Sentiments Drive Boom-Bust Cycles*

Marco Brianti† Vito Cormun‡

August 24, 2022

Abstract

Using data from the Survey of Professional Forecasters, we identify sentiment shocks as shifts in expectations orthogonal to realized and expected fundamentals. We find that a positive sentiment shock leads to boom-bust dynamics in the key macroeconomic aggregates. Booms due to technology improvements, in contrast, are not followed by a bust, at least on average. Finally, we offer a theory that explains why boom-bust dynamics emerge in response to sentiments and *not* in response to technology shocks.

JEL classification: C32, E32
Keywords: Animal Spirit, Boom Bust, Business Cycle, Sunspot

*We are grateful to Susanto Basu, Ryan Chahrour, Jaromir Nosal, Pablo Guerrón-Quintana, Peter Ireland, and Fabio Schiantarelli for their generous guidance and support. We also thank Carola Binder for helpful comments and suggestions. This paper previously circulated under "What are the sources of Boom-Bust Cycles?"

†University of Alberta, brianti@ualberta.ca
‡Santa Clara University, vcormun@scu.edu

This paper uncovers a new finding on the role of expectations in shaping economic fluctuations. Sentiment shocks – defined as changes in expectations unrelated to fundamentals – drive boom-bust dynamics in the key macroeconomic indicators[1]. That is, given a positive shift in sentiments, output initially increases, but after some time, it significantly falls below trend. By contrast, technology shocks bring about trend-reverting dynamics that are absent of any oscillatory pattern.

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, there is a broad consensus in the business cycles literature that the economy is primarily driven by demand disturbances, while changes in technology drive only a small fraction of business cycle fluctuations (see, for example, Angeletos et al., 2020). Within this paradigm, sentiment shocks represent a natural candidate of demand-driven fluctuations. Second, narratives of economic fluctuations driven by sentiments pervade the history. For example, Hall (1993) argues that the 1990-1991 recession has no clear fundamental source, rather it originated from a spontaneous fall in consumption.[2] Another piece of evidence is the swift recovery post 9/11, that Shiller (2020) attributes to an unexpected change in national sentiment due to the public resolution to defy the attackers by carrying on with life as normal. Even the Great Recession is hard to justify by solely relying on depressed fundamentals (see, among others, Farmer, 2012 and Bacchetta and Van Wincoop, 2016).

Besides showing that sentiments are 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. A direct consequence of our result is that expansions fueled by sentiments are more likely to culminate into a recession than those expansions driven by technology improvements. Therefore, distinguishing between sentiments and fundamentals become even more

[1] By change in fundamentals we mean any exogenous change in payoff-relevant variables and beliefs thereof, including technology, oil, monetary and fiscal shocks, as well as changes in preferences or endowments.

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

relevant for policy makers, whose aim is to prevent inefficient economic fluctuations. We place such distinction at the center of our analysis.

We begin by estimating sentiment shocks. Using quarterly expectations data from the Survey of Professional Forecasters (SPF), we compute the time t revision of the one-year-ahead expectations on real GDP growth formed by analysts in quarter $t-1$. We then extract the sentiment component as the residual of a regression of expectations revisions onto past, present, and future technology growth, as well as onto estimated expectations on future technology growth. Controlling for both expected and actual technology realizations isolates shifts in analysts' expectations due to pure sentiments from those originating from ex-post wrong beliefs on future technology (often labelled as noise shocks). Once we extract the sentiment component from analysts' expectations revisions, we use local projections as in Jordà (2005) to estimate the response of macroeconomic aggregates to sentiment shocks. Remarkably, we find that a positive sentiment 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 of comparable magnitude and length. To our knowledge, this is the first study showing predictable sentiment-led boom-bust dynamics. As such, we subject our results to a vast array of robustness checks. For instance, we check that the results are robust to controlling for other shocks estimated by the literature including monetary, fiscal, and oil price shocks, to using different expectations targets for the identification of sentiment shocks, and to different sample periods.

Next, we show that the oscillatory dynamics that we find in response to sentiment shocks do not emerge in response to fundamental shocks. We carry out two distinct exercises. First, we consider analysts' expectations revisions without controlling for changes in technology, and we find that positive revisions surprises do not predict a future bust. 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 macroaggregates from their long-run trend without exhibiting any oscillatory pattern.

Altogether, our empirical results pose new challenges for business cycle models. On the one hand, workhorse DSGE models (see, for example, Smets and Wouters, 2007) feature no intertemporal dependence between expansions and recessions. For this reason, they are unable to reproduce the oscillatory responses to sentiment shocks. On the other hand, models of endogenous cycles as in Beaudry et al. (2020) feature 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 present a model that shares elements with both families of models and offers an explanation of the conditional emergence of boom-bust cycles.

We augment an otherwise standard RBC model with two main ingredients. First, firms can borrow from households only up to a limit which depends on their market value. Second, firms face a working capital requirement. The interaction of the borrowing limit and the working capital requirement generates amplification and, for some parametrizations, self-fulfilling equilibria. Therefore, the model features local indeterminacy of equilibria around a unique steady state as in Benhabib and Farmer (1994). The intuition behind indeterminacy of equilibria 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, which results in an increase of firm value and a validation of the initial households' optimism.

We then feed the model with sentiment and technology shocks. Consistent with their empirical counterpart, we define sentiments as rational expectation shocks independent from technology. Crucially, 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, households increase their saving desire because they know that a recession will follow. Then a recession occurs as households begin to sell firm assets without internalizing the adverse consequences on the borrowing constraint and on the economic activity. 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 credit crunch.

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 which 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. Our definition of sentiment 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 to a sentiment shock, we document novel evidence of a medium horizon reversal. 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. Our results represent a step forward, in the sense that we attribute to sentiments the *source* of the oscillations documented by Beaudry et al. (2020). More tangentially, there is a growing literature that aims at detecting early warnings 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 arise 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 of agents' expectations. A close paper to ours in this class is Benhabib and Wen (2004), which analyzes a 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 properties of the data. We are similar in spirit but our model also emphasizes the different dynamics implied by technology and sunspot shocks. Lastly,

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

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 Empirical responses to sentiments and fundamentals

In this section we identify sentiment shocks and estimate their effects on the economy. We proceed in two steps. First, we isolate the sentiment component from a time series of expectations on the future economy. We do so by taking the residual from a regression of expectations on past, present, and future realizations of technology growth, as well as on expectations of future technology. Second, we estimate the impulse responses of several macroeconomic aggregates to sentiment shocks via local projections.

Identification of sentiment shocks To proxy expectations of market participants, we use expectations data from the Survey of Professional Forecasters (SPF) maintained by the Philadelphia Fed. The survey consists in quarterly forecasts at several horizons for a number of macroeconomic indicators available from 1968Q4. In our baseline specification, we use the mean of analysts' one-year-ahead forecasts on 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 $t-1$, 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 on annual GDP growth made in quarter $t-1$ and the first term is the updated forecast in quar-

[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 or the Industrial Production Index.

ter t. The difference between the two, S_t, is the forecast revision from $t-1$ to t.[7] To isolate the sentiment component, we regress S_t 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. The regression reads:

$$S_t = \sum_{k=-\underline{K}}^{\overline{K}} \alpha_k \Delta \log TFP_{t-k} + \sum_{j=0}^{J} \beta_j b_{t-j} + \nu_t, \tag{1}$$

where we omit the constant for convenience. We use utilization-adjusted quarterly TFP from Fernald (2014) as a proxy for technology. We set the number of lags $\overline{K}$ and J equal to four and the number of leads $\underline{K}$ to 12.[8] 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 S_t. TFP expectations are not readily available in the survey, thus we compute b_t as the fitted value of the following regression:

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

where the left-hand side is the annual growth rate of quarterly utilization-adjusted TFP, and the right-hand side includes quarterly TFP growth and the matrix **PC** of the first four principal components of the quarterly dataset maintained by McCracken and Ng (2020). The number of lags M and Q is equal to four.[9,10]

[7] Note that the nowcast of x_{t-1} made in $t-1$ and the backcast in 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 D.

[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 D shows that results are robust to changing the number of lags or of principal components.

Table 3 in Appendix C shows the results for both regressions, and Figure 9 in Appendix B illustrates the sentiment shock series. Interestingly, the R-squared of the regression of Equation (1) is slightly above 40%, meaning that more than half of changes in analysts' expectations is not due to realized changes in TFP or noise. This implies that a large share of the variation of the forecast revisions S_t is driven by sentiments.[11]

Impulse responses to sentiment shocks The residual, $\hat{v}_t$, from Equation (1) is our estimate of a sentiment shock at time t. Next, we estimate the impulse responses to a sentiment shock using local projections as in Jordà (2005). Specifically, for each variable of interest y, we run the following projections

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

where the parameter θ_h is the response of y to a sentiment shock after h periods. In the baseline, we control for the first 4 lags, i.e. $P = 4$, of the sentiment shocks $\hat{v}_t$ and the first difference of the endogenous variable Δy_t. In addition, when $h > 0$, we also control for the residual $\hat{u}_{t+1,t+h}$ estimated in the previous regression and forwarded by one period.[12] The right panels of Figure 1 illustrate the responses of both the log of real GDP and the forecast revisions to a one standard deviation increase in sentiments. As a way of comparison, the left panels show the responses to a one standard deviation increase in the forecast revisions. We compute 80% and 90% confidence intervals using heteroskedasticity and autocorrelation-consistent standard errors by Newey and West (1987). Two patterns emerge. First and foremost, the response of GDP depends on whether or not we remove the fundamental component from fore-

[11] The R-squared increases to 52% if we also control for Romer and Romer (2004) monetary policy shocks, Ramey (2011) military spending shocks, Mertens and Ravn (2012) unanticipated and anticipated tax shocks, and Kilian (2008) oil price shocks. Meaning that up to 48% of variation in analysts' forecast revisions is due to sentiments.

[12] The inclusion of the residuals from the previous regression increases the efficiency of the estimator. The reason is that the term $\hat{u}_{t+1,t+h}$ captures part of the forecast error at horizon $h-1$. Figure 10 in Appendix D shows the impulse responses without the residuals.

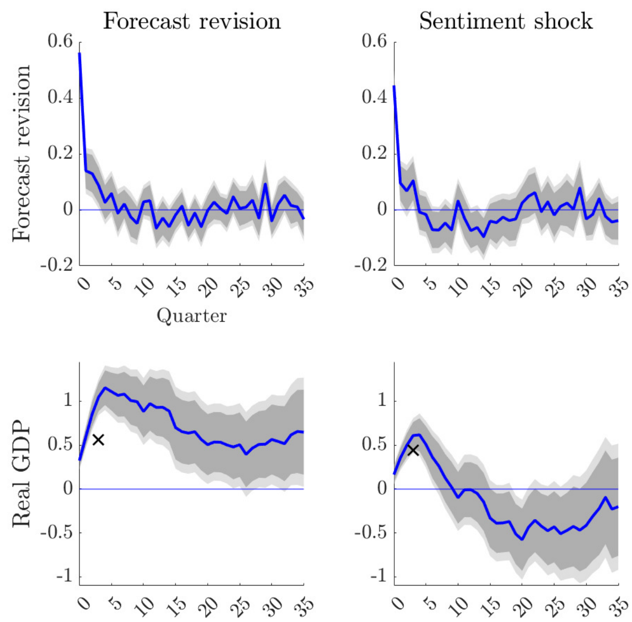


Figure 1: GDP response to a forecast revisions shock and sentiment shock

Note: Impulse responses to a one-standard deviation forecast revision shock (first column) and sentiment shock (second column). Sample period: 1970Q3–2020Q1. Blue lines indicate the point estimates and the shaded areas indicate 80% and 90% confidence bands calculated with heteroskedasticity and autocorrelation-consistent standard errors (Newey and West, 1987). 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. See Appendix A for further details on the variables.

cast 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 a sentiment shock. A positive sentiment shock predicts a gradual increase in the real GDP which remains elevated for about three years, and significantly falls below trend afterward. Second, the cross in the bottom panels marks analysts' forecast of real GDP that they made at the time the shock hit the economy. Interestingly, while analysts tend to underreact in response to a change in forecast revisions – consistent with the findings of Bordalo et al. (2020) – their forecast conditional on sentiment shocks is within the confidence bands of realized GDP, meaning that there is no significant underreaction in response to a sentiment shock. We take the lack of underreaction conditional to sentiment shocks as informative for the model that we offer in Section 2.

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 plots only the responses of real GDP to a sentiment shock. The solid red line along with shaded areas are the responses under the alternative specification, whereas the blue line with circular markers is the baseline response. We address six major concerns. First, the sentiment shocks series may contain the forecast revisions induced by fundamental shocks other than technology, including policy and oil prices shocks. Thus, the first panel plot the GDP response to a sentiment shock $\hat{v}_t$ obtained after adding to the right-hand side of Equation (1) the Romer and Romer (2004) monetary policy shocks series extended by Wieland (2021), Ramey (2011) military spending, unanticipated and anticipated tax shocks by Mertens and Ravn (2012), and the oil price shocks estimated in Kilian (2008). Remarkably, results are largely unvaried despite the sensible loss of observations – the restricted sample ranges from 1971Q1 to 2004Q3. 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, we show results, respectively, using the median analysts' forecast on real GDP growth, and the first principal component of the analysts' forecast of unemployment rate, industrial production, and real GDP. 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 sentiment 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 sentiment shocks from the following modified version of Equation (3):

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

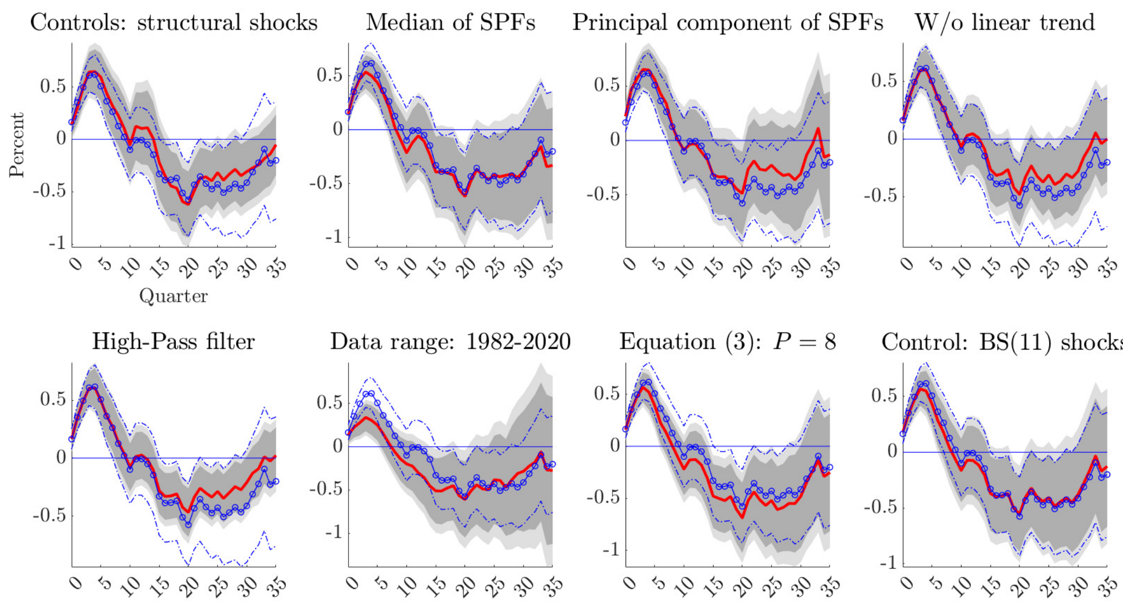


Figure 2: GDP responses to a sentiment shock using different specifications

Note: Impulse responses of real GDP to a one-standard deviation sentiment shock using different specifications. The red line is 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). 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 for monetary policy shocks (Romer and Romer, 2004), unanticipated and anticipated tax shocks (Mertens and Ravn, 2012), government spending shocks (Ramey, 2011), and oil shocks (Kilian, 2008); 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 mean of the expected real GDP growth, industrial production growth, and unemployment rate from the SPF. 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.

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 sentiments 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 unrelated to fundamentals. Such component, that we label sentiments, drives boom-bust dynamics on real GDP.

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. The objective is to trace out the dynamics induced by sentiments so as to inform models of business cycles and learn more about the predictability of boom-bust episodes.

Responses of other variables We characterize the macroeconomic responses to a sentiment shock by estimating Equation (3) for several macroeconomic indicators. Figure 3 considers a one standard deviation shock in sentiments and 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. First, the response of TFP is never statistically different from zero, which indicates that we are controlling for enough leads and lags in Equation (1). Second, investment, consumption, and total

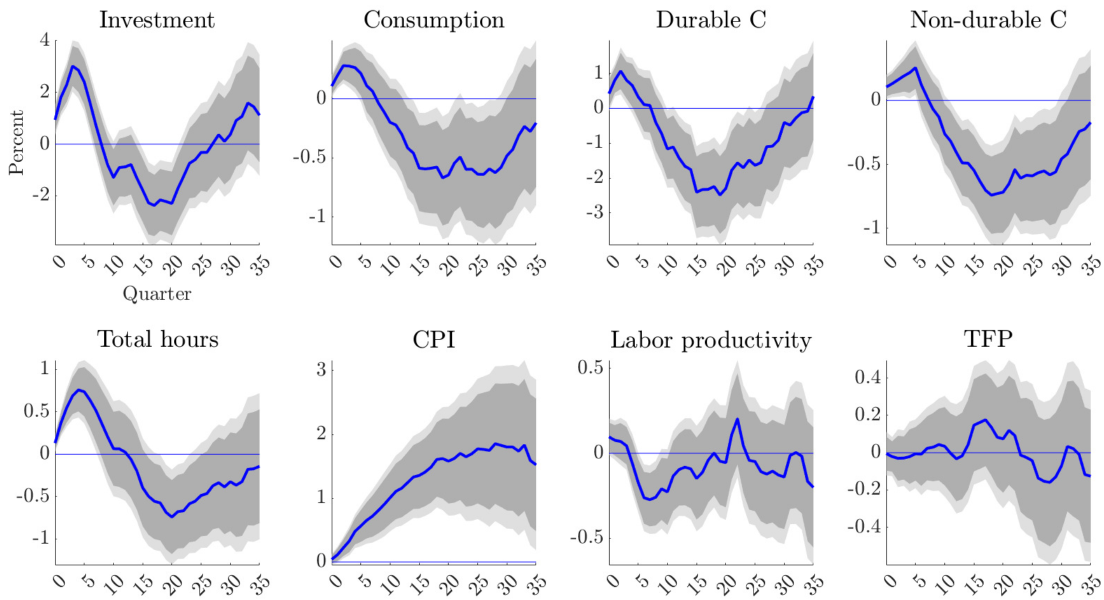


Figure 3: Responses of macro-variables to a sentiment shock

Note: Impulse responses of macro-variables to a one-standard deviation sentiment shock. Sample period: 1970Q3–2020Q1. Blue lines indicate 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 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).

hours comove and display the same boom-bust dynamics observed for real GDP in Figure 1. Third, the positive response of CPI and the comovement among variables suggest that sentiments are a source of demand shocks. Last, 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 falsifies models of production externalities and aggregate increasing returns to scale as candidate explanations of sentiments-driven fluctuations.

Forecast error variance decomposition How much do sentiments explain of the business cycle? We follow Gorodnichenko and Lee (2020) and compute the forecast error variance decomposition of all variables examined in Figures 1 and 3.[13] Table 1 reports the estimated share of the forecast error variance explained by sentiment shocks at four, eight, and twenty quarters. The numbers in parentheses are one standard deviation intervals.[14] Sentiment shocks explain almost one third of the variation of GDP over the first two years. A similar patter

	4 quarters	8 quarters	20 quarters
Real GDP	32.6	30.5	15.7
	(25.8,39.3)	(26.7,34.4)	(4.6,26.8)
Forecast revision	47.7	28.3	28.8
	(40.9,54.5)	(19.2,37.5)	(16.0,41.5)
Investment	30.8	28.6	21.0
	(24.9,36.7)	(21.1,36.1)	(4.6,37.4)
Consumption	16.3	8.6	12.8
	(10.9,21.8)	(6.1,11.1)	(-0.5,26.1)
Durable C	14.0	6.5	17.3
	(11.8,16.2)	(2.3,10.7)	(-0.5,35.1)
Non-durable C	7.6	6.9	18.1
	(6.5,8.8)	(3.5,10.4)	(-3.9,40.2)
Total hours	27.8	25.6	17.6
	(23.5,32.1)	(20.3,30.9)	(-0.7,36.0)
CPI	9.3	14.6	19.9
	(7.1,11.6)	(10.7,18.5)	(15.0,24.8)
Labor productivity	1.5	5.0	3.4
	(-4.4,7.4)	(1.5,8.6)	(-0.5,7.3)
TFP	0.1	0.1	1.1
	(-2.2,2.4)	(-1.8,2.0)	(-1.9,4.1)

Table 1: Forecast error variance explained by sentiment 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 E for additional details.

[13] For additional details on the implementation, see Appendix E.

[14] Table 4 in Appendix E shows the forecast error variance decomposition of sentiment shocks obtained after adding to the right-hand side of Equation (1) the Romer and Romer (2004) monetary policy shocks series extended by Wieland (2021), Ramey (2011) military spending, unanticipated and anticipated tax shocks by Mertens and Ravn (2012), and the oil price shocks estimated in Kilian (2008).

emerges for real investment and total hours. For real consumption and CPI the variance explained is somewhat lower and around 10%-15%.

1.3 Technology shocks and conditional spectral densities

We now analyze the difference between sentiment and fundamental 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 transitory generated 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.[15] We begin by estimating an innovation in TFP growth using a modified version of Equation (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 ε_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 4 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 a sentiment shock. The response of CPI

[15] Estimating permanent and transitory shocks in TFP requires to impose additional structure to the identification strategy. Since we want to design a strategy which is as close as possible to the treatment for sentiment shocks, we opt for investigating the business cycle effects of an innovation in TFP.

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 sentiment shock where we found labor productivity to be countercyclical.

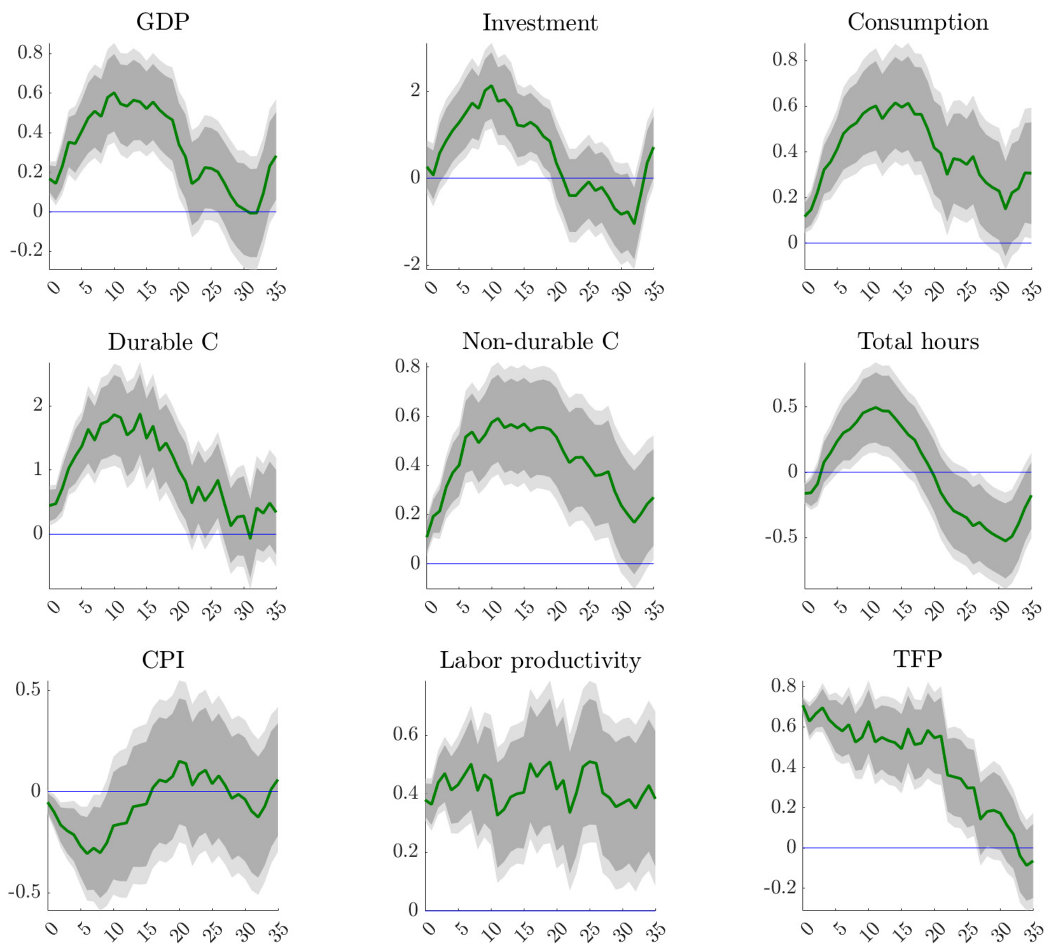


Figure 4: Responses of macro-variables to a technology shock

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 heteroskedasticity and autocorrelation-consistent standard errors (Newey and West, 1987). 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).

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 remarkable differences in the nature and propagation dynamics between non-fundamental and fundamental shocks.

Discussion There are two important corollaries 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 particular, it is possible to compute the spectral densities implied by sentiment and technology shocks, separately. Let the estimated structural moving average conditional to shock $\hat{\varepsilon}_t$ be

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

where H is a truncation horizon that we set equal to 36 quarters.[17] Then, the estimated conditional spectral density of y at frequency ω 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 5 plots the spectral densities of real GDP implied by sentiment and technology shocks. The x-axis depicts the periodicity defined as the inverse of the frequency ω. The spectral density of GDP conditional on sentiment shocks exhibits a peak at a periodicity of about 40 quarters, consistent to what Beaudry

[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.

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

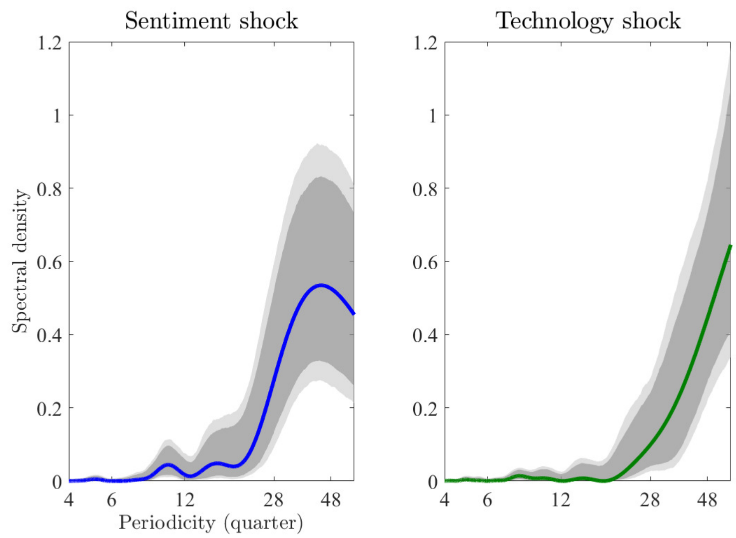


Figure 5: Spectral density of GDP conditional to sentiment and technology shocks

Note: Spectral density of real GDP conditional to sentiment shocks (left panel) and technology shocks (right panel). Sample period: 1970Q3-2020Q1. Blue line indicates the point estimate for sentiment 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 F.1 for details). Horizontal axes measure periodicities 4 to 60 quarters.

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 figure appears when we consider other macroeconomic indicators (see Figure 12 in Appendix F.2).

Taken together our findings provide new discipline for models of business cycles. As in Beaudry et al. (2020), our results favour models of business cycles that embed a strong endogenous mechanism able to reproduce predictable boom-bust dynamics and the spectral density peak. However, the predictability must be stronger conditional on disturbances unrelated to fundamentals. In the remaining part of the paper, we propose a model that can rationalize the conditional emergence of boom-bust dynamics.

2 A model of conditional cycles

We now seek to write a model that can rationalize our main findings. At the very minimum, the model should embed both fundamental and non-fundamental disturbances. Modelling technology shocks is rather trivial as we can assume an exogenous process for technology. To model sentiment shocks, instead, there is not an unambiguous way. As shown in Figure 1, we find no evidence of deviations from rational expectations. In fact, analysts correctly predict the future increase in output conditioning on sentiment shocks. Thus, we draw from the class of models with self-fulfilling (rational) expectations wherein there are sunspot shocks, that is surprise changes in expectations, that drive business cycle fluctuations. In this setting, we model sentiment shocks as sunspot shocks, or more precisely, the part of sunspot shocks that is orthogonal to fundamentals. The workhorse model in this class is the real business cycle model by Benhabib and Farmer (1994) in which equilibrium indeterminacy arises due to a positive production externality resulting in aggregate increasing returns to scale.[18] Due to the aggregate increasing returs to scale, these models predict procyclical labor productivity in response to both sunspot and technology shocks. However, Figures 3 and 4 above show that labor productivity *falls* in response to a positive sentiment shock, while it rises after an improvement in technology. To match this evidence, we depart from the model of Benhabib and Farmer (1994) and offer 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 τ is the tax benefit. Thus, for

[18] Other examples are Wen (1998) and Benhabib and Wen (2004).

$\tau > 0$, 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, ℓ_t, to finance working capital. Because revenues are realized at the end of the period, working capital is required to cover the intraperiod cash flow mismatch. The loan ℓ_t is paid at the end of the period with no interest.[19]

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 γ, in which case its assets will be liquidated and will cease to operate. If a firm is not caught,

[19] 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.

instead, it will continue to retain access to credit in future periods.[20] Thus, a firm defaults if the expected value of defaulting is greater than the expected value of non defaulting, or

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

where $m_{t,t+1}$ is the households' stochastic discount factor, 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

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

The incentive compatible constraint effectively limits both types of firm's debt. The left-hand side is equal to γ 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 ℓ_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 μ_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 be-

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

tween the household's discount factor, $m_{t,t+1}$, 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 μ_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 μ_t decreases according to Equation (9). A decrease in μ_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 σ and ϕ 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.[21] Firm's optimization 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* $\mathbf{s}$*, that are technology* z *and aggregate bonds* B*, a recursive competitive equilibrium is defined as a set of functions for (i) households' policies* $c^h(\mathbf{s}, b)$*,* $n^h(\mathbf{s}, b)$ *and* $b^h(\mathbf{s}, b)$*; (ii) firms' policies* $d(\mathbf{s}, b)$*,* $n(\mathbf{s}, b)$*, and* $b(\mathbf{s}, b)$*; (iii) firms' value* $V(\mathbf{s}, b)$*; (iv) aggregate prices* $w(\mathbf{s})$*,* $r(\mathbf{s})$*, and* $m(\mathbf{s}', \mathbf{s})$*; (v) law of motion for the aggregate states* $\mathbf{s}' = \psi(\mathbf{s})$*. Such that: (i) household's policies satisfy Conditions (12) and (13); (ii) firm's policies are optimal and* $V(\mathbf{s}, b)$ *satisfies the Bellman's Equation (8); (iii) the wage and the interest rate clear the labor and bond markets; (iv) the law of motion* $\psi(\mathbf{s})$ *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 a number of propositions. For analytical simplicity, assume there are no dividend adjustment costs, i.e. $\kappa = 0$, and work with the loglinearized equilibrium equations around the steady state.[22]

Amplification and indeterminacy 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 μ_t. Note that when the tax benefit parameter τ is equal to zero, μ is also equal to

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

[22] Appendix G.1 derives the steady state and shows it is unique. Appendix G.2 shows the loglinearized system of equations.

zero, so that the financial constraint is slack, the last term on the right-hand side of Equation (15) vanishes, and the model reduces to the standard RBC model. When τ is positive, instead, μ is positive so that 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, rearrange the loglinearized first order condition for the intertemporal debt as follows

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

From Equation (16), an increase in current consumption decreases $\hat{\mu}_t$ which, in turn, increases the labor demand in Equation (15). Then, higher labor demand leads to higher consumption, further decreasing $\hat{\mu}_t$. The intuition is that expectations of a temporary boom increase households' saving desire which relaxes the financial constraint and leads to higher supply of credit. By borrowing more, firms increase their labor demand, output increases and so households' (labor) income.

Combine Equations (15) and (16) to get

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

The term ζ 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, ζ increases with the tax advantage τ and decreases with the probability of being caught γ. Note that when ζ is zero, Equation (17) becomes static. When ζ is strictly positive the transmission mechanism relies on expectations of future consumption and the model can admit local indeterminacy of equilibria for sufficiently large values of ζ. 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, two conditions must be satisfied

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

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

Condition *(i)* is always satisfied because the parameters θ, σ, and ϕ are all positive by assumption. ■

The proposition above states that when financial frictions are severe, so that ζ 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 $\zeta(1-E(\hat{c}_{t+1}))$ due to the amplification from financial frictions. Thus, in equilibrium, $\frac{\phi}{1-\theta} + \sigma = \zeta(1-E_t(\hat{c}_{t+1})) - \frac{\theta}{1-\theta}$. 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 ζ.

Indeterminacy and boom-bust dynamics We now turn to the discussion about boom-bust dynamics. As it is apparent from Equation (18) above, 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 carries through 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, 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 in order to feature boom-bust dynamics in equilibrium. The reason why ζ is bounded from above can be seen again from the labor clearing in Equation (15). For sufficiently *small* values of ζ an increase in current consumption is an equilibrium only if future consumption falls.

Conditional boom-bust dynamics Under indeterminacy, 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 ϵ^s is a sentiment shock, defined as $\hat{c}_{t+1} - E_t(\hat{c}_{t+1})$, and ϵ^z is a technology shock. The parameter ψ governs the impact response of consumption to a technology shock which we assume being positive, i.e. $\psi > 0$. Equation (19) states 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 central result of the model. The intuition is that during an expansion equity prices are elevated, so that the financial constraint relaxes and current economic activity improves. However, the nature of the increase in equity prices matters a great deal for the dynamics. During sentiment-driven expansions equity prices are elevated because the temporarily higher current consumption relative to future consumption raises households' stochastic discount factor. Technology improvements, in contrast, increase equity prices because of higher firms' profitability. As the expansion unfolds households will decide the amount of firm assets to sell depending on the nature of the expansion. If the expansion is sentiment-driven, households liquidate firms assets in expectation of a future recession. Then a recession results from households' failure of internalizing the adverse effects of their asset sales on the financial constraint. If the expansion is technology-driven, in contrast, households are aware that equity prices are elevated because of higher profitability and not because of a bout of optimism, as a consequence, they will not reduce credit to firms and a recession will not occur. The proposition below provides the parameters 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 conditional on technology shocks is positive if and only if $-\lambda < \psi \frac{\zeta(1-\theta)}{1+\phi} < -\frac{1}{\lambda}$.*

Proof. The proof is relegated to the Appendix G.3. ■

2.4 Parametrization and impulse responses

Let the dividend adjustment costs be positive 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 sunspot shocks.

Parametrization We calibrate the model to a quarterly frequency and set β to match a 3% annual interest yield on bonds. The utility parameter α is such that the steady state value of hours worked equal to .3. As in Jermann and Quadrini (2012), the tax shield τ and capital's share of income θ are equal to .35 and .36, respectively. We set the inverse of households' intertemporal elasticity of substitution σ 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 ϕ equal to 10 which implies a Frisch elasticity equal to 0.1, that is within the range of the microeconometric estimates by MaCurdy (1981) and Altonji (1986). The probability of being caught γ is equal to 0.085, and the degree of adjustment cost to dividends κ to 20. As per the shock processes, we set ψ equal to .2364 in order to match the impact response of output to a technology shock, the parameter ρ_z governing the persistence of the technology process is set equal to .93 consistent with 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 6 shows the theoretical impulse responses to a sunspot shock and to a technology shock. The dividend adjust-

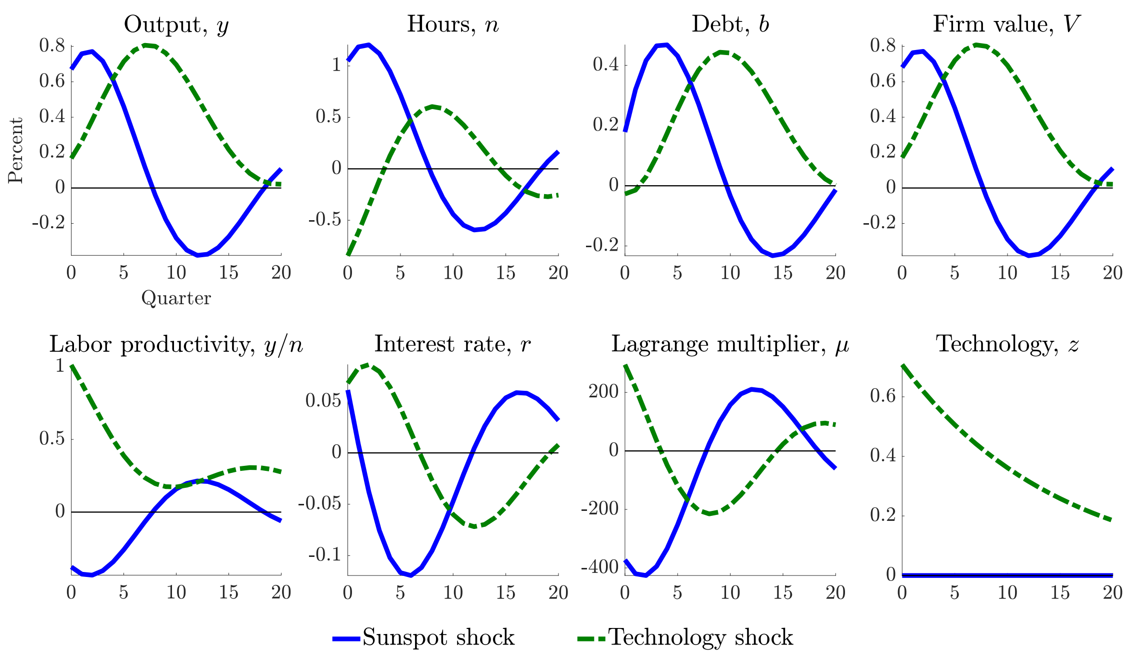


Figure 6: Model-implied impulse responses to a technology shock and sunspot shock

Note: Model-implied impulse responses to a one-standard deviation sunspot 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.

ment cost smooths out the dynamics so that the model's deterministic solution features a pair of complex eigenvalues. In response to a positive sunspot shock, the economy displays boom-bust dynamics qualitatively in line to what we find in the data. A positive sunspot shock originates from agents' expectations of a temporary boom. Due to the temporary nature of the boom, households increase their demand for firms' assets, thereby relaxing the financial constraint and leading to an initial fall in μ_t. As a consequence, 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 by Figure 3. Unlike in models of noisy signals about future TFP, households are well aware that technology has not changed and that equity prices will fall, that the financial constraint will tighten and the economy will enter in a recession. In fact, boom-bust dynamics result from agents' failure of internalizing the effects of their coordinated actions on the financial constraint. As the expectation-led expansion unfolds, households sell firms assets inadvertently tightening the financial constraint and driving the recession.

The dynamics to a surprise improvement in technology are very different from those in response to a sunspot shock. As in the data, a positive technology shock generates hump-shaped dynamics in all the main macroeconomic variables. Importantly, both the Lagrange multiplier μ_t and the intertemporal debt increase, meaning that even though firms can borrow more, financial frictions dampen the responses to technology shocks. As we showed in Proposition 3, the technology-driven expansion does not culminate in a bust because the increase in firm value is due to higher firms' profitability and relatively less by the expectation component.

Conditional spectral density To compare the model performance with the results presented in Section 1.3, Figure 7 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.

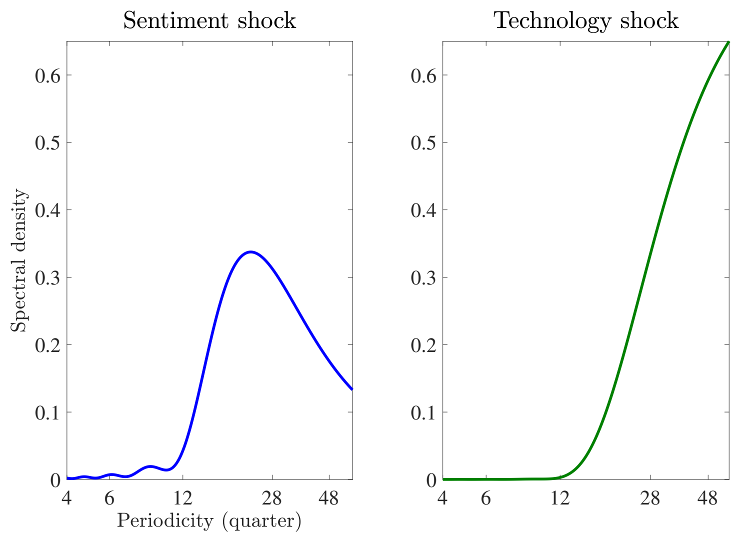


Figure 7: Spectral density of output y conditional to sunspot and technology shocks

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 8 (truncation horizon is 20). Horizontal axes measure periodicities from 4 to 60 quarters.

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, 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

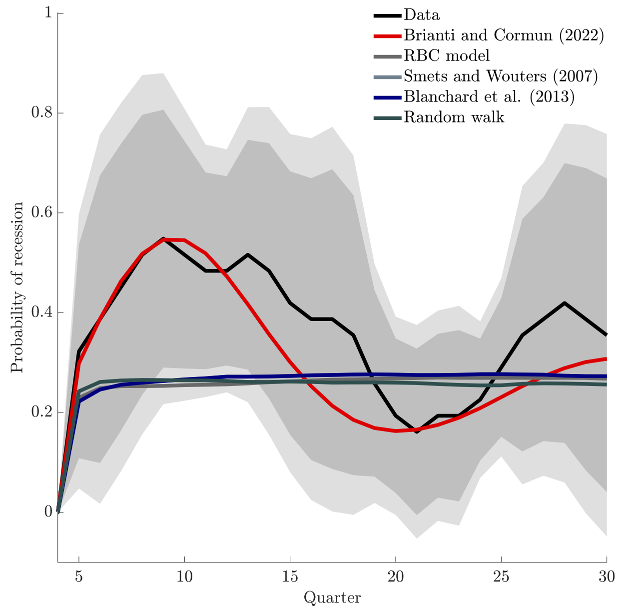


Figure 8: Probability of a recession after an expansion

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 a series of workhorse macro models and from our model (red solid line).

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 8 shows the estimated probability $\hat{\beta}_{0,h} + \hat{\beta}_{1,h}$ that the economy will be in a recession in a two-quarter window around time $t+h$, given an expansion at time t. The conditional probability of a recession increases after an expansion and peaks approximately after two years, after which it converges to its long run value in an oscillatory fashion.

Additionally, Figure 8 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 buffeted 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 shows 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, and recessions originate from negative shocks only. The red line reports the predictions of our model. Remarkably, the 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 after any perturbation, in fact, the economy always oscillates even absent of shocks. In this paper we have uncovered new empirical findings that call for business cycle theories where these two views coexist. In particular, we have shown that changes in sentiments propagate in a way consistent with endogenous cycles theories. Technology shocks, on the other hand, are not responsible of boom-bust cycles, thus in line with the predictions of the dominant view on business cycles.

A Data Appendix

Variable	Code	Source	Transform
TFP	dtfp_util	Fernald (2014)	Cumulated
Forecast $x_{t+h-2\|t}$	RGDPh, $h = 1, 2, \ldots, 6$	Croushore (1993)	Mean across forecasters
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

Table 2: Details on aggregate US data

B Sentiment shock series

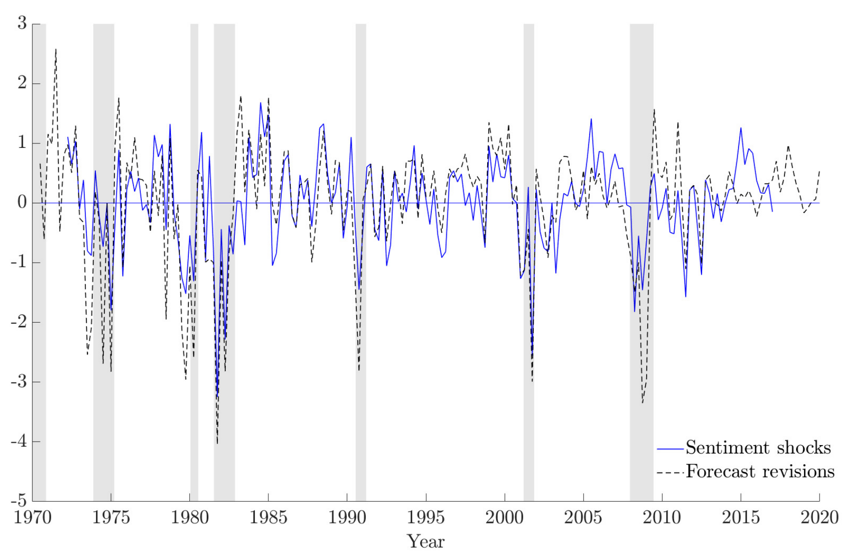


Figure 9: Sentiment shocks and forecast revisions

Note: Time series of sentiment 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		$\text{TFP}_{t+3} - TFP_{t-1}$		ΔTFP_t	
	Constant	1.3007	Constant	0.0062	Constant	0.0022
		(0.2246)		(0.0011)		(0.0007)
	ΔTFP_{t+12}	-1.5560	ΔTFP_t	1.0074	ΔTFP_{t-1}	-0.1638
		(9.1808)		(0.1281)		(0.0771)
	ΔTFP_{t+11}	29.8681	$\text{PC}_{1,t}$	0.0027	$\text{PC}_{1,t-1}$	0.0060
		(8.7799)		(0.0045)		(0.0027)
	ΔTFP_{t+10}	10.1871	$\text{PC}_{2,t}$	0.0125	$\text{PC}_{2,t-1}$	0.0035
		(8.7509)		(0.0069)		(0.0041)
	ΔTFP_{t+9}	18.6346	$\text{PC}_{3,t}$	-0.0019	$\text{PC}_{3,t-1}$	0.0053
		(8.5785)		(0.0053)		(0.0032)
	ΔTFP_{t+8}	13.9804	$\text{PC}_{4,t}$	-0.0001	$\text{PC}_{4,t-1}$	-0.0082
		(8.5914)		(0.0087)		(0.0052)
	ΔTFP_{t+7}	-5.9716	ΔTFP_{t-1}	0.1202	ΔTFP_{t-2}	0.0637
		(8.4714)		(0.1293)		(0.0779)
	ΔTFP_{t+6}	-2.6921	$\text{PC}_{1,t-1}$	-0.0057	$\text{PC}_{1,t-2}$	-0.0047
		(8.5199)		(0.0059)		(0.0036)
	ΔTFP_{t+5}	0.6398	$\text{PC}_{2,t-1}$	0.0054	$\text{PC}_{2,t-2}$	0.0092
		(8.4315)		(0.0079)		(0.0048)
	ΔTFP_{t+4}	27.6713	$\text{PC}_{3,t-1}$	-0.0011	$\text{PC}_{3,t-2}$	-0.0012
		(8.5753)		(0.0062)		(0.0038)
	ΔTFP_{t+3}	16.1045	$\text{PC}_{4,t-1}$	0.0135	$\text{PC}_{4,t-2}$	0.0030
		(8.4910)		(0.0087)		(0.0053)
	ΔTFP_{t+2}	3.0221	ΔTFP_{t-2}	-0.0213	ΔTFP_{t-3}	0.0625
		(8.6210)		(0.1271)		(0.0764)
	ΔTFP_{t+1}	-8.2908	$\text{PC}_{1,t-2}$	0.0072	$\text{PC}_{1,t-3}$	0.0058
		(8.9840)		(0.0060)		(0.0036)
	ΔTFP_t	84.1349	$\text{PC}_{2,t-2}$	-0.0003	$\text{PC}_{2,t-3}$	-0.0009
		(18.3563)		(0.0078)		(0.0046)
	ΔTFP_{t-1}	76.1585	$\text{PC}_{3,t-2}$	-0.0007	$\text{PC}_{3,t-3}$	-0.0064
		(18.9226)		(0.0062)		(0.0037)
	ΔTFP_{t-2}	63.6017	$\text{PC}_{4,t-2}$	0.0028	$\text{PC}_{4,t-3}$	0.0068
		(18.8968)		(0.0087)		(0.0052)
	ΔTFP_{t-3}	28.1657	ΔTFP_{t-3}	-0.0627	ΔTFP_{t-4}	-0.0237
		(18.3682)		(0.1239)		(0.0744)
	ΔTFP_{t-4}	49.6124	$\text{PC}_{1,t-3}$	0.0039	$\text{PC}_{1,t-4}$	-0.0008
		(18.0212)		(0.0053)		(0.0032)
	b_t	-67.4753	$\text{PC}_{2,t-3}$	-0.0010	$\text{PC}_{2,t-4}$	-0.0021
		(17.6801)		(0.0057)		(0.0034)
	b_{t-1}	-61.6620	$\text{PC}_{3,t-3}$	0.0095	$\text{PC}_{3,t-4}$	0.0073
		(18.3102)		(0.0057)		(0.0034)
	b_{t-2}	-53.2164	$\text{PC}_{4,t-3}$	-0.0147	$\text{PC}_{4,t-4}$	0.0013
		(18.6462)		(0.0079)		(0.0047)
	b_{t-3}	-30.1458				
		(18.2893)				
	b_{t-4}	-51.9177				
		(17.5731)				
R-squared		0.4074		0.3346		0.1690
F-test		0.0000		0.0000		0.0273
N observations		179		193		195

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

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

D Additional robustness checks

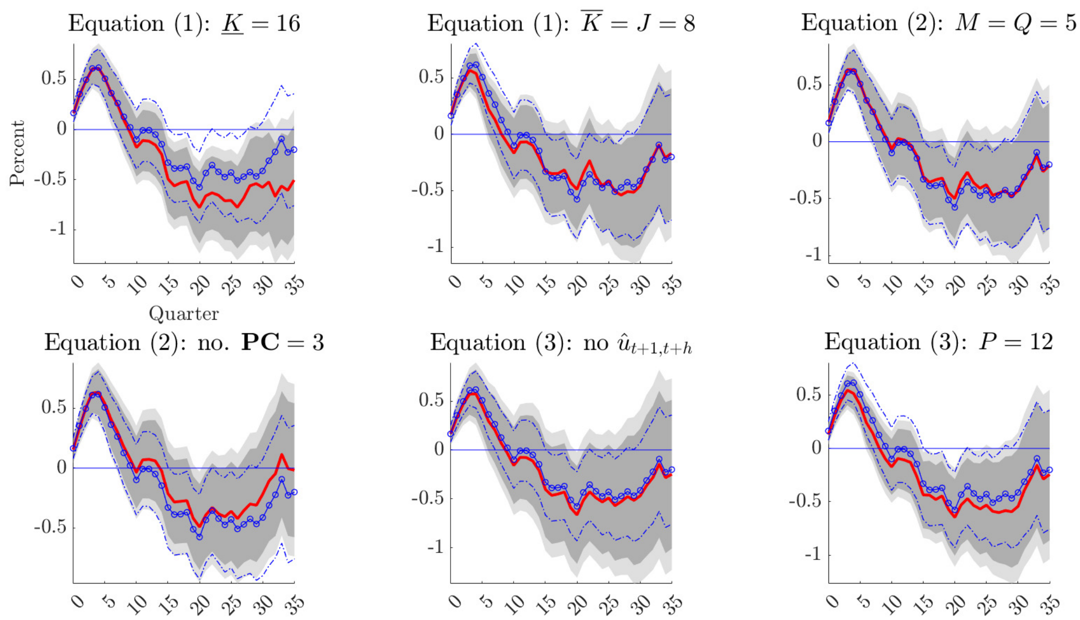


Figure 10: GDP responses to a sentiment shock using different specifications

Note: Impulse responses of real GDP to a one-standard deviation sentiment shock using different specifications. The red line is 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). 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 sentiment shocks and the endogenous variable in Equation (3).

E Forecast Error Variance Decomposition

Consider the following model,

$$y_{t+h} - y_{t-1} = \theta_h \varepsilon_t + c_h + \sum_{l=1}^{L} (\varepsilon_{t-l}, \quad \Delta y_{t-l}) \Gamma_{h,l} + \gamma r_{t+1,t+h} + r_{t,t+h} \tag{20}$$

where c_h is a scalar; θ_h is the impulse response to a shock ε_t of variable y_t at horizon h; $L = 4$ is the desired number of lags for ε_t and Δy_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 (20) using OLS techniques. 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 ι 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, our procedure closely follows the LP-B method (Equation 10, page 923) by Gorodnichenko and Lee (2020). First of all, consider the augmented counterpart of Equation (20):

$$y_{t+h} - y_{t-1} = \theta_h \varepsilon_t + c_h + \sum_{l=1}^{L} (\varepsilon_{t-l}, \quad \Delta y_{t-l}, \quad x_{t-l}) \Gamma^{VD}_{h,l} + r^{VD}_{t,t+h} \tag{21}$$

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 build by McCracken and Ng (2020). It follows that the main differences between

Equation (20) and Equation (21) are that $\Gamma^{VD}_{h,l}$ 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 those changes, at the net of ε_t, we can now interpret the error term $r^{VD}_{t,t+h}$ as the forecast error of $y_{t+h}-y_{t-1}$. This is what we want to estimate in the next step.

As before, we estimate Equation (21) using standard OLS techniques. Define matrix X^{VD}_t as,

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

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

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

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

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

and obtain

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

where

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

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,

$$\hat{fe}_{t-1,t+h} = \hat{r}^{VD}_{t,t+h} + \hat{\theta}_0 \varepsilon^{\perp}_t.$$ [23]

[23] 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 (20).

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 σ_ε and is equal to

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

E.1 Inference

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

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

where the variance V_h is equal to:

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

In addition,

1. Matrix Ω_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. Δ_h is a k-dimensional row vector equal to

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

   where ι_1 is a Q-dimensional column vector equal to one in the first entry and zero otherwise, while $\sigma_{f,h}^2 = var(fe_{t-1,t+h})$.

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

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

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

   where 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

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

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

The estimator of the long-run variance Ω_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

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

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

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.

E.2 Additional table

	4 quarters	8 quarters	20 quarters
Real GDP	31.7	36.4	28.5
	(23.8,39.6)	(30.5,42.2)	(5.9,51.1)
Forecast revision	35.4	28.2	34.5
	(27.5,43.3)	(19.0,37.4)	(22.9,46.2)
Investment	26.4	32.3	26.3
	(21.7,31.1)	(24.1,40.4)	(-1.3,53.8)
Consumption	14.5	7.5	26.5
	(8.3,20.7)	(4.7,10.2)	(3.0,50.0)
Durable C	6.4	4.0	35.9
	(4.1,8.8)	(-1.8,9.8)	(11.5,60.3)
Non-durable C	3.7	5.6	24.6
	(1.1,6.3)	(0.9,10.3)	(-3.4,52.5)
Total hours	28.1	31.0	25.0
	(23.4,32.8)	(26.1,35.9)	(8.7,41.3)
CPI	6.4	17.1	39.9
	(4.3,8.5)	(11.2,23.0)	(30.0,49.8)
Labor productivity	0.5	5.8	11.3
	(-0.5,1.6)	(2.6,9.1)	(0.6,22.1)
TFP	0.2	0.3	2.6
	(-1.7,2.1)	(-3.4,4.1)	(-9.2,14.3)

Table 4: Forecast error variance explained by sentiment shocks after controlling for policy and oil price shocks

F Conditional spectral density

F.1 Inference

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

$$\mathcal{T}_h = [y_{t+h} - y_{t-1},\ \ \varepsilon_t,\ \ \iota,\ \ \varepsilon_{t-1},\ \ \ldots\ \ \varepsilon_{t-L},\ \ y_{t-1},\ \ \ldots y_{t-L},\ \ x_{t-1},\ \ \ldots\ x_{t-L}] \quad (22)$$

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.[24]

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

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

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

[24] 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.

F.2 Additional figures

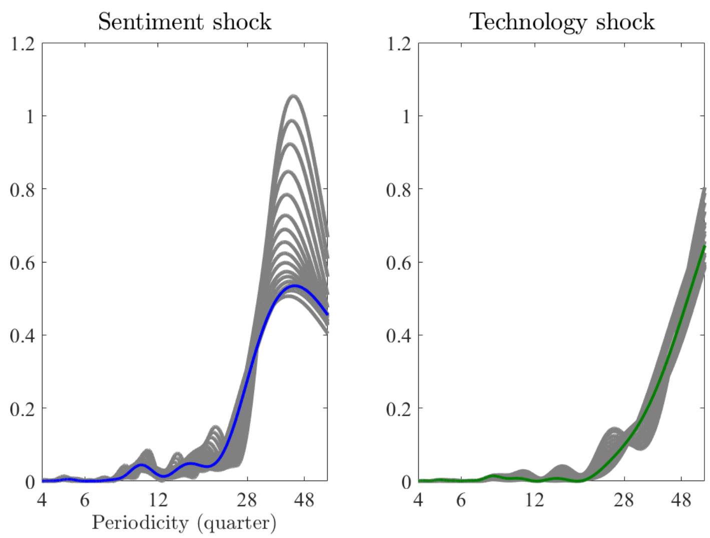
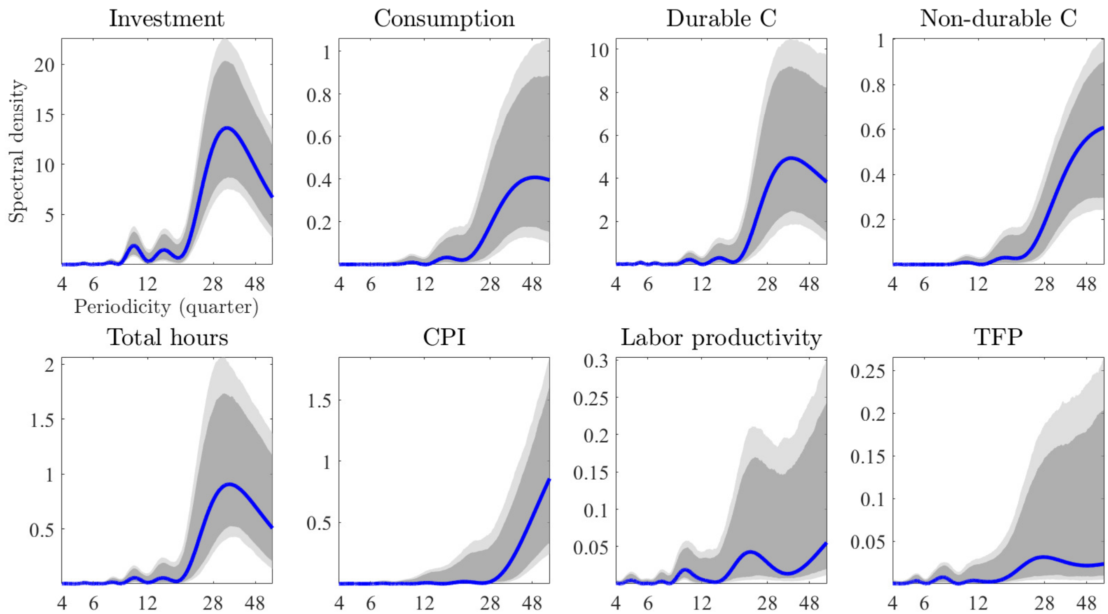
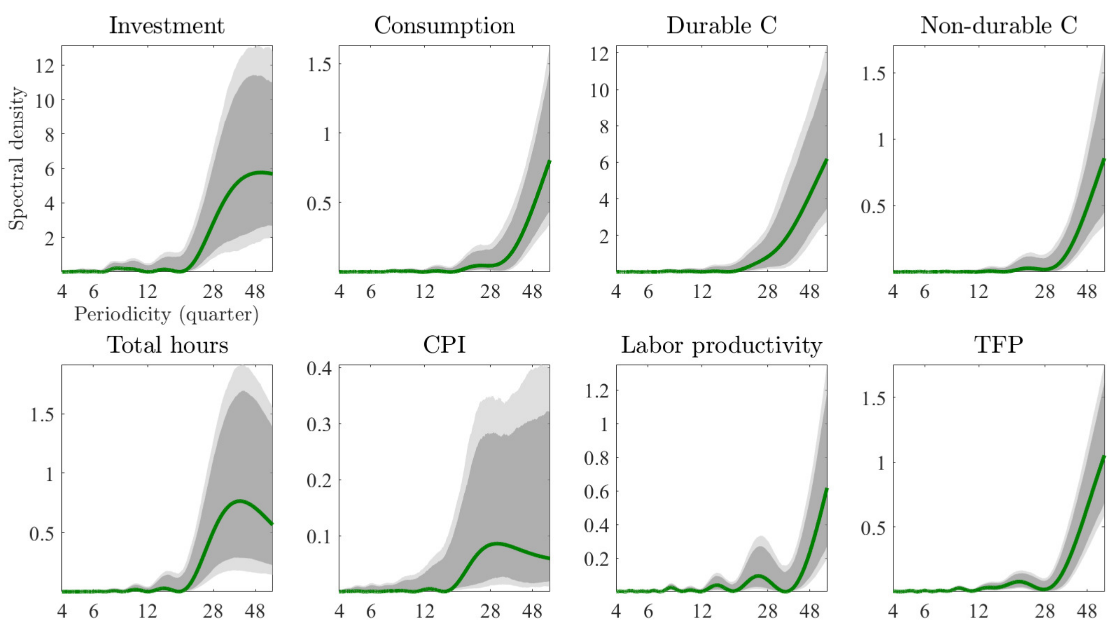


Figure 11: Spectral density of GDP conditional to sentiment and technology shocks

Note: Spectral density of real GDP conditional to sentiment 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 5. Grey solid lines represent estimates using truncation horizon from 30 to 50 quarters.



(a) Sentiment shocks



(b) Technology shocks

Figure 12: Conditional spectral density of macroeconomic variables

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

G Model Appendix

G.1 Steady state values

$$r = \beta^{-1} - 1 \tag{23}$$

$$R = 1 + r(1-\tau) \tag{24}$$

$$m = \beta \tag{25}$$

$$z = 1 \tag{26}$$

$$\mu = \frac{1}{\gamma}\left[\frac{1}{\beta R} - 1\right] \tag{27}$$

$$n = \left[\frac{1}{\alpha}(1-\mu)(1-\theta)\right]^{\frac{1}{\sigma(1-\theta)+\phi+\theta}} \tag{28}$$

$$w = \alpha n^{\sigma(1-\theta)+\phi} \tag{29}$$

$$y = z n^{1-\theta} \tag{30}$$

$$c = y \tag{31}$$

$$V = \frac{1}{\gamma\beta} y \tag{32}$$

$$d = (1-\beta)V \tag{33}$$

$$b = \left(1 - \frac{1}{R}\right)^{-1}(y - wn - d) \tag{34}$$

G.2 Loglinearized equations

$$E_t\left[\hat{m}_{t,t+1} + \hat{V}_{t+1}\right] = \hat{y}_t \tag{35}$$

$$\hat{V}_t = \frac{d}{V}\hat{d}_t + \beta E_t\left[\hat{m}_{t,t+1} + \hat{V}_{t+1}\right] \tag{36}$$

$$\frac{\mu\gamma}{1+\mu\gamma}\hat{\mu}_t + \hat{R}_t + E_t(\hat{m}_{t,t+1}) + 2\kappa d(\hat{d}_t - \hat{d}_{t+1}) = 0 \tag{37}$$

$$\hat{w}_t = \hat{z}_t - \theta\hat{n}_t - \frac{\mu}{1-\mu}\left(\hat{\mu}_t + 2\kappa d\hat{d}_t\right) \tag{38}$$

$$\hat{y}_t = \hat{c}_t \tag{39}$$

$$\hat{w}_t = \sigma \hat{c}_t + \phi \hat{n}_t \tag{40}$$

$$E_t \left[\hat{m}_{t,t+1} + \frac{R}{R-\tau} \hat{R}_t \right] = 0 \tag{41}$$

$$\hat{y}_t = \frac{wn}{y}(\hat{w}_t + \hat{n}_t) + \frac{d}{y}\hat{d}_t + \frac{B}{y}\hat{B}_t - \frac{B/R}{y}\left(\hat{B}_{t+1} - R_t\right) \tag{42}$$

$$\hat{y}_t = \hat{z}_t + (1-\theta)\hat{n}_t \tag{43}$$

$$\hat{m}_{t,t+1} = -\sigma E_t(\hat{c}_{t+1} - \hat{c}_t) \tag{44}$$

$$\hat{z}_t = \rho_z \hat{z}_{t-1} + \epsilon_t^z \tag{45}$$

$$E_t(\hat{c}_{t+1}) = \hat{c}_t + \epsilon_{t+1}^s + \psi \epsilon_{t+1}^z \tag{46}$$

G.3 Proof of Proposition 3

The moving average of consumption conditional on technology shocks is

$$\hat{c}_t = \psi \epsilon_t^z + A\epsilon_{t-1}^z + \lambda A \epsilon_{t-2}^z + \ldots$$

where $A \equiv \lambda\psi + \frac{1+\phi}{\zeta(1-\theta)}$. Then $Cov(\hat{c}_t, \hat{c}_{t-1}) = \sigma_z^2 A\left(\psi + A\frac{\lambda}{1-\lambda^2}\right)$. 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

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

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