What are the Sources of Boom-Bust Cycles?*

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Abstract

Boom-bust cycles are a prevalent feature of economic fluctuations, but there is no consensus on how they come about. Are these cycles the result of recurring positive and negative shocks, or do they arise because of processes internal to the system? Empirically, we find that positive shifts in expectations generate boom-bust dynamics, whereas shocks to fundamentals do not. We rationalize these findings in a Real Business Cycle model with an endogenous borrowing limit. In the model, credit market amplification plays a central role during expectation-driven expansions, while it barely shapes economic dynamics after technology improvements. As in the data, both types of expansions are characterized by an increase in credit growth, suggesting that policies aimed at limiting *all* credit expansions might not be optimal.

JEL classification: E3, E32, E44
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1 Introduction

This paper provides a synthesis of two major views on economic fluctuations. One view maintains that expansions and recessions arise from the interchange of positive and negative persistent exogenous shocks to fundamentals. This is the conventional view that gave rise to the proliferation of shocks used in modern dynamic stochastic general equilibrium models. A second view, which we call the inherent instability view, holds that business cycle fluctuations are due to forces that are internal to the economy and that endogenously favor recurrent periods of boom followed by a bust. In this environment, cycles can occur even in absence of shocks to fundamentals. Conclusive evidence in favor of either view is hard to find. One reason may be that a complete representation of the economy is one in which both views coexist.

We make three contributions. First, we uncover a *cyclicality conundrum* in the data: while unconditional moments reveal the presence of a strong systemic cyclical component in line with the inherent instability view, there is virtually no evidence of boom-bust dynamics in response to identified fundamental shocks. Second, we build a theory that rationalizes the conundrum and proposes non-fundamental shocks to expectations as the key source of boom-bust cycles. Third, we identify expectation shocks using survey data and verify that, indeed, expectations shocks generate boom-bust dynamics in all the key variables and account for a sizeable fraction of business cycle fluctuations.

In the first part of the paper, we show that the spectral densities of a number of U.S. macroeconomic and financial variables display a peak at periodicities of around 8 to 10 years. A hump-shaped spectral density signals the presence of periodic motions that repeat themselves in a regular cycle. In addition, we show that the probability of a recession peaks about two years after an expansion – findings that are *inconsistent* with the predictions of standard DSGE models. Next, we argue that the responses to identified fundamental shocks almost always deliver mean-reverting responses more aligned with the conventional view. We take a temporary shock to utilization-adjusted TFP as the leading case. A positive TFP shock leads to a temporary expansion that is not systematically followed by a recession. By comparing the conditional spectral densities implied by a TFP shock with their unconditional counterparts, we show that these shocks cannot be responsible for the cyclical properties of the data.

In the second part of the paper, we propose a general equilibrium model that rationalizes the conundrum. Given the particularly robust evidence on boom-bust cycles among financial variables, financial frictions play a central role in our theory. The structure of the model echoes Jermann and Quadrini (2012) in that firms borrow from households by issuing short and long-term debt. Short-term debt is useful to satisfy a working capital requirement, whereas firms use long-term debt to smooth out dividends. The central innovation of the model is a borrowing constraint that ensures no default in equilibrium, and depends positively on firms' market value but negatively on their end of period revenues. This type of endogenous borrowing limit generates a strong financial amplification mechanism that causes boom-bust dynamics in response to shifts in agents' expectations, but not in response to technology shocks.

Boom-bust dynamics arise from the interaction between the accumulation of long-term debt and firms' failure to internalize the effects of their choices on the borrowing constraint. The intuition is as follows. Suppose that households become more optimistic regarding firms' future value so that equity prices increase. Increased equity prices relax borrowing constraints and allow firms to increase both short and long-term debt. Because short-term debt is useful to finance production, looser borrowing constraints reduce the labor wedge and raise the demand for labor. The resulting higher wages and labor increase households' desire to save which, in turn, raises equity prices and further relaxes borrowing constraints. Yet, as the economy evolves, firms' long-term debt expands causing a contraction of their market value *ceteris paribus*. Eventually, firms reduce their short-term borrowing to meet the payments on their long-term debt. In doing so, they do not internalize the adverse effects on equity prices stemming from the increase in the labor wedge and the decrease of labor demand. Thus borrowing constraints tighten, production and equity prices fall while the labor wedge increases: a recession.

Intuitively, the amplification channel should deliver similar boom-bust responses after shocks to technology, but it does not. The reason is that while a technology improvement increases equity prices, it also raises end of period revenues which *ceteris paribus* tighten the borrowing constraint. As a result, financial frictions *dampen* the response of output and debt to a technology shock, thereby leading to an impact *increase* in the labor wedge. Thus, during a technology-driven expansion the economy is less exposed to the severe incentive problems that arise from excessive accumulation of long-term debt and that characterize expectation-driven expansions.

We argued that changes in expectations disconnected from technology can rationalize the boom-bust features of the data, but what triggers such changes? The model's answer is that equilibrium outcomes are the product of self-fulfilling shifts in agents' expectations, and when these changes are unrelated to fundamentals they generate boom-bust dynamics. The intuition is that boom-bust dynamics obtain when the internal financial amplification channel is sufficiently strong, but this happens *only* in the case in which the dynamic equilibrium is indeterminate, that is, the economy is subject to self-fulfilling shifts in expectations (a.k.a. sunspots).

In the third part of the paper, we empirically identify expectation shocks and test the predictions of the model. Specifically, we construct an indicator that summarizes the revisions of expectations on the future economic outlook using quarterly data on expectations from the Survey of Professional Forecasters and the Survey of Consumers. We use the indicator to identify exogenous shifts in expectations that are uncorrelated with past, present and future realizations of TFP. In addition, we control for a number of leads and lags of shocks to expectations of TFP in order to isolate shifts in expectations that are pure sentiments from those originating from beliefs on future TFP. Using local projections, we find that expectation shocks generate significant boom-bust dynamics in all the aggregate variables that we examine, and explain up to 40% of real GDP at business cycle frequencies, consistent with the findings of Angeletos et al. (2018) and Chahrour and Ulbricht (2019).

Finally, we show that the mechanism of the model is consistent with many features of the data. First, we find that the model is able to reproduce the empirical impulse responses to both expectation and TFP shocks. As in the model, expectation shocks bring about a countercyclical movement of the labor wedge, while the labor wedge *increases* after TFP improvements. Second, we show that the model can replicate the reduced-form evidence on boom-bust cycles that motivated our analyses. Unlike standard business cycle models, our theory can explain both the hump in the spectral densities of macroeconomic and financial variables, and the rising probability of a recession following an expansion.

Related literature. This paper lies at the intersection between the strand of the finance literature that focuses on credit cycles and the broad macroeconomic literature that aims at understanding the sources of business cycles.

The idea that the financial system is prone to generate economic instability through endogenous credit booms traces back at least to Kindleberger (1978) and Minsky (1975,1986). Minsky (1986) provides groundbreaking insights on the relation between the economic and the financial system. Of particular interest for this paper is his distinction between "periods of tranquility," defined as situations during which the economy is not subject to disruptive changes, and "unstable times" during which market forces lead to a rise of financial instability which culminates in "speculative frenzies". Through the lenses of our model and empirical evidence, we view such "periods of tranquility" as moments during which technological changes are the major contributor to economics fluctuations, whereas "unstable times" are characterized by economic fluctuations primarily driven by changes in market expectations.

More recently, the idea that an increase in credit associated with a decrease in borrowing costs can be a powerful predictor of future economic crises has been empirically tested and verified using both macro and micro level data. For example, Schularick and Taylor (2012) and Jordà et al. (2013), using data on 14 developed countries from 1870 to 2008, demonstrate that rapid credit expansions forecast declines in real activity.[1] Using data on the credit quality of corporate debt issuers, Greenwood and Hanson (2013) find that a high share of risky loans tends to forecast low corporate bond returns. Krishnamurthy and Muir (2017) show that crises are preceded by a period of high credit to GDP growth and leverage, and low spread and risk premium. We complement this literature by providing conditional evidence on the link between a credit boom and the ensuing recession. We show that positive expectation shocks - but not TFP shocks - are systematically followed by a recession. Our evidence on expectation shocks also relates to López-Salido et al. (2017) who focus on credit market sentiment identified using credit spreads and find that high credit market sentiments are a predictor of future negative output growth. We complement their analysis by showing that sentiment shocks not only predict a negative output growth but also prolonged periods during which the *level* of output is below trend.

We relate to the literature that aims at rationalizing boom-bust phenomena. For example, Boissay et al. (2016) rationalize boom-bust episodes in a model where the increase

[1] Other examples include Demirgüç-Kunt and Detragiache (1998), Hardy and Pazarbasioglu (1998), Kaminsky and Reinhart (1999), Gourinchas et al. (2001), Goldfajn and Valdes (2006), Borio and Drehmann (2009), Reinhart and Rogoff (2009), Claessens et al. (2011), Gourinchas and Obstfeld (2012), and Laeven and Valencia (2013).

in households' savings during a boom exacerbates adverse selection problems in the interbank market. In our model, the increase in savings brings about a recession because it reflects an increase in firms' debt which tightens financial markets. A subset of this literature builds model of chaos and limit cycles. Boldrin and Woodford (1990) survey the literature and analyze the conditions under which limit cycles can emerge. In a recent paper, Beaudry et al. (2019) revisit the reduced-form evidence on the spectral densities of a series of economic variables. They build a model of limit cycles where small exogenous shocks give rise to perpetual economic cycles. While our model can also exhibit limit cycles for regions of the parameter space that imply a sufficiently tight financial constraint, our aim is rather to rationalize the fact that only a subset of shocks trigger oscillatory dynamics while other shocks do not. Gorton and Ordonez (2016) distinguish between "good" and "bad" credit booms depending whether or not they end up in a crisis. They find that shocks in the trend of productivity are associated with "good" credit booms, whereas "bad" booms are typically associated with a decline in productivity. We differ from them in at least two aspects. First, we look at cycles at short and medium-run frequencies while their focus is on booms that last ten years on average. Second, we emphasize that the shocks responsible for boom-bust episodes are orthogonal to movements of TFP.

Furthermore, we relate to the class of models that generate self-fulfilling rational expectations equilibria due to credit market amplification. Examples of this class are Benhabib and Wen (2004), Benhabib and Wang (2013), Liu and Wang (2014), and Azariadis et al. (2015). While their emphasis is on a single shock, our model is built to capture the important different responses to fundamental and sunspot shocks.

Lastly, our theoretical framework shares some similarities with models of stock market bubbles as in Miao and Wang (2018), in that, debt limits depend upon firms' market value and sentiment shocks can be interpreted as bubbles. However, models of stock market bubbles formalize the burst of a bubble as an exogenous event. In contrast, in our model sentiment shocks rationalize both the formation of a bubble and its subsequent burst.

2 The *cyclicality* conundrum

Boom-bust cycles are a recurrent feature of the data. Yet, there is virtually no evidence of boom-bust dynamics conditional on shocks. We refer to such empirical incoherence as the *cyclicality* conundrum. This section documents the conundrum by showing that there is a systemic cyclical component in the data which does not manifest in the dynamics induced by shocks to fundamentals.

2.1 Unconditional evidence of cycles

In a recent article, Beaudry et al. (2019) provide evidence in favor of U.S. business cycles being characterized by cyclical forces. In particular, they show that the spectral densities of a number of economic aggregates exhibit a common local peak at periodicities of 32 to 50 quarters. The spectral density is a useful diagnostic tool of cyclicality for two reasons.[2] First, a peak in the spectral density signals the presence of oscillatory dynamics in the autocovariance function of the data. Second, it tells us whether these oscillatory dynamics happen at business cycle frequencies or they reflect lower frequency forces unrelated to business cycles.

Figure 1 reports the spectral density of a series of macroeconomic and financial variables.[3] We use quarterly data from 1967:q1 to 2018:q4 and detrend variables using a band pass filter that removes fluctuations with periodicities longer than 100 quarters.[4,5] Two patterns emerge. First, results point at the presence of a strong common cyclical component. With the exception of utilization-adjusted TFP, all variables exhibit a peak in the spectral density in the interval between 32 and 50 quarters. Furthermore, the fact that there are no notable differences in the shape of the spectral density across variables, suggests the presence of an underlying mechanism responsible for the cyclical patterns rather than idiosyncrasies in the variables examined. Second, financial variables exhibit a more pronounced peak relative to macroeconomic variables suggesting that the cyclical features of the data might originate from shocks propagating through the financial sector, whereas shocks that primarily hit the real sector of the economy generate less oscillatory dynamics.

Importantly, a hump-shaped spectral density is a finding inconsistent with the predictions of standard business cycle models. In Figure 13 in appendix B we run a Monte Carlo simulation on the spectral density of output using a textbook Real Business Cycle model and the New-Keynesian model by Smets and Wouters (2007). We find that the spectral

[2] The notion of cyclicality that we use is analogous to Beaudry et al. (2019), that is a series is cyclical if its autocovariance function displays oscillations.

[3] The spectral density is computed using the Schuster's periodogram.

[4] Because filtering the series could induce a spurious hump in the spectral density, we check that results are robust to various detrending techniques and frequency bands.

[5] The choice of the data sample does not affect the results. We start from 1967 as it is consistent with the longest data sample available for the analyses carried in Section 4.

density of output from model simulated data is counterfactually increasing in the periodicity.

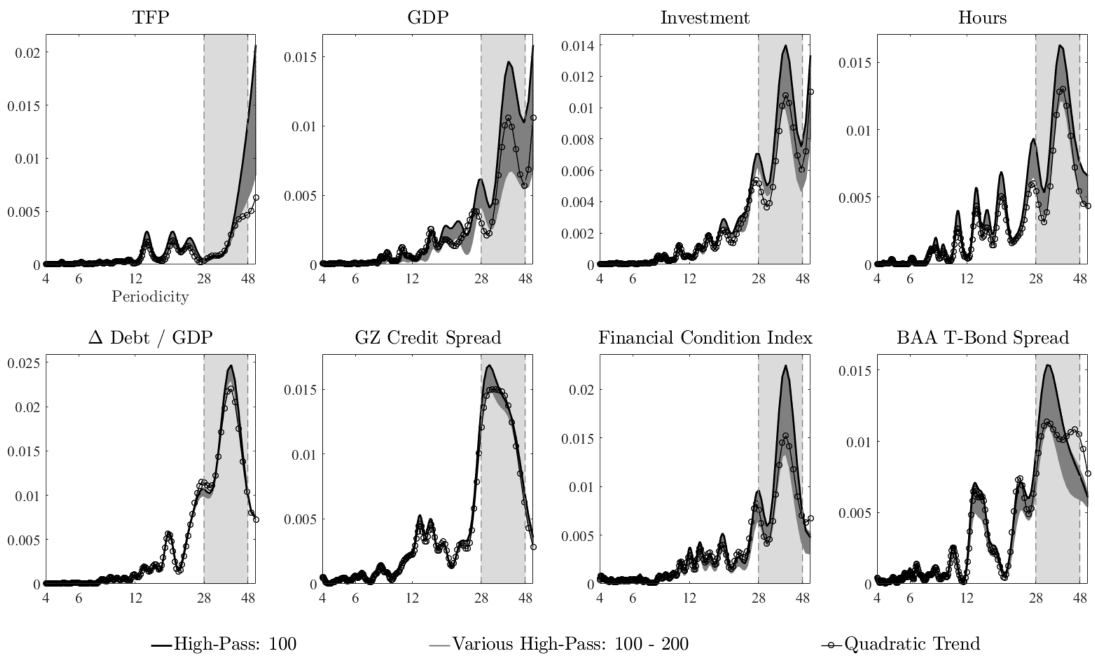

Figure 1: Unconditional spectral densities of quarterly U.S. signal systemic cyclicality

Note: Data from 1967:q1 to 2018:q4. TFP is utilization-adjusted total factor productivity. GDP is real gross domestic product. Investment is real consumption of durables plus real gross private domestic investment. Hours is hours of all persons in non-farm business sector. Change in debt is the flow of nonfinancial business debt securities and loans. GZ Credit Spread is the measure of credit spread described in Gilchrist and Zakrajšek (2012). Financial Conditions Index is provided by Chicago Fed. BAA T-Bill Spread is the difference between the yield of BAA corporate bonds and the treasury note at 10-year horizon. Series are detrended using a quadratic trend (circle-solid line), a filter that excludes fluctuations of period greater than 100 (black line), or from 101 to 200 (dark grey lines).

The presence of a systemic cyclical component in the data implies that the probability that a recession occurs should increase after an expansion. To verify whether this is true, we estimate a simple linear probability model and compute the probability that the economy enters in a recessions after k quarters since the previous expansion. We define expansions as periods in which real GDP growth is above the top quintile for at least two consecutive quarters. Likewise, we construct a recession indicator that takes value equal one if the real GDP growth falls into the bottom quintile for at least two consecutive quarters. Figure 2 plots the probability that the economy will be in a recession in a two-quarter window around time $t+k$ given an expansion at time t. Results confirm the evidence of cyclicality described above. The probability of a recession increases after an expansion and peaks approximately two years after the expansion. The picture also shows the prediction from data simulated using standard business cycle models such as the one described in Smets and Wouters (2007), and the textbook Real Business Cycle model. Both models predict that recessions are essentially unforecastable, so that the probability of a recession quickly converges to its unconditional mean after an expansion. To see this, we plot the results from simulating a random walk process in levels and show that the results from both the New Keynesian model, and the RBC model are indistinguishable from those obtained by simulating a random walk.

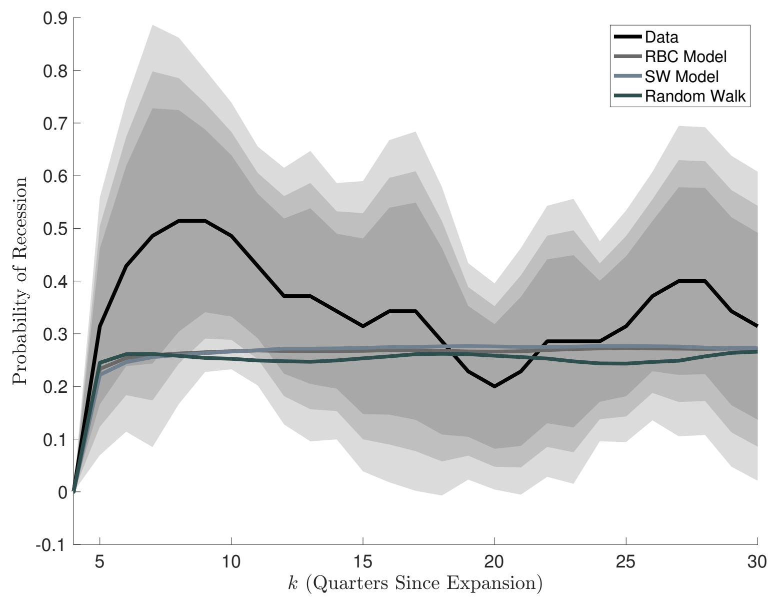

Figure 2: Probability of a recession peaks two years after an expansion

Note: Probability of recession in a two-quarter window after k quarters since expansion. Confidence intervals are 68%, 80%,and 90% (shaded areas) around the point estimate (solid black line).

2.2 Conditional rejection of cycles

Ultimately, we are interested in understanding the *sources* of the oscillatory behaviour documented above. To this end, we ask whether technology shocks account for these empirical regularities. We use quarterly utilization-adjusted TFP (Basu et al., 2006) and identify technology shocks as the innovation of detrended TFP after regressing it on its own lags, lags of the first principal component of a large dataset of aggregate economic variables and news shocks estimated following Barsky and Sims (2011).[6] We estimate impulse responses using the method of local projections proposed by Jordà (2005). Specifically, we estimate the h-th coefficient of the impulse response function by regressing each variable at time $t+h$ on the shock at time t.[7] We choose to implement the method of local projections because unlike vector autoregressions (VAR), it does not require to specify the lag structure of the data generating process.

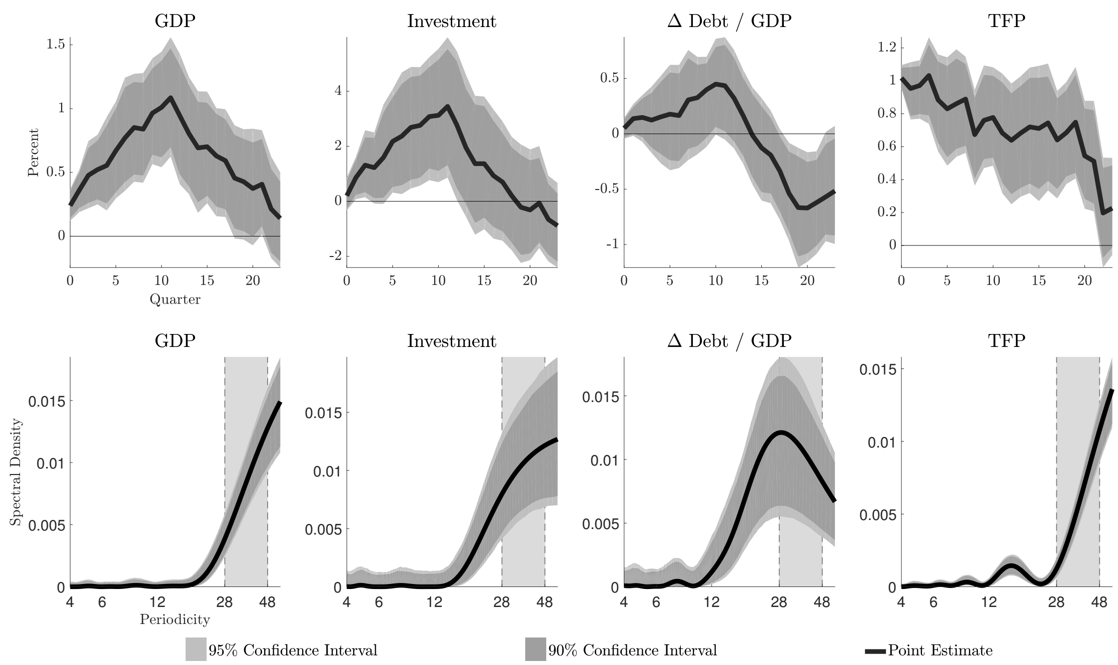

Figure 3: Impulse responses and spectral densities of a TFP shock.

Note: Technology shocks are the innovation of detrended TFP after regressing it on its own lags, lags of the first principal component of a large dataset of aggregate economic variables and news shocks estimated as in Barsky and Sims (2011). Impulse responses (top panel) are estimated using local projections method. Confidence intervals are computed using the block-bootstrap method described in Kilian and Kim (2011). Conditional spectral densities (bottom panel) are computed from the Fourier transform of the estimated MA.

The top panel of Figure 3 shows the impulse responses of real GDP, investment and the change in nonfinancial corporate debt as a fraction of GDP, to a positive transitory technology shock. An unanticipated improvement of TFP leads to a hump-shaped response of real GDP and investment, aggregate debt rises during the initial build-up and decreases while the economy returns to its long run trend. To verify whether these impulse responses

[6] Results are robust to different detrending techniques, additional controls, and different number of lags and principal components. See Appendix C for results and additional details.
[7] Details on local projections are in the Appendix E.

can account for the spectral properties of the data, we compute the spectral densities implied by the estimated coefficients of the moving averages. The bottom panel of Figure 3 shows that the spectral densities of real GDP and investment conditional to a TFP shock are monotonically increasing over business cycle periodicities. This poses a challenge to TFP-based explanations of boom-bust cycles.

Conditional test for the presence of a local peak The lack of a local peak in the spectral density of output, investment, and TFP observed in Figure 3 suggests that technology shocks cannot account for spectral properties of the data shown in Figure 1. To make the point, we construct a test for the presence of a significant local peak in the spectral density conditional to a structural shock. The test procedure echoes Canova (1996) and Reiter and Woitek (1999) who design a test for the presence of a peak for the unconditional spectral density. Details of our procedure are presented in the Appendix G. The idea is to test if the shape of the conditional spectral density around a particular frequency range is not statistically different from the spectral density implied by an autoregressive process of order one. More specifically, define D_1 the average estimated spectral density over a range around 34 quarters, and D_2 the average estimated spectral density over a range around 45 quarters. The test statistic is the ratio $D \equiv D_1/D_2$. A value of D bigger than one indicates the spectral density is decreasing in the range 34 to 45 quarters. The spectral density associated to an AR(1) process, in contrast, is monotonically increasing in the periodicity. Therefore we test the null hypothesis $H_0 : D = D^*$ where D^* is the value implied by an AR(1) with persistent parameter estimated from the data, against the alternative $H_1 : D > D^*$. Results for the technology-implied spectral density are reported in Table 2. We fail to reject the null hypothesis of absence of a local peak for GDP, investment, and TFP.

Taken together our reduced form and conditional evidence points at the presence of oscillatory properties of the data that do not appear to be captured by movements in TFP. In the next section we build a model that helps us rationalizing the findings and propose “pure" sentiment shock - defined as shifts in expectations unrelated to fundamental - as a natural candidate to explain the spectral properties of the data. In section 4 we construct novel empirical evidence in favor of this hypothesis and show that the model can reproduce the responses to sentiment and technology shocks together with the unconditional spectral densities of the data.

3 A model of conditional cycles

In this section we show that a standard Real Business Cycle model augmented with financial frictions can rationalize the cyclicality conundrum. Azariadis et al. (2015) document that unsecured firm credit is procyclical whereas collateralized debt is acyclical. Building on their findings, we assume a type of solvency constraint that allows firms to borrow up to a fraction of their market value. Furthermore, we introduce short and long term debt as in Jermann and Quadrini (2012). This form of financial friction combined with procyclical fluctuations of long-term debt generate strong internal amplification and cyclical dynamics in response to serially uncorrelated shifts in expectations. For plausible parametrizations of the financial constraint, we find that the model displays dynamic multiplicity of equilibria due to self-fulfilling changes in expectations (a.k.a sunspots). In this environment, waves of optimism unrelated to present and future fundamentals, generate temporary expansions followed by recessions.

Importantly, our model stands in stark contrast to the class of models of self-fulfilling business cycle that provide microfoundations to the aggregate increasing returns to scale economy described in Benhabib and Farmer (1994).[8] Amplification in the form of increasing returns would strongly influence the transmission of technology shocks, thus, while these models can generate endogenous oscillatory dynamics, they cannot *simultaneously* account for the empirical evidence on technology shocks.

For expositional reasons, we present first a benchmark model featuring intertemporal debt as the only state variable. In the next section we identify sentiment shocks in the data and augment the model with capital and external consumption habit to match empirical responses. We further validate model's performance by showing that it does a good job in matching the spectral properties of the data.

3.1 Firm sector

There is a continuum $i \in [0,1]$ of firms with a gross revenue function $F(z_t, k_t, n_t) = z_t k_t^{\theta} n_t^{1-\theta}$. The variable z_t is the stochastic level of productivity common to all firms, n_t is the labor input, k_t is the capital input which we assume to be constant and equal to one for now.

[8] Examples of this class are Benhabib and Wang (2013) and Liu and Wang (2014).

Firms issue noncontingent bonds b_{t+1} at a price b_{t+1}/R_t. We assume that firms receive a tax advantage such that given the interest rate r_t, the effective gross interest rate for the firm is $R_t = 1 + r_t(1-\tau)$ where τ is the tax benefit. Thus, firms are effectively more impatient than households so that if financial markets are not too tight the equilibrium stock of debt will be positive. In addition to the intertemporal debt, firms raise funds with an intraperiod loan, ℓ_t, to finance working capital. Because revenues are realized at the end of the period, working capital is required to cover the intraperiod cash flow mismatch. The loan ℓ_t is paid at the end of the period with no interest.[9]

The timing of the events is the same as in Jermann and Quadrini (2012). Shocks realize at the beginning of the period. Firms enter the period with outstanding debt equal to b_t and choose labor n_t, the new intertemporal debt b_{t+1} and distribute dividends d_t. Since payments are made before producing, the intraperiod loan is

$$\ell_t = w_t n_t + \phi(d_t) + b_t - b_{t+1}/R_t,$$

where $\phi(d_t) = d_t + \kappa(d_t - \bar{d})^2$ includes a convex distribution cost of dividends which captures documented evidence of preferences for dividend smoothing (Lintner, 1956). The end of period firm's budget constraint is

$$b_{t+1}/R_t + F(z_t, n_t) = w_t n_t + \phi(d_t) + b_t. \tag{1}$$

It follows that firm's revenues are equal to the intraperiod loan, that is $\ell_t = F(z_t, n_t)$.

Incentive constraint. When production is complete, firms decide whether or not repay the intraperiod loan they owe to the household. Consistent with recent evidence on the procyclicality of unsecured debt (see Azariadis et al., 2015), we assume that contract enforcement is imperfect so that firms have incentives to default. If a firm defaults it can divert its end of period revenues $y_t \equiv F(z_t, n_t)$. However, a defaulting firm can be caught with probability γ, in which case its assets will be liquidated and the firms will cease to operate. If a firm is not caught, it continues to retain access to credit in future periods.[10]

[9] The assumption of two types of debt is made for analytical convenience. In particular the intratemporal debt can be replaced with cash that firms carry from the previous period. Cash would then be used to finance working capital and pay part of dividends.

[10] Assuming that in the case of being caught a firm would also loose its revenues does not quantitatively alter

Specifically, a firm defaults if

$$y_t + (1-\gamma)E_t m_{t,t+1} V_{t+1} > E_t m_{t,t+1} V_{t+1},$$

where $m_{t,t+1}$ is the households' stochastic discount factor, V_{t+1} is the firm's future value defined as the net present value of future dividends.

Because shocks realize at the beginning of period, there is no intraperiod uncertainty. Thus we can write the following incentive constraint that deters default in equilibrium,

$$\gamma E_t m_{t,t+1} V_{t+1} \geq y_t. \tag{2}$$

It is easy to show that firms' market value depends negatively from the intertemporal debt b_{t+1}. Thus the incentive constraint in eq. (2) is effectively limiting both types of firms' debt. An increase in intraperiod debt l_t increases production and therefore raises the right hand side of the constraint. Conversely, an increase in interperiod debt b_{t+1} decreases the left hand side. Importantly, in making their optimal choices of short and long-term debt, firms understand that an increase in b_{t+1} tightens their borrowing constraint, but they do not internalize the effects that a change in production have on their market value through movements in the discount factor $m_{t,t+1}$. This type of externality is crucial to generate both amplification and boom-bust phenomena.

The problem of the individual firm can be written recursively as

$$V_t = \max_{d_t, n_t, b_{t+1}} \left\{ d_t + E_t \left[m_{t,t+1} V_{t+1} \right] \right\} \tag{3}$$

subject to (1) and (2).

Firm's first order conditions are

$$(1+\mu_t \gamma) R_t E_t \left[m_{t,t+1} \frac{\phi'(d_t)}{\phi'(d_{t+1})} \right] = 1 \tag{4}$$

$$(1-\theta)\frac{y_t}{n_t} = \frac{w_t}{1-\mu_t \phi'(d_t)} \tag{5}$$

our results.

where μ_t is the Lagrange multiplier associated to the incentive constraint. Equation (4) is the first order condition of new intertemporal debt b_{t+1}. It states that the marginal cost of debt increases with the tightness of the credit limit μ_t and the effective firm's discount factor which is the household's discount factor times the expected decrease in the adjustment cost of dividends. From the first order condition of labor input (5), looser borrowing constraint increases labor demand and allows firms to borrow more intra-period. The resulting increase in labor income and dividends increases households' asset demands further relaxing the borrowing constraint.

Furthermore, looser credit constraints also increase the intertemporal loan. To see this, combine the budget constraint of the firms with the optimality condition for labor:

$$\frac{b_{t+1}/R_t - b_t}{y_t} = \frac{\phi(d_t)}{y_t} + (1-\theta)(1-\mu_t\phi'(d_t)).$$

As credit market relaxes, that is μ_t decreases, for a given dividend to output ratio, the intertemporal debt rises.

3.2 Households sector and general equilibrium

There is a continuum of homogeneous utility-maximizer households. Households are the owners of firms. They hold equity shares and noncontingent bonds issued by firms. Households' instantaneous utility function is

$$U(c_t, n_t) = \frac{c_t^{1-\omega} - 1}{1-\omega} + \alpha \log(1 - n_t).$$

The household's budget constraint is

$$c_t + s_{t+1}p_t + \frac{b_{t+1}}{1+r_t} = w_t n_t + b_t + s_t(d_t + p_t) - T_t \tag{6}$$

where s_t is the equity shares and p_t is the market price of shares. The government finances the tax benefits to firms through lump-sum taxes equal to $T_t = B_{t+1}/[1 + r_t(1-\tau)] - B_{t+1}/(1 + r_t)$. The first order conditions with respect to n_t,b_{t+1}, and s_t are

$$w_t = -\frac{U_n(c_t, n_t)}{U_c(c_t, n_t)} \tag{7}$$

$$U_c(c_t, n_t) = \beta(1 + r_t)E_t U_c(c_{t+1}, n_{t+1}) \tag{8}$$

$$p_t = \beta E_t \left\{ \frac{U_c(c_{t+1}, n_{t+1})}{U_c(c_t, n_t)} (d_{t+1} + p_{t+1}) \right\} \tag{9}$$

Given the aggregate states **s**, that are productivity z and aggregate bonds B we can define the general equilibrium as follows:

Definition: *A recursive competitive equilibrium is defined as a set of functions for (i) households' policies $c^h(\mathbf{s}, b)$, $n^h(\mathbf{s}, b)$ and $b^h(\mathbf{s}, b)$; (ii) firms' policies $d(\mathbf{s}, b)$, $n(\mathbf{s}, b)$, and $b(\mathbf{s}, b)$; (iii) firms' value $V(\mathbf{s}, b)$; (iv) aggregate prices $w(\mathbf{s})$, $r(\mathbf{s})$, and $m(\mathbf{s}', \mathbf{s})$; (v) law of motion for the aggregate states $\mathbf{s}' = \psi(\mathbf{s})$. Such that: (i) household's policies satisfy conditions (7) and (8); (ii) firm's policies are optimal and $V(\mathbf{s}, b)$ satisfies the Bellman's equation (3); (iii) the wage and the interest rate clear the labor and bond markets; (iv) the law of motion $\psi(\mathbf{s})$ is consistent with individual decisions and stochastic processes for productivity.*

3.3 Inspecting the mechanism

The key externality in the model is that households do not take into account the effects of their savings decisions on the financial constraint. Likewise, firms only partly internalize the effects of their production decisions on their market value. In particular, they understand that a higher level of debt reduces their market value by limiting their ability to distribute dividends, but they do not internalize the effects of their decisions on their market value due to changes in the present and future stochastic discount factor. This generates a positive feedback loop between firms' market value and households' income. Absent of adjustment cost of dividends, *i.e.* $\kappa = 0$, credit market amplification depends upon the elasticity of firms' production to the households' stochastic discount factor. This elasticity is equal to

$$\frac{\partial log(y_t)}{\partial log(m_{t,t+1})} = \frac{\beta\tau}{\gamma(1-\mu)(1-\tau+\tau\beta)^2} \left[\frac{(1-n)(1-\theta)}{(\omega-1)(1-n)(1-\theta)+1} \right] \equiv \xi,$$

where $\mu = \tau(1-\beta)/\gamma(1-\tau+\tau\beta)$.

If credit market frictions are severe, that is the probability of being excluded from financial market γ is low or the tax advantage on debt τ is high, firms are more responsive to changes in their continuation value reflected by changes in the stochastic discount factor. Sufficiently high values of ξ give rise to self-fulfilling equilibria. Suppose lenders and borrowers are optimistic regarding firms' market value, this relaxes the financial constraint and implies an increase in the credit supply. As a consequence, production and households' labor income increase which raise firms' market value through an increase in the stochastic discount factor $m_{t,t+1}$ validating the initial shift in expectations.

Formally, take a first order approximation around the steady state, aggregate output can be expressed as

$$\hat{y}_t = \frac{\omega\xi}{\omega\xi - 1} E_t \hat{y}_{t+1} - \frac{1}{\zeta(\omega\xi - 1)} \hat{z}_t \tag{10}$$

where $\zeta \equiv (\omega - 1)(1 - n)(1 - \theta) + 1$.

When $\omega\xi > 1/2$, current aggregate output is a convex function of future output which is sufficient to generate indeterminacy.

Note that the impact of technology shocks on aggregate output is ambiguous. By increasing end of period revenues, a positive technology shock raises firm's incentives to divert funds thereby increasing the right-end-side of the incentive constraint in eq. (2). Whether firm's market value increases more than firm's revenue depends upon firm's willingness to distribute dividends. We find that for plausible parametrizations, the Lagrange multiplier μ_t *increases* in response to a positive technology shock.

A current loosening of financial constraints leads firms to borrow more and hinge upon their ability to borrow in the future. In fact, firm' s value depends upon the amount of intertemporal debt b_{t+1} which in turn depends positively upon the outstanding debt b_t at the beginning of the period. The resulting dynamic subsitutatibility between current and future production allows for the possibility of boom-bust dynamics. The following proposition lists the necessary conditions under which boom-bust fluctuations may obtain in response to perturbations from the economy's steady state.

Proposition 1 *Boom-bust phenomena obtain only if*
i. The equilibrium is indeterminate.
ii. Adjustment costs are non zero, that is $\kappa > 0$.
Proof is relegated in Appendix H.

Condition (i) states that if the credit market amplification channel is strong enough, so that indeterminacy obtains, then the economy can also be subject to oscillatory dynamics.[11]

[11] This property is not specific to the environment described here. Gu et al. (2013) discuss the link between indeterminacy and cycles in the context of financial frictions of different forms.

The intuition is that after an initial expansion, firms have accumulated large amount of debt which limits their ability to borrow and produce. As firms decrease production they do not internalize the adverse effects on their market value. The stronger are the effects of this externality the larger is the drop in current production. The reason why adjustment cost of dividends is necessary to obtain cycles is more subtle. Besides the static amplification mechanism described above, the model displays dynamic substitutability between current and future production generated by movements in firms' net worth. An increase in new debt brings about higher current production but it decreases future firms' net worth which negatively affects the subsequent level of production. Absent dividend adjustment costs, firms with a high level of outstanding debt would finance production by decreasing the amount of distributed dividends, therefore limiting the impact that changes of net worth on their production decisions, thus preventing the large accumulation of debt after the expansion to generate a recession.

3.4 Parametrization and theoretical impulse responses

The sunspot shock is defined as an i.i.d. expectation error of firm's value that is not correlated with fundamentals

$$V_t - E_{t-1}V_t = u_t$$

where $u_t = \epsilon_{s,t} + \psi_z \epsilon_{z,t}$.

The terms $\varepsilon_{s,t}$ and $\epsilon_{z,t}$ are respectively the sunspot shock and the technology shock.[12] The natural logarithm of technology is assumed to follow an AR(1) process as

$$\widehat{z}_t = \rho_{z,t}\widehat{z}_{t-1} + \epsilon_{z,t}.$$

We calibrate the model to a quarterly frequency consistent with the frequency of the data. We set β in order to match a 3% annual interest yield on bonds. Following Jermann and Quadrini (2012) tax shield τ and capital's share of income θ are set equal to 0.35 and 0.36, respectively. With the aim of emphasizing the difference between the two shocks, we set

[12] Note that inserting the sunspot on output would not alter our results. It is easy to show that

$$V_t - E_{t-1}V_t = \omega(Y_t - E_{t-1}Y_t).$$

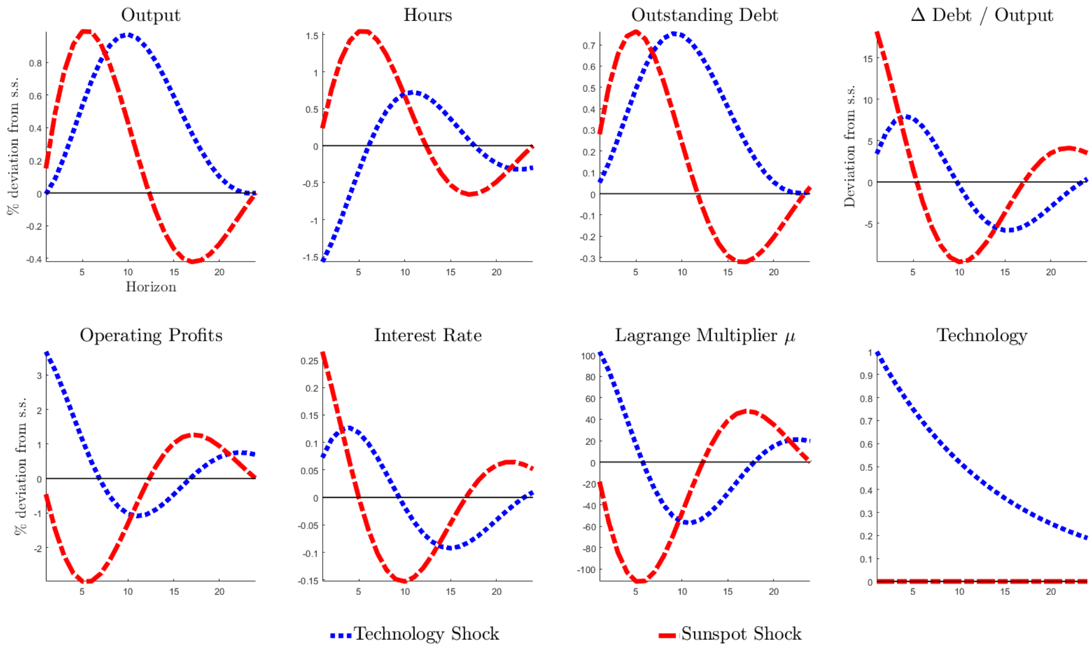

Figure 4: Model impulse responses to a technology shock and to sunspot shock

the inverse of households' intertemporal elasticity of substitution ω to 1.2, the probability of being caught in case of default γ to 0.1 and the degree of adjustment cost to dividends κ to 2.3. The parameter ρ_z governs the persistence of the technology process and is set equal to 0.93 consistent with the law of motion of detrended TFP estimated in the data. We assume the expectation error u_t and the technology shock to be uncorrelated, so that ψ_z is equal to zero.[13]

Figure 4 shows the theoretical impulse responses of the model to a sunspot shock and to a technology shock.

In response to the sunspot shock the economy experiences an initial boom characterized by an increase output, consumption and hours. The associated increase in debt has two effects. On the one hand, it reflects an increase in households' savings which increases the supply of credit generating a decrease in the real rate and an increase in firms' market value. On the other hand, larger outstanding debt hinders firms' ability to pay current and future dividends which deteriorates their market value. Which of these two forces prevails depends upon the level of firms' profitability. As production increases firms' prof-

[13] Note that ψ_z equal zero implies a zero-impact response of output and firm's value after a technology shock. While this is an implausible restriction that will be relaxed in the quantitative exercise, it allows to generate a starker difference between the dynamics induced by the two shocks.

itability decreases so that firms' market value decreases, the financial constraint tightens and output starts declining. During the contraction phase, households are less willing to lend which results in an increase in the real rate, a decrease in firm's value and a further tightening of the financial market. This negative vicious circle reinforces as households' savings decline, ultimately bringing about a recession. Importantly, even though agents know about the incoming recession their actions magnifies the decline in output.
A positive technology shock generates hump-shaped dynamics in all the main macroeconomic variables. By increasing incentives to divert funds, a positive technology shock tightens the financial constraint which dampens the impact response of output. Importantly, the response of debt and output is comparable to the ones after a sunspot shock, suggesting that looking at measures of firms' indebtedness such as the debt to GDP ratio may not be the best predictor of a crisis.

Importantly, expectation-driven fluctuations arise also in an economy where fundamentals, that is technology, preferences, or government policies, do not change and this is common knowledge. This distinguishes them from noise shocks arising from *ex post* erroneous beliefs on future changes of technology. Bearing this distinction in mind, in the next section, we estimate expectation shocks unrelated to fundamentals and to rational expectations of fundamentals. We find that these shocks generate boom-bust dynamics consistent with the quantitative prediction of an extended version of the model.

4 Identifying sunspot shocks using survey data

In this section we estimate the sunspot shock as a "pure" sentiment shock, that is a shock that reflects a change in expectations disconnected from changes in expectations on future TFP and realizations of TFP. To this end, we use quarterly one-year-ahead expectations on a number of key macroeconomic variables formed by both professional forecasters and households. We proceed in three steps.

The Survey of Professional Forecasters and the Survey of Consumer Expectations include expectation data on a number of variables, such as future real GDP growth, investment, and consumption. Our theory does not point at a particular variable, rather expectation shocks should be reflected into a change of expectations common across all variables in the surveys that capture information upon expected future business conditions. Therefore, as a first step, we construct an expectation indicator $\hat{S}_t$ from the first principal component of all the relevant available expectation data. The sample includes seven quarterly variables from 1982:Q2 to 2018:Q4.

Second, we regress the indicator $\hat{S}_t$ on a battery of controls in order to capture variations in expectations that are "extrinsic", that is, exogenous to fundamentals and to changes in expectations on future fundamentals. Formally, let the process of detrendend TFP be represented by the following news representation

$$\log(TFP)_t = A(L)\log TFP_{t-1} + \varepsilon_t^z + \sum_{k=1}^{\infty} \varepsilon_{t-k}^k$$

where ε_{t-k}^k is a news shock on TFP k-period ahead which is part of time t agents' information set, and ε_t^z is the surprise shock of technology. Let S_t^K be the indicator that summarizes revision of agents expectations on the economic activity K-period ahead. We assume that these revisions depend upon current technology shocks, expectations on future technology, and expectation shocks. Specifically,

$$S_t^K = \lambda_0 \log TFP_t + \sum_{k=1}^{K} \alpha_k \varepsilon_t^k + \varepsilon_t^s$$

where expectations on future technology are a linear combination of news upon technology up to K horizons. Hence, in order to identify *extrinsic* expectation shocks one needs to cleanse changes in expectations, proxied by $\hat{S}_t$, from the realized level of TFP and expectations about future TFP up to the horizon K. In other words, we want the estimated expectation shock to satisfy two conditions: (i) the estimated shock must be uncorrelated with future TFP realizations; (ii) the shock has to be uncorrelated with noise shocks, defined as ex-post wrong beliefs on future TFP. [14]

We proxy expectations on future TFP with TFP news shocks identified as in Barsky and Sims (2011). However, this controlling set may no be large enough to satisfy the two conditions above. To overcome this issue we add two additional set of controls. First, we control for future realizations of TFP so as to guarantee that the estimated shock has no impact on future TFP. Second, as shown by Chahrour and Jurado (2018), one can

[14] As shown by Beaudry and Portier (2004) noise shocks in the form of ex-post wrong beliefs on future TFP can give rise to Pigouvian cycles and therefore are a competing candidate to the explanation of the reduced form evidence presented in Section 1. However, we find that controlling for this particular type of beliefs has small quantitative changes on the variance explained by the expectation shock, suggesting that noise shocks play only a minor role in shaping expectations.

recover noise shocks by adding future news and realizations of TFP to the econometrician's information set. Thus, we further control for future realizations of the identified news shock. Specifically, expectation shocks are estimated from the following equation:

$$\hat{\varepsilon}_t^s = \hat{S}_t - \sum_{k=0}^{\bar{k}} \widehat{\lambda}_k TFP_{t+k} + \sum_{k=0}^{\bar{k}} \widehat{\alpha}_k \varepsilon_t^{BS} - \mathbf{X}_t \widehat{\beta}$$

where ε_t^{BS} is the news shock estimated using the procedure in Barsky and Sims (2011), and $\mathbf{X}_t$ is a vector of additional control variables, including past realizations of TFP and news, other shocks to fundamentals such as monetary policy and fiscal shocks, and past values of the first two principal components from a large data set of U.S. aggregate variables. Interestingly, even after controlling for virtually all available sources of fundamental fluctuations, estimated expectation shocks explain approximately half of the changes in the expectation indicator $\hat{S}_t$.

In the last step, we estimate the impulse response to an expectation shock using Local Projections as in Jordà (2005). Specifically, for each variable of interest Y, we run the following series of regressions

$$Y_{t+h} = \theta^h \hat{\varepsilon}_t^s + \sum_{j=1}^{J} \left[\delta_j \hat{\varepsilon}_{t-j}^s + \lambda_j Y_{t-j} + \mathbf{PC}_{t-j} \Gamma_j \right] + \nu_{t+h} \quad \text{for } h = 0, 1, \ldots, H \tag{11}$$

where θ^h is the response of Y to an expectation shock after h periods, and PC is a vector including the first two principal component from a set of U.S. aggregate variables. We use four lags, that is $J = 4$, in the baseline specification.

Figure 5 shows the responses of real GDP, real investment, and the change of non-financial corporate debt divided by real GDP to a one standard deviation expectation shock. Real GDP, investment and debt flow exhibit significant oscillatory dynamics. In particular, after a positive expectation shock, the economy enters an expansion followed by a recession after about two years. Importantly, the conditional spectral densities exhibit a peak associated to periodicities of 8 to 10 years, in line with the reduced form evidence presented earlier. Table 2 in Appendix G reports the p-values for the test of a local peak in the spectral density implied by expectation shocks. The null hypothesis of absence of a local peak is rejected for all variables, with the exception of TFP.

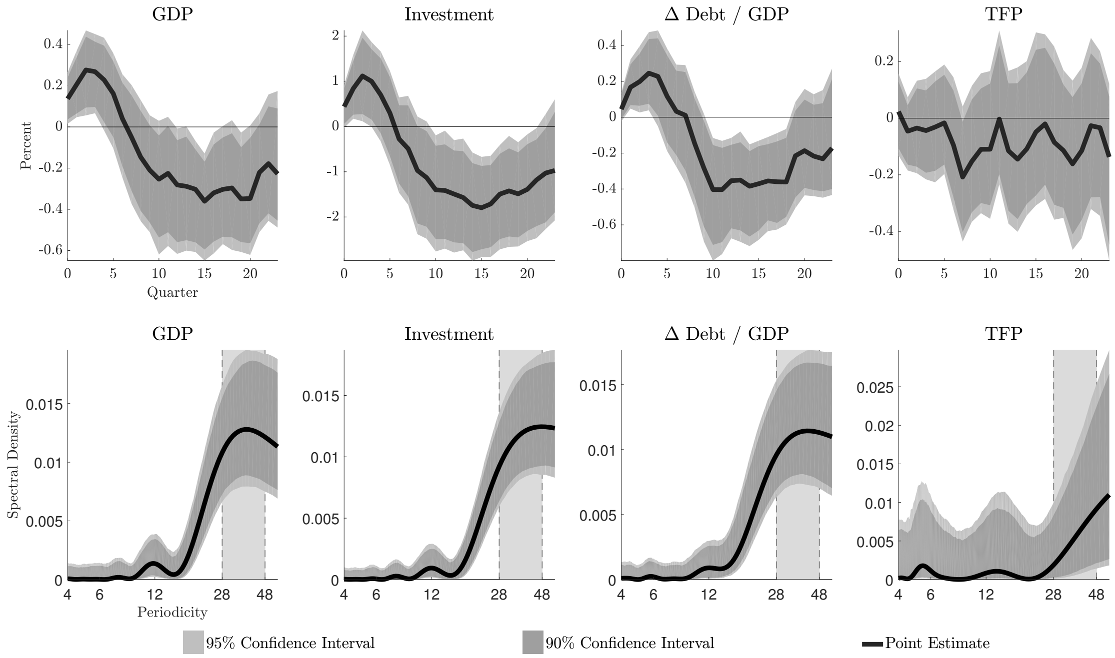

Figure 5: Impulse responses and conditional spectral densities to an expectation shock

Note: Expectation shocks are estimated as the innovations in S_t orthogonal to present, past, and future realization of TFP and expectations on TFP. Impulse responses (top panel) are estimated using local projections method. Confidence intervals are computed using the block-bootstrap method described in Kilian and Kim (2011). Conditional spectral densities (bottom panel) are computed from the Fourier transform of the estimated MA.

4.1 Robustness checks

In this section we show that the results in Figure 5 are robust to different detrending techniques, additional controls, and the expectation variables used to construct the indicator S_t. Given that our endogenous variables are non-stationary, in the baseline specification we detrend the variables using a Band-Pass filter which excludes periodicities above 100 quarters. In order to argue that the oscillatory dynamics implied by an expectation shock is not specific to the detrending technique, in Figure 6 we show robustness checks where endogenous variables are detrended using (i) first differences (and the cumulated), (ii) linear time trend, (iii) quadratic time trend, and (iv) Hodrick-Prescott filter. Results are in line with the baseline specification and most of the estimates lie between the confidence intervals of the main specification.

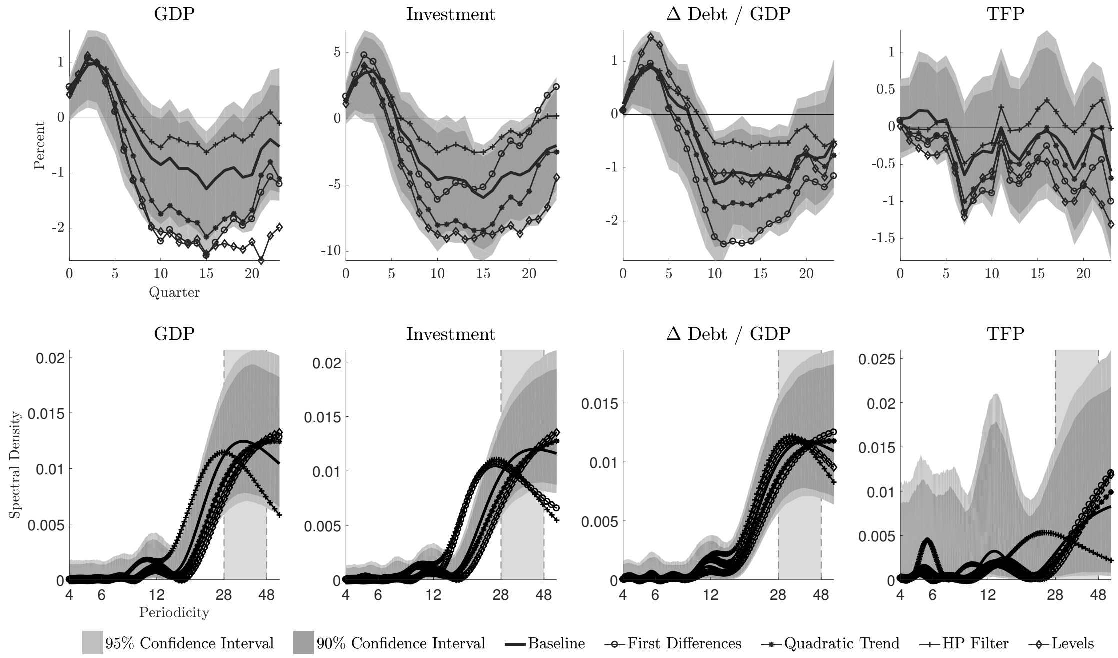

Figure 6: Impulse responses and conditional spectral densities to an expectation shock

Note: Point estimates (continuous line) are from the baseline specification presented in Figure 5. The figure shows the robustness of the point estimate to various detrending techniques.

Figure 7 reports results for four additional variations of the baseline specification. First, we increase the number of lags and the number of principal components in the regression equation of the expectation shock. Second, we control for the present and the past of other shocks to fundamentals such as oil shocks, fiscal shocks, military spending news shocks and monetary policy shocks. Third, we check whether results are sensitive to the choice of the indicator for the revisions of expectations. Specifically, we use only revisions on one-year-ahead output growth from the SPF and find results that are not significantly different from the baseline. Finally, we check that results are robust to the number of lags and principal components used in the LP.

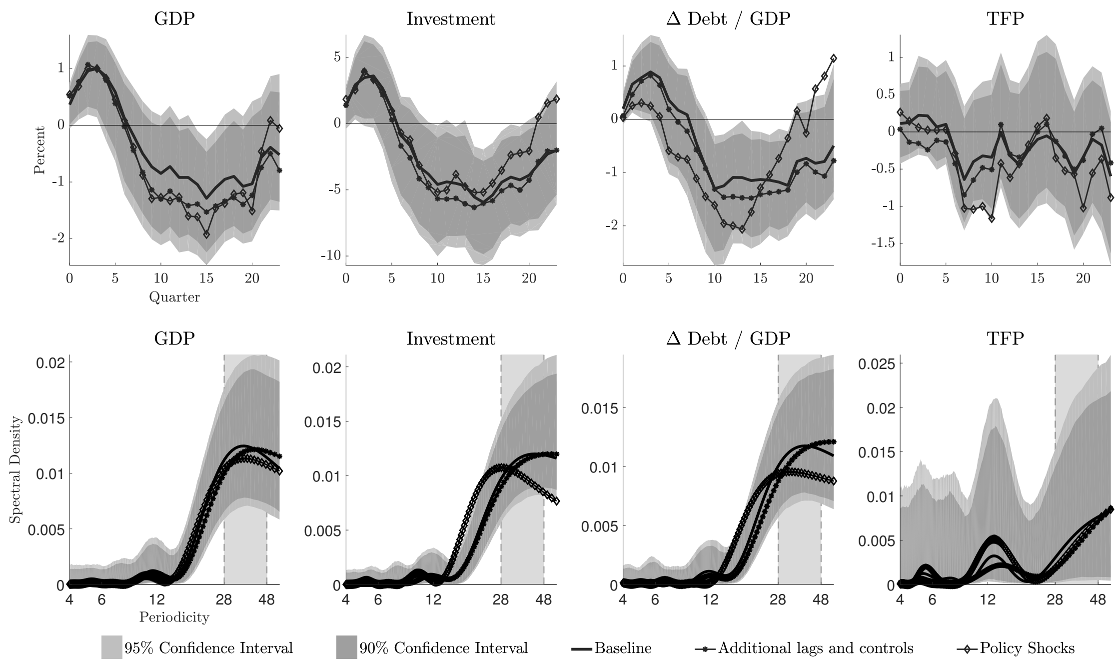

Figure 7: Impulse responses and conditional spectral densities to an expectation shock

Note: Point estimates (continuous line) are from the baseline specification presented in Figure 5. The figure shows the robustness of the point estimate to various controls (see text).

5 Model with capital and external consumption habit

In this section we augment the model with variable capital, investment-adjustment costs and external consumption habit. The equilibrium equations of the extended model are:

$$w_t U_c(c_t, c_{t-1}, n_t) = -U_n(c_t, c_{t-1}, n_t) \tag{12}$$

$$\beta E_t[m_{t,t+1}(R_t - \tau)] = 1 - \tau \tag{13}$$

$$w_t n_t + b_t - \frac{b_{t+1}}{R_t} + d_t = c_t \tag{14}$$

$$[1 - \mu_t \phi'(d_t)] F_n(z_t, k_t, n_t) = w_t \tag{15}$$

$$k_{t+1} = (1-\delta)k_t + \left[\frac{\varsigma_1}{1-\nu}\left(\frac{i_t}{k_t}\right)^{1-\nu} + \varsigma_2\right]k_t \tag{16}$$

$$E_t\Big\{m_{t,t+1}\frac{\phi'(d_t)}{\phi'(d_{t+1})}(1+\mu_t\gamma)\Big\{\big(1-\phi'(d_{t+1})\mu_{t+1}\big)F_k(z_{t+1},k_{t+1},n_{t+1})+ + \frac{1}{\varsigma_1}\Big(\frac{i_{t+1}}{k_{t+1}}\Big)^{\nu}\Big[1-\delta+\frac{\varsigma_1\nu}{1-\nu}\Big(\frac{i_{t+1}}{k_{t+1}}\Big)^{1-\nu}+\varsigma_2\Big]\Big\}\Big\} = \frac{1}{\varsigma_1}\Big(\frac{i_t}{k_{t-1}}\Big)^{\nu} + E_t\big[m_{t,t+1}\phi'(d_t)\mu_t\gamma\big] \tag{17}$$

$$(1+\mu_t\gamma)E_t\Big[m_t\frac{\phi'(d_t)}{\phi'(d_{t+1})}R_t\Big] = 1 \tag{18}$$

$$y_t - w_t n_t - b_t + \frac{b_{t+1}}{R_t} - i_t = \phi_t(d_t) \tag{19}$$

$$\gamma E_t\big[m_{t,t+1}V_{t+1}\big] = y_t \tag{20}$$

where $y_t = F(z_t,k_t,n_t) = z_t k_t^{\theta} n_t^{1-\theta}$ and $\phi(d_t) = d_t + \kappa(d_t - d_{ss})^2$. Moreover, the stochastic discount factor is $m_{t,t+1} = \beta(U_{c,t+1}/U_{c,t})$ and value of the firm is defined as $v_t = d_t + E_t[m_t v_{t+1}]$. Finally, $U_c(c_t,c_{t-1},n_t) = (c_t - \iota c_{t-1})^{-\omega}$ and $U_n(c_t,c_{t-1},n_t) = -\alpha(1-n_t)^{-\omega_2}$.

5.1 Calibration and impulse response matching

Following Christiano et al. (2005) we divide the model parameters in two different groups. The first group is calibrated while the remaining parameters are estimated via impulse response matching. We calibrate the model to a quarterly frequency. The discount factor β, capital's share of income θ, and tax shield τ maintain the same values presented in Section 3. The multiplicative parameter which governs the utility of leisure α is chosen such that the steady state value of n is equal to one third. Moreover, the exponential parameter which governs the utility of leisure ω_2 is set equal to one in order to imply a Frisch labor supply elasticity equal to 2. Moreover, ς_1 and ς_2 – additional parameters related to the investment-adjustment costs – are set such that in the steady state the depreciation rate is equal to δ and the steady state Tobin's q is equal to one. In addition, steady state capital depreciation δ is equal to 0.025. Furthermore, ψ_z - which governs the response of firm's value to a technology shock - is set in order to match the empirical impact response of technology to output.

The second group includes the vector of parameters $\Sigma = (\omega,\iota,\gamma,\kappa,\rho_z)$ includes the inverse of households' intertemporal elasticity of substitution, ω; the external consumption habit parameter, ι; the probability of being caught in case of default, γ; the degree of adjustment cost to dividends, κ; and the persistence of technology process, ρ_z. These parameters are set to minimize the distance between the empirical and model-implied impulse responses. In particular, we chose Σ that minimizes the following objective

$$J = \min_{\Sigma}[\hat{\Psi} - \Psi(\Sigma)]' V^{-1} [\hat{\Psi} - \Psi(\Sigma)]$$

where $\hat{\Psi}$ denotes the empirical impulse responses of GDP, Consumption, hours worked and TFP to both technology and expectation shocks, Σ is the vector of estimated parameters, and $\Psi(\Sigma)$ is the model-implied counterpart of $\hat{\psi}$. V is a diagonal matrix which gives different weights to the target estimates. Table 1 reports the parameter values of the model.

Parameter	Interpretation	Value
α	Disutility of labor	8.785
ω_2	CRRA labor	1
β	Discount factor	0.9926
τ	Tax shield	0.35
θ	Capital share	0.36
δ	Capital depreciation	0.025
ς_1	Capital adj. cost (1)	δ^{ν}
ς_2	Capital adj. cost (2)	$\delta - \delta/(1-\nu)$
ψ_z	Technology on V_t	0.29
ρ_z	Technology persistence	0.93
ω	CRRA consumption	1.3219
ι	Consumption habit	0.699
ν	Capital adj. cost (3)	0.59154
κ	Dividend adj. cost	0.44606
γ	Incentive parameter	0.094009

Table 1: Model's parameter values.

5.2 Model performance

Figures 8 and 9 plot the theoretical impulse response of the model against their empirical counterparts. The model does a good job in reproducing the empirical impulses to both shocks. In particular, we estimate the model consistent measure of labor wedge and find that the responses are in line with the predictions of the model.

Figure 10 shows the empirical conditional spectral densities against their model counterpart. The theoretical spectral densities implied by the model are within the range of the confidence bands of the empirical ones.

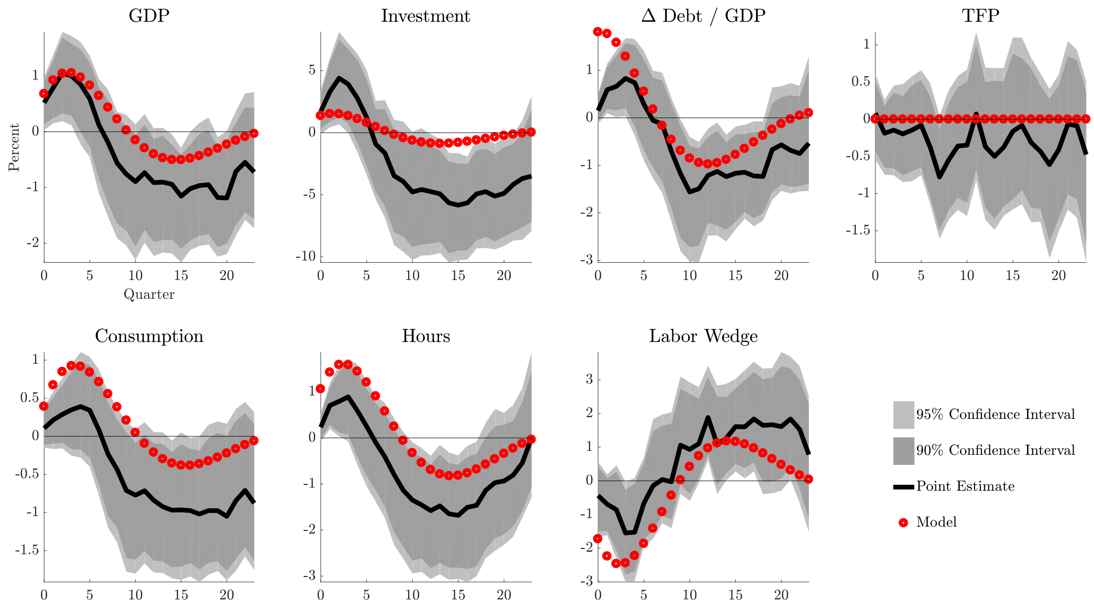

Figure 8: Model vs empirical IRFs to an expectation shock

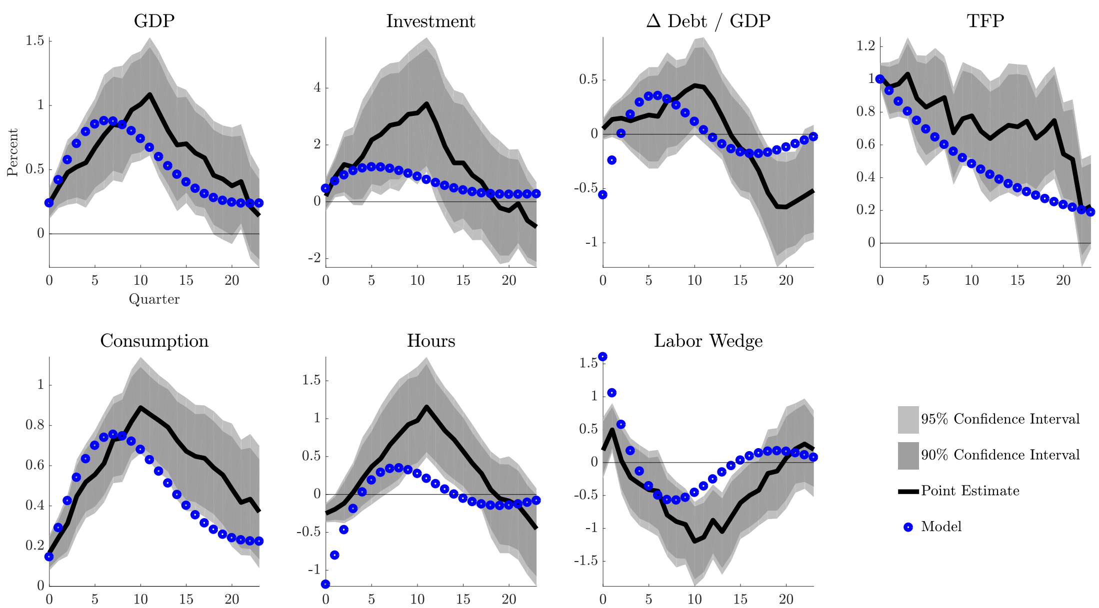

Figure 9: Model vs empirical IRFs to a technology shock

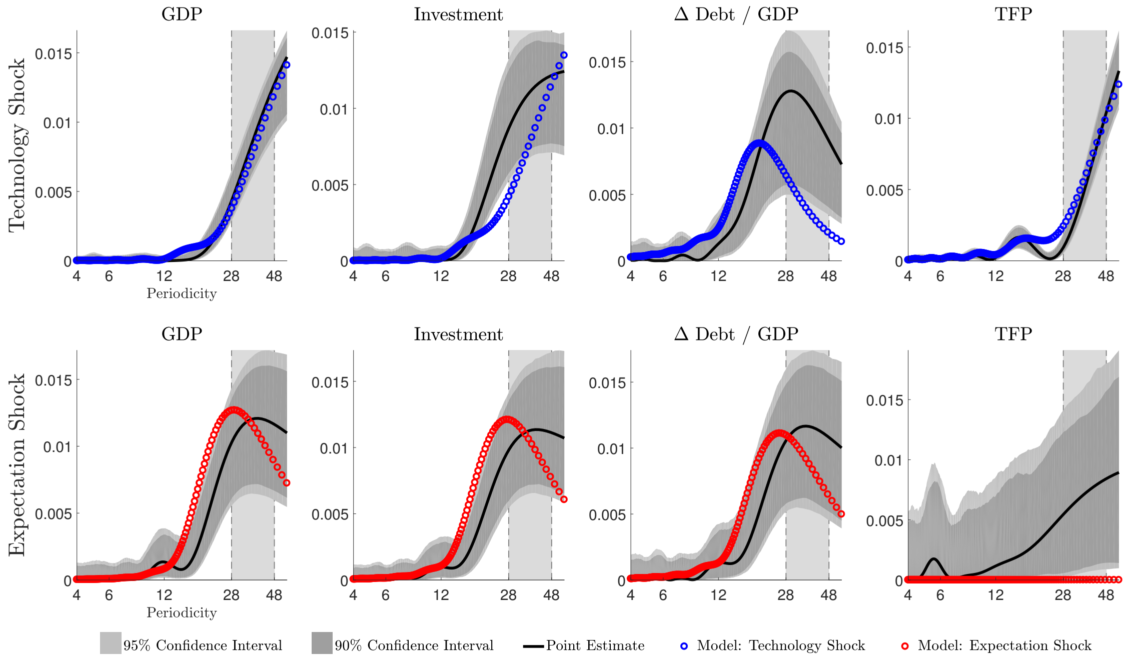

Figure 10: Model vs empirical spectral densities conditional on shocks

As a last validation exercise of the model, we simulate data and reproduce the results on the probability of recession presented in Figure 2. Figure 11 shows that the model can replicate the empirical probability of recession conditional on a previous expansion.

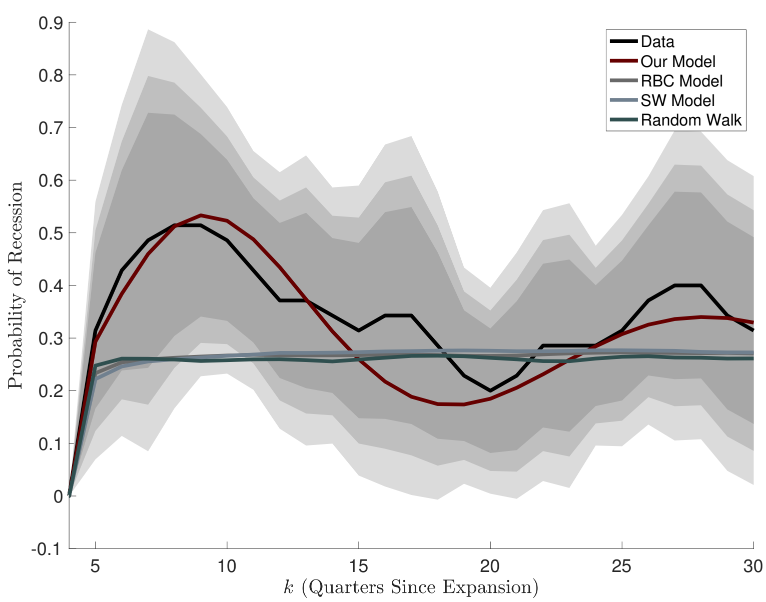

Figure 11: The model explains the dynamics of the recession probability

Note: Probability of recession in a two-quarter window after k quarters since expansion. Confidence intervals are 68%, 80%,and 90% (shaded areas) around the point estimate (solid black line).

6 Conclusion

We provide a simple synthesis of two major approaches to modeling business cycles. Under the first approach business cycles are driven by exogenous shocks that push the economy temporarily away from the long-run steady-state or balanced growth path. The second approach proposes models in which the economy experiences endogenous fluctuations even in the absence of fundamental shocks. However, both types of models fail to provide a unified explanation of the unconditional and conditional moments of the data. In the data, shocks to economic fundamentals induce dynamics that are consistent with the first view. But unconditional moments and results from expectation shocks, suggest to write models consistent with the inherent instability class. Taken together, our findings speak in favor of a theory in which both views coexist. Thus, we provide a model that embeds a strong financial amplification channel which generates boom-bust dynamics in response to i.i.d. expectation shocks. Consistent with the data, the financial amplification channel barely contributes to the propagation of technology shocks which exhibit no systematic relation between expansions and recessions. In sum, a sizeable part of economic recessions is due to preceding expansions. More importantly, those expansions that are not generated by a change in fundamentals are more likely to end in recessions. As a consequence, policy makers should intervene more decisively during expectation-driven expansions than during fundamental-driven expansions. Characterizing the optimal policy in light of our findings is part of our future endeavors.

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A Unconditional Spectral Density

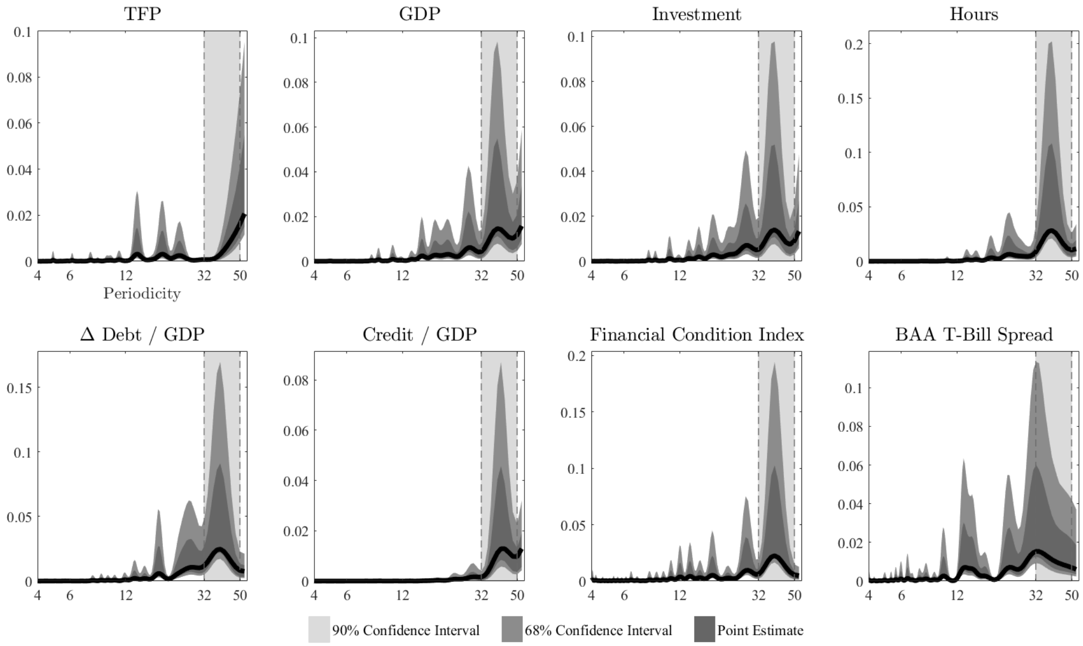

Figure 12: Unconditional spectral density of quarterly and seasonally adjusted U.S. macroeconomic and financial variables from 1981 to 2018. TFP is utilization-adjusted total factor productivity. GDP is real gross domestic product. Investment is real consumption of durables plus real gross private domestic investment. Hours is hours of all persons in nonfarm business sector. Change in debt is the flow of nonfinancial business debt securities and loans. Credit is total credit for private nonfinancial sector. Financial Conditions Index is an index of financial condition provided by Chicago Fed. BAA T-Bill Spread is the difference between the yield of BAA corporate bonds and the treasury bill at 10-year horizon. All variables are stationarized using Band-Pass filter excluding periodicities above 100 quarters. Confidence intervals are computed following the procedure described in Beaudry et al. (2019).

B Spectral density from model simulated data

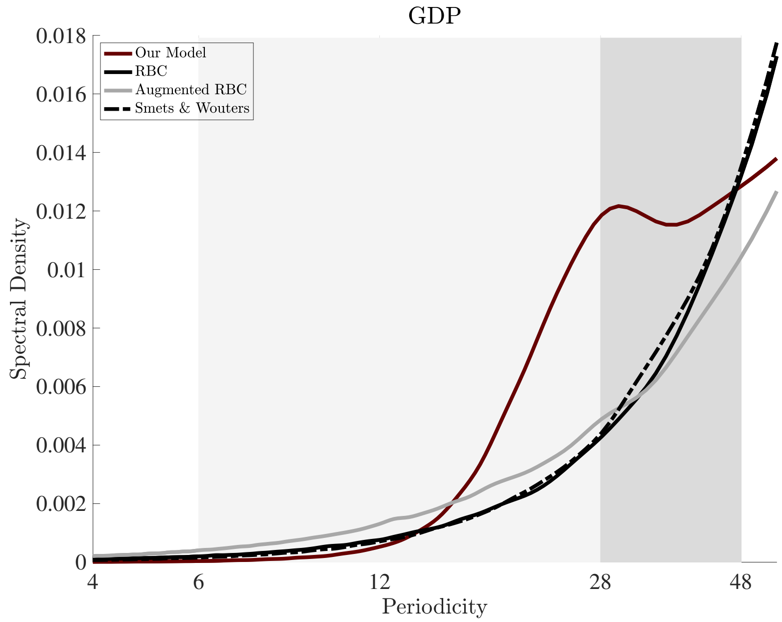

Figure 13: Mean unconditional spectral density of GDP from a Monte Carlo simulation using various standard models and our model (red line). Simulated data are deterended using a band-pass filter that removes fluctuations at periodities greater than 100 quarters.

C Robustness checks on technology Shocks

Figure 16 reports impulse responses together with conditional spectral densities implied by a technology shock for the baseline specification presented in Figure 3 and a series of robustness checks. In particular, RC 1 and RC 2 are the first and the second robustness check where variables are linearly and quadratically detrended, respectively. RC 3 is the third robustness check where TFP is controlled using 8 lags of TFP, the first 2 principal components and news shocks. RC 4 is the last robustness check where we use different number of lags and principal component when we estimate LP impulse responses.

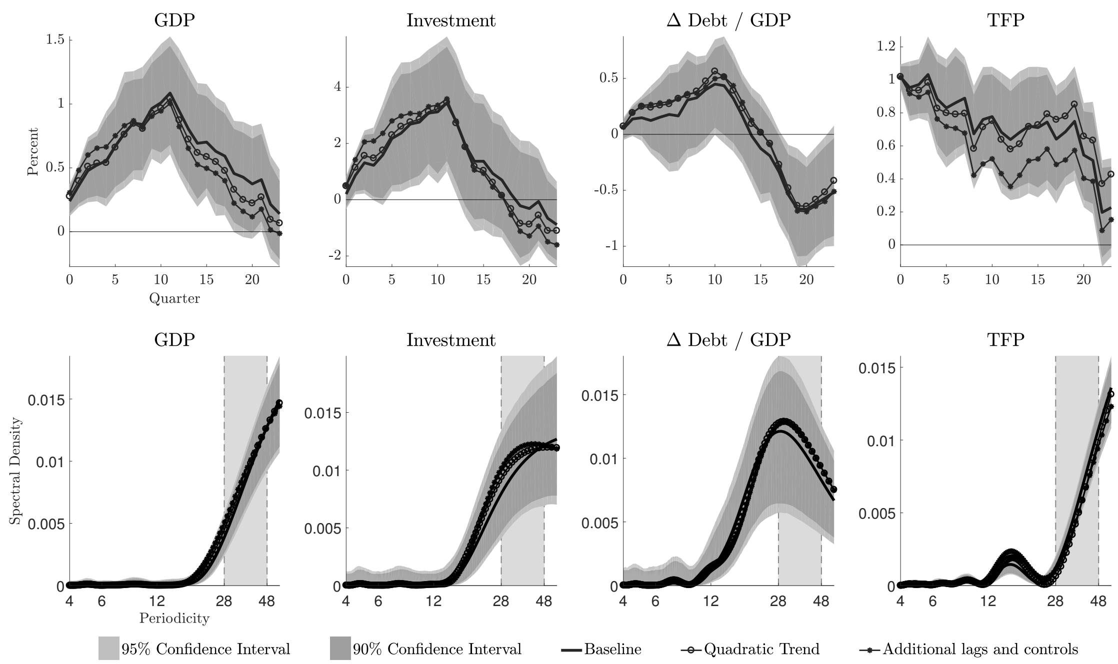

Figure 14: Impulse responses and conditional spectral densities implied by a technology shock. Point Estimates is the baseline specification presented in Figure 3. RC 1 and RC 2 are the first and the second robustness check where variables are linearly and quadratically detrended, respectively. RC 3 is the third robustness check where we add more controls when we estimate a technology shock. RC 4 is the last robustness check where we use different number of lags and principal component when we estimate LP impulse responses.

D Robustness checks on expectation shocks

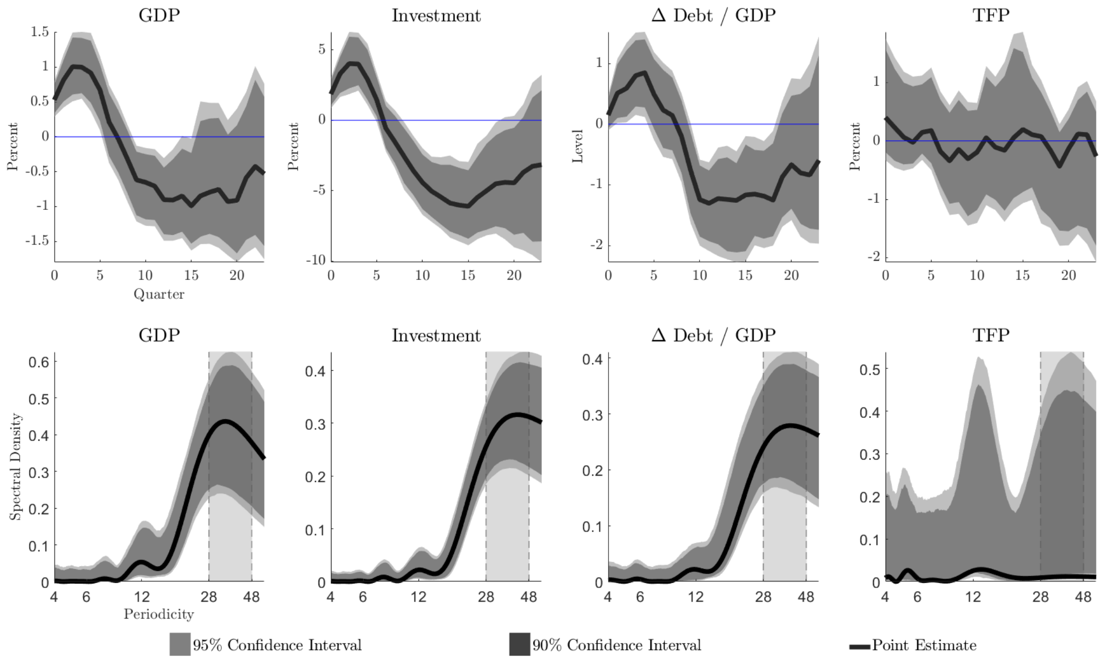

Figure 15: all in LP. S is PC of everything in the baseline. controls are the same as in the baseline.

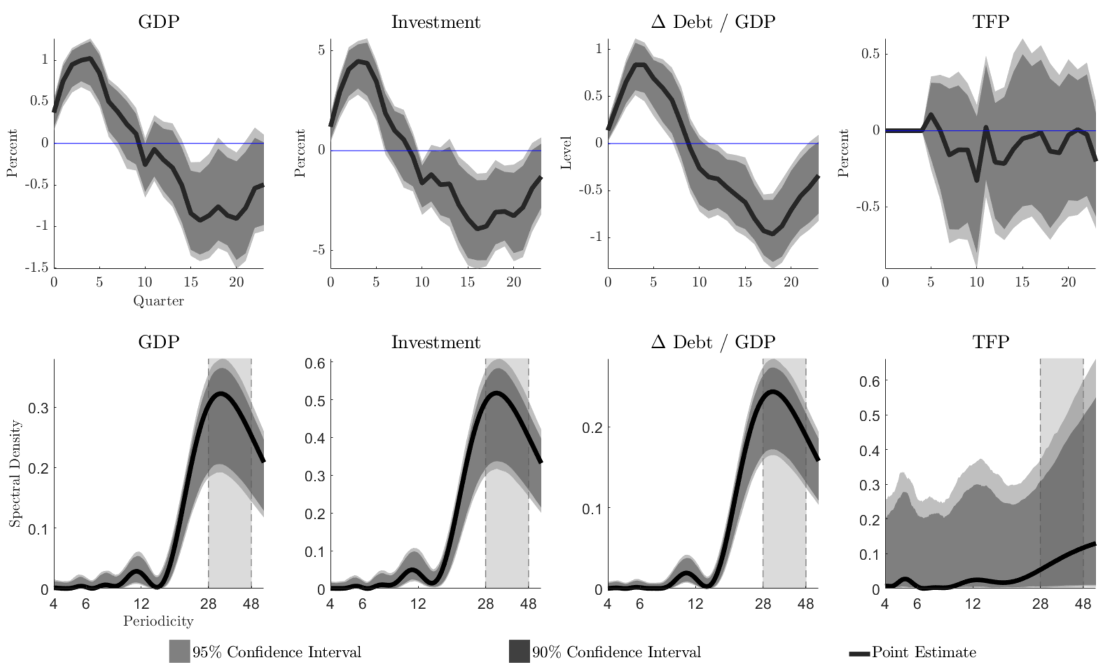

Figure 16: all in LP. S is real GDP growth revision. start in 1967. controls are the same as in the baseline.

E Local Projections

To estimate LP impulse responses we follow standard techniques as firstly introduced by Jordà (2005). Given the stationary series y_t and shock ε_t, impulse responses can be estimated as follows,

$$y_{t+h} = \theta_h \varepsilon_t + \sum_{j=1}^{J} \left[\delta_j \varepsilon_{t-j} + \lambda_j y_{t-j} + \gamma_j x_{t-j} \right] + \nu_{t+h} \text{ for } h = 0, 1, \ldots, H \tag{21}$$

where θ_h represents response of y_t to shock ε_t at horizon h and x_t are additional controls which in our estimation represent principal components from a large dataset of macroeconomic variables.

E.1 Inference

Following Kilian and Kim (2011) we estimate confidence interval using the block bootstrap procedure. As emphasized by Kilian and Kim (2011), we opt for this approach because the error term in the local projections regressions is most likely serially correlated. The LP impulse response estimator for horizon h depends on the tuple,

$$\mathscr{T}_h = [y_{t+h} \;\; \varepsilon_t \;\; \varepsilon_{t-1} \;\; \ldots \;\; \varepsilon_{t-J} \;\; y_{t-1} \;\; \ldots \;\; y_{t-I}] \tag{22}$$

To preserve the correlation in the data, build the set of all $\mathscr{T}_h$ tuples for $h = 0, 1, \ldots, H$. For each tuple $\mathscr{T}_h$, employ the following procedure:

1. Define $g = T - l + 1$ overlapping blocks of $\mathscr{T}_h$ of length l.[15]
2. Draw with replacement from the blocks to form a new tuple $\mathscr{T}_h^b$ of length T.
3. Estimate θ_h^b from $\mathscr{T}_h^b$ using LP estimator.
4. Repeat 1. to 3. B (≥ 2000) times and select confidence intervals.

F Variance Decomposition

Variance decomposition is estimated following Gorodnichenko and Lee (2017). In particular, we define the population share of variance explained by the future innovations in ε_t

[15] Notice that $l = (T - I - J + 2)^{\frac{1}{3}}$ is defined following Berkowitz, Birgean and Kilian (1999). Results are not sensitive to alternative choices of l.

to the total variations in the unpredictable component of y_{t+h} as,

$$v_h = \frac{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i}{Var(f_{t+h|t-1})} \tag{23}$$

where $Var(\varepsilon_t) = \sigma_{\varepsilon_t}^2$ and θ_i are LP estimators. Moreover $f_{t+h|t-1}$ can be estimated from the following regression,

$$y_{t+h} = \sum_{j=1}^{J} \delta_j \varepsilon_{t-j} + \sum_{i=1}^{I} \lambda_i y_{t-i} + \sum_{q=1}^{Q} \gamma_q x_{t-q} + f_{t+h|t-1} \tag{24}$$

where x_{t-q} represents a vector of additional controls.

Since the estimator v_h does not guarantee estimates to be between 0 and 1, we use the following estimator,[16]

$$\tilde{v}_h = \frac{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i}{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i + Var(\nu_{t+h} - \sum_{i=0}^{h-1} \theta_i x_{t+h-i})} \tag{25}$$

where ν_{t+h} is coming from the LP regression,

$$y_{t+h} = \theta_h \varepsilon_t + \sum_{j=1}^{J} \delta_j \varepsilon_{t-j} + \sum_{i=1}^{I} \lambda_i y_{t-i} + \nu_{t+h}. \tag{26}$$

F.1 Inference

To estimate confidence intervals for $\tilde{v}_h$, we directly use the non-parametric confidence intervals estimated for θ_i. In particular, use simulated θ_i^b to estimate,

$$\tilde{v}_h^b = \frac{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i^b}{\sigma_\varepsilon^2 \sum_{i=0}^{h} \theta_i^b + Var(\nu_{t+h} - \sum_{i=0}^{h-1} \theta_i^b x_{t+h-i})} \tag{27}$$

and select confidence intervals.

[16] See Gorodnichenko and Lee (2017) for a detailed description.

G Conditional Spectral Density and Cyclicality Test

Consider the case where stationary variable y_t is explained by two shocks: $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$. In this case, y_t can be represented with the following infinite moving average,

$$y_t = \sum_{h=0}^{\infty} \theta_{1,h}\varepsilon_{1,t-h} + \sum_{h=0}^{\infty} \theta_{2,h}\varepsilon_{2,t-h} \tag{28}$$

Since the estimated impulse responses cannot cover an infinite number of lags consider the truncate moving average,

$$y_t \approx \sum_{h=0}^{H} \theta_{1,h}\varepsilon_{1,t-h} + \sum_{h=0}^{H} \theta_{2,h}\varepsilon_{2,t-h} \tag{29}$$

Since we are interested in the conditional cyclicality implied by the two shocks, we focus on the conditional moving average,

$$y_{k,t} \approx \sum_{h=0}^{H} \theta_{k,h}\varepsilon_{k,t-h} \quad \text{for} \quad k = 1,2. \tag{30}$$

where $y_{k,t}$ represents the realized value of y_t only conditional on shock $\varepsilon_{k,t}$ for $k = 1,2$.

Conditional spectral densities are parametrically estimated by taking the Fourier transform of the estimated truncated moving average. Estimators are,

$$s_k(\omega) \approx \left[\sum_{h=0}^{H} \theta_{k,h} e^{ih\omega}\right] \sigma_k^2 \left[\sum_{h=0}^{H} \theta_{k,h} e^{-ih\omega}\right] \quad \text{for} \quad k = 1,2. \tag{31}$$

where $\omega \in (0\ \pi]$ represents frequencies, $i = \sqrt{-1}$, $\theta_{k,h}$ is the LP estimator, and σ_k^2 is a standard estimator for $Var(\varepsilon_{k,t})$.[17]

G.1 Inference

Similarly to what we have done for the variance decomposition, to estimate confidence intervals for $s_k(\omega)$, we directly use the non-parametric confidence intervals estimated for

[17] Notice that for estimating $s_k(\omega)$ we need to build a grid for $\omega \in (0\ \pi]$. Although results are not sensitive to different grid size, in our main results grid is 0.001 in order to guarantee a precise estimate to ten-year frequencies.

θ_h. In particular, use simulated θ_h^b to estimate,

$$s_k^b(\omega) \approx \left[\sum_{h=0}^{H} \theta_{k,h}^b e^{ih\omega}\right] \sigma_k^2 \left[\sum_{h=0}^{H} \theta_{k,h}^b e^{-ih\omega}\right] \quad \text{for} \quad k = 1, 2. \tag{32}$$

and select confidence intervals.

G.2 Test

1. Filter each variable you want to test using a Band-Pass filter which excludes frequencies below 2 and above 100.

2. Estimate the autoregressive parameter ρ_y implied by this stationary variable using standard regression techniques.

3. Simulate - for each variable y - B (≥ 2000) $AR(1)$ processes with persistence parameter ρ_y fed with normally distributed random disturbances.[18]

4. For each simulated series estimate its disturbances, impulse response coefficients with LP estimator θ_h and conditional spectral density via $s_k(\omega)$ where k is the estimated innovation from each simulated $AR(1)$ process.

5. Following Canova (1998) and Beaudry et al. (2019) we test if the estimated conditional spectral densities for shocks ε_t ($\hat{s}_\varepsilon(\omega)$) are indistinguishable from the ones derived from the simulated $AR(1)$ process ($\hat{s}_a(\omega)$).

   - Notice that $H_0 : \hat{D}_\varepsilon = \hat{D}_a$ and $H_1 : \hat{D}_\varepsilon > \hat{D}_a$
   - $\hat{D}_k = \hat{s}_k(\omega_1)/\hat{s}_k(\omega_2)$
   - $\omega_1 \in (\pi/40, \pi/28)$ and $\omega_1 \in (\pi/72, \pi/48)$

6. Test statistic is estimated as follows

   - Define $\hat{D}_k^b = \hat{s}_k^b(\omega_1)/\hat{s}_k^b(\omega_2)$ as the simulation of $\hat{D}_k$ from $\hat{s}_k^b$.
   - Estimate, for each b, $\hat{\zeta}^b = \hat{D}_\varepsilon^b - \hat{D}_a^b$ as the difference between the simulation for $\hat{D}_\varepsilon^b$ and $\hat{D}_a^b$.

[18] This simulated series has the same length of the data used in the empirical section. Since our sample start slightly after 1980 then we have about 150 observations.

- P-value is the number of $\hat{\zeta}^b > 0$ over the total number of simulations B.

	GDP	Investment	ΔDebt / GDP	TFP
Expectation Shock	3.64%	4.82%	2.24%	28.4%
Technology Shock	28.52%	5.54%	0.1%	89.84%

Table 2: P-values for the test of a local peak in the spectral density implied by expectation shocks (first row) and technology shocks (second row).

H Proof of Proposition 1

Cyclical dynamics obtain if at least two eigenvalues of the reduced form system of the model are complex and conjugate. Under determinacy this is not possible because there would be two eigenvalues, one stable and the other one unstable. Indeterminacy is characterized by a system with two stable eigenvalues, possibly complex and conjugate. The loglinearized deterministic version of the model can be written as,

$$\begin{pmatrix} 2\kappa d & \frac{\tau\beta\omega}{1-\tau+\tau\beta} \\ 1-\beta & \beta-\omega \end{pmatrix} \begin{pmatrix} \hat{d}_{t+1} \\ \hat{y}_{t+1} \end{pmatrix} = \begin{pmatrix} \frac{2\kappa d}{1+\mu\gamma} & M \\ 0 & 1-\omega \end{pmatrix} \begin{pmatrix} \hat{d}_t \\ \hat{y}_t \end{pmatrix} \tag{33}$$

where

$$M \equiv \frac{\tau\beta\omega}{1-\tau+\tau\beta} - \gamma\frac{1-\mu}{1+\gamma\mu}\left(\omega - 1 + \frac{1}{(1-\theta)(1-n)}\right) \tag{34}$$

Notice that when κ is equal to zero then the reduced-form of the system is independent of $\hat{d}_t$ implies that one eigenvalue is equal to zero ruling out the possibility to have two complex and conjugate eigenvalues.