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# Expectation-Driven Boom-Bust Cycles

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# Expectation-driven Boom-Bust Cycles*

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**Abstract**

Using data from the Survey of Professional Forecasters, we find that a large fraction of analysts' expectations about future economic growth is not due to technology or other shocks to fundamentals. The comovement pattern associated with these changes is different from the one driven by fundamental shocks. Specifically, a non-fundamental improvement in expectations of future output predicts boom-bust dynamics in the key macroeconomic aggregates. We offer a novel theory that explains why boom-bust dynamics emerge in response to non-fundamental expectations shocks and not to technology shocks.

*JEL classification*: C32, E32

*Keywords*: Animal Spirit, Boom Bust, Business Cycle, Sunspot

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We uncover a new finding on the role of expectations in shaping economic fluctuations. When changes in expectations are not due to policy or technology shocks, but rather are non-fundamental, they lead to boom-bust dynamics in key macroeconomic indicators. Specifically, after a positive shock to expectations, output initially rises but eventually falls significantly below trend. In contrast, fundamental shocks result in trend-reverting dynamics without any oscillatory patterns.

Broadly speaking, our findings relate to Keynes' idea of the existence of "animal spirits" guiding the actions of economic agents, and driving business cycles. This idea is appealing for at least two reasons. First, it aligns with the consensus in the business cycle literature that the economy is primarily driven by demand disturbances, with changes in technology accounting for only a small fraction of fluctuations (see, for example, Angeletos et al., 2020). Non-fundamental expectation shocks, within this paradigm, represent a natural candidate for demand-driven fluctuations. Second, historical narratives of economic fluctuations driven by sentiments abound. For example, Hall (1993) argues that the 1990-1991 recession originated from a spontaneous fall in consumption, while the swift recovery post 9/11 was attributed by Shiller (2020) to an unexpected positive change in national sentiment. Even the Great Recession cannot be solely attributed to depressed fundamentals (see, for example, Farmer, 2012 and Bacchetta and Van Wincoop, 2016).[1]

Besides showing that our evidence supports the idea of animal spirits being an important contributor of business cycle fluctuations, we find that they shape the economy in a way that is profoundly different from shocks to fundamentals. As a direct consequence of our results, expansions fueled by sentiments are more likely to culminate in a recession than expansions driven by technology improvements. As such, distinguishing between sentiments and fundamentals becomes even more relevant for policymakers, whose aim is to prevent inefficient economic fluctuations. We place such distinction at the center of our analysis.

[1] See also Blanchard (1993) for an "animal spirit" account of the 1990-1991 recession.

To begin, we show that an important fraction of changes in agents' expectations is not due to the fundamental shocks estimated by the business cycle literature.

We use data from the Survey of Professional Forecasters (SPF), and compute the time $t$ revision of one-year-ahead expectations on real GDP growth that analysts formed in quarter $t-1$. We then extract the surprise in analysts' revisions that is unrelated to past, present, and future technology growth, and to the expectations thereof. We find that these non-fundamental expectation shocks explain between 48% and 52% of the changes in analysts' expectations, depending on whether we also control for other fundamental shocks along with technology.

Next, we find that non-fundamental expectation shocks are associated with macroeconomic dynamics that stand in stark contrast to those generally attributed to fundamental shocks. Using local projections method, we estimate that a positive expectation shock leads to boom-bust dynamics in aggregate quantities. Real GDP, consumption, hours, and investment significantly increase on impact, and remain elevated for about three years, after which they display a significant contraction below their long-run trend.

We subject our results to a vast array of robustness checks. First and foremost, we are concerned that our results might be contaminated by fundamental shocks other than anticipated and surprise technology shocks. Thus, we control for other shocks estimated by the literature, including the monetary policy shock series of Romer and Romer (2004) extended by Wieland (2021), the military spending shock series of Ramey (2011), the anticipated and surprise tax shock series of Mertens and Ravn (2012), the oil price shock series estimated in Kilian (2008), and the financial uncertainty of Ludvigson et al. (2021).

Results remain largely unchanged.[2] Additionally, we check that our results hold if we change the expectation targets or the sample period.

In the last part of the robustness checks section, we discuss why other studies adopting similar procedures have not found boom-bust dynamics in response to similarly identified expectation shocks. The closest paper related to our empirical findings is Levchenko and Pandalai-Nayar (2020). Their estimation strategy also entails extracting the residual of analysts' forecasts that is orthogonal to anticipated and surprise technology shocks. But they do not find the boom-bust dynamics that we do. We show that the key innovation of our strategy is to use local projections method which, relatively to Vector Autoregregressions, is better suited to estimate medium to long horizon dynamics.

Before turning to the model, we demonstrate that the oscillatory dynamics obtained in response to non-fundamental expectation shocks do not emerge in response to fundamental shocks. We carry out two distinct exercises. First, we estimate the impulse response to analysts' revisions without controlling for changes in technology or other fundamental shocks. We find that positive revision surprises do not predict a future bust, but boom-bust dynamics obtain only when we remove the fundamental component. Second, we identify technology shocks and estimate their effects on the business cycle. To do so, we extract the unpredictable component of the growth rate of the utilization-adjusted Total Factor Productivity taken from Fernald (2014), and estimate its effect on the economy via local projections. We find that technology shocks lead to significant and positive deviations of macroeconomic aggregates from their long-run trend, without exhibiting any oscillatory pattern.

[2] These controls are only imperfect proxies for the true unobservable fundamental shocks. However, the body of the literature that examines business cycle shocks does not find boom-bust dynamics in response to *any* fundamental source of fluctuations. As such, it is rather unlikely that our results are confounded by such shocks.

Altogether, our empirical results pose new challenges for business cycle models. On the one hand, workhorse DSGE models, as in Smets and Wouters (2007), feature no intertemporal dependence between expansions and recessions. As such, they are unable to reproduce the oscillatory responses that we uncover. On the other hand, models of endogenous cycles, as in Beaudry et al. (2020), predict oscillatory dynamics in response to all shocks, thus they fall short in reproducing the responses to technology shocks. In the second part of the paper, we build a model that shares elements with both families of models and rationalizes the conditional emergence of boom-bust cycles.

The model is a Real Business Cycle model with both expectation and technology shocks. Expectation shocks stem from the interplay of two frictions. First, we assume that firms can borrow from households up to a limit that depends on their market value. Second, we assume that firms face a working capital requirement. We demonstrate that the interaction between the borrowing limit and the working capital requirement generates self-fulfilling equilibria, that is, equilibrium changes in agents' expectations independent from technology. The intuition is as follows. If households become more optimistic regarding firm value, the borrowing constraint relaxes, and firms can finance more production. As firms increase their labor demand, households' income increases and so does their demand for firm assets. Consequently, firm value rises, validating the initial optimism of households.

Next, we feed the model with both i.i.d. expectation shocks orthogonal to technology, i.e., sentiments, and transitory technology shocks. The model rationalizes the conditional boom-bust dynamics that we find in the data. The intuition is that while both sentiment and technology shocks increase firm value, the nature of the increase matters for propagation. During a sentiment-driven expansion, firm value rises because households increase their saving desire in expectation of a future recession. Then, a recession obtains from the interaction between households' sale of firm assets and the tightening of firms' borrowing constraints. During an expansion driven by a temporary improvement in technology, in contrast, firm value increases because firms are more profitable. Since households know that higher firm values are due to higher technology, they will not sell firm assets and, consequently, there will be no crunch in credit.

**Related literature** This paper relates to three strands of the literature. First, our empirical results relate to the literature on the estimation of expectation shocks. The definition of expectation shocks is, however, not uniform across studies. On the one hand, there is a strand of research that draws from Pigou (1927) and focuses on noise shocks, that is, on mistakes about future technology movements.[3] On the other hand, there is a set of papers that identifies expectation shocks as orthogonal to fundamentals and their expectations, labelling them as sentiments . Our definition of expectation shocks is in line with this latter strand of literature. Examples in this class are Leduc and Sill (2013), Fève and Guay (2019), and Levchenko and Pandalai-Nayar (2020), which use Structural Vector Autoregressions (SVARs) to identify sentiment shocks from survey data, and study their empirical responses. We complement these studies by proposing a different method to trace out the dynamics implied by sentiment shocks, which does not rely on SVARs. While we find similar short-horizon responses, we document novel evidence of a medium-horizon reversal. Section 1.1 shows that the key difference between our results and the ones obtained by these papers stems from the choice of the number of lags in the VAR. A related handful of papers uses instrumental variables to identify exogenous expectational shifts. In particular, Benhabib and Spiegel (2019) identifies sentiment shocks from political outcomes, and Lagerborg et al. (2022) from the number of fatalities in mass shootings. Both studies find that sentiment shocks have sizeable effects on the economy while they are silent on their medium-horizon impact.

[3] Works on the estimation of noise shocks include Oh and Waldman (1990), Beaudry and Portier (2004), Lorenzoni (2009), Schmitt-Grohé and Uribe (2012), Blanchard et al. (2013), Hürtgen (2014), Forni et al. (2017), Chahrour and Jurado (2018), Benhima and Poilly (2021), Enders et al. (2021), Chahrour and Jurado (2022), Faccini and Melosi (2022), and Enders et al. (2022).

The second strand of literature related to this paper is the one supporting the endogenous cycle hypothesis. The idea is that the economy features an endogenous propagation mechanism that makes it perpetually oscillating between periods of boom and periods of bust. The endogenous cycle view has received only scattered attention (see Boldrin and Woodford, 1990 for a survey), while a more exogenous view on cycles, according to which cycles manifest due to the alternation of random positive and negative shocks, has popularized the literature. Recently, however, Beaudry et al. (2020) has revived the attention on the endogenous cycle hypothesis. They analyze the spectrum of several macroeconomic indicators and provide novel supportive evidence of perpetual oscillations in the reduced form data of U.S. We make a step forward, in the sense that our findings suggest that sentiments could be the *source* of the oscillations documented by Beaudry et al. (2020). More tangentially, there is a growing literature that aims at detecting early warning indicators of future financial crises. Sufi and Taylor (2021) provides a summary of this literature. Their abstract reads "[...] Crises do not occur randomly, and, as a result, an understanding of financial crises requires an investigation into the booms that precede them." We show that recessions are likely to occur when the boom preceding them has a non-fundamental cause.

Finally, our model is related to the class of models with equilibrium indeterminacy and sunspot shocks. The workhorse model in this literature is the one by Benhabib and Farmer (1994) in which equilibrium indeterminacy arises due to aggregate increasing returns to scale.[4] Their work suggests that economic fluctuations may be driven not only by changes in fundamentals but also by self-fullfilling changes in agents' expectations. A close paper to ours in this class is Benhabib and Wen (2004), which analyzes an RBC model with increasing returns and endogenous capacity utilization. They show that when the model is parametrized in the indeterminacy region, it can better replicate the autocovariance

[4] See also Azariadis (1981), Diamond (1982), Cass and Shell (1983), Woodford (1986), and Cooper and John (1988).

properties of the data. We share a similar spirit, with the distinction that our model also emphasizes the different dynamics implied by technology and sunspot shocks. Lastly, 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 Wang (2013), Liu and Wang (2014), and Azariadis et al. (2015). While their emphasis is either on a single shock or the unconditional properties of the economy, our model is built to rationalize why only non-fundamental shocks can explain the boom-bust patterns observed in the data.

# 1 Expectation shocks and boom-bust dynamics

In this section, we analyze the changes in analysts' expectations that cannot be accounted for by changes in technology, the expectations thereof, and by other shocks to fundamentals. Not only do we find that about 50% of analysts' expectation revisions are not due to the fundamentals we control for, but also that such residual component is associated with dynamics that are remarkably different from the ones generally attributed to fundamental shocks.

**Identification of expectation shocks** We proxy expectations of market participants using expectations data from the Survey of Professional Forecasters (SPF) maintained by the Philadelphia Fed. The survey is avaialable from 1968Q4 and consists in quarterly forecasts of a number of macroeconomic indicators at several horizons. In our baseline specification, we use the mean of analysts' one-year-ahead forecasts of U.S. real GDP growth from 1970Q3 to 2020Q1.[5,6] Let $x_{t+h|t-1}$ be the mean analysts' forecast of $x_{t+h}$ made in quarter

[5] We start from 1970Q3 to avoid discontinuities in the data, while we stop in 2020Q1 to exclude the COVID-19 recession.

[6] In Section 1.1, we show that results are robust to using the median (instead of the mean) or using other macroeconomic indicators included in the Survey, such as unemployment and Industrial Production Index.

$t-1$, we compute the quarter $t$ forecast revision as

$$S_t = \frac{x_{t+3|t}}{x_{t-1|t}} - \frac{x_{t+3|t-1}}{x_{t-1|t-1}},$$

where the second term on the right-hand side is the forecast of annual GDP growth made in quarter $t-1$, and the first term is the updated forecast in quarter $t$. The difference between the two, $S_t$, is the revised forecast that analysts make upon the arrival of new information at time $t$.[7] Next, we regress the forecast revision on the past, present, and future technology, *and* on past and present expectations of future technology. Importantly, including both realized technology and its expectations allows us to control for fluctuations induced by ex-post wrong beliefs about future technology, i.e., noise shocks (see Chahrour and Jurado, 2018). The regression reads:

$$S_t = \alpha S_{t-1} + \sum_{k=-\underline{K}}^{\overline{K}} \beta_k \Delta \log TFP_{t-k} + \sum_{j=0}^{J} \delta_j b_{t-j} + v_t, \tag{1}$$

where we omit the constant for convenience. The regression above includes three sets of controls. First, under full information rational expectations, time-t revisions should only be affected by contemporaneous variables. However, since Coibion and Gorodnichenko (2015) shows that the forecast revisions predict forecast errors, we control for the past value of forecast revision to ensure that the regression residual $v_t$ is not autocorrelated. The second term is the past, present, and future realizations of total factor productivity. We use utilization-adjusted quarterly TFP from Fernald (2014), and control for four lags and twelve leads.[8] Finally, the term $b_t \equiv \hat{E}_t[\log TFP_{t+3} - \log TFP_{t-1}]$ is the estimated beliefs on future annual TFP growth, where we keep the timing consistent with the forecast revisions

[7] Note that the nowcast of $x_{t-1}$ made in $t-1$, $x_{t-1|t-1}$, and the backcast in $t$, $x_{t-1|t}$, are not necessarily the same since analysts do not observe the current values of $x$. See Enders et al. (2021) for an exploration of the economic effects of nowcast errors.

[8] Results are unchanged when using more leads or lags. See Appendix G.

$S_t$. Since TFP expectations are not readily available in the survey, we compute $b_t$ as the fitted value of the following regression:

$$\log TFP_{t+3} - \log TFP_{t-1} = \sum_{m=0}^{M} \alpha_m \Delta \log TFP_{t-m} + \sum_{q=0}^{Q} \beta_q \mathbf{PC}_{t-q} + r_{t+3}, \tag{2}$$

where the left-hand side is the annual growth rate of quarterly TFP, and the right-hand side includes both present and past values of quarterly TFP growth and of the first four principal components of the quarterly dataset maintained by McCracken and Ng (2020). We set the number of lags $M$ and $Q$ equal to four.[9,10]

Table 3 in Appendix C shows the results for both regressions, and Figure 10 in Appendix B illustrates the expectation shock series $\hat{v}_t$. Perhaps surprisingly, the $R$-squared of the regression in Equation (1) is 48%, meaning that more than half of changes in analysts' expectations are not due to realized changes in TFP or noise. Furthermore, the $R$-squared increases only to 52% when we additionally control for several externally identified fundamental shocks. These controls include Romer and Romer (2004) monetary policy shocks, Ramey (2011) military spending shocks, Mertens and Ravn (2012) unanticipated and anticipated tax shocks, Kilian (2008) oil price shocks, and Ludvigson et al. (2021) financial uncertainty series.

**Impulse responses to expectation shocks** The residual, $\hat{v}_t$, from Equation (1) is our object of interest. We estimate the impulse responses to a one standard deviation increase in

[9] The right-hand side of Equation (2) might not fully capture agents' information about future technology, therefore in Section 1.1 we augment the controlling set with the TFP news shocks estimated in our sample using the procedure by Barsky and Sims (2011).

[10] Appendix G shows that results are robust to changing the number of lags or of principal components.

$\hat{v}_t$ using local projections as in Jordà (2005). Specifically, we run the following projections:

$$y_{t+h} - y_{t-1} = \theta_h \hat{v}_t + \sum_{p=1}^{P} \left[ \delta_p \hat{v}_{t-p} + \lambda_p \Delta y_{t-p} \right] + \mathbb{1}_{h>0} \hat{u}_{t+1,t+h} + u_{t,t+h} \quad \text{for} \;\; h = 0, 1, \ldots, H \tag{3}$$

where the parameter $\theta_h$ is the response of $y$ to a positive expectation shock after $h$ periods. In the baseline, we control for the first four lags of both $\hat{v}_t$ and the first difference of $y_t$. In addition, when $h > 0$, we control for the residual $\hat{u}_{t+1,t+h}$ estimated in the $h-1$-th regression and forwarded by one period.[11] The right panels of Figure 1 illustrate the responses of both the log of real GDP and the forecast revisions to an expectation shock. The left panels, in contrast, show the responses to a one standard deviation increase in the forecast revisions. Since we use a lag-augmented local projection estimator, we compute 80% and 90% confidence intervals using Eicker-Huber-White heteroscedasticity-robust standard errors (see Montiel Olea and Plagborg-Møller, 2021 for a discussion). Two patterns emerge. First and foremost, the response of GDP depends on whether or not we remove the fundamental component from forecast revisions. The left panels show a transitory but persistent increase in the real GDP in response to a positive change in forecast revisions. The right panels, in contrast, show boom-bust dynamics in response to an expectation shock. A positive expectation shock predicts a gradual increase in the real GDP which remains elevated for about three years, significantly falling below trend afterward. Second, we find that analysts correctly predict the increase in output after an expectation shock but not after an innovation in forecast revisions. The cross in the bottom panels marks the mean of analysts' forecasts that they made when the shock hit the economy. When we consider

[11] As suggested by Jordà, 2005, pp. 166, the inclusion of the residuals from the previous regression increases the efficiency of the estimator. This is because $\hat{u}_{t+1,t+h}$ is, by construction, orthogonal to the regressor $\hat{v}_t$, therefore, its inclusion improves the accuracy of $\hat{\theta}_h$ (see Wooldridge, 1993, pp. 687). Nevertheless, Figure 12 of Appendix G reveals that our conclusions do not change when we remove the estimated residuals from the set of controls.

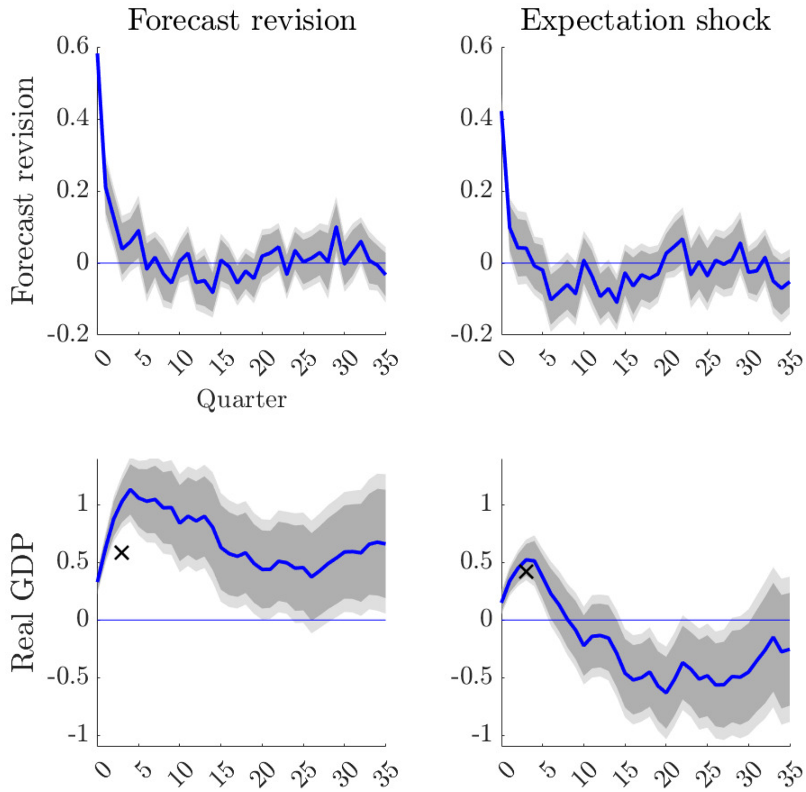


**Figure 1:** GDP response to a forecast revisions shock and expectation shock

*Note*: Impulse responses to a one-standard deviation forecast revision shock (first column) and expectation shock (second column). Sample period: 1970Q3–2020Q1. Shaded areas are the 80% and 90% confidence bands calculated with Eicker-Huber-White heteroscedasticity-robust standard errors. Horizontal axes measure quarters and vertical axes measure percentage points (forecast revision) and percent deviations from pre-shock trend (real GDP). In the second row, the *x* mark is the expected Real GDP growth implied by the impact response of the forecast revision.

forecast revision shocks, analysts under-predict the future increase in output. This finding is consistent with Coibion and Gorodnichenko (2012), which shows that analysts fail to adjust in response to shocks to fundamentals. In contrast, analysts correctly predict the increase in output following an expectation shock, suggesting that our estimated residuals reflect a different relation between expectations and realized outcomes. We interpret this outcome as suggestive evidence that expectation shocks stem from non-fundamental disturbances, that is, shocks originating from a change in agents' expectations, as opposed to shocks that analysts don't perfectly observe. In Section 2, we propose a model that rationalizes the emergence of boom-bust dynamics to non-fundamental expectation shocks without violating the rational expectation assumption.

## 1.1 Robustness checks

We now show that the results documented in Figure 1 are robust to different specifications. In the interest of space, Figure 2 only plots the responses of real GDP. The solid red line along with shaded areas are the responses under the alternative specification, whereas the

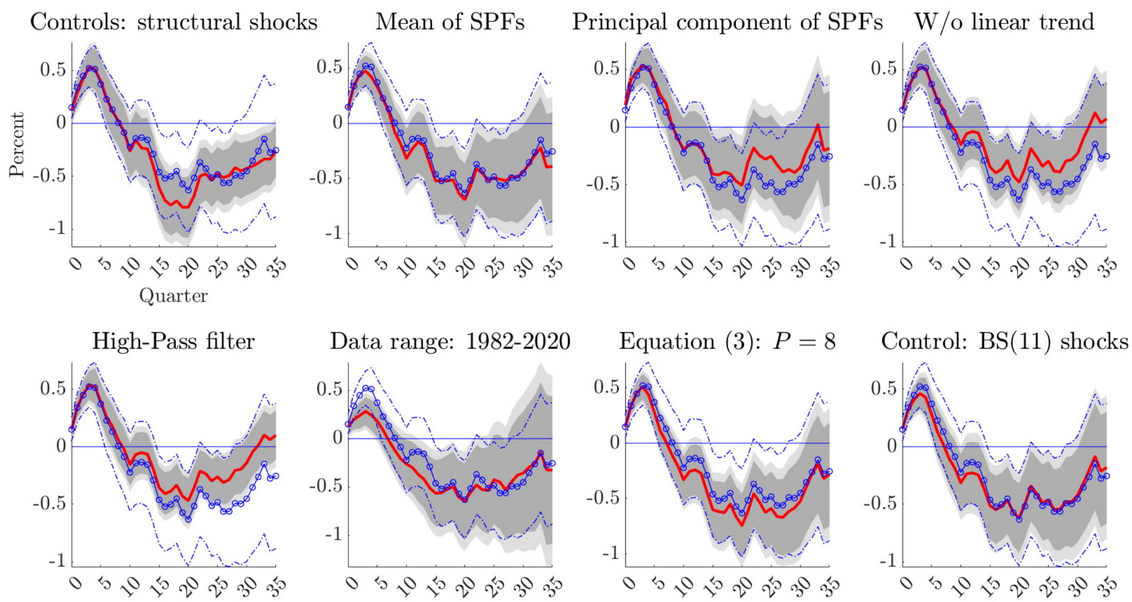


**Figure 2:** GDP responses to an expectation shock using different specifications

*Note*: Impulse responses of real GDP to a one-standard deviation expectation shock under different specifications. The red line is the point estimate and the shaded areas are the 80% and 90% confidence bands calculated with Eicker-Huber-White heteroscedasticity-robust standard errors. Circled and dashed blue lines are the point estimates and the 80% confidence bands of the baseline specification presented in Figure 1. Horizontal axes measure quarters and vertical axes measure percent deviations from pre-shock trend. In the first row, the specification in the first panel controls for monetary policy shocks (Romer and Romer, 2004), unanticipated and anticipated tax shocks (Mertens and Ravn, 2012), government spending shocks (Ramey, 2011), oil price shocks (Kilian, 2008), financial uncertainty (Ludvigson et al., 2021); second panel shows a specification that uses the median of the expected real GDP growth from the SPF; specification in the third panel uses the first principal component of the SPF forecast revisions of real GDP growth, industrial production growth, and unemployment rate. Specifications in the fourth panel (first row) and first panel (second row) detrend the endogenous variable using a linear trend and a High-Pass filter that excludes periodicities over 200 quarters, respectively, and then estimate the responses according to Equation (4). In the second row, in the specification of the second panel the sample period ranges from 1982Q1 to 2020Q1; third and fourth panels show a specification that controls for eight lags of the controls presented in Equation (3) and for news shocks as estimated by Barsky and Sims (2011), respectively.

blue line with circular markers is the baseline response together with 90% confidence intervals. We address six major concerns. First, since the expectation shock series is estimated as a residual in Equation (1), it may contain forecast revisions induced by fundamental shocks other than technology. Thus, the first panel plots the GDP response after adding other fundamental disturbances to the right-hand side of Equation (1). More specifically, we control for the monetary policy shock series of Romer and Romer (2004) and extended by Wieland (2021), the military spending series of Ramey (2011), the unanticipated and anticipated tax shocks estimated by Mertens and Ravn (2012), the oil price shocks estimated by Kilian (2008), and the financial uncertainty series by Ludvigson et al. (2021). The restricted sample ranges from 1971Q1 to 2004Q3. Relatively to the baseline, point estimates are largely unvaried, which is somewhat not surprising given that we found that these shocks contribute very little to the $R$-squared of regression in Equation (1). Confidence bands, on the other hand, are narrower than in the baseline, despite the loss of observations, further suggesting that our results might be driven by non-fundamental expectation shocks. The second source of concern is the choice of the SPF forecast series and its aggregation. In the baseline, we take the mean of the analysts' forecast on real GDP growth. In the second and third panel of the first row, instead, we take the median forecast revisions of real GDP growth, and the first principal component of the forecast revisions of unemployment rate, industrial production, and real GDP, respectively. A third important check consists in the treatment of the left-hand side variable in the local projections. Our baseline does not distinguish between business cycles and low frequency fluctuations induced by expectation shocks. Yet, we find that the real GDP response is transitory. Nevertheless, we can extract the business cycle fluctuations only. To do so, we detrend the real GDP series and estimate its response to expectation shocks from the following modified version of Equation (3):

$$
\begin{aligned}
&y_{t+h}^{det} = \theta_h \hat{v}_t + \sum_{p=1}^{P} \left[ \delta_p \hat{v}_{t-p} + \lambda_p y_{t-p}^{det} \right] + \mathbb{1}_{h>0} \hat{u}_{t+1,t+h} + u_{t,t+h} \\
&\text{for} \quad h = 0, 1, \ldots, H
\end{aligned}
\tag{4}
$$

where $y_t^{det}$ stands for the detrended log of real GDP. Figure 2 shows results after removing a linear trend, or using a High-Pass filter which excludes fluctuations with periodicities over 200 quarters. Since filtering removes long run fluctuations, estimates are more accurate at longer horizons, resulting in narrower confidence bands. As a fourth robustness we restrict the sample to the post-Volcker disinflation period, from 1982Q1 to 2020Q1. The overall pattern doesn't change but the initial boom is less pronounced and the bust occurs few quarters earlier than in our baseline estimates. Fifth, we check that results are robust to increasing the number of lags $P$ in Equation (3) to eight. As a last exercise, we control for news shocks in TFP to better isolate the non-fundamental component. Following Barsky and Sims (2011), we estimate a VAR(4) with log of real GDP, consumption, hours, and TFP using our data sample, and extract news shocks as the shocks orthogonal to current TFP that maximizes the 40-quarter forecast error variance of future TFP. We then insert the estimated news shock as an additional control on the right-hand side of Equation (1).

In conclusion, Figures 1 and 2 suggest the presence of a pervasive component induced by expectation changes likely unrelated to fundamentals. Such component, drives boom-bust dynamics on real GDP.

**Discussion** We are not the first to identify non-fundamental expectation shocks as agents' expectations orthogonal to TFP. In particular, our identification strategy resembles the one adopted by Levchenko and Pandalai-Nayar (2020, LPN henceforth). LPN estimates a structural vector autoregression model including four lags of TFP, real GDP, consumption, hours, and SPF forecasts of real GDP one quarter ahead. The sample ranges from 1968Q4 to 2010Q3. Expectation shocks are estimated as those that maximize the forecast error variance of analysts' forecasts at two-quarter horizon, while being orthogonal to surprise and news of TFP. They find that expectation shocks explain a relevant fraction of U.S. GDP but they do not find evidence of boom-bust dynamics. The reason is that the VAR does not include enough lags to correctly estimate the impulse responses at medium and long horizons. In fact, VAR and local projections estimate the same responses only when enough lags are included (see Plagborg-Møller and Wolf, 2021). To see this, we first replicate the VAR(4) of LPN over their sample. The solid line in Figure 3 shows the response of real GDP.[12] Real GDP rises over the first few quarters, and then slowly returns to trend in a monotonic fashion. Next, we compare these impulse responses with those obtained after increasing the number of lags to eight in the VAR (left panel), or running local projections

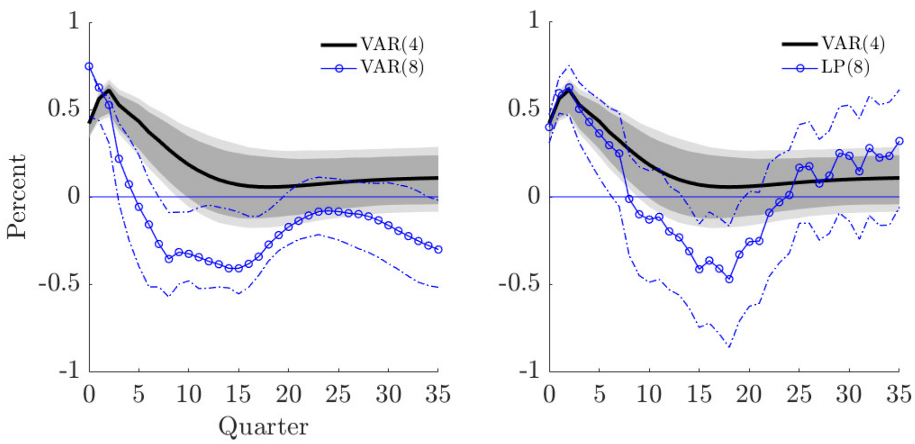


**Figure 3:** GDP responses to an expectation shock identified as in Levchenko and Pandalai-Nayar (2020)

*Note*: Impulse responses of real GDP to a one-standard deviation expectation shock. Sample period: 1968Q4–2010Q3. The black solid line and the shaded areas are the baseline point estimate and 80% and 90% confidence bands (Efron bootstrap) by LPN. On the left, the solid line with circles and dotted lines are the point estimate and 80% confidence bands (Efron bootstrap) of the structural VAR by LPN using eight lags instead of four. On the right, the solid line with circles and dotted lines are the point estimate and 80% confidence bands (Eicker-Huber-White heteroscedasticity-robust standard errors) of the Local Projection estimator with eighth lags in which we project real GDP on the expectation shock series estimated by LPN. Responses are scaled to match the annual cumulative effect of an expectation shock by LPN on real GDP.

[12] See Appendix H for the details about the estimation and the response of all variables included in the VAR.

on LPN's shocks. For the local projections, we use the specification in Equation (3) with eight lags, i.e., $P = 8$. The lines with circles show the responses under these alternative specifications. Both extensions feature significant boom-bust dynamics. Furthermore, despite differences in the identification strategy and the variable selection, the VAR(8) and the local projections predict dynamics that are remarkably similar to the ones obtained in our baseline.

### 1.2 Responses of other variables and variance decomposition

We now extend the analyses to the estimation of the responses of other key macroeconomic indicators. We find boom-bust dynamics in all the real macrovariables we consider. In addition, even though we estimate the response of each variable separately, the timing of the bust roughly coincides across the series. Finally, we argue that the comovement that we find is informative for business cycle theories.

**Responses of other variables** We document the macroeconomic responses to an expectation shock by estimating Equation (3) for several macroeconomic indicators. Figure 4 shows the responses of (the log of) real investment, real total consumption, real durable consumption, real non-durable consumption, total hours, labor productivity, and utilization-adjusted TFP. The response of TFP is never statistically different from zero, which indicates that we are controlling for enough leads and lags in Equation (1). Investment, consumption, and total hours comove and display similar boom-bust dynamics to the ones estimated for real GDP in Figure 1.[13] The positive response of CPI and the comovement among variables suggest that we are capturing a source of demand shocks. Finally, labor productivity decreases during the boom, while it increases during the bust, albeit the estimated response is inaccurate. This pattern is particularly informative from a model standpoint. In fact, as we shall discuss in Section 2, the fall in labor productivity

[13] Figure 11 in Appendix D reveals that stock prices and commercial and industrial loans also display boom-bust dynamics.

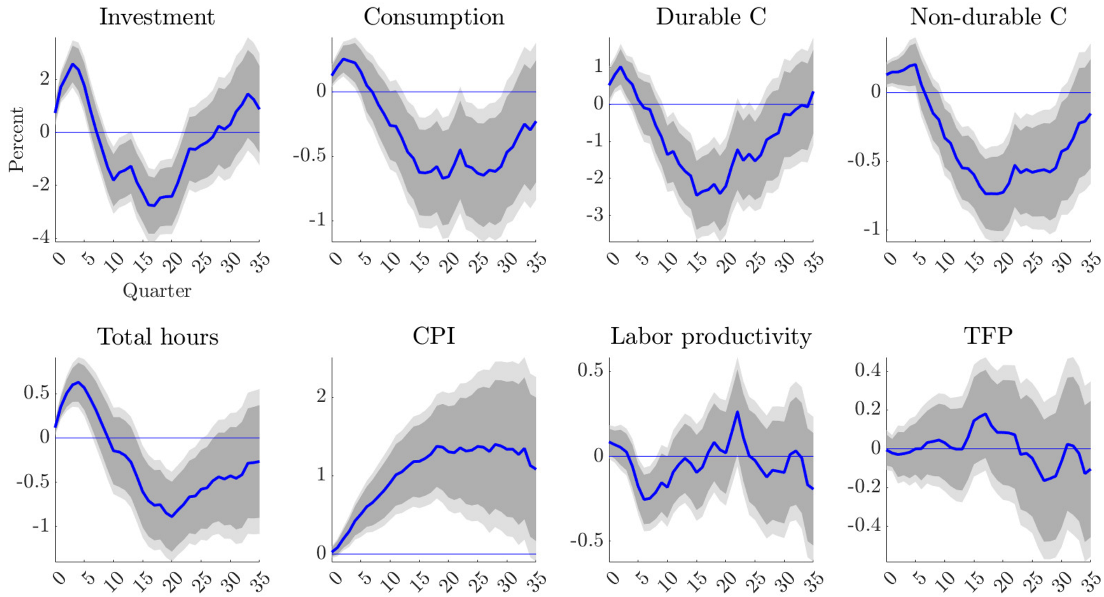


**Figure 4:** Responses of macro-variables to an expectation shock

*Note*: Impulse responses of macro-variables to a one-standard deviation expectation shock. Sample period: 1970Q3–2020Q1. Blue lines indicate the point estimate and the shaded areas indicate 80% and 90% confidence bands calculated with Eicker-Huber-White heteroscedasticity-robust standard errors. Horizontal axes measure quarters and vertical axes measure percent deviation from pre-shock trend. All the variables (with the exception of TFP) are log-transformed and are downloaded (in April 2022) from the quarterly dataset by McCracken and Ng (2020). TFP is from Fernald (2014).

falsifies models of production externalities and aggregate increasing returns to scale as candidate explanations of expectation-driven fluctuations.[14]

**Forecast error variance decomposition** We follow Gorodnichenko and Lee (2020) and compute the forecast error variance decomposition of all variables examined in Figures 1 and 4.[15] Table 1 reports the estimated share of the forecast error variance explained by expectation shocks at four, eight, and twenty quarters. The numbers in parentheses are one standard deviation intervals. Expectation shocks explain up to one third of the variation of GDP. A similar patter emerges for real investment and total hours. For real consumption and CPI the variance explained is somewhat smaller. In addition, Table 4 in

[14] The difference in the conditional cyclicality of labor productivity can also help explain the reduced-form acyclicality of labor productivity found in the data (see Stiroh, 2009).

[15] See Appendix I for details on the implementation.

| | 4 quarters | 8 quarters | 20 quarters |
|---|---|---|---|
| Real GDP | 33.0 | 26.6 | 16.2 |
| | (26.9,39.0) | (23.1,30.1) | (4.3,28.1) |
| Forecast revision | 39.8 | 30.1 | 33.1 |
| | (33.3,46.2) | (21.2,39.0) | (19.1,47.1) |
| Investment | 31.0 | 27.7 | 27.9 |
| | (24.8,37.2) | (19.2,36.2) | (12.3,43.5) |
| Consumption | 15.4 | 6.5 | 14.4 |
| | (10.9,20.0) | (4.8,8.3) | (2.3,26.4) |
| Durable C | 14.0 | 5.7 | 19.6 |
| | (11.8,16.1) | (0.1,11.4) | (3.8,35.3) |
| Non-durable C | 7.7 | 5.4 | 22.3 |
| | (6.6,8.7) | (0.8,9.9) | (1.5,43.0) |
| Total hours | 28.2 | 22.6 | 21.5 |
| | (23.7,32.6) | (16.0,29.2) | (0.6,42.5) |
| CPI | 7.7 | 14.1 | 20.4 |
| | (5.7,9.6) | (10.3,17.9) | (15.3,25.5) |
| Labor productivity | 1.0 | 4.6 | 2.5 |
| | (-4.8,6.9) | (0.9,8.3) | (-2.6,7.6) |
| TFP | 0.1 | 0.1 | 1.1 |
| | (-2.0,2.2) | (-1.7,1.9) | (-2.0,4.1) |

**Table 1:** Forecast error variance explained by expectation shocks

*Notes:* Numbers in parentheses are one standard deviation confidence intervals. Forecast error variance shares are computed as in Gorodnichenko and Lee (2020) (see Equation 10, page 923). See Appendix I for additional details.

Appendix I reports similar values for the shares of forecast error variance after we control for other fundamental shocks in Equation (1).

### 1.3 Technology shocks and conditional spectral densities

We now analyze the difference between expectation and technology shocks, and discuss the implications for the business cycle literature.

**Responses to a technology shock** It is extensively documented that TFP follows a near random-walk process and is the main contributor to long-run fluctuations. Thus, the specification in Equation (3) is not suitable in this case, as it would inevitably capture both the permanent and the transitory effects of a TFP shock. Suppose, indeed, that TFP shocks generated transitory oscillatory dynamics while also affecting the long-run level of output.

Then, impulse responses estimated using Equation (3) would not cross the zero line, and we would erroneously conclude that TFP shocks do not account for boom-bust dynamics at business cycle frequencies. Thus, we choose to study the responses on the detrended variables, so as to isolate the transitory effects of TFP shocks from the permanent ones. We begin by estimating an innovation in TFP growth using a modified version of Equation

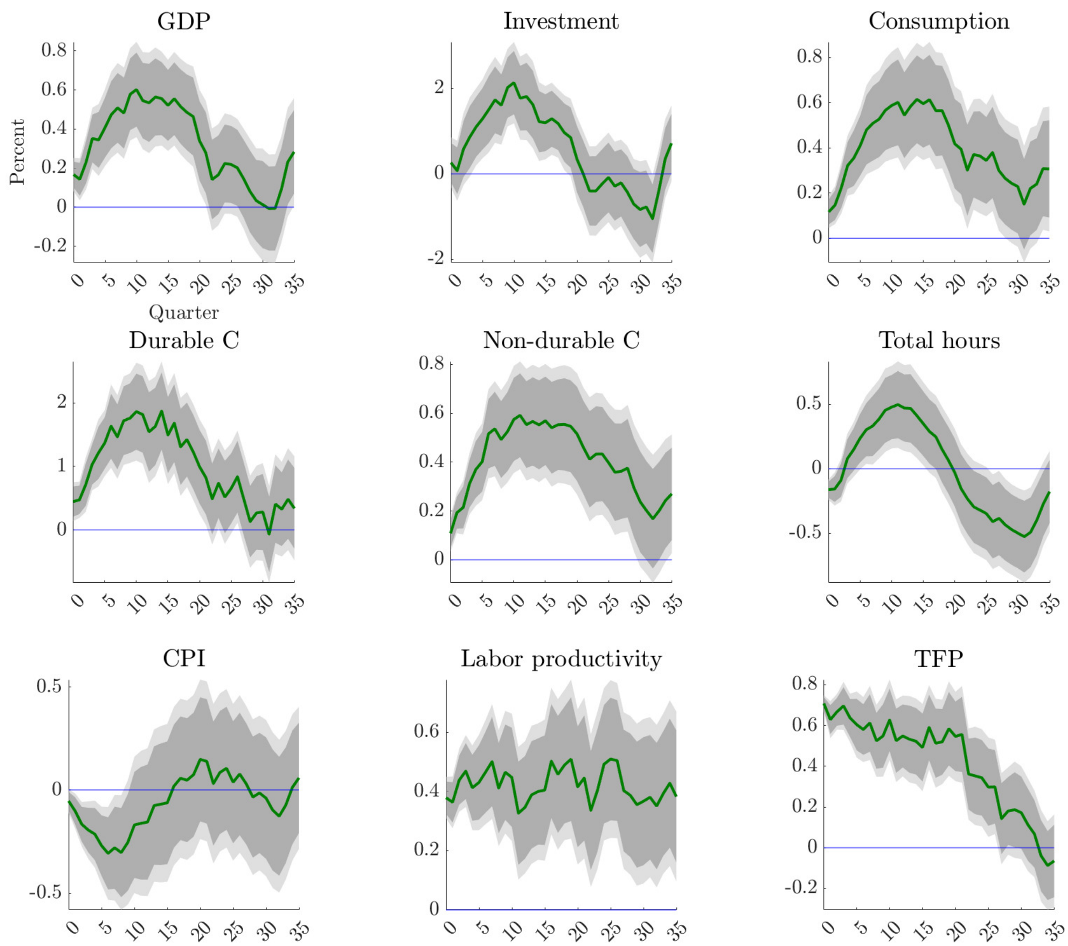


**Figure 5:** Responses of macro-variables to a technology shock

*Note*: Impulse responses of macro-variables to a one-standard deviation technology shock. Sample period: 1970Q3–2020Q1. Green lines indicate the point estimate and the shaded areas indicate 80% and 90% confidence bands calculated with Eicker-Huber-White heteroscedasticity-robust standard errors. Horizontal axes measure quarters and vertical axes measure percent deviation from pre-shock trend. All the variables (with the exception of TFP) are log-transformed and are downloaded (in April 2022) from the quarterly dataset by McCracken and Ng (2020). TFP is from Fernald (2014).

(2), that is:

$$\Delta \log(TFP_t) = \sum_{m=1}^{M} \alpha_m \Delta \log(TFP_{t-m}) + \sum_{q=1}^{Q} \beta_q \mathbf{PC}_{t-q} + \varepsilon_t \tag{5}$$

where $\varepsilon_t$ takes the interpretation of a technology shock. The number of lags $M$ and $Q$ is equal to four. Next, we estimate the business cycle responses by detrending the macroeconomic variables using a High-Pass filter that excludes periodicities over 200 quarters. The responses are estimated following Equation (4). Figure 5 reports the impulse responses of several macroeconomic aggregates. A technology shock brings about a significant comovement of all variables examined. The responses are hump shaped, but there is no significant undershooting, unlike the responses to an expectation shock. The response of CPI is negative and significant confirming the supply-side nature of the shock, and the response of labor productivity is positive and significant, unlike in the case of expectation shock where we found labor productivity to be countercyclical.

Overall, results on technology shocks are not surprising. In fact, there is ample evidence on the effects of technology shocks consistent to what we find (see for example Gali, 1999 and Basu et al., 2006). However, they highlight important differences in the nature and propagation dynamics between non-fundamental and fundamental shocks.

**Discussion** There are two important implications of our findings. First, business cycles should be predictable, at least in part. Second, recessions are more likely to occur after an expansion that has a dominant non-fundamental source. Beaudry et al. (2020) documents the predictability of boom-bust cycles. Specifically, the authors show that the spectral densities of U.S. macroeconomic indicators display a peak at business cycle frequencies.[16] They then show that standard models of business cycles cannot reproduce the spectral density peak. Our results complement the findings of Beaudry et al. (2020) in that we shed light on the source of boom-bust cycles. Building on their work, it is possible to

[16] The spectral density is a useful diagnostic tool of boom-bust dynamics because it decomposes the autocovariance function at different frequencies. A spectral density peak occurring at a given frequency means that the economy oscillates according to a predictable cycle with a length equal to the frequency of the peak.

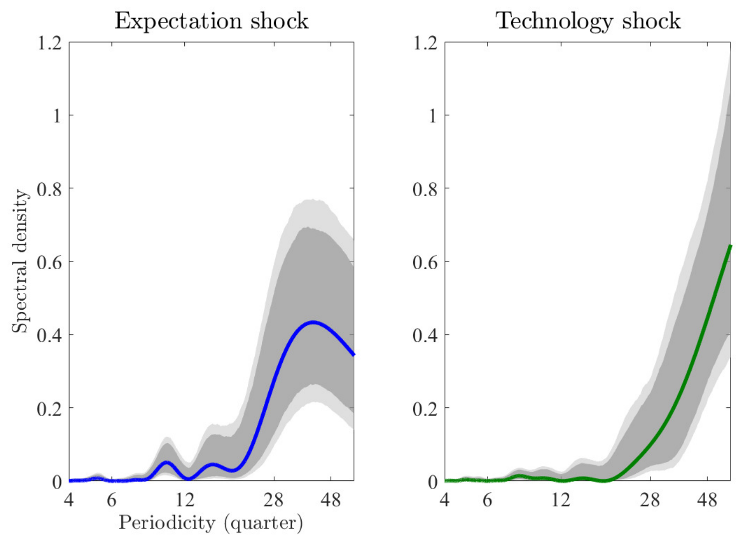


**Figure 6:** Spectral density of GDP conditional to expectation and technology shocks

*Note*: Spectral density of real GDP conditional to expectation shocks (left panel) and technology shocks (right panel). Sample period: 1970Q3-2020Q1. Blue line indicates the point estimate for expectation shocks, green line the point estimate for technology shocks, and the shaded areas indicate 80% and 90% confidence bands calculated using block-bootstrap (see Appendix J.1 for details). Horizontal axes measure periodicities 4 to 60 quarters.

separately compute the spectral densities implied by expectation and technology shocks. Let the estimated structural moving average of variable $y_t$ conditional to a shock $\hat{\varepsilon}_t$ be

$$\hat{y}_{t|\epsilon} = \sum_{h=0}^{H} \hat{\theta}_h \hat{\varepsilon}_{t-h}$$

where $H$ is a truncation horizon that we set equal to 36 quarters.[17] Then, the estimated conditional spectral density of $y$ at frequency $\omega$ implied by the shock $\hat{\varepsilon}$ is

$$\hat{s}_k(\omega) = \frac{\hat{\sigma}_\varepsilon^2}{2\pi} \left[ \sum_{h=0}^{H} \hat{\theta}^{(h)} e^{ih\omega} \right] \left[ \sum_{h=0}^{H} \hat{\theta}^{(h)} e^{-ih\omega} \right].$$

Figure 6 plots the spectral densities of real GDP implied by expectation and technology shocks. The $x$-axis is the periodicity, defined as the inverse of the frequency $\omega$. The spectral density of GDP conditional on expectation shocks exhibits a peak at a periodicity of

[17] In Appendix J.1 we show that our conclusions do not rely on the truncation horizon.

about 40 quarters, consistent to what Beaudry et al. (2020) finds in the reduced form data. The spectral density conditional on technology shocks, in contrast, is monotonically increasing in the periodicity. A similar contrasting pattern appears when we consider other macroeconomic indicators (see Figure 16 in Appendix J.2).

Taken together, our findings provide new discipline for models of business cycles. As in Beaudry et al. (2020), our results favour models that embed a strong endogenous mechanism that is able to reproduce predictable boom-bust dynamics. However, such mechanism should be shock dependent: boom-bust cycles should stem from expectation shocks and not from technology shocks. In the remaining part of the paper, we write a model with one such mechanism.

## 2 A model of conditional cycles

What is causing the boom-bust dynamics displayed in Figure 1? Given our estimation strategy, these can result from either shocks to fundamentals that we do not control for or pure non-fundamental expectation shocks, i.e., sentiments. We argue that the latter is the more plausible explanation for two reasons. First, there is no evidence to support the idea that boom-bust dynamics are driven by fundamental shocks.[18] In fact, Figure 2 shows that when we additionally control for a number of fundamental shocks, the boom-bust dynamics are even more accurately estimated. Second, this section presents evidence that suggests that boom-bust dynamics can emerge in response to sentiments but not technology. We illustrate this in a simple and parsimonious real business cycle model with full information rational expectations.

The model embeds both fundamental and non-fundamental disturbances. We draw on a class of models with self-fulfilling (rational) expectations, where business cycle fluctuations are driven by sunspot shocks, i.e., surprise changes in expectations. In this setting, we model sentiment shocks as the part of sunspots that is independent of fundamentals.

[18] With the exception of the response to Romer and Romer shocks as shown by McKay and Wieland (2021).

The workhorse model in this class is the real business cycle model by Benhabib and Farmer (1994), where equilibrium indeterminacy arises from a positive production externality resulting in aggregate increasing returns to scale.[19] However, due to the production externality, these models predict procyclical labor productivity in response to both sunspot and technology shocks. Contrary to this prediction, Figures 4 and 5 show that labor productivity falls in response to a positive expectation shock, while it rises after an improvement in technology. To reconcile this evidence, we depart from the model of Benhabib and Farmer (1994) and propose a different foundation of equilibrium indeterminacy.

### 2.1 Firms sector

There is a continuum $i \in [0,1]$ of firms with 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 technology common to all firms, $n_t$ is the labor input, and $k_t$ is the capital input which we assume to be constant and equal to one for simplicity. The revenue function then reduces to $y_t \equiv F(z_t, 1, n_t)$. We assume that firms issue noncontingent bonds $b_{t+1}$ at a price $b_{t+1}/r_t$ that can be purchased by the households. In addition, they receive a tax advantage such that given the interest rate $r_t$, the effective gross interest rate paid by the firm is $R_t = 1 + r_t(1-\tau)$ where $\tau$ is the tax benefit. Thus, for $\tau > 0$, firms are effectively more impatient than households so that if financial markets are not too tight, the stock of debt will be positive in equilibrium. Besides the intertemporal debt, firms raise funds with an intraperiod loan $\ell_t$ 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 $\ell_t$ is paid at the end of the period with no interest.[20]

[19] Other examples of models with equilibrium indeterminacy can be found in Wen (1998) and Benhabib and Wen (2004).

[20] 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.

The timing of the events is as follows. Firms enter the period with outstanding debt equal to $b_t$. They first observe the realizations of shocks, and then choose labor expenses $w_t n_t$, the new intertemporal debt $b_{t+1}$, and the amount of dividends $d_t$ to distribute. Since payments are made before the realization of revenues, the intraperiod loan is

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

The term $\chi(d_t) = d_t + \kappa(d_t - d)^2$, where $d$ is the steady state value of dividends and $\kappa \geq 0$, introduces distribution cost of dividends and captures documented evidence of preferences for dividend smoothing (Lintner, 1956). The end of period firms' budget constraint is

$$b_{t+1}/R_t + y_t = w_t n_t + \chi(d_t) + b_t. \tag{6}$$

From the budget constraint and the expression for the intraperiod loan above, it follows that firm revenues are equal to the intraperiod loan, that is $\ell_t = y_t$.

**Incentive compatible constraint** When revenues realize, firms decide whether or not to repay the intraperiod loan they owe to households. 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 $y_t$. However, a defaulting firm can be caught with probability $\gamma$, in which case its assets will be liquidated, and will cease to operate. If a firm is not caught, instead, it will continue to retain access to credit in future periods.[21] Thus, a firm defaults if the expected value of defaulting is greater than the expected value of non defaulting, that is,

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

[21] Assuming that in the case of being caught a firm would also lose its revenues does not quantitatively alter our results.

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

Since shocks realize at the beginning of period, there is no intraperiod uncertainty, so that households can lend an amount that deters default in equilibrium. Using the expression above, the incentive compatible constraint is

$$\gamma E_t[m_{t,t+1}V_{t+1}] \geq y_t. \tag{7}$$

This constraint effectively limits both types of firm's debt. The left-hand side is equal to $\gamma$ times the firm market value, and decreases with the amount of intertemporal debt $b_{t+1}$. Whereas the right-hand side is equal to the end-of-period revenues $y_t$, which are equal to the firm's intraperiod loan $\ell_t$.

**Firm's optimization problem** The problem of the individual firm can be written recursively as

$$V_t = \max_{d_t, n_t, b_{t+1}} \left\{ d_t + E_t \left[ m_{t,t+1} V_{t+1} \right] \right\} \tag{8}$$

*subject to (6) and (7).*

Firm's first order conditions are

$$(1 + \mu_t \gamma) E_t \left[ m_{t,t+1} \frac{\chi'(d_t)}{\chi'(d_{t+1})} \right] = \frac{1}{R_t} \tag{9}$$

$$\frac{w_t}{1 - \mu_t \chi'(d_t)} = (1 - \theta) \frac{y_t}{n_t} \tag{10}$$

where $\mu_t$ is the Lagrange multiplier associated to the incentive constraint. Equation (9) is the first order condition for new intertemporal debt $b_{t+1}$. The term in squared brackets is the firm's effective discount factor, that is the product between the household's discount factor and the expected decrease in the cost of adjusting dividends. Equation (10) is the first order condition for labor input. It shows that financial frictions introduce a time varying labor wedge that depends positively on $\mu_t$. Conditions (9) and (10) highlight the key propagation mechanism of the model. During a boom, equity prices are elevated and the stochastic discount factor is high, thus $\mu_t$ decreases according to Equation (9). A decrease in $\mu_t$, in turn, shifts the labor demand outward as firms can finance more labor.

## 2.2 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' utility function is

$$U(c_t, n_t) = \frac{c_t^{1-\sigma} - 1}{1-\sigma} - \alpha \frac{n_t^{1+\phi}}{1+\phi}$$

where the parameters $\sigma$ and $\phi$ are both strictly greater than zero. The household's budget constraint is

$$c_t + s_{t+1} p_t + \frac{b_{t+1}}{1+r_t} = w_t n_t + b_t + s_t(d_t + p_t) - T_t \tag{11}$$

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 $T_t = B_{t+1}/[1+r_t(1-\tau)] - B_{t+1}/(1+r_t)$, where $B_{t+1}$ is the aggregate stock of firms bonds.

**Household's optimization problem** The household problem is standard. The household maximizes its utility function subject to the budget constraint in Equation (11). The first order conditions with respect to $n_t$, $b_{t+1}$, and $s_t$ are

$$w_t = \alpha c_t^{\sigma} n_t^{\phi} \tag{12}$$

$$c_t^{-\sigma} = \beta(1+r_t) E_t[c_{t+1}^{-\sigma}] \tag{13}$$

$$p_t = \beta E_t \left\{ \left( \frac{c_{t+1}}{c_t} \right)^{-\sigma} (d_{t+1} + p_{t+1}) \right\}. \tag{14}$$

The first two conditions determine the labor supply and the interest rate. The last condition pins down the price of shares.[22] Firm's problem is consistent with households' optimization. Thus, the stochastic discount factor is $m_{t,t+1} = \beta(c_t/c_{t+1})^{\sigma}$.

**General equilibrium** *Given the aggregate states* $\boldsymbol{s}$*, that are technology* $z$ *and aggregate bonds* $B$*, a recursive competitive equilibrium is defined as a set of functions for (i) households' policies* $c^h(\boldsymbol{s},b)$*,* $n^h(\boldsymbol{s},b)$ *and* $b^h(\boldsymbol{s},b)$*; (ii) firms' policies* $d(\boldsymbol{s},b)$*,* $n(\boldsymbol{s},b)$*, and* $b(\boldsymbol{s},b)$*; (iii) firms' value* $V(\boldsymbol{s},b)$*; (iv) aggregate prices* $w(\boldsymbol{s})$*,* $r(\boldsymbol{s})$*, and* $m(\boldsymbol{s}',\boldsymbol{s})$*; (v) law of motion for the aggregate states* $\boldsymbol{s}' = \psi(\boldsymbol{s})$*. Such that: (i) household's policies satisfy Conditions (12) and (13); (ii) firm's policies are optimal and* $V(\boldsymbol{s},b)$ *satisfies the Bellman's Equation (8); (iii) the wage and the interest rate clear the labor and bond markets; (iv) the law of motion* $\psi(\boldsymbol{s})$ *is consistent with individual decisions and stochastic processes for technology.*

### 2.3 Inspecting the mechanism

We now turn to the explanation of the model and derive several propositions. To simplify the analysis, we assume that there are no dividend adjustment costs, i.e., $\kappa = 0$, and work with the loglinearized equilibrium equations around the steady state. The steady state is derived in Appendix F.1, which also shows that it is unique. Additionally, Appendix F.2 presents the loglinearized system of equations.

**Amplification and indeterminacy** Let's consider the loglinearized labor market clearing condition that equates the labor supply to the labor demand

$$\phi \hat{n}_t + \sigma \hat{c}_t = \hat{z}_t - \theta \hat{n}_t - \frac{\mu}{1-\mu}\hat{\mu}_t \tag{15}$$

where hats denote variables expressed as loglinear deviations from the steady state, and $\mu = \frac{\tau(1-\beta)}{\gamma(1-\tau+\tau\beta)}$ is the steady state value of the Lagrange multiplier $\mu_t$. Note that when the tax benefit parameter $\tau$ is equal to zero, $\mu$ is also equal to zero, so that the financial constraint

[22] We normalize the quantity of shares to be equal to 1 in equilibrium.

is slack, the last term on the right-hand side of Equation (15) vanishes, and the model reduces to the standard RBC model. When $\tau$ is positive, instead, $\mu$ is also positive, and the financial constraint binds in the steady state. In this case, time variations in $\hat{\mu}_t$ shift the labor demand, potentially leading to self-fulfilling changes in autonomous consumption.

To see this, we combine the loglinearized version of Equations (9) and (13), and rearrange them to obtain

$$\hat{\mu}_t = -(1+\mu\gamma)\frac{\beta\sigma}{1-\beta}[\hat{c}_t - E_t(\hat{c}_{t+1})]. \tag{16}$$

Equations (15) and (16) capture the key amplification channel due to financial frictions. Specifically, Equation (16) shows that $\hat{\mu}_t$ falls when current consumption is relatively high. In turn, a decrease in $\hat{\mu}_t$ increases labor demand in Equation (15), leading to higher consumption and further reducing $\hat{\mu}_t$. This dynamic arises because, during temporary economic booms, households tend to increase their desire to save, which relaxes the financial constraint and leads to a higher supply of credit. By borrowing more, firms increase their labor demand, output, and households' labor income.

Combine Equations (15) and (16) to obtain

$$\phi\hat{n}_t + \sigma\hat{c}_t = \hat{z}_t - \theta\hat{n}_t + \underbrace{\frac{\mu(1+\mu\gamma)}{1-\mu}\frac{\beta\sigma}{1-\beta}}_{\equiv\zeta}[\hat{c}_t - E_t(\hat{c}_{t+1})]. \tag{17}$$

The term $\zeta$ is the elasticity of labor demand to the inverse of expected consumption growth, and captures the strength of the amplification channel induced by financial frictions. In fact, $\zeta$ increases with the tax advantage $\tau$ and decreases with the probability of being caught $\gamma$. Note that when $\zeta$ is zero, Equation (17) becomes static. For large values of $\zeta$, instead, expectations of future consumption matter, and the model can admit local indeterminacy of equilibria. The following proposition formally solves for the emergence of self-fulfilling equilibria.

**Proposition 1** *Let $\kappa = 0$. The model admits local indeterminacy around the steady state if and only if $\zeta > \bar{\zeta}$, where $\bar{\zeta} \equiv \frac{\sigma(1-\theta)+\phi+\theta}{2(1-\theta)}$.*

**Proof.** Rearrange Equation (17) using the production function and the resource constraint, as

$$E_t(\hat{c}_{t+1}) = \underbrace{\frac{\zeta(1-\theta)-\sigma(1-\theta)-\phi-\theta}{\zeta(1-\theta)}}_{\equiv\lambda}\hat{c}_t + \frac{1+\phi}{\zeta(1-\theta)}\hat{z}_t \tag{18}$$

then local indeterminacy obtains if and only if $|\lambda| < 1$. Thus, the following two conditions must be satisfied

*(i)* $\theta + \sigma(1-\theta) + \phi > 0$

*(ii)* $\zeta > \frac{\phi+\sigma(1-\theta)+\theta}{2(1-\theta)}$.

where condition *(i)* is always satisfied since the parameters $\theta$, $\sigma$, and $\phi$ are all positive by assumption. ■

The proposition above states that when financial frictions are severe, so that $\zeta$ is large, changes in relative consumption are self-fulfilling. Condition *(ii)* is instructive. Consider a one percent increase in consumption, keeping technology at steady state. Using the fact that $\hat{c}_t = \hat{y}_t = (1-\theta)\hat{n}_t$, the effective labor supply increases by $\frac{\phi}{1-\theta} + \sigma$. The labor demand, instead, decreases by $\frac{\theta}{1-\theta}$ as in the standard RBC, while it increases by $\zeta(1-E_t(\hat{c}_{t+1}))$ due to the amplification from financial frictions. Thus, an equilibrium exists if $\frac{\phi}{1-\theta} + \sigma = \zeta(1-E_t(\hat{c}_{t+1})) - \frac{\theta}{1-\theta}$. However, future consumption cannot fall more than one percent otherwise the dynamics will be explosive. It follows that $2\zeta - \frac{\theta}{1-\theta} > \zeta(1-E_t(\hat{c}_{t+1})) - \frac{\theta}{1-\theta} = \frac{\phi}{1-\theta} + \sigma$ which results in condition *(ii)* after solving for $\zeta$.

**Indeterminacy and boom-bust dynamics** We now turn to the discussion about boom-bust dynamics. Equation (18) above indicates that the model admits a simple univariate autoregressive representation. This occurs because we assumed no dividend adjustment costs, so that the amount of outstanding debt can be absorbed by firm's equity issuance without affecting real outcomes in equilibrium. The proposition below provides conditions for the emergence of boom-bust dynamics in this simple case. The same intuition applies in the presence of dividend adjustment costs. We operationalize the notion of boom-bust dynamics as a negative autocorrelation function of consumption (and output).

**Proposition 2** *Let $\kappa = 0$ and $\hat{z}_t = 0$. The model features negative consumption (and output) autocorrelation if and only if $-1 < \lambda < 0$, that is, iff*

$$\frac{\sigma(1-\theta)+\phi+\theta}{2(1-\theta)} < \zeta < \frac{\sigma(1-\theta)+\phi+\theta}{1-\theta}.$$

**Proof.** The autocorrelation function of consumption is $\Gamma(h) = \lambda^h$, with $h = 0, 1, ..$, if the model features indeterminacy of equilibria, otherwise $\Gamma(h) = 0$, $\forall\ h$. Then $\Gamma(h)$ is negative at some horizons if and only if $-1 < \lambda < 0$. ■

In words, in order to obtain boom-bust dynamics, Proposition 2 states that the degree of financial frictions should be strong enough to obtain indeterminacy of equilibria – so that consumption is a persistent process – but not too large. The reason why $\zeta$ is bounded from above can be seen again from the labor clearing in Equation (15). For sufficiently *small* values of $\zeta$, an increase in current consumption is an equilibrium only if future consumption falls.

**Conditional boom-bust dynamics** Under indeterminacy, the forecast error of consumption can arise from either pure sunspot shocks, also known as sentiments, or technology shocks. As a result, the model solution becomes

$$\hat{c}_{t+1} = \lambda \hat{c}_t + \frac{1+\phi}{\zeta(1-\theta)} \hat{z}_t + \epsilon^s_{t+1} + \psi \epsilon^z_{t+1} \tag{19}$$

where $\epsilon^s$ is a sentiment shock, and $\epsilon^z$ is a technology shock. The parameter $\psi$ governs the impact response of consumption to a technology shock which we assume to be positive.

Equation (19) reveals that under indeterminacy of equilibria, not only consumption depends upon its past value – effectively introducing an additional state variable to the system – but also from the past value of technology $z_t$. Importantly, since the loading of current consumption on past technology is positive, the autocorrelation of consumption conditional on technology shocks can be positive even if counsumption is negatively autocorrelated in response to sentiments. This is the key finding of the model.

The intuition behind this result is that during an expansion, equity prices rise and the financial constraint relaxes, leading to an improvement in economic activity. However, the nature of the equity price increase matters greatly for the dynamics that follow. During sentiment-driven expansions, equity prices rise due to higher current consumption relative to future consumption, which raises households' stochastic discount factor. In contrast, technology improvements lead to higher equity prices because of higher firm profitability.

As the expansion progresses, households decide how much firm assets to sell based on the nature of the expansion. If the expansion is sentiment-driven, households sell off firm assets in anticipation of a future slowdown in economic activity, resulting in a recession due to their failure to internalize the adverse effects of their asset sales on the financial constraint. If the expansion is technology-driven, however, households recognize that equity prices are elevated due to higher profitability and not just optimism, and do not reduce credit to firms, preventing a recession. The proposition below provides the parameter conditions for the emergence of conditional boom-bust dynamics.

**Proposition 3** *Let $\kappa = 0$, $z_t \sim i.i.d.$, and $-1 < \lambda < 0$. The autocorrelation of consumption is negative conditional on sentiment shocks, and positive conditional on technology shocks if and only if $-\lambda < \psi \frac{\zeta(1-\theta)}{1+\phi} < -\frac{1}{\lambda}$.*

**Proof.** The proof is relegated to the Appendix F.3. ■

### 2.4 Parametrization and impulse responses

Let the dividend adjustment cost $\kappa$ be positive, the sentiment shock be i.i.d., and technology follow an autoregressive process with persistence parameter $\rho_z > 0$. We first describe the parametrization, and then show the theoretical impulse responses to technology and sentiment shocks.

**Parametrization** We calibrate the model to a quarterly frequency. We set $\beta$ to match a 3% annual interest yield on bonds. The utility parameter $\alpha$ is such that the steady state value of hours worked equal to .3. As in Jermann and Quadrini (2012), the tax shield $\tau$ and capital's share of income $\theta$ are equal to .35 and .36, respectively. We set the inverse of households' intertemporal elasticity of substitution $\sigma$ to 1.06, a value between the log-utility case and the estimates of 1.4-1.5 obtained by Evans (2005) and Groom et al. (2019). We set $\phi$ equal to 10 which implies a Frisch elasticity equal to 0.1, which is within the range of the microeconometric estimates of MaCurdy (1981) and Altonji (1986). The probability of being caught $\gamma$ is equal to 0.085, and the degree of adjustment cost to dividends $\kappa$ to 20. As per the shock processes, we set $\psi$ equal to .24 in order to match the empirical impact response of output to a technology shock, whereas we set the persistence parameter $\rho_z$ equal to .93 so to match the estimated law of motion of detrended TFP. Finally, the standard deviation ratio between sentiment and technology shocks is equal 0.94 so as to match the forecast error variance of output explained by sentiment shocks relative to the share explained by technology shocks.

**Theoretical impulse responses** Figure 7 shows the theoretical impulse responses to a sentiment shock (solid line) and to a technology shock (dashed line). Following a positive sentiment shock, the economy displays boom-bust dynamics qualitatively in line with what we found in the data. A positive sentiment shock stems from agents' expectations of a boom. Due to the temporary nature of the boom, households increase their demand for firms' assets, easing the financial constraint and leading to an initial fall in $\mu_t$. Consequently, firms borrow more and hire more labor. Since technology doesn't change, the increase in labor input leads to a fall in labor productivity, consistent with the empirical findings portrayed in Figure 4. Unlike in models of noisy signals about future TFP, households are well aware that technology has not changed, and that equity prices will fall.

In fact, boom-bust dynamics result from agents' failure to internalize the effects of their coordinated actions on the financial constraint. As the expectation-led expansion unfolds, households sell firms assets, leading to a tightening of the financial constraint. Since firms are forced to deleverage, production decreases and the economy goes into a recession.

The dynamics to a surprise improvement in technology are very different from those in response to a positive sunspot shock. As in the data, a technology shock generates hump-shaped dynamics in all the main macroeconomic variables. Importantly, both the Lagrange multiplier $\mu_t$ and the intertemporal debt $b_{t+1}$ increase, indicating that despite firms' ability to borrow more, financial frictions dampen the responses to technology shocks. As formally shown in Proposition 3, the technology-driven expansion does not culminate in a recession. This is because the increase in firm value primarily stems from higher profitability, rather than expectations of the future consumption path.

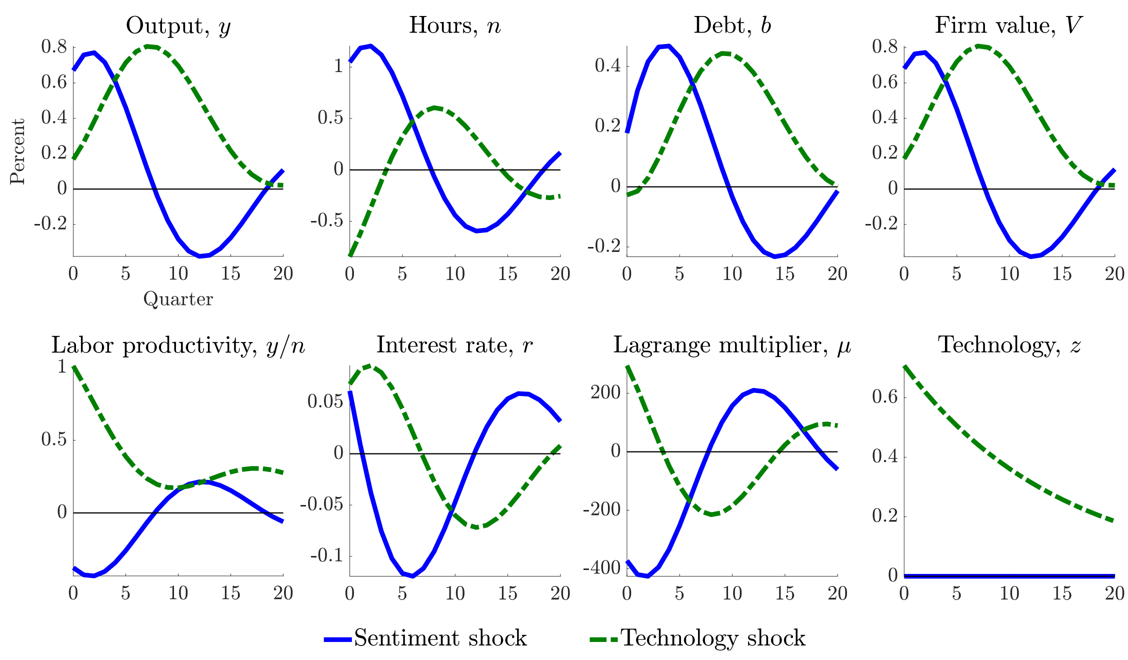


**Figure 7:** Model-implied impulse responses to a sentiment and a technology shock

*Note*: Model-implied impulse responses to a one-standard deviation sentiment shock (solid blue lines) and a one-standard deviation technology shock (dashed green lines). Horizontal axes measure quarters and vertical axes measure percent deviation from the steady state.

**Conditional spectral density** To compare the model performance with the results presented in Section 1.3, Figure 8 shows the model-implied spectral density of output conditional to sunspot and technology shocks. The oscillatory dynamics implied by sunspot shocks are associated with a pronounced peak in the conditional spectral density of output. As in the data counterpart, technology shocks don't generate a spectral density peak.

### 2.5 Sentiments and recession probability

The results presented so far bolster the argument that expansions and recessions should not be studied separately, rather, they are a figment of an endogenous propagation mechanism. Here we broaden the scope of our analysis and look for evidence of recession predictability in the reduced form data. After all, our results suggest that we should be able to detect at least some predictability of recessions, without having to identify the sources of variations. Thus, we take the U.S. quarterly real GDP series used in the foregoing analyses,

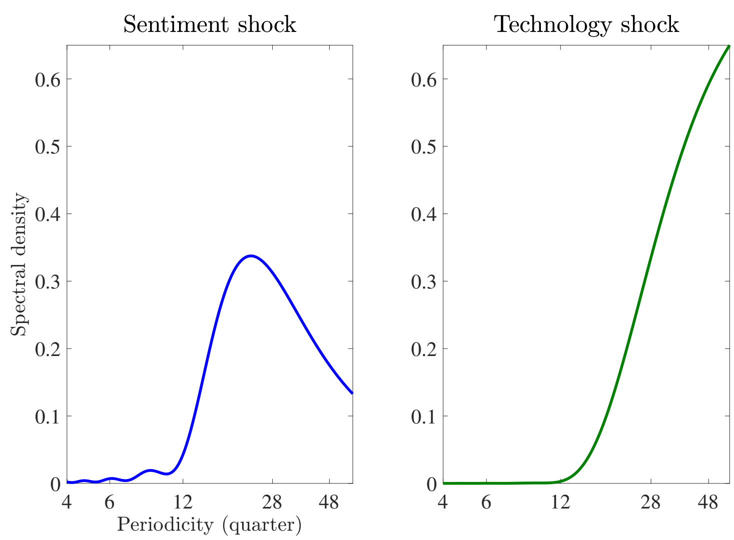


**Figure 8:** Spectral density of output $y$ conditional to sentiment and technology shocks

*Note*: Spectral density of output $y$ conditional to sentiment shocks (left panel) and technology shocks (right panel). To estimate the theoretical spectral density we employ the same procedure described in Section 1.3 using the model-implied impulses responses from Figure 9 (truncation horizon is 20). Horizontal axes measure periodicities from 4 to 60 quarters.

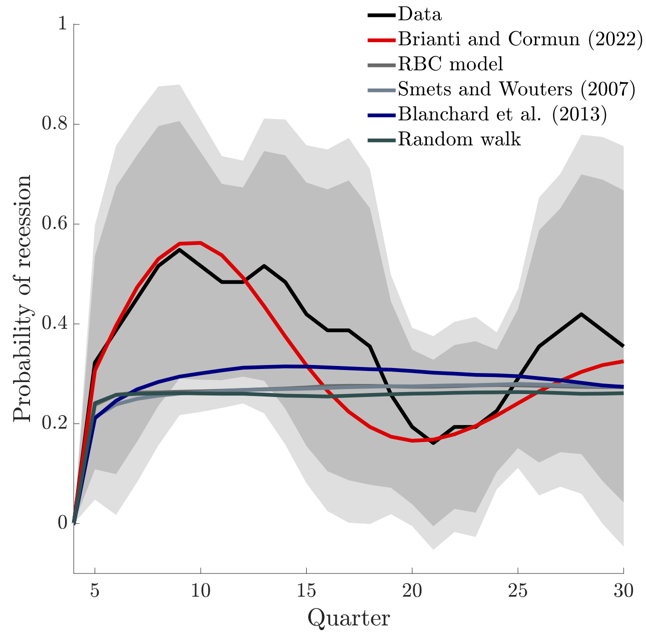


**Figure 9:** Probability of a recession after an expansion

*Note*: Probability of a recession in a two-quarter window after an expansion. Sample period: 1970Q3-2020Q1. The black line indicates the point estimate and the shaded areas indicate 80% and 90% confidence bands calculated with heteroskedasticity and autocorrelation-consistent standard errors (Newey and West, 1987). Horizontal axis measures quarters and vertical axis measures the probability of a recession. Other solid lines are obtained using simulated data from several models.

and estimate the following linear probability model

$$REC_{t+h} = \beta_{0,h} + \beta_{1,h} EXP_t + u_{t+h}$$

where, on the left-hand side, $REC_t$ is a recession indicator that takes value equal to one when the real GDP growth falls into the bottom quintile of its distribution for at least two consecutive quarters, and zero otherwise. Likewise, on the right-hand side, $EXP_t$ is an expansion indicator that equals one when the real GDP growth is above the top quintile for at least two consecutive quarters. The black line in Figure 9 shows the estimated probability that the economy will be in a recession in a two-quarter window around time $t+h$, given an expansion at time $t$. Conditional on an expansion at time $t$, the probability of a recession rises and peaks approximately after two years. Then, it converges to its long run value in an oscillatory fashion.

In addition, Figure 9 shows the prediction using data simulated from three business cycle models: the textbook RBC model, the medium-scale DSGE model of Smets and Wouters (2007), and the incomplete information model with noise shocks of Blanchard et al. (2013). As a benchmark, we plot the results from a simulated random walk process for the real GDP. For each model, we run a Monte Carlo simulation where we set the number of observations equal to the sample size of the real GDP series. The figure plots the mean estimates. The three models predict that recessions are effectively unforecastable. In fact, results are virtually indistinguishable from the predictions of a random walk. The conditional probability of a recession quickly converges to its unconditional mean after an expansion, failing to replicate neither the spike nor the oscillation that we see in the data. The reason is that these models do not feature an endogenous boom-bust propagation mechanism, but recessions originate from negative shocks only. The red line reports the predictions of our model. In contrast to the other models, our model captures both the spike in the conditional probability of a recession and the overall oscillatory dynamics fairly well.

## 3 Conclusion

Much of the business cycle literature focuses on models featuring no connection between expansions and recessions. A smaller literature, instead, proposes models of limit cycles and chaos wherein cycles occur even absent of any perturbation. In this paper, we have uncovered new empirical findings that call for business cycle theories where these two views coexist. In particular, our results suggest that changes in sentiments, defined as changes in expectations unrelated to fundamentals, propagate in a way that is consistent with the predictions of endogenous cycles theories. Technology shocks, on the other hand, bring about economic fluctuations that are in line with the predictions of the dominant business cycle view. We offer one such unifying theory. The main ingredient of our theory is a pecuniary externality stemming from an endogenous financial constraint. We show that, even under rational expectations, this is enough for purely expectation-driven fluctuations to be an independent source of fluctuations, and to shape the economy in a profoundly different way than fundamental-driven fluctuations.

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# A Data Appendix

| Variable | Code | Source | Transformation |
|---|---|---|---|
| TFP | dtfp_util | Fernald (2014) | Cumulated |
| Forecast $x_{t+h-2\|t}$ | RGDP$h$, $h = 1,2,\ldots,6$ | Croushore (1993) | Mean estimate |
| GDP | GDPC1 | McCracken and Ng (2020) | Logarithmic |
| Investment | GPDIC1 | McCracken and Ng (2020) | Logarithmic |
| Consumption | PCECC96 | McCracken and Ng (2020) | Logarithmic |
| Durable C | PCDGx | McCracken and Ng (2020) | Logarithmic |
| Non-durable C | PCNDx | McCracken and Ng (2020) | Logarithmic |
| Total hours | HOANBS | McCracken and Ng (2020) | Logarithmic |
| CPI | CPIAUCSL | McCracken and Ng (2020) | Logarithmic |
| Labor productivity | OPHNFB | McCracken and Ng (2020) | Logarithmic |
| Nasdaq Composite | NASDAQCOM | McCracken and Ng (2020) | Logarithmic |
| S&P 500 | SP500 | McCracken and Ng (2020) | Logarithmic |
| Industrial loans | BUSLOANSx | McCracken and Ng (2020) | Logarithmic |

**Table 2:** Details on aggregate US data

# B Expectation shock series

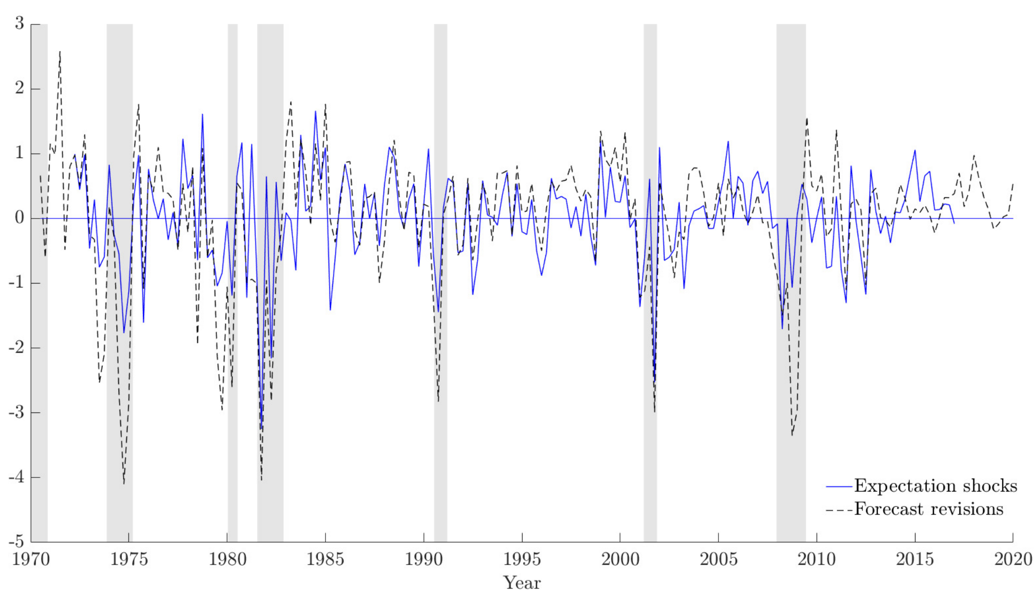


**Figure 10:** Expectation shocks and forecast revisions

*Note*: Time series of expectation shocks $\hat{v}_t$ (solid blue line) and forecast revisions $S_t$ (dashed black line).

# C Regressions table

| Model | Equation (1) | | Equation (2) | | Equation (5) | |
|---|---|---|---|---|---|---|
| Dep. variable | $S_t$ | | $\text{TFP}_{t+3} - TFP_{t-1}$ | | $\Delta TFP_t$ | |
| | Constant | 1.0851 | Constant | 0.0062 | Constant | 0.0022 |
| | | (0.2276) | | (0.0011) | | (0.0007) |
| | $\Delta TFP_{t+12}$ | 2.6703 | $\Delta TFP_t$ | 1.0074 | $\Delta TFP_{t-1}$ | -0.1638 |
| | | (8.7574) | | (0.1281) | | (0.0771) |
| | $\Delta TFP_{t+11}$ | 25.9644 | $\text{PC}_{1,t}$ | 0.0027 | $\text{PC}_{1,t-1}$ | 0.0060 |
| | | (8.4582) | | (0.0045) | | (0.0027) |
| | $\Delta TFP_{t+10}$ | 4.5776 | $\text{PC}_{2,t}$ | 0.0125 | $\text{PC}_{2,t-1}$ | 0.0035 |
| | | (8.6576) | | (0.0069) | | (0.0041) |
| | $\Delta TFP_{t+9}$ | 13.6385 | $\text{PC}_{3,t}$ | -0.0019 | $\text{PC}_{3,t-1}$ | 0.0053 |
| | | (8.3278) | | (0.0053) | | (0.0032) |
| | $\Delta TFP_{t+8}$ | 6.0410 | $\text{PC}_{4,t}$ | -0.0001 | $\text{PC}_{4,t-1}$ | -0.0082 |
| | | (8.4339) | | (0.0087) | | (0.0052) |
| | $\Delta TFP_{t+7}$ | -6.8380 | $\Delta TFP_{t-1}$ | 0.1202 | $\Delta TFP_{t-2}$ | 0.0637 |
| | | (8.2177) | | (0.1293) | | (0.0779) |
| | $\Delta TFP_{t+6}$ | -3.9403 | $\text{PC}_{1,t-1}$ | -0.0057 | $\text{PC}_{1,t-2}$ | -0.0047 |
| | | (8.2170) | | (0.0059) | | (0.0036) |
| | $\Delta TFP_{t+5}$ | 2.2566 | $\text{PC}_{2,t-1}$ | 0.0054 | $\text{PC}_{2,t-2}$ | 0.0092 |
| | | (8.1869) | | (0.0079) | | (0.0048) |
| | $\Delta TFP_{t+4}$ | 30.7886 | $\text{PC}_{3,t-1}$ | -0.0011 | $\text{PC}_{3,t-2}$ | -0.0012 |
| | | (8.2071) | | (0.0062) | | (0.0038) |
| | $\Delta TFP_{t+3}$ | 7.8477 | $\text{PC}_{4,t-1}$ | 0.0135 | $\text{PC}_{4,t-2}$ | 0.0030 |
| | | (8.5582) | | (0.0087) | | (0.0053) |
| | $\Delta TFP_{t+2}$ | -4.0209 | $\Delta TFP_{t-2}$ | -0.0213 | $\Delta TFP_{t-3}$ | 0.0625 |
| | | (8.4117) | | (0.1271) | | (0.0764) |
| | $\Delta TFP_{t+1}$ | -13.3822 | $\text{PC}_{1,t-2}$ | 0.0072 | $\text{PC}_{1,t-3}$ | 0.0058 |
| | | (8.4549) | | (0.0060) | | (0.0036) |
| | $\Delta TFP_t$ | 94.2108 | $\text{PC}_{2,t-2}$ | -0.0003 | $\text{PC}_{2,t-3}$ | -0.0009 |
| | | (17.9040) | | (0.0078) | | (0.0046) |
| | $\Delta TFP_{t-1}$ | 52.2800 | $\text{PC}_{3,t-2}$ | -0.0007 | $\text{PC}_{3,t-3}$ | -0.0064 |
| | | (19.4755) | | (0.0062) | | (0.0037) |
| | $\Delta TFP_{t-2}$ | 45.4575 | $\text{PC}_{4,t-2}$ | 0.0028 | $\text{PC}_{4,t-3}$ | 0.0068 |
| | | (19.0424) | | (0.0087) | | (0.0052) |
| | $\Delta TFP_{t-3}$ | 17.8812 | $\Delta TFP_{t-3}$ | -0.0627 | $\Delta TFP_{t-4}$ | -0.0237 |
| | | (18.1003) | | (0.1239) | | (0.0744) |
| | $\Delta TFP_{t-4}$ | 41.6766 | $\text{PC}_{1,t-3}$ | 0.0039 | $\text{PC}_{1,t-4}$ | -0.0008 |
| | | (17.6503) | | (0.0053) | | (0.0032) |
| | $b_t$ | -76.3258 | $\text{PC}_{2,t-3}$ | -0.0010 | $\text{PC}_{2,t-4}$ | -0.0021 |
| | | (17.0869) | | (0.0057) | | (0.0034) |
| | $b_{t-1}$ | -36.3364 | $\text{PC}_{3,t-3}$ | 0.0095 | $\text{PC}_{3,t-4}$ | 0.0073 |
| | | (18.5829) | | (0.0057) | | (0.0034) |
| | $b_{t-2}$ | -40.9222 | $\text{PC}_{4,t-3}$ | -0.0147 | $\text{PC}_{4,t-4}$ | 0.0013 |
| | | (18.4549) | | (0.0079) | | (0.0047) |
| | $b_{t-3}$ | -20.5774 | | | | |
| | | (17.9761) | | | | |
| | $b_{t-4}$ | -41.9186 | | | | |
| | | (17.3232) | | | | |
| | $\text{S}_{t-1}$ | 0.3118 | | | | |
| | | (0.0733) | | | | |
| $R$-squared | | 0.4881 | | 0.3346 | | 0.1690 |
| $F$-test | | 0.0000 | | 0.0000 | | 0.0273 |
| N observations | | 180 | | 193 | | 195 |

**Table 3:** Estimates of Equation (1), Equation (2), and Equation (5)

*Notes:* Standard errors in parenthesis. TFP is log transformed.

# D Responses of financial variables to an expectation shock

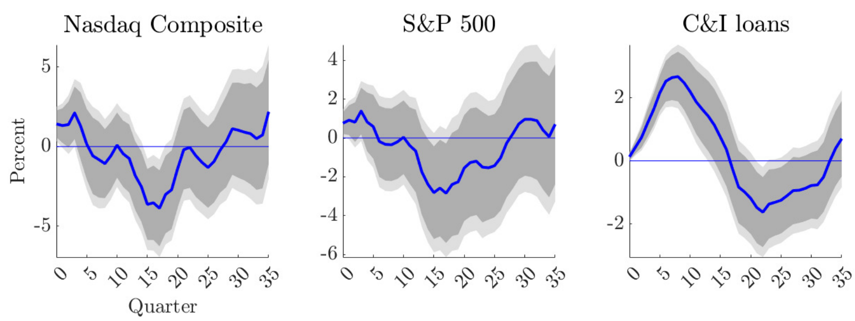


**Figure 11:** Responses of financial variables to an expectation shock

*Note*: Impulse responses of Nasdaq Composite, S&P 500, and of commercial and industrial loans to a one-standard deviation expectation shock. Sample period: 1970Q3–2020Q1. Blue lines indicate the point estimate and the shaded areas indicate 80% and 90% confidence bands calculated with Eicker-Huber-White heteroscedasticity-robust standard errors. Horizontal axes measure quarters and vertical axes measure percent deviation from pre-shock trend. All the variables are downloaded (in April 2022) from the quarterly dataset by McCracken and Ng (2020), deflated using PCE, and log-transformed.

# E Variance decomposition after controlling for several fundmental shocks

| | 4 quarters | 8 quarters | 20 quarters |
|---|---|---|---|
| Real GDP | 28.2 | 30.3 | 37.7 |
| | (22.1,34.4) | (25.0,35.5) | (10.1,65.3) |
| Forecast revision | 33.8 | 31.6 | 38.0 |
| | (26.4,41.1) | (23.3,40.0) | (26.0,50.0) |
| Investment | 21.4 | 26.7 | 45.5 |
| | (17.3,25.5) | (18.3,35.1) | (8.8,82.2) |
| Consumption | 16.5 | 7.7 | 36.3 |
| | (10.5,22.5) | (5.0,10.3) | (14.7,57.9) |
| Durable C | 7.2 | 5.3 | 43.6 |
| | (5.2,9.1) | (-0.4,11.1) | (20.6,66.6) |
| Non-durable C | 4.5 | 4.6 | 38.2 |
| | (2.5,6.5) | (-0.4,9.7) | (7.3,69.2) |
| Total hours | 22.8 | 23.2 | 24.3 |
| | (19.3,26.3) | (18.3,28.1) | (-0.6,49.2) |
| CPI | 8.9 | 23.4 | 41.0 |
| | (5.6,12.3) | (15.2,31.6) | (29.6,52.4) |
| Labor productivity | 0.8 | 5.1 | 11.4 |
| | (-1.1,2.8) | (2.9,7.3) | (-0.5,23.3) |
| TFP | 0.2 | 0.4 | 1.7 |
| | (-0.7,1.1) | (-1.0,1.8) | (-9.7,13.1) |

**Table 4:** Forecast error variance explained by expectation shocks

*Notes:* Forecast error variance explained by expectation shocks after controlling for the Romer and Romer (2004) monetary policy shocks series extended by Wieland (2021), military spending series of Ramey (2011), unanticipated and anticipated tax shocks by Mertens and Ravn (2012), and the oil price shocks estimated in Kilian (2008), and the financial uncertainty series of Ludvigson et al. (2021). Numbers in parentheses are one standard deviation confidence intervals.

# F Model Appendix

## F.1 Steady state values

$$r = \beta^{-1} - 1 \tag{20}$$

$$R = 1 + r(1-\tau) \tag{21}$$

$$m = \beta \tag{22}$$

$$z = 1 \tag{23}$$

$$\mu = \frac{1}{\gamma}\left[\frac{1}{\beta R} - 1\right] \tag{24}$$

$$n = \left[\frac{1}{\alpha}(1-\mu)(1-\theta)\right]^{\frac{1}{\sigma(1-\theta)+\phi+\theta}} \tag{25}$$

$$w = \alpha n^{\sigma(1-\theta)+\phi} \tag{26}$$

$$y = z n^{1-\theta} \tag{27}$$

$$c = y \tag{28}$$

$$V = \frac{1}{\gamma\beta} y \tag{29}$$

$$d = (1-\beta)V \tag{30}$$

$$b = \left(1 - \frac{1}{R}\right)^{-1} (y - wn - d) \tag{31}$$

## F.2 Loglinearized equations

$$E_t\left[\hat{m}_{t,t+1} + \hat{V}_{t+1}\right] = \hat{y}_t \tag{32}$$

$$\hat{V}_t = \frac{d}{V}\hat{d}_t + \beta E_t\left[\hat{m}_{t,t+1} + \hat{V}_{t+1}\right] \tag{33}$$

$$\frac{\mu\gamma}{1+\mu\gamma}\hat{\mu}_t + \hat{R}_t + E_t(\hat{m}_{t,t+1}) + 2\kappa d(\hat{d}_t - \hat{d}_{t+1}) = 0 \tag{34}$$

$$\hat{w}_t = \hat{z}_t - \theta\hat{n}_t - \frac{\mu}{1-\mu}\left(\hat{\mu}_t + 2\kappa d\hat{d}_t\right) \tag{35}$$

$$\hat{y}_t = \hat{c}_t \tag{36}$$

$$\hat{w}_t = \sigma\hat{c}_t + \phi\hat{n}_t \tag{37}$$

$$E_t\left[\hat{m}_{t,t+1} + \frac{R}{R-\tau}\hat{R}_t\right] = 0 \tag{38}$$

$$\hat{y}_t = \frac{wn}{y}(\hat{w}_t + \hat{n}_t) + \frac{d}{y}\hat{d}_t + \frac{B}{y}\hat{B}_t - \frac{B/R}{y}\left(\hat{B}_{t+1} - R_t\right) \tag{39}$$

$$\hat{y}_t = \hat{z}_t + (1-\theta)\hat{n}_t \tag{40}$$

$$\hat{m}_{t,t+1} = -\sigma E_t(\hat{c}_{t+1} - \hat{c}_t) \tag{41}$$

$$\hat{z}_t = \rho_z\hat{z}_{t-1} + \epsilon_t^z \tag{42}$$

$$E_t(\hat{c}_{t+1}) = \hat{c}_t + \epsilon^s_{t+1} + \psi \epsilon^z_{t+1} \tag{43}$$

### F.3 Proof of Proposition 3

The moving average of consumption conditional on technology shocks is

$$\hat{c}_t = \psi \epsilon^z_t + A \epsilon^z_{t-1} + \lambda A \epsilon^z_{t-2} + \lambda^2 A \epsilon^z_{t-3} + \ldots$$

where $A \equiv \lambda \psi + \frac{1+\phi}{\zeta(1-\theta)}$. Then $Cov(\hat{c}_t, \hat{c}_{t-1}) = \sigma^2_z A \left( \psi + A \frac{\lambda}{1-\lambda^2} \right)$. Since $\psi > 0$ and $-1 < \lambda < 0$, the first order autocorrelation of consumption conditional on technology shocks is positive if only if $A > 0$ and $\psi + A \frac{\lambda}{1-\lambda^2} > 0$, or

$$-\lambda \frac{1+\phi}{\zeta(1-\theta)} < \psi < -\frac{1}{\lambda} \frac{1+\phi}{\zeta(1-\theta)}.$$

# Online Appendix of

Expectation-driven Boom-Bust Cycles

*by Brianti M., and Cormun V.*

# G Additional robustness checks

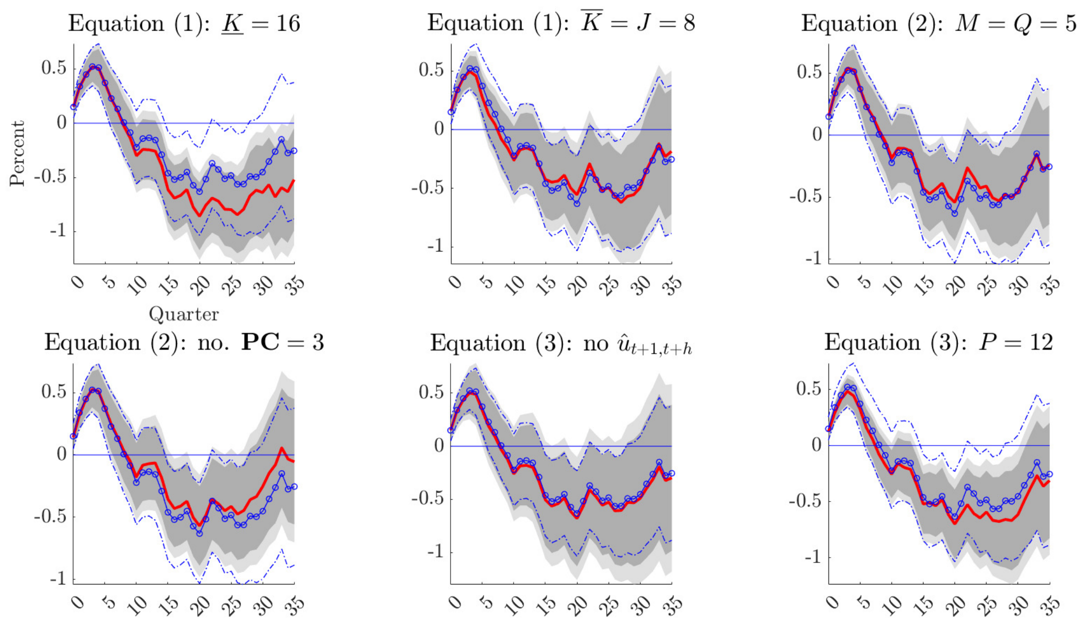


**Figure 12:** GDP responses to an expectation shock using different specifications

*Note*: Impulse responses of real GDP to a one-standard deviation expectation shock using different specifications. The red line is the point estimate and the shaded areas indicate 80% and 90% confidence bands calculated with Eicker-Huber-White heteroscedasticity-robust standard errors. Circled and dashed blue lines are the point estimates and the 80% confidence bands, respectively, of the baseline specification presented in Figure 1. Horizontal axes measure quarters and vertical axes measure percent deviations from pre-shock trend. In the first row, the specification in the first panel controls in Equation (1) for 16 leads (instead of 12) of the TFP growth; the second specification controls in Equation (1) for eighth lags (instead of four) of the TFP growth; and the specification in the third panel controls in the Equation (2) for four lags ($M = Q = 5$) of the TFP growth and the principal components. In the second row, the specification in the first panel controls in Equation (2) for three principal components (instead of four); the second specification excludes estimated residuals from the regression in Equation (3); and the specification in the third panel controls for 12 lags (instead of four) of the past of the expectation shocks and the endogenous variable in Equation (3).

# H Responses to expectation shocks estimated as in LPN

We follow LPN and estimate a VAR with TFP, real GDP, real consumption, hours, and the mean SPF forecasts of the real GDP one quarter ahead, for the sample period between 1968Q4 to 2010Q3.[23] We identify the expectation shock series as the one that maximizes the share of forecast error variance of analysts' forecast up to two quarters, while being or-

[23] Table A reports the source of the variables we used.

thogonal to surprise and news shocks of TFP. Figure 13 shows the results of our replication exercise.

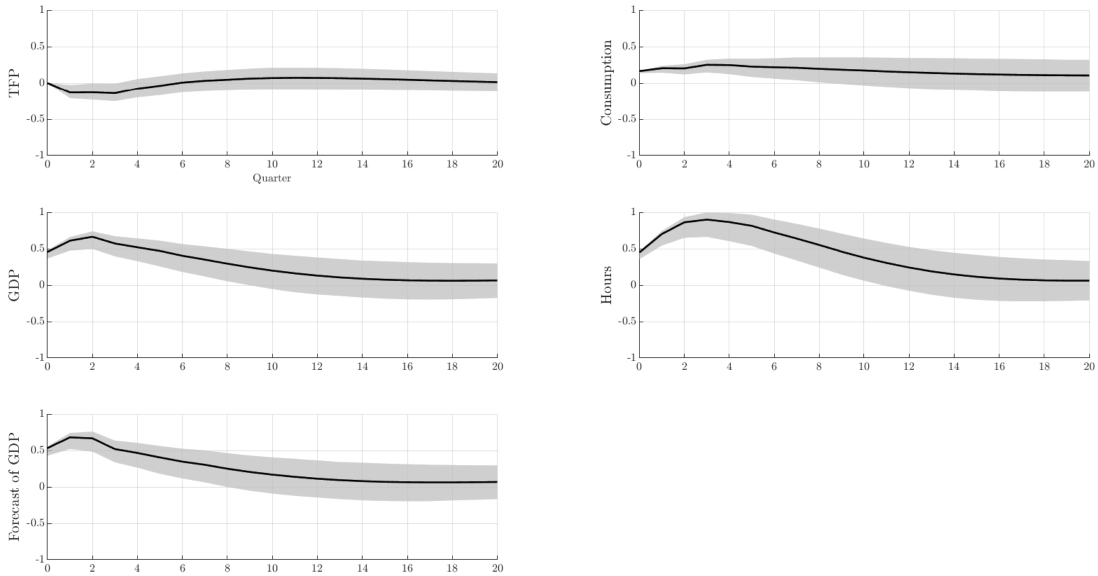


**Figure 13:** Impulse response functions to an expectation shock as in LPN

*Note*: Impulse responses of US TFP, GDP, consumption, hours, and the forecast of the US GDP to a one-standard deviation expectation shock. The black solid line is the point estimate and the shaded areas indicate 90% confidence bands calculated with the Efron bootstap. Horizontal axes measure quarters and vertical axes measure percent deviations from pre-shock trend.

# I Forecast Error Variance Decomposition

Consider the following model,

$$y_{t+h} - y_{t-1} = \theta_h \varepsilon_t + c_h + \sum_{l=1}^{L} (\varepsilon_{t-l}, \ \ \Delta y_{t-l}) \Gamma_{h,l} + \gamma r_{t+1,t+h} + r_{t,t+h} \tag{44}$$

where $c_h$ is a scalar; $\theta_h$ is the impulse response to a shock $\varepsilon_t$ of variable $y_t$ at horizon $h$; $L = 4$ is the desired number of lags for $\varepsilon_t$ and $\Delta y_t$; for any given $h$ and $l$; $\Gamma_{h,l}$ is a bi-dimensional row vector; $r_{t+1,t+h}$ is the error in the $h-1$ stage forwarded by one period; and $r_{t,t+h}$ is the error in the stage $h$.

We estimate Equation (44) using OLS. Define matrix $X_t$ as,

$$X_t = [\varepsilon_t,\ \iota,\ \varepsilon_{t-1},\ \dots\ \varepsilon_{t-L},\ \Delta y_{t-1},\ \dots \Delta y_{t-L},\ \hat{r}_{t+1,t+h}]$$

where $\iota$ is a $(T-h+1)$ constant vector and $\hat{r}_{t+1,t+h}$ is the estimator of $r_{t+1,t+h}$, i.e., the residual of the regression at horizon $h-1$ forwarded by one period. Note that when $h=0$, $r_{t+1,t+h}$ cannot be estimated and therefore it is not included in $X_t$. At this point, the vector of estimated coefficients $\hat{B}_h = (\hat{\theta}_h,\ \hat{c}_h,\ \hat{\Gamma}_{h,1},\ \dots,\hat{\Gamma}_{h,L},\ \hat{\gamma})$ of dimension $Q = 3 + 2 \times L$ is estimated as follows,

$$\hat{B}_h = \left(X_t' X_t\right)^{-1} \left(X_t'(y_{t+h} - y_{t-1})\right)$$

where $\hat{r}_{t,t+h}$ is defined as $(y_{t+h} - y_{t-1}) - X_t \hat{B}_h$. From $\hat{B}_h$ we obtain $\hat{\theta}_h$, the empirical impulse responses shown in the main text of the paper.

To estimate the variance decomposition, we follow the LP-B method of Gorodnichenko and Lee (2020) (Equation 10, page 923). First, consider the augmented counterpart of Equation (44):

$$y_{t+h} - y_{t-1} = \theta_h \varepsilon_t + c_h + \sum_{l=1}^{L} (\varepsilon_{t-l},\ \ \Delta y_{t-l},\ \ x_{t-l}) \Gamma_{h,l}^{VD} + r_{t,t+h}^{VD} \tag{45}$$

where $x_t$ is a set of additional stationary controls of size $(T,J)$ that we define as the first 5 principal components of the large dataset of US macro variables of McCracken and Ng (2020). It follows that the main differences between Equation (44) and Equation (45) are that $\Gamma_{h,l}^{VD}$ is now a $J+2$ row vector and that the error term $r_{t+1,t+h}$ from the regression at horizon $h-1$ is not anymore on the right-hand size. Given these changes, net of $\varepsilon_t$, we can interpret the error term $r_{t,t+h}^{VD}$ as the forecast error of $y_{t+h} - y_{t-1}$. This is what we estimate in the next step.

As before, we estimate Equation (45) using OLS. Define matrix $X_t^{VD}$ as,

$$X_t^{VD} = [\varepsilon_t,\ \iota,\ \varepsilon_{t-1},\ \dots\ \varepsilon_{t-L},\ y_{t-1},\ \dots y_{t-L},\ x_{t-1},\ \dots\ x_{t-L}],$$

and the vector of estimated coefficients $\hat{B}_h^{VD}$ of dimension $Q = 2 + (J+2) \times L$ is estimated as follows,

$$\hat{B}_h^{VD} = [(X_t^{VD})' X_t^{VD}]^{-1} [(X_t^{VD})'(y_{t+h} - y_{t-1})]$$

where $\hat{r}_{t,t+h}^{VD}$ is defined as $(y_{t+h} - y_{t-1}) - X_t^{VD} \hat{B}_h^{VD}$. Define then $\tilde{X}_t^{VD}$ equal to $X_t^{VD}$ without the first column vector $\varepsilon_t$,

$$\tilde{X}_t^{VD} = [\iota,\ \varepsilon_{t-1},\ \dots\ \varepsilon_{t-L},\ y_{t-1},\ \dots y_{t-L},\ x_{t-1},\ \dots\ x_{t-L}],$$

and obtain

$$\varepsilon_t^{\perp} = \varepsilon_t - \tilde{X}_t^{VD} \tilde{B}_h^{VD}$$

where

$$\tilde{B}_h^{VD} = [(\tilde{X}_t^{VD})' \tilde{X}_t^{VD}]^{-1} [(\tilde{X}_t^{VD})' \varepsilon_t].$$

Finally, the estimated forecast error is $\hat{fe}_{t,t+h}$ of variable $y_{t+h} - y_{t-1}$ with information up to $t-1$ equal to,

$$\hat{fe}_{t-1,t+h} = \hat{r}_{t,t+h}^{VD} + \hat{\theta}_0 \varepsilon_t^{\perp}.$$ [24]

An estimator for the forecast error variance decomposition is,

$$\hat{s}_h = \frac{\sum_{h=0}^{H} \hat{\theta}_h^2 \hat{\sigma}_\varepsilon^2}{\sum_{h=0}^{H} \hat{\theta}_h^2 \hat{\sigma}_\varepsilon^2 + \sum_{t=L}^{T-h} \left( \hat{fe}_{t-1,t+h} - \sum_{h=0}^{H} \hat{\theta}_{H-h} \varepsilon_{t+h} \right)^2 / (T-L-h)}$$

where $\hat{\sigma}_\varepsilon$ is the estimator of the variance of the shock $\sigma_\varepsilon$ and is equal to

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{T-1} \sum_{t=0}^{T} (\varepsilon_t)^2.$$

[24] Note that $\hat{\theta}_0$ as well as $\hat{\theta}_h$ in the definition of the estimato $\hat{s}_h$ is the one estimated using Equation (44).

### I.1 Inference

Following Gorodnichenko and Lee (2020), we estimate the confidence intervals of the estimator $s_h$ from the following result

$$\sqrt{T}\Big(\hat{s}_h - s_h\Big) \xrightarrow{d} \mathcal{N}(0, V_h)$$

where the variance $V_h$ is

$$V_h = \Delta_h (G_h)^{-1} \Omega_h (G'_h)^{-1} \Delta'_h.$$

In addition,

1. Matrix $\Omega_h$ of dimension $(K, K)$, where $K = 2 + (H+1)Q$, is equal to

$$\Omega_h = \sum_{l=-\infty}^{+\infty} \Gamma(l)$$

where $\Gamma(l)$ is the autocovariance of $g_{t+h}(\theta_0)$ at lag $l$, and $g_{t+h}(\theta_0)$ is a $K$-dimensional vector equal to

$$g_{t+h}(\theta_0) = \begin{pmatrix} (X_t^{VD})'(y_t - y_{t-1} - X_T^{VD} B_0^{VD}) \\ \vdots \\ (X_t^{VD})'(y_{t+h} - y_{t-1} - X_T^{VD} B_h^{VD}) \\ \varepsilon_t^2 - \sigma_\varepsilon^2 \\ (fe_{t-1,t+h} - \sum_{i=0}^{h} \theta_{h-i} \varepsilon_{t+i})^2 - \sigma_{v,h}^2 \end{pmatrix}$$

and

$$\sigma_{v,h}^2 = var\Big(fe_{t-1,t+h} - \sum_{i=0}^{h} \theta_{h-i} \varepsilon_{t+i}\Big)$$

2. Matrix $G_h$ of dimension $(K,K)$ is equal to

$$G_h = -\begin{pmatrix} I_{h+1} \otimes (X_t^{VD})' X_t^{VD} & 0 & 0 \\ \cdots \; 0 \; \cdots & 1 & 0 \\ \cdots \; 0 \; \cdots & 0 & 1 \end{pmatrix}$$

where $I_{h+1}$ is a $(h+1)$-dimensional identity matrix, and $\otimes$ is the kronecker product.

3. $\Delta_h$ is a $k$-dimensional row vector equal to

$$\Delta_h = \frac{1-s_h}{\sigma^2_{f,h}} \begin{pmatrix} 2\theta_0 \sigma^2_\varepsilon \iota_1 \\ \vdots \\ 2\theta_h \sigma^2_\varepsilon \iota_1 \\ \sum_{i=0}^h \theta_i^2 \\ -s_h/(1-s_h) \end{pmatrix}^T$$

where $\iota_1$ is a $Q$-dimensional column vector equal to one in the first entry and zero otherwise, while $\sigma^2_{f,h} = var(fe_{t-1,t+h})$.

The objective is to estimate the objects $\Omega_h$, $G_h$, and $\Delta_h$ using estimators $\hat{\Omega}_h$, $\hat{G}_h$, and $\hat{\Delta}_h$.

1. Estimator $\hat{G}_h$ is

$$\hat{G}_h = -\text{dial}\left( I_{h+1} \otimes \frac{1}{T-L-h} (X_t^{VD})' X_t^{VD}, I_2 \right)$$

where $\text{diag}(A,B)$ is the block diagonal matrix whose diagonal components are A and B in order, and $I_n$ is the $n$-dimensional identity matrix.

2. To derive estimator $\hat{\Omega}_h$, we need to define matrix $Z_{t+h}$ of dimension $(T,K)$ equal to

$$Z_{t,h} = \begin{pmatrix} (X_t^{VD})'(y_t - X_T^{VD}\hat{B}_0^{VD}) \\ \vdots \\ (X_t^{VD})'(y_{t+h} - X_T^{VD}\hat{B}_h^{VD}) \\ \varepsilon_t^2 - \hat{\sigma}_\varepsilon^2 \\ (\hat{fe}_{t-1,t+h} - \sum_{i=0}^h \hat{\theta}_{h-i}\varepsilon_{t+i})^2 - \hat{\sigma}^2_{v,h} \end{pmatrix}^T$$

$$\hat{\sigma}^2_{v,h} = \sum_{t=L}^{T-h}\left(\hat{fe}_{t-1,t+h} - \sum_{i=0}^{h}\hat{\theta}_{h-i}\varepsilon_{t+i}\right)/(T-L-h).$$

The estimator of the long-run variance $\Omega_h$ is

$$\hat{\Omega}_h = \hat{\Gamma}_{Zh,0} + \frac{1}{1+L_{L_{NW}}}\left(\hat{\Gamma}_{Zh,1} + (\hat{\Gamma}_{Zh,1})'\right) + \cdots + \frac{L_{NW}}{1+L_{L_{NW}}}\left(\hat{\Gamma}_{Zh,LNW} + (\hat{\Gamma}_{Zh,LNW})'\right)$$

where

- $\hat{\Gamma}_{Zh,0} = (Z_t'Z_t)/(T-L-h)$
- $\hat{\Gamma}_{Zh,i} = [(Z_{t,h})'Z_{t+i,h}]/(T-L-h)$ (when moving $Z_t$ forward, append zeros at the beginning)
- $L_{NW} \approx 3/4 \times (T-L-h)^{\frac{1}{3}}$

3. Estimator $\hat{\Delta}_h$ is equal to

$$\Delta_h = \frac{1-\hat{s}_h}{\hat{\sigma}^2_{f,h}}\begin{pmatrix} 2\hat{\theta}_0\hat{\sigma}^2_\varepsilon\iota_1 \\ \vdots \\ 2\hat{\theta}_h\hat{\sigma}^2_\varepsilon\iota_1 \\ \sum_{i=0}^h \hat{\theta}_i^2 \\ -\hat{s}_h/(1-\hat{s}_h) \end{pmatrix}^T$$

where $\hat{\sigma}^2_{f,h} = \sum_{t=L}^{T-h}\left(\hat{fe}_{t-1,t+h}\right)/(T-L-h)$.

The estimator $\hat{V}_h$ for $V_h$ is

$$\hat{V}_h = \hat{\Delta}_h(\hat{G}_h)^{-1}\hat{\Omega}_h(\hat{G}_h')^{-1}\hat{\Delta}_h'/(T-L-h),$$

and confidence intervals are

$$\hat{s}_{CI} = \hat{s}_h \pm t_{\alpha,df}\sqrt{\hat{V}_h}$$

where $t_{\alpha,df}$ is the $(100\times\alpha)\%$ critical value of a $t$-distribution with $df = T-L-h$ degrees of freedom.

# J Conditional spectral density

## J.1 Inference

We estimate confidence intervals of the conditional spectral density using the block bootstrap procedure of Kilian and Kim (2011). Define the tuple:

$$\mathcal{T}_h = [y_{t+h}-y_{t-1},\ \ \varepsilon_t,\ \ \iota,\ \ \varepsilon_{t-1},\ \ \ldots\ \ \varepsilon_{t-L},\ \ y_{t-1},\ \ \ldots y_{t-L},\ \ x_{t-1},\ \ \ldots\ x_{t-L}]. \tag{46}$$

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

1. Define $g = T-l+1$ overlapping blocks of $\mathcal{T}_h$ of length $l$.[25]
2. Draw with replacement from the blocks to form a new tuple $\mathcal{T}_h^b$ of length $T$.
3. Obtain $\hat{\theta}_h^b$ from $\mathcal{T}_h^b$ using the local projection estimator.
4. Use bootstrapped impulse response $\hat{\theta}_h^b$ with $h = 0,1,\ldots,H$ to estimate $\hat{s}_k^b(\omega)$ as follows

$$\hat{s}_k^b(\omega) = \frac{\hat{\sigma}_\varepsilon^2}{2\pi}\left[\sum_{h=0}^{H}\hat{\theta}_h^b e^{ih\omega}\right]\left[\sum_{h=0}^{H}\hat{\theta}_h^b e^{-ih\omega}\right].$$

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

5. Repeat 1. to 4. 2000 times and select confidence intervals for the conditional spectral density.

### J.2 Additional figures

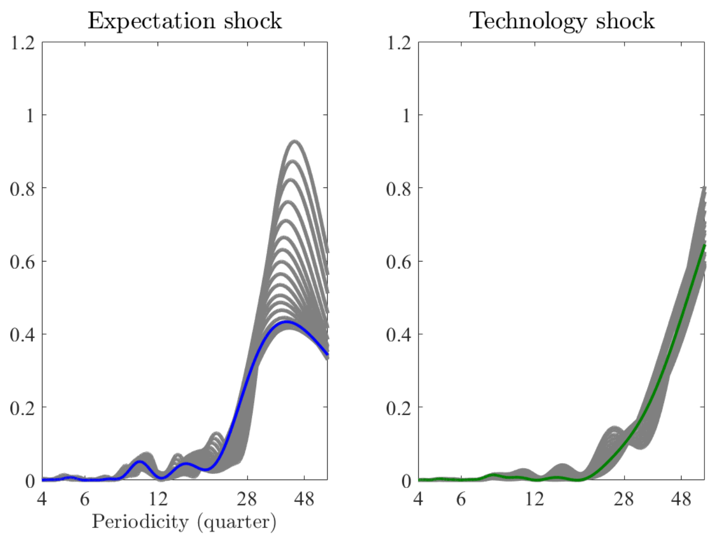


**Figure 14:** Spectral density of GDP conditional to expectation and technology shocks

*Note*: Spectral density of real GDP conditional to expectation shocks (left panel) and technology shocks (right panel). Sample period: 1970Q3-2020Q1. Solid blue line and solid green line indicate the baseline point estimates presented in Figure 6. Grey solid lines represent estimates using truncation horizon from 30 to 50 quarters.

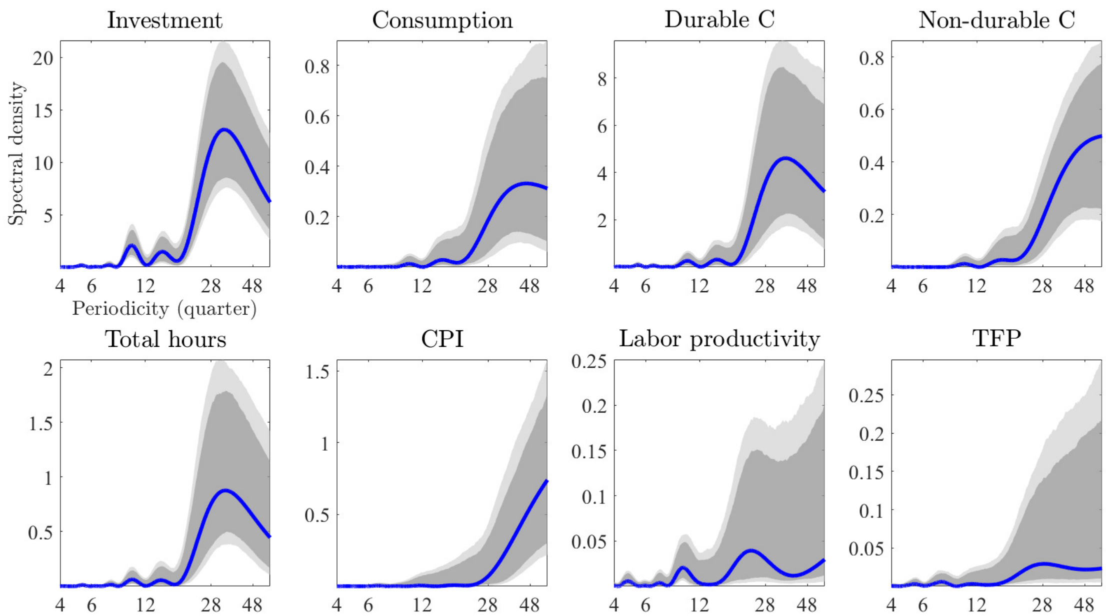


**Figure 15:** Spectral density of macroeconomic variables conditional to expectation shocks

*Note*: Spectral density of investment, consumption, durable consumption, non-durable consumption, total hours, CPI, labor producitivity, and TFP conditional to expectation shocks. Sample period: 1970Q3-2020Q1. Blue lines indicate the point estimate for expectation shocks and the shaded areas indicate 80% and 90% confidence bands calculated with the block-bootstrap (see Appendix J.1 for details). Horizontal axes measure periodicities 4 to 60 quarters.

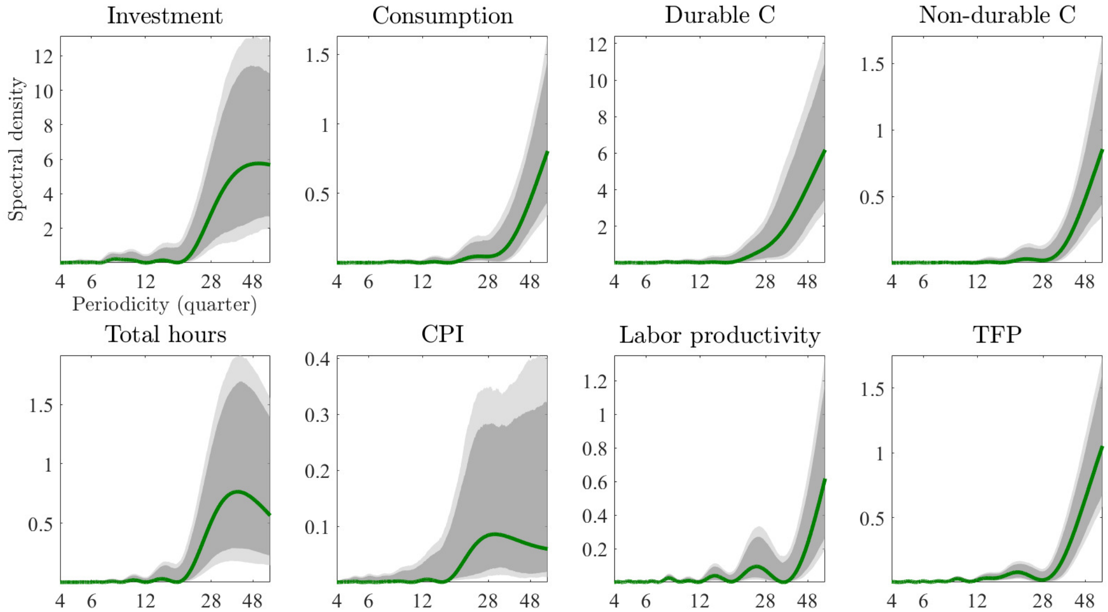


**Figure 16:** Spectral density of macroeconomic variables conditional to technology shocks

*Note*: Spectral density of investment, consumption, durable consumption, non-durable consumption, total hours, CPI, labor producitivity, and TFP conditional to technology shocks. Sample period: 1970Q3-2020Q1. Green lines indicate the point estimate for technology shocks, and the shaded areas indicate 80% and 90% confidence bands calculated with the block-bootstrap (see Appendix J.1 for details). Horizontal axes measure periodicities 4 to 60 quarters.

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