Financial Regulation and Shadow Banking:
A 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 the 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 30\% between 2005 and 2015.

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

JEL Class.: C32, E32.

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1 Introduction

There seems to be 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 following Great Recession; and that financial regulation needs therefore 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. 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 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 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 there are tradable and backed by a pool of loans. As a result, the ABS are less subject to regulation than the 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 Gertler et al. (2016) and Meeks et al. (2016). However, a key difference is the way financial constraints are introduced. As explained, we assume asymmetric regulations whereas they 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 through lower frictions. In our paper, the shadow bank instead 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 for a period for which Basel I mainly operates (a period with regulation on traditional loans without countercyclical buffer).\(^1\) The model also includes habits in leisure so as to reproduce

\(^1\)As shown in Cerutti et al. (2016), more severe macro-prudential policies have only been effectively imple-
the persistence in aggregate variables, so yielding a reasonable fit of the data. The model includes three aggregate disturbances (technology, labor wedge and shadow wedge shocks) as well as a measurement error on the share of the shadow banking sector. Importantly for our macro-prudential policy experiments, we estimate a portfolio adjustment cost parameter for the 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 the paper is to show that shadow banking seriously interferes with macro-prudential policies. First, regulating only the traditional activity (loans to the real economy) of the traditional sector stabilizes less than a similar regulation without shadow banks. Indeed, only a fraction of the financial sector is regulated and moreover, this asymmetric regulation causes a leak towards the shadow sector. Second, regulating the whole activities of the whole banking sector stabilizes more than a 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 and sector-specific shocks, the countercyclical buffer rule of Basel III must react to total credit to the economy rather than a narrower measure represented by credit supplied by the traditional sector. Finally, as a side result from above, we conduct a counterfactual experiment. We show that a full implementation of Basel III (regulation of the whole activities of the whole banking sector, including a countercyclical buffer rule) would have limited the drop of investment during the Great Recession and allowed for a faster recovery in the aftermath.

There are only few dynamic general equilibrium models with shadow banking. We already explained above the modeling approach of 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 the traditional banking and how their model can capture a financial collapse. Verona et al. (2013) propose an opposite 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 markup rule. They show that only the model augmented with shadow banking can predict a substantial boom and bust following a too low for too long monetary policy.
Goodhart et al. (2013) build a 2-period model. As in our model, shadow banks are funded by the traditional banks. They consider the shadow bank 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 time, which may however become illiquid when uncertainty spikes. They show that shadow banking stimulates growth but also creates fragility. The literature on macro-prudential regulation – in DSGE models – is more important. Let us mention a few recent papers. De Walque et al. (2010) and Covas and Fujita (2010) show the procyclicality of time-varying capital requirements as in Basel II. Angeloni and Faia (2013) compute the optimal combination of capital regulation and monetary policy. They conclude that the best combination is a mildly countercyclical 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 time (supply shock), monetary policy is more powerful to stabilize the economy whereas in stress time (financial shock), the benefit of a countercyclical macro-prudential policy becomes 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 looking at macro-prudential regulation effects. Section 5 briefly concludes.

2 Model

We extend the standard Real Business Cycle model by introducing a banking sector composed of traditional banks and shadow banks. The traditional bank finances assets through deposits and regulatory own capital. The shadow bank has no access to deposits, and is therefore not regulated, and finances assets by issuing securities. In this economy, the household owns all the other agents (firm and banks). Table 1 shows the aggregate balance sheet of the different agents in this economy.
Table 1: Aggregate balance sheet of the different agents

<table>
<thead>
<tr>
<th>Firms</th>
<th>Traditional banks</th>
<th>Shadow banks</th>
<th>Households</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$</td>
<td>$s^c$</td>
<td>$s^d$</td>
<td>$ABS$</td>
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</table>

2.1 Firms and Banks

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 $\epsilon_t = \epsilon_{t-1} \exp(\sigma_u u_{\epsilon,t})$ is a random walk process with $\sigma_u > 0$ and $u_{\epsilon,t} \sim i.i.d. N(0,1)$. The firm rents capital at a price $r^k_t$ and pays an hourly wage $w_t$. The profit maximization gives

$$F(1-\alpha)F_t/k_{t-1} = r^k_t,$$
$$\alpha F_t/h_t = w_t,$$

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

The traditional bank holds two types of assets. The first type is an amount $s^c_t$ of firm’s capital and the second type is asset backed securities $ABS_t$ issued by the shadow bank. It finances these assets through deposits $d_t$ and own capital $n_t$. The bank balance sheet is therefore

$$s^c_t + ABS_t = n_t + d_t.$$  

Bank’s own capital $n_t$ should not be lower than a – possibly time varying – fraction $\eta_t$ of assets $s^c_t$. We assume there is no regulation related to the securitized assets $ABS_t$. Formally, we define excess capital $x_t = n_t - \eta_t s^c_t$ 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 $C(.)$ 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

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2The macro-prudential regulation during most of our sample period was based on the Basel I Accord. This set of rules gives a weight of 100% for corporate debt and of only 20% for securitizations with the highest rating (as were supposed most securitizations before the 2008 crisis). To make things simpler, we adopt here an even more dichotomous approach with 100% and 0% weights for $s^c_t$ and $ABS_t$, respectively. Finally, still along the Basel I lines, we impose a fixed capital requirement ratio $\eta_t = \bar{\eta}$. We relax all these historical assumptions in section 4 when looking at the Basel III Accord.
shown by the dashed blue line. More precisely, the cost $C(x_t)$ is such that $C(0) = 0$, $C'(.) < 0$ and $C''(.) > 0$. 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 3.1 how we fix the first and second derivatives of the cost function around the steady state.

We have seen above that the traditional bank holds firm’s capital $s_t^c$ and $ABS_t$ as assets. On the one hand, capital assets are usually illiquid, can’t be sold on their own and must be kept until maturity. On the other hand, the underlying assets of an ABS are illiquid but the ABS themselves are normally liquid and marketable. In other words, the bank cannot easily substitute capital assets with ABS assets. In our model, we simply capture this imperfect substitution between assets with a portfolio adjustment costs $P(ABS_t/s_t^c)$ with $P(ABS/\bar{s}) = 0$, $P'(ABS/\bar{s}) = 0$ and $P''(.) > 0$, where $\bar{z}$ 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.\footnote{This kind of cost related to banking changes (here portfolio changes) is also very common in the micro-banking literature. For instance, in Freixas and Rochet (2013), restructuring the bank bears a positive cost.}

The bank receives a net of depreciation return $r_t^k - \delta$ from firm’s capital holdings 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 other assets (here \(s^c_t\)). The bank also pays a predetermined interest rate \(r^d_{t-1}\) on deposits. The bank’s budget constraint in period \(t\) is

\[
\pi^c_t = d_t + (1 + r^k_t - \delta)s^c_{t-1} + (1 + r^d_{t-1})ABS_{t-1} - s^c_t - ABS_t - (1 + r^d_{t-1})d_{t-1} - C(x_t) - \mathcal{P}(ABS_t/s^c_t),
\]

where \(\pi^c_t\) is the profit (dividend) generated by the bank. Note that, using the balance sheet constraint and the lump-sum definition, we can re-write the budget constraint as

\[
\pi^c_t + \Delta n_t = (r^k_t - \delta)s^c_{t-1} + r^d_{t-1}ABS_{t-1} - r^d_{t-1}d_{t-1} - C(x_t) - \mathcal{P}(ABS_t/s^c_t).
\]

This equation means that the operating surplus (income minus costs) is split in profits distributed to the household and variation \(\Delta n_t\) of own capital. The profit maximization with respect to deposits, capital and ABS implies, respectively

\[
1 + C'_t = E_t \Lambda_{t,t+1} (1 + r^d_t),
\]

\[
1 + (1 - \eta_t)C'_t - \mathcal{P}'(ABS_t/s^c_t) = E_t \Lambda_{t,t+1} (1 + r^k_{t+1} - \delta),
\]

\[
1 + C'_t + \mathcal{P}'(1/s^c_t) = E_t \Lambda_{t,t+1} (1 + r^d_t),
\]

where \(\Lambda_{t,t+1}\) represents the household’s stochastic discount factor between \(t\) and \(t+1\). All these first order conditions equalize the (expected) marginal cost to the (expected) marginal return of issuing deposits or raising loans. To understand these FOCs, we must notice that raising 1 unit of deposits reduces excess capital by 1 unit (when the bank holds constant its other bank balance sheet items). Similarly, raising 1 unit of capital loans (resp. ABS holding) increases excess capital by \(1 - \eta_t\) unit (resp. 1 unit). The linearization of the difference between the first order condition related to ABS and the first order condition related to deposits gives

\[
\frac{\mathcal{P}''}{s^c} \left( \frac{ABS_t}{s^c_t} \right) = \overline{\text{K}} (r^d_t - r^d_t),
\]

where \(\overline{\text{z}}\) stands for the steady state of any variable or function \(z_t\) and \(\hat{z}_t = z_t - \overline{\text{z}}\). This equation shows a very simple relationship between the shadow spread and the shadow assets. It means that, ceteris paribus, an increase in the ABS return stimulates the holding of ABS. The lower is the convexity \(\mathcal{P}''\) of the portfolio adjustment cost, the higher is the transmission. However, there are many disturbances related to the shadow sector and affecting this relationship that
our stylized banking representation does not model. As a shortcut, we capture all these disturbances through a shadow wedge shock which is not directly related to the structure of the economy and the above equation becomes

\[
\frac{\Phi''}{\Phi'} \left( \frac{ABS_t}{s_t^c} \right) + E_t \Gamma_{t+1} = \Lambda (\hat{r}_t - \hat{r}_t^d) .
\] (1)

We assume the disturbance follows the first-order autoregressive process \( \Gamma_t = \rho \Gamma_{t-1} + \sigma \Gamma u_{t,\Gamma} \), with \( |\rho| < 1 \), \( \sigma > 0 \) and \( u_{t,\Gamma} \sim i.i.d. N(0, 1) \). An expected positive shock to this shadow wedge increases the required return on ABS and/or reduces the holding of ABS. This kind of shock is similar to the exogenous risk premium shock which is used for instance in Smets and Wouters (2003) or Smets and Wouters (2007).\(^4\)

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 buy new capital goods \( s_t^c \), which gives \( s_t^c = (1 - a) ABS_t \).\(^5\) In the second period \( t+1 \), it makes the profit \( \pi_{t+1}^s = (1 + r^k_{t+1} - \delta) s_t^c - (1 + r^a_t) ABS_t \) and leaves the market.\(^6\) We assume free entry in \( t \) with expected 0-profit condition \( E_t \pi_t^s = 0 \). Using the first period budget constraint, it gives

\[
(1 - a) E_t (1 + r^k_{t+1} - \delta) = 1 + r^a_t .
\]

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 noting the shadow bank is not regulated. This is in accordance with the Basel I Accord, where only insured depository institutions were regulated.\(^7\)

### 2.2 Households and Aggregate Conditions

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

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

\(^4\)In appendix A, we provide an economic interpretation to this shock.

\(^5\)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 the management of some liabilities requires capital services, labor and excess reserves as inputs to a Cobb-Douglas technology.

\(^6\)We find more appealing to model shadow banking as an overlapping generation structure (limited life time) but we recognize it would be strictly equivalent to consider an infinitely-lived agent representation.

\(^7\)As already mentioned, the Basel I regulation was implemented during most of the sample period we use for estimation. We depart from this historical assumption in section 4.
θ > 0 and we therefore assume that deposits provide utility to the household (liquidity motive). This allows to calibrate $C'(.) < 0$ at the steady state.\footnote{It is easy to show that when $θ = 0$, $r^d = 1/β$ (household’s Euler equation) which implies $C' = 0$ (traditional bank’s first order condition). A strictly positive $θ$ lowers $r^d$ and allows for a negative marginal cost.} We use the same functional form for the sub-utility of deposits and the sub-utility of consumption, as is often the case in 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 $ψ ≥ 0$ captures the curvature in labor disutility and $ϕ$ the habit persistence in leisure. $ϕ < 0$ implies intertemporal substitutability of labor supply whereas $ϕ > 0$ implies intertemporal complementarity. Several papers (Eichenbaum et al., 1988; Wen, 1998; Bouakez and Kano, 2006; Dupaigne et al., 2007; Fève et al., 2013, for instance) show the specification with $ϕ > 0$ is empirically relevant as it translates leisure habits into output persistence. Moreover, labor disutility is subject to a stochastic preference shock $m_t = \bar{m}_t \left(1 - \rho_m \frac{m_t}{m_{t-1}} \exp(σ_m u_{m,t}) \right)$ with $|ρ_m| < 1$, $σ_m > 0$ 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. This shock also allows to capture the 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 $c_t + d_t = w_t h_t + (1 + r^d_{t-1}) d_{t-1} + π_c^t + π_s^t$. Utility maximization with respect to deposits and hours gives, respectively

$$\frac{1}{c_t} = \frac{\theta}{d_t} + β E_t \frac{1 + r^d_t}{c_{t+1}},$$

$$m_t Z_t = α F_t \frac{c_t}{c_t} + βϕ E_t m_{t+1} Z_{t+1},$$

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

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

$$F(k_{t-1}, h_t) = c_t + i_t + C(x_t) + P(ABS_t/s^c_t) + a ABS_t$$
and we define GDP as $y_t = c_t + i_t$. Finally, we also define the shadow banking share, the credit spread and the traditional bank leverage as $share_t = \frac{s^t_t}{k_t}$, $spread_t = r^f_t - \delta - r^d_{t-1}$ and $leverage_t = (s^t_t + ABS_t)/n_t$, respectively.

### 3 Data and Estimation

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

#### 3.1 Data

After normalizing trending variables by the stochastic trend component in labor factor productivity, we log-linearized the resulting system in the neighborhood of the non-stochastic steady state. Let $\Theta$ denote the vector of model’s 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

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

where $\zeta_t \sim i.i.d.N(0, \Sigma)$ is a vector of innovations to the three structural shocks, and the system matrices $F(\Theta)$ and $G(\Theta)$ are functions of the model’s parameters. We use as observable variables in estimation the logs of investment and hours worked, the share of shadow banking and the spread (investment, hours, share and spread are $i_t$, $h_t$, $share_t = \frac{s^t_t}{k_t}$ and $spread_t = r^f_t - \delta - r^d_{t-1}$ in the model’s notations, respectively). We take the first difference in the log of investment and the share. The measurement equation is

$$\begin{pmatrix}
\Delta \log(i_t) \\
\log(h_t) \\
\Delta share_t \\
spread_t
\end{pmatrix} = C\hat{x}_t + D\epsilon_t,$$

where $C$ and $D$ are selection matrices and $\epsilon_t$ is a vector of measurement errors that we discuss in more details below. For a given $\Theta$ 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. Notice that all variable are demeaned prior to estimation.

We use for estimation quarterly frequency data and the sample runs between 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). 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 the 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). Figure 9 in appendix B displays the data used for estimation.

Equation (3) contains a measurement error shock $e_t$. Imposing constraints on the selection matrix $D$, this measurement error is introduced in front of the share of shadow banking only, thus capturing the distance between the model and the data (see for instance Altug, 1989; Sargent, 1989; Ireland, 2004). We acknowledge that, while containing powerful ingredients to account for salient features of US data, the DSGE model can be considered as being too stylized to be taken directly to the data (especially the specification of the two banking sectors), yielding potentially biased estimates of the model’s parameters. Augmenting the model with serially correlated errors then allow us to properly conduct estimation and statistical inference. We assume that this shock follows an AR(1) process

$$e_t = \rho_e e_{t-1} + \sigma_e u_{e,t},$$

with $|\rho_e| < 1$, $\sigma_e > 0$ and $u_{e,t} \sim i.i.d. N(0,1)$. The innovation $u_{e,t}$ is also uncorrelated with the other structural innovations of the model. So the evaluation of the log-likelihood is obtained from equations (2), (3) and (4).

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9See the website http://ecomweb.ucsd.edu/~ramey/research.html#data for regularly updated data.
10Meeks et al. (2016) use the same definition of shadow vs. traditional banking.
3.2 Estimation Results

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

\[
C(x_t) = -p_1 \ln (1 + p_2 x_t),
\]

\[
\mathcal{P}\left(\frac{\text{ABS}_t}{s^*_t}\right) = \frac{\gamma}{2} \left(\frac{\text{ABS}_t}{s^*_t} - \frac{\text{ABS}}{s^*}\right)^2,
\]

with \( p_1, p_2, \gamma > 0 \). Note that the capital cost specification implies \( C'(0) = -p_1 \ p_2 < 0 \) and \( C''(0) = -C'(0) \ p_2 > 0 \). Finally, at this stage, we assume that \( \eta_t = \bar{\eta} \), according to the Basel I regulation. We relax this assumption in section 4 where we investigate the Basel III counter-cyclical requirements.

We split the parameters into vectors \( \Theta_1, \Theta_2 \) and \( \Theta_3 \). The vector \( \Theta_1 = (\alpha, \delta, \bar{m}, \theta, \bar{\eta}, \beta, C'(0), a) \) includes parameters that we calibrate to match specific steady state values. The vector \( \Theta_2 = (\psi, C''(0)) \) includes parameters difficult to estimate within our framework and that we calibrate prior to the estimation. The vector \( \Theta_3 = (\phi, \gamma, \rho_r, \rho_m, \rho_e, \sigma_r, \sigma_m, \sigma_e) \) includes the remaining parameters that we estimate.

Regarding the parameters in \( \Theta_1 \), we set \( \alpha = 2/3 \) and \( \delta = 2.5\% \). These values are standard and allow to reproduce the labor share and the investment to output ratio. We calibrate \( \bar{m} \) to obtain the standard value of \( \bar{h} = 0.2 \), \( \theta \) 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 \( \text{leverage}_t = (s^*_t + \text{ABS}_t)/n_t \) 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 the traditional and the shadow banking) over total liabilities minus total deposits (in the traditional banking). We obtain a more stable leverage ratio 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).\(^{11}\) Finally, we calibrate \( \beta, C'(0) \) and \( a \) in order to reproduce 3 specific steady states, namely \( \bar{x} = 0 \) (zero excess capital), \( r^d = 0 \) (zero return on deposits) and \( \bar{\text{spread}} = 0.0065 \). This latter value represents the average spread between AAA bond return and Fed Funds between 1980 and 2015.\(^{12}\) All the calibrated parameters in \( \Theta_1 \) are

\(^{11}\)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 \( 1/(1 - 0.3) \times 4.5 = 6.4 \).

\(^{12}\)More precisely, we obtain from the banks’ first order conditions: \( \beta = \bar{\eta}/(\bar{\text{spread}} + \bar{\eta}(1 + r^d)) \), \( a = \text{spread}/(1 + \ldots) \).
reported in the top panel of table 2.13

Table 2: Calibrated Parameter Values (Quarterly when Applicable)

<table>
<thead>
<tr>
<th>Notation</th>
<th>Value</th>
<th>Description</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameters in $\Theta_1$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>$2/3$</td>
<td>labor share</td>
<td>labor share: $(\bar{w}/\bar{h})/\bar{F} = 2/3$</td>
</tr>
<tr>
<td>$\delta$</td>
<td>$0.025$</td>
<td>capital depreciation rate</td>
<td>investment to GDP ratio: $i/\bar{y} = 0.27$</td>
</tr>
<tr>
<td>$\eta$</td>
<td>$21.63$</td>
<td>weight on hours in (dis-)utility</td>
<td>hours: $\bar{h} = 0.2$</td>
</tr>
<tr>
<td>$\bar{\eta}$</td>
<td>$0.2828$</td>
<td>weight on deposits in utility</td>
<td>shadow share: $share = 0.3$</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$0.9765$</td>
<td>capital requirements</td>
<td>traditional bank leverage: leverage = 5.3</td>
</tr>
<tr>
<td>$C'(0)$</td>
<td>$-0.0235$</td>
<td>marginal excess capital cost</td>
<td>excess capital: $\bar{x} = 0$</td>
</tr>
<tr>
<td>$a$</td>
<td>$0.0065$</td>
<td>ABS issuing cost</td>
<td>credit spread: spread = 0.0065</td>
</tr>
<tr>
<td>Parameters in $\Theta_2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\psi$</td>
<td>$2$</td>
<td>hours curvature in (dis-)utility</td>
<td>Frisch: $1/((1-\phi)(1+\psi)-1) = 0.5$ when $\phi = 0$</td>
</tr>
<tr>
<td>$C''(0)$</td>
<td>$0.0094$</td>
<td>convexity of excess capital cost</td>
<td>spread to capital req. elasticity: $-\epsilon_s = 0.0125$</td>
</tr>
</tbody>
</table>

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

Regarding the parameters in $\Theta_2$, we set $\psi = 2$ in accordance with previous studies (for instance, Smets and Wouters, 2007, estimate this parameter at 1.92).14 To calibrate $C''(0)$, it may first be interesting to re-write some equations. Assuming that $\gamma = \phi = 0$ (these parameters belong to the vector $\Theta_3$ and will be estimated later) and simplifying $\Lambda_{t,t+1} \equiv \beta$, we obtain from the traditional bank first order conditions $-\bar{\eta} C'_t = \beta spread_{t+1}$. A first order Taylor expansion around the steady state gives

$$-\bar{\eta} C''(0) \hat{x}_t = \beta spread_{t+1},$$

where a variable with a hat denotes its absolute deviation from its steady state. Over the last years, several papers estimated the effects of bank capital requirements on the lending spread. The range for the estimations is wide. For instance, Hanson et al. (2011) estimate on US data that 1 percentage point increase in the capital requirements increases the lending spread by 2.5 to 4.5 basis points per year. Still with US data, Baker and Wurgler (2015) report that 1 ppt increase in the ratio of capital to risk weighted assets pushes up spreads by 6 to 9 bps.15 Based

\[ \bar{r} + spread \) and $C'(0) = -spread / (spread + \bar{\eta}(1 + r^d)).$\]

The calibration implies that at the steady state, the total ABS issuing costs represent about 2% of the gross output $F(\ldots)$. 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 the gross output.

14The Frisch elasticity of labor supply is $1/((1-\phi)(1+\psi)-1)$. The estimation of Smets and Wouters (2007), in a model with $\phi = 0$, therefore implies an elasticity of 0.5. Since we estimate $\phi$ later and that this estimation may significantly differ from zero, our implied elasticity will no longer be necessarily equal to 0.5.

15However, other reports under the auspices of the BIS or the OECD, looking at a larger set of countries, provide higher estimations up to 15 bps.
on these US studies, we assume in our calibration that 1 ppt increase in the required capital ratio (or equivalently a fall by 1 ppt in the excess capital ratio) raises the spread by 5 bps per year, that is \( \varepsilon_s = \frac{\text{spread}_{t+1}/(\hat{s}_t/\bar{s})}{(0.0005/4)/(0.01)} = -0.0125 \). As a result, we obtain \( C''(0) = -\beta \varepsilon_s/(\bar{s}\bar{\eta}) > 0 \). Since the calibration of the parameters in \( \Theta_2 \) are not neutral to the \( \Theta_3 \) parameter values (we have supposed at this stage that \( \phi = \gamma = 0 \) but we estimate them hereafter), we conduct robustness analysis with respect to the \( \Theta_2 \) parameters in the next section.\(^{16}\) Note that \( C'(0) \) and \( C''(0) \) immediately determine the parameters of the cost function with \( p_2 = -C''(0)/C'(0) > 0 \) and \( p_1 = (C'(0))^2/C''(0) > 0 \). All the calibrated parameters in \( \Theta_2 \) are reported in the bottom panel of table 2.

The remaining parameters contained in \( \Theta_3 \) are then estimated. The vector \( \Theta_3 \) includes two structural parameters, the habit parameter \( \phi \) on leisure and the portfolio adjustment cost parameter \( \gamma \). The other parameters concern the process of the shock as well as the measurement error. We conduct a two-step estimation strategy in order to correctly estimate the autoregressive parameter \( \rho_m \) of the labor wedge shock. Indeed, this parameter reaches its upper boundary of unit root when the model is estimated with the four observables.

In the first-step procedure, we then use only the (log of) hours worked as observable and estimate only the preference parameter \( \phi \) together with the process of the labor wedge shock \( m_t \) (see table 7 in appendix C for the estimation results in the first step). In the second-step, we use the four observables but we take the results of the first-step to fix the autoregressive parameter \( \rho_m \). The estimation results are reported in table 3 and we consider three specifications. In specification (1), the habit parameter is freely estimated (together with the portfolio adjustment cost parameter) and we set \( \rho_m = 0.9776 \) (value obtained from alternative (2) in table 7). Specification (2) considers a model’s version without habit but keeping \( \rho_m = 0.9776 \). Specification (3) still considers a model without habit and therefore accounts for a larger degree of serial correlation in hours worked, as found in the data (value \( \rho_m = 0.9912 \) obtained from alternative (1) in table 7).

Estimation results clearly reveal that specification (1) in table 3 yields the best fit of the four observables (see the log-likelihood associated to each specification). Thus, omitting the habit persistence in leisure deeply reduces the ability of the model to reproduce salient features of the data. This is confirmed by table 8 in appendix D that includes moments documenting the volatility, persistence, and co-movement of key variables. The two model versions

\(^{16}\)We have also tried to directly estimate the parameter \( C''(0) \). We find a value of 0.0070, i.e. a value close to our calibration, but this estimation is not precise (standard error of 0.014).
Table 3: Estimation Results – Step 2 with 4 Observables

<table>
<thead>
<tr>
<th>Specification (1) $\rho_m = 0.9776$</th>
<th>Specification (2) $\rho_m = 0.9776, \phi = 0$</th>
<th>Specification (3) $\rho_m = 0.9912, \phi = 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi$</td>
<td>0.4798</td>
<td>NaN</td>
</tr>
<tr>
<td></td>
<td>(0.0370)</td>
<td>(NaN)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>10.6476</td>
<td>11.1304</td>
</tr>
<tr>
<td></td>
<td>(6.5581)</td>
<td>(7.1230)</td>
</tr>
<tr>
<td>$\rho_T$</td>
<td>0.7514</td>
<td>0.7704</td>
</tr>
<tr>
<td></td>
<td>(0.0291)</td>
<td>(0.0284)</td>
</tr>
<tr>
<td>$\rho_e$</td>
<td>0.3185</td>
<td>0.3175</td>
</tr>
<tr>
<td></td>
<td>(0.0794)</td>
<td>(0.0794)</td>
</tr>
<tr>
<td>$\sigma_e$</td>
<td>0.0210</td>
<td>0.0236</td>
</tr>
<tr>
<td></td>
<td>(0.0013)</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>$\sigma_m$</td>
<td>0.0787</td>
<td>0.0925</td>
</tr>
<tr>
<td></td>
<td>(0.0047)</td>
<td>(0.0055)</td>
</tr>
<tr>
<td>$\sigma_T$</td>
<td>0.0091</td>
<td>0.0088</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>$\sigma_e$</td>
<td>0.0076</td>
<td>0.0076</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>$\log L$</td>
<td>1918.2944</td>
<td>1879.4698</td>
</tr>
</tbody>
</table>

Notes. Sample period: 1980:I–2015:III. $\log L$ represents the log-likelihood. Standard errors between brackets. The observables are $\Delta \log (i_t)\log (h_t)$, $\Delta share$, and $spread_t$, where $\Delta$ is the first difference operator.

perform equally well in terms of fitting standard errors and co-movements of key aggregate variables. But when it turns to the persistence properties, habit persistence is essential to reproduce the autocorrelation of order one of the growth rate of investment, consumption and hours worked.\(^{17}\) For example, with US data we obtain for hours worked a parameter equal to 0.4653, to be compared to 0.5381 with habit and to $-0.0155$ without habit. Notice that this persistence in hours is then translated into persistence in output growth. Another important parameter is the one associated to portfolio adjustment cost. The parameter is not very precisely estimated (significant at 10% level) and estimation is weakly affected by the specification of hours (with or without habit and persistence of the labor wedge shock). We nevertheless show in section 3.3 that this estimated value is robust and that the shadow share as observable is crucial to identify it.

From the estimation results of our preferred specification, we can compute the contribution of the four shocks to the main aggregates (see table 4). Let us first consider output, consumption and investment. It appears that the technology and the labor wedge shocks are the main drivers of these variables. However, the shadow wedge shock appears to have non-negligible effects on consumption and investment (around 10%). The variance of hours appears almost totally

\(^{17}\)The lack of persistence property of the standard RBC model has been exemplified by Cogley and Nason (1995).
explained by the labor wedge shock. This means that our two-step procedure, from which the persistence of the labor supply shock is calibrated prior to the estimation in a second step, does not bias our estimates. Regarding the spread, we obtain that 97% of its variance is due to the shadow wedge shock. This is a consequence of our specification because this shock appears as a wedge between ABS and deposit returns in the problem of traditional bank, which indirectly affects the capital return $r_k$. The change in leverage is mainly explained by the labor wedge shock (around 60%), but both technology and shadow wedge shocks have a non-negligible effects. Finally, the change in the share of shadow banking is almost totally explained by the measurement error shock (98%), with a small contribution of the shadow wedge shock (2%). This results may appear unsatisfactory as the DSGE model does not provide any structural explanation to the relative change of the banking sectors. So, one may wonder why we do not exclude the change in shadow share from our estimation. The reason is that this variable matters a lot for the identification and estimation of the the portfolio adjustment cost parameter.

Table 4: Variance Decomposition under Specification (1)

<table>
<thead>
<tr>
<th></th>
<th>$\epsilon_t$</th>
<th>$m_t$</th>
<th>$\Gamma_t$</th>
<th>$\epsilon_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta gdp$</td>
<td>48.54</td>
<td>51.08</td>
<td>0.38</td>
<td>0.00</td>
</tr>
<tr>
<td>$\Delta i$</td>
<td>41.34</td>
<td>48.81</td>
<td>9.85</td>
<td>0.00</td>
</tr>
<tr>
<td>$\Delta c$</td>
<td>37.36</td>
<td>51.64</td>
<td>11.00</td>
<td>0.00</td>
</tr>
<tr>
<td>$\Delta h$</td>
<td>1.53</td>
<td>97.98</td>
<td>0.49</td>
<td>0.00</td>
</tr>
<tr>
<td>$\Delta share$</td>
<td>0.00</td>
<td>0.00</td>
<td>1.86</td>
<td>98.14</td>
</tr>
<tr>
<td>spread</td>
<td>0.58</td>
<td>2.02</td>
<td>97.40</td>
<td>0.00</td>
</tr>
<tr>
<td>$\Delta n$</td>
<td>30.40</td>
<td>59.17</td>
<td>10.42</td>
<td>0.00</td>
</tr>
<tr>
<td>$\Delta leverage$</td>
<td>34.66</td>
<td>54.09</td>
<td>11.24</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Notes. Sample period: 1980:I–2015:III. $\Delta$ is the first difference operator. $\epsilon_t$ is the productivity shock, $m_t$ is the labor wedge shock, $\Gamma_t$ is the shadow wedge shock and $\epsilon_t$ is the measurement error shock. $n$ is bank capital.

3.3 Shadow Share and Portfolio Cost

To illustrate the important role of the shadow share for $\gamma$, we conduct two types of experiments. In a first experiment, we re-estimate the model with three observables (investment, hours and spread) and three shocks (the measurement error shock is set to zero). With three observed variables, we obtain an estimate for $\gamma$ close to zero (0.0606). But this value with only three observables is not supported by the data if we consider a four variable system. To show this, we fix a grid of values between 0 and 20 for $\gamma$ and we re-estimate the model with four observables for each particular value of $\gamma$ on this grid. From the log-likelihood of each estimation, we compute the likelihood ratio statistics and the probability of not rejecting the null hypothesis.
(\(\gamma\) constrained). The results are reported in figure 2. We obtain that the estimated value (0.0606) obtained from a system that excludes the shadow share is far from the one of the benchmark and this value is strongly rejected by the data.

Figure 2: Estimation Results when \(\gamma\) is Constrained: Probability of not Rejecting the Restricted Model (H0)

![Figure 2](image)

Notes. Sample period: 1980:I–2015:III. The null hypothesis H0 corresponds to the restricted model with \(\gamma\) calibrated whereas the non-null hypothesis H1 corresponds to the non-restricted model with \(\gamma\) estimated. The likelihood ratio statistic is \(LR = 2(\log L(H1) - \log L(H0))\). We assume that under the null, the LR statistic is distributed as a chi-squared with 1 degree of freedom.

In a second experiment, we fix values for \(\sigma_e\), such that the variance of shadow share is less and less explained by the measurement error shock (and thus more and more by the shadow wedge shock, because the contribution of the technology and the labor wedge shocks remains insignificant). Figure 3 reports the results. The left panel shows the estimated values of the portfolio adjustment cost parameter \(\gamma\) when \(\sigma_e\) varies such that the measurement error shock explains between 30% and almost 100% of the variance of the change in shadow share. The central panel reports the same exercise for the habit persistence parameter \(\phi\). For these two figures, we also include the 95% confidence interval. Finally, in the right panel, we report the log-likelihood function. Fixing value for \(\sigma_e\) dramatically deteriorate the fit of the model (see the log-likelihood). However, changing the contribution of the measurement error shock to the shadow share has a little effect on the point estimates of \(\gamma\) and \(\phi\). Moreover, we obtain more precise estimates for the portfolio adjustment cost parameter when the size measurement error decreases. The shadow share as observable is therefore crucial to properly identify \(\gamma\).
Notes. Sample period: 1980:I–2015:III. Var(\cdot) represents the variance and Δ is the first difference operator.

3.4 Robustness Analysis

We check the robustness of our estimation results to alternative data and sample periods.\textsuperscript{18} These robustness checks are detailed as follows:

**Bench.** We reproduce our benchmark specification, that is specification (1) in tables 3 and 8. It also corresponds to the variance decomposition shown in table 4.

**Check (1).** We use a larger measure of traditional credit (see section 3.1 for details), \textit{i.e.} a narrower measure for the variable \textit{share}_t.

**Check (2).** We use a different definition for the variable \textit{spread}_t (BAA minus Fed Funds instead of AAA minus Fed Funds, see section 3.1 for details).

**Check (3).** The size of the shadow banking was low but very volatile at the beginning of our sample (between 1980 and 1984). We therefore start the sample in 1985:I to remove this initial volatility.

**Check (4).** Similarly, the financial crisis has severely downsized the shadow banking sector. We therefore end the sample in 2007:IV, at the very beginning of the financial crisis, to remove this end of sample volatility.

Table 5 contains this robustness analysis. As it is clear from the table, the estimated values for \phi are unaffected by these perturbations. The estimations for the parameter \gamma displays more sensitivity (except for the new definition of the shadow share), especially when we modify the sample period. Notice that when we use another definition of the spread variable (see check 2),

\textsuperscript{18}Additional robustness exercises related to real rigidities, elasticity of the spread to excess capital and elasticity of labor supply are reported in appendix E.
we obtain a more precise estimate for $\gamma$. For all these experiments, we obtain that the variance of consumption and investment explained by the shadow wedge shock is roughly the same (around 10%).

### Table 5: Robustness Checks – Selected Estimation and Simulation Results

<table>
<thead>
<tr>
<th></th>
<th>Bench.</th>
<th>Check (1) $\Delta$share</th>
<th>Check (2) spread</th>
<th>Check (3) 1985:1–2015:III</th>
<th>Check (4) 1980:1–2007:IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td></td>
<td>(NaN)</td>
<td>(NaN)</td>
<td>(NaN)</td>
<td>(NaN)</td>
<td>(NaN)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td></td>
<td>(NaN)</td>
<td>(NaN)</td>
<td>(NaN)</td>
<td>(NaN)</td>
<td>(NaN)</td>
</tr>
<tr>
<td>$\phi$</td>
<td>0.4798</td>
<td>0.4798</td>
<td>0.4841</td>
<td>0.4583</td>
<td>0.4507</td>
</tr>
<tr>
<td></td>
<td>(0.0370)</td>
<td>(0.0370)</td>
<td>(0.0361)</td>
<td>(0.0436)</td>
<td>(0.0453)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>10.6476</td>
<td>10.5947</td>
<td>7.1806</td>
<td>2.0440</td>
<td>23.0683</td>
</tr>
<tr>
<td></td>
<td>(6.5577)</td>
<td>(6.1425)</td>
<td>(2.8780)</td>
<td>(0.4835)</td>
<td>(29.4496)</td>
</tr>
<tr>
<td>$\log L$</td>
<td>1918.2944</td>
<td>1925.3313</td>
<td>1917.3391</td>
<td>1720.1800</td>
<td>1506.5447</td>
</tr>
</tbody>
</table>

Notes. Sample period: 1980:1–2015:III unless mentioned. Standard errors between brackets. $\log L$ represents the log-likelihood. $\Gamma_t \sim \text{Var}(\Delta i)$ gives the variance share of the variable $\Delta i$ explained by the shadow wedge shock $\Gamma_t$ and $\Gamma_t \sim \text{Var}(\Delta c)$ gives the variance share of the variable $\Delta c$ explained by the shadow wedge shock $\Gamma_t$, where $\Delta$ is the first difference operator.

### 4 Macro-prudential Policies

The macro-prudential regulation during most of our estimation period was based on the 1988 Basel I Accord. 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. Basel II is therefore a transitory period between Basel I (used when we estimate the model on historical data) and Basel III (used for the policy simulations) which we do not look at. Shortly and among others, the Basel III regulation introduces a countercyclical capital buffer and extends the regulation beyond the traditional loans. In this section, we then study how the move from a Basel I to a 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 $\eta_t$ and then we make this change in capital requirement endogenous (countercyclical capital buffer). Second, we extend the regulation from the traditional loans only to the whole assets of the traditional banks and/or of the shadow banks.
4.1 Regulation Shock

To understand how the economy functions, we first assume a simple AR(1) stochastic regulation shock \( \eta_t = \bar{\eta}^{1-\rho_\eta} \cdot \eta_{t-1}^{\rho_\eta} \cdot \exp(\sigma_\eta \cdot u_{\eta,t}) \) where \( |\rho_\eta| < 1, \sigma_\eta > 0, u_{\eta,t} \sim i.i.d. N(0,1) \). We calibrate the persistence \( \rho_\eta = 0.90 \) as in Angelini et al. (2014) and we set \( \sigma_\eta \) to obtain an initial increase in \( \eta_t \) of 1.25 percentage points. The figure 4 displays the impulse response functions.

Before looking at the transmission in our benchmark economy, we start with a counterfactual simulation without shadow banking (dashed line). A higher regulation, in order 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 and in fine output. There are two main differences when a shadow sector exists (solid line). First, the regulation only relates to a fraction of the traditional bank assets and the regulation 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 non regulated ABS assets which results in a higher shadow share. Regulation therefore requires a lower spread increase and the fall in total credit and output is less pronounced. It is worth noting that in the benchmark economy, a 1.25 ppt increase in capital requirements increases the yearly spread by 10 bps. The simulated elasticity is therefore in line with empirical studies, which supports our calibration of \( C''(0) \) (see section 3.2).

4.2 Basel III and the Countercyclical Buffer

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

\[ \eta_t = \bar{\eta}^{1-\rho_\eta} \cdot \eta_{t-1}^{\rho_\eta} \cdot \left( \frac{v_t}{\bar{v}} \right)^{\kappa(1-\rho_\eta)} \]

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
\[ v_t = \frac{(s^c_t - (1 - \delta)s^c_{t-1})}{y_t} = \Delta s^c_t / y_t \]

A maximum 2.5 percentage points increase as stated in Basel III means in our model that \( \eta_t \in (\bar{\eta} - 0.0125, \bar{\eta} + 0.0125) \) during the business cycles. We assume, obviously in a simplified way, that business cycles are solely driven by productivity shocks. We used the standard deviation \( \sigma_e \) for this shock obtained from the estimation (see table 3) and we calibrate \( \kappa_\eta \) to match a maximum deviation for \( \eta_t \) of 0.0125. This gives \( \kappa_\eta = 2.65 \) for the two policies (P1 and P2). To better grasp the implications of this calibration, we may notice that

\[ \frac{\partial \eta_t}{\partial v_t} \bigg|_{v_{t-1}=\bar{\eta}} = \bar{\eta} \kappa_\eta (1 - \rho_\eta). \]

Applying our calibration to this equation means that an unexpected increase of 1% in credit (broad or narrow) initially raises the requirement ratio by 0.07 percentage point. Note that the Basel I policy correspond to the limit case with \( \kappa_\eta = 0 \).

Figure 5 displays the effects of a 1% productivity shock under a Basel I vs. Basel III regulation. We here use the P1 rule on the broad credit but the P2 rule on narrow credit delivers similar results. As before, we start with a counterfactual simulation without shadow banking (dashed-dotted blue line for Basel I and dotted black line for Basel III). We observe that a productivity shock obviously stimulates the whole economy. From a banking point of view, the higher level of credit requires a higher level of net worth which reduces excess capital. Under Basel III, the requirement ratio moreover increases and this reduces even further the excess capital. The induced extra cost forces the traditional bank to raise more the lending spread and the economic expansion is less important. This underlines the countercyclical effect of Basel III. When a shadow sector exists (dashed red line for Basel I and solid green line for Basel III), the traditional bank has an incentive to substitute regulated credit with non regulated ABS. This is especially true under the Basel III regulation since the difference in regulation between \( s^c_t \) and \( ABS_t \) increases. This substitution helps to relax the excess capital problem and the economy moves faster – than in the case without a shadow sector. As a conclusion, the countercyclical dimension of Basel III is less operative when a shadow sector exists.

Figure 5 displays the effects of a 1% shadow wedge shock under a Basel I vs. Basel III regulation. To calibrate the persistence of the shock, we use the value obtained from the estimation (see table 3). As explained before, the shadow wedge shocks corresponds to a mistrust to the

\[^{19}\] Assuming instead that business cycles are driven by the labor wedge shock would result in \( \kappa_\eta = 1.45 \). Alternatively, assuming that business cycles are driven by the shadow wedge shock would result in \( \kappa_\eta = 10.3 \). In any case, a different value for \( \kappa_\eta \) would not modify the summary elasticities we show in table 6.
shadow bank, which leads the traditional bank to substitutes the ABS asset with traditional credit. This portfolio reallocation is costly and the traditional bank increases its lending spread and draws on its net worth. It increases the leverage and reduces excess capital. Globally, total credit and GDP fall. When the regulator abandons Basel I and instead follows a total credit countercyclical policy rule (P1-type), she softens the capital requirements (solid blue line). The fall in excess capital is therefore less important which benefits in the end to the economy. When the regulator follows a narrow credit countercyclical policy rule (P2-type), she is initially mislead by the initial substitution effect and she strengthens the requirements (dashed dotted black line). The net worth is higher than with the P1 rule but at the cost of a lower excess capital. In fine, the fall in output is initially more important, although the policy is supposed to be countercyclical. As a conclusion, it is important to monitor the traditional credit but also the shadow credit when following a Basel III-type rule.

4.3 Basel III and the Regulation of Other Assets and Banks

Basel III is not limited solely to the discretionary capital buffer studied above but also refines the risk-weight applicable to the different classes of assets. In particular, the weight applicable to ABS goes from a 20% floor up 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 leave the steady state unchanged, we suppose that $\bar{\eta}_a = 0$. The linearized spread shown in equation (1) becomes

$$-C'(0) \eta_t^a + \frac{P''}{s_c} \left( \frac{ABS_t}{s_t^c} \right) + E_t \Gamma_{t+1} = \Lambda \left( \hat{r}_a^t - \hat{r}_d^t \right).$$

Since $C'(0) < 0$, this equation shows that an increase in the ABS regulation forces the traditional bank to ask for a higher ABS return and/or to reduce ABS holdings. Moreover, Basel III also implies that systemically important financial institutions that are not traditional banks might also be subject to regulation (on a case by case basis). Again, we modify our benchmark model in order to also regulate the shadow sector. To do so, we assume an infinitely lived shadow bank with the balance sheet and the profit as, respectively

$$s_t^s = (1 - a) ABS_t + n_t^s = (1 - a) ABS_t + \eta_t^s s_t^s + x_t^s,$$

$$\pi_t^s = (1 - a) ABS_t - s_t^s + (1 + r_t^k - \delta) s_{t-1}^s - (1 + r_{t-1}^d) ABS_{t-1} - C^s(x_t^s).$$

\(^{20}\)To keep this paper concise, we do not present the effects of a countercyclical policy under a labor wedge shock. The conclusions would be similar to ones obtained with an aggregate supply shock.
We define $\text{spread}_t = r_t^k - \delta - r_{t-1}^d$. The first order conditions with respect to $ABS_t$ and $s_t^s$ are, respectively

$$
(1 - a)(1 + C_t^{st}) = E_t \Lambda_{t,t+1} (1 + r_t^d),
$$
$$
1 + (1 - \eta_t^s)C_t^{st} = E_t \Lambda_{t,t+1} (1 + r_{t+1}^k - \delta).
$$

The functional form for $C^s(x_t^s)$ is similar to the one for $C(x_t)$ and we also assume that $\bar{x}^s = 0$. To leave the steady state unchanged, we suppose that $\bar{\eta}^s = 0$ and we calibrate $C^{st}(0)$ accordingly. Finally, we impose $C^{stt}(0) = C''(0)$.

The figure 7 displays the impulse response functions of an AR(1) stochastic shock on $\eta_t$ (benchmark economy, dashed red line), on $\eta_t$ plus $\eta_t^a$ (regulation also on ABS, solid blue line), and on $\eta_t$ plus $\eta_t^s$ and $\eta_t^a$ (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 $\eta_t$ only is well known and already explained in figure 4. 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 incentive anymore to substitute $s_t^c$ with $ABS_t$. As a result, the fall in excess capital is higher and the bank increases further the lending spread. The economic slowdown is in fine more pronounced. The third case leads to substantial changes. The shadow bank must also use own capital to provide credit. It is worth noting that the bank cannot completely substitute ABS with own capital as source of liabilities to finance credit, because of the portfolio adjustment cost of the traditional bank. As a result, shadow credit increases – at least initially – which reduces further traditional credit. The fact that the shadow bank has negative excess capital means that she also has to raise the credit spread. In the end, the third case is the one where regulation is the more powerful to slow down the economy.

4.4 Numerical Summary

Table 6 summarizes the above results. The first line shows that, in an economy without shadow sector, a 1 percentage point increase in the capital requirement ratio reduces output by 0.11% and investment by 0.32%. It is worth noting that in this economy, there only exist traditional banks – and loans – and therefore all banks – and assets – are regulated ($s_t^c = k_t$). The next three lines conduct similar exercises but with a shadow sector. When the traditional bank only is regulated (either on a fraction or on all assets), the regulation effect is less important than in the no shadow case, because of a leak to shadow banking. This is no longer true when both
Figure 4: 1.25 Percentage Points Initial Increase in the Capital Requirement Ratio $\eta_t$

Notes. Deviations are expressed in percentage points for variables $s_t^c/k_t$, $\text{spread}_t$, $\eta_t$ and $x_t/\bar{k}$. Deviations are expressed in percent for all the other variables. $\text{spread}_t$ is in annual term.
Figure 5: 1% Initial Increase in the Productivity $\epsilon_t$ and Basel Policies

Notes. The Basel I policy corresponds to $\eta_t = \bar{\eta}$. The Basel III policy corresponds to the P1 rule on $i_t$. The P2 rule on $\Delta s^c_t$ gives similar results. Deviations are expressed in percentage points for variables $s^c_t/k_t$, $\text{spread}_t$, $\eta_t$, and $x_t/k$. Deviations are expressed in percent for all the other variables. $\text{spread}_t$ is in annual term.
Figure 6: 1% Initial Increase in the Shadow Wedge Shock $\Gamma_t$ and Basel Policies

Notes. The Basel I policy corresponds to $\eta_t = \bar{\eta}$. Deviations are expressed in percentage points for variables $s_t^c/k_t$, $\text{spread}_t$, $\eta_t$ and $s_t^c/k_t$. Deviations are expressed in percent for all the other variables. $\text{spread}_t$ is in annual term.
Figure 7: 1.25 Percentage Points Initial Increase in the Capital Requirement Ratio(s) \( \eta_t - \eta^a_t - \eta^s_t \)

**Notes.** Deviations are expressed in percentage points for variables \( s_t^c/k_t \), \( \text{spread}_t \), \( \eta_t \), \( x_t^e/k_t \), \( x_t^s/k_t \), \( n_t^e/k_t \) and \( \text{spread}_t^e \). Deviations are expressed in percent for all the other variables. \( \text{spread}_t \) and \( \text{spread}_t^e \) are in annual term. \( \Delta \eta_t \) is our benchmark economy with regulation only on \( s_t^c \); \( \Delta \eta_t + \Delta \eta^a_t \) is an extension along the lines of Basel III with regulation on \( s_t^c \) and \( \text{ABS}_t \); \( \Delta \eta_t + \Delta \eta^a_t + \Delta \eta^s_t \) is a larger extension along the lines of Basel III with regulation on \( s_t^c \), \( \text{ABS}_t \) and \( s_t^s \).
the traditional banks (either on a fraction or on all assets) and the shadow banks are regulated. In this case, regulation is more powerful than in an economy without shadow. The last three lines suggest that the countercyclical buffer policy (when applied to traditional loans only) is more powerful when the economy is hit by an aggregate productivity shock than by a specific shadow wedge shock. Finally, in case of shadow wedge shocks, the countercyclical rule should rather react to the broad credit than to the narrow credit.

Table 6: Numerical Effects of a Change in the Capital Requirement Ratio(s)

<table>
<thead>
<tr>
<th>Regulated assets</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(1)/(3)</th>
<th>(2)/(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \eta_t ) AR(1) no shadow</td>
<td>( s_t^c = k_t )</td>
<td>-0.0642</td>
<td>-0.1904</td>
<td>0.5910</td>
<td>1.0871</td>
</tr>
<tr>
<td>( \eta_t ) AR(1)</td>
<td>( s_t^c &lt; k_t )</td>
<td>-0.0420</td>
<td>-0.1225</td>
<td>0.5910</td>
<td>0.1070</td>
</tr>
<tr>
<td>( \eta_t + \eta_t^a ) AR(1)</td>
<td>( s_t^c + ABS_t = k_t )</td>
<td>-0.0599</td>
<td>-0.1748</td>
<td>0.5910</td>
<td>0.1014</td>
</tr>
<tr>
<td>( \eta_t + \eta_t^a ) AR(1)</td>
<td>( s_t^c + s_t^c + k_t )</td>
<td>-0.0681</td>
<td>-0.1992</td>
<td>0.5910</td>
<td>0.1152</td>
</tr>
<tr>
<td>( \eta_t + \eta_t^a + \eta_t^b ) AR(1)</td>
<td>( s_t^c + ABS_t + s_t^c &gt; k_t )</td>
<td>-0.0832</td>
<td>-0.2432</td>
<td>0.5910</td>
<td>0.1408</td>
</tr>
<tr>
<td>( \epsilon_t + \eta_t, P1 )</td>
<td>( s_t^c &lt; k_t )</td>
<td>-0.0383</td>
<td>-0.1327</td>
<td>0.4701</td>
<td>0.0814</td>
</tr>
<tr>
<td>( \Gamma_t + \eta_t, P1 )</td>
<td>( s_t^c &lt; k_t )</td>
<td>0.0176</td>
<td>0.0508</td>
<td>0.2525</td>
<td>0.0697</td>
</tr>
<tr>
<td>( \Gamma_t + \eta_t, P2 )</td>
<td>( s_t^c &lt; k_t )</td>
<td>0.0146</td>
<td>0.0448</td>
<td>0.2383</td>
<td>0.0611</td>
</tr>
</tbody>
</table>

Notes. Columns (1) to (3) compute the average difference between impulse response functions when \( \eta_t \) follows a rule (AR(1) or policy) and when \( \eta_t \) is fixed. The average is computed over the first 20 periods and weighted by \( \beta^s \). The last two columns give a measure of efficiency, that is compute by how many percent the economy (GDP \( y_t \) or investment \( i_t \)) slows down (on average) when the capital requirement ratio increases by 1 percentage point (on average).

4.5 Basel III and Historical Aggregate Fluctuations

We have shown the relevance of a shadow banking sector for a proper quantitative assessment of regulation policies. In order to illustrate further this result, we now investigate the consequence 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, under Basel I which corresponds to our benchmark estimation of table 3. Then, we reproduce the same simulation exercise but under Basel III, a situation where all banking sectors and all assets are subject to a countercyclical buffer regulation, as described in sections 4.2 and 4.3. We assume the buffer requirement follows a P1 rule, that is reacts to the total credit to the economy. We report in figure 8 the results of this experiment for the cyclical components of investment and GDP (in percentage deviation from their trend component). We zoom on the period 2005-2015, i.e. around the Great recession, as a natural evaluation of the effectiveness of Basel III for macroeconomic stabilization.
Figure 8: Basel I vs. Basel III from an Historical Perspective

Notes. Investment and GDP are shown in percentage deviation from their trend component. The sample period for the estimation is 1980:I-2015:III and we zoom on the period 2005I-2015:III. The shaded area corresponds to NBER recession dates.

As figure 8 makes clear, it appears that Basel III leads to sizable reduction in both investment and output fluctuations. First, before the crisis, Basel III would have reduced the high level of investment. Second, this countercyclical policy would have limited a lot the huge drop in investment. Third, one would have obtained a faster recovery in the aftermath of the crisis. Similar patterns would have held for GDP, but slightly less pronounced. Numerically, between 2005 and 2015, Basel III would have reduce investment fluctuations by 29.7% and output fluctuations by 27.3%. As a comparison, over the whole historical simulation (between 1980 and 2015), Basel III would have reduce investment fluctuations by 18.2% and output fluctuations by 1.2%.

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 in the understanding of shadow banking and macro-prudential policies, and could be extended along several directions. First, the measurement error shock explains most of the shadow share volatility. Some transmission mechanisms between the shadow sector and the rest of the economy are therefore probably 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 be interesting. Second, we propose a real business cycle model therefore abstracting from the monetary dimension. However, this monetary dimension adds another asymmetry (through access vs. no access to the central bank) between the traditional and the shadow. A medium-scale model with price stickiness and monetary policy could also be worthwhile to develop. 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 left these for future research.
References


Appendix

A 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 $\Gamma_t$ 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

$$\pi_c^t = d_t + (1 + r^k_t - \delta)s_{t-1}^c + (1 - \Gamma_t)(1 + r^d_t)ABS_{t-1} - s_t^c - ABS_t - (1 + r^d_{t-1})d_{t-1} - \mathcal{C}(x_t) - \mathcal{P}(ABS_t/s_t^c) + T_t,$$

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

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

$$\pi_s^t = (1 + r^k_t - \delta)s_{t-1}^s - (1 - \Gamma_t)(1 + r^d_t)ABS_{t-1} - T_t,$$

$$(1 - \alpha) E_t (1 + r^k_{t+1} - \delta) = E_t \left[ (1 - \Gamma_{t+1})(1 + r^d_t) + \frac{T_{t+1}}{ABS_t} \right].$$

If we assume that the lump sum transfer fully compensates the losses, i.e. $T_t = \Gamma_t(1 + r^d_{t-1})ABS_{t-1}$, then 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.
B Data

Figure 9: Quarterly US Data Used as Observables to Estimate the Model

Notes. $\Delta$ is the first difference operator. Shaded areas correspond to NBER recession dates. Sources. See section 3.1.
C Estimations Results for the First Step

In the first step, we impose that hours worked are only driven by labor wedge shock (see table 7). This restriction is consistent with previous results, as for example from Sala et al. (2010). We also investigate the sensitivity of the estimation to the size of the portfolio adjustment cost parameter (we select the values \(\gamma = 0, 10, 20\)). The table reports the log-likelihood \(\log L\) for each model specification, which we use naturally as our selection criterion. Four alternative estimations are considered.

In alternative (1), we set \(\phi = 0\) and \(\gamma = 0\) and we only estimate \(\rho_m\) and \(\sigma_m\). The estimated value for \(\rho_m\) is very large (0.9912) and close to its upper bound, but without convergence problem during the estimation stage. This close to unity value 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; Sala et al., 2010). In alternative (2), we still maintain \(\gamma = 0\), but we now also estimate the habit parameter \(\phi\). The estimated value for \(\phi\) 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. Notice that the model’s alternative (1) with \(\phi = 0\) is strongly rejected by the data as indicating by the difference in the log-likelihood functions. With habit persistence, the autoregressive parameters is still large (0.9776) but smaller that the one obtains in alternative (1). This is because habit persistence partly captures the high degree of serial correlation in hours worked. Our finding is consistent with previous research on the persistence of hours. For example, when Chang et al. (2007) allow for labor adjustment cost (another specification yielding similar patterns as habits in leisure), the autocorrelation drops from almost 1 to values between 0.8 and 0.9. Alternatives (3) and (4) are obtained with two different values for the portfolio adjustment cost parameter (\(\gamma = 10, 20\)). Estimation results are mainly unaffected, as well as the fit of the model.

<table>
<thead>
<tr>
<th>Table 7: Estimation Results – Step 1 with (h_t) as only Observable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(\phi)</td>
</tr>
<tr>
<td>(\rho_m)</td>
</tr>
<tr>
<td>(\sigma_m)</td>
</tr>
<tr>
<td>(\log L)</td>
</tr>
</tbody>
</table>


\(^{21}\)We obtain the same results when the model is estimated (in the second step) with four observables. Almost all the variance of hours is explained by this shock (see table 4). See Gali and Rabanal (2005) for a similar finding.
## D Moments

Table 8: Moments Comparison

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Specification (1) $\rho_m = 0.9776$</th>
<th>Specification (2) $\rho_m = 0.9776, \phi = 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma(\Delta i)$</td>
<td>0.0273</td>
<td>0.0814</td>
<td>0.0937</td>
</tr>
<tr>
<td>$\sigma(\Delta c)/\sigma(\Delta i)$</td>
<td>0.1961</td>
<td>0.2596</td>
<td>0.1941</td>
</tr>
<tr>
<td>$\sigma(\Delta h)/\sigma(\Delta i)$</td>
<td>0.2416</td>
<td>0.4452</td>
<td>0.3884</td>
</tr>
<tr>
<td>$\sigma(\Delta share)$</td>
<td>0.0081</td>
<td>0.0081</td>
<td>0.0081</td>
</tr>
<tr>
<td>$\sigma(spread)$</td>
<td>0.0046</td>
<td>0.0032</td>
<td>0.0032</td>
</tr>
<tr>
<td>$corr(\Delta i, \Delta c)$</td>
<td>0.3789</td>
<td>0.5891</td>
<td>0.6795</td>
</tr>
<tr>
<td>$corr(\Delta i, \Delta h)$</td>
<td>0.6486</td>
<td>0.7346</td>
<td>0.7864</td>
</tr>
<tr>
<td>$corr(\Delta c, \Delta h)$</td>
<td>0.4817</td>
<td>0.6504</td>
<td>0.5322</td>
</tr>
<tr>
<td>$corr(\Delta share, \Delta h)$</td>
<td>0.1285</td>
<td>0.0091</td>
<td>0.0117</td>
</tr>
<tr>
<td>$corr(spread, \Delta h)$</td>
<td>0.0087</td>
<td>-0.1236</td>
<td>-0.0041</td>
</tr>
<tr>
<td>$corr(\Delta i, spread)$</td>
<td>0.0614</td>
<td>-0.1737</td>
<td>-0.0720</td>
</tr>
<tr>
<td>$corr(\Delta c, spread)$</td>
<td>0.0075</td>
<td>0.0689</td>
<td>0.1616</td>
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<tr>
<td>$corr(\Delta share, spread)$</td>
<td>-0.2330</td>
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<td>-0.0431</td>
</tr>
<tr>
<td>$\rho(\Delta i)$</td>
<td>0.4483</td>
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<td>0.4312</td>
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<td>0.0880</td>
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<tr>
<td>$\rho(\Delta h)$</td>
<td>0.4653</td>
<td>0.5381</td>
<td>-0.0155</td>
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<tr>
<td>$\rho(\Delta share)$</td>
<td>0.3166</td>
<td>0.3103</td>
<td>0.3103</td>
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<tr>
<td>$\rho(spread)$</td>
<td>0.8726</td>
<td>0.7480</td>
<td>0.7738</td>
</tr>
</tbody>
</table>

Notes. Sample period: 1980:I–2015:III. $\sigma(.)$, $corr(.,.)$ and $\rho(.)$ represent standard deviation, correlation and first-order autocorrelation, respectively. $\Delta$ is the first difference operator. $i, c, h, share = s^d/k$ and $spread = r^d - \delta - r^d$ stand for investment, consumption, hours, shadow share and credit spread, respectively.
E Additional Robustness Checks

Let us review the additional estimations that we consider:

**Check (5).** Convex investment adjustment costs are popular in estimated DSGE models in order to smooth investment reaction to shocks (see for instance Smets and Wouters, 2007, among many others). In practice, we introduce a capital good producer who creates new capital goods using old depreciated capital goods and gross investment \(1 + S(i_t/i_{t-1})\), where \(S(i_t/i_{t-1}) = \mu/2(i_t/i_{t-1} - 1)^2\) is a standard investment adjustment cost. The price of capital is the Tobin’s \(q_t\) and the new first order condition with respect to investment is \(q_t = 1 + S_t + S'_t(i_t/i_{t-1}) - E_t \Lambda_{t+1} S''_{t+1}(i_{t+1}/i_t)^2\). We estimate the parameter \(\mu \geq 0\).

**Check (6).** Another popular real friction in the empirical DSGE literature is external habit in consumption (see again Smets and Wouters, 2007, among many others), which helps to smooth the consumption reaction. In the household’s momentary utility function, we replace \(\ln c_t\) with \(\ln(c_t - \chi \bar{c}_{t-1})\), which slightly modifies the household’s first order conditions with respect to deposits and hours, as well as the definition of the stochastic discount factor \(\Lambda_{t+1}\). We estimate the parameter \(\chi\).

**Checks (7) and (8).** The vector \(\Theta_2\) contains parameters difficult to estimate and that we calibrate prior to the estimation (see section 3.2). We explain in section 3.2 that we calibrate \(\psi''(0)\) in order to fix the elasticity \(\epsilon_s\) of the spread to excess capital at -0.0125, as an average from the related empirical literature. We use as robustness exercises elasticities 50% lower and 50% higher, respectively.

**Checks (9) and (10).** \(\Theta_2\) also includes the curvature \(\psi\) of the household’s disutility. Using Bayesian techniques, Smets and Wouters (2007) assume this parameter to be normally distributed and estimate it at 1.92 (0.91 at 5% and 2.78 at 95%). In our benchmark specification, we calibrate \(\psi = 2\) in line with the mode estimate from Smets and Wouters (2007). As robustness exercises, we use values (0.5 and 4, respectively) below and above the 5%-95% thresholds.

Checks (5) and (6) in table 9 concern investment adjustment costs and habits persistence in consumption. When these are included and estimated, they do not significantly contribute to the model’s fit. A standard likelihood ratio test would not reject the restriction of no habits in consumption and/or no dynamic adjustment costs. The habits in consumption parameter \(\chi\) is equal to -0.1232 (not significantly different from zero at 5%) and the adjustment cost parameter \(\mu\) is almost zero. This is the mere consequence of habits in leisure that already provides sufficient persistence properties to the model, as already shown in Fève et al. (2013). Checks (7) and (8) report the estimation results with a lower (in absolute terms) and higher elasticity \(\epsilon_s\) of the spread to excess capital. Neither the habit persistence in leisure nor the portfolio adjustment cost parameter are altered compared to the benchmark estimation. Finally, checks (9) and (10) inspect the sensitivity of our estimations to alternative values of the Frisch elasticity of labor supply. Our results appear almost insensitive to this perturbation. Again, for all the checks
of table 9, the share of the variance of consumption and investment explained by the shadow wedge shock remains stable across the different robustness exercises.

Table 9: Additional Robustness Checks – Selected Estimation and Simulation Results

<table>
<thead>
<tr>
<th></th>
<th>Check (5)</th>
<th>Check (6)</th>
<th>Check (7)</th>
<th>Check (8)</th>
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<th>Check (10)</th>
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<td>$\chi$</td>
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<td>(NaN)</td>
<td>(NaN)</td>
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</tr>
<tr>
<td>$\phi$</td>
<td>0.4775</td>
<td>0.4304</td>
<td>0.4664</td>
<td>0.4865</td>
<td>0.4372</td>
<td>0.4871</td>
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<tr>
<td></td>
<td>(0.0418)</td>
<td>(0.0444)</td>
<td>(0.0364)</td>
<td>(0.0374)</td>
<td>(0.0348)</td>
<td>(0.0379)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>10.7273</td>
<td>10.5707</td>
<td>10.9816</td>
<td>10.4989</td>
<td>10.7336</td>
<td>10.6376</td>
</tr>
<tr>
<td>$\log L$</td>
<td>1918.3019</td>
<td>1919.6936</td>
<td>1918.2863</td>
<td>1918.2549</td>
<td>1893.0720</td>
<td>1825.3913</td>
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<tr>
<td>$\Gamma_t \sim Var(\Delta i)$</td>
<td>9.8839</td>
<td>11.7068</td>
<td>10.8028</td>
<td>9.4019</td>
<td>11.0644</td>
<td>9.5041</td>
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<tr>
<td>$\Gamma_t \sim Var(\Delta c)$</td>
<td>11.0380</td>
<td>11.8803</td>
<td>10.8907</td>
<td>11.0366</td>
<td>7.6662</td>
<td>12.3594</td>
</tr>
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</table>

Notes. Sample period: 1980:I–2015:III. Standard errors between brackets. $\log L$ represents the log-likelihood. $\Gamma_t \sim Var(\Delta i)$ gives the variance share of the variable $\Delta i$ explained by the shadow wedge shock $\Gamma_t$ and $\Gamma_t \sim Var(\Delta c)$ gives the variance share of the variable $\Delta c$ explained by the shadow wedge shock $\Gamma_t$, where $\Delta$ is the first difference operator.