Deepening Contractions and Collateral Constraints

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Abstract

The skewness of the US business cycle has become increasingly negative over the last decades. This finding can be explained by the concurrent increases in the loan-to-value ratios of both households and firms. To demonstrate this point, we devise a DSGE model with collateralized borrowing and occasionally non-binding credit constraints. Easier credit access increases the likelihood that constraints become slack in the face of expansionary shocks, while contractionary shocks are further amplified due to tighter constraints. As a result, busts gradually become deeper than booms. Based on the differential impact that occasionally non-binding constraints exert on the shape of expansions and contractions, we are also able to reconcile a more negatively skewed business cycle with a moderation in its volatility. Finally, our model can account for an intrinsic feature of economic downturns preceded by private credit build-ups: Financially driven expansions lead to deeper contractions, as compared to equally-sized non-financial expansions.

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1 Introduction

Economic fluctuations across the industrialized world are typically characterized by asymmetries in the shape of expansions and contractions in aggregate activity. A prolific literature has extensively studied the statistical properties of this phenomenon, reporting that relative to expansions, contractions are periods of larger and negative output fluctuations; see, among others Neftci (1984), Hamilton (1989), Sichel (1993) and, more recently, Morley and Piger (2012). While most of these studies consider static measures of skewness in economic aggregates, focusing on the time-varying characteristics of business cycle asymmetry reveals a wider perspective: The skewness of the US business cycle has become increasingly negative during the last decades. Figure 1 illustrates this by reporting the rolling skewness of a filtered measure of real GDP for 1970Q1–2005Q2. Importantly, this finding is robust to excluding the Great Recession from the sample.[1]

Explaining this pattern represents a challenge for existing business cycle models. To meet this, a theory is needed that involves non linearities as well as a secular development capable of shaping the evolution in the skewness of the business cycle. In this respect, the importance of borrowing constraints as a source of business cycle asymmetries has long been recognized in the literature; see, e.g., the survey by Brunnermeier *et al.* (2013). In expansions, credit-constrained households and firms occasionally find themselves unconstrained, whereas credit constraints tighten during recessions. This non-linearity translates into a negatively skewed business cycle. As for a secular pattern, the past decades have witnessed a massive deregulation of financial markets, with one result being a substantial increase in the loan-to-value (LTV) ratios of households and firms; see Figure 2. We claim that this development in LTV ratios is at the root of the more and more negatively skewed business cycle. To empirically assess the simultaneous developments in credit markets and the asymmetry of the business cycle, we regress output skewness as graphed in Figure 1 against a constant, a trend, the log of real GDP, and each of the LTV measures reported

[1] Appendix A provides further evidence in support of this finding. As an example, we report an analogous measure of rolling skewness of the annualized growth rates of real GDP. The drop in the skewness of this business cycle indicator is more gradual, while starting earlier in the sample. In this respect, Psaradakis and Sola (2003) stress that their test for skewness—which is employed to construct the confidence bands around the various skewness measures—has low power when applied to time series that have been pre-filtered. In light of this property, whenever skewness can in fact be detected in filtered series, as the one employed in Figure 1, it can generally be interpreted as a strong signal of asymmetry. As a further robustness check we also consider alternative rolling windows and samples.

Figure 1: *Skewness of filtered United States real GDP, 1970Q1–2005Q2.*
Notes: We use a band-pass filter to remove the trend from the series. We then compute the skewness of an 80-quarter forward-looking rolling window. Beginning in 1995Q3, the size of the window is successively reduced by one quarter, as the sample ends in 2015Q2. The final observation, 2005Q2, is thus computed using 40 quarters. The confidence band is computed following Psaradakis and Sola (2003).
Source: Federal Reserve Bank of St. Louis (FRED database).

in Figure 2.[2] The results, reported in Table A.1 in Appendix A, show that in both regressions the coefficient on the LTV variable is large, negative, and strongly significant. While we wish to be careful in the interpretation of any associated causal effects, these results confirm a negative relationship between output skewness and the LTV ratios.[3]

To account for these facts we present a DSGE model that allows for the possibility that the collateral constraints faced by firms and a fraction of the households do not always

[2]Note that the forward-looking nature of our skewness series avoids concerns of reverse causality.

[3]A non-exhaustive list of mechanisms that may give rise to business cycle asymmetries includes non linearities in investment (Bertola and Caballero, 1994), nominal rigidities in goods and labor markets (Ball and Mankiw, 1994), and state-dependent pricing and convexities in aggregate supply (Devereux and Siu, 2007). Recently, Abbritti and Fahr (2013) have shown that downward nominal wage rigidity is at the core of various asymmetries in the labor market, as well as in aggregate output. Downward wage rigidity implies that wages fail to adjust during recessions, giving rise to positive skewness in nominal wages. In turn, this may force firms to cut back excessively on employment or investment in a recession, giving rise to negative skewness in real aggregate variables. This mechanism offers a testable implication: If nominal wages have become more rigid during the last decades, this could potentially lead to more severe negative output skewness. However, we have not found sign of this pattern in nominal wage data for the US.

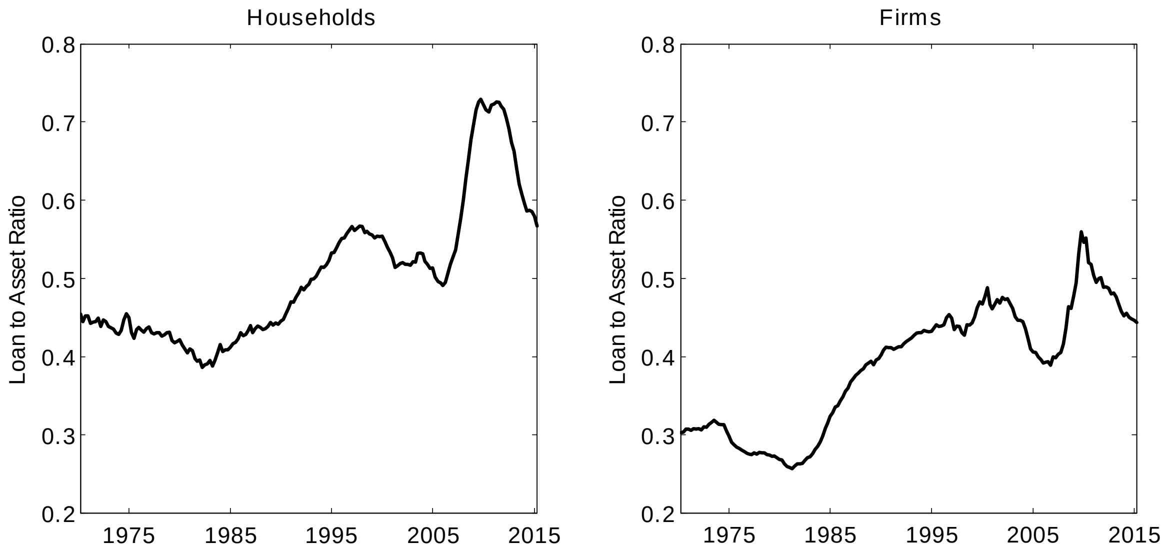

Figure 2: *The ratio of loans to assets for households and firms in the United States, 1970Q1–2015Q1.*
Source: Jensen *et al.* (2015) based on Flow of Funds data.

bind. Output skewness is practically zero going from low to intermediate values of the average LTV ratio, as collateral constraints tend to bind in either cyclical phase. Further increasing the average LTV ratio raises the likelihood of financial constraints becoming slack in the face of expansionary shocks, dampening the magnitude of the resulting boom. On the other hand, in the face of contractionary shocks, borrowers remain financially constrained, making their debt reduction increasingly burdensome. This, in turn, deepens contractions, so that the skewness of the business cycle becomes progressively negative, as in the reported evidence. We also show that this pattern is transmitted onto aggregate consumption and investment dynamics, in line with empirical evidence reported in Appendix A, where the rolling skewness of consumption and investment are shown to display downward movements similar to those highlighted for real GDP.

Our findings carry important information about recent changes in the shape of business fluctuations. To elaborate on this, we juxtapose the drop in the skewness of the business cycle with the Great Moderation in macroeconomic volatility. While increasing LTV ratios cannot necessarily be pointed to as a main driver of the Great Moderation, our model reconciles the increase in the asymmetry of the business cycle with a drop in its volatility. In line with recent empirical evidence reported by Gadea-Rivas *et al.* (2014, 2015), neither changes to the depth nor to the frequency of recessionary episodes account for the stabilization of macroeconomic activity. In fact, the adjustment in macroeconomic volatility mostly rests on the characteristics of the expansions, whose magnitude declines as an effect of collateral constraints becoming increasingly non-binding in the face of higher credit limits.

Recently, increasing attention has been devoted to the connection between the driving factors behind business cycle expansions and the extent of the subsequent contractions. Jordà *et al.* (2013) report that more credit-intensive expansions tend to be followed by deeper recessions—irrespective of whether the latter are accompanied by a financial crisis. Our model accounts for this feature along two dimensions. First, we show that contractions become increasingly deeper as the average LTV ratio increases, even though the boom-bust cycle is generated by the same combination of expansionary and contractionary shocks. Second, we show that financially-driven expansions lead to deeper contractions, as compared with similar-sized expansions generated by non-financial shocks. Both exercises emphasize that, following a contractionary shock, the repercussion of constrained agents' deleveraging increases in the size of their debt. As a result, increasing leverage makes it harder for savers to compensate for the drop in consumption and investment of constrained agents. This narrative of the boom-bust cycle characterized by debt overhang is consistent with the results of Mian and Sufi (2010), who identify a close connection at the county level in the US between pre-crisis household leverage and the severity of the Great Recession.

The idea that occasionally binding credit constraints may give rise to macroeconomic asymmetries is not new, and has recently been examined in detail by Jensen *et al.* (2015), Guerrieri and Iacoviello (2014) and Maffezzoli and Monacelli (2015).[4] Compared to Guerrieri and Iacoviello (2014), whose focus is on the recent boom-bust cycle in the US housing market and its connection with private consumption, we examine the impact of secular variations in both households' and firms' credit limits on the shape of output fluctuations. In this respect, our study implies that non-binding credit constraints are likely to have become a more salient feature of the macroeconomy in recent decades. This intuition is indirectly supported by Guerrieri and Iacoviello (2014), who show that non-binding credit constraints were prevalent during the last pre-crisis boom in the US. Maffezzoli and Monacelli (2015) provide an extensive account of the characteristics of financially-

[4] This idea is also closely related to the 'sudden stop' literature, in which a small open economy faces an occasionally binding constraint on its access to external credit. See, e.g., Mendoza (2010) and Benigno *et al.* (2013).

driven contractions, and also report that the aggregate implications of deleverage shocks are state-dependent, with the economy's response being greatly amplified in situations where agents switch from being financially unconstrained to being constrained. However, while Maffezzoli and Monacelli (2015) focus on the characteristics of drops in economic activity induced by financial shocks and conditional on different degrees of firm leverage, we design our experiments so as to generate boom-bust cycles where expansions can be either credit-fueled or driven by non-financial shocks. In line with the boom-bust episodes studied by Jordà *et al.* (2013), we show that the nature of the driving forces behind a given expansion are crucial for predicting the deepness of the ensuing contraction.

Regarding the connection between financial liberalization and business cycle asymmetry, our paper is related to a recent empirical literature. Popov (2014) studies business cycle asymmetry in a large panel of developed and developing countries. Two main results are documented. First, the average business cycle skewness across all countries became markedly negative after 1991, consistent with our findings for the US. Second, this pattern is particularly distinct in countries that liberalized their financial markets. Bekaert and Popov (2015) examine a large cross-section of countries, reporting that more financially developed economies have more negatively skewed business cycles. Ordoñez (2013) documents that countries with more developed financial markets display less asymmetry than countries with a more rudimentary financial system. While this finding is at odds with our results and those of the aforementioned papers, Ordoñez (2013) does not focus on the business cycle effects of a secular process of financial development in industrialized countries. Moreover, he considers financial development as improved monitoring, which alleviates amplification of negative shocks, whereas we consider increasing credit limits, resulting in collateral constraints becoming non-binding more often. Rancière *et al.* (2008) establish a cross-country link between real GDP growth and the skewness of credit growth—a link which is stronger in financially liberalized countries. While we focus on the asymmetry of output, our credit measure shares this property, making our results comparable with their findings.

The rest of the paper is organized as follows. Section 2 presents our model. Section 3 discusses our main result and connects our findings to the Great Moderation in economic volatility. Section 4 shows that the model is capable of producing the type of debt overhang recession emphasized in recent empirical studies. Section 5 concludes. The Appendices contain supplementary material concerning the model solution and empirical details.

2 The model

We adopt a standard real business cycle model augmented with collateral constraints along the lines of Kiyotaki and Moore (1997), Iacoviello (2005), Liu *et al.* (2013), Justiniano *et al.* (2015), *inter alia.*[5] The economy is populated by three types of agents, whose total mass equals one. These agents differ by their discount factors, with the so-called patient households displaying the highest degree of time preference, while impatient households (of mass $0 < n_I < 1$) and entrepreneurs (of mass $0 < n_E < 1$) have relatively lower discount factors. As a result, patient households will be acting as lenders. Moreover, patient and impatient households supply labor, consume non-durable goods and land. Entrepreneurs only consume non-durable goods, and accumulate both land and physical capital, which they rent to firms. These are of unit mass and operate under perfect competition, taking labor inputs from both types of households, along with capital and land from the entrepreneurs. The resulting gross product may be used for investment and non-durable consumption.

2.1 Patient households

The utility function of patient households is given by:

$$\mathrm{E}_0 \left\{ \sum_{t=0}^{\infty} \left(\beta^P\right)^t \left[\frac{1}{1-\sigma_C^P} \left(C_t^P\right)^{1-\sigma_C^P} + \frac{\varepsilon_t}{1-\sigma_H^P} \left(H_t^P\right)^{1-\sigma_H^P} + \frac{\nu^P}{1-\sigma_N^P} \left(1-N_t^P\right)^{1-\sigma_N^P} \right] \right\}, \quad (1)$$

where C_t^P denotes non-durable consumption, H_t^P is the stock of land, and N_t^P denotes the fraction of time devoted to labor. Moreover, $0 < \beta^P < 1$ is the discount factor, $\sigma_C^P > 0$, $\sigma_H^P > 0$ and $\sigma_N^P > 0$ are the coefficients of relative risk aversion pertaining to non-durable consumption, land services and leisure, respectively, and $\nu^P > 0$ is the weight of labor disutility. Finally, ε_t is a land-preference shock satisfying

$$\log \varepsilon_t = \log \varepsilon + \rho_\varepsilon \left(\log \varepsilon_{t-1} - \log \varepsilon\right) + u_t, \qquad 0 < \rho_\varepsilon < 1, \quad (2)$$

[5] Jensen *et al.* (2015) employ this framework to examine the impact of secular changes in credit limits on business cycle volatility and comovement between private debt and consumption/investment dynamics.

where $\varepsilon > 0$ denotes the steady-state value and where $u_t \sim \mathcal{N}\left(0, \sigma_\varepsilon^2\right)$. Utility maximization is subject to the following budget constraint

$$C_t^P + Q_t\left(H_t^P - H_{t-1}^P\right) + R_{t-1}B_{t-1}^P = B_t^P + W_t^P N_t^P, \tag{3}$$

where B_t^P denotes the stock of one-period debt held at the end of period t, R_t is the gross real interest rate on debt, Q_t is the price of land in units of consumption goods, and W_t^P is the real wage.

2.2 Impatient households

The utility of impatient households takes the same form as that of patient households:

$$\mathrm{E}_0\left\{\sum_{t=0}^{\infty}\left(\beta^I\right)^t\left[\frac{1}{1-\sigma_C^I}\left(C_t^I\right)^{1-\sigma_C^I} + \frac{\varepsilon_t}{1-\sigma_H^I}\left(H_t^I\right)^{1-\sigma_H^I} + \frac{\nu^I}{1-\sigma_N^I}\left(1-N_t^I\right)^{1-\sigma_N^I}\right]\right\}, \tag{4}$$

$$\sigma_C^I > 0, \sigma_H^I > 0, \sigma_N^I > 0,\ \nu^I > 0,$$

where, as for the patient households, C_t^I denotes non-durable consumption, H_t^I is the stock of land, and N_t^I denotes the fraction of time devoted to labor. Households' different impatience is captured by assuming $\beta^P > \beta^I$. This ensures that, in the steady state, patient and impatient households act as lenders and borrowers, respectively. Impatient households are also subject to the following budget constraint

$$C_t^I + Q_t\left(H_t^I - H_{t-1}^I\right) + R_{t-1}B_{t-1}^I = B_t^I + W_t^I N_t^I. \tag{5}$$

Moreover, impatient households are subject to a collateral constraint, according to which their borrowing B_t^I is bounded above by a fraction s_t of the expected present value of durable goods holdings at the beginning of period $t+1$:

$$B_t^I \leq s_t \frac{\mathrm{E}_t\left\{Q_{t+1}\right\} H_t^I}{R_t}, \tag{6}$$

This constraint can be rationalized in terms of limited enforcement, as in Kiyotaki and Moore (1997) and Iacoviello (2005). The loan-to-value (LTV) ratio (or credit limit), s_t, is stochastic and aims at capturing financial shocks (see, e.g., Jermann and Quadrini, 2012 and Liu *et al.*, 2013):

$$\log s_t = \log s + \rho_s (\log s_{t-1} - \log s) + \upsilon_t, \qquad 0 < \rho_s < 1, \tag{7}$$

where $\upsilon_t \sim \mathcal{N}(0, \sigma_s^2)$ and s, the steady-state LTV ratio, is a proxy for the *average* stance of credit availability.

2.3 Entrepreneurs

Entrepreneurs have preferences over non durables only (cf. Iacoviello, 2005; Liu *et al.*, 2013), and maximize

$$\mathrm{E}_0 \left\{ \sum_{t=0}^{\infty} \left(\beta^E\right)^t \frac{1}{1-\sigma_C^E} \left(C_t^E\right)^{1-\sigma_C^E} \right\}, \qquad \sigma_C^E > 0, \tag{8}$$

where C_t^E denotes entrepreneurial non-durable consumption and $\beta^P > \beta^E$. Utility maximization is subject to the following budget constraint

$$C_t^E + I_t + Q_t \left(H_t^E - H_{t-1}^E\right) + R_{t-1} B_{t-1}^E = B_t^E + r_{t-1}^K K_{t-1} + r_{t-1}^H H_{t-1}^E, \tag{9}$$

where I_t denotes investment in physical capital, K_{t-1} is the physical capital stock rented to firms at the end of period $t-1$, and H_{t-1}^E is the stock of land rented to firms. Finally, r_{t-1}^K and r_{t-1}^H are the rental rates on capital and land, respectively. Capital accumulation is given by the law of motion

$$K_t = (1-\delta) K_{t-1} + \left[1 - \frac{\Omega}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2\right] I_t, \qquad 1 > \delta > 0, \quad \Omega > 0, \tag{10}$$

whereby quadratic investment adjustment costs are assumed. Like impatient households, entrepreneurs are credit constrained, but they are able to use both capital and their holdings of land as collateral:[6]

$$B_t^E \leq s_t \mathrm{E}_t \left\{ \frac{Q_{t+1}^K K_t + Q_{t+1} H_t^E}{R_t} \right\}, \tag{11}$$

[6] The importance of real estate as collateral for business loans has recently been emphasized by Chaney *et al.* (2012) and Liu *et al.* (2013).

where Q_t^K denotes the price of installed capital in consumption units. For simplicity, we assume that households and entrepreneurs are subject to common credit limits.[7]

2.4 Firms

Firms operate under perfect competition, employing a constant-returns-to-scale technology. They rent capital and land from the entrepreneurs and hire labor from both types of households in order to maximize their profits. The production technology for output, Y_t, is given by:[8]

$$Y_t = A_t \left[\left(N_t^P \right)^{\alpha} \left(N_t^I \right)^{1-\alpha} \right]^{\gamma} \left[\left(H_{t-1}^E \right)^{\phi} K_{t-1}^{1-\phi} \right]^{1-\gamma}, \qquad 0 < \alpha,\ \phi,\ \gamma < 1, \tag{12}$$

with total factor productivity A_t evolving according to

$$\log A_t = \log A + \rho_A \left(\log A_{t-1} - \log A \right) + z_t, \qquad 0 < \rho_A < 1, \tag{13}$$

where $A > 0$ is the steady-state value of A_t, and $z_t \sim \mathcal{N}\left(0, \sigma_A^2\right)$.

2.5 Market clearing

Aggregate supply of land is fixed at H, implying that land-market clearing is given by

$$H = \left(1 - n_I - n_E\right) H_t^P + n_I H_t^I + n_E H_t^E. \tag{14}$$

The economy-wide net financial position is zero, such that

$$\left(1 - n_I - n_E\right) B_t^P + n_I B_t^I + n_E B_t^E = 0. \tag{15}$$

[7] The ratios of loans to assets in Figure 2 do not suggest large differences between households and firms. In Iacoviello (2005), the LTV ratio faced by entrepreneurs (0.89) is much higher than that faced by impatient households (0.55), while the opposite is the case in Gerali *et al.* (2010), who set 0.35 for entrepreneurs and 0.7 for households. In sum, in lack of conclusive evidence that LTV ratios faced by firms are systematically higher or lower than those faced by households, we assume that they are equal.

[8] The assumption of imperfect substitutability between labor types follows Iacoviello (2005) and Justiniano *et al.* (2015), among others. Iacoviello and Neri (2010) note that perfect substitutability complicates the solution of their model substantially, but yields similar results.

Finally, the aggregate resource constraint can be written as

$$nY_t = (1 - n_I - n_E)\, C_t^P + n_I C_t^I + n_E C_t^E + n_E I_t, \tag{16}$$

where $n \equiv \left[(1 - n_I - n_E)^{\alpha} (n_I)^{1-\alpha}\right]^{\gamma} n_E^{1-\gamma}$.

2.6 Equilibrium and solution method

An equilibrium is defined as a sequence of prices and quantities which, conditional on the sequence of shocks $\{A_t, \varepsilon_t, s_t\}_{t=0}^{\infty}$ and the initial conditions, satisfy the optimality conditions, the budget and credit constraints, as well as the technological constraints and the market-clearing conditions. We provide the optimality conditions in Appendix B, while the steady state and the log-linearized version of the model are presented in the Additional Appendix to this paper. Due to the assumptions about the discount factors, $\beta^P < \beta^I$ and $\beta^P < \beta^E$, both collateral constraints are binding in steady state. The steady-state real interest rate is pinned down by patient households' Euler equation, whereas impatient households and entrepreneurs have a higher subjective real rate of interest. However, the optimal level of debt of one or both agents may fall short of the credit limit when the model is not at its steady state, in which case the collateral constraint will be non-binding.

To account for the occasionally non-binding nature of the collateral constraints, our solution method follows Laséen and Svensson (2011) and Holden and Paetz (2012), who develop a solution method for log-linearized DSGE models featuring inequalities. The idea is to introduce a set of (anticipated) "shadow value shocks" to ensure that the shadow values associated with each of the two collateral constraints remain non-negative at all times. For first-order perturbations, our solution method produces similar simulated moments as the method of Guerrieri and Iacoviello (2014, 2015); cf. Holden and Paetz (2012). We present the technical details of the method in the Additional Appendix.

2.7 Parameterization

The calibrated parameters are summarized in Table 1, while Appendix C contains an extensive description of the calibrated parameter values.[9] As our perspective is on the

[9] Our parameterization follows closely the one employed in Jensen *et al.* (2015), and is broadly in line with parameter values used in existing calibrated as well as estimated models (e.g., Iacoviello, 2005; Liu

Parameter	**Interpretation**	**Value**
	Preference parameters	
β^P	Discount factor, patient households	0.99
β^i, $i = \{I, E\}$	Discount factor, impatient agents	0.97
σ_C^i, $i = \{P, I, E\}$	CRRA coefficient for consumption	1
σ_H^i, $i = \{P, I\}$	CRRA coefficient for housing	1
σ_H^i, $i = \{P, I\}$	CRRA coefficient for labor	9
ε	Weight on housing utility	0.085
ν^i, $i = \{P, I\}$	Weight on labor disutility	0.27
	Technology parameters	
γ	Labor share of production	0.7
α	Income share of patient households	0.7
ϕ	Non-labor input share of land	0.15
Ω	Investment adjustment cost parameter	4
δ	Capital depreciation rate	0.035
n^i, $i = \{I, E\}$	Mass of each type of agent	1/3
	Shock parameters	
ρ_A	Persistence of technology shock	0.97
ρ_s	Persistence of credit-limit shock	0.98
ρ_ε	Persistence of land-demand shock	0.96
σ_A	Std. dev. of technology shock	0.005
σ_s	Std. dev. of credit-limit shock	0.0119
σ_ε	Std. dev. of land-demand shock	0.06

Table 1: Calibrated parameter values

secular behavior of business cycle asymmetry, the calibration strategy is designed so as to match a set of "big ratios" for the US economy as reported, e.g., by Liu *et al.* (2013): this implies a steady-state ratio of residential land to output around 1.45, a ratio of commercial land to output of 0.65 and a capital to output ratio of 1.15, all at the annual level. These values are compatible with $s = 0.7$.

To account for a gradual relaxation of both households' and firms' credit limits, we let the steady-state LTV ratio faced by households and entrepreneurs, s, vary over the range [0.3,0.9] and report statistics for 13 different values within this range.[10] In this way, we obtain a comprehensive picture of the effects of different LTV ratios on the macroeconomy.

et al., 2013).

[10]Changing s within this range allows us to match values of the big ratios that are close to the proposed calibration. For values of s below 0.3, the credit constraints become non-binding only very rarely, so that our statistic of main interest, the skewness of output, is always very close to zero. We have chosen the upper bound of the range to 0.9 so that given the process for s_t, actual LTV ratios remain below 1 in 95 percent of all periods. While LTV ratios above 1 may sometimes occur empirically, it is hard to reconcile with the idea of limited contract enforcement which we follow in this paper.

When we report impulse responses, however, we do so only for two values of s. The first is a "high" LTV regime, where $s = 0.7$. The second, a "low" LTV regime, has $s = 0.35$.[11]

3 Asymmetric business cycles and collateral constraints

We are now ready to explore the ability of our model in generating stronger business cycle asymmetry as s increases. We do so in three steps. First, we inspect a set of impulse responses to build intuition around the non-linear transmission of different shocks. Next, we present the skewness of output and other variables implied by the model, based on a large number of stochastic simulations. Finally, we examine the behavior of skewness in conjunction with the Great Moderation in macroeconomic volatility.

3.1 Inspecting the mechanism: impulse responses

To gain a preliminary insight into the nature of the asymmetry generated by our framework, and how this evolves under different LTVs, we study the propagation of 'large' shocks, which have the potential to make the borrowing constraints non-binding.[12] Figure 3 displays the response of output to a set of large, positive shocks, as well as the mirror image of the response to equally-sized negative shocks, under a high and a low LTV ratio.[13] Under a high average LTV ratio, a positive technology shock renders the borrowing constraint of the entrepreneurs slack for six quarters, while impatient households remain constrained throughout. Therefore, entrepreneurs optimally choose to borrow less than they are able to: This attenuates the expansionary effect on their demand for land and, in turn, dampens the boom in aggregate economic activity. On the contrary, following a negative technology shock, borrowing constraints remain binding throughout. As a result, impatient households and entrepreneurs are forced to cut back on their borrowing in response to the drop in the value of their collateral assets. This produces a stronger output response. In other words, under high LTV ratios a large, negative technology shock has a

[11] Both of these values are within the range of values typically used in the literature; e.g., Mendoza (2010) reports 0.2–0.3, Calza *et al.* (2013) use 0.6, Liu *et al.* (2013) report 0.75, while Justiniano *et al.* (2014) set a value of 0.8.

[12] In our stochastic simulations, instead, combinations of positive 'normal' shocks will be sufficient to make the constraints non-binding.

[13] The impulse responses of a selection of key variables to 'large' shocks of each of the three types are reported in Figures D.1-D.6 in Appendix D.

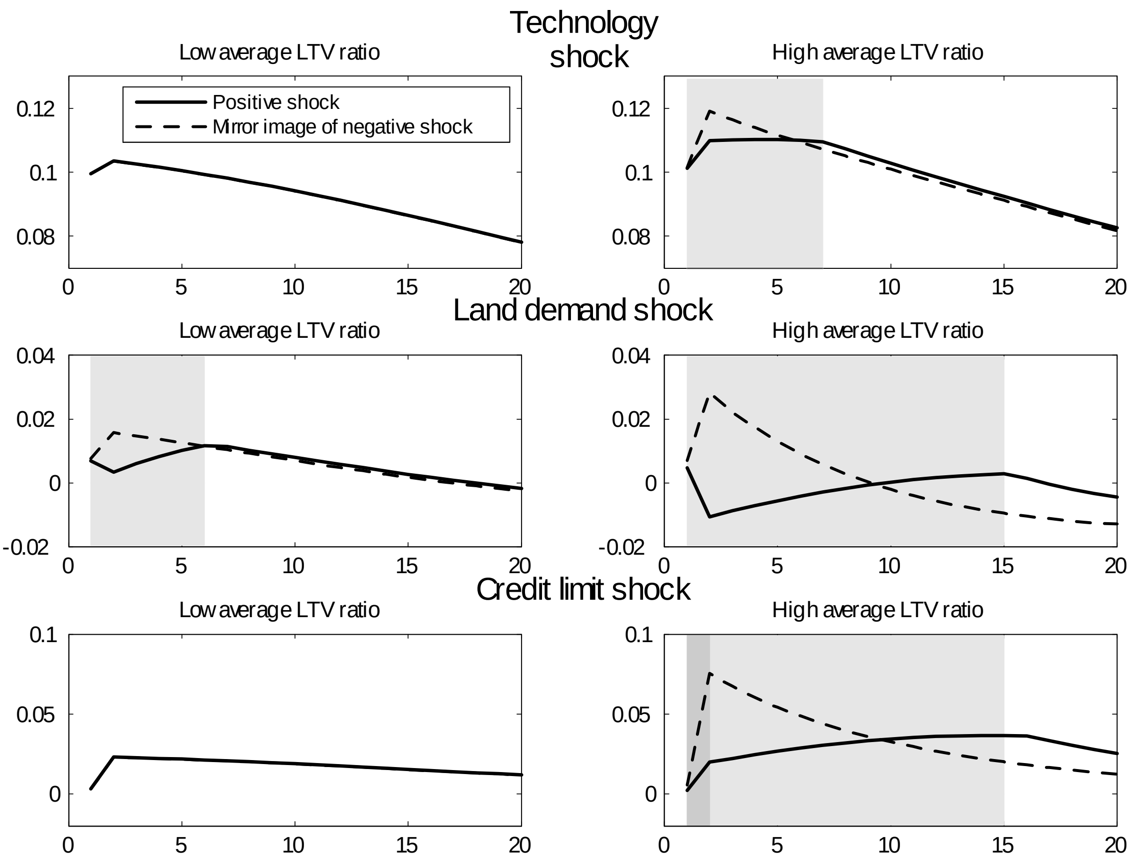

Figure 3: *Impulse responses of output to large (20 standard deviations) shocks to technology (row 1), land demand (row 2), and credit limits (row 3) for two different LTV ratios;* $s = 0.35$ *(left column) and* $s = 0.70$ *(right column).*

Notes: Light-grey periods are ones where the entrepreneurs are unconstrained; solid-grey periods are ones where all agents are unconstrained.

larger impact on output than a similar-sized positive shock when occasionally non-binding constraints are taken into account.

The second row of Figure 3 reports the response to large land demand shocks. In this case, the shock makes the entrepreneurs' collateral constraint non-binding during the first 14 quarters after the shock in the high LTV regime, while impatient households remain constrained throughout. As a result, entrepreneurs have no incentive to expand their borrowing capacity by increasing their stock of land. In fact, entrepreneurs lower their land holdings on impact, allowing patient and impatient households to increase their stock of land at the expense of non-durable consumption. In turn, the drop in land available for production leads output to contract. On the other hand, there is no attenuation of large negative shocks to the economy. In that case, both collateral constraints remain binding, giving rise to a large drop in output. The skewness emerging from large demand shocks is much weaker when the LTV ratio is low. In this case, the collateral constraint of the entrepreneur becomes non-binding for only five quarters, while the impatient household again remains constrained.

The bottom row of Figure 3 shows the effects of large credit limit shocks. Under a high average LTV ratio, the entrepreneurs are unconstrained during the first 14 periods after a positive shock, while impatient households become unconstrained for one period. For the reasons discussed above, this leads to a muted response of output. In contrast, a large negative shock forces entrepreneurs into a sizeable deleveraging, reducing the stock of land available for production. Simultaneously, impatient households are also forced to deleverage and bring down their stock of land, which further depresses the land price, and thus the borrowing capacity of both constrained agents. The result is a large drop in output. For low LTV ratios, credit constraints remain binding throughout.

3.2 Deepening contractions

The impulse responses in the previous subsection offer a clear message: For high average LTV ratios, episodes of non-binding credit constraints are more frequent. Hence, economic contractions tend to become larger than expansions as the average LTV ratio increases, paving the way for a negatively skewed business cycle. Moreover, all three types of shock contribute to generating a more negatively skewed business cycle as the LTV ratio increases, so that their relative contribution is not crucial to our qualitative findings.

To deepen our understanding of the properties of the model over the entire range of feasible LTV ratios, we conduct a large set of stochastic simulations, retrieving statistics from 501 runs of 2000 periods each. Figure 4 displays the skewness of filtered output: This is practically zero going from low to intermediate values of the average LTV ratio, but becomes increasingly negative as credit limits increase further and collateral constraints become non binding more often. As illustrated in the left panel of Figure 5, the entrepreneur finds himself unconstrained as much as 50% of the time at very high LTV ratios, while impatient households only experience this instance rarely. Finally, note that the skewness of investment and aggregate consumption display a pattern similar to that of output, as it can be appreciated in the last two panels of Figure 5.[14]

[14]In our dynamic simulations, impatient households and entrepreneurs may sometimes find themselves unconstrained even during economic downturns as a result of, e.g., a positive credit limit shock and a negative non-financial shock. In such situations—which are most likely to occur at high LTV ratios—even recessions may be dampened, thereby mitigating business cycle skewness. This explains the small reversal

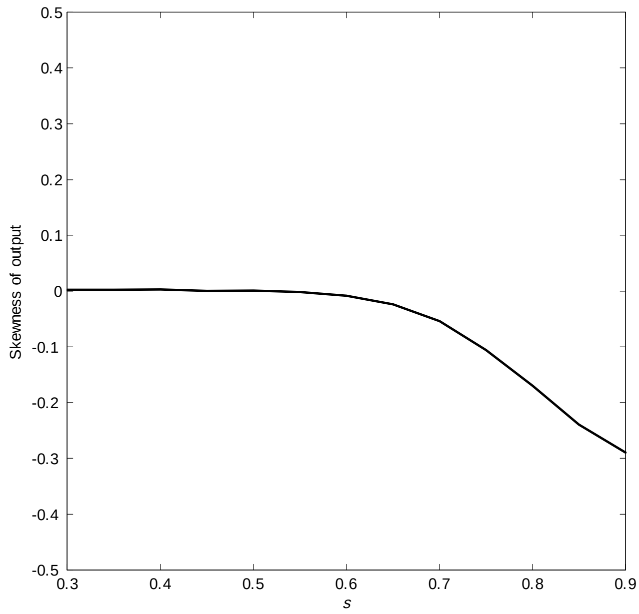

Figure 4: *Skewness of output for different LTV ratios.*
Notes: Numbers are median values from 501 stochastic model simulations of 2000 periods. All time series used to produce business cycle statistics have been preliminarily filtered.

3.3 Skewness and volatility

The Great Moderation is widely regarded as the main development in the statistical properties of the US business cycle since the 1980s. While many have argued that the severity of the Great Recession might have marked the end of this period of relatively tranquil times, there is evidence that the US economy has not reverted back to the levels of volatility observed in the 1970s (see, e.g., Coibion and Gorodnichenko, 2011; Stock and Watson, 2012). Even more important relative to our results, recent statistical evidence has demonstrated that the Great Moderation was never associated with smaller or less frequent downturns, but has been driven exclusively by the characteristics of the expansions, whose magnitude has declined over time (Gadea-Rivas *et al.*, 2014, 2015). Our scope here is not to contribute to the literature on the roots of the Great Moderation, but rather to examine this major statistical development in conjunction with the change in the skewness of the business cycle, which has largely occurred over the same time span.To assess our model's ability to account for these empirical facts, the left panel of Figure 6 reports the standard deviation of output as a function of the average LTV ratio.[15] As discussed in Jensen *et al.* (2015), macroeconomic volatility displays a hump-shaped pattern in response to changes

of investment skewness at $s = 0.90$. We return to this issue in the next subsection.

[15]Having established in the previous subsection that the model displays very little skewness at average LTV ratios below $s \approx 0.6$, we focus on LTV ratios at or above this level in the remainder.

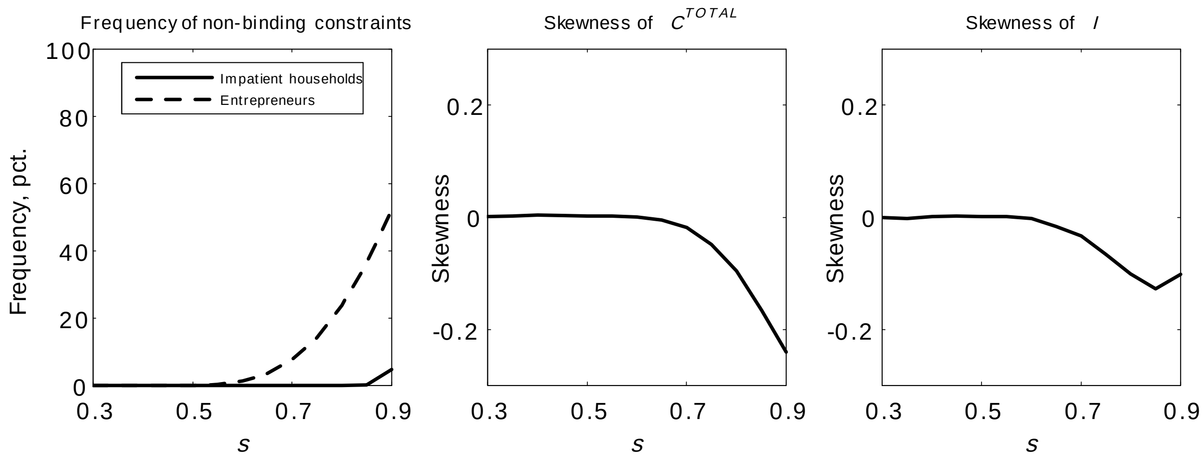

Figure 5: *Left panel: frequency of episodes of non-binding constraints for each agent. Middle and right panel: Skewness of aggregate consumption and investment for different LTV ratios.*

Notes: See the notes to Figure 4.

in the LTV ratio: Starting from low credit limits, higher availability of credit allows financially constrained agents to engage in debt-financed consumption and investment, as dictated by their relative impatience, thus reinforcing the macroeconomic repercussions of shocks that affect their borrowing capacity. This pattern eventually reverses, as higher LTV ratios increase the likelihood that credit constraints become non-binding. In such cases, the consumption and investment decisions of households and entrepreneurs tend to delink from changes in the value of their collateral assets, dampening the volatility of aggregate economic activity.

However, the volatility reversal is much stronger for positive than for negative shocks, in the face of which financial constraints tend to remain binding. This inherent property of our framework indicates that the drop in output volatility observed beyond $s \approx 0.8$ is mostly connected with expansionary periods, as in the evidence reported by Gadea-Rivas *et al.* (2014, 2015). The right panel of Figure 6 confirms this intuition: Here we compare the dispersion of expansionary and contractionary episodes, respectively, as a function of the average LTV ratio. The volatility of expansions is always lower than that of contractions, and declines over a wider range of average credit limits. The volatility of contractions, on the other hand, is declining only at the very end of the range of average LTV ratios we consider. This decline is due to the fact that at very high LTV ratios, financial constraints may sometimes be non-binding even during economic contractions in our simulations. Such situations may arise if, e.g., a negative technology shock coin-

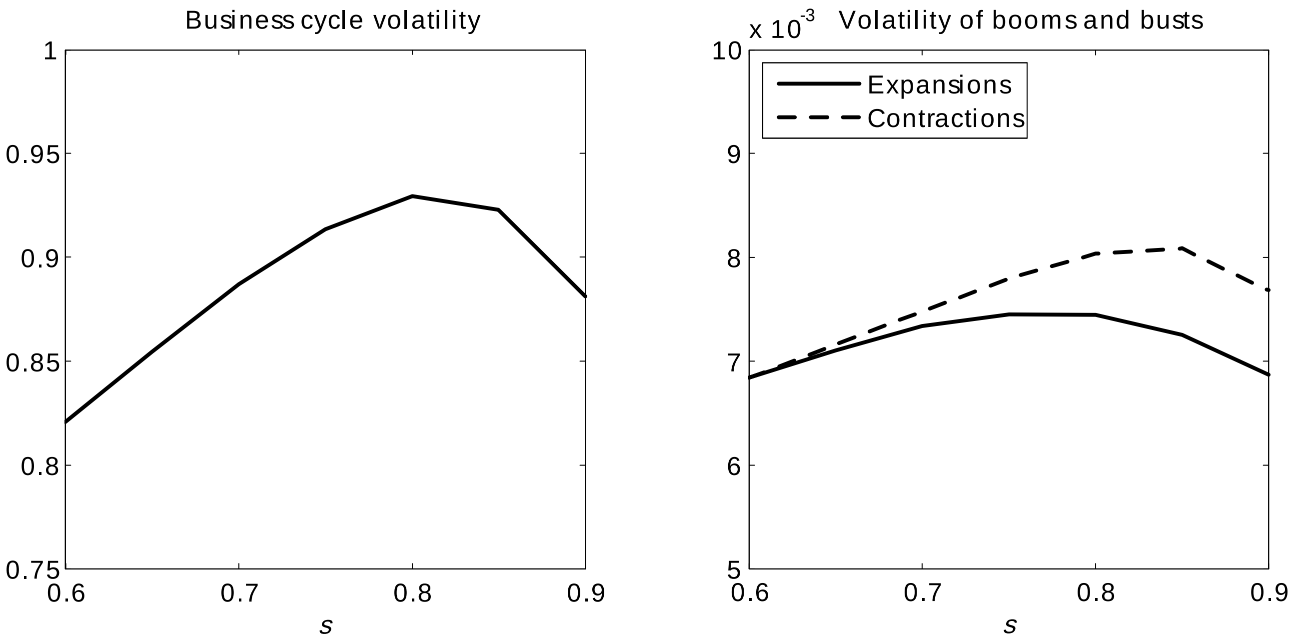

Figure 6: *Left panel: standard deviation of output. Right panel: Interquantile range for contractions (dashed line) and expansions (solid line).*

Notes: See the notes to Figure 4. In the right panel we split our simulated samples into expansions and contractions based on whether filtered output is positive or negative, after which we compute the interquartile range for each of the two subsamples.

cides with a positive credit limit shock. This notwithstanding, the results in Figure 6 show that the empirically observed changes in the volatility of the business cycle and its skewness may be reconciled within our framework: The decline in the overall volatility of the system primarily rests on the attenuation of expansionary movements in real activity, while skewness increases as a result of the widening gap between the magnitude of expansionary and contractionary phases of the cycle, as the average LTV ratio increases. While the left panel of Figure 6 points to a hump-shaped relationship between credit limits and macroeconomic volatility, the key driver of business cycle asymmetry in our framework—occasionally non-binding credit constraints—in itself works as an impetus of lower macroeconomic volatility, *ceteris paribus*. Thus, while our analysis does not warrant the claim that the empirical developments in the volatility and skewness of the business cycle necessarily have the same origin, higher credit limits do eventually lead to a drop in the overall volatility of our model economy by making financial constraints increasingly slack.[16]

[16] A large literature suggests that innovation in the credit market—especially in consumer credit and home mortgages—have played a role in the Great Moderation; see den Haan and Sterk (2010) for a review.

Notably, the increasing prevalence of non-binding credit constraints allows the model to account for different correlations between the volatility and the skewness of the output gap, conditional on different credit limits. Based on the comparison between Figure 4 and the left panel of Figure 6, this correlation is essentially zero up to $s \approx 0.6$, thus turning more and more negative until $s \approx 0.8$ is approached, before finally becoming positive as financial development reaches very advanced stages. These results are reminiscent of the evidence reported by Bekaert and Popov (2015), who document a positive long-run correlation between the second and third moment of output growth in a large cross-section of countries, but also a negative short-run relationship in financially developed economies.[17]

4 Debt overhang and business cycle asymmetries

Several authors have recently pointed to the nature of the boom phase of the business cycle as a key determinant of the subsequent recession. Using data for 14 advanced economies for the period 1870–2008, Jordà *et al.* (2013) find that more credit-intensive expansions tend to be followed by deeper recessions, whether or not the recession is accompanied by a financial crisis. This evidence is consistent with the results of Mian and Sufi (2010), who identify a close connection at the county level in the US between pre-crisis household leverage and the severity of the Great Recession.

In this section we demonstrate that our model is capable of reproducing these empirical facts. To this end, Figure 7 reports the results of the following experiment: Starting in the economy's steady state, we generate a boom-bust cycle for a range of different steady-state debt levels, as reflected by different LTV ratios. In the first 5 periods, we calibrate the size of the expansionary shocks hitting the economy so as to make sure that the boom in output is identical for all the LTV ratios. In periods 6 to 10, we then feed an identical set of contractionary shock realizations into the economy. This ensures that the severity of the recession is determined by the endogenous response of the model at each different LTV ratio.[18] As the figure illustrates, the deepness of the contraction increases with the LTV

[17] Clearly, our model cannot account for the link between the skewness and volatility of output growth in economies at early stages of their financial development. As pointed out by Bekaert and Popov (2015), while occasionally hit by crises and sudden stops, these countries experience periods of rapid economic growth that tend to generate high volatility along with positive skewness.

[18] During both the boom and the bust, the economy is hit by all three types of shocks in each period, keeping their relative sizes fixed in accordance with their standard deviations as calibrated in Subsection 2.7, but setting their persistence parameters to zero, so as to avoid that the shape of the recession may

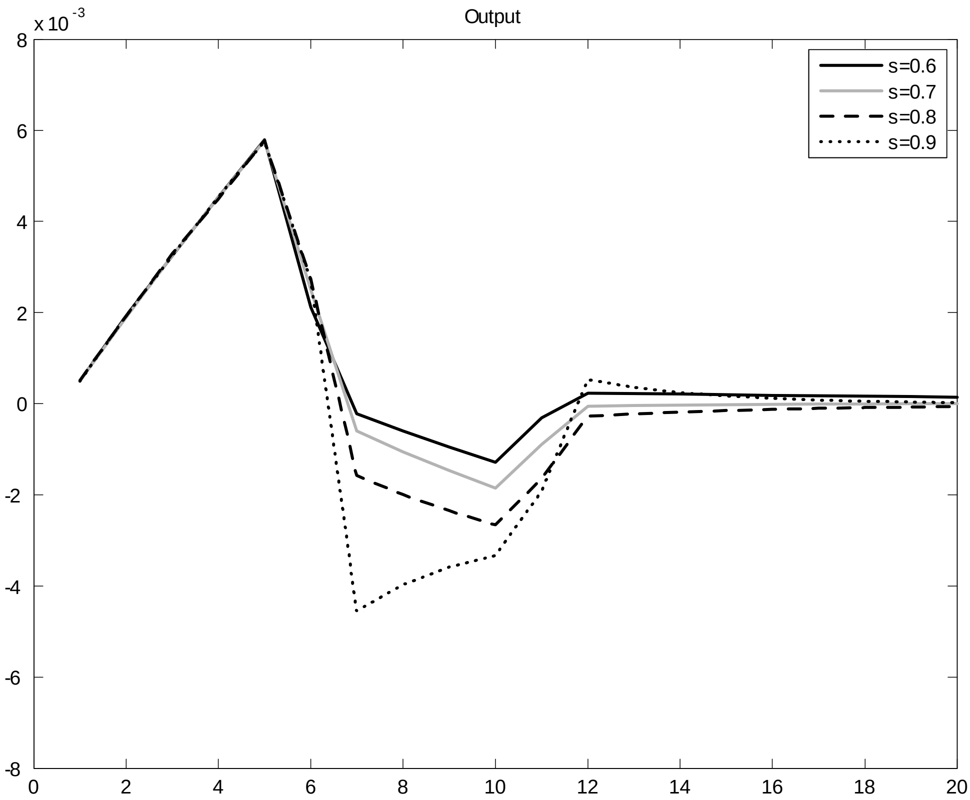

Figure 7: *Boom-bust cycles for different LTV ratios.*

ratio. A boom of a given size is followed by a more severe recession when debt levels are high, as compared with the case of scarcer credit availability. When LTV ratios are high, households and entrepreneurs are more leveraged during the boom, and they therefore need to face a more severe process of deleveraging when the recession hits. By contrast, when credit levels are low, financially constrained agents are precluded from using the credit market to shift consumption and investment forward in time during booms, and are therefore less vulnerable to contractionary shocks.

We next focus on the nature of the boom and how this reflects into the ensuing contraction. The top left panel of Figure 8 compares the path of output in two different boom-bust cycles, while the top right panel shows the corresponding paths for aggregate debt. The dashed line represents a non-financial boom generated by a combination of technology and land demand shocks, while the solid line denotes a financial boom generated by credit limit shocks, calibrated to deliver an identical increase in output during the boom (which again lasts for the first 5 periods). As in the previous experiment, we

be affected by lagged values of the shocks during the boom. We make sure that impatient households and entrepreneurs remain constrained in all periods of each of the experiments reported here, so as to enhance comparability.

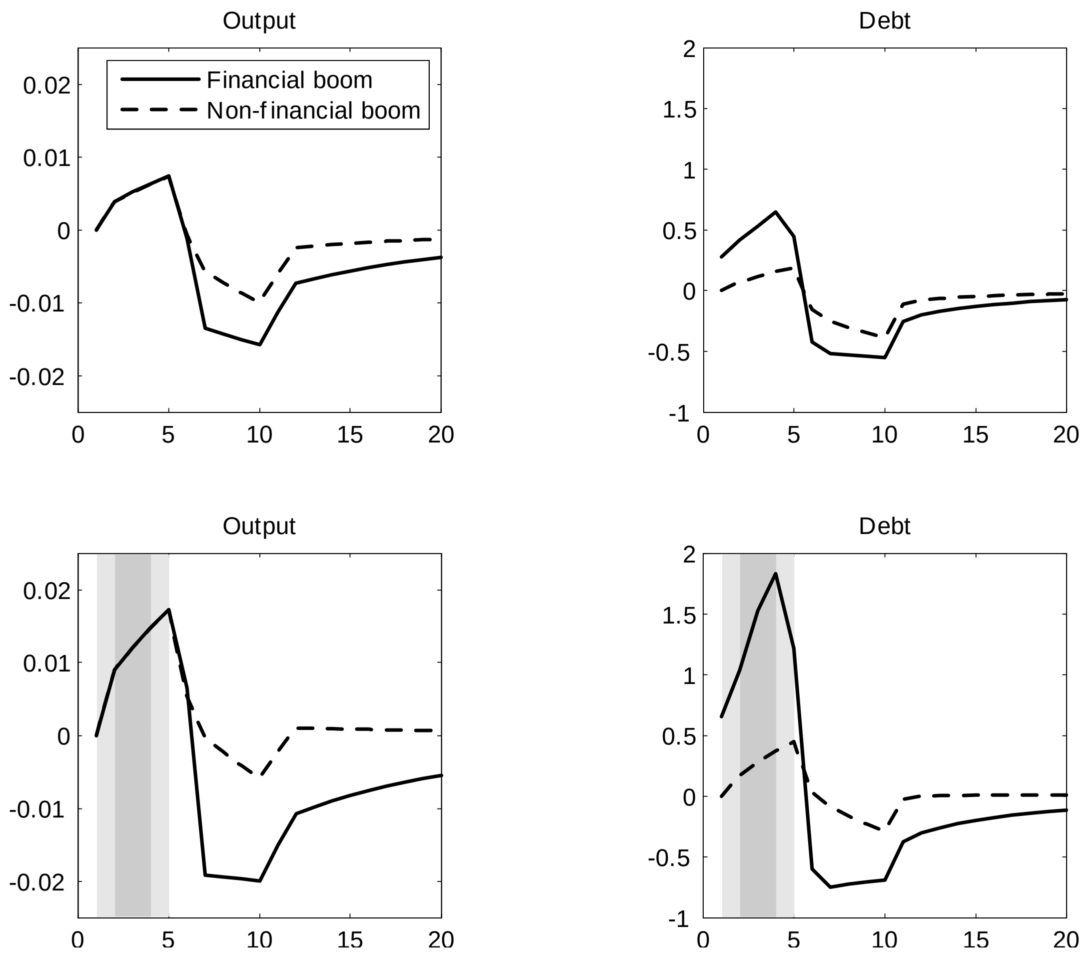

Figure 8: *Boom-bust cycles of output and aggregate debt with normal shocks (top row) and large shocks (bottom row), for* $s = 0.70$.

Notes: Solid lines represent a financial boom, while dashed lines represent a non-financial boom. Light-grey areas denote periods where the entrepreneurs are unconstrained during financial booms; solid-grey periods are ones where all agents are unconstrained during financial booms. Both impatient households and entrepreneurs remain constrained at all times during non-financial booms.

then subject the economy to identical sets of contractionary shocks (of all three types and during periods 6-10) in each of the two cases, so as to isolate the role played by the specific type of boom in shaping the ensuing recession.[19] While the size of the booms in output is identical, the same is not the case for total debt, which displays a larger increase during the financial boom. The consequences of this show up during the subsequent contraction, which is deepest in the aftermath of the financial boom, in line with the empirical results of Jordà *et al.* (2013) and Mian and Sufi (2010).

The previous exercise confirms that the impact of constrained agents' deleveraging increases in the size of their debt. Our focus on occasionally non-binding constraints allows

[19] As in the experiment above, we set the persistence parameters of all the shock processes to zero.

us to dig deeper into this point: While impatient households and entrepreneurs remain constrained at all times in the experiments reported in the top row of Figure 8, we examine the role of non-binding credit constraints in the bottom row of the figure. We do so by repeating the previous exercise for a set of larger, expansionary shocks, so that impatient households and entrepreneurs find themselves unconstrained in response to the positive financial shocks, while keeping the size and composition of the contractionary shocks during the downturn identical to those in the top row of the figure. The debt overhang narrative has even more bite in this case, as the downturn following the financial boom is now more than three times as large as that following the non-financial one. This demonstrates the importance of allowing for occasionally non-binding credit constraints: In the bottom row of Figure 8, impatient households and entrepreneurs are (temporarily) unconstrained during the boom, but become constrained with the onset of the contraction, giving rise to a sharp deleveraging and decline in output. These findings are in line with those of Maffezzoli and Monacelli (2015), who find that the effect of a deleverage shock on output displays an S-shaped pattern with respect to the initial debt level. At low (high) levels of initial debt, a deleverage shock has a moderate effect on output, as agents remain constrained (unconstrained) before and after the shock. The largest macroeconomic effects of such shocks are observed at intermediate debt levels, when agents switch from being unconstrained to being constrained.

5 Concluding comments

We have documented a pattern of stronger negative skewness in the US business cycle over the last decades, and pointed to the concurrent increase in the LTV ratios of households and firms as a potential explanation thereof. To substantiate this claim, we have presented a dynamic general equilibrium model with credit-constrained households and firms, in which we have shown that increasing average LTV ratios translate into a more negatively skewed business cycle, as seen in the data. This finding relies on the occasionally-binding nature of financial constraints: As LTV ratios increase, households and firms are more likely to become temporarily unconstrained during booms, while credit constraints tend to remain binding during downturns.

Our results are of interest to macroprudential policymakers for two main reasons.

First, one focus of such policies has typically been to reduce LTV ratios in order to curb macroeconomic volatility. According to our findings, a reduction of the LTV ratio may have ambiguous effects on business cycle volatility. Even a policy of state-dependent LTV ratios should be carefully designed in order to properly account for the asymmetric role played by credit constraints in booms and busts. A suitable welfare analysis needs to optimally weigh these factors. This is a topic we are investigating in ongoing work. Second, our results add to a recent literature emphasizing that the seeds of the recession are sown during the boom: The nature of the boom phase, as much as its size, is an important determinant of the ensuing downturn, and policymakers should pay close attention to the build-up of credit during expansions in macroeconomic activity. Indeed, Mian *et al.* (2015) find that IMF and OECD forecasts made after large increases in household debt tend to overestimate subsequent output growth, and that those forecasts could be improved by adjusting them downwards to account for past increases in household as well as firm credit.

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Appendices

A Skewness of the US business cycle

In this appendix, we provide additional robustness checks of our main empirical finding, i.e., that the business cycle has become more negatively skewed over time. As documented in the introduction, the skewness of the US business cycle has become increasingly negative in recent decades. This result is obtained by computing the rolling skewness of real GDP over an 80 quarter horizon. The first panel of Figure A.1 shows that the drop in the skewness of the business cycle also obtains by taking an alternative indicator of cyclical movements in real GDP, namely its annualized growth rate: In this case the downward movement is more gradual, while starting earlier in the sample under consideration. The next two panels focus instead on the main components of aggregate (private) demand, showing that also the skewness of (band-pass filtered) consumption and investment display similar downward movements. Taken together, these graphs confirm the overall picture emerging from Figure 1, implying that the skewness decline characterizes not only output, but also its main components, and may be detected using different statistical methods. It is important to stress a point emphasized by Psaradakis and Sola (2003): Their test for skewness has low power when applied to time series that have been pre-filtered to isolate the cyclical component of the series itself. This means that whenever skewness can in fact be detected in filtered series, this can be interpreted as a strong sign of asymmetry.

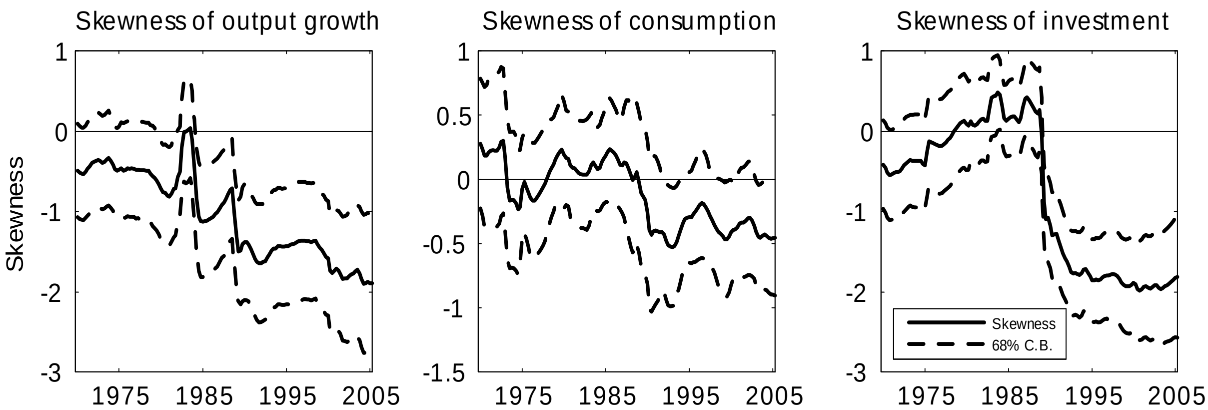

Figure A.1: *Skewness of various variables, US data, 1970Q1–2005Q2.*

Notes: The left panel reports the rolling skewness of the annualized growth rate of real GDP, while the next two panels report the rolling skewness of band-pass filtered consumption and investment. In all graphs we compute the skewness of an 80-quarter forward-looking rolling window. Beginning in 1995Q3, the size of the window is successively reduced by one quarter, as the sample ends in 2015Q2. The final observation, 2005Q2, is thus computed using 40 quarters. The confidence band is computed following Psaradakis and Sola (2003).

Source: Federal Reserve Bank of St. Louis (FRED database).

We also show that the key result reported in Figure 1 is not specific to the choice of a forward-looking rolling window. The left panel of Figure A.2 shows skewness of bandpass-filtered output using instead a centered rolling window, keeping the window length fixed at 80 quarters. In this case, we can extend the sample period for which we display results by an additional 20 quarters without reducing too dramatically the number of observations underlying each data point. As the figure shows, our main result is robust to this change, although in this case, unsurprisingly, skewness becomes significantly negative only at a later date. However, it largely maintains its declining pattern through to 2010. In other words, the choice of a forward-looking window does not seem to be decisive for our results. Next, we remove the Great Recession from our sample to assert that our findings are not driven only by this event. To do so, we use data only up until the 4th quarter of 2007, and apply the band-pass filter to this series. Of course, this means that with an 80 quarter forward-looking window, we would have to end the sample very early. To avoid this, we instead use a 40 quarter forward-looking window, allowing us to plot the skewness of filtered output up until the 4th quarter of 2002. As the right panel of Figure A.2 shows, even in this case we observe a significant drop in output skewness towards the end of the sample, although only in the very last periods.[20] In other words, while the Great Recession clearly is a quantitatively important observation, we find it reassuring that a significant drop in output skewness can be obtained even when this observation is excluded.

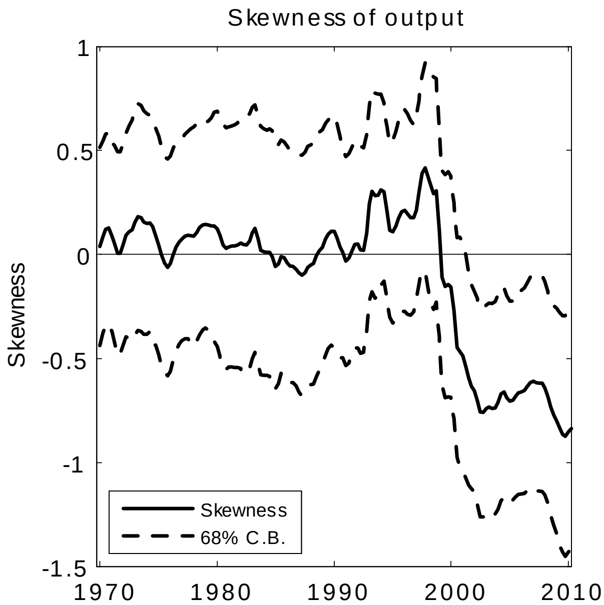

Figure A.2: *Skewness of filtered US output.*

Notes: The left panel shows the rolling skewness of filtered output using a centered, 80-quarter rolling window for the sample period 1970Q1–2010Q2. Beginning in 2005Q3, the size of the window is successively reduced by one quarter, as the sample ends in 2015Q2. The final observation, 2010Q2, is thus computed using 40 quarters backward and 20 quarters forward. The right panel shows the rolling skewness of filtered output using a forward-looking, 40-quarter rolling window for the sample period 1970Q1–2002Q4. Beginning in 1998Q1, the size of the window is successively reduced by one quarter, as the sample ends in 2007Q4. The final observation, 2002Q4, is thus computed using 20 quarters. Source: Federal Reserve Bank of St. Louis (FRED database).

We finally seek to establish a link between output skewness and the LTV measures reported in Figure 2. These are computed from Flow of Funds data from the Board of Governors of the Federal Reserve System. Business liabilities are credit market instruments of nonfinancial corporate and noncorporate business, while business assets include these two sectors' equipment and software as well as real estate at market value, as in Liu *et al.* (2013). For households and nonprofit organizations, we use credit market instruments as liabilities, while assets include real estate at market value plus equipment and software of nonprofit organizations. For further details, see Jensen *et al.* (2015). To test empirically the relationship between output skewness

[20] The tighter window applied in this case partly accounts for this delayed drop, as does the fact that we can only consider developments up until 2002.

Dependent Variable	*Skewness of Real GDP*	
Constant	-6.347 (9.417)	-7.328 (12.016)
Trend	-0.012 (0.009)	-0.013 (0.012)
GDP (in logs)	1.107 (1.118)	1.052 (1.478)
Households' LTV ratio	-5.482^{***} (1.219)	
Firms' LTV ratio		-2.676^{***} (0.932)

Notes: HAC standard errors are reported in brackets, while *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. In each regression, the dependent variable in period t is computed as the skewness of filtered output beginning in period $t+1$, while the regressors are period-t observations.

Table A.1: Skewness of output and credit limits, 1970Q1–2005Q2

and LTV ratios, we regress output skewness against a constant, a trend, the log of real GDP, and each of the LTV measures reported in Figure 2.[21] The results of these regressions are presented in Table A.1. In each regression the coefficient on the LTV ratio is large, negative, and strongly significant. The estimated coefficients imply that a 1 %-point increase in the LTV ratio of households and firms is associated with a drop in the skewness coefficient of output of 0.055 and 0.027, respectively, although we wish to be careful in the interpretation of these numbers. If we include both LTV measures in the regression at the same time, the LTV ratio of households remains negative and strongly significant, while the LTV ratio of firms, while still negative, becomes insignificant.

B First-order conditions

We report the first-order conditions for each type of agent below.

B.1 Patient households

Patient households' optimal behavior is described by the following first-order conditions:

$$\left(C_t^P\right)^{-\sigma_C^P} = \lambda_t^P, \tag{B.1}$$

$$\nu^P \left(1 - N_t^P\right)^{-\sigma_N^P} = \lambda_t^P W_t^P, \tag{B.2}$$

$$\lambda_t^P = \beta^P R_t \mathrm{E}_t \left\{\lambda_{t+1}^P\right\}, \tag{B.3}$$

$$Q_t = \varepsilon_t \frac{\left(H_t^P\right)^{-\sigma_H^P}}{\lambda_t^P} + \beta^P \mathrm{E}_t \left\{ \frac{\lambda_{t+1}^P}{\lambda_t^P} Q_{t+1} \right\}, \tag{B.4}$$

where λ_t^P is the multiplier associated with (3) for $i = P$.

[21] Note that the forward-looking nature of our skewness series avoids concerns of reverse causality.

B.2 Impatient households

The first-order conditions of the impatient households are given by:

$$\left(C_t^I\right)^{-\sigma_C^I} = \lambda_t^I, \tag{B.5}$$

$$\nu^I\left(1-N_t^I\right)^{-\sigma_N^I} = \lambda_t^I W_t^I, \tag{B.6}$$

$$\lambda_t^I - \mu_t^I = \beta^I R_t \mathrm{E}_t\left\{\lambda_{t+1}^I\right\}, \tag{B.7}$$

$$Q_t = \varepsilon_t \frac{\left(H_t^I\right)^{-\sigma_H^I}}{\lambda_t^I} + \beta^I \mathrm{E}_t\left\{\frac{\lambda_{t+1}^I}{\lambda_t^I} Q_{t+1}\right\} + s_t \frac{\mu_t}{\lambda_t^I}\frac{\mathrm{E}_t\left\{Q_{t+1}\right\}}{R_t}, \tag{B.8}$$

where λ_t^I is the multiplier associated with (5) for $i = I$, and μ_t^I is the multiplier associated with (6). Additionally, the complementary slackness condition

$$\mu_t^I\left(B_t^I - s_t \frac{\mathrm{E}_t\left\{Q_{t+1}\right\} H_t^I}{R_t}\right) = 0, \tag{B.9}$$

must hold along with $\mu_t^I \geq 0$ and (6).

B.3 Entrepreneurs

The optimal behavior of the entrepreneurs is characterized by:

$$\left(C_t^E\right)^{-\sigma_C^E} = \lambda_t^E, \tag{B.10}$$

$$\lambda_t^E - \mu_t^E = \beta^E R_t \mathrm{E}_t\left\{\lambda_{t+1}^E\right\}, \tag{B.11}$$

$$\lambda_t^E = \psi_t^E\left[1 - \frac{\Omega}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2 - \Omega\frac{I_t}{I_{t-1}}\left(\frac{I_t}{I_{t-1}} - 1\right)\right] + \beta^E \Omega \mathrm{E}_t\left\{\psi_{t+1}^E\left(\frac{I_{t+1}}{I_t}\right)^2\left(\frac{I_{t+1}}{I_t} - 1\right)\right\}, \tag{B.12}$$

$$\psi_t^E = \beta^E r_t^K \mathrm{E}_t\left\{\lambda_{t+1}^E\right\} + \beta^E(1-\delta)\mathrm{E}_t\left\{\psi_{t+1}^E\right\} + \mu_t^E s_t \frac{\mathrm{E}_t\left\{Q_{t+1}^K\right\}}{R_t}, \tag{B.13}$$

$$Q_t = \beta^E r_t^H \mathrm{E}_t\left\{\frac{\lambda_{t+1}^E}{\lambda_t^E}\right\} + \beta^E \mathrm{E}_t\left\{\frac{\lambda_{t+1}^E}{\lambda_t^E} Q_{t+1}\right\} + s_t \frac{\mu_t^E}{\lambda_t^E}\frac{\mathrm{E}_t\left\{Q_{t+1}\right\}}{R_t}, \tag{B.14}$$

where λ_t^E, μ_t^E and ψ_t^E are the multipliers associated with (9), (10), and (11), respectively. Moreover,

$$\mu_t^E\left(B_t^E - s_t \mathrm{E}_t\left\{\frac{Q_{t+1}^K K_t + Q_{t+1} H_t^E}{R_t}\right\}\right) = 0, \tag{B.15}$$

holds along with $\mu_t^E \geq 0$ and (11). Finally, the definition of Q_t^K implies that

$$Q_t^K = \psi_t^E / \lambda_t^E. \tag{B.16}$$

B.4 Firms

The first-order conditions for the firms determine the optimal demand for the input factors:

$$\begin{aligned}\alpha\gamma Y_t/N_t^P &= W_t^P,\\ (1-\alpha)\,\gamma Y_t/N_t^I &= W_t^I,\\ (1-\gamma)\,(1-\phi)\,\mathrm{E}_t\,\{Y_{t+1}\}\,/K_t &= r_t^K,\\ (1-\gamma)\,\phi\mathrm{E}_t\,\{Y_{t+1}\}\,/H_t^E &= r_t^H.\end{aligned}$$

In a competitive equilibrium, these first-order conditions can be rewritten to account for the different masses of supplied factors:

$$\alpha\gamma n Y_t/\left[(1-n_I-n_E)\,N_t^P\right] = W_t^P, \tag{B.17}$$

$$(1-\alpha)\,\gamma n Y_t/\left(n_I N_t^I\right) = W_t^I, \tag{B.18}$$

$$(1-\gamma)\,(1-\phi)\,n\mathrm{E}_t\,\{Y_{t+1}\}\,/\,(n_E K_t) = r_t^K, \tag{B.19}$$

$$(1-\gamma)\,\phi n\mathrm{E}_t\,\{Y_{t+1}\}\,/\left(n_E H_t^E\right) = r_t^H. \tag{B.20}$$

where $n \equiv \left[(1-n_I-n_E)^{\alpha}\,(n_I)^{1-\alpha}\right]^{\gamma} n_E^{1-\gamma}$.

B.5 Equilibrium

An equilibrium is sequences of quantities and prices, $\{Y_t,\ C_t^P,\ C_t^I,\ C_t^E,\ I_t,\ H_t^P,\ H_t^I,\ H_t^E,\ K_t,\ N_t^P,\ N_t^I,\ B_t^P,\ B_t^I,\ B_t^E\}_{t=0}^{\infty}$ and $\{\lambda_t^P,\ \lambda_t^I,\ \lambda_t^E,\ \mu_t^I,\ \mu_t^E,\ \psi_t^E,\ r_t^K,\ r_t^H,\ Q_t^K,\ Q_t,\ W_t^P,\ W_t^I,\ R_t\}_{t=0}^{\infty}$, respectively, which conditional on sequences of shocks $\{A_t, \varepsilon_t, s_t\}_{t=0}^{\infty}$ and initial conditions, satisfy the optimality conditions [(B.1), (B.2), (B.3), (B.4), (B.5), (B.6), (B.7), (B.8), (B.10), (B.11), (B.12), (B.13), (B.14), and (B.16)], the budget and credit constraints [(5), (6), (9), and (11)], as well as the technological constraints and market-clearing conditions [(10), (12), (14), (15), (16), (B.17), (B.18), (B.19), and (B.20)].

C Baseline parameter values

Agents are assumed to be of identical mass; $n^I = n^E = 1/3$. Discount factors are set as $\beta^I = \beta^E = 0.97$ and $\beta^P = 0.99$. We assume that households have log utility in land services and non-durable consumption, i.e., $\sigma_C^i = 1$ for $i = \{P, I, E\}$, and similarly $\sigma_H^i = 1$ for $i = \{P, I\}$. The Frisch elasticity of labor supply is given by the inverse of σ_N^i times the steady-state ratio of leisure to work. Keeping the latter to around 3 for both types of households, a Frisch elasticity of labor supply of 1/3 implies $\sigma_N^i = 9$, $i = \{P, I\}$. We use $\nu^i = 0.27$ for $i = \{P, I\}$, in order to ensure that patient households work about 1/4 of their time in steady state, and impatient households slightly more. We calibrate the model so as to obtain a steady-state ratio of residential land to output around 1.45, and of commercial land to output around 0.65, both at the annual level, following values reported by Liu *et al.* (2013). This requires a value of $\varepsilon = 0.085$.

As to the production technology, we set $\gamma = 0.7$, implying a non-labor share in the production function slightly below 1/3. We set the labor income share of patient households to $\alpha = 0.7$, in line with available estimates: Iacoviello (2005) obtains an estimate of 0.64 by matching impulse responses from his model to those from a VAR, while Iacoviello and Neri (2010) find a value of 0.79 using Bayesian estimation. The parameter ϕ, which multiplied by $(1-\gamma)$ measures land's share of inputs, is set to 0.13, somewhat higher than the estimated value from Liu *et al.* (2013). We assume a capital depreciation rate of $\delta = 0.035$. The implied annual ratio of capital to output is around 1.15, as in Liu *et al.* (2013). For the investment adjustment cost parameter, Ω, empirical estimates from estimated general equilibrium models range from nearly to zero in Liu *et al.* (2013) to above 10 in Christiano *et al.* (2014). We choose an intermediate value of $\Omega = 4$.

For the technology shock, we choose values similar to those applied in most of the real business cycle literature, $\rho_A = 0.97$ and $\sigma_A = 0.005$ (see., e.g., Mandelman *et al.*, 2011). These values are largely in line with those obtained from recently estimated DSGE models; see, e.g., Jermann and Quadrini (2012) and Iacoviello (2015). For the land demand shock, we set $\rho_\varepsilon = 0.98$, reflecting the high degree of persistence of this shock found by Liu *et al.* (2013), and $\sigma_\varepsilon = 0.06$, in line with these authors as well as Iacoviello and Neri (2010) and Iacoviello (2015). For the credit limit shock, we set the persistence parameter $\rho_s = 0.98$, in line with estimated coefficients from univariate regressions of the LTV-series displayed in the Introduction. We then calibrate σ_s to obtain a standard deviation of the process for $\log s_t - \log s$ of around 0.06, as estimated by Liu *et al.* (2013). This implies $\sigma_s = 0.0119$. These values are very close to those reported by Jermann and Quadrini (2012), while Iacoviello (2015) finds a somewhat lower persistence.

D Additional figures

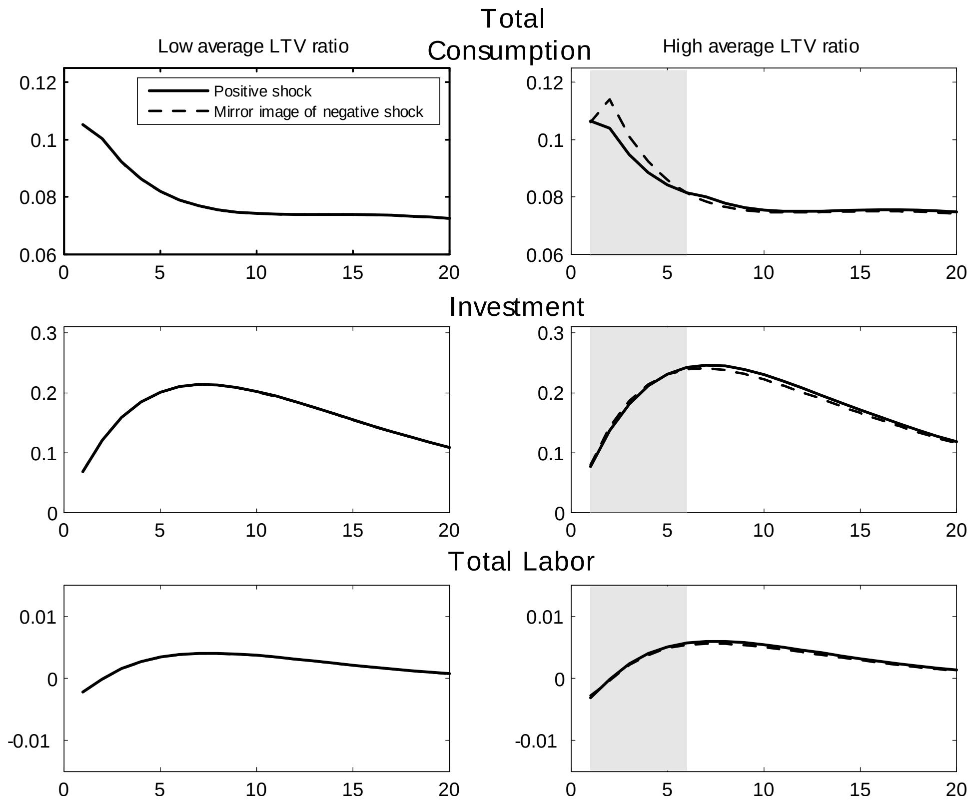

Figure D.1: *Impulse responses of key variables to a large (20 standard deviations) technology shock for two different LTV ratios;* $s = 0.35$ *(left column) and* $s = 0.70$ *(right column).*

Notes: Light-grey periods are ones where the entrepreneurs are unconstrained; solid-grey periods are ones where all agents are unconstrained.

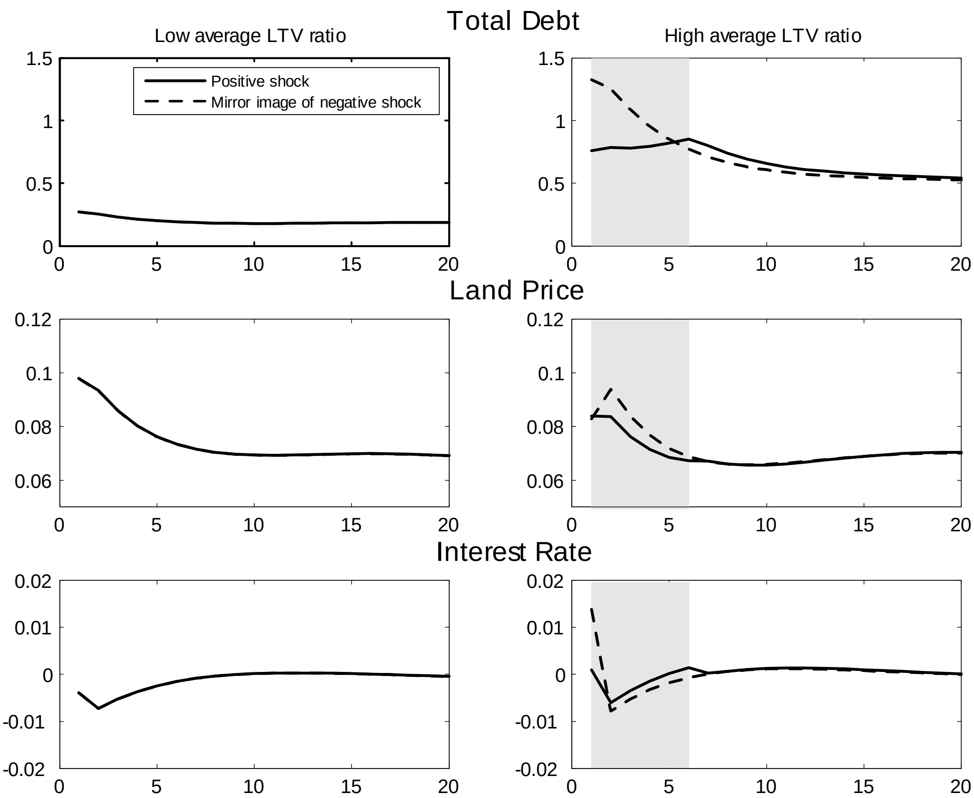

Figure D.2: *Impulse responses of key variables to a large (20 standard deviations) technology shock for two different LTV ratios; $s = 0.35$ (left column) and $s = 0.70$ (right column).*

Notes: Light-grey periods are ones where the entrepreneurs are unconstrained; solid-grey periods are ones where all agents are unconstrained.

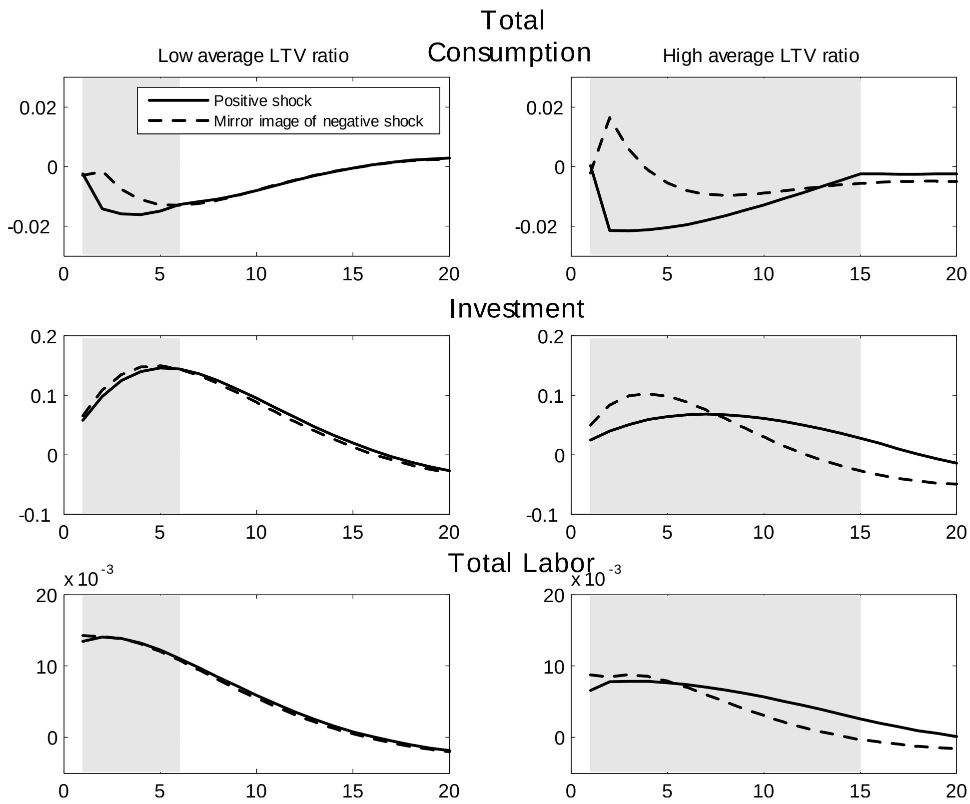

Figure D.3: *Impulse responses of key variables to a large (20 standard deviations) land demand shock for two different LTV ratios;* $s = 0.35$ *(left column) and* $s = 0.70$ *(right column).*

Notes: Light-grey periods are ones where the entrepreneurs are unconstrained; solid-grey periods are ones where all agents are unconstrained.

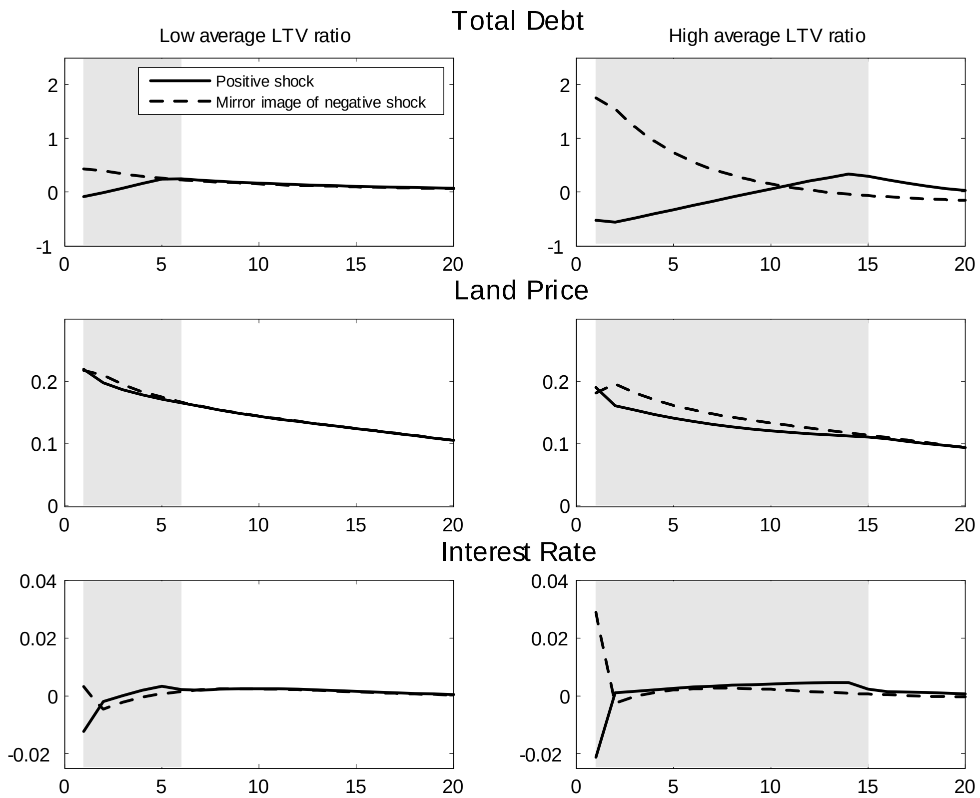

Figure D.4: *Impulse responses of key variables to a large (20 standard deviations) land demand shock for two different LTV ratios; $s = 0.35$ (left column) and $s = 0.70$ (right column).*

Notes: Light-grey periods are ones where the entrepreneurs are unconstrained; solid-grey periods are ones where all agents are unconstrained.

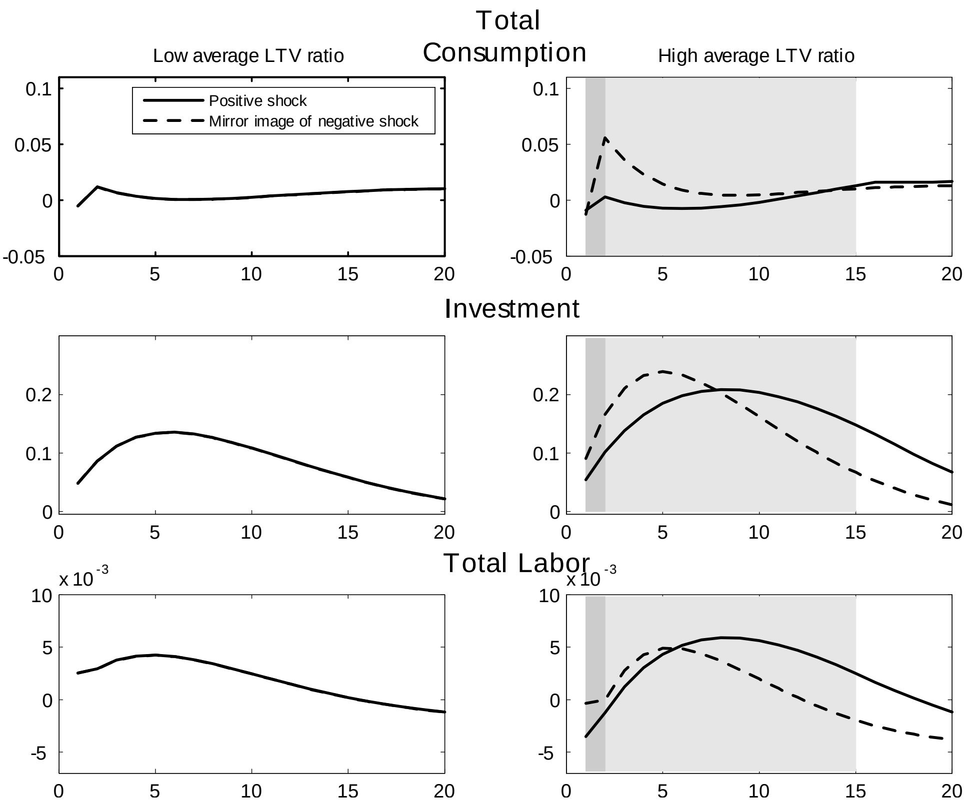

Figure D.5: *Impulse responses of key variables to a large (20 standard deviations) credit limit shock for two different LTV ratios; s = 0.35 (left column) and s = 0.70 (right column).*

Notes: Light-grey periods are ones where the entrepreneurs are unconstrained; solid-grey periods are ones where all agents are unconstrained.

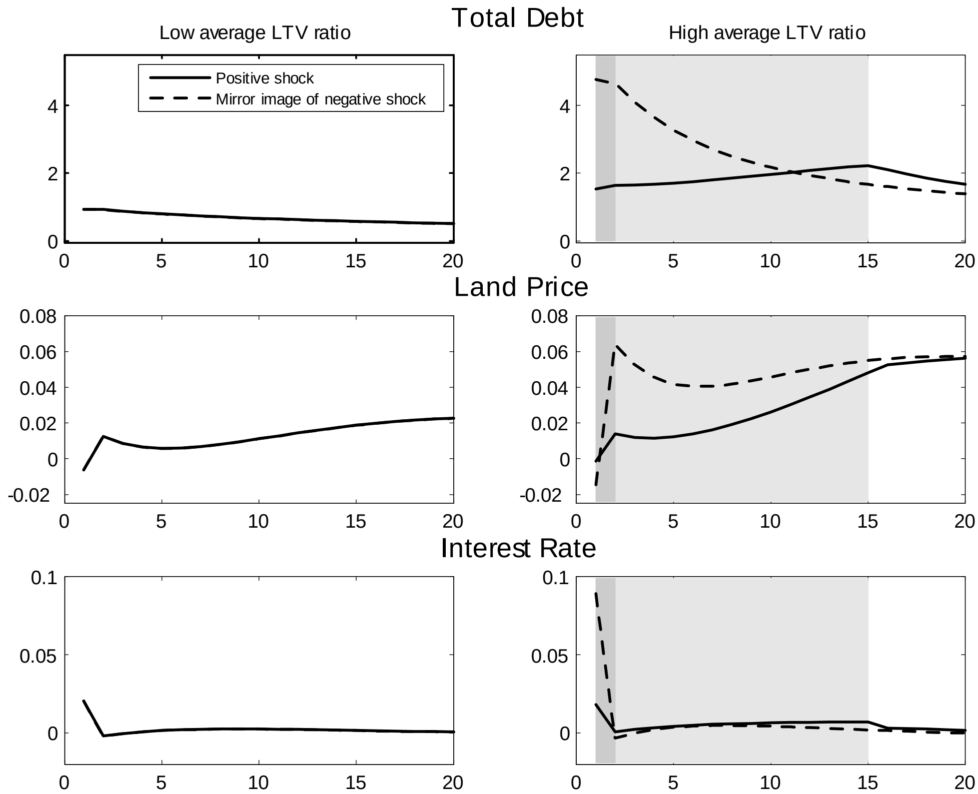

Figure D.6: *Impulse responses of key variables to a large (20 standard deviations) credit limit shock for two different LTV ratios; s = 0.35 (left column) and s = 0.70 (right column).*

Notes: Light-grey periods are ones where the entrepreneurs are unconstrained; solid-grey periods are ones where all agents are unconstrained.