-down. The right panel of Figure B2 shows that asset write-down accounts for less than 1% of the total asset value through the whole crisis period. This indicates that the dramatic asset contraction in the 2007-2009 financial crisis was mainly driven by the changes in new asset issuance. Shadow banks start to recognize the losses on their existing assets after the crisis. This is consistent with Laux and Leuz (2010) who find that extant rules have various safeguards and offer substantial discretion to banks, which allows them to avoid marking their asset to distorted market prices. They show that banks use this flexibility during the crisis and find that the claim that fair-value accounting exacerbated the crisis is largely unfounded.

[59] In the data, I could not directly observe what fraction of asset will mature in each period. I also do not have direct bank-level measure for asset issuance. I back out the measure for new asset issuance using data of assets and asset write-down (impaired loan, and securities and other credit impairment charges), assuming in each year λ_a fraction of assets matures: $\text{maturing asset}_t = \lambda_a \cdot \text{asset}_t$, where the annual asset maturing rate $\lambda_a = 1 - (1-\lambda)^4$. The change in new asset issuance measures the increase or decrease in bank investment.

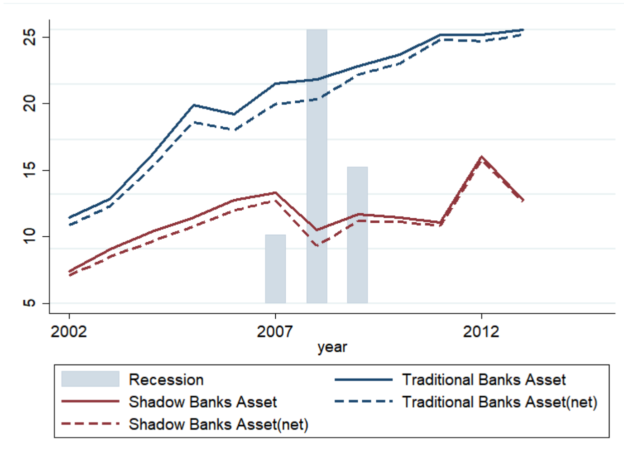

Figure B3: **Robustness Check: Netting Out Cross-holdings of Assets**. This figure illustrates the total asset value of the shadow banking industry after netting out cross-holdings of assets.

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 also calculate the total assets of shadow banking sector after netting out cross-holding of assets. The results are plotted in Figure B3. It can be seen that the changes in assets are similar after netting out cross-holdings of assets. From Figure 4 and Figure B3, one can conclude that the assets of the shadow banking sector shrank during the 2007-2009 recession and the total banking credit shrinkage mainly came from the contraction in the shadow banking sector.

B.5 Heterogeneity in Asset Contraction

It is worthwhile to explore if the asset contraction in the shadow banking industry is driven by a particular type of shadow banks. I calculate the total size of different types of shadow banks and calculate their asset growth rates. I find that there is cross-sectional variations in the degree of asset contraction across different types of shadow banks.

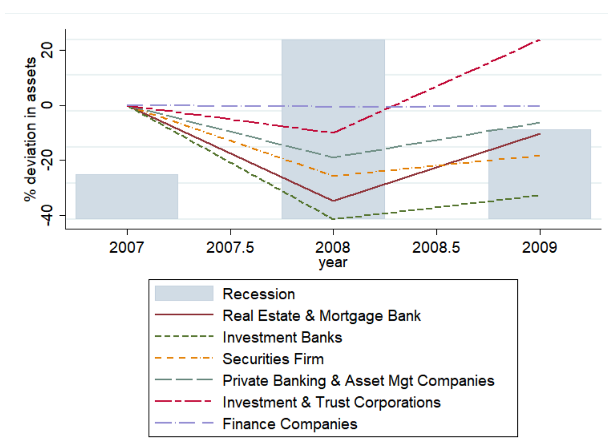

Figure B4: **Heterogeneity in Asset Contraction**. This figure illustrates the percentage deviation in asset sizes of different types of shadow banks during the 2007-2009 financial crisis.

I normalize the total assets of different types of shadow banks by calculating the percentage deviations from their base values at the year 2007. From Figure B4, we can see that the assets of all types of shadow banks contract but by different proportion. Investment banks and real estate and mortgage banks decrease the most. Finance companies decrease less. But the contraction is not driven by only one type of institution. To check the cross-sectional fitness of the model, I sort the shadow banks based on the measures of fire-sale costs and maturity mismatch and split the full sample into subsamples. I reestimate the model based on these subsamples and report the average deleveraging and asset contraction in each subsample. The results are shown in Table 11. First, the actual data reported in columns 1 and 2 of Table 11 reveals that deleveraging and asset contraction are much stronger in bank subsamples with higher fire-sale costs and higher maturity mismatch. Next, I compare the model-generated moments with those observed in the actual data, and conclude that the model can fit the heterogeneous bank characteristics in each subsample. The over-identification tests fail to reject the baseline model in each subsample. The simulated moments are not statistically significantly different from the actual moments, so the baseline model is valid. Last, relying on the structural model, I compare the contribution of uncertainty shocks to deleveraging and the asset contraction in each subsample. I find that uncertainty shocks can account for a slightly larger portion of deleveraging and asset contraction in banks with higher fire-sale costs and higher maturity mismatch.

B.6 The Conversion of TED spread

The TED spread is calculated as the difference between 3-month LIBOR rate and 3-month T-Bill rate. It is a proxy for bank funding cost. The TED spread plotted in Figure 3 is the annualized rate which is available at daily frequency.

The data for interbank spread is converted from daily frequency to annual frequency in Figure 9. There are at least two ways to carry out this conversion. One way is to simply calculate the arithmetic mean of the TED spread shown in Figure 3 for all days in each year. The other way is as follow: first, convert the annualized daily-frequency LIBOR rate and T-Bill rate to daily rate for each day in each year:

$$r_d^{\text{daily libor}} = (1 + r_d^{\text{annualized libor}})^{1/360} - 1 \tag{34}$$

$$r_d^{\text{daily tbill}} = (1 + r_d^{\text{annualized tbill}})^{1/360} - 1 \tag{35}$$

where $r_d^{\text{daily libor}}$ and $r_d^{\text{daily tbill}}$ are the daily rate of LIBOR and T-bill for each day d, respectively.

Then for each year t, calculate the annual rate for LIBOR and T-bill based on the daily rates. The following equations hold:

$$\prod_{d=1}^{N_t} (1 + r_d^{\text{daily libor}}) = (1 + r_t^{\text{libor}})^{\frac{N_t}{360}} \tag{36}$$

$$\prod_{d=1}^{N_t} (1 + r_d^{\text{daily tbill}}) = (1 + r_t^{\text{tbill}})^{\frac{N_t}{360}} \tag{37}$$

where N_t is the number of daily observations in year t. r_t^{libor} and r_t^{tbill} are the annual rate of LIBOR and

T-bill respectively at year t.

The annual rate of TED spread at year t is calculated as the difference between these two rates:

$$r_t^{\text{TED}} = r_t^{\text{libor}} - r_t^{\text{tbill}} \tag{38}$$

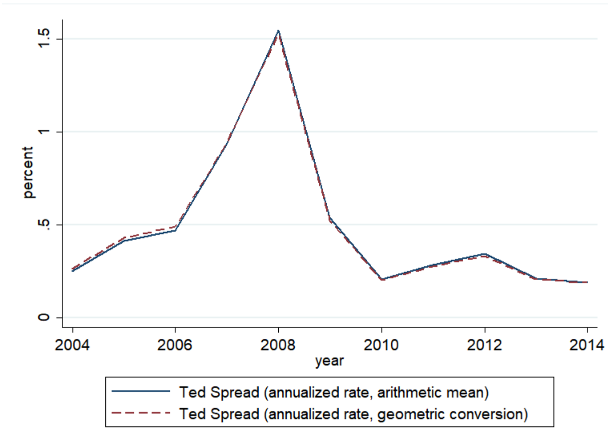

Figure B5: **Annual TED Spread.** This figure illustrates the annual rate of TED spread calculated based on two methods: simple arithmetic mean and geometric conversion.

As shown in Figure B5, both methods generate very similar changes in TED spread. Since interest higher than 3% only happened in very few days of 2008, taking the annual mean of the spread naturally will average out these changes. The simulated quarterly spread also fits the data very well. The spike in the quarterly simulate spread is higher since the rate is averaged at the quarterly frequency. In Figure 9 , I construct all the moments at the annual frequency to facilitate comparisons between the model and the data.

B.7 Alternative Measurement of Banking Funding Cost

I also construct the other proxy for bank funding costs. I first calculate the bank-level interest rate by dividing the total interest expenses of each bank by its total funding. Then I calculate the mean of these funding costs across banks for each year. Since the total interest expenses include the expenses spent on all funding sources, the average interest rate captures the average cost of short-term funding, long-term funding, and customer deposits. Figure B6 shows that the 3-month annualized LIBOR rate captures the average funding cost of the shadow banks quite well. This is well expected since short-term funding accounts for more than 75% of total funding in the shadow banking industry.

B.8 The Illustration of Policy Function Margin and Distribution Margin

Figure B7 illustrates the leverage for different asset quantiles of banks using the bank-level data. Shadow banks of different asset sizes on average choose a lower leverage during the crisis. This captures the policy function margin. Figure B7 also shows that bigger banks tend to have higher leverage; this positive correlation is robust for both types of banks. This result is consistent with Adrian

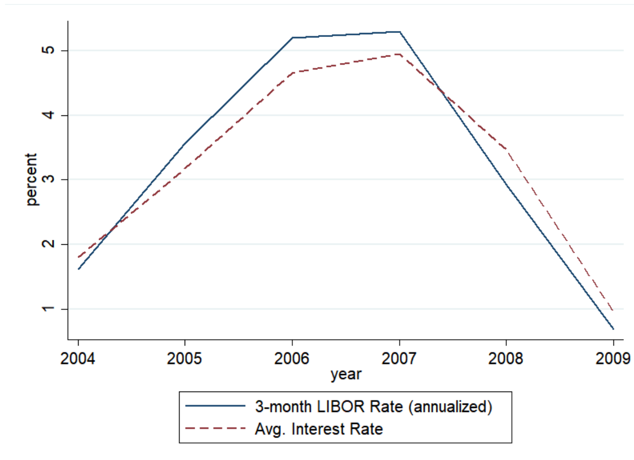

Figure B6: **3-month LIBOR Rate and The Average Funding Cost of the Shadow Banks**. This figure illustrates the 3-month LIBOR rate and the average funding cost of the shadow banking industry. To calculate the average interest rate. I first calculate the bank-level interest rate by dividing the total interest expenses of each bank by its total funding. Then I calculate the average of these funding costs across banks for each year.

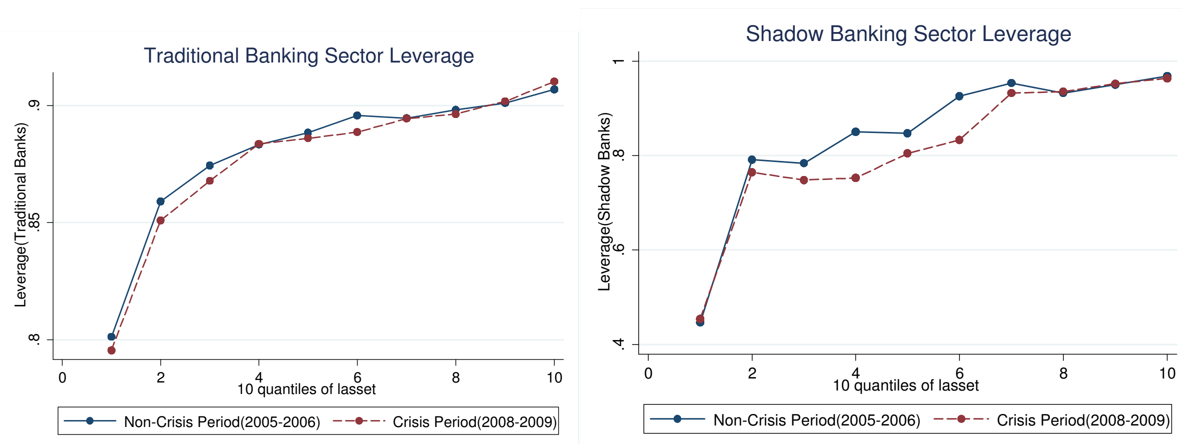

Figure B7: **Leverage Over Asset Quantiles**. This figure depicts the change in leverage ratio of shadow banks and traditional banks over 10 asset quantiles. The leverage ratio is defined as the total debt-to-total asset ratio within each asset quantile. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009.

and Shin (2010). As Adrian and Shin (2010) argued, if banks target a leverage ratio, the optimal leverage will not increase with asset values. However, 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 B8 depicts the change in bank asset distribution. Shadow banks choose a smaller asset size and the whole asset distribution becomes more skewed toward the lower asset level region. This captures the distribution margin.

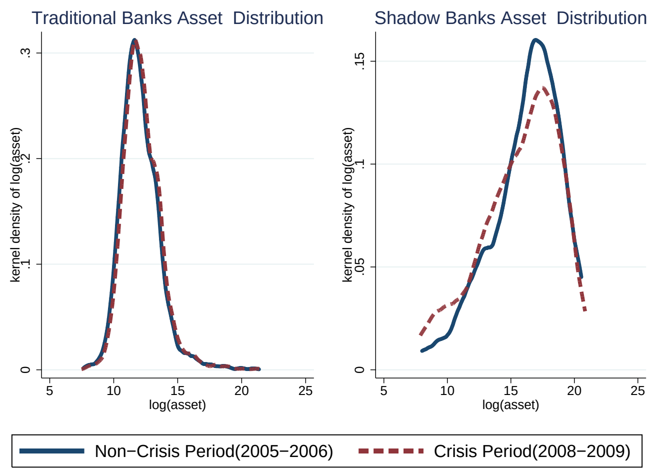

Figure B8: **Asset Distribution**. This figure depicts the change in asset distribution of shadow banks and traditional banks. The measure of small and medium-sized shadow banks increases during the recession whereas the distribution of traditional banks barely changes. Non-crisis periods are defined as from 2005 to 2006, whereas crisis periods are defined as from 2008 to 2009.

B.9 Cross-sectional Variation in Asset Contraction and Deleveraging

I also split the sample into three types based on maturity mismatch and fire-sale cost.[60] As shown in Table D1, there exists a certain degree of nonlinearity in the responses. For the shadow banks with medium maturity mismatch and fire-sale cost, the effect of uncertainty shocks lies in the middle and is slightly smaller than what its value should be if the relationship between the effect of uncertainty shocks and maturity mismatch or fire-sale cost is linear. To be more specific, I first calculate what the responses of medium type should be based on linear interpolation using data of high and low types, and then compare the actual responses with the linearly-predicted responses. For instance, if the relationship between asset contraction and firesale cost is linear, based on the firesale cost index and asset contraction of low and high types, the linear prediction of asset contraction for the medium type should be 19.11%. But its actual value is 16.48%, which is lower than its linearly-predicted value.

[60] Since there is no bank-level information on maturity, I use aggregate data to obtain the maturity mismatch and fire-sale cost estimates of shadow banks (see Appendix B.2 for more details).

C Theory Appendix

C.1 The Timeline of the Baseline Model

The timing of the baseline model can be summarized in Figure C1. In each period, based on idiosyncratic state variables z, k, b and an aggregate state variable vector $\mathbf{s} = \{\sigma, x\}$, the incumbent bank would choose whether to default, as well as how much to borrow from the interbank market - b' , and how much risky asset to initiate - k'. Potential entrants decide whether to start a new bank based on the aggregate shocks and signals about their productivities.

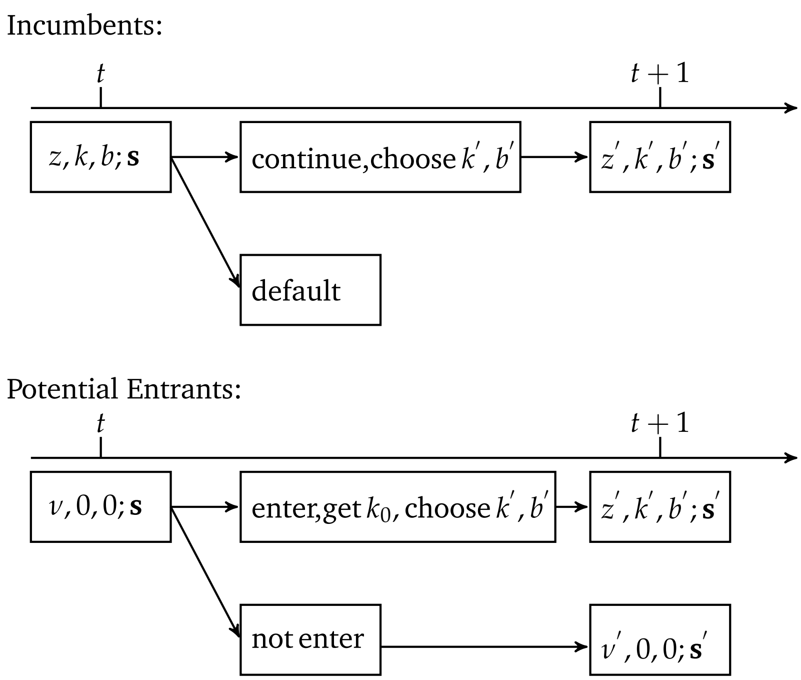

Figure C1: **Timeline from Period** t **to** $t+1$. This figure illustrates the timeline of the full model. In each period, based on idiosyncratic state variables z, k, b and an aggregate state variable vector $\mathbf{s} = \{\sigma, x\}$, the incumbent bank would choose whether to default, as well as how much to borrow from the interbank market - b', and how much risky assets to initiate - k'. Potential entrants decide whether to start a new bank based on the aggregate shocks and signal ν about their productivities. A potential entrant will start a new bank if the value of entry V^e is higher or equal to entry cost f_e. An entrant starts with start-up asset k_0 and decides the optimal k' and b'.

C.2 The Impact of Uncertainty Shocks in Models without Maturity Mismatch or Fire-sale Costs

To further check whether models without maturity mismatch or fire-sale costs can also generate similar impacts on interbank spreads, bank asset sizes and leverages, I also carry out two counterfactual experiments by re-simulating the baseline model under two alternative specifications: one without maturity mismatch in which I impose the maturity mismatch parameter $\lambda = 1$; one without fire-sale cost in which I impose the fire-sale cost parameter $\zeta = 1$. In both simulation, I fit in the sequence of asset return uncertainty shocks in the baseline model, and the values of other parameters are kept the same as in the baseline model, such that the differences in responses can only result from the differences in maturity mismatch or fire-sale costs. The simulations reveal what would have happened in counterfactual economies if there were no maturity mismatch or fire-sale costs. The simulated pathways of spread, asset, and leverage are shown in Figure C2. Uncertainty shocks in the model without maturity mismatch or fire-sale costs explain only around 30% of the change in the interbank spread, leverage, and asset of the U.S. shadow banking sector. This implies that maturity mismatch and firesale cost amplify the impact of uncertainty shocks.[61] I also re-estimate the model under these alternative specifications and carry out the event studies using these re-estimated parameters. The results of the event studies are quantitatively similar.

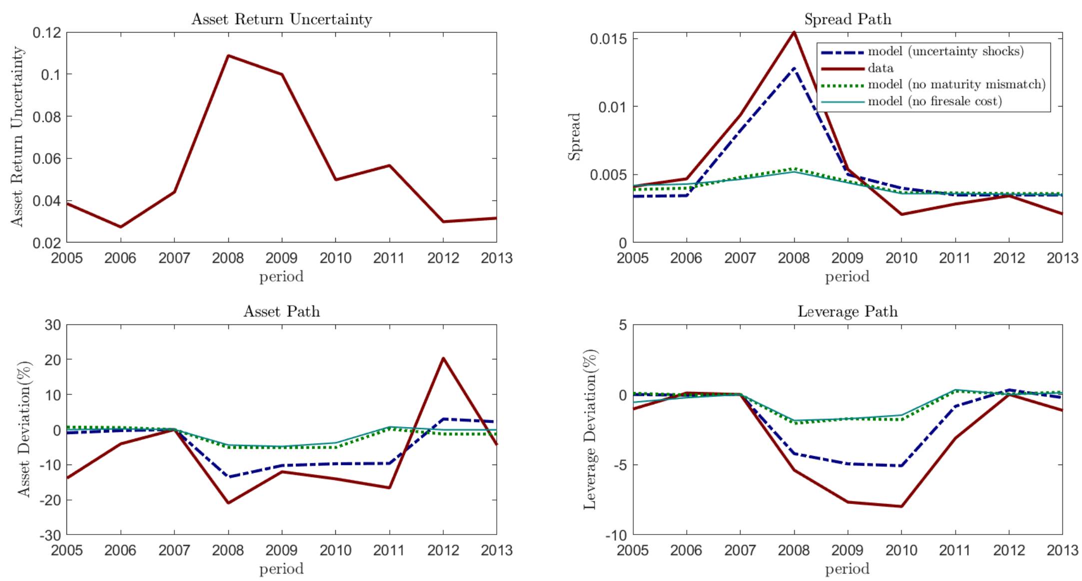

Figure C2: **Event Study: model(no maturity mismatch/no fire-sale cost) vs. data**. The figure depicts the simulated evolution paths of total assets, aggregate leverage ratio and mean interest spread of shadow banks in two alternative models (without maturity mismatch or without fire-sale cost) compared with the baseline model and their data counterparts. Leverage is defined as the total-debt-to-total-asset ratio.

C.3 Spread Schedule Comparison in the Baseline Model

The left panel of Figure C3 shows the spread schedule of risky debt for bank's with a smaller asset size under low and high asset return uncertainty in the baseline model, respectively. The 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 C3 shows the spread schedule of risky debt for banks with lower asset return under low and high asset return uncertainty. Interest spread is higher 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.

[61] In another related quantitative exercise, I shut down maturity mismatch or firesale cost in the model with purely first-moment shocks. Maturity mismatch and firesale cost amplify the impact of first-moment shocks by a similar proportion as they do to the uncertainty shocks.

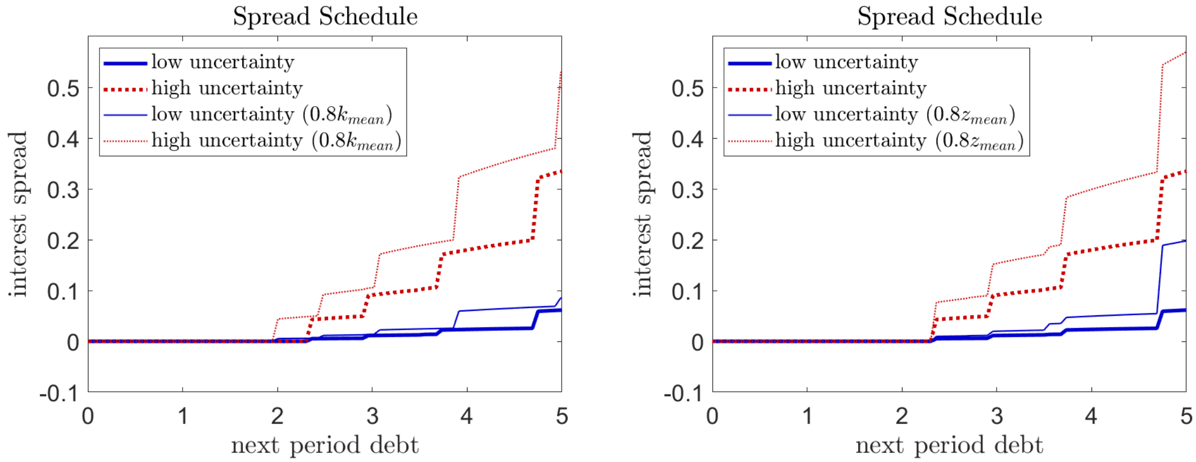

Figure C3: **Spread Schedule Comparison**. The left panel shows the interbank interest spread as a function of the debt issuance for a bank with mean permanent asset return component, stochastic asset return component and 80% of mean asset level. The right panel shows the interbank interest spread as a function of the debt issuance for a bank with mean permanent asset return component, asset level and 80% of mean stochastic shocks.

C.4 Policy Experiment

In the policy experiments, I consider the following three possible interventions:

(a) *TARP*: The government purchases a certain fraction of long term illiquid asset (5% of total assets for banks which are in distress (banks whose cash balance is negative)).

(b) *Debt Guarantee with exogenous bailout probability*: When a bank defaults, the government purchases its debt with a fixed probability $\bar{p}$.

(c) *Debt Guarantee with endogenous bailout probability*: When a bank defaults, the government purchases its debt with probability p, where p is a function of bank size and asset return.

In Table 10, the government interventions are chosen such that the total government resources used in each case are equal. Under a debt guarantee, two bailout probability strategies are chosen such that the expected bailout probabilities are the same in the two cases. Thus we have the following equation:[62]

$$\int \bar{p}b\mathbb{1}\{d_b(z,k,b;\mathbf{s})=1\}\mu_b(z,k,b)d(z\times k\times b)=0.05*\int \mathbb{1}\{c_a<0\}k\mu_a(z,k,b)d(z\times k\times b)$$

where $\mu_a(z,k,b)$ and $\mu_b(z,k,b)$ is the stationary distribution of banks under policy intervention a and b, respectively; $d_b(z,k,b;\mathbf{s})$ is the default choice of banks under policy intervention b; c_a is the cash balance of banks under policy intervention a. The value of $\mathbb{1}\{.\}$ equals 1 if the condition in the brackets holds, and equals 0 otherwise. The left side is the amount of resources the government need to spend under debt guarantee with exogenous bailout probability $\bar{p}$. The right side is the amount of

[62]To ease notations, I use a, b, c in the subscript to denote the policy functions and distributions of banks under each scenario.

resources the government need to spend under TARP. From this equation, I can numerically solve for the exogenous bailout probability $\bar{p}$.

Assume the endogenous bailout probability p is an increasing function of the bank's size and its asset return: $p = \kappa(zx)^{\chi}k^{1-\chi}$. Then we have the following two equations:

$$\int pb\mathbb{1}\{d_c(z,k,b;\mathbf{s}) = 1\}\mu_c(z,k,b)d(z \times k \times b) = 0.05 * \int \mathbb{1}\{c_a < 0\}k\mu_a(z,k,b)d(z \times k \times b) \quad (39)$$

$$\int p\mathbb{1}\{d_c(z,k,b;\mathbf{s}) = 1\}\mu_c(z,k,b)d(z \times k \times b) = \bar{p} \int \mathbb{1}\{d_b(z,k,b;\mathbf{s}) = 1\}\mu_b(z,k,b)d(z \times k \times b) \quad (40)$$

The first equation makes sure the amount of resources spent under TARP equals the amount of resources spend under debt guarantee with endogenous bailout probability p. The second equation ensures the expected bailout probabilities are the same in the two cases under debt guarantee. With these two equations, I can numerically solve for the values of two unknown parameters, κ and χ.

C.5 Additional Subsample Estimation

To test the fitness of the model over time, I also estimate the model on the early subsample of data from 1998 to 2005 and late subsample of data from 2006 to 2013. The estimation results are reported in Table D6 in the Appendix. For each subsample, I compare the model-generated moments with those observed in the actual data, and conclude that the model is able to fit the data well in each subsample. The over-identification tests fail to reject the baseline model in each subsample at the significance level of 5%.[63] The simulated moments are not statistically significantly different from the actual moments, reconfirming the validity of the baseline model.

C.6 Incorporating Endogenous Asset Portfolio Choices

In this section, I further tackle alternative extensions of the first-moment shock model to check if it is possible that alternative extensions of the first-moment shock model could fit the data as well as the baseline model. One possibility is that different banks have different exposure to certain types of risky assets, and when the return to this type of asset changes, this endogenously generates the increased asset return uncertainty. I find that this conjecture is not true.

I extend the baseline model by allowing the shadow banks to choose its asset portfolio endogenously. Assume the bank could choose two types of assets, a risky asset and a risk-free asset. In the spirit of Gamba and Triantis (2008), assume there is a debt adjustment cost such that the bank would hold risk-free assets and debt simultaneously. Specifically, following Gamba and Triantis (2008), I assume there is no direct cost associated with paying down debt. There is, however, a proportional cost on new debt issued. $\Phi(b, b')$ is the debt adjustment cost:

$$\Phi^b(b, b') = \begin{cases} \phi_b\,(b' - b) & \text{if } b' > b \\ 0 & \text{if } b' < b \end{cases} \quad (41)$$

[63] The J-statistics and p-values for the overidentification test are 2.2317 and 0.6932 in the early subsample, 2.1098 and 0.7156 in the late subsample.

The debt adjustment cost creates an incentive for the bank to hold both debt and risk-free asset simultaneously since it can help increase the bank value. In times of low profitability, the bank needs to reduce net debt to avoid triggering financial distress. There are two ways to reduce net debt: reducing debt or increasing risk-free asset holding. With the debt issuance cost, the bank chooses to increase risk-free asset holding rather than paying down debt. This is because the bank may later wish to restore its net debt to a higher level to take advantage of interest tax shields. It will be better off paying out cash to shareholders at that time rather than issuing new debt and incurring issuance costs.

Denote $\pi \equiv (zx-1)k_1$ as the bank's profit from they risky asset. The shadow bank chooses the optimal asset portfolio and debt issuance to maximize its value:

$$V^c(z,k_1,k_2,b;\mathbf{s}) = \max_{\{b',k_1',k_2'\}} \left\{(1+\gamma_e 1_{\{e<0\}} - \tau_d 1_{\{e>0\}})e + \mathbb{E}_{z,s} m(\mathbf{s},\mathbf{s}')V(z',k_1',k_2',b';\mathbf{s}')\right\} \tag{42}$$

s.t.

$$e = \begin{cases} c + (1-\lambda)k_1 - k_1' - \Phi(k_1',k_1) - k_2' & \text{if } c \geq 0 \\ (1-\lambda)k_1 + \frac{c}{\zeta} - k_1' - \Phi(k_1',k_1) - k_2' & \text{if } c < 0 \end{cases} \tag{43}$$

$$c = (1-\tau_c)\pi + \lambda k_1 + (1+r(1-\tau_c))k_2 - b + qb' + \frac{\tau_c(b'-qb')}{1+r} - \Phi^b(b,b') - \xi \tag{44}$$

For the extended first-moment shock model with endogenous asset portfolio choice, the aggregate state variable $\mathbf{s} = x$. The asset return uncertainty is determined by a fixed parameter $\overline{\sigma}$, which is estimated to match the average asset return uncertainty. The debt adjustment cost parameter is estimated jointly with other parameters in the estimation. I add one more moment- the fraction of risky assets in the estimation, which helps me to pin down the value for the debt adjustment cost parameter. Increasing the value of this parameter will increase the incentive for banks to hold risk-free assets to avoid costly debt adjustment. The estimation results are shown in Table D10. I find that an extended first-moment shock model with asset portfolio choice cannot match the mean default rate, the mean interest spread, and the standard deviation of new asset issuance/asset ratio and interest spread. Thus, in the baseline analysis, I intentionally keep the model as parsimonious as possible while incorporating the crucial features of the shadow banking sector such as fire-sale cost and maturity mismatch. Instead of endogenizing the data-generating process of asset return, I focus on developing a tractable framework to study the impact of time-varying uncertainty and potential policy implications.

C.7 Incorporating Systemic Risk

The other extension concerns systemic risk. I redefine the asset return of each bank as $zx^{1+\theta}$, where θ follows an AR(1) process:

$$log\,(\theta_t) = (1-\rho_\theta)\,log\,(\mu_\theta) + \rho_\theta log\,(\theta_{t-1}) + \varepsilon_t,\ \varepsilon_t \sim N(0,\varphi_\theta^2) \tag{45}$$

The increase of θ_1 captures the increase in intraclass correlation of the bank asset returns. I add the mean, standard deviation, and persistent of systemic risk in the target moments.[64] These extra

[64] System risk is measured as the intraclass correlation of bank return on assets based on rolling window estimation.

moments help pinning down the parameters governing the AR(1) process- μ_θ, ρ_θ, and φ_θ.

The results are shown in Table D11 in the Appendix. I find the estimate of the persistence is very low, and the variance of the innovation to the systemic risk process is both high and imprecisely estimated. The extended model with only first-moment shocks and systemic risk shocks still significantly underestimates the mean default rate, the mean interest spread, and the standard deviation of new asset issuance/asset ratio and interest spread. Although systemic risk undoubtedly varies over time, I do not find that adding a systemic risk shock to the model takes it as far as adding a second-moment shock.

C.8 Introducing Time Variations to the Volatility of Aggregate Productivity

To further check the robustness of the quantitative results, I introduce time variations to the volatility of aggregate productivity as well to check to what extent the impact of uncertainty shocks will be affected if there are changes in the volatility of aggregate productivity as well. The aggregate productivity x_t follows a Markov process with transition function $\pi_x(x_t|x_{t-1}, \sigma^x_{t-1})$, where σ^x_{t-1} is an aggregate shock to the standard deviation of aggregate state shocks. The aggregate shock σ^x_t follows a Markov process with transition function $\pi_{\sigma^x}(\sigma^x_t|\sigma^x_{t-1})$. Now the aggregate state variable vector $\mathbf{s} = \{\sigma, \sigma^x, x\}$. The aggregate productivity x_t follows an AR(1) process,

$$log\,(x_t) = \rho_x log\,(x_{t-1}) + \sigma^x_t \epsilon^x_t \tag{46}$$

where ϵ^x_t is an i.i.d standard normal variable, the variance of innovations σ^x_{t-1} move over time, generating periods of low and high macro-uncertainty. Following Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2019), I assume macroeconomic uncertainty σ^x_t follows the same two-state Markov chain as the microeconomic uncertainty σ_t:

$$\sigma^x_t \in \{\sigma^x_L, \sigma^x_H\}\,,\ \text{where}\ Pr(\sigma^x_{t+1} = \sigma^x_j|\sigma^x_t = \sigma^x_k) = \pi^\sigma_{k,j}. \tag{47}$$

I choose the average volatility of the aggregate productivity, $\sigma_x = 0.007$, following Lin and Zhang (2013). Following Bloom (2009), high volatility has twice the value of low volatility, so that σ^x_L and σ^x_H, are chosen to match the average volatility of the aggregate productivity. I reestimate the model and carry out the same event study. The results are overall robust, preserving the dynamics reported in Figure 9. The relative contributions of each shocks remain similar to the baseline estimates.

C.9 Incorporating a Traditional Banking Sector

We observe a much smaller deleveraging in the traditional banking sector. Multiple factors could contribute to this fact, including the differences in leverage, maturity mismatch, fire-sale cost, shock processes, and regulatory oversight. To decompose the contribution of each factor to the smaller deleveraging in the traditional banking sector, I also build and estimate a model incorporating a

$\text{SystemicRisk}_t = \sum_{i \neq j, t \in w_{t-4,t}} corr(\text{ROA}_{i,t}, \text{ROA}_{jt}) \cdot \omega_{ij}$, where $\omega_{ij} = \frac{\text{asset}_{it} + \text{asset}_{jt}}{\text{totalasset}_t}$, $w_{t-4,t}$ is rolling windows of 5 years from period $t-4$ to period t, i and j are any two different shadow banks within the window $w_{t-4,t}$.

traditional banking sector and carry out a series of counterfactual experiments. The traditional banks issue long-term loans and risk-free assets and borrow using customer deposits, subject to capital requirements.

The traditional banks invest in long-term loans k_1 and a risk-free asset k_2. They finance their investment using customer deposits b. After investment and financing decisions have been made, the bank capital w' can be defined as:

$$w' \quad = \quad k_1' + k_2' - b' \tag{48}$$

Following Begenau and Salomao (2019) and Corbae and D'Erasmo (2018), I assume commercial banks are subject to Basel-III-type capital requirements. The Basel III accords stipulate that banks must back a specific percentage of risk-weighted assets with capital. Safe assets and risky assets have different risk weights. The capital requirement can be written as:

$$w' \quad \geq \quad \kappa(\omega_1 k_1' + \omega_2 k_2') \tag{49}$$

where κ is capital requirement parameter, ω_1 and ω_2 are the risk weights of risky assets and risk-free assets, w is the bank capital.

Following Corbae and D'Erasmo (2018), I set $\omega_1 = 1$, $\omega_2 = 0$, and $\kappa = 0.04$. These values are associated with regulation in place before the recent financial crisis. Given $\omega_1 > \omega_2$, holding risk-free assets helps the traditional banks relax the capital requirement constraint, but it might reduce the bank profitability and solvency. This creates an precautionary motive for the banks to hold the risk-free assets. In the equilibrium, the bank might choose a capital equity ratio higher than the required level.

The bank's problem is written recursively. Rewriting the capital requirement constraint as the following collateral constraint is helpful in stating the problem:

$$b' \quad \leq \quad (1-\kappa)k_1' + k_2' \tag{50}$$

The traditional bank's problem can be written as follows:

$$V(z, k_1, k_2, b; \mathbf{s}) = \max_{\{b', k_1', k_2'\}} \left\{ (1 + \gamma_e 1_{\{e<0\}} - \tau_d 1_{\{e>0\}})e + \mathbb{E}_{z,s} m(\mathbf{s}, \mathbf{s}') V(z', k_1', k_2', b'; \mathbf{s}') \right\} \tag{51}$$

s.t.

$$e \quad = \quad \begin{cases} c + (1-\lambda)k_1 - k_1' - \Phi(k_1', k_1) - k_2' & \text{if } c \geq 0 \\ (1-\lambda)k_1 + \frac{c}{\zeta} - k_1' - \Phi(k_1', k_1) - k_2' & \text{if } c < 0 \end{cases} \tag{52}$$

$$c \quad = \quad (1-\tau_c)\pi + \lambda k_1 + (1 + r(1-\tau_c))k_2 - b(1+r_d) + b' + \tau_c r_d b - \xi \tag{53}$$

$$b' \quad \leq \quad (1-\kappa)k_1' + k_2' \tag{54}$$

where r_d is the deposit rate. In the calibration, its value is set to 0.659% following Corbae and D'Erasmo (2018). $\pi \equiv (zx - 1)k_1$ is the bank's profit from the risky assets.

The empirical measurement for maturity mismatch and fire-sale cost reveals that traditional banks have much lower maturity mismatch and fire-sale cost. I set the maturity mismatch parameter to $\lambda = 0.2301$ based on the maturity mismatch index. The estimation reveals that asset return uncertainty in this sector is much smaller than that of the shadow banking sector. Also, due to the reserve requirements and lower asset return, this sector has much lower leverage. To estimate the contribution of each factor, I first feed in the uncertainty and asset return shocks processes of the shadow banking sector to the traditional banking sector, this generates a deleveraging that is only 21% as large as the deleveraging in the shadow banking sector. Then I impose the leverage ratio of the traditional banking sector to be the same as that of the shadow banking sector prior to the arrival of the shocks in the simulation by relaxing the reserve requirement. This generates a deleveraging that is only 32% as large as the deleveraging in the shadow banking sector. Then I further change the maturity mismatch and fire-sale cost parameters in the traditional banking sector to their values in the shadow banking sector. The traditional banks' deleveraging increases to 67% of its value in the shadow banking sector. The remaining 33% of difference in deleveraging can be attributed to the difference in the financing methods in these two sectors.

C.10 Additional Robustness Checks for the Impact of Financial Shocks and Firesale Cost Shocks

To further check the robustness of the results regarding the impact of financial shocks, I also test the robustness of the results under two alternative specifications. In the first alternative specification, I assume the financial shocks follow the same transition matrix as the business cycle (Cooley and Prescott (1995)); In the second alternative specification, I assume it follows the same transition matrix of the uncertainty shocks. The magnitudes of the quantitative results generated using these alternative specifications are slightly larger than the baseline since the shock processes are more persistent. In these two alternative specifications, the relative contributions of each component remain stable. Uncertainty shocks remain as the most important factor. To further check the robustness of the model, I also estimate a Pseudo General Equilibrium (Pseudo-GE) model in the spirit of Bloom (2009). I estimate the actual changes in interest rates that arise after an asset return uncertainty shock and directly feed them into the model with risk-neutral investors in an expectations consistent way. The relative contributions of each components in this alternative setting are quantitatively similar to the baseline extended model.

To further check the robustness of the results regarding the impact of firesale cost shocks, I also test the robustness of the results under three alternative specifications. In the first alternative specification, I assume the fire-sale cost follows the same transition matrix as the business cycle (Cooley and Prescott (1995)); In the second alternative specification, I assume it follows the same transition matrix of Gilchrist, Sim, and Zakrajsek (2014)'s capital resale shocks; In the third alternative specification, I assume it follows the same transition matrix of the uncertainty shocks. The magnitude of the quantitative results generated using these alternative specifications are slightly larger than the baseline. In all these alternative specifications, the relative contributions of each component remain stable. Uncertainty shocks remain as the most important factor. For instance, if I use the transition matrix of business cycle, fire-sale cost shocks and uncertainty shocks together can explain around 81% of asset contraction and 80% of deleveraging, whereas fire-sale cost shocks and first-moment shocks together can at most explain 32% of asset contraction and 30% of deleveraging. To further check the robustness of the model, I also estimate a Pseudo General Equilibrium (Pseudo-GE) model in the spirit of Bloom (2009). I estimate the actual changes in interest rates that arise after an asset return uncertainty shock and feed them into the model with risk-neutral investors in an expectations consistent way. Again, the relative contributions of each component remain stable in this alternative setting.

D Additional Tables

Table D1: Cross-sectional Variation in Asset Contraction and Deleveraging

A: Split by asset fire-sale cost	FCI	deleveraging		asset contraction	
		actual	linear prediction	actual	linear prediction
high fire-sale cost	0.40	11.36%	-	34.46%	-
medium fire-sale cost	0.18	5.50%	6.57%	16.48%	19.11%
low fire-sale cost	0.12	5.25%	-	14.88%	-
B: Split by maturity mismatch	MMI	deleveraging		asset contraction	
		actual	linear prediction	actual	linear prediction
high maturity mismatch	11.72	9.01%	-	28.89%	-
medium maturity mismatch	9.67	7.02%	7.10%	21.53%	22.10%
low maturity mismatch	4.58	2.36%	-	5.24%	-

Notes: This table reports the cross-sectional variations of asset contraction and deleveraging in the shadow banking sector. I sort the shadow banks based on the measures of fire-sale costs or maturity mismatch and split the full sample into three subsamples. FCI is firesale cost index. MMI is maturity mismatch index. See Appendix B.2 for more details about measurement construction. For shadow banks with medium maturity mismatch and firesale cost, I report both their actual responses and the responses calculated based on linear interpolation using data of high and low types.

Table D2: Moments Across Alternative Model Specifications

Target Moments	Actual Moments	Baseline Model	First-moment Shocks	No Fire-sale Cost: $\zeta = 1$	No Maturity Mismatch: $\lambda = 1$	No Adjustment Cost: $\phi = 0$
mean of leverage	0.932	0.930	0.974	0.998	0.999	0.989
mean of new asset issuance/asset ratio	0.437	0.432	0.427	0.428	1.111	0.506
stdv. of new asset issuance/asset ratio	0.152	0.143	0.050	0.058	0.062	0.211
autocorrelation of new asset issuance/asset ratio	0.876	0.865	0.926	0.858	0.823	0.807
mean default rate	1.10%	1.09%	0.19%	0.29%	0.47%	0.89%
mean of dividend/asset ratio	0.021	0.026	0.059	0.044	0.063	0.035
stdv. of dividend/asset ratio	0.015	0.017	0.005	0.006	0.005	0.026
autocorrelation of dividend/asset ratio	0.795	0.725	0.864	0.781	0.776	0.692
mean equity issuance/asset ratio	0.012	0.012	0.007	0.005	0.005	0.006
leverage-asset slope	0.043	0.048	0.049	0.050	0.049	0.054
mean entrant growth	0.242	0.216	0.291	0.296	0.290	0.299
entrant relative size	0.201	0.211	0.202	0.192	0.203	0.204
mean of interest spread	0.55%	0.53%	0.09%	0.14%	0.23%	0.45%
stdv. of interest spread	0.44%	0.41%	0.06%	0.11%	0.17%	0.37%
mean of asset return uncertainty	0.064	0.063	0.063	0.063	0.062	0.062
stdv. of asset return uncertainty	0.045	0.045	-	0.044	0.045	0.044
autocorrelation of asset return uncertainty	0.732	0.711	-	0.717	0.709	0.708
skewness of asset return uncertainty	0.931	0.984	-	1.109	0.998	0.989
J-statistics		2.5034	11.5786	17.1414	32.1257	9.4896
p-value		0.6440	0.0208	0.0042	<1e-5	0.0911

Notes: Calculations are based on an annual sample of shadow banks from the Bankscope and Worldscope databases. 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.

Table D3: Assessing The Impact of Uncertainty Shocks, First-moment Shocks, Financial Shocks, and Fire-sale Cost Shocks

	With Financial Shocks				With Fire-sale Shocks				With both Financial and Fire-sale Shocks			
	1	2	3	4	5	6	7	8	9	10	11	12
Uncertainty Shocks	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
First-moment Shocks	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Fire-sale Cost	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity Mismatch	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial Shocks	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes
Fire-sale Shocks	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asset Contraction	92.54%	75.78%	25.42%	11.30%	95.88%	78.20%	27.35%	13.59%	98.15%	85.99%	35.89%	24.04%
Deleveraging	92.82%	76.57%	25.69%	11.56%	95.16%	77.41%	27.09%	13.37%	97.68%	85.52%	35.25%	23.71%
Δ Interest Spread	93.49%	77.78%	27.09%	12.24%	96.72%	79.47%	29.15%	14.58%	99.04%	86.08%	36.91%	25.39%

Notes: This table reports to what extent each extended model specification could explain the asset contraction, deleveraging, and changes in interest spread. The results for the extended model with time-varying financial shocks are shown in columns 1-4. The results for the extended model with time-varying fire-sale cost shocks are shown in columns 5-8. The results for the extended model with both time-varying financial shocks and time-varying fire-sale cost shocks are shown in columns 9-12. To study in a comprehensive manner the impact of alternative shocks that could have explained the contraction of credit in the shadow banking sector, for each extended model, using the estimated parameters, I gauge its explanatory power under four specifications: with both uncertainty and first-moment shocks, with only uncertainty shocks, with only first-moment shocks, and without uncertainty shocks or first-moment shocks. Column 1 reports the joint contribution of uncertainty shocks, first-moment shocks, and financial shocks. Column 2 reports the joint contribution of uncertainty shocks and financial shocks. Column 3 reports the joint contribution of first-moment shocks and financial shocks. Column 4 reports the pure contribution of financial shocks. Column 5 reports the joint contribution of uncertainty shocks, first-moment shocks, and fire-sale cost shocks. Column 6 reports the joint contribution of uncertainty shocks and fire-sale cost shocks. Column 7 reports the joint contribution of first-moment shocks and fire-sale shocks. Column 8 reports the pure contribution of fire-sale shocks. Column 9 reports the joint contribution of uncertainty shocks, first-moment shocks, financial shocks, and fire-sale cost shocks. Column 10 reports the joint contribution of uncertainty shocks, financial shocks, and fire-sale cost shocks. Column 11 reports the joint contribution of first-moment shocks, financial shocks, and fire-sale shocks. Column 12 reports the joint contribution of financial shocks and fire-sale shocks.

Table D4: Summary Statistics

Variable	Mean	SD	p25	p50	p75
size (log(asset))	15.530	2.545	13.822	16.198	17.883
leverage	0.932	0.091	0.894	0.958	0.975
new asset issuance/asset ratio	0.437	0.152	0.293	0.404	0.543
equity issuance/asset ratio	0.012	0.019	0.001	0.008	0.018
dividend/asset ratio	0.021	0.015	0.016	0.020	0.031
short term funding fraction	0.744	0.112	0.689	0.736	0.806
fraction of risky asset	0.610	0.163	0.533	0.585	0.655
customer deposit funding fraction	0.043	0.025	0.024	0.030	0.063

Table D5: Parameter Estimates for Alternative Model Specifications

First-Moment Shock Model

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\bar{\sigma}$	μ	A	f_e	ω
0.0608	0.6857	0.0066	0.0028	0.1580	0.9185	0.0318	3.3120	17.5217	0.0038	3.2155
(0.0091)	(0.0398)	(0.0012)	(0.0006)	(0.0125)	(0.0340)	(0.0127)	(0.3197)	(2.3539)	(0.0010)	(0.3120)

No Fire-sale Cost Model

γ_e	ξ	k_0	ϕ	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0619	0.0074	0.0032	0.1554	0.9311	0.9442	0.9787	0.0676	0.0165	3.2809	17.1223	0.0035	3.1548
(0.0121)	(0.0016)	(0.0004)	(0.0124)	(0.0352)	(0.0121)	(0.0177)	(0.0104)	(0.0077)	(0.2701)	(1.9974)	(0.0008)	(0.2986)

No Maturity Mismatch Model

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0621	0.6071	0.0071	0.0034	0.1325	0.9342	0.9456	0.9768	0.0672	0.0167	3.2401	17.4424	0.0034	3.1754
(0.0120)	(0.1221)	(0.0009)	(0.0008)	(0.0104)	(0.0360)	(0.0220)	(0.0258)	(0.0108)	(0.0062)	(0.4129)	(1.9678)	(0.0007)	(0.3356)

No Asset Adjustment Cost Model

γ_e	ζ	ξ	k_0	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0609	0.6905	0.0069	0.0032	0.9379	0.9460	0.9763	0.0670	0.0166	3.2631	17.4097	0.0036	3.1685
(0.0099)	(0.1466)	(0.0008)	(0.0007)	(0.0371)	(0.0221)	(0.0257)	(0.0101)	(0.0062)	(0.4170)	(1.9432)	(0.0008)	(0.3208)

Notes: 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. This table reports the estimated parameters, with clustered standard deviation in the parentheses.

Table D6: Parameter Estimates for Subsamples

High Maturity Mismatch Subsample

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0619	0.6389	0.0069	0.0036	0.1912	0.9307	0.9458	0.9789	0.0673	0.0169	3.3485	17.2908	0.0035	2.8570
(0.0118)	(0.0395)	(0.0007)	(0.0008)	(0.0170)	(0.0361)	(0.0252)	(0.0275)	(0.0110)	(0.0018)	(0.6153)	(1.9106)	(0.0008)	(0.2965)

Low Maturity Mismatch Subsample

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0609	0.8251	0.0070	0.0035	0.1829	0.9289	0.9447	0.9768	0.0666	0.0163	3.2450	17.5009	0.0037	3.0925
(0.0109)	(0.0595)	(0.0011)	(0.0008)	(0.0151)	(0.0340)	(0.0210)	(0.0258)	(0.0108)	(0.0011)	(0.6066)	(1.9760)	(0.0009)	(0.3309)

High Fire-sale Cost Subsample

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0621	0.5901	0.0068	0.0035	0.1926	0.9306	0.9459	0.9771	0.0675	0.0170	3.3501	17.2551	0.0032	2.8752
(0.0120)	(0.0385)	(0.0008)	(0.0009)	(0.0186)	(0.0358)	(0.0247)	(0.0260)	(0.0108)	(0.0015)	(0.6203)	(1.9325)	(0.0006)	(0.2958)

Low Fire-sale Cost Subsample

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0610	0.8052	0.0072	0.0034	0.1822	0.9301	0.9445	0.9765	0.0671	0.0166	3.2128	17.4638	0.0034	3.0501
(0.0101)	(0.0554)	(0.0011)	(0.0008)	(0.0128)	(0.0345)	(0.0208)	(0.0255)	(0.0108)	(0.0010)	(0.6081)	(1.9721)	(0.0007)	(0.3259)

Early Subsample

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0615	0.7107	0.0081	0.0033	0.1889	0.9308	0.9456	0.9769	0.0681	0.0170	3.3320	17.4421	0.0035	3.2361
(0.0118)	(0.0423)	(0.0008)	(0.0007)	(0.0179)	(0.0348)	(0.0221)	(0.0259)	(0.0112)	(0.0021)	(0.6215)	(1.9586)	(0.0009)	(0.3581)

Late Subsample

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\pi^{\sigma}_{H,H}$	$\pi^{\sigma}_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.0624	0.6971	0.0045	0.0035	0.1878	0.9311	0.9447	0.9780	0.0670	0.0165	3.2125	17.4435	0.0033	2.8969
(0.0121)	(0.0417)	(0.0009)	(0.0008)	(0.0172)	(0.0356)	(0.0218)	(0.0257)	(0.0097)	(0.0019)	(0.6124)	(1.9689)	(0.0007)	(0.3265)

Notes: 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. This table reports the estimated parameters, with clustered standard deviation in the parentheses.

Table D7: Simulated Moments Estimation: Extended Model with Financial Shocks

A. Moments

Target Moments	Data	Model	t-statistics
mean of leverage	0.932	0.930	0.119
mean of new asset issuance/asset ratio	0.437	0.441	-0.142
stdv. of new asset issuance/asset ratio	0.152	0.152	-0.133
autocorrelation of new asset issuance/asset ratio	0.876	0.862	0.243
mean default rate	1.10%	1.12%	-0.130
mean of dividend/asset ratio	0.021	0.022	-0.052
stdv. of dividend/asset ratio	0.015	0.017	-0.367
autocorrelation of dividend/asset ratio	0.795	0.732	0.745
mean of asset return uncertainty	0.064	0.064	-0.003
stdv. of asset return uncertainty	0.045	0.045	-0.015
autocorrelation of asset return uncertainty	0.732	0.717	0.219
skewness of asset return uncertainty	0.931	1.012	-0.552
mean of equity issuance/asset ratio	0.012	0.012	0.113
stdv. of equity issuance/asset ratio	0.019	0.014	1.014
covariance (equity issuance, new asset issuance)	0.0008	0.0009	-0.158
leverage-asset slope	0.043	0.048	-0.324
mean entrant leverage	0.972	0.979	-0.140
mean entrant growth	0.242	0.210	0.403
entrant relative size	0.201	0.192	0.133
mean of interest spread	0.55%	0.56%	-0.114
stdv. of interest spread	0.44%	0.43%	0.096

B. Parameter estimates

ρ_γ	σ_γ	μ_γ	ζ	ξ	k_0	ϕ	ρ_v	$\pi^\sigma_{H,H}$	$\pi^\sigma_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.686	0.281	0.061	0.713	0.006	0.003	0.161	0.915	0.944	0.978	0.067	0.017	3.254	17.25	0.003	2.931
(0.074)	(0.037)	(0.018)	(0.041)	(0.001)	(0.001)	(0.019)	(0.035)	(0.025)	(0.019)	(0.002)	(0.001)	(0.600)	(1.896)	(0.001)	(0.385)

Notes: Calculations are based an annual sample of shadow banks from the Bankscope and Worldscope databases. 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 simulated and actual moments and the clustered t-statistics for the differences between the corresponding moments. Panel B reports the estimated parameters, with clustered standard deviation in the parentheses.

Table D8: Simulated Moments Estimation: Extended Model with Fire-sale Cost Shocks

A. Moments

Target Moments	Data	Model	t-statistics
mean of leverage	0.932	0.931	0.054
stdv. of leverage	0.091	0.085	0.341
covariance (leverage, new asset issuance)	-0.0021	-0.0029	0.870
mean of new asset issuance/asset ratio	0.437	0.430	0.175
stdv. of new asset issuance/asset ratio	0.152	0.145	0.136
autocorrelation of new asset issuance/asset ratio	0.876	0.863	0.212
mean default rate	1.10%	1.08%	0.123
mean of dividend/asset ratio	0.021	0.020	0.112
stdv. of dividend/asset ratio	0.015	0.016	-0.206
autocorrelation of dividend/asset ratio	0.795	0.735	0.691
mean of asset return uncertainty	0.064	0.064	-0.011
stdv. of asset return uncertainty	0.045	0.045	-0.015
autocorrelation of asset return uncertainty	0.732	0.713	0.335
skewness of asset return uncertainty	0.931	1.001	-0.596
mean of equity issuance/asset ratio	0.012	0.012	0.112
leverage-asset slope	0.043	0.047	-0.299
mean entrant growth	0.242	0.220	0.288
entrant relative size	0.201	0.222	-0.211
mean of interest spread	0.55%	0.54%	0.110
stdv. of interest spread	0.44%	0.42%	0.157

B. Parameter estimates

ρ_ζ	σ_ζ	μ_ζ	γ_e	ξ	k_0	ϕ	ρ_v	$\pi^\sigma_{H,H}$	$\pi^\sigma_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.891	0.182	0.701	0.060	0.005	0.003	0.150	0.921	0.947	0.979	0.0676	0.0167	3.052	17.60	0.003	2.945
(0.072)	(0.035)	(0.018)	(0.009)	(0.001)	(0.001)	(0.012)	(0.013)	(0.023)	(0.019)	(0.010)	(0.005)	(0.536)	(1.637)	(0.001)	(0.324)

Notes: Calculations are based an annual sample of shadow banks from the Bankscope and Worldscope databases. 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 simulated and actual moments and the clustered t-statistics for the differences between the corresponding moments. Panel B reports the estimated parameters, with clustered standard deviation in the parentheses.

Table D9: Simulated Moments Estimation: Extended Model with both Financial Shocks and Fire-sale Cost Shocks

A. Moments

Target Moments	Data	Model	t-statistics
mean of leverage	0.932	0.930	0.104
stdv. of leverage	0.091	0.0925	-0.366
covariance (leverage, new asset issuance)	-0.0021	-0.0025	0.658
mean of new asset issuance/asset ratio	0.437	0.441	-0.478
stdv. of new asset issuance/asset ratio	0.152	0.153	-0.232
autocorrelation of new asset issuance/asset ratio	0.876	0.861	0.286
mean default rate	1.10%	1.11%	-0.087
mean of dividend/asset ratio	0.021	0.024	-0.423
stdv. of dividend/asset ratio	0.015	0.016	-0.300
autocorrelation of dividend/asset ratio	0.795	0.743	0.620
mean of asset return uncertainty	0.064	0.064	0.009
stdv. of asset return uncertainty	0.045	0.045	-0.016
autocorrelation of asset return uncertainty	0.732	0.716	0.335
skewness of asset return uncertainty	0.931	0.982	-0.344
mean of equity issuance/asset ratio	0.012	0.012	0.112
stdv. of equity issuance/asset ratio	0.019	0.015	0.204
covariance (equity issuance, new asset issuance)	0.0008	0.0007	0.137
leverage-asset slope	0.043	0.040	0.211
mean entrant growth	0.242	0.221	0.257
entrant relative size	0.201	0.215	-0.139
mean of interest spread	0.55%	0.56%	-0.154
stdv. of interest spread	0.44%	0.42%	0.157

B. Parameter estimates

ρ_γ	σ_γ	μ_γ	ρ_ζ	σ_ζ	μ_ζ	ξ	k_0	ϕ	ρ_v	$\pi^\sigma_{H,H}$	$\pi^\sigma_{L,L}$	σ_H	σ_L	μ	A	f_e	ω
0.682	0.285	0.060	0.889	0.178	0.705	0.005	0.002	0.201	0.910	0.942	0.979	0.067	0.017	3.014	17.68	0.003	2.943
(0.068)	(0.036)	(0.013)	(0.078)	(0.034)	(0.023)	(0.001)	(0.001)	(0.019)	(0.024)	(0.031)	(0.050)	(0.019)	(0.009)	(0.635)	(1.864)	(0.001)	(0.297)

Notes: Calculations are based an annual sample of shadow banks from the Bankscope and Worldscope databases. 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 simulated and actual moments and the clustered t-statistics for the differences between the corresponding moments. Panel B reports the estimated parameters, with clustered standard deviation in the parentheses.

Table D10: Simulated Moments Estimation: Extended First-moment Shock Model with Asset Portfolio Choices

A. Moments

Target Moments	Data	Model	t-statistics
mean of leverage	0.932	0.943	-0.848
mean of new asset issuance/asset ratio	0.437	0.442	-0.152
stdv. of new asset issuance/asset ratio	0.152	0.082	1.593
autocorrelation of new asset issuance/asset ratio	0.876	0.863	0.212
mean default rate	1.10%	0.35%	3.016
mean of dividend/asset ratio	0.021	0.036	-1.265
stdv. of dividend/asset ratio	0.015	0.004	1.669
autocorrelation of dividend/asset ratio	0.795	0.851	-1.125
mean of asset return uncertainty	0.064	0.064	0.005
mean of equity issuance/asset ratio	0.012	0.009	0.126
fraction of risky asset	0.610	0.601	0.258
leverage-asset slope	0.043	0.049	-0.355
mean entrant growth	0.242	0.261	-0.290
entrant relative size	0.201	0.209	-0.091
mean of interest spread	0.55%	0.18%	3.121
stdv. of interest spread	0.44%	0.14%	2.869

B. Parameter estimates

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\overline{\sigma}$	μ	A	f_e	ϕ_b	ω
0.0660	0.6714	0.0067	0.0034	0.1425	0.9231	0.0318	3.2147	17.6814	0.0035	0.0033	2.9515
(0.0098)	(0.0402)	(0.0012)	(0.0012)	(0.0115)	(0.0304)	(0.0126)	(0.4222)	(2.3318)	(0.0009)	(0.0008)	(0.3252)

Notes: Calculations are based an annual sample of shadow banks from the Bankscope and Worldscope databases. 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 simulated and actual moments and the clustered t-statistics for the differences between the corresponding moments. Panel B reports the estimated parameters, with clustered standard deviation in the parentheses. ϕ_b is the debt adjustment cost parameter.

Table D11: Simulated Moments Estimation: Extended First-Moment Shock Model with Systemic Risk Shocks

A. Moments

Target Moments	Data	Model	t-statistics
mean of leverage	0.932	0.951	-1.325
mean of new asset issuance/asset ratio	0.437	0.447	-0.170
stdv. of new asset issuance/asset ratio	0.152	0.090	1.504
autocorrelation of new asset issuance/asset ratio	0.876	0.852	0.322
mean default rate	1.10%	0.31%	3.131
mean of dividend/asset ratio	0.021	0.040	-1.466
stdv. of dividend/asset ratio	0.015	0.005	1.325
autocorrelation of dividend/asset ratio	0.795	0.856	-1.297
mean of asset return uncertainty	0.064	0.064	-0.010
mean of systemic risk	0.0015	0.0011	0.169
stdv. of systemic risk	0.695	0.636	0.870
autocorrelation. of systemic risk	0.025	0.023	0.376
mean of equity issuance/asset ratio	0.012	0.033	-0.226
leverage-asset slope	0.043	0.050	-0.431
mean entrant growth	0.242	0.246	-0.140
entrant relative size	0.201	0.216	-0.150
mean of interest spread	0.55%	0.17%	3.322
stdv. of interest spread	0.44%	0.12%	3.011

B. Parameter estimates

γ_e	ζ	ξ	k_0	ϕ	ρ_v	$\overline{\sigma}$	μ	A	μ_θ	ρ_θ	φ_θ	f_e	ω
0.0662	0.6438	0.0089	0.0038	0.1380	0.9005	0.0320	3.0210	18.6004	0.0008	0.0354	0.5489	0.0043	2.9712
(0.0117)	(0.0321)	(0.0015)	(0.0005)	(0.0109)	(0.0231)	(0.0101)	(0.3999)	(1.9251)	(0.8621)	(3.3379)	(5.0125)	(0.0011)	(0.3577)

Notes: Calculations are based on an annual sample of shadow banks from the Bankscope and Worldscope databases. 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 simulated and actual moments and the clustered t-statistics for the differences between the corresponding moments. Panel B reports the estimated parameters, with clustered standard deviation in the parentheses. μ_θ, ρ_θ, and φ_θ govern the mean, persistence, and standard deviation of the systemic risk process.

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