Financial Regulation and Shadow Banking: A Small-Scale DSGE Perspective

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Abstract

In this paper, we revisit the role of regulation in a small-scale dynamic stochastic general equilibrium (DSGE) model with interacting traditional and shadow banks. We estimate the model on US data and we show that shadow banking may seriously interfere with macro-prudential policies. More precisely, asymmetric regulation causes a leak towards shadow banking which weakens its expected stabilizing effect. We conduct a counterfactual experiment showing that a regulation of the whole banking sector would have reduced investment fluctuations by 10% between 2005 and 2015.

KEYWORDS: Shadow Banking, DSGE models, Macro-prudential Policy.

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1 Introduction

There seems to be an agreement among both academics and policy makers that limited regulation of non-depository financial institutions, or shadow banks, was one of the major causes of the subprime mortgage crisis and the ensuing Great Recession. As a result, they argue that financial regulation needs to move into a more global, macro-prudential direction (see for instance Hanson et al., 2011; Bernanke, 2013). However, as mentioned in Gertler et al. (2016), most of the macroeconomic modeling of the financial sector only features traditional banking and therefore probably misses some important considerations for regulatory design. In this paper, we revisit the role of regulation in a small-scale dynamic stochastic general equilibrium (DSGE) model with interacting traditional and shadow banks.[1] We estimate the model on US data and we show that shadow banking may seriously interfere with macro-prudential policies.

The model works as follows. The shadow bank purchases physical capital from non-financial firms ('shadow loans') by issuing Asset-Backed Securities (ABS, hereafter) against the pool of loans they acquire. The shadow bank has no access to the deposit market and completely escapes from regulation. The traditional bank purchases not only physical capital from firms ('traditional loans') but also the ABS issued by the shadow bank. The traditional bank has access to the deposit market and is subject to regulation. It has an incentive to invest in ABS because they are tradable and backed by a pool of loans. As a result, the ABS are subject to less regulation than traditional loans and this allows the traditional bank to increase its leverage. The roles of the shadow and the traditional banks, as well as their interactions, are similar to those in Gertler et al. (2016) and Meeks et al. (2016). However, a key difference is the way financial constraints are introduced. We assume asymmetric regulations whereas these other authors assume asymmetric financial frictions. More precisely, in their papers, the traditional bank may more easily divert loans than ABS and the fraction of divertible loans is higher for traditional banks than for shadow banks. The existence of a shadow bank therefore increases the efficiency of intermediation by lowering frictions. In our paper instead, the shadow bank increases the efficiency of intermediation through lower regulation (costs).

The DSGE model with shadow banking is estimated through maximum likelihood techniques using US quarterly data for the period 1980-2015. It is worth noting that the model is estimated over a period when Basel I regulation was mainly in effect (a period with regulation on tradi-

[1] Appendix A provides more details on traditional versus shadow banking.

tional loans without a countercyclical buffer).[2] The model also includes habits in leisure so as to reproduce the persistence in aggregate variables, ensuring a reasonable fit to the data. The model includes four aggregate disturbances (total factor productivity, labor wedge, screening cost and shadow wedge shocks). Importantly for our macro-prudential policy experiments, we estimate a portfolio adjustment cost parameter for traditional banks and conduct various robustness exercises regarding this parameter (data measurement, sample period, sensitivity analysis). Our estimation results remain unaffected by these perturbations. From these estimations, we then conduct various policy experiments and counterfactual analysis with a Basel III type of regulation of the banking sector.

The main contribution of this paper is to show that shadow banking seriously interferes with macro-prudential policies. First, regulating only intermediation activity (loans) by the traditional banking sector is less effective at stabilization than similar regulation without shadow banks, *i.e.* when the traditional bank holds no ABS assets. Indeed, only a fraction of the financial sector is regulated and this asymmetry causes a leak towards the shadow sector. Second, all activities by the whole banking sector is more effective at stabilization than regulation in an economy without shadow banks. Because of portfolio adjustment costs, the shadow bank cannot easily deleverage and thus restores profit margins through higher lending spreads. Third, in the presence of shadow banking, the Basel III countercyclical buffer rule must react to total credit in the economy rather than a narrower measure represented by credit supplied by the traditional banking sector. Fourth, a counterfactual experiment shows that full implementation of Basel III (regulation of all activities by the whole banking sector with a countercyclical buffer rule reacting to total credit) would have reduced investment fluctuations by 10% between 2005 and 2015.

There are only few dynamic general equilibrium models with shadow banking. Above, we already described the modeling approach by Meeks et al. (2016) and Gertler et al. (2016). Meeks et al. (2016) show that their calibrated model can reproduce business cycle moments observed in the data. Gertler et al. (2016) explain how a shadow crisis can affect traditional banks and how their model can capture a financial collapse. Verona et al. (2013) propose a different approach in which both the traditional and the shadow sectors intermediate between households and firms. The shadow banking system is monopolistic and it sets its lending rate as a markup over the risk-free interest rate. Importantly, they introduce an exogenous and countercyclical

[2]See appendix B for a detailed review of Basel regulation in the US (from Basel I to Basel III and the Dodd-Frank Act) and its possible implementation in a small-scale DSGE model.

markup rule. They show that only the model augmented with shadow banking can predict a substantial boom and bust following monetary policy that is too low for too long. Goodhart et al. (2013) build a 2-period model. As in our model, shadow banks are funded by traditional banks. They consider shadow banks to be less risk averse and not subject to capital requirements and they study various types of financial regulation. Moreira and Savov (2016) develop a continuous time model. Shadow banks transform risky assets into liquid securities in quiet times, which may however become illiquid when uncertainty spikes. They show that shadow banking stimulates growth but also creates fragility. There is a broader literature on macro-prudential regulation in DSGE models. Let us mention a few recent papers. De Walque et al. (2010) and Covas and Fujita (2010) illustrate the procyclicality of time-varying capital requirements as in Basel II. Angeloni and Faia (2013) derive the optimal combination of capital regulation and monetary policy. They conclude that the best combination is a mildly coutercyclical capital ratio and a monetary policy reacting to asset prices or bank leverage. Angelini et al. (2014) look at the interaction between monetary policy and macro-prudential policy. They show that in normal times (supply shocks), monetary policy is more powerful to stabilize the economy whereas in stress times (financial shocks), the benefits of a countercyclical macro-prudential policy become sizable. In our paper, we also investigate the effects of macro-prudential regulation, but taking into account the existence of a shadow sector.

The paper proceeds as follows. Section 2 describes the model. Section 3 explains the data, the calibration and the estimation results. Section 4 presents the main results, that is the importance of shadow banking when considering the effects of macro-prudential regulation. Section 5 briefly concludes.

2 Model

We extend the standard Real Business Cycle model by introducing a banking sector composed of traditional and shadow banks. The traditional bank finances assets (traditional loans and ABS) with deposits and regulatory bank capital. The shadow bank has no access to deposits and does not need regulatory bank capital. It finances assets by issuing securities. In this economy, the household owns all economic agents (firm and banks). We base the macro-prudential regulation on the Basel I Accord, which was in force during most of our sample period. Under this regulation, the bank capital of the traditional bank must be above a constant fraction $\bar{\eta} > 0$ of risk-weighted assets. The risk weight on traditional loans is 100% and the risk weight on securitizations with the highest rating (as were supposed most securitizations before the 2008 crisis) is 20%. To make things simpler, we adopt here an even more dichotomous approach with a 100% weight on loans and a 0% weight on ABS. Figure 8 in appendix B presents the aggregate balance sheet of the different agents in this economy. We modify this regulatory setup in section 4 to analyze the Basel III framework.

2.1 Non-Financial Firms

The representative firm produces final goods using a Cobb-Douglas technology

$$F(k_{t-1}, h_t) = \epsilon_t \, k_{t-1}^{1-\alpha} \, h_t^{\alpha},$$

where k_{t-1} and h_t are capital and hour inputs, respectively. $\alpha \in (0,1)$ is the elasticity of output with respect to hours and $\epsilon_t = \epsilon_{t-1}^{\rho_\epsilon} \exp(\sigma_\epsilon u_{\epsilon,t})$ is a total factor productivity shock following a first-order autoregressive process with $|\rho_\epsilon| < 1$, $\sigma_\epsilon > 0$ and $u_{\epsilon,t} \sim i.i.d.N(0,1)$. The firm rents capital at a price r_t^k and pays an hourly wage w_t. The profit maximization gives

$$\begin{aligned}(1-\alpha)F_t/k_{t-1} &= r_t^k, \\ \alpha F_t/h_t &= w_t,\end{aligned}$$

where $F_t = F(k_{t-1}, h_t)$. It is worth noting that the firm rents capital both from the traditional bank (s_t^c) and the shadow bank (s_t^s) such that $k_t = s_t^c + s_t^s$.

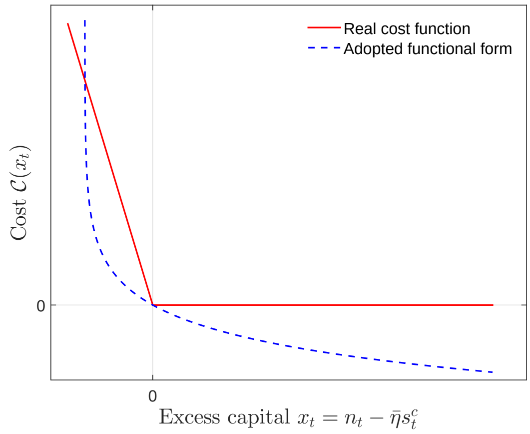
2.2 Traditional Banks

The representative traditional bank holds two types of assets. The first type is traditional loans s_t^c and the second type is asset backed securities ABS_t issued by the shadow bank. It finances these assets through deposits d_t and bank capital n_t. The bank balance sheet is therefore

$$s_t^c + ABS_t = n_t + d_t.$$

Bank capital n_t should not be lower than a constant fraction $\bar{\eta}$ of assets s_t^c. As already explained, we assume there is no regulation related to securitized assets ABS_t. Formally, we define excess capital $x_t = n_t - \bar{\eta} s_t^c$ and the capital constraint should imply $x_t \geq 0$. We nevertheless allow the bank to hold less capital than required but subject to a penalty cost $\mathcal{C}(.)$ proportional to the capital gap. The solid red line in figure 1 represents this cost function. However, in order to avoid this occasionally binding cost, we adopt a more convenient functional form, as shown by the dashed blue line. More precisely, the cost $\mathcal{C}(x_t)$ is such that $\mathcal{C}(0) = 0$, $\mathcal{C}'(.) < 0$ and $\mathcal{C}''(.) > 0$. This approach with a differentiable cost function avoids a more complex occasionally binding capital constraint and is also used in Enders et al. (2011) or Kollmann (2013). We explain in section 3.2 how we fix the first and second derivatives of the cost function around the steady state.

Figure 1: Capital Requirement Constraint



We have seen above that the traditional bank holds loans s_t^c and ABS_t as assets. Loans are usually long term assets and therefore illiquid in the short term. Although the assets (long term loans) underlying ABS are illiquid, the ABS themselves are normally liquid and marketable. In other words, loans and ABS are different types of assets and the bank cannot easily exchange them. In our model, we capture this imperfect substitution between assets with portfolio adjustment costs $\mathcal{P}(ABS_t/s_t^c)$ where $\mathcal{P}(\overline{ABS}/\overline{s^c}) = 0$, $\mathcal{P}'(\overline{ABS}/\overline{s^c}) = 0$, $\mathcal{P}''(.) > 0$, and $\bar{z}$ stands for the steady state of any variable z_t. Andrès et al. (2004) or Chen et al. (2012) use a very similar functional form to introduce imperfect substitution between short-term and long-term assets. This kind of cost related to adjustment in banking (here portfolio reallocation) is also very common in the micro-banking literature (see for instance Freixas and Rochet, 2013).

The bank receives a net of depreciation return $r_t^k - \delta$ from loans and a predetermined return r_{t-1}^a from ABS holdings. Indeed, an ABS is a fixed income instrument structured as a securitized interest in a pool of riskier and more illiquid assets. In the model, we translate this difference through the predetermined return on ABS and the current return on loans. The bank also pays a predetermined interest rate r_{t-1}^d on deposits. The bank's budget constraint in period t is

$$\begin{aligned}\pi_t^c \quad = \quad & d_t + (1 + r_t^k - \delta)s_{t-1}^c + (1 + r_{t-1}^a)ABS_{t-1} - (1 + e_t)s_t^c - ABS_t - (1 + r_{t-1}^d)d_{t-1} \\ & -\mathcal{C}(x_t) - \mathcal{P}(ABS_t/s_t^c),\end{aligned}$$

where π_t^c is the profit (dividend) generated by the bank. e_t is a cost paid per unit of supplied loans, incurred by the need to screen the borrowers. We represent this cost as a shock following a first-order autoregressive process $e_t = \rho_e \ e_{t-1} + \sigma_e \ u_{e,t}$ with $|\rho_e| < 1$, $\sigma_e > 0$ and $u_{e,t} \sim i.i.d.N(0,1)$. Since it directly affects the lending rate, it therefore captures any time varying lending risk premium that we do not explicitly model. Note that, using the balance sheet constraint, we can re-write the budget constraint as

$$\pi_t^c + \Delta n_t = (r_t^k - \delta)s_{t-1}^c + r_{t-1}^a ABS_{t-1} - r_{t-1}^d d_{t-1} - e_t s_t^c - \mathcal{C}(x_t) - \mathcal{P}(ABS_t/s_t^c).$$

This equation means that the operating surplus (income minus costs) is split into profits distributed to the household and Δn_t changes in bank capital. The profit maximization with respect to deposits, loans and ABS implies, respectively

$$\begin{aligned}
1 + \mathcal{C}_t' &= E_t \ \Lambda_{t,t+1} \ (1 + r_t^d), \\
e_t - \bar{\eta}\mathcal{C}_t' - \mathcal{P}_t' \frac{ABS_t}{(s_t^c)^2} &= E_t \ \Lambda_{t,t+1} \ (r_{t+1}^k - \delta - r_t^d), \\
\mathcal{P}_t' \frac{1}{s_t^c} &= E_t \ \Lambda_{t,t+1} \ (r_t^a - r_t^d),
\end{aligned}$$

where $\Lambda_{t,t+1}$ represents the household's stochastic discount factor between t and $t+1$, that we define later. The first FOC equalizes the marginal costs of issuing liabilities through bank capital (left hand side) or deposits (right hand side). The second FOC means that the spread between the lending and deposits rates must cover all costs related to the traditional loans, i.e. a screening cost e_t, a cost $-\bar{\eta}\mathcal{C}_t' > 0$ related to the regulatory requirements and a cost related to the portfolio reallocation (zero at the steady state). The last FOC shows that the spread between the ABS return and the deposit cost only covers a portfolio reallocation cost. Indeed there is neither screening nor regulatory requirement costs related to ABS. In order to better understand the effect of the portfolio adjustment cost, we linearize the last FOC, which gives

$$\frac{\overline{\mathcal{P}}''}{\bar{s}^c} \left(\widehat{\frac{ABS_t}{s_t^c}} \right) = \overline{\Lambda} \ (\hat{r}_t^a - \hat{r}_t^d) \ ,$$

where $\bar{z}$ stands for the steady state of any variable or function z_t and $\hat{z}_t = z_t - \bar{z}$. This equation illustrates a very simple relationship between shadow spread and shadow assets. It means that, *ceteris paribus*, an increase in the ABS return stimulates ABS holdings. The lower is the convexity $\overline{\mathcal{P}}''$ of the portfolio adjustment cost, the higher is transmission. However, there are many disturbances related to the shadow sector that affect this relationship and are not captured by our stylized banking representation. We include all these disturbances through a shadow wedge shock which is not directly related to the structure of the economy and the above equation becomes

$$\frac{\overline{\mathcal{P}}''}{\bar{s}^c} \left(\widehat{\frac{ABS_t}{s_t^c}} \right) + E_t \ \Gamma_{t+1} = \overline{\Lambda} \ (\hat{r}_t^a - \hat{r}_t^d) \ . \tag{1}$$

We assume the disturbance follows a first-order autoregressive process $\Gamma_t = \rho_\Gamma \ \Gamma_{t-1} + \sigma_\Gamma \ u_{\Gamma,t}$ with $|\rho_\Gamma| < 1, \sigma_\Gamma > 0$ and $u_{\Gamma,t} \sim i.i.d.N(0,1)$. An expected positive shock to this shadow wedge increases the required return on ABS and/or reduces ABS holdings. In appendix C, we provide a micro-foundation (risk of default by the shadow bank) to this shock.

2.3 Shadow Banks

To model shadow banking, we adopt an overlapping generation structure. The shadow bank lives 2 periods. In the first period t, it enters the market and issues ABS_t with a per unit issuing cost $a > 0$ to provide loans s_t^s, which gives $s_t^s = (1-a)ABS_t$. We also find this issuing or management cost in Enders et al. (2011). It can be seen as a shortcut to more sophisticated management costs, as for instance in Christiano et al. (2003) where management of certain liabilities requires capital services, labor and excess reserves as inputs to a Cobb-Douglas technology. In the second period $t+1$, the shadow bank makes the profit $\pi_{t+1}^s = (1 + r_{t+1}^k - \delta)s_t^s - (1 + r_t^a)ABS_t$ and leaves the market. We assume free entry in t with expected 0-profit condition $E_t \pi_{t+1}^s = 0$. Using the first period budget constraint, this yields

$$(1-a) \ E_t \ (1 + r_{t+1}^k - \delta) = 1 + r_t^a.$$

This condition means that the marginal cost of 1 unit of ABS (right hand side) is equal to its expected return (left hand side). It is worth reflecting that the shadow bank is not regulated. This is in accordance with the Basel I Accord, which only regulates insured depository institutions.

2.4 Households

The household owns the whole economy and maximizes $E_s \ \sum_{t=s}^{\infty} \ \beta^{t-s} \ \mathcal{U}(c_t, d_t, h_t)$, where $\beta \in (0,1)$ is the household's psychological discount parameter and its momentary utility is defined

$$\mathcal{U}(c_t, d_t, h_t) = \ln c_t + \theta \ln d_t - \frac{m_t}{1+\psi} \left(\frac{h_t}{h_{t-1}^{\phi}} \right)^{1+\psi}.$$

$\theta > 0$ and we therefore assume that deposits provide utility to the household (liquidity motive). This allows us to calibrate $\mathcal{C}'(.) < 0$ at the steady state.[3] We use the same functional form for the sub-utility of deposits and the sub-utility of consumption, as is often the case in the macro literature with money-in-the-utility function (deposits can be seen as real money balances). We also refer to Enders et al. (2011) for a similar specification. The parameter $\psi \geq 0$ captures the

[3] It is easy to show that when $\theta = 0$, $\bar{r}^d = 1/\beta$ (household's Euler equation) which implies $\overline{\mathcal{C}}' = 0$ (traditional bank's first order condition). A strictly positive θ lowers $\bar{r}^d$ and allows for a negative marginal cost.

curvature in labor disutility and ϕ the habit persistence in leisure. $\phi < 0$ implies intertemporal substitutability of labor supply whereas $\phi > 0$ implies intertemporal complementarity. Several papers (Eichenbaum et al., 1988; Wen, 1998; Bouakez and Kano, 2006; Dupaigne et al., 2007; Fève et al., 2013) show that the specification with $\phi > 0$ is empirically relevant as it translates leisure habits into output persistence. Labor disutility is subject to a stochastic preference shock $m_t = \bar{m}^{1-\rho_m}\ m_{t-1}^{\rho_m}\ \exp(\sigma_m u_{m,t})$ with $|\rho_m| < 1$, $\sigma_m > 0$ and $u_{m,t} \sim i.i.d.N(0,1)$. As noted by Galí (2005), this shock accounts for a sizable portion of aggregate fluctuations and captures various distortions in the labor market (we call it labor wedge hereafter as Chari et al., 2007) that are not explicitly introduced in the model. Every period, the household must respect its instantaneous budget constraint

$$c_t + d_t = w_t h_t + (1 + r_{t-1}^d) d_{t-1} + \pi_t^c + \pi_t^s.$$

Utility maximization with respect to deposits and hours gives, respectively

$$\begin{aligned} \frac{1}{c_t} &= \frac{\theta}{d_t} + \beta\ E_t\ \frac{1 + r_t^d}{c_{t+1}}, \\ m_t\ Z_t &= \frac{\alpha F_t}{c_t} + \beta\phi\ E_t\ m_{t+1} Z_{t+1}, \end{aligned}$$

where $Z_t \equiv (h_t / h_{t-1}^{\phi})^{1+\psi}$. The first FOC states that at equilibrium the household is indifferent between consuming today or deriving utility from deposits and consuming tomorrow. The second FOC equalizes the marginal disutility of hours to the marginal utility of consuming the marginal product of hours. Due to habit persistence in leisure, we see that increasing hours today increases the current disutility (left hand side) but also decreases disutility tomorrow (right hand side). Finally, we observe that when $\theta = \phi = 0$, the two first order conditions simplify into the usual Euler and labor supply equations.

2.5 Aggregate Conditions

The household's stochastic discount factor between t and $t+1$ is $\Lambda_{t,t+1} = \beta\ c_t / c_{t+1}$. We define physical investment as $i_t = k_t - (1-\delta) k_{t-1}$ where $\delta \in (0,1)$ is the capital depreciation rate. The sum of all budget constraints gives

$$F(k_{t-1}, h_t) = c_t + i_t + \mathcal{C}(x_t) + \mathcal{P}(ABS_t / s_t^c) + e_t s_t^c + aABS_t\,.$$

We define GDP, shadow banking share, credit spread and traditional bank leverage as $y_t = c_t + i_t$, $share_t = s_t^s / k_t$, $spread_t = r_t^k - \delta - r_{t-1}^d$ and $leverage_t = (s_t^c + ABS_t)/n_t$, respectively.

3 Data and Estimation

We first describe the estimation technique and the US data. We then present the estimation results and the robustness checks.

3.1 Data

We log-linearized the resulting system in the neighborhood of the non-stochastic steady state. Let Θ denote the vector of model parameters and $\hat{x}_t$ be a vector of variables. The state-space form of the different model specifications is characterized by the state equation

$$\hat{x}_t = \mathbf{F}(\Theta)\hat{x}_{t-1} + \mathbf{G}(\Theta)\zeta_t, \tag{2}$$

where $\zeta_t \sim i.i.d.N(0, \Sigma)$ is a vector of innovations to the four shocks, and the system matrices $\mathbf{F}(\Theta)$ and $\mathbf{G}(\Theta)$ are functions of the model parameters. We use as observable variables in estimation the logs of investment and hours worked, the share of shadow banking and the spread ($\log(i_t)$, $\log(h_t)$, $share_t = s_t^s/k_t$ and $spread_t = r_t^k - \delta - r_{t-1}^d$). As in Iacoviello (2015), we take the deviation from the quadratic trend except for the spread.[4] Figure 10 in appendix D displays the detrended and demeaned data. The measurement equation is

$$\begin{pmatrix} \log(i_t) \\ \log(h_t) \\ share_t \\ spread_t \end{pmatrix} = \mathbf{C}\hat{x}_t, \tag{3}$$

where $\mathbf{C}$ is a selection matrix For a given Θ and using equations (2) and (3), the log-likelihood is evaluated via standard Kalman filtering techniques. The estimated parameters are then obtained by maximizing the log-likelihood.

For estimation, we use quarterly frequency data over the period 1980:I to 2015:III. Data come from the St. Louis' FRED database, the BLS and the Financial Accounts of the United States (Z.1) published by the Federal Reserve Board. Investment is defined as the sum of personal consumption expenditures on durable goods (PCDG) and gross private domestic investment (GDPI), divided by the implicit GDP deflator (GDPDEF) and by the civilian population over 16 (CNP16OV). Hours are borrowed from Neville and Ramey (2009) and represent total economy hours worked, divided by the civilian population over 16 (CNP16OV).[5] We borrow the defini-

[4] As also stated in Iacoviello (2015), it is nontrivial to introduce stochastic or deterministic trends in a model with financial variables, since several financial variables (for instance shadow loans here) may have specific trends.

[5] See the website http://econweb.ucsd.edu/~vramey/research.html#data for regularly updated data.

tions of shadow *vs.* traditional banking from Meeks et al. (2016). We consider as shadow banking the Security brokers and dealers (L.129) and the Issuers of asset-backed securities (L.126). We define shadow credit as the sum of their total financial assets. We consider as traditional banking the U.S.-chartered depository institutions (L.111) and the Credit unions (L.114). We define traditional credit as the sum of their total financial assets minus vault cash and reserves at the Federal Reserve, corporate and foreign bonds and agency- and GSE-backed securities. The shadow share is then defined as the ratio between shadow credit and total (shadow plus traditional) credit. In the robustness analysis, we also use an alternative and larger measure of traditional credit as the sum of their total financial assets minus vault cash and reserves at the Federal Reserve, corporate and foreign bonds. Finally, to compute the spread between the lending rate and the deposit rate, we use Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate series (AAAFFM). In the robustness analysis, we also use an alternative spread corresponding to Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate (BAAFFM).

3.2 Estimation Results

We specify the cost $\mathcal{C}(.)$ related to – negative – excess capital as well as the portfolio adjustment cost $\mathcal{P}(.)$ as

$$\begin{aligned} \mathcal{C}(x_t) &= -\, p_1 \, \ln\left(1 + p_2 \, x_t\right), \\ \mathcal{P}(ABS_t/s_t^c) &= \frac{\gamma}{2}\left(\frac{ABS_t}{s_t^c} - \frac{\overline{ABS}}{\overline{s^c}}\right)^2, \end{aligned}$$

with $p_1, p_2, \gamma \geq 0$. Note that the capital cost specification implies $\mathcal{C}'(0) = -p_1 \; p_2 \leq 0$ and $\mathcal{C}''(0) = -\mathcal{C}'(0) \; p_2 \geq 0$.

We split the whole set of parameters into the three vectors Θ_1, Θ_2 and Θ_3. The vector $\Theta_1 = (\alpha,\ \delta,\ \bar{m},\ \theta,\ \bar{\eta},\ \beta,\ \mathcal{C}'(0),\ a)$ includes parameters that we calibrate to match specific steady state values. The vector $\Theta_2 = (\psi,\ \mathcal{C}''(0))$ includes parameters that are difficult to estimate within our model so we calibrate them prior to estimation. The remaining parameters that we estimate are included in the vector $\Theta_3 = (\phi,\ \gamma,\ \rho_\epsilon,\ \rho_\Gamma,\ \rho_m,\ \rho_e,\ \sigma_\epsilon,\ \sigma_\Gamma,\ \sigma_m,\ \sigma_e)$.

Regarding the parameters in Θ_1, we set $\alpha = 2/3$ and $\delta = 2.5\%$. These values are standard and allow to match the observed labor share and investment to output ratio. We calibrate $\bar{m}$ to obtain the standard value of $\bar{h} = 0.2$, θ to obtain a shadow share of 30% and $\bar{\eta}$ to target a leverage ratio of 5.3. The shadow share computed from the data was less than 5% in the early 80's, reached 50% around 2005 and fell back to 30% in 2015. We chose to calibrate the model on the 2015 value. The leverage ratio ($leverage_t = (s_t^c + ABS_t)/n_t$ in the model) is calibrated using data from the Financial Accounts of the United States (Z.1). We use the same definition as above for traditional banking and shadow banking. We define leverage as the ratio between total assets (in traditional and shadow banking) over total liabilities minus total deposits (in traditional banking). We obtain a leverage ratio that is more stable across time than the shadow share and we calibrate the model on its average value of 5.3. This leverage number is close to the number reported in Meeks et al. (2016).[6] Finally, we calibrate β, $\mathcal{C}'(0)$ and a in order to reproduce 3 specific steady states, namely $\bar{x} = 0$ (zero excess capital), $\bar{r}^d = 0$ (zero return on deposits) and $\overline{spread} = 0.0065$. This latter value represents the average spread between AAA bond return and Fed Funds between 1980 and 2015. More precisely, banks' first order conditions give $\beta = \bar{\eta}/(\overline{spread} + \bar{\eta}(1+\bar{r}^d))$, $a = \overline{spread}/(1+\bar{r}^d + \overline{spread})$ and $\mathcal{C}'(0) = -\overline{spread}/(\overline{spread} + \bar{\eta}(1+\bar{r}^d))$. All the calibrated parameters in Θ_1 are reported in the top panel of table 1.[7]

Table 1: Calibrated Parameter Values (Quarterly when Applicable)

Notation	Value	Description	Target
Parameters in Θ_1			
α	2/3	labor share	labor share: $(\bar{w}\bar{h})/\bar{F} = 2/3$
δ	0.025	capital depreciation rate	investment to GDP ratio: $\bar{i}/\bar{y} = 0.27$
$\bar{m}$	21.63	weight on hours in (dis-)utility	hours: $\bar{h} = 0.2$
θ	0.2828	weight on deposits in utility	shadow share: $\overline{share} = 0.3$
$\bar{\eta}$	0.27	capital requirements	traditional bank leverage: $\overline{leverage} = 5.3$
β	0.9765	discount factor	deposit rate: $\bar{r}^d = 0$
$\mathcal{C}'(0)$	-0.0235	marginal excess capital cost	excess capital: $\bar{x} = 0$
a	0.0065	ABS issuing cost	credit spread: $\overline{spread} = 0.0065$
Parameters in Θ_2			
ψ	2	hours curvature in (dis-)utility	Frisch: $1/((1-\phi)(1+\psi)-1) = 0.5$ when $\phi = 0$
$\mathcal{C}''(0)$	0.001	convexity of excess capital cost	yearly spread to capital requ. elasticity = 0.05

Notes. All targets taken from data or from empirical studies. See the explanations in the main text. When needed, the sample period is 1980:I–2015:III.

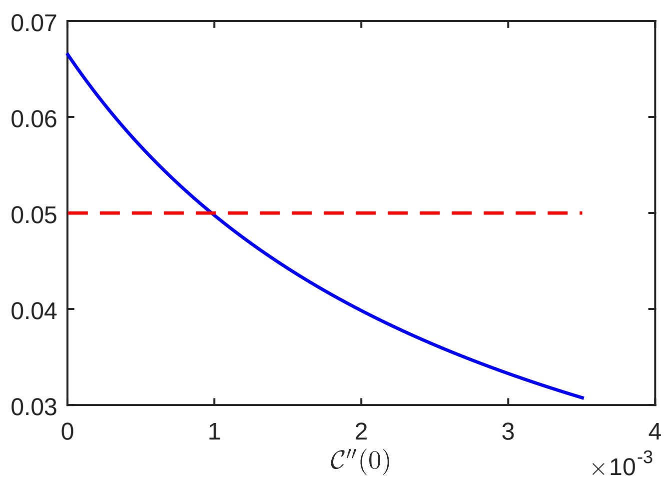
Regarding the parameters in Θ_2, we set $\psi = 2$ in accordance with previous studies (for instance, Smets and Wouters, 2007, estimate this parameter at 1.92). The Frisch elasticity of labor supply is $1/((1-\phi)(1+\psi)-1)$. The estimation by Smets and Wouters (2007), in a model with $\phi = 0$,

[6] They report a ratio of traditional loans to equity of 4.5 and a share of securitized assets of 0.3. This implies a leverage of $1/(1-0.3) \times 4.5 = 6.4$.

[7] The calibration implies that at the steady state, total ABS issuing costs represent about 2% of the gross output $F(.,.)$. This is in line with the related literature. For instance, Enders et al. (2011) introduce asset and liabilities management costs which amount to 1% of gross output.

therefore implies an elasticity of 0.5. Since we estimate ϕ later and that this estimation may significantly differ from zero, our implied elasticity will no longer be necessarily equal to 0.5. The calibration of $\mathcal{C}''(0)$ deserves more comments. $\mathcal{C}''(0)$ mainly governs the effect of regulation on the lending rate. Since our capital adequacy ratio $\bar{\eta}$ is constant over the whole simulation period (Basel I), it is difficult to estimate $\mathcal{C}''(0)$ with sufficient precision and we instead calibrate this parameter looking at empirical literature. Hanson et al. (2011) estimate on US data that, in the long run, 1 percentage point increase in the capital requirements increases the yearly loan rates by 2.5 to 4.5 basis points. Also using US data, Baker and Wurgler (2015) report that 1 ppt increase in the ratio of capital to risk weighted assets raises loan rates by 6 to 9 bps. We assume a mean value of 5 bps. We then simulate our model with a 1 ppt permanent increase in $\bar{\eta}$ for different values of $\mathcal{C}''(0)$, and pick the parameter value such that the increase in the yearly loan rate is 5 bps. We report these simulations in figure 2. All the calibrated parameters in Θ_2 are reported in the bottom panel of table 1. In section 3.3, we conduct robustness analysis with respect to the Θ_2 parameters, i.e. we estimate the Θ_3 parameters under alternative values for the Θ_2 parameters.

Figure 2: Loan Rate r_t^k Reaction to a 1 ppt Permanent Increase in the Capital Adequacy Ratio $\bar{\eta}$, for Different Values of $\mathcal{C}''(0)$



Notes. r_t^k is in annual term and the reaction is expressed in percentage point deviation from its steady state. Solid blue line: model estimation. Dashed red line: average of estimations reported in Hanson et al. (2011) and Baker and Wurgler (2015).

The remaining parameters contained in Θ_3 are then estimated. The vector Θ_3 includes two structural parameters: the habit in leisure parameter ϕ and the portfolio adjustment cost parameter γ. The eight other parameters concern the four shock processes. Table 2 reports the estimation results under various model configurations (see columns `Bench.` for the benchmark case that includes both habits and portfolio adjustment costs, `Alt.(1)` when habits are shut down and `Alt.(2)` when adjustment costs are set to zero).[8]

We describe our main findings below. First, our results strongly support the benchmark specification with habit persistence and portfolio adjustment costs. The comparison of column `Bench.` with columns `Alt.(1)` where $\phi = 0$ and `Alt.(2)` where $\gamma = 0$ shows that both restrictions are rejected by the data (see the log-likelihood). Second, the estimated value for ϕ is positive and precisely estimated. The estimated value is very close to the one obtained in Dupaigne et al. (2007) and Fève et al. (2013), indicating a sizable degree of habits in leisure and strong intertemporal complementarity in labor supply. Note that with habit persistence, the estimated autoregressive parameters are large but smaller that the ones obtains in `Alt.(1)`.[9] This is because habit persistence partly captures the high degree of serial correlation in hours worked. Third, the portfolio adjustment cost is precisely estimated and the restriction $\phi = 0$ is strongly rejected by the data, as indicating by the difference in the log-likelihood functions of columns `Bench.` and `Alt.(2)`. As for habits in leisure, setting or not the portfolio adjustment cost parameter to zero modifies the estimated values for the autoregressive parameters of shocks, thus reflecting the propagation mechanism induced by this cost function.

From the estimation results of our benchmark specification, we compute the contribution of the four shocks to aggregate variables (see table 3). Let us first consider output (gdp), consumption (c) and investment (i). It appears that the technology and labor wedge shocks are the main drivers of these variables (between 58% and 98%). However, the shadow wedge and screening cost shocks have non-negligible effects on investment (around 25%). The variance of hours (h) appears almost totally explained by the labor wedge shock. The shadow share (*share*) is only explained by the two shocks originating from the heterogeneous banking sector. Regarding the spread, we obtain that 99% of its variance is due to screening cost and the shadow wedge shocks. The screening cost has a direct effect whereas the wedge shock has an indirect effect though the ABS return. The bank capital (n) is mostly affected by the labor wedge shock. This labor shock indeed determines hours which, in the short run, drive output, investment and *in fine* the bank capital. The remaining bank capital fluctuations are essentially explained

[8]We also estimate a version where both habits and adjustment costs are removed. Data strongly reject this version.

[9]The close to unity value of the autoregressive parameter ρ_m of the labor wedge shock is in line with previous research showing that data favor non-stationarity of hours absent other real frictions in the model (see *e.g.* Christiano et al., 2007; Chang et al., 2007; Zanetti, 2008).

Table 2: Estimation Results

	`Bench.`	`Alt.(1)` $\phi = 0$	`Alt.(2)` $\gamma = 0$	`Rob.(1)` *share* bis	`Rob.(2)` *spread* bis	`Rob.(3)` 1985:I–2015:III	`Rob.(4)` 1980:1–2007:IV
ϕ	0.6904	NaN	0.4527	0.6903	0.7109	0.6264	0.6808
	(0.0526)	(NaN)	(0.0696)	(0.0523)	(0.0501)	(0.0734)	(0.0673)
γ	0.6962	0.7354	NaN	0.7250	0.7394	0.5200	0.7612
	(0.0567)	(0.0610)	(NaN)	(0.0591)	(0.0604)	(0.0462)	(0.0709)
ρ_ϵ	0.7648	0.8201	0.9415	0.7660	0.7764	0.8935	0.7409
	(0.0345)	(0.0417)	(0.0240)	(0.0344)	(0.0329)	(0.0277)	(0.0451)
ρ_m	0.9968	0.9974	0.9857	0.9969	0.9971	0.9958	0.9953
	(0.0036)	(0.0025)	(0.0129)	(0.0035)	(0.0032)	(0.0054)	(0.0064)
ρ_Γ	0.9335	0.9390	0.9876	0.9346	0.9276	0.9262	0.9477
	(0.0129)	(0.0135)	(0.0060)	(0.0126)	(0.0134)	(0.0152)	(0.0141)
ρ_e	0.8740	0.8751	0.7761	0.8788	0.8827	0.9175	0.8733
	(0.0267)	(0.0247)	(0.0383)	(0.0260)	(0.0250)	(0.0190)	(0.0324)
σ_ϵ	0.0192	0.0202	0.0068	0.0192	0.0195	0.0142	0.0213
	(0.0013)	(0.0013)	(0.0006)	(0.0013)	(0.0013)	(0.0011)	(0.0016)
σ_m	0.0167	0.0228	0.0232	0.0166	0.0167	0.0145	0.0177
	(0.0011)	(0.0014)	(0.0015)	(0.0010)	(0.0010)	(0.0011)	(0.0014)
σ_Γ	0.0035	0.0036	0.0020	0.0036	0.0039	0.0026	0.0035
	(0.0003)	(0.0003)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
σ_e	0.0019	0.0019	0.0021	0.0019	0.0019	0.0012	0.0021
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
$log\mathcal{L}$	1840.1582	1805.4091	1058.7431	1845.5356	1831.7737	1712.6043	1418.2410

Notes. Sample period: 1980:I–2015:III unless mentioned. $log\mathcal{L}$ represents the log-likelihood. Standard errors between brackets. The observables are $\log(i_t)$, $\log(h_t)$, $share_t$ and $spread_t$. The two alternative estimations fix some of the structural parameters to 0. The four robustness exercises use different definitions for some observables or different estimation periods.

by the shadow wedge shock (21%) and the screening cost shock (10%), the technology shock explaining only a small portion of its variance. The two shocks originating from the banking sectors explain most of the fluctuations of the leverage (65%), the remaining part coming mostly from the labor wedge shock (29%). Summing up, the shadow wedge and screening cost shocks appear to have non negligible effects on the financial but also on the real US business cycles.

Table 3: Variance Decomposition

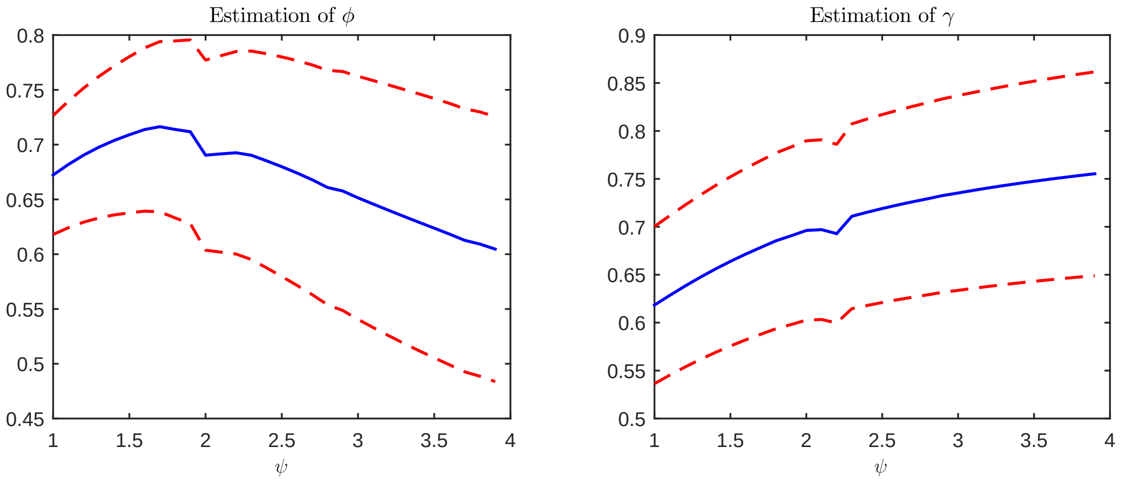
	ϵ_t	m_t	Γ_t	e_t
gdp	3.68	92.43	1.47	2.42
i	16.17	58.10	10.83	14.90
c	0.83	97.81	0.78	0.58
h	0.82	97.58	1.11	0.49
share	0.00	0.00	83.96	16.04
spread	0.53	0.17	50.13	49.17
n	4.99	63.19	21.37	10.45
leverage	6.76	28.78	45.15	19.32

Notes. Variance decomposition under the benchmark specification reported in table 2. Sample period: 1980:I–2015:III. ϵ_t is the productivity shock, m_t is the labor wedge shock, Γ_t is the shadow wedge shock and e_t is the screening cost shock.

3.3 Robustness Analysis

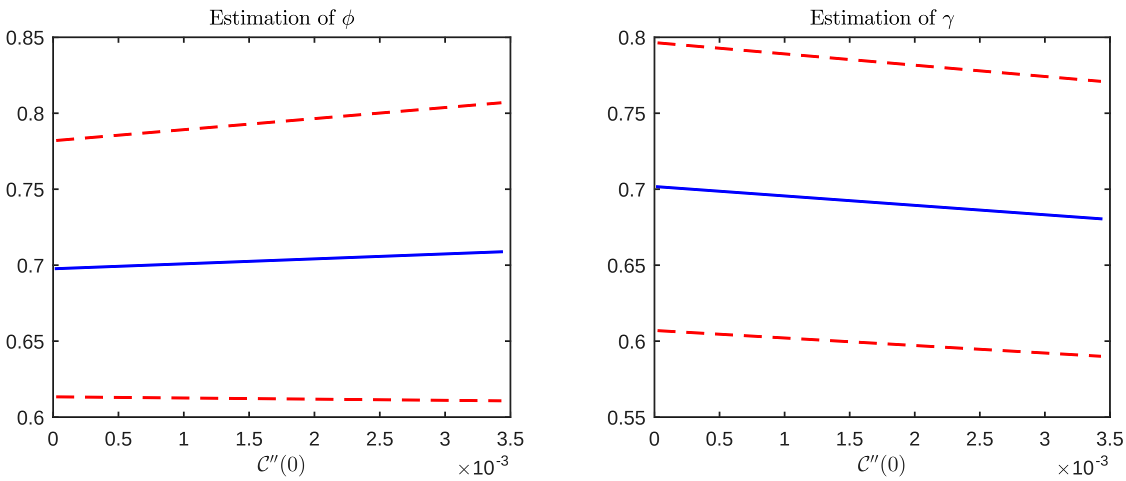
We conduct three types of robustness analysis. First, we explore the sensitivity of our estimations to changes in the (inverse of) labor supply elasticity ψ and the convexity $\mathcal{C}''(0)$ of the excess bank capital cost function. To perform this exercise, we re-estimate the model with different values for ψ and $\mathcal{C}''(0)$. We then check how the estimated values of the habit persistence parameter ϕ and the portfolio adjustment cost γ are sensitive to these calibrated values. Let us first consider the parameter ψ (see figure 3). As shown in the left panel of figure 3, moving ψ from 1 to 4 has small consequences on the estimated values of the habit persistence parameter (between 0.6 and 0.71). Moreover, the estimated parameter obtained from our benchmark calibration always remains inside the confidence interval when ψ moves between 1 and 4. We obtain a similar result when it comes to the sensitivity of γ to ψ. The estimated values for γ vary between 0.62 and 0.70, but the estimated value obtained from the benchmark calibration of ψ is always within the confidence interval. Figure 4 reports the sensitivity of the estimated parameters ϕ and γ with respect to a change in the convexity $\mathcal{C}''(0)$ of the cost function on excess capital. As this figure shows, our estimation results are weakly affected by the shape of the cost function on excess capital.

Figure 3: Estimation Results for Different Values of ψ



Notes. Sample period: 1980:I–2015:III. The observables are $\log(i_t)$, $\log(h_t)$, $share_t$ and $spread_t$. The dashed red lines represent the 90% confidence interval bounds.

Figure 4: Estimation Results for Different Values of $\mathcal{C}''(0)$



Notes. Sample period: 1980:I–2015:III. The observables are $\log(i_t)$, $\log(h_t)$, $share_t$ and $spread_t$. The dashed red lines represent the 90% confidence interval bounds.

Second, we check the robustness of our findings to alternative data and sample periods. These robustness checks are detailed as follows:

`Rob.(1)`. We use a larger measure of traditional credit (see section 3.1 for details), *i.e.* a narrower measure for the variable $share_t$.

`Rob.(2)`. We use a different definition for the variable $spread_t$ (BAA minus Fed Funds instead of AAA minus Fed Funds, see section 3.1 for details).

`Rob.(3)`. Our detrending procedure may attribute excessive relative size of the shadow share in the beginning of the sample, i.e. between 1980 and 1985 (see figure 10 in appendix D). We start the sample in 1985:I to remove these initial movements in the shadow share.

`Rob.(4)`. Similarly, the financial crisis severely downsized the shadow banking sector. So we end the sample in 2007:IV to remove this end of sample volatility.

Columns `Rob.(1)` to `Rob.(4)` in table 2 report the results of this robustness analysis. The estimated values for ϕ are weakly affected by these new samples and data measurements. The estimations for the parameter γ display a similar pattern. One exception concerns the `Rob.(3)` exercise for which both the habit persistence and the portfolio adjustment cost parameters decrease (and thus the estimated persistence of shocks increase). Note however that the ϕ and γ are very precisely estimated and still remain within the confidence interval of the benchmark estimation.

Third, we want to assess by how much omitting the shadow banking sector would alter our previous empirical results (estimation, moments, variance decomposition). To do so, we calibrate the shadow share to 0%. Consequently, there is no portfolio adjustment cost anymore because ABS are irrelevant in an economy without shadow banks, we discard the $share_t$ variable as observable in the measurement equation (3) as well as the shadow wedge shock Γ_t in the state-space representation (2). We are therefore left with three observables (investment, hours worked and the spread) and three shocks (technology, labor wedge and screening cost). We estimate this `NoShadow` model and compare the parameter estimates with those obtained from our benchmark representation. Table 6 in appendix E reports the results. In the `NoShadow` version, we obtain an important increase in the habit persistence parameter, whereas the other parameters associated to the forcing variables remain almost identical. This finding suggests that omitting the shadow banking sector and the relevant observations on its relative share lead to miss an important propagation/transmission mechanism. Comparing the moments illustrates further the importance of the shadow banking sector. Table 7 in appendix E shows that ignoring the shadow sector at the estimation stage has detrimental consequences on the fit of the model, both in terms of volatility and co-movements. Moreover, we see from the variance decomposition exercise displayed in figure 4, that the omission of the shadow banking sector and thus the shadow wedge shock dramatically changes the picture, and may lead to spurious conclusions about the sources of economic fluctuations. Let us consider two illustrative examples. First, the share of investment fluctuations due to shocks in the banking sector (screening cost shocks only) is very small (around 8%) and is severely underestimated. Indeed, in the benchmark model, the shadow wedge and the screening cost shocks explain 11% and 15 % of the variance of investment, respectively. Second, consider the capital of the traditional bank. In the counterfactual exercise with three observables, we obtain that the screening cost shock only explains 2% of the bank capital. The lack of shadow banking sector leads to underestimate the contribution of this shock, as it explains more than 10% of the bank capital in the benchmark model with the shadow sector. In addition, it misses the contribution of the shadow wedge shock that accounts for more than 20% of the variance of bank capital. This last exercise illustrates that the shadow banking sector can not be ignored for a proper quantitative investigation of the sources of US business cycle.

Table 4: Variance Decomposition with a Counterfactual `NoShadow` Economy

	ϵ_t	m_t	Γ_t	e_t
gdp	1.10	98.16	NaN	0.74
i	7.19	85.16	NaN	7.65
c	0.20	99.72	NaN	0.07
h	0.42	99.20	NaN	0.39
$share$	NaN	NaN	NaN	NaN
$spread$	0.86	0.73	NaN	98.41
n	1.87	95.78	NaN	2.34
$leverage$	7.54	78.64	NaN	13.82

Notes. Variance decomposition under the counterfactual `NoShadow` specification reported in table 6. Sample period: 1980:I–2015:III. ϵ_t is the productivity shock, m_t is the labor wedge shock and e_t is the screening cost shock. In the `NoShadow` economy, $share_t = 0$ and the shadow wedge shock Γ_t is irrelevant.

4 Macro-prudential Policies

During most of our estimation period, macro-prudential regulation was based on the 1988 Basel I Accord. As detailed in appendix B, a new set of rules named Basel II was initially published in 2004 but was not yet fully implemented when the 2008 financial crisis arose. The Basel III agreement with more stringent standards was then quickly adopted and its full implementation is currently underway. Briefly, Basel III extends regulation beyond traditional loans and introduces a countercyclical capital buffer. Figure 9 in appendix B illustrates the aggregate balance sheet of the different agents in the model under such a regulation. In this section, we study how the move from Basel I to Basel III regulation modifies the resilience of the economy to shocks. First, we investigate how the current economy reacts to an exogenous increase in the capital requirements η_t depending on which types of assets are regulated. Second, we make the change in the capital requirement endogenous (countercyclical capital buffer).

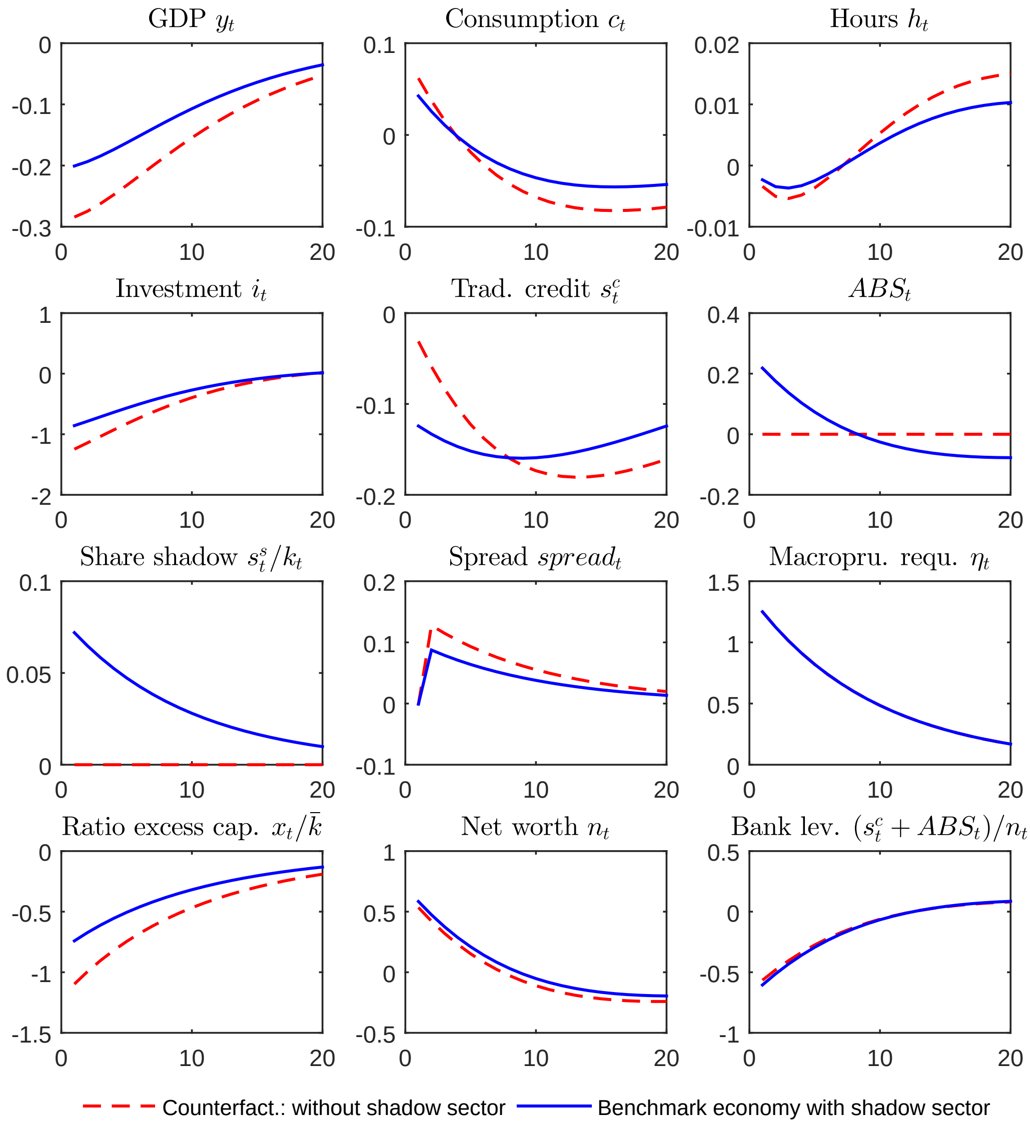
4.1 Regulation Shock

To understand how the economy functions, we first replace the capital ratio parameter $\bar{\eta}$ with a simple AR(1) stochastic regulation shock $\eta_t = \bar{\eta}^{1-\rho_\eta}\ \eta_{t-1}^{\rho_\eta}\ \exp(\sigma_\eta\ u_{\eta,t})$ where $|\rho_\eta| < 1, \sigma_\eta > 0$, $u_{\eta,t} \sim i.i.d.N(0,1)$. We calibrate the persistence parameter $\rho_\eta = 0.90$ as in Angelini et al. (2014) and we set σ_η to obtain an initial increase in the capital ratio η_t of 1.25 percentage points. Figure 5 displays the impulse response functions.

Before examining the transmission in our benchmark economy, we start with a counterfactual simulation without shadow banking (dashed line), meaning that $s_t^c = k_t$. In this counterfactual simulation, we regulate more assets ($\bar{k}$ instead of $\bar{s}^c = 0.7 \times \bar{k}$, at the steady state) and we obviously rescale the excess capital cost function accordingly.[10] More stringent regulation aiming to increase net worth and reduce leverage, lowers excess capital which is costly for the bank. As a result, the bank raises the lending spread, which decreases credit demand i_t and *in fine* output. There are two main differences when a shadow sector is introduced (solid line). First, regulation only applies to a fraction of traditional bank assets and is therefore less 'expensive' for the bank as shown by the lower fall in excess capital. Second, the traditional bank substitutes regulated credit s_t^c with unregulated ABS assets which results in a higher shadow share. Regulation therefore requires a lower increase in the spread and the fall in total credit and output is less pronounced.

[10] More precisely, we calibrate the parameters of the excess capital cost function we use in the counterfactual simulation as $\mathcal{C}'_{cf}(0) = \mathcal{C}'(0)$ and $\mathcal{C}''_{cf}(0) = \mathcal{C}''(0) \times \bar{s}^c/\bar{k}$.

Figure 5: 1.25 Percentage Points Initial Increase in the Capital Adequacy Ratio η_t



Notes. Deviations from steady states are expressed in percentage points for variables s_t^s/k_t, $spread_t$, η_t and $x_t/\bar{k}$. Deviations from steady states are expressed in percent for all the other variables. $spread_t$ is in annual term.

4.2 Basel III and the Regulation of Other Assets and Banks

Basel III refines the risk-weights applicable to different asset classes. In particular, the weight applicable to ABS ranges from a 20% floor to 1250% for certain excessively risky junior tranches. We therefore modify our benchmark model to include ABS as regulated assets. To do so, we modify the excess capital definition which becomes $x_t = n_t - \eta_t s_t^c - \eta_t^a ABS_t$. To keep the steady state unchanged, we suppose that $\bar{\eta}^a = 0$.[11] The linearized spread shown in equation (1) becomes

$$-\mathcal{C}'(0)\ \hat{\eta}_t^a + \frac{\overline{\mathcal{P}}''}{\bar{s}^c} \left(\widehat{\frac{ABS_t}{s_t^c}} \right) + E_t\ \Gamma_{t+1} = \overline{\Lambda}\ (\hat{r}_t^a - \hat{r}_t^d)\ .$$

Since $\mathcal{C}'(0) < 0$, this equation shows that an increase in ABS regulation forces the traditional bank to demand higher ABS returns and/or reduce ABS holdings.

Moreover, Basel III also implies that systemically important financial institutions (SIFIs) that are not traditional banks might also be subject to regulation (on a case-by-case basis). We assume that the shadow bank is a SIFI and we modify our benchmark model so that it is also regulated. To do so, we assume an infinitely lived shadow bank with the following balance sheet and profit

$$\begin{aligned}
s_t^s &= (1-a)ABS_t + n_t^s = (1-a)ABS_t + \eta_t^s s_t^s + x_t^s\ ,\\
\pi_t^s &= (1-a)ABS_t - s_t^s + (1 + r_t^k - \delta)s_{t-1}^s - (1 + r_{t-1}^a)ABS_{t-1} - \mathcal{C}^s(x_t^s) - \frac{\kappa}{2}\,(n_t^s)^2\ .
\end{aligned}$$

The shadow bank balance sheet shows that the bank can easily substitute between bank capital and security issuance to finance assets. In order to tame the substitution between balance sheet liabilities, we introduce an adjustment cost $\kappa \geq 0$ on shadow bank capital. The first order conditions with respect to ABS_t and s_t^s are, respectively

$$\begin{aligned}
(1-a)(1 + \mathcal{C}_t^{s\prime} + \kappa n_t^s) &= E_t\ \Lambda_{t,t+1}\ (1 + r_t^a),\\
1 + (1 - \eta_t^s)\mathcal{C}_t^{s\prime} + \kappa n_t^s &= E_t\ \Lambda_{t,t+1}\ (1 + r_{t+1}^k - \delta).
\end{aligned}$$

We assume that $\bar{x}^s = 0$ and the functional form for $\mathcal{C}^s(x_t^s)$ is similar to that for $\mathcal{C}(x_t)$. To keep the steady state unchanged, we suppose that $\bar{\eta}^s = 0$ and we calibrate $\mathcal{C}^{s\prime}(0)$ accordingly. We fix $\mathcal{C}^{s\prime\prime}(0) = \mathcal{C}''(0) \times \bar{s}^c/\bar{s}^s$ in order to take into account the volume of regulated assets (see also footnote 10). Finally, we calibrate the adjustment cost $\kappa = 0.05$ such that the reaction of the shadow spread ($spread_t^s = r_t^k - \delta - r_{t-1}^a$) under a Basel III regulation shock is the same as the

[11] As already explained in the footnote 10, we nevertheless rescale the excess capital cost function in order to take into account that more assets are regulated under Basel III.

reaction of the traditional spread ($spread_t = r^k_t - \delta - r^d_{t-1}$) under a Basel I regulation shock.

Figure 6 displays the impulse response functions to an AR(1) stochastic shock on η_t (benchmark economy, dashed red line), on η_t plus η^a_t (regulation also on ABS, solid blue line), and on η_t plus η^a_t and η^s_t (regulation also on ABS and shadow assets, dashed-dotted black line). In each case, we look at initial increase(s) in capital requirements of 1.25 percentage points and we assume a persistence $\rho_\eta = 0.90$. The first case, with an increase in η_t only, is well known and already explained in figure 5. The second case means that (i) all assets of the traditional bank – instead of a fraction of them – are regulated and (ii) there is no longer an incentive to substitute s^c_t with ABS_t. As a result, excess capital declines more and the bank further increases its lending spread. The economic slowdown is *in fine* more pronounced. The third case implies a double cost on ABS, since they are directly regulated as asset of the traditional bank and indirectly as liabilities (backing the assets) of the shadow bank. This double cost causes the shadow share to decline. In the end, the third case is the one where regulation has the most dampening effect on the economy.

4.3 Basel III and the Countercyclical Buffer

Basel III regulation also introduces a new macroprudential instrument in the form of a countercyclical time-varying capital buffer. Indeed, Basel III states that national regulators may require a capital ratio up to 2.5 percentage points higher during periods of high credit growth. 'High credit growth' is left to the discretion of the regulator, so in our model we distinguish two types of credit: broad credit, which corresponds to the total credit to the economy supplied by both traditional and shadow banking (policy **P1** below); and narrow credit, which corresponds only to credit supplied by traditional banking (policy **P2** below). In model language, we translate the countercyclical requirement into the AR(1) rule

$$\eta_t = \bar{\eta}^{1-\rho_\eta}\ \eta_{t-1}^{\rho_\eta}\ \left(\frac{v_t}{\bar{v}}\right)^{\kappa_\eta(1-\rho_\eta)},$$

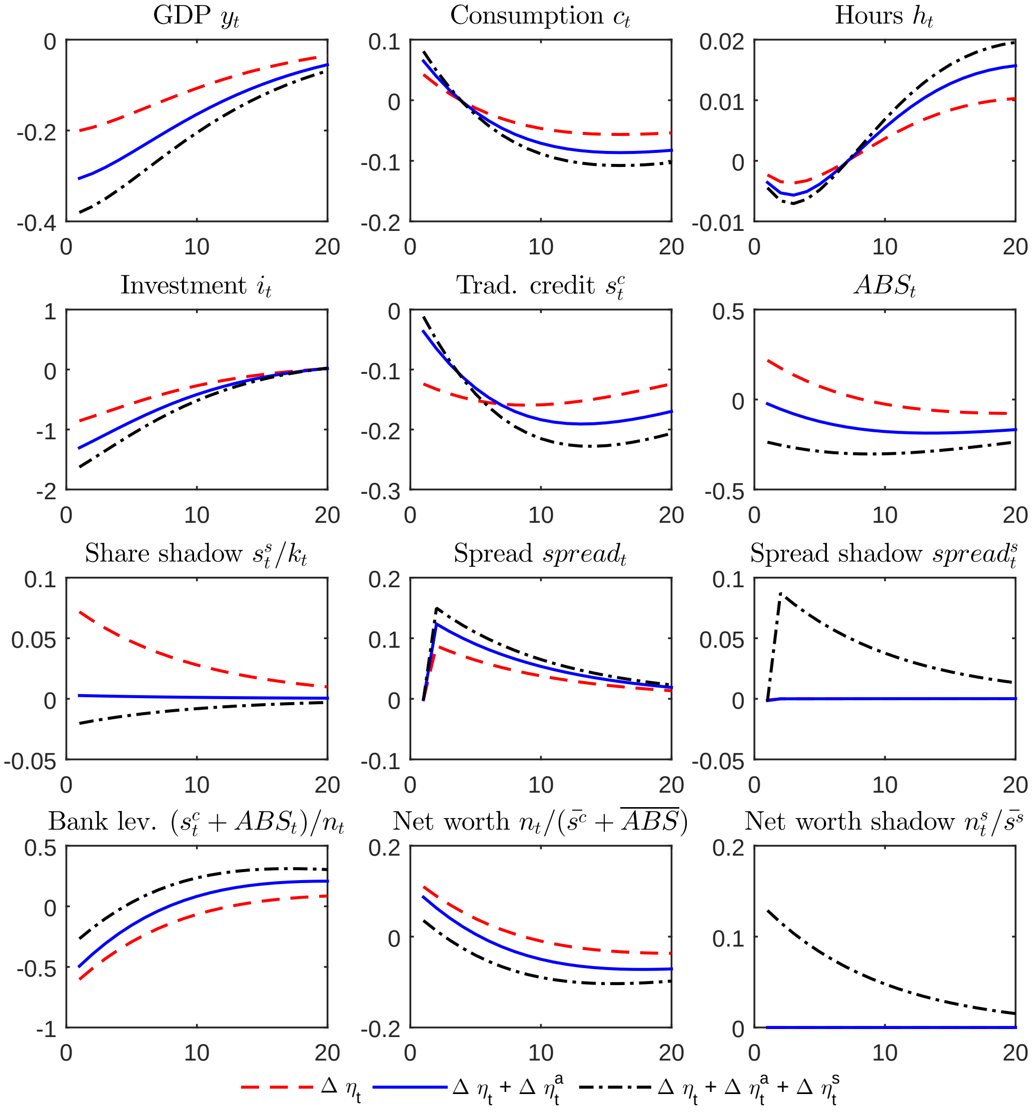
where we set $\rho_\eta = 0.90$ as above (see Angelini et al., 2014) and $\bar{v}$ represents the steady state of the variable v_t which can be

P1: ratio of total credit to GDP with $v_t = i_t/y_t$

P2: ratio of traditional credit to GDP with $v_t = (s^c_t - (1-\delta)s^c_{t-1})/y_t \cong \Delta s^c_t/y_t$

The Basel III maximum 2.5 percentage points increase means in our model that $\eta_t \in (\bar{\eta} - 0.0125, \bar{\eta} + 0.0125)$ through the business cycle. We apply these two rules to the model implied

Figure 6: 1.25 Percentage Points Initial Increase in the Capital Adequacy Ratio(s) $\eta_t - \eta_t^a - \eta_t^s$

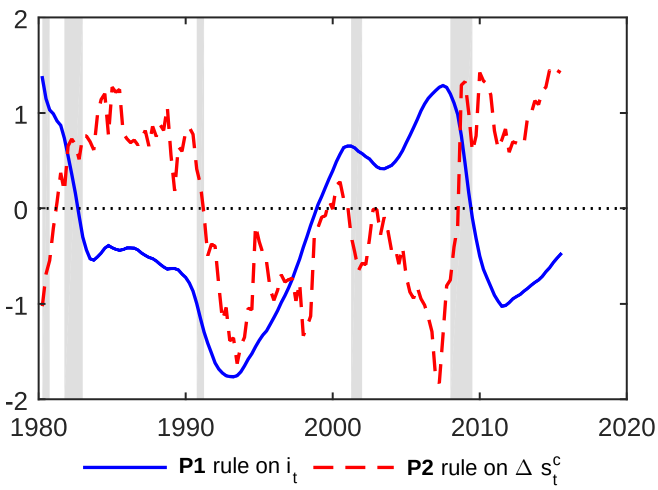


Notes. Deviations from steady states are expressed in percentage points for variables s_t^s/k_t, $spread_t$, $spread_t^s$, $n_t/(\bar{s^c} + \overline{ABS})$ and $n_t^s/\bar{s^s}$. Deviations from steady states are expressed in percent for all the other variables. $spread_t$ and $spread_t^s$ are in annual term. $\Delta\eta_t$ is our benchmark economy with regulation only on s_t^c; $\Delta\eta_t + \Delta\eta_t^a$ is an extension along the lines of Basel III with regulation on s_t^c and ABS_t; $\Delta\eta_t + \Delta\eta_t^a + \Delta\eta_t^s$ is a larger extension along the lines of Basel III with regulation on s_t^c, ABS_t and s_t^s.

evolutions of v_t over the estimation period. We calibrate κ_η to match a maximum deviation for η_t of 0.0125. This yields $\kappa_\eta = 0.5$ under the **P1** rule and $\kappa_\eta = 0.25$ under the **P2** rule. Note that the Basel I policy corresponds to the limit case with $\kappa_\eta = 0$.

Figure 7 reproduces the historical countercyclical capital requirements which would have been implied by the evolutions of the model variables. We observe that the **P1** rule (based on total credit i_t, solid blue line) would have been progressively increased from 1992 to 2007, that is until the onset of the Great Recession. Then the capital adequacy ratio would have been reduced by more than 2 percentage points in the following three years. The **P2** rule (based on traditional credit Δs_t^c only, dashed red line) is more volatile but is positively correlated with **P1** most of the time, except in the early 80's ('double-dip' recession) and around the Great Recession, where it follows a completely opposite pattern. The **P2** capital adequacy ratio would indeed have been at its lowest level in 2007 and reached its highest in 2010. In other words, a countercyclical rule based on a narrow measure of credit may be misleading for the aggregate economy, and in the end even generate procyclicality. We illustrate this in the next section.

Figure 7: Implied Evolutions of Basel III Countercyclical Capital Requirements η_t, from an Historical Perspective



Notes. η_t is expressed in percentage point deviation from its steady state $\bar{\eta}$. Shaded areas correspond to NBER recession dates.

4.4 Basel I vs. Basel III from an Historical Perspective.

We have shown how shadow banking sector is relevant for a proper quantitative assessment of regulation. To further quantify this result, we now compare the effects of Basel III *vs.* Basel I through a counterfactual historical exercise using our estimated DSGE model. We first feed the model with our estimated shocks, for the usual period 1980-2015, applying Basel I regulation, which corresponds to our benchmark estimation in table 2. Then, we repeat the same simulation exercise but applying Basel III regulation, with all banking sectors and all assets subject to a countercyclical buffer regulation, as described in sections 4.2 and 4.3. We assume the buffer requirement may follow a **P1** rule or a **P2** rule, meaning that it may react to total credit to the economy or to traditional credit only. The line 'Basel I' in table 5 reports the standard deviation of investment in the benchmark simulation. It is worth noting this is also the true deviation of investment since investment is an observable for in the estimation exercise. We also zoom in on the period 2005-2015, *i.e.* around the Great Recession, as a natural period to evaluate the effectiveness of Basel regulation for macroeconomic stabilization. The line 'Basel III **P1**' shows that a Basel III countercyclical regulation based on total credit and applied to all banks and assets would have reduced the volatility of investment both over the whole estimation period and over the Great Recession period. This investment reduction is moreover substantial. The line 'Basel III **P2**' illustrates that a similar Basel III regulation, but based on traditional credit only, decreases less the volatility over the whole sample period and even increases it around the Great Recession. Moreover, the volatility of the **P2** rule is higher than the **P1** rule, wichh makes the latter rule definitively less efficient than the former one in reducing investment volatility.

Table 5: Basel I vs. Counterfactual Basel III from an Historical Perspective – Standard Deviation of Investment and Capital Adequacy Ratio

	Full sample 1980:I-2015:III		Crisis 2005:I-2015:III	
	i_t	η_t	i_t	η_t
Estimated Basel I	0.0976	–	0.1171	–
Counterfact. Basel III **P1**	0.0886	0.0076	0.1056	0.0080
Counterfact. Basel III **P2**	0.0947	0.0081	0.1194	0.0086

Notes. Basel I is the benchmark economy with regulation $\eta_t = \bar{\eta}$ applied only to s_t^c assets. Basel III is the implementation of a countercyclical **P1** rule (based on i_t) or **P2** rule (based on Δs_t^c) applied to all s_t^c, ABS_t and s_t^s assets.

5 Conclusion

In this paper, we revisit the role of regulation in a small-scale dynamic stochastic general equilibrium (DSGE) model with interacting traditional and shadow banks. We estimate the model on US data and we show that shadow banking may seriously interfere with macro-prudential policies.

This paper is a first step to understanding how shadow banking and macro-prudential policies interact, and could be extended along several directions. First, it seems likely that in a such simple model, some transmission mechanisms between the shadow banking sector and the rest of the economy are missing. For instance, our assumption that households own the whole economy implies that shadow bank bankruptcy would be irrelevant. An extension without this perfect insurance mechanism and with an occasional binding constraint (default) would probably reinforce the propagation of negative shocks. Second, we propose a real business cycle model, therefore abstracting from the monetary dimension. However, monetary policy adds another asymmetry, through limited access to central bank liquidity, between traditional and shadow banks. A medium-scale model with price stickiness and monetary policy could also be worth developing. Third, our countercyclical rules are similar for all sectors/assets. We could look at specific and optimal rules as well as at their interactions with monetary policy (see above). We leave these topics for future research.

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Appendix

A Review of Traditional *vs.* Shadow Banks in the US

In the traditional banking system, institutions issue deposits in order to extend loans. They also issue debt and equity to capitalize this credit intermediation and transformation activities. Furthermore, they have access to public sources of liquidity (for instance from the Fed) or to public sources of insurance (for instance from the FDIC). It is also worth noting that credit intermediation occurs in a single entity. In the shadow banking system, institutions also conduct credit transformation but they do not have access neither to public liquidity nor public insurance. Moreover, credit intermediation is performed in a chain of different institutions through a multistep process. To keep it simple, we can say that a single traditional institution transforms retail-deposit-funding to hold-to-maturity-lending whereas a chain of shadow institutions transforms wholesale funding to lending through a complex securitization-based process. According to Pozsar et al. (2013), shadow liabilities reached a peak of $22 trillions in 2007, compared to traditional liabilities of $14 trillions in the same year.

The term shadow banking therefore refers to a wide array of activities. In this paper, we follow Meeks et al. (2016) and Gertler et al. (2016) and retrict our shadow banking definition to institutions performing credit transformation by issuing tradeable securities (wholesale funding) against an underlying pool of assets (lending). These institutions operate outside the Fed regulatory framework. In other words, these institutions replicate the functions of the traditional banks but (i) rely on wholesale funding instead of retail-deposit funding and (ii) bear the same risks but with much less capital (in fact we assume zero-capital in our model). More precisely, we define the shadow banking as the sum of Security brokers and dealers and Issuers of asset-backed securities. We consider as traditional banking the sum of U.S.-chartered depository institutions and Credit unions. Under our restricted definitions, shadow liabilities reached a peak of $10 trillions in 2007 while traditional liabilities amounted to about $12 trillions. Our restricted shadow sector therefore represents about 50% of the whole shadow sector as shown in Pozsar et al. (2013) whereas the size of our traditional banking is quite similar.

B Review of Financial Regulation in the US and Application to a Simple Model

This appendix reviews the evolution of the Basel regulation with a special focus on the US. It then suggests how to introduce – part of – this regulation into a simple model with traditional and shadow banks. Among the large descriptive literature on banking regulation, the interested reader may find more detailed informations in Masera (2013), Paskelian and Bell (2013) or Niemeyer (2016).

B.1 From Basel I to Basel III

The Basel Committee develops minimum standards for banking regulation. Countries are therefore free to implement stricter rules in their countries but not rules that are less strict. Formally, the Committee has no power and decisions must be enforced by each country's legislative authority. Basel I, Basel II, Basel 2.5 and Basel III are gradual refinements of one regulatory framework, rather than entirely new independent regulatory frameworks. We briefly present them below.

The Basel I agreement was reached in 1988 and implemented in the following years. The accord stipulates that banks should have capital equal to at least 8% of their (credit) risk-weighted assets (RWA). The highest risk weight is 100% (*e.g.* for corporate lending) and the lowest risk weight is 0% (*e.g.* for certain government securities). This agreement evolved through time, notably to take into account the market risk, on top of the credit risk.

The more complex Basel II accord was concluded in 2004 with the aim to refine the computation of the RWA and hence of the capital requirements. Basel II comprises 3 pillars. Pillar 1 defines the quantitative minimum capital requirements, which must cover the credit risks, the market risks and the operational risks. These quantitative minimum requirements are based on standardized approaches (legal requirements for each risk and each type of assets) and/or internal models (bank themselves may estimate certain parameters under the approval of the supervisory authority). Under Pillar 2, the supervisory authority may place additional capital requirements specific to individual banks, based on a more qualitative assessment of the bank's aggregate risk. Pillar 3 contains detailed requirements for the risks and exposures the bank must make public. When the financial crisis arose in 2007-2008, Basel II was not yet fully implemented in most countries.

The aim of Basel 2.5, agreed in 2009, was to quickly rectify some shortcomings of the Basel II regulation that had become clear during the financial crisis. In particular the fact that banks had underestimated the risk of securitization and complex exposures on the asset side. Basel 2.5 was however only a partial solution and a larger reform package known as Basel III was adopted in 2010 and 2011, and will be progressively implemented until 2023.

A key element of Basel III is to increase the quantity of capital. On top of the 8% of RWA, Basel III adds 2.5% of capital conservation buffer, 2.5% of countercyclical buffer (high in good times and low in bad times) and 2.5% of extra buffer for globally systemically important banks (G-SIBs). It is worth noting that with the countercyclical buffer, the Basel Committee introduces an explicit macroeconomic dimension to the prudential regulation. Another key element is to increase the quality of capital, with most of the regulatory capital, including all the buffers, consisting of Common equity Tier 1 capital (CET1). Basel III also includes, among others, (i) the strengthening of capital requirements for certain securitizations, (ii) the possibility for countries to nominate more banks or financial institutions as systematically important (SIFIs), (iii) capital overcharge when lending to SIFIs, (iv) the guarantee that banks have a minimum level of liquid assets, (v) the limitation of the maturity mismatch between (long) assets and (short) liabilities, (vi) the introduction of a complementary leverage ratio requirement not based on RWA in order to avoid a mispricing of risk, (vii) the restriction on exposures to individual counterparties and (viii) the limitation of the possibility to move exposures between the trading book and the banking book.

B.2 Basel III and the Dodd-Frank Act

In the US, the Dodd-Frank Act (DFA) was passed in 2010 to curb and prevent the financial and regulatory shortcomings that have been blamed for causing the 2007-2008 crisis. This is a sweeping legislation which creates a top layer of oversight (Financial Stability Oversight Council, FSOC) for financial institutions and already existing regulatory agencies, provides a new resolution procedure for financial companies, places new regulatory restriction on the derivative sector, etc. As Basel III, the DFA – and more precisely the Collins Amendment portion of the DFA – also addresses the issue of higher quantitative and qualitative capital requirements. It is worth noting that the Collins Amendment only allows the US regulatory agencies to adopt Basel III capital guidelines as long as these guidelines do not violate the Collins Amendment floors. The US Basel III Final Rule on capital standards therefore adapts the international Basel III framework to the requirements contained in the US DFA. We present some of the specificities of the US Basel III rule below:

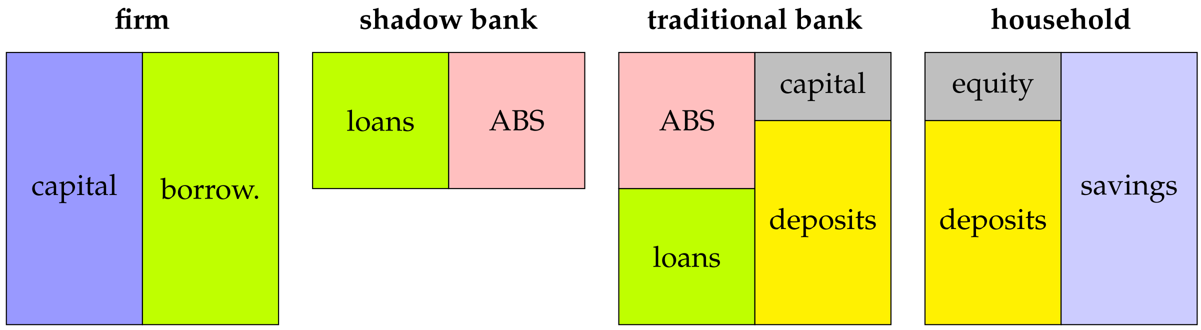
- The US implementation of Basel III is modulated according to bank size, *i.e.* all banks must respect the basic minimum capital rules but additional requirements are imposed on banking organizations on the basis of size and complexity. Conversely, the EU has a more 'one-size-fits-all' approach.
- The regulation applies to all depositary institutions but also to systematically important non-bank financial institutions (SIFIs), designed by the FSOC.
- The US strengthens the non-risk-weighted asset capital requirements. As a result, this non-risk weighted requirements may become binding for large banks whereas the RWA capital requirements are binding for all banks in the EU.
- It is also important to mention that the DFA requires that originators of securitized assets retain 5% of the asset credit risk. In contrast, Basel III does not include such a requirement.

B.3 The Basel/DFA Regulation in a Simple Model of the US Economy

We now suggest how to transpose some elements of the Basel regulation in a simple model. We first focus on the Basel I regulation. Since Basel II was never fully implemented and Basel 2.5 was only a quick and temporary solution, we then immediately move to the Basel III/DFA regulation.

Let us assume a banking sector composed of traditional banks and shadow banks and a Basel I regulation. The traditional bank finances assets (corporate loans and ABS) through deposits and regulatory capital. The capital must be equal to at least a constant fraction η^I of the RWA. We assume a high weight α^h for corporate loans and a low weight α^l for ABS, seen as high quality securitization with minimal risk. The traditional bank capital must therefore respects $capital \geq \eta^I RWA = \eta^I(\alpha^h\ loans + \alpha^l ABS)$. The shadow bank has no access to deposits and finances assets (corporate loans) by issuing ABS. Basel I does not apply to this type of financial institutions. Figure 8 summarizes this banking representation under Basel I.

Figure 8: Aggregate Balance Sheet of the Different Agents Under Basel I



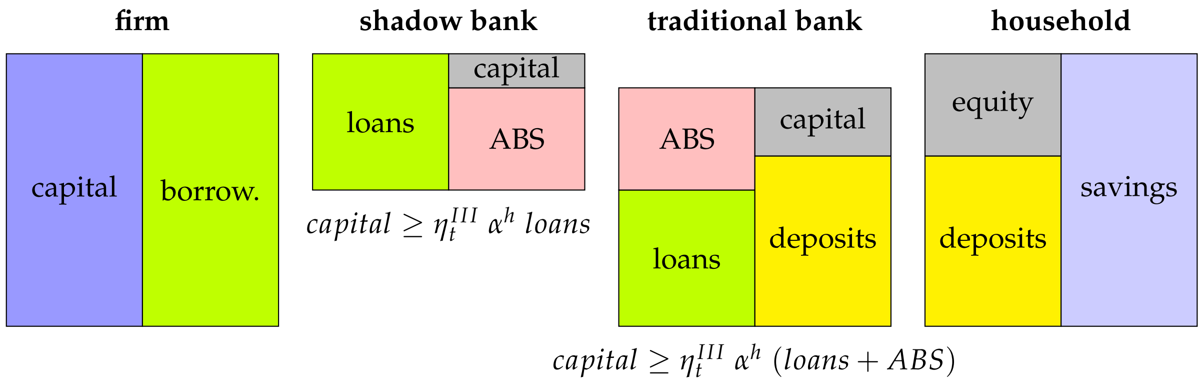
$capital \geq \eta^I(\alpha^h\ loans + \alpha^l ABS)$

Let us now assume a similar banking sector but a Basel III regulation. First, Basel III requires a higher quantity of capital, that is $\eta^{III} \geq \eta^I$. Second, Basel III strengthens capital requirements for certain securitizations and we increase the weight on ABS from α^l to α^h. Third, Basel III introduces an explicit countercyclical buffer and η^{III} becomes η_t^{III}, increasing in good time and decreasing in bad time. The traditional bank capital must now therefore respects $capital \geq \eta_t^{III}\ RWA = \eta_t^{III}\ \alpha^h\ (loans + ABS)$. Fourth, the shadow bank may be seen as a SIFI and in this case Basel III would apply to this type of financial institution. As a result, the shadow bank is subject to capital requirements respecting $capital \geq \eta_t^{III}\ RWA = \eta_t^{III}\ \alpha^h\ loans$. Figure 9 summarizes this banking representation under Basel III.

It might be interesting to add two more comments directly related to our banking representation under Basel III:

- The countercyclical buffer must increase in 'good time' and decrease in 'bad time' (η_t^{III} in figure 9). Basel III suggests to base this buffer on credit-to-GDP ratio. In its final

Figure 9: Aggregate Balance Sheet of the Different Agents Under Basel III



policy statement on 'Regulatory Capital Rules: The Federal Reserve Board's Framework for Implementing the U.S. Basel III Countercyclical Capital Buffer' from October 2016, the Fed acknowledges that credit-to-GDP is useful in identifying period of financial excess followed by a period of crisis, but does not expect this indicator to be used in isolation.

- Basel III implies to regulate the loans (ABS assets) from the traditional bank to the shadow bank (SIFI) through increased requirements for securitizations and/or capital overcharge when lending to SIFIs (see above). At the same time, Basel III requires the SIFIs to have higher capital. Figure 9 shows these 'double requirements'. *A priori*, one might doubt the necessity of both requirements as either the lender (traditional bank) increases capital because of higher risks or the borrower (shadow bank) increases capital to reduce its probability of default (see for instance Penikas, 2015, for a discussion). *Ex post*, we however show in our paper that the double requirements improve the resilience of the economy to shocks.

Obviously, there are lots of elements (capital quality, liquidity, maturity mismatch and many others) of the Basel III/DFA that are more difficult to take into account in such a stylized model.

C Shadow Wedge Shock

As explained in section 2, we capture the disturbances related to the shadow sector through a shadow wedge shock not directly related to the structure of the economy. We show below this could be explained as a shadow default risk shock.

Let us assume that every period, the ABS issuer (shadow bank) may partially default with Γ_t indicating the share of default. However, in case of default, the shadow bank compensates the traditional bank for losses through a lump-sum compensation T_t. The profit of the traditional bank and the first order condition with respect to ABS_t are

$$\begin{aligned}\pi_t^c &= d_t + (1 + r_t^k - \delta)s_{t-1}^c + (1 - \Gamma_t)(1 + r_{t-1}^a)ABS_{t-1} - s_t^c - ABS_t - (1 + r_{t-1}^d)d_{t-1} \\ &\quad -\mathcal{C}(x_t) - \mathcal{P}(ABS_t/s_t^c) + T_t,\end{aligned}$$

$$1 + \mathcal{C}_t' + \mathcal{P}_t' \frac{1}{s_t^c} = E_t \, \Lambda_{t,t+1} \, (1 - \Gamma_{t+1})(1 + r_t^a).$$

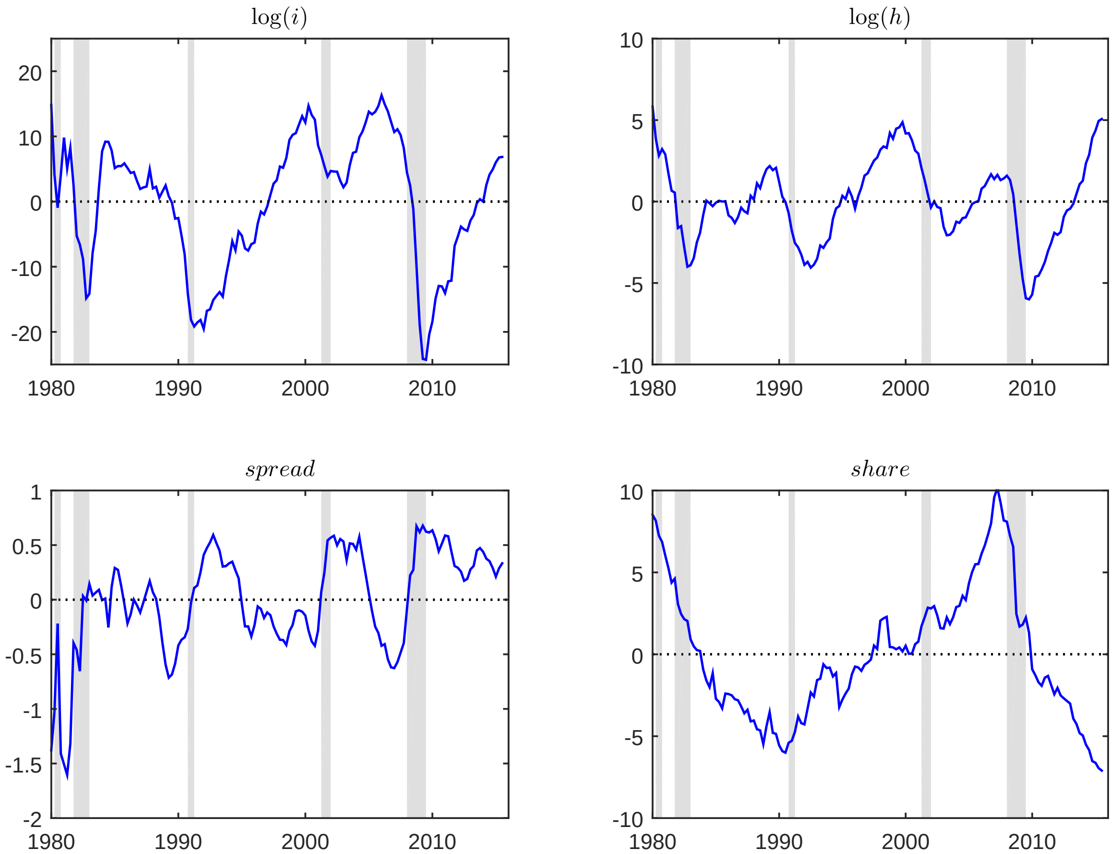
The profit and the expected zero-profit condition of the shadow bank are

$$\begin{aligned}\pi_t^s &= (1 + r_t^k - \delta)s_{t-1}^s - (1 - \Gamma_t)(1 + r_{t-1}^a)ABS_{t-1} - T_t \, , \\ (1 - a) \, E_t \, (1 + r_{t+1}^k - \delta) &= E_t \left[(1 - \Gamma_{t+1})(1 + r_t^a) + \frac{T_{t+1}}{ABS_t}\right].\end{aligned}$$

When the lump sum transfer fully compensates the losses, *i.e.* $T_t = \Gamma_t(1 + r_{t-1}^a)ABS_{t-1}$, the above equations are strictly equivalent to the model presented in section 2 with the shadow wedge shock. Corsetti et al. (2013) use exactly the same risk specification, but related to the sovereign debt market instead of the shadow ABS market.

D Data

Figure 10: Quarterly US Data Used as Observables to Estimate the Model



Notes. Shaded areas correspond to NBER recession dates. *Sources.* See section 3.1.

E Counterfactual `NoShadow` Economy

Table 6: Estimation Results with a Counterfactual `NoShadow` Economy

	`Bench.` 4 observables	`NoShadow` 3 observables
ϕ	0.6904 (0.0526)	0.7956 (0.0295)
γ	0.6962 (0.0567)	NaN (NaN)
ρ_ϵ	0.7648 (0.0345)	0.7494 (0.0376)
ρ_m	0.9968 (0.0036)	0.9979 (0.0000)
ρ_Γ	0.9335 (0.0129)	NaN (NaN)
ρ_e	0.8740 (0.0267)	0.8152 (0.0331)
σ_ϵ	0.0192 (0.0013)	0.0203 (0.0014)
σ_m	0.0167 (0.0011)	0.0173 (0.0011)
σ_Γ	0.0035 (0.0003)	NaN (NaN)
σ_e	0.0019 (0.0001)	0.0018 (0.0001)
$log\mathcal{L}$	1840.1582	1334.6731 4

Notes. Sample period: 1980:I–2015:III. $log\mathcal{L}$ represents the log-likelihood. Standard errors between brackets. The 4 observables in the benchmark specification are $\log(i_t)$, $\log(h_t)$, $share_t$ and $spread_t$. In the counterfactual `NoShadow` economy, $share_t = 0$ and cannot be an observable anymore; and the shadow wedge shock Γ_t is irrelevant.

Table 7: Moments Comparison

	Data	`Bench.` 4 observables	`NoShadow` 3 observables
$\sigma(i)$	0.0981	0.3429	0.5538
$\sigma(c)/\sigma(i)$	0.1957	0.6607	0.8015
$\sigma(h)/\sigma(i)$	0.2586	0.6904	0.8351
$\sigma(share)$	0.0401	0.0231	NaN
$\sigma(spread)$	0.0046	0.0039	0.0032
$corr(i,c)$	0.6681	0.7064	0.8579
$corr(i,h)$	0.7383	0.8133	0.9231
$corr(c,h)$	0.4509	0.9411	0.9674
$corr(share,h)$	0.1165	0.0777	NaN
$corr(spread,h)$	-0.5668	-0.0357	0.0294
$corr(i,spread)$	-0.4410	-0.4352	-0.1993
$corr(c,spread)$	-0.4251	0.0005	0.0064
$corr(share,spread)$	-0.3487	-0.3678	NaN
$\rho(i)$	0.9504	0.9484	0.9735
$\rho(c)$	0.9239	0.9988	0.9996
$\rho(h)$	0.9328	0.9986	0.9994
$\rho(share)$	0.9554	0.9239	NaN
$\rho(spread)$	0.8726	0.9011	0.8160

Notes. Sample period: 1980:I–2015:III. $\sigma(.)$, $corr(.,.)$ and $\rho(.)$ represent standard deviation, correlation and first-order autocorrelation, respectively. i, c, h, $share = s^s/k$ and $spread = r^k - \delta - r^d$ stand for investment, consumption, hours, shadow share and credit spread, respectively. In the counterfactual `NoShadow` economy, $share_t = 0$.