



# Systemic risk, real GDP growth, and sentiment

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## Abstract

Using a mixed frequency VAR methodology, which can accommodate variables with different frequencies in a VAR framework, we model the relation between monthly systemic risk and real GDP growth. To identify the importance of business and consumer sentiment in this relation, a Kalman filter approach is adopted to extract the systemic risk-driven sentiment expectations. Our contributions are as follows. Systemic risk in the U.S. has a significant and negative impact on real GDP growth, and the channel of this impact is business and consumer sentiment. We illustrate that systemic risk is an important determinant of sentiment and sentiment expectations which, in turn, exercise a significant effect on GDP. These results extend previous evidence on the impact of systemic risk on *monthly* measures of economic activity, and carry implications for recent research exploring systemic risk and sentiments as factors driving the macro-economy. They also suggest that ‘offsetting’ *sentiment*-targeting policies may be adopted in order to curtail the detrimental effects of systemic risk on GDP.

**Keywords** Systemic risk · Real DP growth · Sentiment · Mixed frequency VAR · Expectations

**JEL Classification** G01 · G02 · G21 · G28 · C5

## 1 Introduction

Research on drivers of the macro-economy has recently focused on two factors, systemic risk and sentiment. Systemic risk, reflecting distress in the financial system, has been found to exercise a significant effect at the 20th percentile of the distribution of *monthly* measures of real economic activity including industrial production, the Chicago Fed National Activity Index (CFNAI) and its components (Giglio et al. 2016). A channel of this impact is through aggregate lending (Allen et al. 2012). Sentiments, *extrinsic* shocks which can drive expectations without shifts in preferences or technologies, may affect the business

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cycle as well (Angeletos and La'O 2013). Variations in sentiment have been documented to be responsible for a sizable portion of historical U.S. business cycle fluctuations (Milani 2017).

The present paper examines if systemic risk in the U.S. exercises an effect on the *quarterly* U.S. real GDP growth, and whether business and consumer sentiment is a possible mechanism through which this effect is channeled.<sup>1</sup> The justification for focusing on the *quarterly* real GDP growth, rather than the *monthly* industrial production growth, is based on the following arguments related to both systemic risk and sentiment. Firstly, systemic risk is linked with the recently developed by the IMF framework of Growth-at-Risk measured in terms of *GDP* rather than of industrial production (Prasad et al. 2019). Specifically, systemic risk generates *aggregate* financial fragility which, in turn, triggers financial crises inducing a plunge in economic activity. Growth-at-Risk aims at assessing the macro-financial risks in terms of GDP growth (Prasad et al. 2019). Secondly, systemic risk is related to the 'total credit to *GDP*' ratio, known as the 'Basel III gap', which plays a prominent role in Basel III regulations and provides *aggregate* early warning signals for banking crises (Borio and Lowe 2002; Detken et al. 2014). Indeed, the 'Basel III gap', denominated in *GDP* rather than in industrial production, reflects the impact of systemic risk on the financial fragility conditions of the *overall* economy reflected in *GDP*. In addition, banking indicators, measuring banking stability and performance, are also denominated in *GDP* rather than in industrial production: such indicators include the 'bank assets to *GDP*' and the 'bank debt to *GDP*' ratios (Langfield and Pagano 2015). Given that the 'Basel III gap' and other systemic risk related indicators are denominated in *GDP*, focusing on the quarterly *GDP* data, rather than on monthly industrial production data, is of paramount importance. Thirdly, sentiments are perceived to have medium-term or long-term impact on economic activity, further justifying the focus on the quarterly *GDP* data. Indeed, the idea that sentiment plays an important role in macro-economic activity is in line with Keynes' (1936) 'animal spirits', according to which *aggregate* economic activity may be driven by *long-run* expectations of consumers and entrepreneurs, namely by how economic agents perceive the evolution of *long-run* economic conditions. Long-run economic conditions are better approximated by quarterly real *GDP* rather than monthly industrial production data (van Aarle and Moons 2017). Lastly, several contributions on the role of sentiment on economic activity have focused on quarterly rather than monthly frequency. Specifically, Milani (2017), using a medium-scale DSGE model, has shown that sentiment is an important contributor to historical U.S. business cycle fluctuations based on quarterly *GDP* data, and Angeletos and La'O (2013), using simulations for the dynamics of the U.S. economy within a variant of the Real Business Cycle (RBC) model, worked at quarterly rather than monthly frequency.

By addressing the impact of systemic risk on real *GDP* and examining whether this impact is channeled through business and consumer sentiment, the paper contributes to the literature in the following ways. Firstly, we show that systemic risk exercises an impact on quarterly U.S. macroeconomic measures (real *GDP* growth), thereby extending previous evidence (Giglio et al. 2016; Allen et al. 2012) on *monthly* measures.<sup>2</sup> In addition, we

<sup>1</sup> Contributions have differentiated systemic financial risk, risk which triggers economic value loss, from systemic real risk, which triggers real activity loss (De Nicolo and Lucchetta 2010). Our approach focuses on systemic real risk.

<sup>2</sup> Allen et al. (2012) present evidence for *monthly* *GDP*, generating monthly *GDP* growth series by linear interpolation of quarterly nominal *GDP* data assuming a constant month-to-month *GDP* growth rate within each quarter. In the present paper, the evidence refers to the *quarterly* *GDP* using a mixed frequency esti-

extend Giglio et al. (2016) by illustrating that this impact is relevant for the *conditional mean*, rather than for the 20th percentile of the distribution of macro measures. Secondly, we reveal a *further* channel of the impact of systemic risk on the macroeconomy (GDP): this channel is sentiment. We document that systemic risk affects both business sentiment and consumer sentiment, and extract the business sentiment expectations and consumer sentiment expectations driven by systemic risk. We show that these expectations have explanatory power for GDP, suggesting that systemic risk is not only a variable watched by businesses and consumers but also a determinant of their sentiment, namely it is taken into consideration in forming expectations. These expectations, in turn, are relevant factors affecting GDP. These findings echo the conjecture that systemic risk triggers waves of optimism or pessimism to businesses and consumers, which, subsequently, impact the business cycle.

The present paper makes several contributions to the existing literature. In relation to the theoretical and empirical results in Angeletos and La'O (2013) on sentiment and the macro-economy, the present findings imply several extensions. Specifically, Angeletos and La'O (2013) develop a theory accommodating 'animal spirits' and 'market sentiment', and show that aggregate fluctuations in agents' expectations and the business cycle are affected by sentiments. In their model, sentiments are assumed to be *extrinsic*. Our findings extend the framework of *extrinsic* sentiment by showing that sentiments *can* be driven by systemic risk. Thus sentiments can be *intrinsic*, namely systemic risk-driven, rather than extrinsic assumed by Angeletos and La'O (2013). Furthermore, our findings indicate that aggregate fluctuations in expectations may be affected by *intrinsic*, systemic risk-driven, rather than extrinsic sentiments, thereby echoing that the ultimate driver of these fluctuations is systemic risk. In term of empirical results, Angeletos and La'O (2013) simulate the dynamics of the economy using a variant of the RBC model that replaces technology shocks with sentiment shocks, and show that sentiment affects employment, consumption and investment. Our empirical findings, using real data rather than simulations and a MF-VAR model accommodating quarterly real GDP growth and monthly systemic risk, reveal a strong link from systemic risk to real GDP and illustrate that this link is channeled through sentiment. In other words, we extend the empirical results of Angeletos and La'O (2013) by empirically illustrating that sentiment is an interim variable, 'receiving' the impact of systemic risk and 'exporting' this impact on to real GDP.

Our findings also provide insights for extending the theoretical results of Benhabib et al. (2017). These authors develop a model to reflect the Keynesian idea that employment and production decisions are based on consumer sentiment of aggregate demand, and that realized aggregate demand follows firms' employment and production decisions. Within this setting, Benhabib et al. (2017) illustrate that there exist *sentiment-driven* multiple rational expectations equilibria, because firms must make their decisions based on signals about aggregate demand and prior to its realisation. Our findings indicate that the sentiment, which drives the equilibria in the Benhabib et al. (2017) setting, is itself driven by systemic risk. Therefore, an interesting extension to Benhabib et al. (2017) would involve addressing whether these multiple equilibria are driven not by sentiment but by systemic risk observed by firms prior to the realization of aggregate demand.

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Footnote 2 (continued)

mation approach, rather than a linear interpolation of quarterly nominal GDP which is bound to contain interpolation errors.

A further implication relates to the literature on the relation between systemic risk and the macroeconomy (Giglio et al. 2016; Milani 2017). The present results suggest that sentiment is an in-between link in this relation. Further, in terms of the literature on the channel of the systemic risk impact, our results add a further mechanism to lending, namely sentiment. Lastly, our finding that systemic risk affects GDP through sentiment suggests that increasing systemic risk can be controlled by adopting *sentiment-targeting* offsetting measures aiming at increasing business and consumer sentiment. Such measures can neutralize the impact of systemic risk on sentiment, namely cut the link between the two (identified in the present paper) and, consequently, curtail the detrimental effects of systemic risk on real economic activity.

In the present paper, systemic risk is measured using CATFIN (Allen et al. 2012). CATFIN is an aggregate measure of systemic risk taking in the banking system, and has been found to affect monthly measures of macro-economy through the lending activity channel (Allen et al. 2012).<sup>3</sup> Business sentiment is measured using three measures, including the Institute for Supply Management's (ISM's) Purchasing Managers Index (PMI), the Leading Index (Stock and Watson 1989), and the OECD indicator for Business Tendency Surveys for manufacturing. For consumer sentiment, we consider the University of Michigan Consumer Sentiment index and the OECD indicator for Consumer Opinion Surveys. Using a mixed frequency VAR model, we show that *monthly* CATFIN exercises a strong and negative effect on *quarterly* real GDP growth, extending the Giglio et al. (2016) and Allen et al. (2012) results to a *quarterly* (rather than monthly) time framework, and the Giglio et al. (2016) results to the *conditional mean* (rather than the 20th percentile of the distribution) of real economic activity measures. Further, we document that there is a unidirectional causality running from CATFIN to all five measures of business and consumer sentiment, and that none of the sentiment measures causes CATFIN. Given this causality result, we explore if the CATFIN-driven expectations on business and consumer sentiment cause real GDP growth. We employ a Kalman filter approach to extract these expectations, and show that they are significant drivers of GDP.

The paper unfolds as follows. Section 2 provides a brief discussion of the business sentiment and the consumer sentiment indicators. Section 3 outlines the data and describes the econometric approaches employed. Section 4 reports the results. Finally, Sect. 5 concludes.

## 2 Business and consumer sentiment

Business sentiment is measured in the present paper using three measures. We firstly consider the survey-based Purchasing Managers' Index (PMI). Questionnaires on both current and *expected* business conditions and activity are sent monthly to purchasing and supply executives overseeing operations in manufacturing firms (Koenig 2002; Erik et al. 2019). The survey questions cover a broad range of future and present business conditions faced by respondent firms, including output, employment, new orders, prices, costs, backlogs of work, purchases of intermediate goods, stocks of inputs and finished goods, suppliers'

<sup>3</sup> For CATFIN, publicly available data exist for a relatively extended sample period, from 1973 to 2019.

delivery times, new and outstanding business, and expected business activity. By-and-large, PMI surveys ask whether respondent businesses are experiencing expansion or contraction across the previous range of metrics. The survey providers compile the responses of senior managers to survey questions and distil them into the PMI measure estimating the percentage of business reporting expansion (both overall and across sub-gauges) over a specific month.<sup>4</sup> The purchasing managers' index has been extensively used in the literature as a reliable indicator of business sentiment (Christiansen et al. 2014). In addition, it has attracted widespread attention from experts, investors,<sup>5</sup> and the media, and is among the most closely followed indicators of future business and economic sentiment, especially during times of economic crisis (Christiansen et al. 2014). PMI has several important features including timeliness and the breadth of its coverage, with its readings being released immediately after the end of the reference month (Erik et al. 2019).

In addition to PMI, we measure business sentiment using the Business Tendency Surveys for manufacturing in the U.S., also called the 'business climate' surveys, available on a monthly basis.<sup>6</sup> As with PMI, business tendency surveys ask company managers about the current situation of their business and about their *expectations* for the near future.<sup>7</sup> Experience has shown that such surveys provide information that is valuable to the respondents themselves and to economic policy makers. They can be used to predict changes in output, sales, investment or employment and thus, they are particularly useful for analyzing the business cycle and for reflecting business sentiment. Priority of selection of variables goes to indicators which measure an early stage of production (e.g. new orders, order books), respond rapidly to changes in economic activity (e.g. stocks), and measure expectations or are sensitive to expectations (e.g. future production plans, business climate). The variables included in the survey are not only relevant from a theoretical point of view but also in the view of the managers of the enterprises.

A third indicator considered for business sentiment is the monthly Leading Index (Stock and Watson 1989). This index predicts the six-month growth rate of the coincident index along with other variables that lead the economy. These additional variables include the housing permits, initial unemployment insurance claims, delivery times from the Institute for Supply Management (ISM) manufacturing survey, and the interest rate spread between the 10 year Treasury bond and the 3 month Treasury bill. By-and-large, the leading index is a 'portfolio' of survey-based, finance-based and broader economics-based measures.

Consumer sentiment is measured using two measures. The first is the University of Michigan Consumer Sentiment Index, an extensively used consumer survey-based index used to gauge consumer sentiment and *expectations* (Angeletos et al. 2018). This index, uncorrelated with utilization adjusted Total Factor Productivity (TFP), is known to reflect expectations on future employment and output, and is constructed on the basis of answers to qualitative questions. Angeletos et al. (2018) have argued that whilst this index co-moves

<sup>4</sup> <https://www.telegraph.co.uk/money/finser-investments-uk/purchasing-managers-indexes>.

<sup>5</sup> For example, <https://www.telegraph.co.uk/money/finser-investments-uk/purchasing-managers-indexes>. In addition, Japanese stock market investors were seeing adopting a wait-and-see approach ahead of the releases of Chinese as well as U.S. purchasing managers' index (The Japan Times News, 27 December 2019, <https://www.japantimes.co.jp/news/2019/12/27/business/financial-markets/nikkei-loses-ground-ex-dividend-impact-profit-taking/#.XjACIGzaHt>).

<sup>6</sup> OECD, Business Tendency Surveys for Manufacturing: Production: Tendency: European Commission and National Indicators for the United States [BSPRTE02USM460S], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/BSPRTE02USM460S>.

<sup>7</sup> <https://www.oecd.org/sdd/leading-indicators/31837055.pdf>

with the business cycle, this co-movement may be ‘driven by some other fundamental’.<sup>8</sup> To ensure robustness, we also consider a second measure, the OECD index for Consumer Opinion Surveys. This index, used by several empirical studies on consumer sentiment in the U.S. and other economies (United Nations 2015; Zohar 2019; Kocenda and Poghosyan 2018; Celik et al. 2010; Falagiarda and Sousa 2017; Caputo and Duch 2020), reflects consumer confidence, *expected* economic situation, and price expectations. It is based on consumer opinion survey data standardized by OECD to ensure equal smoothness and the same amplitude of cyclical movements. This index captures cyclical patterns in household consumption, and provides information on consumer sentiment based on both the general economic situation and the financial situation of the individual or family. The information collected in consumer opinion surveys is described as qualitative because respondents are asked to assign qualities (opinions), rather than quantities, to the variables of interest. Data obtained from these surveys are useful in their own right but are also used in the compilation of consumer confidence indicators.

### 3 Data and methodology

#### 3.1 Data

Quarterly real GDP growth data span the period 1973Q1–2019Q4.<sup>9</sup> For systemic risk, monthly CATFIN data are available for 1973M01–2019M12 from Turan Bali’s web site.<sup>10</sup> For business sentiment, we consider monthly data for the ISM’s Purchasing Managers Index (PMI) over the period 1973M01–2019M12 from MacroBond,<sup>11</sup> for the Leading Index over the period 1982M01–2019M12<sup>12</sup> (data availability), and for the OECD Indicator for Business Tendency Surveys for Manufacturing over the period 1973M01–2019M12.<sup>13</sup> For consumer sentiment, we use monthly data for the University of Michigan Consumer Sentiment indicator over the period 1979M01–2019M12<sup>14</sup> (data availability<sup>15</sup>), and for the

<sup>8</sup> It is shown later in the paper that this fundamental may include systemic risk.

<sup>9</sup> U.S. Bureau of Economic Analysis, Real Gross Domestic Product [GDPC1], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/GDPC1>.

<sup>10</sup> <https://sites.google.com/a/georgetown.edu/turan-bali/data-working-papers>. See also Iqbal and Vähämaa (2019), Grundke (2018), and Kanas and Zervopoulos (2020).

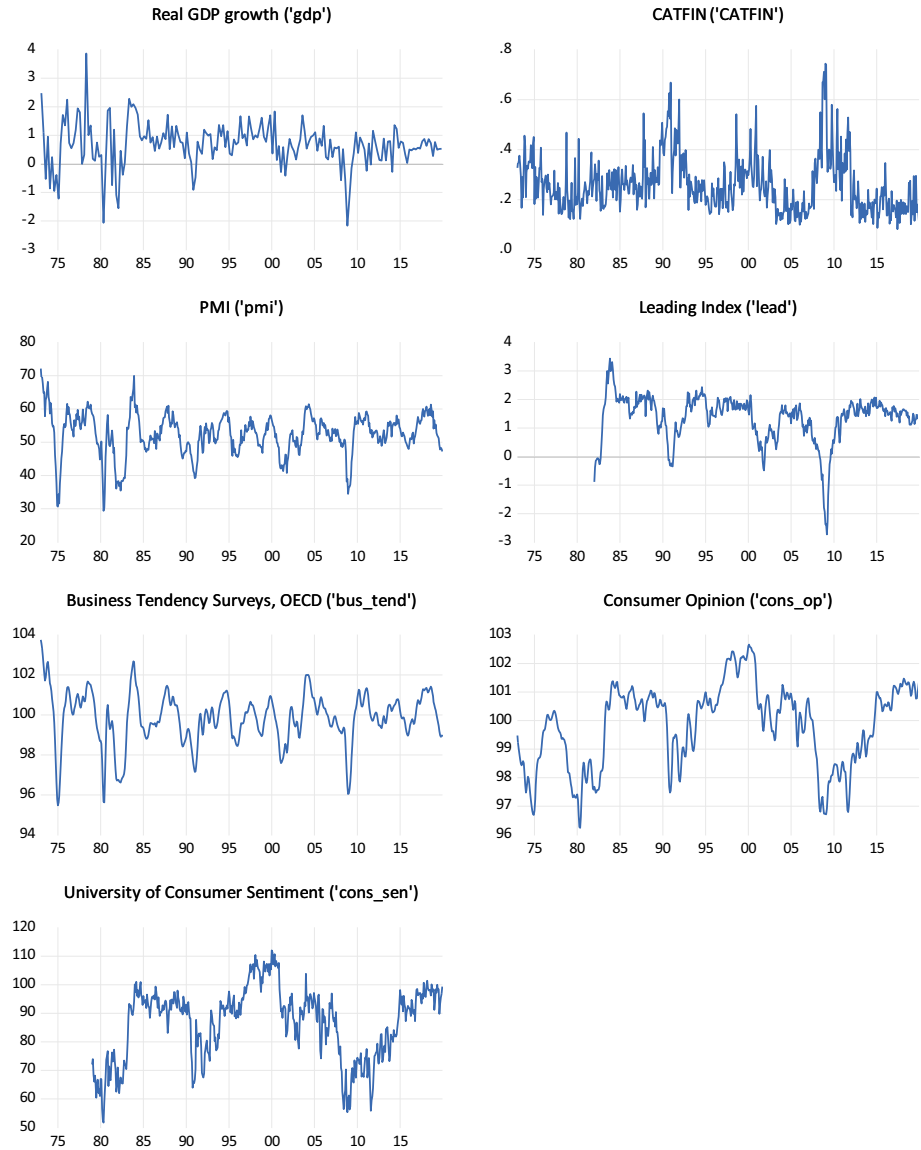
<sup>11</sup> For the last three months of 2019, from [www.investing.com](http://www.investing.com).

<sup>12</sup> Federal Reserve Bank of Philadelphia, Leading Index for the United States [USSSLIND], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/USSSLIND>.

<sup>13</sup> Organization for Economic Co-operation and Development, Business Tendency Surveys for Manufacturing: Confidence Indicators: Composite Indicators: OECD Indicator for the United States [BSCIC-P03USM665S], retrieved from FRED, Fed. Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/BSCICP03USM665S>.

<sup>14</sup> University of Michigan, University of Michigan: Consumer Sentiment [UMCSENT], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/UMCSENT>.

<sup>15</sup> Although data for this series is sporadically (not for every consecutive month) provided from 1952, they are not available on a *continuous* monthly basis until 1978. To rule out any potential inconsistencies in the early implementation of this index, we exclude the data for 1978, hence we focus on a sample starting from 1979. See also footnote 20.



**Fig. 1** Pictorial presentation of variables

OECD indicator for Consumer Opinion Surveys over the period 1973M01–2019M12.<sup>16</sup> Data series are presented in Fig. 1. Based on the KPSS unit root test, all variables are stationary. Unit root tests and descriptive statistics are reported in Table 1.

<sup>16</sup> Organization for Economic Co-operation and Development, Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: OECD Indicator for the United States [CSCICP03USM665S], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/CSCICP03USM665S>.

**Table 1** Descriptive statistics and stationarity tests

Variable	Mean	Standard deviation	KPSS stationarity test
Real GDP growth ( <i>gdp</i> )	0.68	0.63	0.20
CATFIN (CATFIN)	0.26	0.11	0.22
PMI ( <i>pmi</i> )	52.23	5.38	0.07
Leading index ( <i>lead</i> )	1.34	0.83	0.23
Business tendency surveys ( <i>bus_tend</i> )	99.82	1.13	0.07
Consumer Opinion ( <i>cons_op</i> )	100.13	1.33	0.37
University of michigan consumer sentiment ( <i>cons_sen</i> )	88.01	11.80	0.23

KPSS tests with constant. 5% critical value is 0.463 (Kwiatkowski et al. (1992) (Table 1). Null hypothesis is that of stationarity

### 3.2 Mixed frequency VAR (MF-VAR) model

In the MF-VAR model employed in this paper, we consider two frequencies of data, a monthly (high) frequency and a low (quarterly) frequency, so there are  $m=3$  high frequency periods per low frequency period. The VAR comprises of  $k_L = 1$  variable  $y_L^i$  observed at low frequency. This variable includes the quarterly real GDP growth (*gdp*). Similarly, in the VAR there is  $k_H = 1$  variable  $y_H^i$  observed at high (monthly) frequency including one of the following five sentiment measures: PMI (*pmi*), the Leading Index (*lead*), the Business Tendency Survey Index (*bus\_tend*), the University of Michigan Consumer Sentiment index (*cons\_sen*), and the Consumer Opinion Survey Index (*cons\_op*). Further, let,  $y_{L,t_L}^i$  represent the  $i$ -th low frequency variable observed during the low frequency period  $t_L$ , and  $y_{H,t_L,t}^i$  represent the  $i$ -th high frequency variable observed at the  $t$ -th high frequency period during low frequency period  $t_L$ . For example, for the real GDP growth observed at the 2nd quarter of year  $t$ , we have  $y_L^i = gdp$ , and  $y_{L,t_2}^i = gdp_{t_2}$ , and for the *pmi* observed at the 1st month of the 2nd quarter of year  $t$  we have  $y_H^i = pmi$  and  $y_{H,t_2,1}^i = pmi_{t_2,1}$ . To represent the MF-VAR, we stack the  $k_L$  and  $k_H$  variables into the matrices  $Y_L$  and  $Y_H$  respectively. The VAR is then written (ignoring the intercepts) as:

$$\begin{bmatrix} Y_{H,t_L,1} \\ Y_{H,t_L,2} \\ Y_{H,t_L,3} \\ Y_{L,t_L} \end{bmatrix} = \sum_{j=1}^p \begin{bmatrix} \Pi_j^{1,1} & \dots & \Pi_j^{1,4} \\ \vdots & \ddots & \vdots \\ \Pi_j^{4,1} & \dots & \Pi_j^{4,4} \end{bmatrix} \begin{bmatrix} Y_{H,t_L-j,1} \\ Y_{H,t_L-j,2} \\ Y_{H,t_L-j,3} \\ Y_{L,t_L-j} \end{bmatrix} + \begin{bmatrix} E_{H,t_L,1} \\ E_{H,t_L,2} \\ E_{H,t_L,3} \\ E_{L,t_L} \end{bmatrix} \tag{1}$$

where  $\Pi_j^{a,b}$  is  $k_H \times k_H$ ,  $\Pi_j^{4,b}$  is  $k_L \times k_H$ , and  $\Pi_j^{a,4}$  is  $k_H \times k_L$  for all  $j, a, b = 1, \dots, 3$ , and  $\Pi_j^{4,4}$  is  $k_L \times k_L$ . To interpret (1), for quarterly data we stack for example the months of January, February and March (of *pmi*) together with the 1st quarter of low frequency *gdp* data. Similarly, we stack April, May and June *pmi* data with the 2nd quarter *gdp* data, etc.



Estimation of (1) can be carried out using either the unrestricted MIDAS (U-MIDAS) or the Bayesian approach (Ghysels 2016). The former applies VAR least squares to estimate the stacked matrix of coefficients, denoted by  $B$  in (1), and will be the main estimation method. For robustness, we will also consider Bayesian estimation. This approach is analogous to Bayesian VAR, and requires the specification of prior distributions for  $\beta = \text{vec}(B')$  and the residual covariance matrix  $\Sigma$ . Following Ghysels (2016),  $\beta \sim N(\beta, V)$  and  $\Sigma \sim IW(\underline{S}, \bar{v})$ . These priors together with the standard likelihood of a VAR model yield conditional posteriors for  $\beta$  and  $\Sigma$ .<sup>17</sup> Granger causality tests and impulse response analysis can be carried out following the MF-VAR model U-MIDAS estimation, on the basis of Ghysels (2016).

### 3.3 Extraction of CATFIN-driven expectations using the Kalman filter (Harvey 1993)

Business and consumer sentiment reflects expectations on numerous facets of future business and economic activity. For business sentiment, for instance, such facets include output, employment, new orders, prices, costs, backlogs of work, purchases of immediate goods, stocks of inputs and finished goods, supplier's delivery times, and new and outstanding business. For consumer sentiment, such facets include household consumption, and the financial situation of the individual and the family. Each of these facets contributes to the formation of specific expectations reflected in the observed sentiment indices. For instance, views on employment contribute to the formation of employment-driven expectations, views on prices to prices-driven expectations, etc., all reflected in the business sentiment indices data. Thus, each business sentiment index is a portfolio of output-driven expectations, employment-driven expectations, and so on. Similarly, each consumer sentiment index is a portfolio containing a component of household consumption-driven expectations, a component of financial situation-driven expectations, and so on (Curtin 2007; Ludvigson 2004).

If systemic risk affects sentiment, business and consumer sentiment indices data will also contain systemic risk-driven expectations. Assuming that systemic risk is approximated by CATFIN, this implies that sentiment indices data will incorporate, in addition to other expectations, CATFIN-driven expectations as well. To explore the role of sentiments as the channel of the impact of systemic risk on real GDP, we need to recover the CATFIN-driven expectations from the sentiment indices data (which contain not only CATFIN-driven expectations but also other components of expectations i.e. output-driven expectations, employment-driven expectations, etc.). In other words, if CATFIN affects the observed business and consumer sentiment indices, we need to extract the specific component of CATFIN-driven expectations from those indices. The methodology for extracting CATFIN-driven expectations is discussed below.

Let  $y_t$  be the  $n \times 1$  vector of the dependent variable (*pmi*, or *lead*, or *bus\_tend*, or *cons\_sen*, or *cons\_op*) and  $x_t$  be the independent variable CATFIN. The classical linear regression model is.

$$y_t = x_t' \beta + e_t \quad (2)$$

<sup>17</sup> For more technical details, Ghysels (2016).

As all five observable sentiment measures contain information not only on current but also on *expected* economic conditions, we extract expectations under the assumption that these were driven by CATFIN. Based on the Granger causality results, we treat CATFIN (=  $x_t$ ) as the independent variable, and wish to extract expectations for the dependent sentiment variable (=  $y_t$ ). A state space representation of the dynamics of  $y_t$  is given by the system of signal (measurement) and state (transition) equations:

$$y_t = Z_t a_t + c_t + \varepsilon_t \text{ (signal equation)} \tag{3}$$

$$a_{t+1} = d_t + T_t a_t + u_t \text{ (state equation)} \tag{4}$$

where  $a_t$  is the  $m \times 1$  state vector,  $c_t, Z_t, d_t, T_t$  are conformable vectors and matrices, and  $\varepsilon_t, u_t$  are vectors of mean zero and Gaussian disturbances, with contemporaneous variance structure:

$$\Omega_t = \begin{bmatrix} H_t & G_t \\ G_t' & Q_t \end{bmatrix} \tag{5}$$

where  $H_t$  is an  $n \times n$  symmetric variance matrix,  $Q_t$  is an  $m \times m$  symmetric variance matrix, and  $G_t$  is an  $n \times m$  matrix of co-variances. The above specification can be generalized by setting  $Z_t = x_t, a_t = \beta$ . The state equation is  $a_t = a_{t-1}$ . Recursive estimation of (3) can be carried out using recursive least squares which can be regarded as an application of Kalman filter (Harvey 1993). If an estimator of  $\beta$  in (2) has been calculated using the first  $(n - 1)$  observations, the  $n$ -th observation may be used to construct a new estimator without inverting a cross-product matrix as implied by a direct use of the OLS formula. This is done by means of formulae recursive updating.<sup>18</sup> Assuming that  $x_t = \tilde{x}_1, \dots, \tilde{x}_n$ , then

$$b_t = b_{t-1} + (x_t' x_{t-1})^{-1} \tilde{x}_n (y_t - \tilde{x}_n' b_{t-1}) / f_t \tag{6}$$

where  $f_t = 1 + \tilde{x}_n' (x_{t-1}' x_{t-1})^{-1} \tilde{x}_n$ .

Based on the above, and assuming that  $y_t = pmi$  and  $x_t = CATFIN$ , one extract the CATFIN-driven (conditional) expectations of  $pmi$  by calculating the one-step ahead expectation of  $y_t, E_{t-1}(y_t)$ , using:

$$E_{t-1}(y_t) = E(y_t | b_{t|t-1}) = c_t + x_t b_{t|t-1} \tag{7}$$

Similarly, we extract the CATFIN-driven (conditional) expectations of *lead* if  $x_t = lead$ , of *cons\_sen* if  $x_t = cons\_sen$ , of *cons\_op* if  $x_t = cons\_op$ , and of *bus\_tend* if  $x_t = bus\_tend$ .

<sup>18</sup> The recursive least squares updating formulae can be derived using the inversion lemma given in Appendix B of Harvey (1993). For technical details, see Harvey (1993, pages 82–100, and Appendix B).

**Table 2** CATFIN and real GDP growth (*gdp*): unrestricted MIDAS estimation

	CATFIN_1	CATFIN_2	CATFIN_3	<i>gdp</i>
CATFIN_1(-1)	-0.08 [-0.88]	-0.05 [-0.63]	0.16 [1.74]	-0.48 [-0.63]
CATFIN_1(-2)	0.03 [0.35]	0.16* [1.98]	0.19 [2.11]	0.43 [0.56]
CATFIN_2(-1)	0.10 [0.97]	0.27* [2.82]	-0.06 [-0.53]	0.23 [0.25]
CATFIN_2(-2)	0.04 [0.38]	-0.10 [-1.01]	0.11 [1.04]	-0.58 [-0.65]
CATFIN_3(-1)	0.44* [5.00]	0.24* [2.94]	0.49* [5.36]	-1.89* [-2.52]
CATFIN_3(-2)	0.09 [1.00]	0.23* [2.57]	0.05 [0.46]	0.74 [0.92]
<i>gdp</i> (-1)	-0.01 [-1.64]	-0.01 [-1.66]	0.00 [0.20]	0.28* [3.70]
<i>gdp</i> (-2)	0.02* [2.29]	0.02 [2.05]	0.01 [0.76]	0.09 [1.25]
C	0.09* [3.81]	0.06* [2.98]	0.03 [1.37]	0.822* [4.22]
Adj. R-squared	0.43	0.52	0.49	0.21

\*denotes statistical significance at the 5% level. CATFIN\_1 refers to the first month of the quarter, CATFIN\_2 to the second month, and CATFIN\_3 to the third. CATFIN\_1(-1) is the first month of the previous (lagged, denoted by '(-1)') quarter. For example, if the reference quarter is the 1st quarter of 2000, CATFIN\_1 refers to January 2000, and CATFIN\_1(-1) refers to October of 1999 (i.e. the first month of the 4th quarter of 1999)

**Table 3** VAR Granger causality (Block exogeneity) Wald tests

Causality from:	Chi-square	df	Probability
Causality to: <i>gdp</i>			
CATFIN_1	0.785888	2	0.6751
CATFIN_2	0.442117	2	0.8017
CATFIN_3	6.467269	2	0.0394*
All	15.01357	6	0.0202*

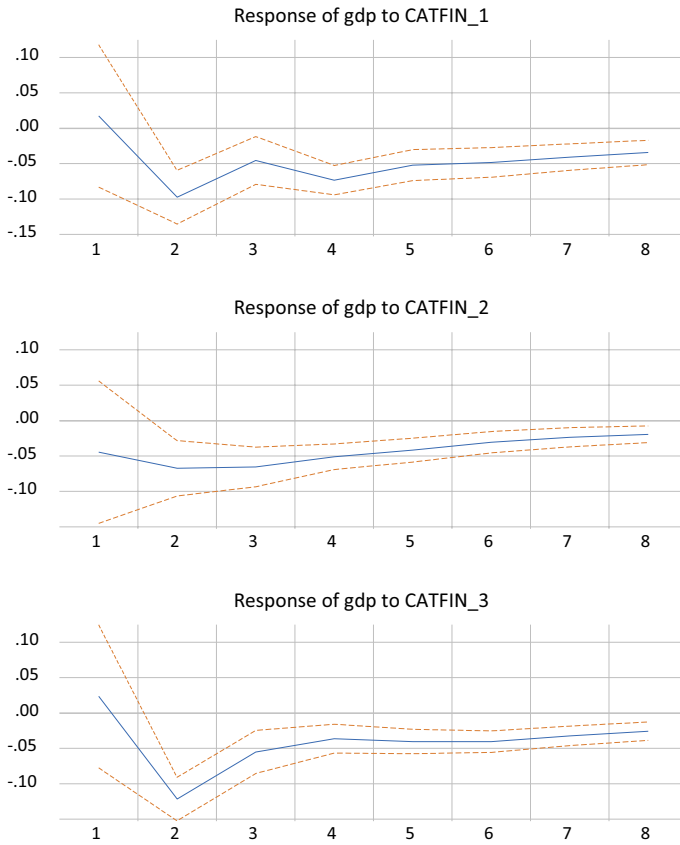
df denotes degrees of freedom

\*denotes significance at the 5% level

## 4 Empirical findings

### 4.1 Systemic risk and real GDP growth

We start by estimating a baseline mixed frequency VAR model including the monthly CATFIN and the quarterly real GDP growth (*gdp*), as reflected in (1). Table 2 reports the results based on the U-MIDAS approach. For the estimation, CATFIN is transformed into



**Fig. 2** Impulse response of real GDP growth (*gdp*) based on the MF-VAR model. Response to Cholesky one SD (degrees of freedom adjusted) innovations  $\pm 2$  standard errors. CATFIN\_1 is the first month of the quarter, CATFIN\_2 is the second month, and CATFIN\_3 is the third

three separate variables, one variable for each month in the quarter. In Table 2, CATFIN\_1 is the variable for the first month of the quarter, CATFIN\_2 is for the second month, and CATFIN\_3 is for the third month. In line with the discussion of the MF-VAR model in (1), CATFIN\_1, CATFIN\_2, and CATFIN\_3 appear as endogenous variables along with the real GDP growth. Further, CATFIN\_1(-1) refers to the first month of the previous (lagged, denoted by '(-1)') quarter. For example, if the reference quarter is the 1st quarter of 2000, CATFIN\_1 refers to January 2000, and CATFIN\_1(-1) refers to October of 1999 (i.e. the first month of the 4th quarter of 1999).

As shown in Table 2, CATFIN\_3(-1) exercises a statistically significant and negative effect on *gdp*, as its coefficient in the *gdp* equation is  $-1.89$  with a t-statistic of  $-2.52$ . This suggests that an increase in CATFIN in the third month of the current quarter (CATFIN\_3 (-1)) entails a decrease in *gdp* in the following quarter. This finding extends the

**Table 4** CATFIN and real GDP growth (*gdp*): Bayesian estimation

	CATFIN_1	CATFIN_2	CATFIN_3	<i>gdp</i>
CATFIN_1(-1)	-0.08 (0.08)	-0.05 (0.08)	0.16 (0.09)	-0.40 (0.59)
CATFIN_1(-2)	0.03 (0.08)	0.16 (0.08)	0.20 (0.09)	0.28 (0.68)
CATFIN_2(-1)	0.10 (0.10)	0.28 (0.10)	-0.05 (0.11)	-0.14 (0.64)
CATFIN_2(-2)	0.04 (0.10)	-0.10 (0.09)	0.11 (0.11)	-0.38 (0.77)
CATFIN_3(-1)	0.44 (0.08)	0.23 (0.08)	0.49 (0.09)	-1.30 (0.57)
CATFIN_3(-2)	0.09 (0.09)	0.23 (0.09)	-0.05 (0.10)	0.44 (0.71)
<i>gdp</i> (-1)	-0.01 (0.01)	-0.01 (0.01)	-0.02 (0.01)	0.27 (0.07)
<i>gdp</i> (-2)	0.02 (0.01)	0.02 (0.01)	0.01 (0.01)	0.09 (0.07)
C	0.09 (0.02)	0.06 (0.02)	0.03 (0.02)	0.81 (0.19)
Adj. R-squared	0.43	0.51	0.49	0.20

CATFIN\_1 refers to the first month of the quarter, CATFIN\_2 to the second month of the quarter, and CATFIN\_3 to the third month. CATFIN\_1(-1) is the first month of the previous (lagged, denoted by '(-1)') quarter. For example, if the reference quarter is the 1st quarter of 2000, CATFIN\_1 refers to January 2000, and CATFIN\_1(-1) refers to October of 1999 (i.e. the first month of the 4th quarter of 1999)

evidence by Giglio et al. (2016) on *monthly* macroeconomic variables. Further, this effect is found for the *conditional mean* of *gdp*, thereby offering a further extension to Giglio et al.'s (2016) results on the *20th percentile* of distribution of monthly macro variables.

To explore further the effect of CATFIN on *gdp*, Granger causality (block exogeneity) tests are carried out, both for each monthly CATFIN variable individually and for the block of (all three) CATFIN variables (CATFIN\_1, CATFIN\_2, CATFIN\_3). The results are reported in Table 3. The tests suggest that there is Granger causality from CATFIN\_3 to *gdp* (Chi-square statistic = 6.47, with a marginal probability of 0.039). Similarly, all three CATFIN\_1, CATFIN\_2 and CATFIN\_3 variables Granger cause *gdp* (Chi-square statistic = 15.01, with a marginal probability of 0.02). We finally look at the impulse response of *gdp* to CATFIN. Figure 2 presents the results. As shown in this Figure, the response of *gdp* to each monthly CATFIN shock is statistically significant and takes longer than 2 years to disappear. These results provide strong support to the conclusion that CATFIN is a significant driver of *gdp*.

**Table 5** Bivariate VAR models comprising of CATFIN and each of the five sentiment measures (y)

	y = pmi		y = lead		y = bus_tend		y = cons_op		y = cons_sen	
	CATFIN	y	CATFIN	y	CATFIN	y	CATFIN	y	CATFIN	y
CATFIN(-1)	0.55* (13.19)	-4.44* (-3.84)	0.55* (11.88)	-0.43* (-3.15)	0.54* (13.06)	-0.30* (-4.01)	0.53* (12.57)	-0.30* (-4.14)	0.56* (12.59)	-10.30* (-4.70)
CATFIN(-2)	0.23* (5.52)	0.73 (0.62)	0.22* (4.62)	-0.06 (-0.48)	0.22* (5.35)	0.12 (1.53)	0.22* (5.26)	0.33* (4.52)	0.23* (5.11)	4.77* (2.17)
y(-1)	0.00 (1.05)	1.03* (24.46)	-0.00 (-0.03)	0.96* (20.40)	-0.00 (-0.15)	1.80* (84.38)	-0.02 (-1.56)	1.75* (62.67)	0.00 (0.96)	0.90* (19.74)
y(-2)	-0.00 (-1.11)	-0.12* (-2.91)	-0.01 (-0.59)	-0.04 (-0.77)	0.00 (0.06)	-0.85* (-40.70)	0.02 (1.46)	-0.76* (-27.73)	-0.00 (-1.01)	0.04 (0.99)
C	0.06 (1.88)	5.66* (6.37)	0.07* (5.01)	0.24* (5.46)	0.17 (0.65)	5.04* (10.46)	0.26 (1.08)	1.74* (4.15)	0.06 (1.93)	6.39* (4.42)
Adj R-sq	0.52		0.57		0.52		0.52		0.55	

t—statistics in parentheses

\* denotes statistical significance at the 5% level

**Table 6** Bivariate Granger causality tests based on the bivariate VAR models in Table 5

Null hypothesis:	Obs	F-Statistic	Prob
1. CATFIN and <i>pmi</i>			
<i>pmi</i> does not granger cause CATFIN	562	0.61	0.54
CATFIN does not Granger Cause <i>pmi</i>		11.10	0.00*
2. CATFIN and <i>lead</i>			
<i>lead</i> does not granger cause CATFIN	454	1.99	0.13
CATFIN does not granger cause <i>lead</i>		11.29	0.00*
3. CATFIN and <i>bus_tend</i>			
<i>bus_tend</i> does not granger cause CATFIN	562	0.09	0.91
CATFIN does not granger cause <i>bus_tend</i>		9.25	0.00*
4. CATFIN and <i>cons_op</i>			
<i>cons_op</i> does not granger cause CATFIN	562	1.39	0.25
CATFIN does not granger cause <i>cons_op</i>		11.45	0.00*
5. CATFIN and <i>cons_sen</i>			
<i>cons_sen</i> does not granger cause CATFIN	490	0.51	0.5986
CATFIN does not granger cause <i>cons_sen</i>		12.17	0.00*

\*denotes rejection of the null at the 5% level. A lag length of 2 was used

To assess whether the results in Table 2 are robust to alternative estimation approaches, the MF-VAR model is estimated using the Bayesian approach. The results are reported in Table 4. As shown in this Table, the results are qualitatively similar to those in Table 2. Thus, the significant and negative effect of CATFIN on *gdp* is robust to alternative estimation methods.

## 4.2 Systemic risk, and business and consumer sentiment

We next focus on the relation between CATFIN and each of the five business and consumer sentiment indices, namely *pmi*, *lead*, *bus\_tend*, *cons\_op*, and *cons\_sen*, using bivariate (monthly) VARs. We estimate five bivariate VARs, one VAR for each pair, namely CATFIN-*pmi*, CATFIN-*lead*, CATFIN-*bus\_tend*, CATFIN-*cons\_op*, and CATFIN-*cons\_sen*.<sup>19</sup> On the basis of these VARs, Granger causality tests are conducted, following Barone-Adesi et al. (2012, pp. 21–22) who used similar tests for the relation between systemic risk and *financial* sentiment of investors within financial markets. Table 5 reports the results.

As shown in Table 5, in each VAR the coefficient of the lagged CATFIN in the sentiment equation is negative and statistically significant. For instance, for the ( $y =$ ) *pmi* VAR, the lagged CATFIN coefficient in the *pmi* equation is  $-4.44$  with a t-statistic of  $-3.84$ . Similarly, for the ( $y =$ ) *lead* VAR, the lagged CATFIN coefficient is  $-0.43$  (t-statistic =  $-3.15$ ), for the ( $y =$ ) *bus\_tend* VAR, the coefficient is  $-0.30$  (t-statistic =  $-4.01$ ), for the ( $y =$ ) *cons\_op* VAR, it is  $-0.30$  (t-statistic =  $-4.14$ ), and for the ( $y =$ ) *cons\_sen* VAR, it is  $-10.30$  (t-statistic =  $-4.70$ ).<sup>20</sup> Importantly, none of the coefficients of the sentiment variables is

<sup>19</sup> In all bivariate VARs, a lag length of 2 is considered.

<sup>20</sup> If we consider 1978 as the start of the sample for this series (see footnote 15), the results are qualitatively similar with those reported here. Indeed, the estimated coefficient is  $-9.76$  with a t-statistic of  $-4.52$ .

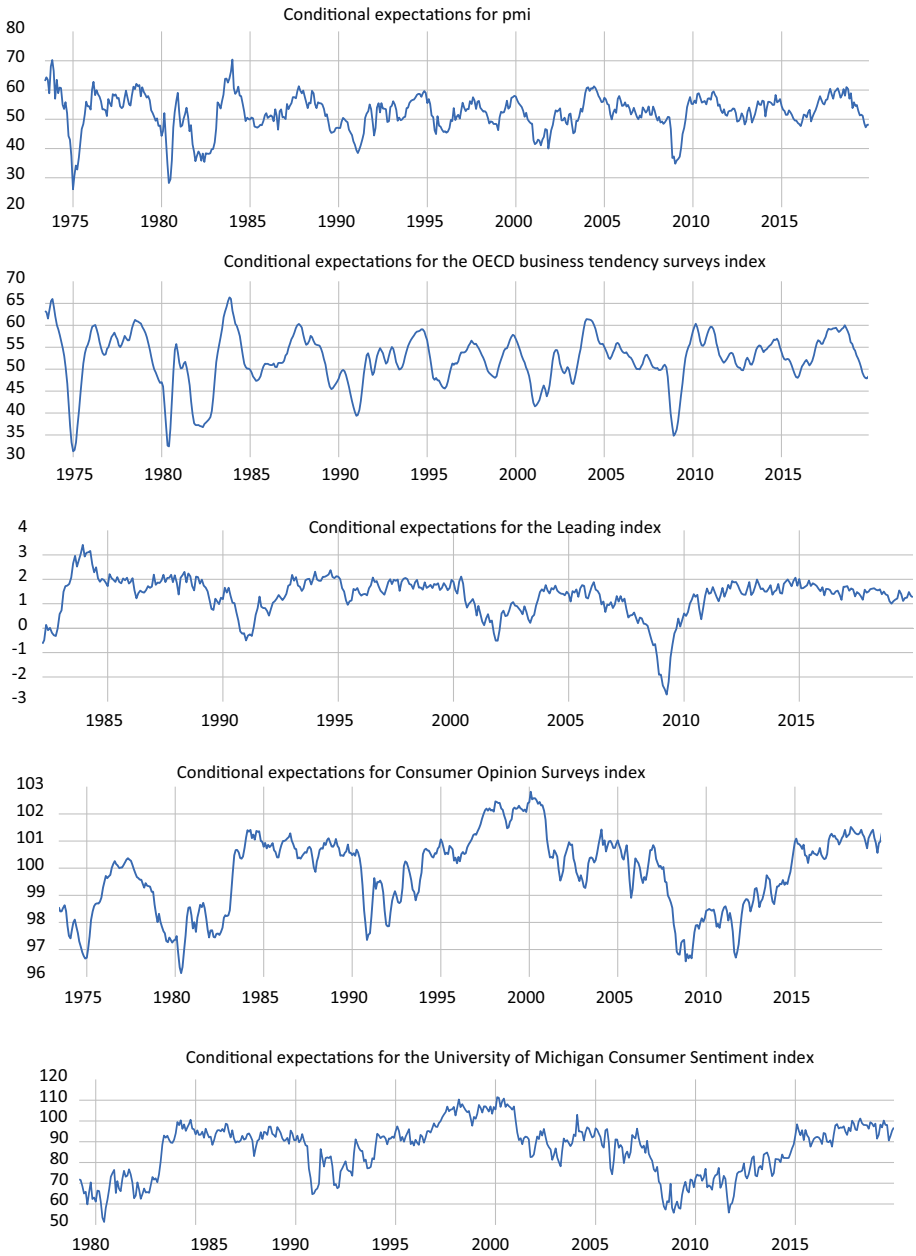


Fig. 3 Sentiment expectations driven by CATFIN (Conditional expectations)



**Table 7** MF-VAR model estimation for quarterly real GDP growth (*gdp*) and monthly CATFIN-driven *pmi* expectations (*pmi\_exp*)

	<i>pmi_exp_1</i>	<i>pmi_exp_2</i>	<i>pmi_exp_3</i>	<i>gdp</i>
<i>pmi_exp_1(-1)</i>	0.13 [1.18]	0.17 [1.17]	0.12 [0.65]	0.01 [0.24]
<i>pmi_exp_1(-2)</i>	0.01 [0.08]	0.03 [0.30]	0.03 [0.26]	0.00 [0.08]
<i>pmi_exp_2(-1)</i>	-0.19 [-1.55]	0.00 [0.00]	-0.15 [-0.76]	-0.04 [-1.24]
<i>pmi_exp_2(-2)</i>	0.02 [0.15]	-0.00 [-0.02]	-0.12 [-0.58]	0.01 [0.46]
<i>pmi_exp_3(-1)</i>	1.07* [11.85]	0.71* [5.92]	0.69* [4.69]	0.06* [2.51]
<i>pmi_exp_3(-2)</i>	-0.14 [-1.12]	-0.14 [-0.88]	0.00 [0.01]	-0.04 [-1.27]
<i>gdp(-1)</i>	0.30 [0.92]	0.98 [2.26]	1.26* [2.38]	0.21* [2.49]
<i>gdp(-2)</i>	0.38 [1.17]	-0.15 [-0.33]	0.10 [0.19]	0.18* [2.13]
C	5.19* [2.26]	11.25* [3.65]	21.57* [5.76]	0.35 [0.58]
Adj. R-squared	0.84	0.69	0.51	0.18

\*denotes statistical significance at the 5% level. *pmi\_exp\_1* refers to the *pmi* expectations for the first month of the quarter, *pmi\_exp\_2* refers to the *pmi* expectations for the second month of the quarter, and *pmi\_exp\_3* refers to the *pmi* expectations for the third month of the quarter. *pmi\_exp\_1(-1)* refers to the first month of the previous (lagged, denoted by '(-1)') quarter, *pmi\_exp\_1(-2)* refers to the first month of the 2<sup>nd</sup> quarterly lag (2<sup>nd</sup> quarterly lag, denoted by '(-2)')

significant in any VAR. This result suggests that the causality runs *from* CATFIN *to* business and consumer sentiment, and not the opposite way.

To shed further light on this conclusion, we carry out Granger causality tests on the basis of the previous bivariate VARs (Barone-Adesi 2012). The results are reported in Table 6. In all cases, there is a strongly significant (at the 1% level) Granger causality effect from CATFIN to all sentiment measures. Further, none of the sentiment measures Granger causes CATFIN. Therefore, we conclude that CATFIN is a driver of business and consumer sentiment: firms and consumers watch CATFIN-mirrored systemic risk, and their expectations on future economic conditions are formed using CATFIN as input, i.e. they are CATFIN-driven.

**Table 8** MF-VAR model estimation for quarterly real GDP growth (*gdp*) and monthly CATFIN-driven leading index expectations (*lead\_exp*)

	<i>lead_exp_1</i>	<i>lead_exp_2</i>	<i>lead_exp_3</i>	<i>gdp</i>
<i>lead_exp_1(-1)</i>	-0.09 [-0.97]	-0.12 [-0.87]	-0.11 [-0.61]	-0.18 [-0.55]
<i>lead_exp_1(-2)</i>	-0.06 [-1.01]	0.13 [1.40]	0.10 [0.90]	-0.22 [-1.00]
<i>lead_exp_2(-1)</i>	-0.13 [-1.49]	-0.28* [-2.05]	-0.08 [-0.47]	-0.15 [-0.49]
<i>lead_exp_2(-2)</i>	-0.22* [-2.56]	-0.42* [-3.09]	-0.10 [-0.63]	0.05 [0.16]
<i>lead_exp_3(-1)</i>	1.08* [16.51]	1.17* [11.51]	1.07* [8.75]	0.56* [2.42]
<i>lead_exp_3(-2)</i>	0.39* [3.84]	0.46 [2.92]	0.02 [0.10]	0.12 [0.34]
<i>gdp(-1)</i>	0.01 [0.60]	0.03 [0.78]	0.02 [0.55]	0.17* [2.17]
<i>gdp(-2)</i>	0.01 [0.62]	-0.02 [-0.59]	-0.04 [-1.01]	0.07 [0.94]
<i>C</i>	0.01 [0.58]	0.06 [1.59]	0.11* [2.49]	0.29* [3.42]
Adj. R-squared	0.95	0.89	0.83	0.20

\*denotes statistical significance at the 5% level. *lead\_exp\_1* refers to the *lead* expectations for the first month of the quarter, *lead\_exp\_2* refers to the *lead* expectations for the second month of the quarter, and *lead\_exp\_3* refers to the *lead* expectations for the third month of the quarter. *lead\_exp\_1(-1)* refers to the first month of the previous (lagged, denoted by ‘(-1)’) quarter, *lead\_exp\_1(-2)* refers to the first month of the 2nd quarterly lag (2nd quarterly lag, denoted by ‘(-2)’) quarter.

### 4.3 CATFIN- driven sentiment expectations and real GDP growth

As all five observable sentiment measures contain information not only on current but also on *expected* economic conditions, we extract these expectations assuming that these were driven by CATFIN. Given that all sentiment measures are Granger caused by CATFIN whilst none causes CATFIN, we treat CATFIN as the independent (driver) variable, and extract expectations for the dependent sentiment variable using (3–4). In terms of the state space representation in (3–4), we set each of the sentiment measures as the dependent variable ( $y_t$ ), and CATFIN as the exogenous variable ( $x_t$ ). On the basis of (5) and (7), we obtain the (conditional) expectations for *pmi*, *bus\_tend*, and *lead* that firms would form if they used CATFIN as input in the process of expectations formation. Similarly, we obtain the expectations for *cons\_op*, and *cons\_sen* that consumers would form if CATFIN was an input variable in their expectations formation. The

**Table 9** MF-VAR model estimation for quarterly real GDP growth (*gdp*) and monthly CATFIN-driven business tendency survey expectations (*bus\_tend\_exp*)

	<i>bus_tend_exp_1</i>	<i>bus_tend_exp_2</i>	<i>bus_tend_exp_3</i>	<i>gdp</i>
<i>bus_tend_exp_1(-1)</i>	-0.11 [-0.62]	-0.07 [-0.18]	-0.09 [-0.14]	-0.23 [-1.29]
<i>bus_tend_exp_1(-2)</i>	-0.06 [-6.53]	-0.09 [-4.93]	-0.16 [-5.13]	0.01 [1.39]
<i>bus_tend_exp_2(-1)</i>	-1.49* [-9.79]	-3.19* [-9.32]	-4.23* [-7.31]	-0.31* [-1.97]
<i>bus_tend_exp_2(-2)</i>	-0.14* [-2.09]	-0.57* [-3.93]	-0.93* [-3.80]	-0.28* [-4.23]
<i>bus_tend_exp_3(-1)</i>	2.20 * [34.70]	3.32* [23.32]	3.90* [16.17]	0.33* [5.16]
<i>bus_tend_exp_3(-2)</i>	0.55* [3.85]	1.49* [4.60]	2.29* [4.19]	0.50* [3.40]
<i>gdp(-1)</i>	0.05 [0.66]	0.06 [0.34]	0.15 [0.55]	0.06 [0.89]
<i>gdp(-2)</i>	-0.02 [-0.35]	-0.045 [-0.30]	-0.11 [-0.40]	0.18* [2.44]
<i>C</i>	2.02* [4.00]	6.27* [5.53]	12.14* [6.33]	-0.72 [-1.40]
Adj. R-squared	0.99	0.96	0.87	0.42

\*denotes statistical significance at the 5% level. *bus\_tend\_exp\_1* refers to the *bus\_tend* expectations for the first month of the quarter, *bus\_tend\_exp\_2* refers to the *bus\_tend* expectations for the second month of the quarter, and *bus\_tend\_exp\_3* refers to the *bus\_tend* expectations for the third month of the quarter. *bus\_tend\_exp\_1(-1)* refers to the first month of the previous (lagged, denoted by '(-1)') quarter, *bus\_tend\_exp\_1(-2)* refers to the first month of the 2nd quarterly lag (2nd quarterly lag, denoted by '(-2)')

five expectations series are pictorially presented in Fig. 3. As the sentiment series are monthly, the so obtained expectations series are also monthly.

We next use each of these expectations series to estimate five bivariate MF-VAR models (using the U-MIDAS approach), with each model including the quarterly *gdp* and one monthly expectations series. The results are reported in Tables 7 (for *pmi* expectations, *pmi\_exp*), 8 (for *lead* expectations, *lead\_exp*), 9 (for *bus\_tend* expectations, *bus\_tend\_exp*), 10 (for *cons\_op* expectations, *cons\_op\_exp*), and 11 (for *cons\_sen* expectations, *cons\_sen\_exp*). In all Tables, there is a statistically significant effect from lagged expectations to *gdp*. Most significant effects arise from the expectations of the 1st and the 3rd month in the previous quarter (*pmi\_exp\_3(-1)*, *lead\_exp\_3(-1)*, *cons\_op\_3(-1)*, *cons\_sen\_1(-1)*).

To provide further evidence on the impact of CATFIN-driven sentiment expectations on *gdp*, Granger causality tests are conducted using the MF-VAR models estimated in Tables 7, 8, 9, 10 and 11. The results are reported in Table 5, Panels A–E. In line with the previous result, there is strong evidence that these expectations Granger cause *gdp*.<sup>21</sup>

<sup>21</sup> The CATFIN-driven expectations for *cons\_sen* Granger cause *gdp* at the 10% level.

**Table 10** MF-VAR model estimation for quarterly real GDP growth (*gdp*) and monthly CATFIN-driven consumer opinion survey expectations (*cons\_op\_exp*)

	<i>cons_op_exp_1</i>	<i>cons_op_exp_2</i>	<i>cons_op_exp_3</i>	<i>gdp</i>
<i>cons_op_exp_1(-1)</i>	-0.61* [-5.91]	-0.27 [-1.51]	-0.40 [-1.49]	0.40 [1.12]
<i>cons_op_exp_1(-2)</i>	-0.03* [-2.58]	-0.03 [-1.46]	-0.04 [-1.23]	0.07 [1.85]
<i>cons_op_exp_2(-1)</i>	-0.28* [-2.62]	-1.07* [-5.70]	-1.09* [-3.86]	-0.60 [-1.63]
<i>cons_op_exp_2(-2)</i>	-0.01 [-0.10]	-0.05 [-0.31]	-0.13 [-0.58]	-0.20 [-0.71]
<i>cons_op_exp_3(-1)</i>	1.50* [24.33]	1.90* [17.55]	1.78* [10.95]	0.72* [3.40]
<i>cons_op_exp_3(-2)</i>	0.41* [3.20]	0.48* [2.16]	0.81* [2.42]	-0.27 [-0.61]
<i>gdp(-1)</i>	0.00 [0.17]	0.06 [1.45]	0.09 [1.62]	0.18* [2.40]
<i>gdp(-2)</i>	0.01 [0.25]	-0.02 [-0.51]	-0.06 [-1.04]	0.11 [1.44]
<i>C</i>	1.74 [1.45]	3.60 [1.70]	6.91* [2.19]	-11.49* [-2.78]
Adj. R-squared	0.98	0.95	0.88	0.28

\*denotes statistical significance at the 5% level. *cons\_op\_exp\_1* refers to the *cons\_op* expectations for the first month of the quarter, *cons\_op\_exp\_2* refers to the *cons\_op* expectations for the second month of the quarter, and *cons\_op\_exp\_3* refers to the *cons\_op* expectations for the third month of the quarter. *cons\_op\_exp\_1(-1)* refers to the first month of the previous (lagged, denoted by '(-1)') quarter, *cons\_op\_exp\_1(-2)* refers to the first month of the 2nd quarterly lag (2nd quarterly lag, denoted by '(-2)')

Further, we look at *gdp* impulse responses, based on the MF-VARs in Tables 7, 8, 9, 10 and 11. These are graphically presented in Fig. 4. This Figure depicts the *gdp* response to each expectations series. The graphs in Fig. 4 further support the previous finding on the role of CATFIN-based expectations in driving *gdp*. By-and-large, these findings suggest that CATFIN produces 'waves of sentiment ('optimism or pessimism') which, in turn, affect *gdp*. This conclusion extends the previous finding that CATFIN impacts the macroeconomy through aggregate lending (Allen et al. 2012): CATFIN affects real economic activity *not only* through lending *but also* through sentiment (Table 12).

**Table 11** MF-VAR model estimation for quarterly real GDP growth (*gdp*) and monthly CATFIN-driven consumer sentiment survey expectations (*cons\_sen\_exp*)

	<i>cons_sen_exp_1</i>	<i>cons_sen_exp_2</i>	<i>cons_sen_exp_3</i>	<i>gdp</i>
<i>cons_sen_exp_1(-1)</i>	-0.03 [-0.38]	0.05 [0.29]	0.11 [0.61]	0.03* [1.96]
<i>cons_sen_exp_1(-2)</i>	0.05 [1.17]	0.10 [1.16]	0.04 [0.48]	-0.01 [-1.11]
<i>cons_sen_exp_2(-1)</i>	-0.13 [-1.43]	-0.15 [-0.83]	-0.24 [-1.21]	-0.03 [-1.61]
<i>cons_sen_exp_2(-2)</i>	0.18 [1.87]	0.19 [1.02]	0.18 [0.88]	0.00 [0.21]
<i>cons_sen_exp_3(-1)</i>	1.05* [12.36]	0.99* [5.91]	1.01* [5.62]	0.03 [1.88]
<i>cons_sen_exp_3(-2)</i>	-0.12 [-1.03]	-0.22 [-0.94]	-0.14 [-0.58]	-0.03 [-1.21]
<i>gdp(-1)</i>	-0.08 [-0.22]	0.784 [1.05]	0.78 [0.98]	0.27* [3.61]
<i>gdp(-2)</i>	-0.16 [-0.42]	0.02 [0.03]	0.04 [0.05]	0.13 [1.82]
<i>C</i>	1.08 [1.47]	3.29* [2.27]	3.49* [2.25]	0.31* [2.13]
Adj. R-squared	0.99	0.95	0.94	0.18

\*denotes statistical significance at the 5% level. *cons\_sen\_exp\_1* refers to the *cons\_sen* expectations for the first month of the quarter, *cons\_sen\_exp\_2* refers to the *cons\_sen* expectations for the second month of the quarter, and *cons\_sen\_exp\_3* refers to the *cons\_sen* expectations for the third month of the quarter. *cons\_sen\_exp\_1(-1)* refers to the first month of the previous (lagged, denoted by '(-1)') quarter, *cons\_sen\_exp\_1(-2)* refers to the first month of the 2nd quarterly lag (2nd quarterly lag, denoted by '(-2)')

Our findings extend the framework of *extrinsic* sentiment of Angeletos and La'O (2013), by showing that sentiment *can* be driven by systemic risk and thus, systemic risk has an important role in sentiment formation. Our findings show that sentiments can be *intrinsic*, namely systemic risk driven. Intrinsic sentiments can in turn affect aggregate demand fluctuations, thereby echoing that the ultimate driver of these fluctuations is systemic risk. Our findings also extend the results of Benhabib et al. (2017) who illustrate that there exist *sentiment driven* multiple rational expectations equilibria, because firms must make their decisions based on signals about aggregate demand and prior to its realization. Our findings indicate that the sentiment, which drives the equilibria in the Benhabib et al. (2017) setting, is itself driven by systemic risk. An interesting extension to Benhabib et al. (2017)

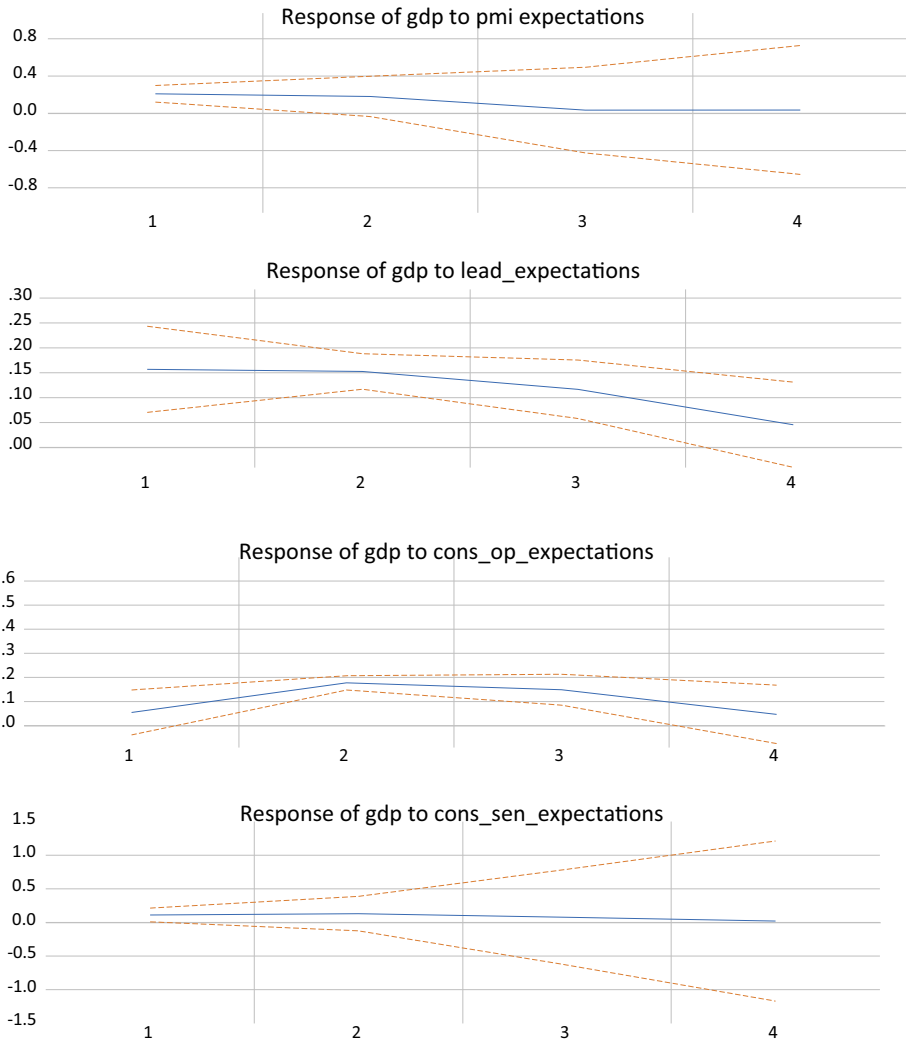
**Table 12** Granger causality (Block exogeneity) tests based on the MF-VAR models in Tables 7, 8, 9, 10 and 11

Causality from:	Chi-square	df	Probability
A. Causality to: <i>gdp</i>			
<i>pmi_exp_1</i>	0.06	2	0.97
<i>pmi_exp_2</i>	1.61	2	0.45
<i>pmi_exp_3</i>	7.52	2	0.02*
All	10.25	6	0.11
B. Causality to: <i>gdp</i>			
<i>lead_exp_1</i>	1.29	2	0.53
<i>lead_exp_2</i>	0.30	2	0.86
<i>lead_exp_3</i>	6.14	2	0.04*
All	14.41	6	0.02*
C. Causality to: <i>gdp</i>			
<i>bus_tend_exp_1</i>	3.64	2	0.16
<i>bus_tend_exp_2</i>	20.74	2	0.00*
<i>bus_tend_exp_3</i>	37.94	2	0.00*
All	88.41	6	0.00*
D. Causality to: <i>gdp</i>			
Causality from:	Chi-square	df	Probability
<i>cons_op_exp_1</i>	3.83	2	0.15
<i>cons_op_exp_2</i>	2.67	2	0.26
<i>cons_op_exp_3</i>	15.29	2	0.00*
All	36.10	6	0.00*
E. Causality to: <i>gdp</i>			
<i>cons_sen_exp_1</i>	4.69	2	0.09 <sup>n</sup>
<i>cons_sen_exp_2</i>	2.61	2	0.27
<i>cons_sen_exp_3</i>	4.63	2	0.09 <sup>n</sup>
All	8.67	6	0.19

n denotes significance at the 10% level

\*denotes significance at the 5% level

model would thus involve exploring whether these multiple equilibria are driven by systemic risk. Furthermore, in terms of the literature on the relation between systemic risk and the macro-economy (Giglio et al. 2016; Milani 2017), the present results add a new dimension by showing that sentiments is an intermediate link in this relation. Lastly, our findings suggest that in order to avoid the detrimental macroeconomic effects of systemic risk measures targeting at increasing business and consumer sentiment may be adopted. Such measures can neutralize the impact of systemic risk on business and consumer sentiment, namely cut the link between the two (identified in the present paper) and consequently curtail the detrimental effects of systemic risk on the real economic activity.



**Fig. 4** Impulse response of real GDP growth ( $gdp$ ) to sentiment expectations. Response to Cholesky one SD (degrees of freedom adjusted)  $\pm 2$  standard errors. Conditional expectations formed at month 3 in each quarter

## 5 Conclusion

The present paper has shown that systemic risk, reflecting distress in the financial system, can affect not only financial sentiment but also business and consumer sentiment and, through the latter, the real GDP growth. It illustrates that the monthly CATFIN measure of systemic risk exercises a negative effect on the conditional mean of real GDP growth. It also shows that CATFIN Granger causes business and consumer sentiment, and is an important driver of sentiment expectations by firms, consumers and households. We extract these sentiment expectations, and show that they exercise a significant impact on GDP.

Thus, we reveal that a *further* mechanism through which CATFIN affects the macro-economy, in addition to aggregate lending documented by Allen et al. (2012), is business and consumer sentiment. This result carries important implications for the literature exploring sentiment and systemic risk as drivers for GDP.

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