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Jensen, Henrik; Petrella, Ivan; Ravn, Søren Hove; Santoro, Emiliano

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Leverage and Deepening Business-Cycle Skewness

By Henrik Jensen, Ivan Petrella, Søren Hove Ravn, and Emiliano Santoro

We document that the United States and other G7 economies have been characterized by an increasingly negative business-cycle asymmetry over the last three decades. This finding can be explained by the concurrent increase in the financial leverage of households and firms. To support this view, we devise and estimate a dynamic general equilibrium model with collateralized borrowing and occasionally binding credit constraints. Improved access to credit increases the likelihood that financial constraints become nonbinding in the face of expansionary shocks, allowing agents to freely substitute inter-temporally. Contractionary shocks, however, are further amplified by drops in collateral values, since constraints remain binding. As a result, booms become progressively smoother and more prolonged than busts. Finally, in line with recent empirical evidence, financially driven expansions lead to deeper contractions, as compared with equally sized nonfinancial expansions. (JEL D14, E23, E32, E44)

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 empirical regularity, reporting that the magnitude of contractions tends to be larger than that of expansions; see, among others, Neftçi (1984), Hamilton (1989), Sichel (1993) and,
more recently, Morley and Piger (2012) and Adrian, Boyarchenko, and Giannone (2019). While these studies have generally indicated that business fluctuations are negatively skewed, the possibility that business-cycle asymmetry has changed over time has been overlooked. Yet, the shape of the business cycle has evolved over the last three decades: for instance, since the mid-1980s the US economy has displayed a marked decline in macroeconomic volatility, a phenomenon known as the Great Moderation (Kim and Nelson 1999, McConnell and Perez-Quiros 2000). This paper documents that, over the same period, the skewness of the US business cycle has become increasingly negative. Our key contribution is to show that occasionally binding financial constraints, combined with a sustained increase in financial leverage, allow us to account for several facts associated with the evolution of business-cycle asymmetry.

Figure 1 reports the post-WWII rate of growth of US real GDP, together with the 68 percent and 90 percent confidence intervals from a Gaussian density fitted on pre- and post-1984 data. Three facts stand out: first, as discussed above, the US business cycle has become less volatile in the second part of the sample, even if we take into account the major turmoil induced by the Great Recession. Second, real GDP growth displays large swings in both directions during the first part of the sample, while in the post-1984 period, the large downswings associated with the three recessionary episodes are not matched by similar-sized upswings. In fact, if we examine the size of economic contractions in conjunction with the drop in volatility occurring since the mid-1980s, it appears that recessions have become relatively more “violent,” whereas the ensuing recoveries have become smoother, as recently pointed out by Fatás and Mihov (2013). Finally, recessionary episodes have become less frequent, thus implying more prolonged expansions.

These properties, which are shared by all the G7 economies, translate into business cycles displaying increasingly negative asymmetry over the last three decades. Explaining this pattern represents a challenge for existing business-cycle models. To meet this, a theory is needed that involves both nonlinearities and a secular development of the underlying mechanism, so as to shape the evolution in business-cycle skewness. As for the first prerequisite, 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, Eisenbach, and Sannikov (2013). In expansions, households and firms may find it optimal to borrow less than their available credit limit. Instead, financial constraints tend to be binding during recessions, so that borrowing is tied to the value of collateral assets. The resulting nonlinearity translates into a negatively skewed business cycle. As for the second prerequisite, the past decades have witnessed a major deregulation of financial markets, with one result being a substantial increase in the degree of leverage of advanced economies. To see this, Figure 2 reports the credit-to-GDP and the loan-to-asset (LTA) ratios of both households and the corporate sector in the United States.1

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1 As we discuss in online Appendix A, the aggregate LTA ratios reported in Figure 2 are likely to understate the actual loan-to-value (LTV) requirements faced by the marginal borrower. While alternative measures may yield higher LTV ratios, they point to the same behavior of leverage over time (see also Graham, Leary, and Roberts 2015 and Jordà, Schularick, and Taylor 2017).
process is also confirmed, e.g., by Jordà, Schularick, and Taylor (2017) in a large cross section of countries.

Based on these insights, the objective of this paper is to propose a structural explanation of deepening business-cycle asymmetry. To this end, we devise and estimate a dynamic stochastic general equilibrium (DSGE) model that allows for the collateral constraints faced by the firms and a fraction of the households not to bind at all points in time. We examine the model in the presence of a realistic increase in the maximum loan-to-value (LTV) ratios facing both households and firms. Due to easier access to credit, the likelihood that collateral constraints become nonbinding increases when expansionary shocks hit. The magnitude of the resulting boom is therefore attenuated as agents can freely smooth their actions over time. The model predicts this is typically the case for corporate borrowing. By contrast, financially constrained households never find themselves unconstrained, primarily because their debt contracts are mostly long-term, so that shocks tend to affect a relatively small part of the stock of debt being refinanced in each period.² In the face of contractionary shocks, instead, both types of borrowers tend to remain financially constrained. In light of these effects, business cycles become increasingly negatively

²However, the presence of long-term household borrowing proves to be important to reproduce other key features of changing business-cycle asymmetry. Primarily, the substantial increase in the duration of expansions that has been observed since the mid-1980s.
skewed. Following an increase in household and corporate leverage, as observed in the post-1984 sample, the model accounts for up to 50 percent of the asymmetry in the growth of real GDP, as measured by both the skewness and the ratio between the downside and the upside semivolatility of GDP growth. The model also predicts that the average duration of contractions does not change much as leverage increases, whereas that of expansions increases substantially in the post-1984 sample, closely in line with the changes observed in the data.

We then juxtapose the deepening in business-cycle asymmetry with the Great Moderation in macroeconomic volatility. While increasing leverage cannot in itself account for the Great Moderation, our analysis shows that the deepening asymmetry of the business cycle is compatible with a drop in its volatility. Additionally, the decline in macroeconomic volatility mostly rests on the characteristics of the expansions, whose magnitude declines as an effect of collateral constraints becoming increasingly lax. This is in line with the empirical findings of Gadea Rivas et al. (2014, 2015), who show that neither changes to the depth nor to the frequency of recessionary episodes account for the stabilization of macroeconomic activity in the United States.3

3 In this respect, downward wage rigidity has recently been pointed to as an alternative source of macroeconomic asymmetry (see Abbritti and Fahr 2013). However, for this to act as a driver of deepening business-cycle asymmetry, one would need to observe stronger rigidity over time. Most importantly, even if such a mechanism was at work, the resulting change in the skewness of the business cycle would primarily rest on the emergence of more...
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, Schularick, and Taylor (2013) reports 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, financially driven expansions lead to deeper contractions, when compared to similar-sized expansions generated by nonfinancial shocks. Both exercises emphasize that, following a contractionary shock, the aggregate repercussions of financially 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 a debt overhang is consistent with the results of Mian and Sufi (2010), who identify a close connection at the county level in the United States between pre-crisis growth of household leverage and the severity of the Great Recession. Likewise, Giroud and Mueller (2017) documents that, over the same period, counties with highly leveraged firms suffered larger employment losses.

Our analysis stresses the functioning of occasionally binding financial constraints in combination with a sustained increase in financial leverage. This is consistent with existing accounts of the widespread financial liberalization that started in the United States during the 1980s, which provide evidence of a relaxation of financial constraints over time (see, e.g., Justiniano and Primiceri 2008). For households, Dynan, Elmendorf, and Sichel (2006) and Campbell and Hercowitz (2009) have discussed how the wave of financial deregulation taking place in the early 1980s paved the way for a substantial reduction in down payment requirements and the rise of the subprime mortgage market. Combined with the boom in securitization some years later, this profoundly transformed household credit markets and gave rise to the leveraging process observed in Figure 2. As for the corporate sector, the period since around 1980 has witnessed the emergence of a market for high-risk, high-yield bonds (Gertler and Lown 1999) along with enhanced access to both equity markets and bank credit for especially small- and medium-sized firms (Jermann and Quadrini 2009). Over the same period, the investment-cash flow sensitivity in the United States has declined substantially, a fact interpreted by several authors as an alleviation of firms’ financial frictions (see, e.g., Ağca and Mozumdar 2008 and Brown and Petersen 2009). Our findings point to these developments as an impetus of the deepening asymmetry of the US business cycle observed during the same period.

The observation that occasionally binding credit constraints may give rise to macroeconomic asymmetries is not new. Mendoza (2010) explores this idea in the

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4 Specifically, Brown and Petersen (2009) shows that the investment-cash flow sensitivity declined from around 0.3–0.4 in the 1970–1981 period to around 0.1–0.2 in the post-1982 period.
context of a small open economy facing a constraint on its access to foreign credit. As this constraint becomes binding, the economy enters a “sudden stop” episode characterized by a sharp decline in consumption. Maffezzoli and Monacelli (2015) show that the aggregate implications of financial shocks are state dependent, with the economy’s response being greatly amplified in situations where agents switch from being financially unconstrained to being constrained. In a similar spirit, Guerrieri and Iacoviello (2017) reports that house prices exerted a much larger effect on private consumption during the Great Recession—when credit constraints became binding—than in the preceding expansion. While all these studies focus on specific economic disturbances and/or historical episodes, a key insight of this paper is to show how different evolving traits of business-cycle asymmetry may be accounted for by a secular process of financial liberalization, conditional on both financial and nonfinancial disturbances.

We document a strong connection between leverage and business-cycle asymmetry across the G7 countries. This result is related to the findings of Jordà, Schularick, and Taylor (2017), who report a positive correlation between the skewness of real GDP growth and the credit-to-GDP ratio for a large cross section of countries observed over a long time span. Popov (2014) exclusively focuses on business-cycle asymmetry in a large panel of developed and developing countries, documenting two main results. First, the average business-cycle skewness across all countries became markedly negative after 1991, consistent with our findings. Second, this pattern is particularly distinct in countries that liberalized their financial markets. Also, Bekaert and Popov (2013) examines a large cross section of countries, reporting that more financially developed economies have more negatively skewed business cycles. Finally, Rancière, Tornell, and Westermann (2008) establishes a negative cross-country relationship between real GDP growth and the skewness of credit growth in financially liberalized countries. While we focus on the asymmetry of output, we observe a similar pattern for credit, making our results comparable with their findings. On a more general note, all of these studies focus on the connection between business-cycle skewness and financial factors in the cross-country dimension, whereas we examine how financial leverage may have shaped various dimensions of business-cycle asymmetry over time.

The rest of the paper is organized as follows. In Section I, we report a host of evidence on the connection between leverage and changes in the shape of the business cycle. Section II inspects the key mechanisms at play in our narrative within a simple two-period model. Section III presents our DSGE model, and Section IV discusses its solution and estimation. Section V reports the quantitative results based on the DSGE model. Section VI shows that the model is capable of producing the type of debt-overhang recession emphasized in recent empirical studies. Section VII concludes. The online appendices contain supplementary material concerning the model solution and various empirical and computational details.

I. Empirical Evidence

We first examine various aspects of business-cycle asymmetry in the United States, and how they have changed over the last three decades. We then enlarge our view
to other G7 countries, and investigate how changes in business-cycle asymmetry connect to the role of leverage. Finally, we take advantage of cross-sectional variation across US states to document an empirical relationship between household leverage and the deepness of state-level contractions during the Great Recession.

### A. Changing Business-Cycle Asymmetry

A number of empirical studies have documented a major reduction in the volatility of the US business cycle since the mid-1980s. In this section, we document changes in the asymmetry of the cycle that have occurred over the same time span. Table 1 reports the skewness of the rate of growth of different macroeconomic aggregates in the pre- and post-1984 period.

The skewness is typically negative and not too distant from zero in the first part of the sample, but becomes more negative thereafter. To supplement this finding, we employ a battery of normality tests, which all reject normality in the second subsample, regardless of how the growth rate of real GDP is computed. For instance, we use the Kolmogorov-Smirnov test with estimated parameters (see Lilliefors 1967), with the null hypothesis being that (year-on-year) GDP growth data in either of the two periods are drawn from a normal distribution: this is strongly rejected for the second subsample ($p$-value $= 0.004$), whereas it cannot be rejected in the first one ($p$-value $= 0.289$).

### Table 1—Skewness of the US Business Cycle

<table>
<thead>
<tr>
<th></th>
<th>Quarter-on-quarter growth</th>
<th>Year-on-year growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>$-0.118$ $[-0.325; 0.088]$</td>
<td>$-0.098$ $[-0.285; 0.073]$</td>
</tr>
<tr>
<td></td>
<td>$-1.212$ $[-1.559; -0.573]$</td>
<td>$-1.304$ $[-1.516; -0.936]$</td>
</tr>
<tr>
<td>Consumption</td>
<td>$-0.506$ $[-1.134; 0.128]$</td>
<td>$-0.202$ $[-0.368; -0.038]$</td>
</tr>
<tr>
<td></td>
<td>$-0.468$ $[-0.725; -0.119]$</td>
<td>$1.000$ $[-1.181; -0.737]$</td>
</tr>
<tr>
<td>Investment</td>
<td>$-0.210$ $[-0.497; 0.096]$</td>
<td>$-0.007$ $[-0.280; 0.229]$</td>
</tr>
<tr>
<td></td>
<td>$-0.827$ $[-1.161; -0.277]$</td>
<td>$-1.399$ $[-1.684; -0.983]$</td>
</tr>
</tbody>
</table>

**Notes:** For different macroeconomic aggregates, we report the coefficient of skewness computed on the quarter-on-quarter and year-on-year growth rates, over the 1947:I–1984:II and 1984:III–2016:II samples. Sixty-eight percent confidence intervals (in brackets) are constructed by bootstrapping with 5,000 replications.

**Source:** Federal Reserve Economic Data

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5 Online Appendix B1 reports measures of time-varying volatility and skewness of real GDP growth, based on a nonparametric estimator. The downward pattern in business-cycle skewness emerges as a robust feature of the data, along with the widely documented decline in macroeconomic volatility.

6 Additional normality tests are reported in online Appendix B2. We also check that the drop in the skewness does not result from a moderate asymmetry in the first part of the sample being magnified by a fall in the volatility, such as the Great Moderation. The skewness of a random variable is defined as $m_3/\sigma^3$, where $m_3$ is the third central moment of the distribution and $\sigma$ denotes its standard deviation: therefore, an increase in the absolute size of the skewness could merely reflect a fall in $\sigma$, with $m_3$ remaining close to invariant. However, this is not the case, as $m_3 = -2.817$ for the year-on-year growth rate of real GDP in the pre-1984 sample, while it equals $-6.875$ afterward.
Another way to highlight changes in the shape of the business cycle is to compare the upside and the downside semivolatilities of real GDP growth over the two subsamples. The upside (downside) semivolatility is obtained as the square root of the average of the squared deviation from the mean of observations that are above (below) the mean. The overall volatility of the business cycle during the Great Moderation has dropped by more than 40 percent, compared to the pre-moderation period (from 3.07 to 1.75 percent, when calculated on year-on-year GDP growth).

However, as indicated in Table 2, this drop has not been symmetric. In fact, whereas the upside and downside semivolatilities are roughly equal in the pre-moderation sample, in the post-1984 sample the downside semivolatility is around 35 percent larger than its upside counterpart, when calculated on year-on-year GDP growth. As highlighted in Figure 1, this implies an increase in the smoothness of the expansions, indicating that the emergence of the Great Moderation mostly rests on the characteristics of the upsides of the cycle, as recently argued by Gadea Rivas et al. (2014, 2015). All in all, our evidence suggests that the US business cycle has become more asymmetric in the last three decades.

The next step in the analysis consists of translating changes in the business-cycle asymmetry into some explicit measure of the deepness of economic contractions, while accounting for time-variation in the dispersion of the growth rate process. In line with Jordà, Schularick, and Taylor (2017), the first column of Table 3 reports the fall of real GDP during a given recession, divided by the duration of the recession itself: this measure is labeled as “violence.”

Comparing the violence of the contractionary episodes before and after 1984, we notice that the 1991 and 2001 recessions have not been very different from

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Table 2—US Business-Cycle Volatility and Semivolatilities

<table>
<thead>
<tr>
<th></th>
<th>GDP growth (quarter-on-quarter)</th>
<th>GDP growth (year-on-year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>σ</td>
<td>4.702</td>
<td>2.358</td>
</tr>
<tr>
<td>σ−/σ+</td>
<td>1.035</td>
<td>1.289</td>
</tr>
<tr>
<td></td>
<td>[0.977; 1.0940]</td>
<td>[1.141; 1.409]</td>
</tr>
</tbody>
</table>

Notes: Table 2 reports the volatility of real GDP growth (both on a quarter-on-quarter and on a year-on-year basis) and the ratio between its downside and upside semivolatility. Specifically, $\sigma = \sqrt{\frac{\sum_{t=1}^{T} (x_t - \bar{x})^2}{T}}$, while the upside and downside semivolatility are defined as $\sigma^+ = \sqrt{\frac{\sum_{t=1}^{T} (x_t - \bar{x})^2 1(x_t \geq \bar{x})}{T}}$ and $\sigma^- = \sqrt{\frac{\sum_{t=1}^{T} (x_t - \bar{x})^2 1(x_t < \bar{x})}{T}}$, respectively, where $1(z)$ is an indicator function taking value 1 when condition $z$ is true, and 0 otherwise. Sixty-eight percent confidence intervals (in brackets) are constructed by bootstrapping with 5,000 replications.

Source: Federal Reserve Economic Data

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7 It is worth highlighting that the major drop in business-cycle asymmetry does not uniquely depend on the Great Recession. If one looks at the asymmetry of real GDP growth over the 1984:III–2007:II sample, a sizable drop in the skewness can still be appreciated (from −0.09 to −0.70 for year-on-year growth, and from −0.11 to −0.39 for quarter-on-quarter growth). In addition, the ratio between the downside and the upside semivolatility of GDP growth goes from 1.06 to 1.24 in the case of year-on-year growth rates, and from 1.03 to 1.09 for quarter-on-quarter growth.

8 For earlier analyses on the violence (and brevity) of economic contractions, see Mitchell (1927) and, more recently, McKay and Reis (2008).
earlier contractions. However, to compare the relative magnitude of different recessions over a period that displays major changes in the volatility of the business cycle, it is appropriate to control for the average variability of the cycle around a given recessionary episode. To this end, the second column of Table 3 reports standardized violence, which is obtained by normalizing violence by a measure of the variability of real GDP growth. Using this metric, we get a rather different picture. The three recessionary episodes that occurred during the Great Moderation appear substantially deeper than the pre-1984 ones: averaging out the first seven recessionary episodes returns a standardized violence of 1.22 percent, against an average of 2.90 percent for the post-1984 period. Moreover, as highlighted in the last two columns of Table 3, the duration of business-cycle contractions does not change much between the two samples, while the duration of the expansions doubles. This contributes to picturing the business cycle in the post-1984 sample as consisting of more smoothed and prolonged expansions, interrupted by short—yet, more dramatic—contractionary episodes.

Table 3—The Violence of the Recessions in the United States

<table>
<thead>
<tr>
<th>Year</th>
<th>Violence</th>
<th>Std. violence</th>
<th>Duration (quarters)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1953:II–1954:II</td>
<td>3.411</td>
<td>0.949</td>
<td>4</td>
</tr>
<tr>
<td>1960:II–1961:1</td>
<td>1.801</td>
<td>0.572</td>
<td>3</td>
</tr>
<tr>
<td>1969:IV–1970:IV</td>
<td>0.471</td>
<td>0.267</td>
<td>4</td>
</tr>
<tr>
<td>1973:IV–1975:1</td>
<td>2.529</td>
<td>1.228</td>
<td>5</td>
</tr>
</tbody>
</table>

Average

Pre-1984 3.229 1.217 3.714 15.333
Post-1984 2.270 2.902 3.667 31.667

Notes: For every recession, we calculate “Violence” as the annualized fall of real GDP from the peak to the trough of the contractionary episode, divided by the length of the recession; “Std. violence” standardizes the violence of the recession by the average business cycle volatility prior to the recession. The business-cycle volatility is calculated as the standard deviation of the year-on-year growth rate of real GDP over a five-year window. We exclude the period running up to the recession by calculating the standard deviation up to a year before the recession begins.

Source: NBER and Federal Reserve Economic Data

9The volatility is calculated as the standard deviation of the year-on-year growth rate of real GDP over a five-year window. We exclude the period running up to the recession by calculating the standard deviation up to a year before the recession begins. Weighting violence by various alternative measures of business-cycle volatility returns a qualitatively similar picture: online Appendix B3 reports additional robustness evidence on the standardized violence of the recessions in the United States.
semivolatility of real GDP growth. We use data over the 1961:II to 2016:II time fluctuations, and how they connect to the degree of leverage. our view to the G7 countries, and investigate changes in the asymmetry of business cycle and connects this phenomenon to the role of leverage. To this end, we enlarge window, and split the sample in the second quarter of 1984. For all countries, Canada −0.397; [−1.258; 0.976; 1.106; −1.124; [−1.192; 1.187; 1.222; −0.692; −0.768; 1.359; 1.394; −0.711; −0.904; 1.207; 1.241; −0.2026; −0.616; 1.359; 1.318; −0.508; −1.074; 1.172; 1.221; −0.710; −1.353; 1.094; 1.083; −0.281; −0.580; 1.246; 1.337; −0.431; −1.420; 1.143; 1.440; −0.611; −1.648; 1.067; 1.318; −0.221; −1.023; 1.212; 1.537; −0.527; −1.021; 1.166; 1.247; −0.716; −1.348; 1.088; 1.116; −0.311; −0.451; 1.243; 1.361; −0.436; −1.492; 1.148; 1.469; −0.685; −1.735; 1.064; 1.330; −0.175; −1.105; 1.232; 1.582; 254 AMERICAN ECONOMIC JOURNAL: MACROECONOMICS JANUARY 2020

Notes: For each country, the table reports the skewness and the ratio between the downside and the upside semivolatility of detrended GDP growth ($\sigma^-/\sigma^+$) over the 1961:1–2016:II sample (both quarter-on-quarter and year-on-year). Sixty-eight percent confidence intervals (in brackets) are constructed by bootstrapping with 5,000 replications.

Source: OECD database

B. International Evidence

This subsection brings further evidence on evolving asymmetries in the business cycle and connects this phenomenon to the role of leverage. To this end, we enlarge our view to the G7 countries, and investigate changes in the asymmetry of business fluctuations, and how they connect to the degree of leverage. Table 4 reports the skewness and the ratio between the downside and the upside semivolatility of real GDP growth.$^{10}$ We use data over the 1961:II to 2016:II time window, and split the sample in the second quarter of 1984.$^{11}$ For all countries, we detect a more negative skewness, along with a relative increase in the downside semivolatility during the post-1984 sample, which implies that the volatility of expansions has declined relative to that of contractions.

The results so far highlight a more pronounced business-cycle asymmetry in the post-1984 sample, both for the United States and the remaining G7 countries. This period is also associated with an increase in leverage on a global scale, the so-called financial “hockey stick” highlighted by Schularick and Taylor (2012). To

$^{10}$To calculate asymmetry statistics for these countries, we remove the underlying long-run growth appropriately, as the country-specific growth rates display large changes over the sample under investigation (see Antolin-Diaz, Drechsel, and Petrelli 2017). This phenomenon is less evident for the United States, though the results reported in Table 1 are robust to subtracting the underlying long-run growth rate. We estimate long-run growth as the first difference in the smooth trend of the real GDP series. The latter is retrieved through the modified HP filter of Rotemberg (1999). Using alternative filters delivers similar results.

$^{11}$Stock and Watson (2005) have shown that, for these countries, the mid-1980s are associated with a sharp reduction in macroeconomic volatility. The results are robust to delaying the cutoff date.
gauge the connection between business-cycle asymmetry and leverage, we follow Jordà, Schularick, and Taylor (2017), and summarize the correlation between some asymmetry statistics—namely, the skewness and the ratio between the downside and the upside semivolatilities ($\sigma^- / \sigma^+$). To construct the data points, we take quarterly GDP growth rates for all the countries under investigation and construct eight-year rolling windows of data. Thus, we compute country-window specific moments, and relate them to the average credit-to-GDP ratio calculated over the same sample. The dots displayed in the figure are summary data for each moment, computed by grouping the credit-to-GDP ratio into 30 bins. The regression line is obtained by assuming a quadratic relationship between the two variables (accounting for country-level fixed effects).

**Figure 3. Leverage and Asymmetry: G7 Countries**

Notes: Panel A reports the skewness of quarter-on-quarter GDP growth, computed for the G7 countries, against their loan-to-GDP ratio. Panel B replaces the skewness of GDP growth with the ratio between its downside and upside semivolatilities ($\sigma^- / \sigma^+$). To construct the data points, we take quarterly GDP growth rates for the G7 countries, and construct eight-year rolling windows of data. Thus, we compute country-window specific moments, and relate them to the average credit-to-GDP ratio calculated over the same sample. The dots displayed in the figure are summary data for each moment, computed by grouping the credit-to-GDP ratio into 30 bins. The regression line is obtained by assuming a quadratic relationship between the two variables (accounting for country-level fixed effects).

Source: OECD and Jordà-Schularick-Taylor Macrohistory Database

So far we have established that the post-1984 period is characterized by a smoother path of the expansionary periods and a stronger standardized violence

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12 For the loan-to-GDP ratio, we use the annual data provided by Jordà, Schularick, and Taylor (2017). In online Appendix B4, we reproduce the same charts focusing on the loan-to-GDP ratio for the household and the corporate sectors, respectively, confirming the results reported here for the aggregate. Using a short window to compute moments implicitly takes care of low-frequency variation in GDP growth. The results obtained by removing the trend in GDP growth (available upon request) are virtually unchanged.
of the recessionary episodes, as compared with the pre-1984 period. In addition, over the same time window, the process of financial deregulation has been associated with a sizeable increase in leverage of households and firms, both in the United States and other G7 countries. We now produce related evidence based on US state-level data. Specifically, we take data on quarterly real gross state product (GSP) from the BEA Regional Economic Accounts and compute both the skewness of GSP growth and the violence of the Great Recession in the US states. Figure 4 correlates the resulting statistics to the average debt-to-income ratio prior to the recession. Notably, states where households were more leveraged not only have witnessed more severe GSP contractions during the last recession, but have also displayed a more negatively skewed GSP growth over the 2005–2016 time window.

To gain further insights into the cross-sectional connection between the magnitude of the Great Recession and business-cycle dynamics, we order the US states according to households’ average pre-crisis debt-to-income ratio. We then construct two synthetic series, computed as the growth rates of the median real GSP of the top and the bottom ten states in terms of leverage, respectively. According to Figure 5, there are no noticeable differences in the performance of the two groups

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13 To account for the possibility that the recession does not begin/end in the same period across the United States, we define the start of the recession in a given state as the period with the highest level of real GSP in the window that goes from five quarters before the NBER peak date to one quarter after that. Similarly, the end of the recession is calculated as the period with the lowest real GSP in the window from one quarter before to five quarters after the NBER trough date.
before and after the Great Recession, with both of them growing at a roughly similar
pace. However, the drop in real activity has been much deeper for relatively more
leveraged states. Altogether, this evidence points to a close link between leverage
and business-cycle asymmetries.

II. A Two-Period Model

Some preliminary insights about our main model can be offered through a sim-
ple model of collateralized debt. The model shares many of the central aspects of
our DSGE economy, most notably entrepreneurs facing an asset-based credit con-
straint. The representative entrepreneur has utility

\[ U = \log C_1 + \beta \log C_2, \]

where \( \beta \in (0, 1) \) is the discount factor and \( C_t \) denotes the consumption of a nondurable
good at time \( t = 1, 2 \). In both periods, production is carried out by a representative
firm employing capital, \( K_{t-1} \), and labor, \( L_t \), as production inputs:

\[ Y_t = A_t K_{t-1}^\alpha L_t^{1-\alpha}, \]

where \( A_1 \) is an exogenous stochastic variable with cumulative distribution function
\( F \) (with \( F' > 0 \)), and \( \alpha \in [0, 1] \). As we will focus on the effects of technology
shocks taking place in the first period, \( A_2 \) is set to a constant, \( A \). We assume that

![Figure 5. GSP Dynamics and Household Leverage](image-url)

**Notes:** Growth rates of two synthetic GSP series obtained by ranking the US states according to their average
debt-to-income ratio in the five years before the Great Recession. The solid blue line is calculated from the median
real GSP of the top ten states, while the dashed green line is obtained from the median for the bottom ten states. The
resulting statistics have been normalized to zero at the beginning of the Great Recession (i.e., 2007:IV). The vertical

**Source:** State-level household debt statistics produced by the New York Fed and BEA Regional Economic Accounts.
entrepreneurs work as executives in the firms, and inelastically supply labor, \( L_t = 1 \), for \( t = 1, 2 \). The entrepreneurs’ dynamic budget constraints in periods 1 and 2 are, respectively,

\[
C_1 + I_1 - B_1 = r^K_1 K_0 + W_1 - RB_0,
\]

(2)

\[
C_2 = (1 + r^K_2) K_1 + W_2 - RB_1,
\]

(3)

with \( K_0 > 0 \) and \( B_0 \) given,

where \( W_t \) denotes the real labor income and \( r^K_t \) is the capital rental rate, for \( t = 1, 2 \), and \( R > 1 \) is the gross interest rate. The initial stock of debt is denoted by \( B_0 \). According to conventional arguments, we rule out debt in the second period, so that \( B_2 = 0 \). Investment is performed in period 1 only:

\[
I_1 = K_1 - (1 - \delta)K_0,
\]

(4)

where \( \delta \in [0, 1] \) is the depreciation rate. Finally, the stock of debt in period 1 cannot exceed a fraction of the present value of capital:

\[
B_1 \leq s \frac{K_1}{R}, \quad s \in (0, 1),
\]

(5)

where \( s \) is the LTV ratio.

Online Appendix C shows in detail the derivation of the model’s competitive equilibrium. Here, it suffices to consider the capital stock, and thus investment, in period 1. When the constraint (5) does not bind, we obtain

\[
K_1 = \left( \frac{\alpha A}{R - 1} \right)^{\frac{1}{1 - \alpha}}.
\]

(6)

If (5) binds, instead, the solution for \( K_1 \) is characterized by

\[
\Psi(K_1; A_1) = 0,
\]

(7)

where

\[
\Psi(K_1; A_1) \equiv \beta(1 + \alpha AK_1^{\alpha - 1} - s)[A_1 K_0^{\alpha} - RB_0 - \left( 1 - \frac{s}{R} \right) K_1 + (1 - \delta)K_0] - \left[ (1 - s) K_1 + AK_1^{\alpha} \right] \left( 1 - \frac{s}{R} \right).
\]

(8)

Differentiating \( \Psi(K_1; A_1) \) with respect to \( K_1 \) shows that

\[
\frac{\partial \Psi(K_1; A_1)}{\partial K_1} < 0.
\]

(9)
Furthermore,

\[
\lim_{K_1 \to 0} \Psi(K_1; A_1) = \infty,
\]

(10)\]

\[
\lim_{K_1 \to \Upsilon} \Psi(K_1; A_1) = -\frac{(1 - s)\Upsilon + A\Upsilon^{\alpha}}{R - s},
\]

(11)\]

where \(\Upsilon \equiv R[A_1K_0^\alpha - RB_0 + (1 - \delta)K_0]/(R - s)\). Note that \(K_1 \to \Upsilon\) from below corresponds to moving toward zero period-1 consumption. Hence, as \(\Psi(K_1; A_1)\) is a continuously decreasing function—which tends to infinity for \(K_1 \to 0\), and moves downward toward a finite negative number as \(K_1 \to \Upsilon\)—a solution for \(K_1 \in \mathbb{R}_+\) exists and is unique.

Crucially, in the face of an expansionary shock, \(\Psi(K_1; A_1)\) moves up, for any \(K_1\). Hence, when the credit constraint binds, investment responds to temporary shocks, which it does not in the unconstrained case, as implied by (6). In light of this, a negative shock will have adverse investment repercussions, while a similar-sized positive shock may have no impact at all, if it makes the entrepreneur unconstrained. This type of discontinuity—which extends to the behavior of production and consumption—is at the heart of negative asymmetry in the model. To refine our analysis, it is useful to denote with \(\bar{A}_1\) the value of the technology shock that makes investment the same in the constrained and unconstrained regimes. The case of \(A_1 > \bar{A}_1\) will then be one in which the credit constraint does not bind, and vice versa for \(A_1 < \bar{A}_1\). It can be shown that

\[
\bar{A}_1 = \left[1 + \beta R - s(1 + \beta)\right]^{-1} \frac{1}{\beta RK_0^\alpha} \left(\frac{\alpha A}{R - 1}\right)^{\frac{1}{1 - \alpha}}
\]

(12)

\[
\bar{A}_1 = -\frac{A_1^{1-\alpha}}{\beta RK_0^\alpha} \left(\frac{\alpha}{R - 1}\right)^{\frac{\alpha}{1 - \alpha}} + \frac{RB_0}{K_0^\alpha} - (1 - \delta)K_0^{1-\alpha}.
\]

Coherently, \(\mathcal{F}(\bar{A}_1)\) is the probability that the economy is below the turning point between the constrained and the unconstrained regime, i.e., the probability that the entrepreneur is constrained. From (12), we can see that \(\partial\bar{A}_1/\partial s < 0\), i.e., as the amount of debt that can be contracted for a given level of collateral increases, the minimum realization of the technology shock that makes the entrepreneur unconstrained decreases. In other words, a higher \(s\) implies that the entrepreneur has higher chances of becoming financially unconstrained when technology fluctuates.

Intuitively, when \(s\) is relatively high, the entrepreneur can obtain a debt level relatively close to what she would have desired in the absence of credit constraints. Therefore, it takes a relatively small positive technology shock to make the constraint slack by increasing income and reducing the need for debt. In contrast, had \(s\) been relatively low, the entrepreneur would be relatively far from obtaining the desired debt level, and it would require a much larger technology shock to increase
income sufficiently to make the entrepreneur desire no more debt and become unconstrained. In sum, the range of technology shocks that render the entrepreneur unconstrained increases with $s$. This explains why the probability of becoming unconstrained, $1 - \mathcal{F}(\tilde{A}_i)$, increases with $s$.

The next section introduces a DSGE model where the mechanisms we have just described produce increasingly negative asymmetry in connection with a process of financial leveraging. Essentially, in such a model, aggregate dynamics emerges as a mixture of the behavioral rules governing consumption and investment decisions under different regimes. A higher probability of nonbinding financial constraints will be associated with a more marked business-cycle asymmetry, as documented in Section I.

### III. A DSGE Model

We adopt a standard real business-cycle model augmented with collateral constraints, along the lines of Kiyotaki and Moore (1997); Iacoviello (2005); Liu, Wang, and Zha (2013); and Justiniano, Primiceri, and Tambalotti (2015), inter alia. The economy is populated by three types of agents, each of mass one. These agents differ by their discount factors, with the so-called patient households displaying the highest degree of time preference, while impatient households and entrepreneurs have relatively lower discount factors. Patient and impatient households supply labor and consume nondurable goods and land services. Entrepreneurs only consume nondurable goods, and accumulate both land and physical capital, which they rent to firms. The latter 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 nondurable consumption.

#### A. Patient Households

The utility function of patient households is given by

\[
\mathbb{E}_0\left\{\sum_{t=0}^{\infty} (\beta^p)^t \left[ \log(C_t^p - \theta^p C_{t-1}^p) + \varepsilon_t \log(H_t^p) + \frac{\nu^p}{1 - \varphi^p} (1 - N_t^p)^{1 - \varphi^p} \right] \right\},
\]

where $0 < \beta^p < 1$, $\varphi^p \geq 0$, $\varphi^p \neq 1$, $\nu^p > 0$, $0 \leq \theta^p < 1$

where $C_t^p$ denotes their nondurable consumption, $H_t^p$ denotes land holdings, and $N_t^p$ denotes the fraction of time devoted to labor. Moreover, $\beta^p$ is the discount factor, $\theta^p$ measures the degree of habit formation in nondurable consumption and $\varphi^p$ is the coefficient of relative risk aversion pertaining to leisure. Finally, $\varepsilon_t$ is a land-preference shock satisfying

\[
\log \varepsilon_t = \log \varepsilon + \rho_\varepsilon (\log \varepsilon_{t-1} - \log \varepsilon) + u_t, \quad 0 < \rho_\varepsilon < 1,
\]
where $\varepsilon > 0$ denotes the steady-state value and where $u_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. Utility maximization is subject to the budget constraint

\begin{equation}
C_t^p + Q_t(H_t^p - H_{t-1}^p) + R_{t-1}B_{t-1}^p = B_t^p + W_t^pN_t^p,
\end{equation}

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

### B. Impatient Households

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

\begin{equation}
\mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \left( \beta^I \right)^t \left[ \log(C_t^I - \theta^I C_t^I) + \varepsilon_t \log(H_t^I) + \frac{\nu^I}{1 - \varphi^I} (1 - N_t^I)^{1-\varphi^I} \right] \right\},
\end{equation}

where, as for the patient households, $C_t^I$ denotes nondurable consumption, $H_t^I$ denotes land holdings, and $N_t^I$ denotes the fraction of time devoted to labor. Households’ difference in the degree of time preference is captured by imposing $\beta^p > \beta^I$. This ensures that, in the steady state, patient and impatient households act as lenders and borrowers, respectively. Impatient households are subject to the following budget constraint:

\begin{equation}
C_t^I + Q_t(H_t^I - H_{t-1}^I) + R_{t-1}B_{t-1}^I = B_t^I + W_t^IN_t^I.
\end{equation}

Impatient households are also subject to a collateral constraint. The nature of the constraint reflects the fact that the vast majority of household debt is effectively long term. Specifically, building on the work of Garriga, Kydland, and Šustek (2017) and Gelain, Lansing, and Natvik (2018), we assume that impatient households’ stock of debt, $B_t^I$, is constrained from above:

\begin{equation}
B_t^I \leq \vartheta^I s_t^I \frac{\mathbb{E}_t(Q_{t+1})H_t^I}{R_t} + (1 - \vartheta^I)(1 - \xi^I)B_{t-1}^I, \quad 0 < \vartheta^I, \xi^I < 1,
\end{equation}

where we assume that impatient households refinance a fraction $\vartheta^I$ of their outstanding debt in each period. Their “new” borrowing cannot exceed a fraction $s_t^I$ of the expected present value of their land holdings at the beginning of period $t + 1$. Of the remaining, nonrefinanced, stock of debt, impatient households are assumed to amortize a constant fraction, $\xi^I$.\(^{14}\) Finally, the LTV ratio (or credit

\(^{14}\)Garriga, Kydland, and Šustek (2017) demonstrates that, with a time-varying amortization rate, the model-implied repayment profile mimics that of a standard annuity loan arbitrarily well. Given the different focus of our paper, we opt for a constant amortization rate.
limit) on new borrowing, $s_t^l$, is stochastic and aims at capturing financial shocks (as in, e.g., Jermann and Quadrini 2012 and Liu, Wang, and Zha 2013):

\begin{equation}
\log s_t^l = \log s^l + \log s_t,
\end{equation}

\begin{equation}
\log s_t = \rho_s \log s_{t-1} + v_t, \quad 0 < \rho_s < 1,
\end{equation}

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

\section*{C. Entrepreneurs}

Entrepreneurs have preferences over nondurables only (see Iacoviello 2005; Liu, Wang, and Zha 2013), and maximize

\begin{equation}
\mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} (\beta^E)^t \log \left( C_t^E - \theta^E C_{t-1}^E \right) \right\}, \quad 0 < \beta^E < \beta^p, \quad 0 \leq \theta^E < 1,
\end{equation}

where $C_t^E$ denotes entrepreneurial nondurable consumption. Utility maximization is subject to the following budget constraint:

\begin{equation}
C_t^E + I_t + Q_t (H_t^E - H_{t-1}^E) + 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,
\end{equation}

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 depreciates at the rate $\delta$, and its accumulation is subject to quadratic investment adjustment costs, so that its law of motion reads as

\begin{equation}
K_t = (1 - \delta) K_{t-1} + \left[ 1 - \frac{\Omega}{2} \left( \frac{I_t}{I_{t-1}} - 1 \right) \right]^2 I_t, \quad 0 < \delta < 1, \quad \Omega > 0.
\end{equation}

As the impatient households, entrepreneurs are subject to a credit constraint on their new borrowing, but are able to use both capital and their holdings of land as collateral assets:

\begin{equation}
B_t^E \leq \vartheta^E s_t^E \mathbb{E}_t \left\{ \frac{Q_{t}^K K_t + Q_{t+1}^H H_{t}^E}{R_t} \right\} + (1 - \vartheta^E)(1 - \xi^E) B_{t-1}^E, \quad 0 < \vartheta^E, \xi^E < 1,
\end{equation}

\footnote{The importance of real estate as collateral for business loans has recently been emphasized by Chaney, Sraer, and Thesmar (2012) and Liu, Wang, and Zha (2013).}
where $Q^K_t$ denotes the price of installed capital in consumption units and $s^E_t$ behaves in accordance with

$$\log s^E_t = \log s^E + \log s_t,$$

where $s^E$ denotes entrepreneurs’ steady-state LTV ratio. Together with households’ average LTV ratio, this parameter will assume a key role in the analysis of the evolving connection between macroeconomic asymmetries and financial leverage.

**D. 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

$$Y_t = A_t \left[ \left( N^P_t \right)^\alpha \left( N^I_t \right)^{1-\alpha} \right]^{1-\gamma} \left[ (H^E_{t-1})^\phi (K_{t-1})^{1-\phi} \right]^{1-\gamma}, \quad 0 < \alpha, \phi, \gamma < 1,$$

with total factor productivity $A_t$ evolving according to

$$\log A_t = \log A + \rho_A (\log A_{t-1} - \log A) + z_t, \quad 0 < \rho_A < 1,$$

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

**E. Market Clearing**

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

$$H = H^P_t + H^I_t + H^E_t.$$

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

$$B^P_t + B^I_t + B^E_t = 0.$$

The labor markets for each labor type clear, and the aggregate resource constraint reads as

$$Y_t = C^P_t + C^I_t + C^E_t + I_t.$$

16 As we discuss in online Appendix A1, once the low-frequency components of the LTA series reported in the right panel of Figure 2 are removed, their cyclical components strongly comove. In light of this, we opt for a common financial shock.
IV. Equilibrium, Solution, and Estimation

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 initial conditions, satisfy the agents’ optimality conditions, the budget and credit constraints, as well as the technological constraints and the market-clearing conditions. The optimality conditions are reported in online Appendix D. Due to the assumptions about the discount factors, \( \beta^I < \beta^P \) and \( \beta^E < \beta^P \), both collateral constraints are binding in the steady state. 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 constraints will be nonbinding.

To account for the occasionally binding nature of the credit constraints, our solution method follows Lasèen and Svensson (2011) and Holden and Paetz (2012). 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 nonnegative at all times.\(^\text{17}\) We present the technical details of the method in online Appendix E.

Calibration and Estimation.—In the remainder, we aim at assessing the extent to which a relaxation of the credit limits faced by the borrowers can account for the evolution of the asymmetry of the business cycle. With this in mind, we assign parameter values that allow us to match a set of characteristics of the US business cycle in the pre-1984 sample. We do this by calibrating a subset of the parameters, while estimating the remaining ones using the simulated method of moments (SMM). Next, we simulate the model for progressively higher average LTV ratios faced by households and firms, and track the implied changes in the skewness of output and other macroeconomic variables, as well as other business-cycle statistics.

Calibrated Parameters.—The calibrated parameters are summarized in panel A of Table 5. We choose to calibrate a subset of the model parameters that can be pinned down using a combination of existing studies and first moments of US data. We interpret one period as a quarter. We therefore set \( \beta^P = 0.99 \), implying an annualized steady-state rate of interest of about 4 percent. Moreover, we set \( \beta^I = \beta^E = 0.96 \), in the ballpark of the available estimates for relatively more impatient agents (see, e.g., Iacoviello 2005 and references therein). The utility weight of leisure is set to ensure that both types of households work \( \frac{1}{4} \) of their time in the steady state. This implies a value of \( \nu^i = 0.27 \) for \( i = \{P, I\} \). The Frisch elasticity of labor supply is given by the inverse of \( \varphi^i \), multiplied by the steady-state ratio of leisure to labor hours. Having pinned down the latter to 3, we set \( \varphi^I = 9, i = \{P, I\} \), implying a Frisch elasticity of \( \frac{1}{3} \), a value that is broadly in line with the available estimates (see, e.g., Herbst and Schorfheide 2014). In line with Iacoviello (2005) and Iacoviello and Neri (2010), we set the share of

\(^{17}\)For first-order perturbations, we have verified that our solution produces similar simulated moments as using the method of Guerrieri and Iacoviello (2015); see also Holden and Paetz (2012).
To pin down the labor income share, we follow Elsby, Hobijn, and Şahin (2013) and use the official estimate of the Bureau of Labor Statistics: the average value for the 1948–1983 time span implies $\gamma = 0.636$.

Regarding the parameters governing the refinancing and amortization of household debt, we build on Kydland, Rupert, and Šustek (2016), who employ a steady-state amortization rate, $\xi^I$, of 0.014. The implied maturity of a mortgage loan is close to 24 years, slightly longer than in Alpanda and Zubairy (2017), who report that the average remaining term of outstanding household mortgages in the United States was 22.4 years in 2016.

### Table 5—Parameter Values

<table>
<thead>
<tr>
<th>Parameter Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A. Calibrated parameters</td>
<td></td>
</tr>
<tr>
<td>$\beta^P$ Discount factor, patient households</td>
<td>0.99</td>
</tr>
<tr>
<td>$\beta^I = {I, E}$ Discount factor, impatient households, and entrepreneurs</td>
<td>0.96</td>
</tr>
<tr>
<td>$\varphi^I = {P, I}$ Curvature of utility of leisure</td>
<td>9</td>
</tr>
<tr>
<td>$\nu^I = {P, I}$ Weight of labor disutility</td>
<td>0.27</td>
</tr>
<tr>
<td>$\varepsilon$ Weight of land utility</td>
<td>0.084</td>
</tr>
<tr>
<td>$\phi$ Nonlabor input share of land</td>
<td>0.134</td>
</tr>
<tr>
<td>$\gamma$ Labor share of production</td>
<td>0.636</td>
</tr>
<tr>
<td>$\delta$ Capital depreciation rate</td>
<td>0.052</td>
</tr>
<tr>
<td>$\alpha$ Income share of patient households</td>
<td>0.7</td>
</tr>
<tr>
<td>$s^I$ Initial loan-to-value ratio, impatient households</td>
<td>0.673</td>
</tr>
<tr>
<td>$s^E$ Initial loan-to-value ratio, entrepreneurs</td>
<td>0.763</td>
</tr>
<tr>
<td>$\varrho^I$ Refinancing rate, impatient households</td>
<td>0.009</td>
</tr>
<tr>
<td>$\varrho^E$ Refinancing rate, entrepreneurs</td>
<td>0.698</td>
</tr>
<tr>
<td>$\xi^I$ Amortization rate, impatient households</td>
<td>0.014</td>
</tr>
<tr>
<td>$\xi^E$ Amortization rate, entrepreneurs</td>
<td>0.125</td>
</tr>
<tr>
<td>Panel B. Estimated parameters</td>
<td></td>
</tr>
<tr>
<td>$\Omega$ Investment adjustment cost parameter</td>
<td>8.933 (2.940)</td>
</tr>
<tr>
<td>$\theta^P$ Habit formation, patient households</td>
<td>0.361 (0.112)</td>
</tr>
<tr>
<td>$\theta^I$ Habit formation, impatient households + entrepreneurs</td>
<td>0.941 (0.045)</td>
</tr>
<tr>
<td>$\rho_A$ Persistence of technology shock</td>
<td>0.987 (0.044)</td>
</tr>
<tr>
<td>$\rho_s$ Persistence of credit-limit shock</td>
<td>0.853 (0.043)</td>
</tr>
<tr>
<td>$\rho_c$ Persistence of land-demand shock</td>
<td>0.880 (0.398)</td>
</tr>
<tr>
<td>$\sigma_A$ Standard deviation of technology shock</td>
<td>0.009 (0.001)</td>
</tr>
<tr>
<td>$\sigma_s$ Standard deviation of credit-limit shock</td>
<td>0.033 (0.001)</td>
</tr>
<tr>
<td>$\sigma_c$ Standard deviation of land-demand shock</td>
<td>0.072 (0.356)</td>
</tr>
</tbody>
</table>

*Note: The standard errors of the estimated parameters are reported in brackets.*
States is close to 20 years.\footnote{Following Alpanda and Zubairy (2017), we approximate maturity by two times the half-life of a loan.} In addition, Kydland, Rupert, and Šustek (2016) reports a refinancing share of total mortgage lending of 39 percent. As we show in online Appendix D1, matching this number implies a refinancing parameter $\vartheta^I = 0.009$. We then turn to the entrepreneurs. Most of the existing business-cycle studies treat corporate debt as short term (see, e.g., Jermann and Quadrini 2012 and Liu, Wang, and Zha 2013), with a duration of one quarter. Chodorow-Reich and Falato (2017) reports an average maturity of long-term corporate debt of around three years, with long-term debt defined as bank loans with at least one year of residual maturity. This implies a weighted average maturity of total debt between two and three years. Based on Compustat data, Poeschl (2018) reports an average maturity of corporate debt of 2.3 years. Relying on these figures, we target a maturity of 2.5 years. To this end, we set $\xi_E = 0.125$.\footnote{The amortization rates we employ are, if anything, on the conservative side. For households, Alpanda and Zubairy (2017) and Gelain, Lansing, and Natvik (2018) both use slightly higher values than we do. For firms, it is important to stress that business loans are frequently renegotiated. In a large sample of private credit agreements to publicly traded US firms, Roberts and Sufi (2009) finds that 90 percent of debt contracts with maturities longer than one year are renegotiated prior to maturity. Moreover, Chodorow-Reich and Falato (2017) emphasizes the role of the “loan covenant channel”: while only 10 percent of bank loans to firms had a remaining maturity of less than a year at the onset of the financial crisis in 2008; a much larger share of firms breached a covenant associated with their loan during the crisis, thus allowing the lender to dictate new terms. We have verified that our results are robust to realistic changes in the amortization rates for both households and firms.} Thus, we pin down the refinancing rate, $\vartheta^E$, so as to ensure that the steady-state fraction of total lending that goes to refinance old debt equals 83 percent, as in the Thompson Reuters LPC Dealscan data (see Drechsel 2019). This implies a value of $\vartheta^E = 0.698$ (see online Appendix D1 for the details on this computation).

Given these parameters, we set $\delta, \varepsilon, \phi,$ and $s^I$ to jointly match the following four ratios (all at the annual frequency) for the period from World War II until 1984: A ratio of residential land to output of 1.098, a ratio of commercial land to output of 0.631, an average capital to output ratio of 1.109, and an average ratio of private nonresidential investment to output of 0.230.\footnote{Our computations of these ratios largely follow those of Liu, Wang, and Zha (2013). For residential land, we use owner occupied real estate from the Flow of Funds tables. For commercial land, Liu, Wang, and Zha (2013) uses Bureau of Labor Statistics data on land inputs in production, which are not available for the sample period we consider. Instead, we compute the sum of the real estate holdings of nonfinancial corporate and nonfinancial noncorporate businesses from the Flow of Funds, and then follow Liu, Wang, and Zha (2013) in multiplying this number by a factor of 0.5 to impute the value of land. For capital, we compute the sum of the annual stocks of equipment and intellectual property products of the private sector and consumer durables. We use the corresponding flow variables to measure investment. Finally, we measure output as the sum of investment (as just defined) and private consumption expenditures on nondurable goods and services.} The depreciation rate of capital consistent with these figures is 0.052, somewhat higher than standard values, as it reflects that our measure of capital excludes residential capital and structures, which feature lower depreciation rates than, e.g., intellectual properties. We obtain a value of $\phi = 0.134$, which, multiplied by $(1 - \gamma)$, measures land’s share of inputs, and a weight of land in the utility function of $\varepsilon = 0.084$. The implied value for impatient households’ average LTV ratio is 0.673. The spread between the household and the entrepreneurial steady-state LTV ratios is calibrated to match the average difference in the low-frequency components over the entire sample, which is roughly equal to $0.698$ (see online Appendix D1 for the details on this computation).
the average difference in the original series. As a result, the entrepreneurial average LTV ratio, \( s^E \), is set to 0.763.\(^{21}\)

Estimates Parameters.—We rely on the SMM to estimate the remaining model parameters, as this method is particularly well-suited for DSGE models involving nonbinding constraints or other nonlinearities. Ruge-Murcia (2012) studies the properties of SMM estimation of nonlinear DSGE models, and finds that this method is computationally efficient and delivers accurate parameter estimates. Moreover, Ruge-Murcia (2007) performs a comparison of the SMM with other widely used estimation techniques applied to a basic RBC model, showing it fares quite well in terms of accuracy and computing efficiency, along with being less prone to misspecification issues than likelihood-based methods.

We estimate the following parameters: the investment adjustment cost parameter \((\Omega)\), the parameters measuring habit formation in consumption \((\theta^P, \theta^I, \text{and } \theta^E)\), and the parameters governing the persistence and volatility of the shocks \((\rho_A, \rho_s, \rho_A, \sigma_A, \sigma_s, \sigma_e)\).\(^{22}\) In the estimation, we use five macroeconomic time series for the US economy spanning the sample period 1952:I–1984:II: the growth rates of real GDP, real private consumption, real nonresidential investment, real house prices, and the cyclical component of the LTA series in Figure 2, with the trend being computed as in Müller and Watson (2018).\(^{23}\) The beginning of the sample is dictated by the availability of quarterly Flow of Funds data, while the end of the sample coincides with the onset of the Great Moderation.\(^{24}\) In the estimation, we match the following empirical moments: the standard deviations and first-order autoregressive parameters of each of the five variables, the correlation of consumption, investment, and house prices with output, and the skewness of output, consumption, and investment. This gives a total of 16 moment conditions to estimate nine parameters. We provide more details about the data and our estimation strategy in online Appendix F.

The estimated parameters are reported in panel B of Table 5. The estimate of \(\Omega\) is in line with existing results from estimated DSGE models (see, e.g., Christiano, Motto, and Rostagno 2014). The degree of habit formation of patient households is close to the estimate of Liu, Wang, and Zha (2013), whereas the estimated habit parameter for impatient households and entrepreneurs is somewhat higher than most of the available estimates. The volatility and persistence parameters of the technology shock are in line with those typically found in the real business-cycle literature; see, e.g., Mandelman et al. (2011). The finding of rather large land-demand shocks is consistent with the results of Iacoviello and Neri (2010)

21 These values for the average LTV ratios are lower than those typically employed in models calibrated over the Great Moderation sample (see, e.g., Calza, Monacelli, and Stracca 2013; Liu, Wang, and Zha 2013; and Justiniano, Primiceri, and Tambalotti 2019), as our calibration covers the period before the subsequent wave of financial liberalization.

22 In the estimation, we impose that \(\theta^I = \theta^E\), as initial attempts to identify these two parameters separately proved unsuccessful.

23 Since the cyclical components of the two LTA series are strongly correlated, we use the one obtained for the households. All results are robust to using the corporate one.

24 In fact, house prices are only available starting in 1963:I. We choose not to delay the beginning of other data series to this date.
and Liu, Wang, and Zha (2013). Finally, the financial shocks in our model are more volatile than found by Jermann and Quadrini (2012) and Liu, Wang, and Zha (2013), but less persistent.

The model-implied matched moments and their data counterparts are reported in Table F1 in online Appendix F. Moreover, it is worth highlighting that we match quite closely a set of nontargeted moments of interest. For example, the ratio between the downside and the upside semivolatility of real GDP growth and the standardized violence are 1.072 and 1.165, respectively, while the corresponding numbers in the data are 1.061 and 1.217. Moreover, applying the business-cycle dating algorithm of Harding and Pagan (2002) to the simulated data, we obtain a duration of expansions and contractions of 22.156 and 3.765 quarters, respectively, as compared with 15.333 and 3.714 quarters in the data. While the duration of expansions is somewhat overestimated, these numbers confirm that the model generally produces a close match of key properties of the data over the pre-1984 sample.

V. Asymmetric Business Cycles and Collateral Constraints

We can now examine how our model generates stronger business-cycle asymmetries as financial leverage increases. We do so in three steps. First, we inspect a set of impulse responses to build some intuition around the nonlinear transmission of different shocks. Next, we present various business-cycle statistics obtained from simulating the model at different degrees of leverage. Finally, we examine the behavior of business-cycle asymmetry in conjunction with the behavior of macroeconomic volatility. Our quantitative exercises primarily aim at assessing the model’s ability to reproduce various dimensions of changing business-cycle asymmetry, relying exclusively on an increase in financial leverage.25

A. Impulse-Response Analysis

To gain some preliminary insights into the nature of our framework and how its properties evolve under different LTV ratios, we study the propagation of different shocks. Figure 6 displays the response of output to a set of positive shocks, as well as the mirror image of the response to equally sized negative shocks, under different credit limits.26 For purely illustrative purposes, we report impulse responses from a version of the model in which long-term debt is temporarily “shut off,” i.e., where both corporate and household debt have a duration of one period. This enhances the likelihood of observing episodes of nonbinding collateral constraints in the face of a one-off expansionary shock.27

25 The aim of the exercise is not to account for the process of financial innovation and liberalization lying behind the increase in leverage in the last decades—a task the model is not suitable for. Instead, we take this increase for granted and examine how it has affected the shape of the business cycle.

26 Online Appendix G1 reports the corresponding impulse responses for total consumption, investment, and total debt.

27 In the dynamic simulations reported in the next subsections, instead, combinations of all the shocks at their baseline calibration have the potential to generate episodes of nonbinding constraints, even in the presence of long-term debt.
Looking at the first row of the figure, technology shocks of either sign produce symmetric responses under the calibrated LTV ratios for impatient households and entrepreneurs. By contrast, at higher credit limits a positive technology shock renders the borrowing constraint of the entrepreneurs slack for eight quarters, while impatient households remain constrained throughout. Entrepreneurs optimally choose to borrow less than they are able to. This attenuates the expansionary effect on their demand for land and capital, dampening and prolonging the boom in aggregate economic activity. On the contrary, following a similar-sized negative technology shock, the borrowing constraints remain binding throughout. As a result, both 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 and swifter output response.

As for the stochastic shifts in household preferences, the second row of Figure 6 indicates that entrepreneurs’ collateral constraint becomes nonbinding for three quarters after a positive land demand shock in the scenario with high

Figure 6. Impulse Responses for Different Degrees of Leverage

Notes: Impulse responses of output (in percentage deviation from the steady state) to a one standard deviation shock to technology (panel A), a two standard deviation shock to land demand (panel B), and a one standard deviation shock to credit limits (panel C) in a model with debt duration of one quarter. Left column: $s^I = 0.67, s^E = 0.76$; right column: $s^I = 0.85, s^E = 0.94$. The shadowed bands indicate the periods in which the entrepreneurs are financially unconstrained.
LTV ratios, while impatient households remain constrained throughout. Therefore, entrepreneurs have no incentive to expand their borrowing capacity by increasing their stock of land. By contrast, there is no attenuation of negative shocks to the economy. In that case, both collateral constraints remain binding, giving rise to a large and immediate output drop.

Similar observations apply to the transmission of the financial shock. Under high average LTV ratios, the entrepreneurs are unconstrained during the first three periods following a positive shock. For the reasons discussed above, this leads to a smooth response of output, as compared with what happens following a negative shock. In this case, entrepreneurs are forced into a sizeable deleveraging, reducing the stock of land available for production. Also impatient households deleverage and bring down their stock of land, which further depresses the land price, and thus the borrowing capacity of both types of constrained agents. The result is a large drop in output.

The impulse-response analysis offers a clear message: As leverage increases, economic expansions tend to become smoother and more prolonged than contractions, paving the way to a negatively skewed business cycle. This is broadly consistent with the observation of lower volatility of the upside of the business cycle, as compared with its downside. Moreover, all of the three types of shock we consider have the potential to generate episodes of nonbinding constraints in response to positive innovations, thus contributing to business-cycle asymmetries.

B. Leverage and Asymmetries

To deepen our understanding of the model, we report a number of statistics from a rich set of dynamic simulations based on a gradual increase in the average LTV ratios of the financially constrained agents. Following the approach of Müller and Watson (2018), online Appendix A1 documents that, at very low frequencies, the LTA series for the household and corporate sector display strong comovement. Therefore, starting from their calibrated values, both agents’ steady-state LTV ratios are progressively raised by 23 basis points, in line with the increase in the low-frequency components of the LTA series reported in Figure 2 over the 1984–2016 time window.28

Figure 7 displays two key dimensions of business-cycle asymmetry: panel A reports the skewness of the growth rates of output, aggregate consumption, and investment, while panel B reports the ratio between the downside and the upside semivolatility of output growth. All the statistics in panel A are negative at our calibrated average LTV ratios, and decline thereafter. Similarly, we observe a stable increase in the ratio between the downside and the upside semivolatility of output growth. Therefore, in connection with an increase in financial leverage, the model

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28 In each simulation reported in this section, the entrepreneurial average LTV ratio is adjusted to be nine basis points greater than any value we consider for impatient households’ credit limit, in line with the baseline calibration of the model. In Section VC, instead, we feed in the estimated low-frequency components of the LTA ratios of households and firms. In both cases, we compute the statistics of interest as median values from 501 simulations, all of which run for 2,000 periods.
is capable of generating an increasingly negatively skewed business cycle. In fact, relying exclusively on the role of occasionally binding financial constraints, the model accounts for up to 50 percent of the asymmetry in the year-on-year growth of real GDP in the post-1984 sample, as measured by both the skewness and the ratio between the downside and the upside semivolatility of GDP growth.

These properties reflect into a marked transformation in the shape of the business cycle. As leverage increases, the model is capable of reproducing relative changes in the average duration of contractions and expansions that are broadly in line with those documented in Table 3: while the former invariantly last one year, the latter increase their duration from around four to five years to roughly eight years (see Figure 8). However, higher leverage is associated with relatively more severe contractionary episodes, as implied by the standardized violence reported in the last panel of the figure. These findings have a common root: an increase in their average LTV ratios allows financially constrained agents to be in a better position to smooth consumption and investment during expansions.

It is important to mention that changes in business-cycle skewness are predominantly driven by the firm sector becoming increasingly unconstrained as the average LTV ratio increases. Impatient households, instead, never find themselves unconstrained, primarily because their debt contracts are long term, implying that shocks tend to affect a relatively small part of the stock of debt being refinanced in

Notes: Panel A of the figure reports the skewness of the year-on-year growth rate of output, consumption, and investment, while panel B displays the ratio between the downside and the upside semivolatility of year-on-year output growth, for different average LTV ratios faced by the financially constrained agents. To identify the recessionary episodes in the simulated series, we use the Harding and Pagan (2002) algorithm. Across all the simulations, the entrepreneurial average LTV ratio is adjusted to be nine basis points greater than any value we consider for impatient households’ credit limits, in line with the baseline calibration of the model.

Though the functioning of occasionally binding constraints does not primarily hinge on the prices of collateral assets, these play a quantitatively important role. To see this, the reader is referred to Figure G8 in online Appendix G4, where we report a set of statistics obtained by simulating an alternative version of the model where the collateral assets are pledged at their steady-state prices.
However, household borrowing helps to account for some desirable quantitative properties, primarily a sizeable increase in the duration of expansions (see online Appendix G3).

C. Skewness and Volatility

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). We now examine this finding in conjunction with the change in the asymmetry of the business cycle, which has largely occurred over the same time span.

Panel A of Figure 9 reports the standard deviation of output growth as a function of the average LTV ratios. As shown by Jensen, Ravn, and Santoro (2018) in a similar model, macroeconomic volatility displays a hump-shaped pattern: 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 reverts, as higher LTV

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Notes: Panels A and B report the duration (in quarters) of expansions and contractions, respectively. Panel C displays the standardized violence of recessionary episodes. To identify expansions and contractions in the simulated gross output series, we use the Harding and Pagan (2002) algorithm. We compute the violence as the average fall of output over a given recession, divided by the length of the recession itself. Finally, we standardize the violence by means of the volatility of year-on-year output growth over the five years prior to the recession. All statistics are conditional on different average LTV ratios faced by the financially constrained agents. Across all the simulations the entrepreneurial average LTV ratio is adjusted to be nine basis points greater than any value we consider for impatient households’ credit limits, in line with the baseline calibration of the model.

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30 The frequency of nonbinding constraints for both impatient households and the entrepreneurs is reported in Figure G4 in online Appendix G2. Guerrieri and Iacoviello (2017) reports that nonbinding credit constraints were prevalent among US households from the late 1990s until the onset of the Great Recession. The difference between our results and their evidence mainly lies in the fact that they calibrate a smaller degree of inertia in the borrowing limit.

31 Moreover, households only feature one type of collateral asset in their borrowing constraint. This limits the amplification of shocks affecting their borrowing capacity.
ratios increase the likelihood that credit constraints become nonbinding. In such cases, the consumption and investment decisions of households and entrepreneurs may delink from changes in the value of their collateral assets, dampening the volatility of aggregate economic activity. In fact, at the upper end of the range of average LTV ratios we consider, volatility drops below the value we match under the baseline calibration.

A key property of a model with occasionally binding constraints is that 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 $s^I \approx 0.8$ is mostly connected with expansionary periods. Panel B of Figure 9 confirms this view: here, we compare the volatility of expansionary and contractionary episodes, respectively, as a function of the average LTV ratios. The volatility of expansions is always lower than that of contractions, and declines over the entire range of average credit limits. The volatility of contractions, however, increases steadily.

Notably, increasing leverage allows the model to account for different correlations between the volatility and the skewness of output growth. Based on the comparison between Figure 7 and panel A of Figure 9, this correlation is increasingly negative until $s^I \approx 0.8$, thus becoming positive as financial deepening reaches very advanced stages. These results are reminiscent of the evidence reported by Bekaert and Popov (2013), who document a positive long-run correlation between the volatility and skewness of output growth in a large cross section of countries, but also a negative short-run relationship: as financial leverage reaches a certain level across advanced economies, our results predict that skewness and volatility will eventually decline in conjunction.

**Figure 9. Leverage and Volatility**

Notes: Panel A reports the standard deviation of year-on-year output growth, while panel B reports the standard deviation of expansions (solid blue line) and contractions (dashed green line) in economic activity. These are determined based on whether output is above or below its steady-state level. Across all the simulations, the entrepreneurial average LTV ratio is adjusted so as to be nine basis points greater than any value we consider for impatient households’ credit limits, in line with the baseline calibration of the model.
A word of caution is in order at this stage. While our framework points to a hump-shaped relationship between credit limits and macroeconomic volatility, the key driver of business-cycle asymmetry—endogenous shifts between binding and nonbinding collateral constraints—in itself works as an impetus of lower macroeconomic volatility, ceteris paribus. Thus, despite our analysis not warranting 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. A related question is whether our main finding of increasingly negative business-cycle asymmetry would survive in the presence of a reduction in macroeconomic volatility of the magnitude observed during the Great Moderation. The next subsection tackles this point.

**Counterfactual Exercises: Accounting for the Great Moderation.**—We now turn to a counterfactual exercise aimed at reconciling our main finding of increasingly negative business-cycle asymmetry with a reduction in macroeconomic volatility of the magnitude observed during the Great Moderation. To this end, we conduct two experiments: in the first experiment, we take a perspective similar to that of Section VB, but feed in the actual, estimated low-frequency components of the LTV ratios of households and firms, respectively, rather than relying on a linear and parallel increase in the leverage of the two agents. In the second experiment, we repeat the exercise in combination with a gradual reduction of the standard deviations of all the shocks in the model. This reduction is reverse-engineered to obtain a decline in macroeconomic volatility similar to the one observed in the data during the Great Moderation. Specifically, we target a decline in the volatility of output growth of around 40 percent, in line with the evidence reported in Section IA. To this end, we assume that the reduction in the magnitude of the shocks starts in 1984, and is completed by 1989.

The results from our experiments are reported in Figure 10: here, the skewness, the ratio between the downside and the upside semivolatility, and the volatility of output growth are reported over the 1980–2016 time span. In both experiments, the skewness displays a decline of roughly the same magnitude as that observed in Figure 7, reaching a level of about $-0.6$ by the end of the sample—about half of

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32 In fact, several authors have pointed to financial liberalization and the associated easing of the financial constraints of both households and firms as a contributor to the Great Moderation (see, e.g., Justiniano and Primiceri 2008 and, for a review of the literature, Den Haan and Sterk 2011).

33 In this respect, it is important to recognize that none of the factors to which the Great Moderation is typically ascribed are featured in our model. The most popular narratives about the Great Moderation are a drop in the volatility of economic shocks (see, e.g., Justiniano and Primiceri 2008) and improvements in the conduct of monetary policy (see, e.g., Boivin and Giannoni 2006).

34 Specifically, for each year in the 1980–2016 time window, we feed in the annual average of the quarterly long-run LTV components, as depicted in Figure A1 in online Appendix A1. To make up for the difference in levels between the aggregated series and the (somewhat higher) calibrated LTV ratios, we add an (agent-specific) constant to the low-frequency components. If, at any time, the implied LTV ratio exceeds 0.99, we cap it at this value. The implied paths of the LTV series are reported in Figure G10 of online Appendix G5.

35 This exercise is thus consistent with the “Good Luck” narrative of the Great Moderation (Stock and Watson 2003). Throughout both experiments, we keep the relative size of the shocks fixed and in accordance with the estimation reported in Section IVA. The path of the scaling factor is illustrated in Figure G9 of online Appendix G5. The results are generally robust to alternative choices of the transition window.
the corresponding level reported in Table 1. The ratio between the business-cycle semivolatilities behaves coherently. As for the standard deviation, it drops by about 40 percent when we reduce the size of the shocks hitting the economy (by construction), while displaying a very small decline in the alternative scenario. Although the increase in LTV ratios in these experiments is not too different from the exercises in the previous subsection, it is important to stress that the coexistence of a large change in the asymmetry and the volatility of the business cycle is not trivial: all else equal, reducing the size of the shocks hitting the economy lowers the probability that collateral constraints become nonbinding, thus potentially weakening the key driver of business-cycle asymmetry in the model. However, we find that smaller shocks only slightly mitigate the potential to produce sizable nonlinearities.

**VI. 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. For example, using data for 14 advanced economies for the period 1870–2008, Jordà, Schularick, and Taylor (2013) finds that more credit-intensive expansions tend to be followed by deeper recessions, whether or not the recession is accompanied by a financial crisis.

Note: The figure displays changes in the skewness, the ratio between the downside and the upside semivolatility and the standard deviation of (year-on-year) output growth. Two counterfactual experiments are performed. In both of them, we feed the estimated trends of the LTV ratios of households and firms into the model (see online Appendix A1), from 1980 to 2016. The solid blue line refers to an experiment in which we keep the magnitude of the shocks to the economy constant and equal to their estimated values. The dashed green line, instead, refers to an experiment in which the size of the shocks is gradually reduced so as to obtain a 40 percent reduction in the volatility of output growth over the 1984–1989 time span, and kept constant thereafter.

36 The initial hike (drop) in the skewness (ratio between the downside and upside semivolatility) of output growth can be explained by the fact that, in the face of a reduction in the volatility of the shocks taking place over a rather limited time span, the LTV ratios of both agents rise over a much larger time window.
In this section, we demonstrate that our model is also capable of reproducing these empirical facts. Figure 11 reports the results of the following experiment: starting in the steady state, we generate a boom-bust cycle for different average LTV ratios. We first feed the economy with a series of positive shocks of all three types in the first five periods (up to period 0 in the figure). During the boom phase, we calibrate the size of the expansionary shocks hitting the economy so as to make sure that the boom in output is identical across all the experiments. Hereafter, starting in period 1 in the figure, we shock the economy with contractionary shocks of all three types for two periods, after which the negative shocks are “phased out” over the next three periods. Crucially, the contractionary shocks are identical across calibrations. This ensures that the severity of the recession is solely determined by the endogenous response of the model at each different LTV ratio. As the figure illustrates, the deepness of the contraction increases with the steady-state LTV ratios. A boom of a given size is followed by a more severe recession when debt is relatively high, as compared with the case of more scarce credit availability. At higher average LTV ratios, 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 relatively low, financially constrained agents face lower credit availability 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 spills over to the ensuing contraction. Panel A of Figure 12 compares the path of output in two different boom-bust cycles, while panel B shows the corresponding paths for aggregate debt. In each panel, the dashed line represents a nonfinancial boom generated by a combination of technology and land-demand shocks, while the solid line denotes a financial boom generated by credit limit shocks. We calibrate the size of the expansionary shocks so as to deliver an identical increase in output during each type of boom (which lasts for five periods, up until period 0 in the figure). As in the previous experiment, we then subject the economy to identical sets of contractionary shocks of all three types, so as to isolate the role played by the specific type of boom in shaping the subsequent recession. The contractionary shocks hit in periods 1 and 2 in the figure, and are then “phased out” over the next three periods. While the size of the expansion in output is identical in each type of boom, the same is not the case for total debt, which increases by more than twice as much during the financial boom. The consequences of this build up of credit show up during the subsequent contraction, which is much deeper following the financially fueled expansion, in line with the empirical findings of Jordà, Schularick, and Taylor (2013). As in Mian

37 During both the boom and the bust, we keep the relative size of the three shocks fixed and equal to their estimated standard deviations. However, we set their persistence parameters to zero in order to avoid that the shape of the recession may be determined by lagged values of the shocks during the boom. Finally, we make sure that impatient households and entrepreneurs remain constrained in all periods of each of the cases, so as to enhance comparability.

38 In the nonfinancial boom, we keep the relative size of the technology and land-demand shocks in line with the values estimated in Section IV A. As in the previous experiment, we set the persistence parameters of all the shock processes to zero.
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Figure 11. Boom-Bust Cycles and Leverage

Notes: The figure shows the path of output (in percentage deviation from the steady state). Starting in steady state, we generate a boom-bust cycle for different steady-state debt levels, as implied by different average LTV ratios. We first feed the economy with a series of positive shocks during the first five periods, up until period 0. The size of the expansionary shocks is set so as to make sure that the boom is identical across all the calibrations. Then, we shock the economy with identical contractionary shocks for two periods, after which the negative shocks are “phased out” over the next three periods, i.e., their size is reduced successively and linearly. Across all the simulations the entrepreneurial average LTV ratio is adjusted so as to be nine basis points greater than any value we consider for impatient households’ credit limits, in line with the baseline calibration of the model.

Figure 12. Financial versus Nonfinancial Recessions

Notes: The figure shows the path of output (panel A) and aggregate debt (panel B), both in percentage deviations from the steady state. The solid blue line represents a financial boom, while the dashed green line represents a non-financial boom. Impatient households and entrepreneurs remain constrained throughout both types of booms. In this experiment, we set the average LTV ratios to \( s^I = 0.85 \) and \( s^E = 0.94 \). We calibrate the size of the expansionary shocks so as to deliver an identical increase in output during each type of boom (which lasts for five periods, up until period 0). We then subject the economy to identical sets of contractionary shocks of all three types. The contractionary shocks hit in periods 1 and 2, and are then “phased out” over the next three periods, i.e., their size is reduced linearly.
VII. Concluding Comments

We have documented how different dimensions of business-cycle asymmetry in the United States and other G7 countries have changed over the last decades, and pointed to the concurrent increase in private debt as a potential driver of these phenomena. We have presented a dynamic general equilibrium model with credit-constrained households and firms, in which increasing leverage translates into a more negatively skewed business cycle. This finding relies on the occasionally binding nature of financial constraints: as their credit limits increase, financially constrained agents are more likely to become unconstrained during booms, while credit constraints tend to remain binding during downturns.

These insights shed new light on the analysis of the business cycle and its developments. The Great Moderation is widely regarded as the main development in the statistical properties of the US business cycle since the 1980s. We point to a simultaneous change in the shape of the business cycle closely connected with financial factors. Enhanced credit access as observed over the last few decades implies both a prolonging and a smoothing of expansionary periods as well as less frequent—yet, relatively more dramatic—economic contractions, exacerbated by deeper deleveraging episodes. As for the first part of this story, several contributions have pointed to the attenuation of the upside of the business cycle as the main statistical trait of the Great Moderation. Nevertheless, insofar as financial liberalization and enhanced credit access can be pointed to as key drivers of an increasingly asymmetric business cycle, the second insight implies that large contractionary episodes, albeit less frequent, might represent a “new normal.”

Our results are also of interest to macroprudential policymakers, as we complement a recent empirical literature emphasizing that the seeds of the recession are sown during the boom (see, e.g., Mian, Sufi, and Verner 2017). The nature of the expansionary phase, as much as its size, is an important determinant of the ensuing downturn, and policymakers should pay close attention to the sources of a buildup of credit during expansions in macroeconomic activity.

REFERENCES


39 Addressing the endogeneity of credit and business-cycle dynamics, Gadea Rivas and Perez-Quiros (2015) stresses that growing credit is not a predictor of future contractions. Our model simulations are consistent with this view. In fact, as displayed by Figure 12, output and credit growth are strongly correlated, regardless of whether the boom is driven by financial shocks. At the same time, the model predicts that a boom driven by financial shocks is associated with a stronger increase in debt and a deeper contraction, as compared with an equally sized nonfinancial boom.


