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Are consumer sentiment shocks state-dependent?☆,☆☆

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ABSTRACT

This paper examines the effects of sentiment shocks on economic conditions, with an emphasis on the roles of uncertainty and state dependence, using monthly U.S. data from 1997 to 2024. We first show that Economic Policy Uncertainty (EPU) Granger-causes consumer confidence. Building on this result, we construct a sentiment shock as the innovation in consumer confidence that is orthogonal to EPU and news, ensuring that it captures unexpected movements in sentiment. This orthogonalized shock is then used as an external instrument in a Vector Autoregressive (VAR) Local Projection (VAR-LP) framework. Linear VAR–LP estimates indicate that a sentiment shock leads to modest increases in output and capacity utilization, along with a temporary rise in inflation, while providing no robust evidence of a systematic monetary policy response. Extending the analysis to a state-dependent setting shows that the effects of sentiment shocks are stronger and more immediate during periods of elevated uncertainty, whereas responses in low-uncertainty states are muted and often statistically indistinguishable from zero. Overall, the results suggest that the influence of consumer sentiment on the business cycle is amplified during episodes of heightened uncertainty.

1. Introduction

Consumer confidence is widely monitored as an indicator of economic conditions and is often viewed as a potential driver of business-cycle fluctuations. Periods of heightened economic uncertainty pose a particular challenge for policymakers, as expectations can shift rapidly in response to news, narratives, and policy signals. In this context, consumer confidence is closely linked to households' expectations about economic conditions. This paper addresses this question by studying how the macroeconomic effects of consumer sentiment shocks vary across states of Economic Policy Uncertainty (EPU).

In this context, the literature is commonly divided into two broad perspectives. One perspective — the non-fundamental view — dating back to Keynes (1936)—emphasizes that sentiment may also reflect changes in beliefs, narratives, or attitudes that are not tightly linked to contemporaneous fundamentals. Recent work by Shiller (2020) highlights how narratives and psychological

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factors can propagate sentiment independently of standard economic indicators. While these perspectives differ in interpretation, both imply that the macroeconomic effects of sentiment are unlikely to be uniform over time. The fundamental view argues that sentiment primarily reflects information about current and expected economic conditions and therefore contains little independent causal content. This interpretation is emphasized by Barsky and Sims (2012) and Blanchard et al. (2013), who argue that innovations in confidence largely capture news about future fundamentals, particularly productivity. Under this view, movements in sentiment are largely driven by economic news rather than autonomous shifts in beliefs.

An important dimension that has received comparatively little attention is the role of economic uncertainty in conditioning the transmission of sentiment shocks. EPU, introduced by Baker et al. (2016), captures uncertainty surrounding fiscal, monetary, and regulatory policy and has been shown to influence investment, consumption, asset prices, unemployment, and consumer confidence (e.g., Bloom, 2009; Kang et al., 2014; Caggiano et al., 2014; Ginn, 2023). This paper addresses this gap by analyzing how EPU not only influences consumer sentiment but also conditions its macroeconomic effects. In doing so, our analysis builds on the influential contributions of Barsky and Sims (2012) and Blanchard et al. (2013), who interpret sentiment innovations primarily as news about future productivity. While productivity-related news is an important driver of expectations, such an information set may be too narrow to capture the broader, high-frequency news environment faced by households. Productivity is a supply-side concept, closely tied to technological change, and its effects materialize primarily through output, while productivity data are available only at low frequency and with non-trivial publication lags.[1] By contrast, consumers form expectations using timely and salient information about current economic conditions and policy uncertainty, which is reflected in monthly measures such as EPU. Our analysis is also closely related to the recent work of Boeck et al. (2025), who show that sentiment shocks affect economic activity only when forecasters' disagreement is high, but have negligible effects when disagreement is low. In their New Keynesian framework, disagreement arises from dispersed information and amplifies the role of sentiment by limiting agents' ability to infer fundamentals. Our findings are complementary to this mechanism: rather than focusing on cross-sectional disagreement among professional forecasters, we study EPU as a state variable capturing uncertainty about the policy environment faced by households and firms. Elevated EPU plausibly coincides with greater informational frictions and heterogeneous beliefs, creating conditions under which sentiment shocks are more likely to translate into real economic adjustments. From this perspective, our state-dependent evidence suggests that sentiment matters most in environments characterized by heightened uncertainty and limited informational clarity, consistent with the disagreement-based amplification mechanism emphasized by Boeck et al. (2025).

Drawing on real options theory (Bernanke, 1983), we argue that uncertainty can alter the adjustment margins available to firms and households. Elevated uncertainty increases the option value of waiting (Bloom, 2009), leading economic agents to postpone investment and hiring decisions and to operate below potential. This behavior generates economic slack in the form of lower capacity utilization and a negative output gap. In such environments, a positive sentiment shock may have relatively strong short-run effects by activating previously idle resources. Conversely, during periods of low uncertainty — when the economy operates closer to potential — the same sentiment shock is likely to produce weaker or delayed responses. This mechanism is closely related to the "vulnerability paradox" described by Hallegatte and Ghil (2008). Accordingly, Hallegatte and Ghil (2008) posit that economies in recession — characterized by idle resources and lower employment — are more resilient to disasters than booming economies where capacity is fully utilized. Empirical findings by Ginn (2022) lend support to the "vulnerability paradox" for the US economy. We extend this line of reasoning to sentiment shocks: in high-EPU states, slack in the economy may enable a larger response when expectations shift. Conversely, in low-EPU periods, the economy may already be operating near potential, muting the effect of sentiment.

Motivated by these considerations, this paper examines whether EPU conditions the macroeconomic transmission of consumer sentiment shocks. Using monthly U.S. data from September 1997 to November 2024, we first document a Granger-causal relationship running from EPU to consumer confidence. Building on this result, we construct an externally identified sentiment shock as the component of consumer confidence innovations that is orthogonal to both policy uncertainty and news heard. To do so, we extract residuals from both Generalized Method of Moments (GMM) and Vector Autoregressive (VAR) specifications and combine them using principal component analysis, yielding a parsimonious measure of unexpected sentiment.

We then trace the macroeconomic effects of this sentiment shock using a VAR Local Projection (VAR–LP) framework (Jordà, 2005). In a linear specification that averages across states, sentiment shocks are associated with modest and transitory increases in capacity utilization and a temporary narrowing of the output gap, while the interest rate response is statistically insignificant. These average effects suggest that sentiment shocks have limited relevance on economic conditions.

The central contribution of the paper is to extend the analysis to a state-dependent VAR–LP model in which the propagation of sentiment shocks varies across states of economic uncertainty. A novel feature of our approach is a two-step identification strategy: first, we orthogonalize sentiment shocks with respect to EPU and news. Second, we then condition the analysis on a continuous transition function based on a one-sided Kalman-filtered measure of EPU. This design ensures that the uncertainty state is predetermined and allows impulse responses to differ across high- and low-uncertainty states without relying on ad hoc regime classifications. The estimated impulse responses suggest that sentiment shocks generate stronger and more immediate increases in capacity utilization and the output gap during periods of elevated uncertainty, whereas responses in low-uncertainty states are muted and often statistically indistinguishable from zero. Overall, the findings imply that sentiment shocks are unlikely to warrant a systematic monetary policy response, given their transitory and state-contingent nature. However, during periods of elevated

[1] Labor productivity (output per hour) for all workers (FRED mnemonic OPHPBS) is reported on a quarterly basis, with a delay of slightly more than two months.

uncertainty — when economic slack is greater — sentiment may nonetheless provide useful information about short-run fluctuations in real activity.

The remainder of the paper is organized as follows. Section 2 describes the data and Section 3 outlines the empirical methodology. Section 4 concludes.

2. Data

The sample consists of monthly U.S. data from 1997:09 to 2024:12, with the start date determined by the availability of the Global Supply Chain Pressure Index (GSCPI). The choice of variables follows the objective of capturing the main channels through which consumer sentiment and uncertainty affect macroeconomic conditions. Because consumer confidence and uncertainty can respond rapidly to shifts in news and economic conditions, monthly data are particularly appropriate for our analysis. Quarterly data may risk smoothing out these potentially short-lived fluctuations and attenuating the very mechanism — sentiment–uncertainty interactions that may unfold rapidly — that our framework seeks to capture.

Real activity is measured by industrial production, and the output gap is computed via the HP filter. Capacity utilization (TCU) is included to capture resource slack, which is, as we will later show, central to interpreting state dependence in the transmission of sentiment shocks. Prices are proxied by the aggregate consumer price index (CPI), complemented by the 1-year inflation expectations series. Monetary policy is captured by the federal funds rate in the baseline specification. We also consider the shadow interest rate (Wu and Xia, 2016) in robustness checks.

We define *sentiment* as unexpected shifts in households' economic outlook that are not fully explained by economic fundamentals. Sentiment therefore reflects changes in optimism or pessimism about current and future economic conditions. We use the University of Michigan Consumer Sentiment Index (MCSI), a widely used survey-based measure of consumer sentiment that has been shown to be particularly informative for expectations-driven consumption behavior (e.g., Carroll et al., 1994; Barsky and Sims, 2012; Starr, 2012).[2] In our empirical framework, sentiment is measured using the MCSI, and sentiment innovations are identified as the residual component of changes in consumer sentiment that is orthogonal to the University of Michigan news heard series and economic policy uncertainty, thereby capturing unexpected shifts in households' beliefs rather than changes driven by fundamentals or the information environment.

We define *uncertainty* as the degree of ambiguity and unpredictability surrounding future economic and policy outcomes. Unlike sentiment, which captures the direction of expectations, uncertainty reflects the reliability of the economic environment and affects behavior through precautionary savings, real-options effects, and delayed investment decisions (Bernanke, 1983; Bloom, 2009; Baker et al., 2016). To account for macroeconomic uncertainty, we use the EPU index, which does not correspond to a specific forecast horizon (Baker et al., 2016). The EPU index is available at both daily and monthly frequencies and is constructed from the frequency of newspaper articles that reference policy-related uncertainty, including discussions of economic policy uncertainty, tax code expirations, and federal spending.[3] We complement this measure with two forward-looking indicators: the 1-month-ahead JLN macroeconomic uncertainty index (Jurado et al., 2015) and the 1-month-ahead LMN financial uncertainty index (Ludvigson et al., 2021).[4]

The MCSI is a survey-based, forward-looking indicator that measures how consumers feel about their personal finances, buying conditions for durables, and the overall economy. We summarize the core questions used to construct the Index of Consumer Sentiment for both the web-based and telephone survey questionnaires in Table 1.[5] The index is released in two stages each month: a preliminary report and a final report, typically around the end of the month. The preliminary reading is based on approximately 400 interviews, although the exact number may vary depending on interview schedules. The final reading incorporates a larger sample, typically reflects approximately 1000 completed interviews each month.[6] The preliminary index is based on an early subset of responses collected during the initial part of the survey window, while the final index incorporates all interviews received up to the official sampling cutoff for that month. In our empirical analysis, we employ the final monthly Consumer Sentiment Index, which reflects information aggregated over the full available survey window and is therefore consistent with a monthly frequency framework.

The GSCPI is obtained from (Benigno et al., 2022)[7] and is included due to its relevance in capturing global supply-chain disruptions that affect inflation. Real equity prices are constructed by deflating the S&P 500 index by CPI.

All growth variables are expressed as the log-difference percentage multiplied by 100. The data is summarized in Table 2. Fig. 1 plots the economic data.

[2] The Conference Board's Consumer Confidence Index is a widely used alternative.

[3] The daily series is mnemonic USEPUINDXD, while the monthly series is USEPUINDXM for the United States.

[4] Other commonly used uncertainty measures include forecast disagreement based on the Survey of Professional Forecasters and financial market volatility (VIX).

[5] See https://data.sca.isr.umich.edu/survey-info.php.

[6] The survey employs a simple random sampling design drawn from a comprehensive list of all postal addresses in the 48 coterminous U.S. states and the District of Columbia, ensuring that the resulting sample is nationally representative.

[7] GSCPI is calculated using a combination of various indicators that reflect the state of global supply chain conditions. It incorporates data on shipping costs, freight rates, inventory levels and delays (Benigno et al., 2022). High (low) values of the GSCPI indicate significant disruptions (stable conditions) in global supply chains.

Table 1
Core questions of the index of consumer sentiment.

Item	Survey question
Q1	We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?
Q2	Now looking ahead—do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?
Q3	Now turning to business conditions in the country as a whole—do you think that during the next 12 months we will have good times financially, or bad times, or what?
Q4	Looking ahead, which would you say is more likely—that in the country as a whole we will have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression, or what?
Q5	About the big things people buy for their homes—such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?

Table 2
Variable Selection.

Item	Symbol	Source	Description (Mnemonic)
Output	$\ln Y_t$	FRED	U.S. Industrial Production (INDPRO)
Unemployment Rate	U_t	FRED	Unemployment Rate (UNRATE)
Consumption	$\ln C_t$	FRED	Personal Consumption Expenditures (PCE)
Aggregate CPI	$\ln P_t$	FRED	CPI: All items (CPIAUCSL)
Expected Inflation	$\pi_t^{E,1Y}$	FRED	U.S. 1-Year Expected Inflation (EXPINF1YR)
Interest Rate	R_t	FRED	Short-term interest rate (FEDFUNDS)
Shadow Rate	R_t^{Shadow}	Wu and Xia (2016)	U.S. Shadow Interest Rate
Capacity Utilization	TCU_t	FRED	U.S. TCU (TCU)
Consumer Sentiment	$\ln MCSI_t$	FRED	Consumer Sentiment for the U.S. (UMCSENT)
Supply Chain Pressure	$GSCPI_t$	NY Fed	GSCPI (Benigno et al., 2022)
Policy Uncertainty	$\ln EPU_t$	FRED	U.S. EPU (USEPUINDXM)
Macroeconomic Uncertainty	$\ln(1+U_t^{JLN})$	FRED	JLN 1-Month Macroeconomic Uncertainty (JLNUM1M)
Financial Uncertainty	$\ln(1+U_t^{LMN})$	FRED	LMN 1-Month Financial Uncertainty (LMNUF1M)
News	$News_t$	UMICH	News Heard of Recent Changes in Business Conditions
Real Equity Returns (S&P500)	$\Delta \ln E_t$	FRED	Real Equity Returns (SP500)

3. Methodology and results

Our empirical strategy consists of constructing a sentiment shock that captures the portion of consumer confidence orthogonal to observable economic drivers and tracing its macroeconomic effects through both linear and non-linear VAR-LP. The approach is carried out in three steps. First, we construct a sentiment shock as the innovation in MCSI that is orthogonal to EPU and news, ensuring that the resulting series captures unexpected movements in sentiment. This orthogonalized sentiment shock is then used as an external shock in the subsequent VAR-LP models. Second, we estimate a linear VAR-LP model to analyze how the external sentiment shock affects economic conditions. Third, we estimate a state-dependent VAR-LP model to examine how the transmission of the external sentiment shock varies across high- and low-uncertainty periods, as defined by EPU.

Each step is discussed in turn.

3.1. Determinants of consumer confidence

To construct the sentiment shock used in the empirical analysis, we begin by estimating innovations in consumer confidence after accounting for the influence of news and EPU. Because our objective is to isolate shocks to confidence that are not driven by these observables, it is important to assess whether news and EPU contain predictive information for movements in sentiment. We therefore analyze Granger-causality relationships among the three variables to understand their dynamic interactions and to guide the specification of the models used to extract confidence innovations. On this basis, we estimate residual movements in MCSI using both a GMM framework and a VAR model that condition on news and EPU. To obtain a unified sentiment disturbance, we standardize the resulting innovations and extract the principal component analysis (PCA), which serves as our external sentiment shock.

Utilizing a GMM model, we estimate MCSI using three model variants considered based on the combination of using the University of Michigan's News Heard data and EPU data as explanatory variables to estimate consumer sentiment (MCSI).

(Starr, 2012) finds a positive relationship between news heard and consumer confidence. Fig. 2 plots fluctuations of news heard items in business condition over the sample period, decomposed by category. For the majority of the sample periods, news about employment is the main topic considered for favorable and non-favorable news, where prices have been a source of negative news during the post pandemic period, mainly due to global supply chain pressures (Benigno et al., 2022). There is a notable increase in negative sentiment during recessionary periods.

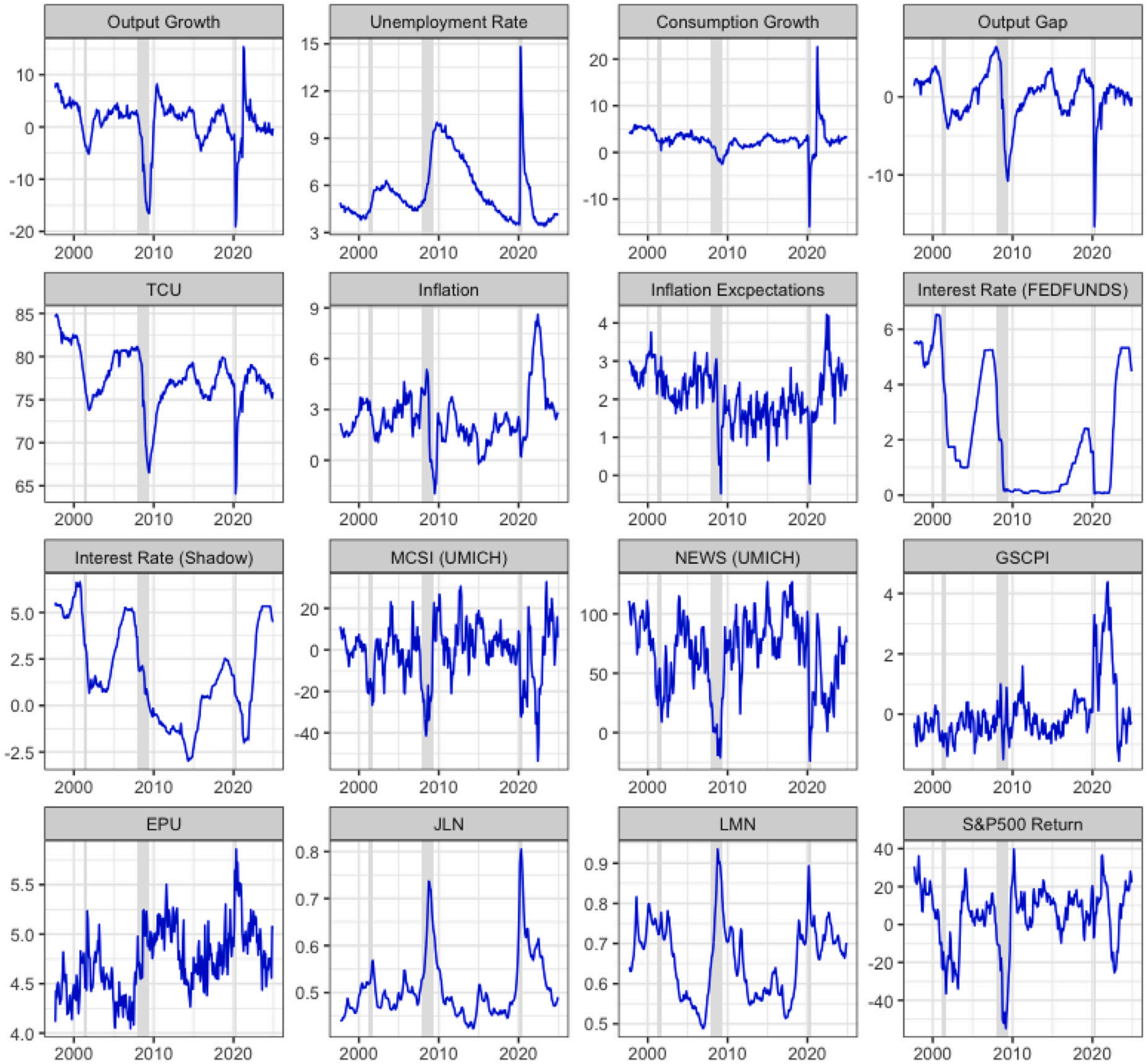

Fig. 1. Economic data.
Shaded areas indicate NBER recession dates. 'MCSI (UMICH)' is the University of Michigan MCSI; 'NEWS (UMICH)' is the University of Michigan news heard; 'GSCPI' is global supply chain pressure index; 'EPU' is Economic Policy Uncertainty; 'JLN' is Macroeconomic Uncertainty; 'LMN' is Financial Uncertainty. See Table 2 for further details. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The rationale and one of the novelties of the paper for including EPU as a control augments the model to account for the broader economic conditions and uncertainty (e.g., fiscal, monetary, trade policies) in a parsimonious manner, where the residuals reflect deviations from fundamentals. Rooj et al. (2024) demonstrate that EPU has a negative and significant impact on MCSI. EPU has an established empirical relationship with key macroeconomic indicators, including output growth, inflation and the interest rate (Bloom, 2009; Baker et al., 2016; Hailemariam et al., 2019; Ginn, 2022; Dufrénot et al., 2024a,b). We further test the causal relationship between News and EPU as it relates to MCSI. We use the final monthly release of the MCSI.[8] The Granger causality tests presented in Table 3 for up to six lags. Accordingly, we find that news heard ($News_t$) Granger causes consumer confidence ($\Delta \ln MCSI_t$) for lags two and three, where we find that consumer confidence Granger-causes News for all lags considered. We also find that EPU Granger causes consumer confidence for all lags except the first lag, whereas there is no statistical relationship in reverse.

[8] The survey is conducted throughout the month, with the final estimate incorporating both early- and late-month interviews. The index therefore reflects information available during most of month.

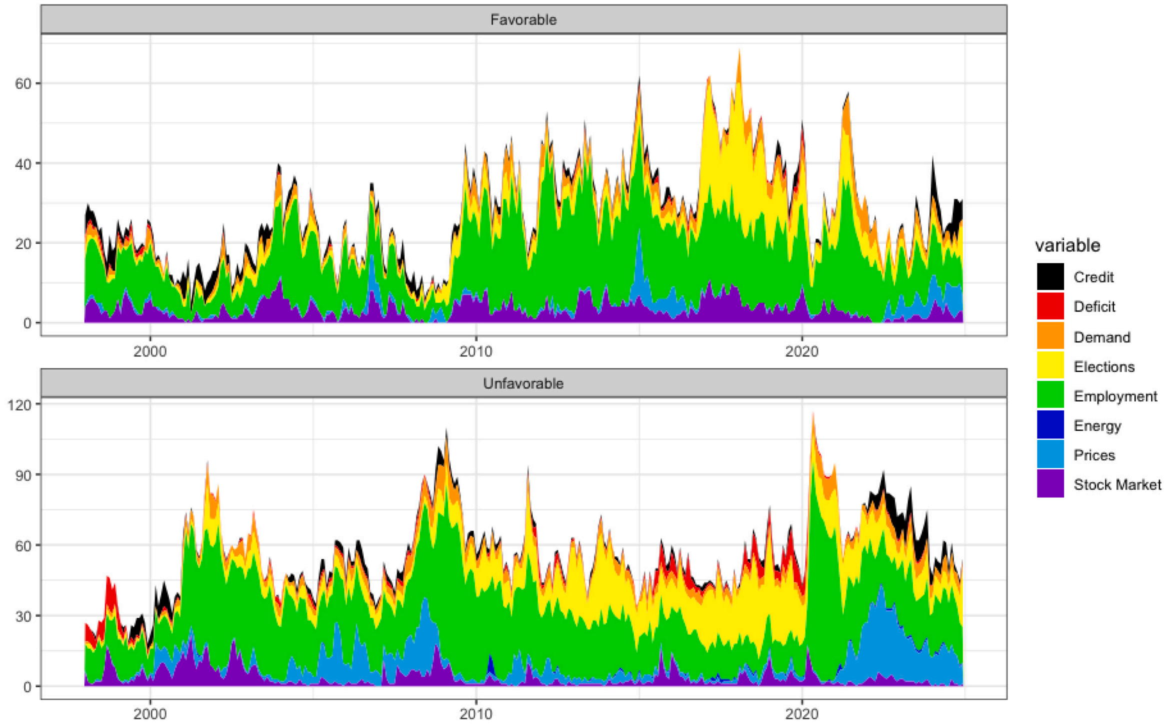

Fig. 2. News items heard in business conditions. *Source:* University of Michigan, news items heard of recent changes in business conditions (Table 24). Favorable and unfavorable news categories are decomposed by topic.

Table 3
Granger test.

Null Hypothesis	Metric	Lag length					
		1	2	3	4	5	6
$\Delta \ln MCSI_t$ does not Granger cause $News_t$	F-Stat.	3.027	2.427	2.935	3.038	2.665	2.360
	p-value	0.083*	0.090*	0.034**	0.018**	0.022*	0.030*
$News_t$ does not Granger cause $\Delta \ln MCSI_t$	F-Stat.	1.474	2.788	2.310	1.775	1.638	1.543
	p-value	0.226	0.063*	0.076*	0.134	0.150	0.164
$\Delta \ln MCSI_t$ does not Granger cause $\Delta \ln EPU_t$	F-Stat.	1.092	0.640	0.556	0.346	0.409	0.426
	p-value	0.297	0.528	0.644	0.847	0.843	0.862
$\Delta \ln EPU_t$ does not Granger cause $\Delta \ln MCSI_t$	F-Stat.	7.728	6.103	4.115	3.374	3.239	3.094
	p-value	0.006***	0.003***	0.007***	0.011**	0.007***	0.006***

Note: the Table reports the p-value from the Granger test. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Given the potential bidirectional causality between the variables, we use the GMM framework to address potential endogeneity concerns.[9] The GMM model for MCSI is specified as follows:

$$\Delta \ln MCSI_t = \alpha + \beta^T x_t + \rho \Delta \ln MCSI_{t-1} + B(L)\Theta_t + u_t \tag{1}$$

where x_t is a vector of two control variables based on two model variants. The first model (Model 1) includes news heard ($News_t$). Model 2 replaces news with EPU ($\Delta \ln EPU_t$). Model 3 is an extension to include news and EPU. The model also includes an intercept (α), a vector of lagged control variables (Θ_t) and an error term (u_t), with the lag operator ($B(L)$) set to 1.

The GMM regression results for MCSI are summarized in Table 4. We observe that news heard (EPU) has a positive (negative) relationship with MCSI. Models 1 indicates that relative news heard has a positive impact on consumer confidence. Models 2 indicates

[9] Unlike Ordinary Least Squares, which assumes the exogeneity of explanatory variables, GMM allows for the use of lagged control variables, thereby providing more reliable estimates by accounting for endogeneity.

Table 4
GMM regression for consumer sentiment.

		Model 1	Model 2	Model 3
(Intercept)	α	-7.271^{***}	-0.183	-6.000^{***}
		(1.146)	(0.418)	(1.126)
News Heard	β_{News}	0.102^{***}		0.084^{***}
		(0.016)		(0.015)
Autoregressive Term	ρ	0.698^{***}	0.786^{***}	0.669^{***}
		(0.036)	(0.041)	(0.035)
$\Delta \ln EPU$	β_{EPU}		-0.077^{***}	-0.063^{***}
			(0.016)	(0.012)
BIC		1201.252	1202.979	1180.347
Pseudo R^2		0.765	0.763	0.783

Note: *, ** and *** denote significance at 10%, 5% and 1%, respectively.

that heightened uncertainty dampens consumer confidence. The inclusion of news heard and EPU has a statistically significant impact on MCSI for all models considered. Table 4 shows that the fit of the models improves when including relative news heard and EPU based on the Bayesian information criterion (BIC; the R^2 is also higher). Therefore, we utilize Model 3 for the GMM in the empirical analysis.

Additionally, we estimate a VAR model, where the endogenous variables include EPU ($\Delta \ln EPU_t$), news heard ($News_t$) and MCSI ($\Delta \ln MCSI_t$). The rationale for the ordering is that EPU serves as a measure of economic uncertainty, which can influence news exposure, ultimately affecting consumer confidence. Both sentiment shocks are then standardized by centering (subtracting the mean) and scaling (dividing by the standard deviation) to ensure that the resulting variable has a mean of zero and a standard deviation of unity.[10]

To obtain a single and parsimonious measure of sentiment disturbances, we combine the consumer confidence innovations derived from the GMM and VAR models using principal component analysis (PCA) and retain the first principal component, which captures the dominant common variation in sentiment innovations. Fig. 3 illustrates this construction: the top and middle panels display the standardized GMM- and VAR-based sentiment innovations, respectively, while the bottom panel reports their first principal component, which we define as the external sentiment shock. The sentiment innovations from the GMM and VAR models are highly correlated with the PCA factor (0.98 in both cases, significant at the 1% level), and the first eigenvalue explains 96.7% of the total variance. We therefore use the first principal component as the external sentiment shock in the VAR-LP analysis.

We define this sentiment shock as the innovation in consumer confidence that is orthogonal to EPU and news. Our goal is not to isolate a purely non-fundamental (animal spirits) component, but rather the residual variation in sentiment not captured by these observables. Although we apply an orthogonalization to the shock term, we intentionally avoid asserting that any specific orthogonalization reflects the "true" structural representation.

3.2. VAR-LP model

We estimate a linear Local Projection model as follows:

$$\mathbf{y}_{t+h} = \boldsymbol{\alpha}_h + \mathbf{B}_1^h \mathbf{y}_{t-1} + \mathbf{B}_2^h \mathbf{y}_{t-2} + \cdots + \mathbf{B}_p^h \mathbf{y}_{t-p} + \boldsymbol{\phi}^h \mathbf{x}_t + \boldsymbol{\beta}_h \, shock_t + \boldsymbol{\epsilon}_{t+h} \tag{2}$$

where $\mathbf{y}_{t+h}$ is projected on the space generated by lagged endogenous variables (p defined by AIC); $\mathbf{x}_t$ is a set of control variables $(GFC_t,\ GSCPI_t)$[11]; $\mathbf{y}_t^T$ is the transpose of a column vector; α_h is an intercept term; $\mathbf{B}_i^h$ are autoregressive coefficients for future horizon $h = 1, \ldots, H$; and ϵ_{t+h} is a disturbance. β_h is the coefficient on the external sentiment shock. As there is serial correlation present in the error terms, the Newey–West correction is used for standard errors. The VAR-LP is estimated with an external sentiment shock variable. The vector of macroeconomic variables includes the following:

$$\mathbf{y}_t^T = [TCU_t, \Delta \ln Y_t, \Delta \ln P_t, R_t] \tag{3}$$

where $\mathbf{y}_t^T$ includes TCU, output growth, inflation and the interest rate. TCU is ordered first. The subsequent variables — output growth, aggregate inflation, and interest rate — are ordered following the existing literature (e.g., Boivin and Giannoni, 2006).

Fig. 4 plots impulse response functions from the linear VAR–LP model. Capacity utilization (TCU) captures the extent to which firms employ existing productive capacity. An increase in TCU indicates that firms are operating closer to capacity, typically in response to stronger demand, and often precedes increases in output. Output growth reflects broader real activity but is constrained by available capacity, making TCU a key adjustment margin in the short run.

[10] This transformation makes the variable dimensionless, allowing for easier comparison across different scales.

[11] As the sample period overlaps with the Global Financial Crisis (GFC) and COVID-19 period and its aftermath, we include a GFC indicator and Global Supply Chain Pressure Index (GSCPI) as control variables. Recent research highlights disruptions in global supply chains associated with lower output and as primary drivers of inflation (e.g., Benigno et al., 2022; Diaz et al., 2023; Asadollah et al., 2024; Ascari et al., 2024; Ginn, 2024; Ginn and Saadaoui, 2025a,b).

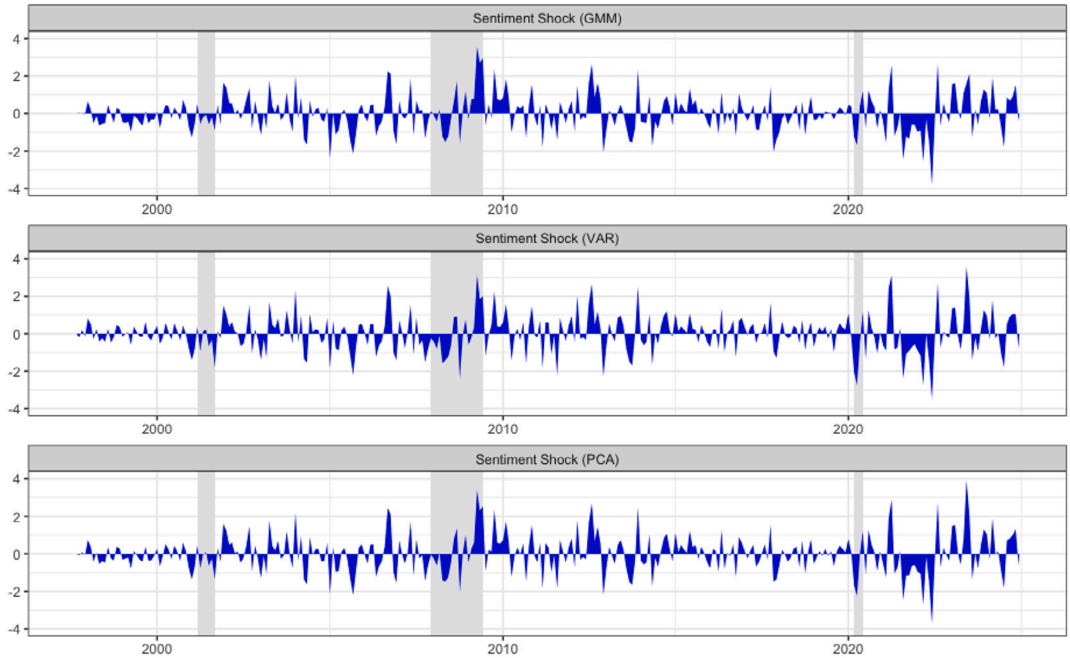

Fig. 3. Sentiment shocks.
Note: Sentiment shocks derived from residuals of GMM and VAR models, standardized to zero mean and unit variance. The series represent non-fundamental innovations in consumer confidence after controlling for EPU and news.

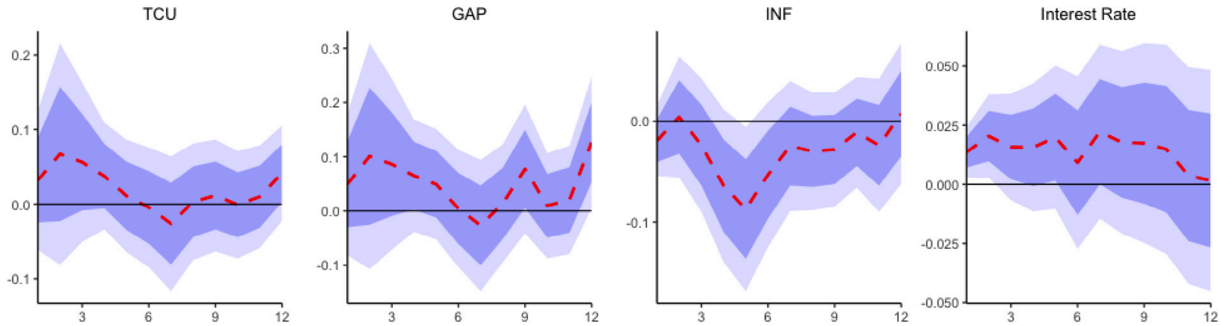

Fig. 4. Linear model impulse response functions to a sentiment shock.
Note: IRFs from a one standard deviation consumer sentiment shock. Shaded areas indicate 68% and 90% confidence intervals based on Newey–West robust standard errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 4 shows that a positive sentiment shock leads to a modest but economically meaningful increase in real activity. Capacity utilization rises on impact, peaking at approximately 0.08 percentage points within the first few months, while the output gap increases by roughly 0.1 percentage points at its peak.

Inflation declines to around 0.09 percentage points in period 5, and remains below zero for several horizons before gradually reverting. This pattern is more consistent with a supply-side adjustment than with a demand-driven expansion, as higher output is achieved without immediate inflationary pressure. The response of the policy interest rate is small and positive on average, peaking at roughly 0.02 percentage points, but it is not statistically significant at conventional confidence levels for most horizons.

Overall, the linear impulse responses are characterized by wide confidence bands. As such, while the linear model suggests that sentiment shocks are mildly expansionary on average, the results should be interpreted with caution and motivate the state-dependent analysis that follows.

For robustness, We consider an alternative linear VAR-LP model (“Alternative Linear Model 1”) which is estimated prior to the global pandemic (i.e., 1997 to 2019). The IRFs are provided in Fig. 9. Accordingly, both linear VAR-LP models reveal that a sentiment shock is stimulative, raises capital utilization, is inflationary and results in a higher interest rate response. The finding that a sentiment shock is stimulative (output gap) aligns with the literature which shows that shocks to sentiment increase consumption (e.g., Carroll et al., 1994, Ludvigson, 2004, Starr, 2012).[12]

3.3. Non-linear VAR-LP model

Using a non-linear VAR-LP, we specify the prediction of y_{t+h} to differ according to a high EPU ("H") and a low EPU ("L") state of the economy. That is, y_t is estimated that includes a smooth transition function $F(\zeta_t)$ that represents the state of the economy:

$$F(\zeta_{i,t}) = \frac{\exp(-\gamma\zeta_{i,t})}{1+\exp\left(\gamma\zeta_{i,t}\right)}, \quad \gamma > 0, \quad |\zeta_t| < \infty \tag{4}$$

where ζ_t is a standardized transition variable and γ controls the degree of smoothness of the transition between states.

The choice of the EPU index as the transition variable is grounded in both conceptual and empirical considerations. The central economic mechanism motivating our empirical design is straightforward and revolves around how uncertainty shapes capacity utilization. During periods of elevated economic policy uncertainty, firms face greater difficulty forecasting demand, input costs, and policy conditions. In such environments, real-options theory (Bernanke, 1983) implies that firms adopt a cautious "wait-and-see" posture such that uncertainty raises the option value of waiting (Bloom, 2009), delaying hiring, investment, and production adjustments. These decisions generate slack in the economy in the form of lower capacity utilization—not because firms are less able to produce, but because they choose to operate below potential while awaiting clearer signals about future conditions.

Theoretical work highlights two opposing channels through which uncertainty may affect real activity. The Oi–Hartman–Abel mechanism (Oi, 1961; Hartman, 1972; Abel, 1983) suggests that when profits are convex and factor adjustment is costless, volatility can be expansionary. In contrast, real-options theory emphasizes irreversibility in investment and hiring decisions, predicting that higher uncertainty depresses investment and employment by encouraging a wait-and-see strategy. A large empirical literature overwhelmingly supports the dominance of this real-options channel in practice, documenting that policy and geopolitical uncertainty reduce investment and hiring and generate economic slack (e.g., Bloom, 2009; Baker et al., 2016).

This dominance has direct implications for the transmission of sentiment shocks. In high-uncertainty environments, firms operate with excess capacity because production and investment decisions have been postponed. As a result, positive shifts in consumer sentiment can unlock delayed decisions and translate relatively quickly into higher production and capacity utilization, as firms can activate idle resources without facing binding constraints. By contrast, when uncertainty is low and the economy operates closer to potential, adjustment margins are tighter and sentiment shocks tend to produce weaker and more delayed effects. This mechanism provides a clear economic rationale for conditioning the transmission of sentiment shocks on the level of uncertainty and motivates our state-dependent empirical framework: sentiment matters most when firms have room to adjust.

We use EPU as the main transition variable for three reasons. First, EPU is a news-based index constructed from policy-related newspaper coverage (Baker et al., 2016), and our sentiment shock is likewise extracted from a news-driven measure of consumer confidence. Because both variables originate from the same informational environment — economic news reported in the media — EPU is the most conceptually aligned measure for capturing the news conditions under which consumer confidence forms. In contrast, uncertainty measures such as the JLN macroeconomic uncertainty (Jurado et al., 2015) or LMN financial uncertainty (Ludvigson et al., 2021) indicators primarily capture latent or market-implied uncertainty rather than shifts in the economic news directly observed by households. Second, unlike market-based uncertainty indicators such as the VIX or model-based measures such as the one-year-ahead JLN and LMN indicators, EPU does not embed a specific forecast horizon, making it particularly suitable for conditioning state-dependent local projections on the prevailing level of uncertainty. Third, our results indicate that EPU Granger-causes consumer confidence, in the sense that past realizations of EPU help predict future movements in consumer confidence. This empirical relationship reinforces the interpretation of EPU as an economically meaningful state variable that shapes the environment in which consumer confidence forms.

A key requirement for state-dependent local projections is that the state variable be predetermined with respect to the shock of interest. As emphasized by Gonçalves et al. (2024), endogeneity of the state variable can distort estimated impulse responses by conflating regime shifts with contemporaneous responses to the shock itself. In our setting, this concern is addressed through a two-step identification strategy. First, the sentiment shock is constructed to be orthogonal to EPU and news, ensuring that the identified sentiment shock does not contemporaneously affect the uncertainty measure. This orthogonalization mitigates contemporaneous feedback between the shock and the state variable. Second, to ensure predetermination of the uncertainty state, we use a one-sided Kalman filter to extract the persistent component of EPU and condition the local projections on its lagged value. The Kalman filter relies exclusively on information available up to time t, thereby avoiding "look-ahead" bias and preventing the uncertainty state from responding contemporaneously to the sentiment innovation. Together, the orthogonalization of the sentiment shock and the use of a lagged, Kalman-filtered uncertainty measure ensure that the state variable satisfies the predetermination requirement highlighted by Gonçalves et al. (2024). This approach allows the state-dependent VAR–LP framework to recover meaningful differences in the dynamic effects of sentiment shocks across uncertainty regimes.

We estimate the persistent component of EPU using a local level state–space model, which decomposes the observed EPU index into a latent trend and a transitory noise component. The system is specified as follows:

$$\mathrm{EPU}_t = \mu_t + \varepsilon_t, \tag{5}$$

[12] Starr (2012) finds that shocks to sentiment increases consumption, even when controlling for news shocks.

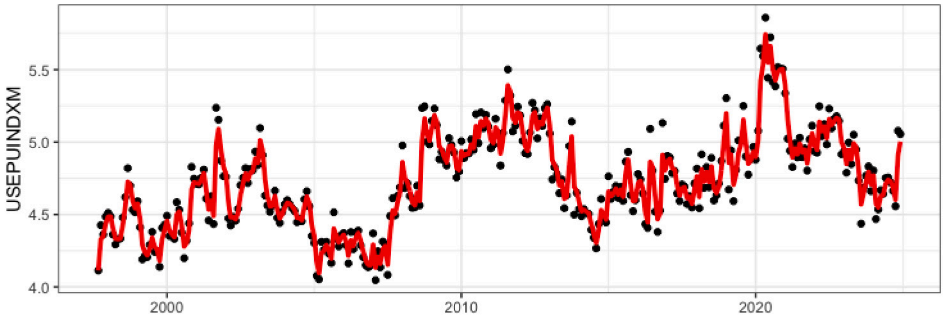

Fig. 5. Monthly U.S. EPU index and Kalman-filtered trend.
Note: The black dots represent the raw Economic Policy Uncertainty (EPU) index; the red line shows the latent trend component estimated with a one-sided Kalman filter. The filtered trend captures the persistent (low-frequency) component of uncertainty. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$\mu_t = \mu_{t-1} + \eta_t, \tag{6}$$

where μ_t is the unobserved state capturing the low-frequency, persistent component of EPU. The error terms $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ and $\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$ are mutually independent white noise processes. The Kalman filter provides real-time estimates of μ_t using only data available up to time t, ensuring a strictly one-sided (causal) smoothing process. To ensure full predetermination, we use the lagged value μ_{t-1} as the state variable in the local projection model. This approach avoids the pitfalls of symmetric smoothers such as centered moving averages or kernel methods, which rely on future information and thus risk introducing "look-ahead" bias.

Fig. 5 plots the monthly U.S. EPU index (black dots) alongside its Kalman-filtered trend (red line). The filtered trend captures the persistent regime of uncertainty, free from the influence of transitory shocks that might contaminate identification in nonlinear impulse response estimation.

The combination of a sentiment shock orthogonalized to EPU and a lagged, filtered EPU state variable ensures that the shock is exogenous to the prevailing regime, thus facilitating an approach to estimate how the transmission of sentiment shocks varies across uncertainty states. As shown in Gonçalves et al. (2024), when the state of the economy evolves independently of macroeconomic shocks, state-dependent local projections recover the conditional response function in the limit.

The non-linear VAR-LP model is specified as:

$$\mathbf{y}_{t+h} = F(\zeta_{t-1})\left(\boldsymbol{\alpha}_L^h + \sum_{i=1}^{p} \mathbf{B}_{i,L}^h \mathbf{y}_{t-i} + \boldsymbol{\phi}_L^h \mathbf{x}_t + \boldsymbol{\beta}_L^h\, shock_t\right) + \left(1 - F(\zeta_{t-1})\right)\left(\boldsymbol{\alpha}_H^h + \sum_{i=1}^{p} \mathbf{B}_{i,H}^h \mathbf{y}_{t-i} + \boldsymbol{\phi}_H^h \mathbf{x}_t + \boldsymbol{\beta}_H^h\, shock_t\right) + \epsilon_{t+h}. \tag{7}$$

where the propagation of the sentiment shock ($shock_t$) may differ across states low (β_h^L) and high (β_h^H) EPU states. The coefficients $\mathbf{B}_{i,L}^h$ and $\mathbf{B}_{i,H}^h$ represent the dynamic responses during low and high EPU regimes, respectively. Following (Auerbach and Gorodnichenko, 2012), the transition function is lagged to $t-1$ to prevent contemporaneous feedback from shocks to the state itself. Lagged EPU as state ensures predetermination In the VAR-LP, we include the lagged EPU based on the Kalman filter as the state. Consistent with standard practice in the literature (e.g., Auerbach and Gorodnichenko, 2013, Ramey and Zubairy, 2018), we set $\gamma = 1.5$.

The impulse response functions (IRFs) for sentiment shocks decomposed by low- and high-uncertainty periods are presented in Fig. 6. The corresponding transition function for the non-linear VAR–LP model is shown in Fig. 7, where higher values of the transition variable indicate periods of elevated economic policy uncertainty (EPU). Together, these figures illustrate how the macroeconomic effects of sentiment shocks depend on the prevailing uncertainty environment.

Fig. 6 reports impulse response functions from the state-dependent VAR–LP model, decomposed by periods of high and low EPU. The central insight from these responses is not that sentiment shocks generate uniformly estimated effects, but rather that their transmission differs across uncertainty regimes in economically meaningful ways.

In high-EPU states, a one-standard-deviation sentiment shock generates immediate and economically meaningful increases in real activity. Capacity utilization (TCU) and the output gap rise, with peak responses occurring approximately 8–10 months after the shock. Quantitatively, TCU increases by about 0.2 percentage points at its peak, while the output gap rises by roughly 0.4 percentage points. These responses are consistent with a real-options interpretation: when uncertainty is elevated, firms delay investment and hiring decisions and operate below potential. Positive shifts in sentiment can therefore translate relatively quickly into higher production by activating previously idle capacity. Inflation initially declines slightly on impact but subsequently rises modestly at medium horizons, suggesting that higher output is achieved primarily through utilization margins rather than through immediate price pressures.

In contrast, during low-EPU states, the sentiment shock produces markedly weaker responses. Both TCU and the output gap display muted reactions and turn negative at medium horizons, with the output gap reaching a trough of approximately −0.35 percentage points and TCU declining by around −0.2 percentage points. This pattern suggests that when uncertainty is low and

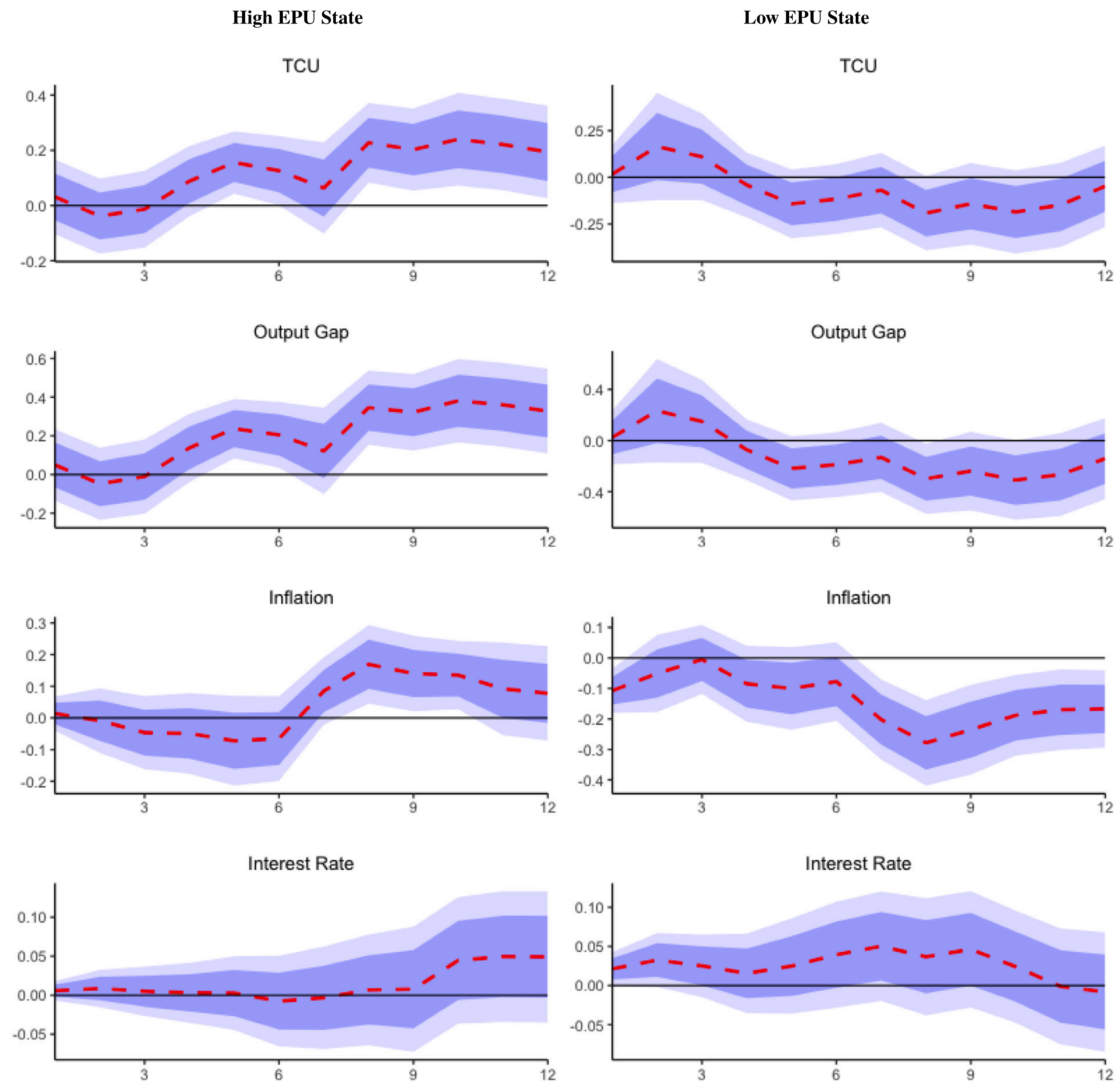

Fig. 6. Non-linear model impulse response functions to a sentiment shock.
Note: "High EPU State" ("Low EPU State") represents periods of elevated (subdued) filtered EPU. Each response corresponds to a one-standard-deviation sentiment shock. Confidence bands are 68% and 90% Newey–West corrected intervals.

the economy operates closer to potential, adjustment margins are more limited, and sentiment shocks are less likely to have scope to affect real activity, where we note that the associated confidence intervals frequently overlap with zero for the low-EPU state. Inflation declines more persistently in low-EPU states, further reinforcing the interpretation that sentiment shocks do not generate demand-driven overheating when slack is limited.

The response of the policy interest rate is small in magnitude in both states and statistically insignificant at conventional confidence levels across most horizons. Accordingly, we do not find evidence of a systematic monetary policy reaction to sentiment shocks. One possible explanation is that, although sentiment shocks affect real activity — particularly in high-uncertainty states — their effects on inflation are modest and short-lived, providing little justification for an active policy response. Moreover, monetary policy operates with non-negligible lags, such that reacting to transitory fluctuations in sentiment may risk amplifying, rather than stabilizing economic conditions. Overall, the evidence does not support a robust interest-rate response to sentiment shocks.

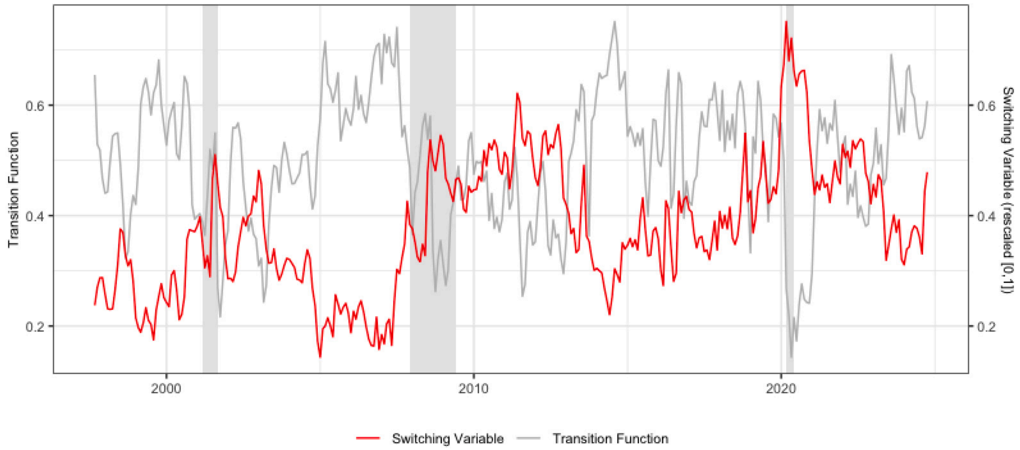

Fig. 7. Transition function (Non-linear model).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

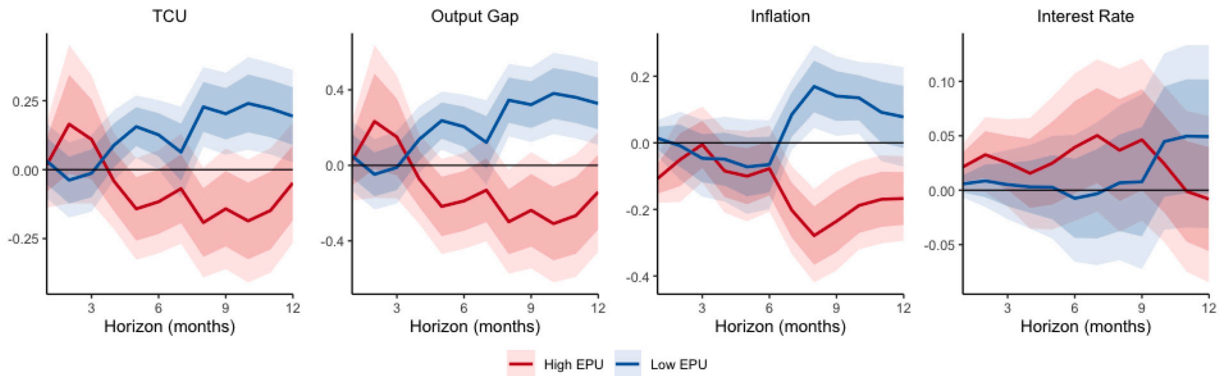

Fig. 8. Comparison of impulse responses across states.
Note: "High EPU State" ("Low EPU State") represents periods of elevated (subdued) filtered EPU. Each response corresponds to a one-standard-deviation sentiment shock. Confidence bands are 68% and 90% Newey–West corrected intervals.

We make two additional comparisons to clarify the role of state dependence. First, a comparison between the linear model (Fig. 4) and the non-linear model (Fig. 6) reveals substantial differences in the estimated responses. The linear specification imposes uniform effects of sentiment shocks across all states of the economy, which can mask important nonlinearities in the transmission mechanism.

Second, Fig. 8 directly compares impulse responses across uncertainty regimes. In high-EPU states, sentiment shocks generate statistically significant increases in capacity utilization and the output gap over several horizons, whereas the corresponding responses in low-EPU states are generally smaller and not statistically distinguishable from zero. Although confidence intervals overlap across regimes, differences in the timing, magnitude, and statistical significance of the responses indicate that the transmission of sentiment shocks depends on the prevailing level of economic uncertainty. These asymmetric effects are consistent with real-options theory: elevated uncertainty raises the option value of waiting, leading firms to delay investment and hiring and to operate below potential. The resulting economic slack allows positive sentiment shocks to translate more readily into higher production and capacity utilization. By contrast, during low-uncertainty periods — when utilization is closer to potential — adjustment margins are more limited, and sentiment shocks tend to produce weaker or more delayed effects.

Overall, point estimates indicate that sentiment shocks generate larger and more contemporaneous responses during high-EPU periods than during low-EPU periods. Although confidence bands partially overlap across uncertainty states, the estimated responses exhibit economic differences in their timing, magnitude, and propagation. Taken together, the evidence supports the view that sentiment shocks are more likely to have meaningful macroeconomic effects when economic uncertainty is elevated and unused productive capacity is available.

To ensure that our findings are not driven by model specification, transition-variable choice, or assumptions about the degree of state dependence, we conduct a comprehensive battery of robustness tests across a number of alternative non-linear VAR–LP models.

These variants probe (i) alternative sample periods, (ii) different definitions of the transition variable, (iii) alternative measures of uncertainty, (iv) substitutions of key macroeconomic controls, (v) extensions of the information set used to construct sentiment shocks, and (vi) different smoothness parameters governing the transition function. Specifically, we consider the following thirteen alternative VAR-LP models:

- **Alternative Non-Linear Model 1** is estimated prior to the global pandemic (i.e., 1997:09 to 2019:12). The IRFs and transition function are plotted in the Appendix in Figs. 10 and 11, respectively.
- **Alternative Non-Linear Model 2** is estimated by replacing the EPU derived by the Kalman filter with the EPU. The IRFs and transition function are plotted in the Appendix in Figs. 12 and 13, respectively.
- **Alternative Non-Linear Model 3** is estimated by replacing the EPU derived by the Kalman filter with the EPU and estimated prior to the global pandemic (i.e., 1997:09 to 2019:12). The IRFs and transition function are plotted in the Appendix in Figs. 14 and 15, respectively.
- **Alternative Non-Linear Model 4** replaces the output gap in the Baseline Non-Linear Model with output growth. The IRFs and transition function are plotted in the Appendix in Figs. 16 and 17, respectively.
- **Alternative Non-Linear Model 5** replaces GSCPI used as a control variable in the Baseline Non-Linear Model with U.S. Infectious Diseases Equity Market Volatility Tracker (Baker et al., 2019).[13] The IRFs and transition function are plotted in the Appendix in Figs. 18 and 19, respectively.
- **Alternative Non-Linear Model 6** replaces the interest rate (Fed Funds) variable in the Baseline Non-Linear Model with the U.S. shadow interest rate.[14] The IRFs and transition function are plotted in the Appendix in Figs. 20 and 21, respectively.
- **Alternative Non-Linear Model 7** replaces inflation variable in the Baseline Non-Linear Model with inflation expectations.[15] The IRFs and transition function are plotted in the Appendix in Figs. 22 and 23, respectively.
- **Alternative Non-Linear Model 8** replaces EPU variable in the Baseline Non-Linear Model transition with the output gap. The IRFs and transition function are plotted in the Appendix in Figs. 24 and 25, respectively.
- **Alternative Non-Linear Model 9** replaces EPU variable in the Baseline Non-Linear Model with the 1-Month Ahead Macroeconomic Uncertainty data by Jurado et al. (2015). The IRFs and transition function are plotted in the Appendix in Figs. 26 and 27, respectively.
- **Alternative Non-Linear Model 10** replaces EPU variable in the Baseline Non-Linear Model with the 1 Month Ahead Financial Uncertainty data by Ludvigson et al. (2021). The IRFs and transition function are plotted in the Appendix in Figs. 28 and 29, respectively.
- **Alternative Non-Linear Model 11** we extend the baseline sentiment shock by adding unemployment, consumption growth, output growth, and real S&P500 returns to the VAR model (we do not change the GMM model).[16] The IRFs and transition function are plotted in the Appendix in Figs. 30 and 31, respectively. The resulting shocks remain highly correlated with the baseline measure, and the IRFs are qualitatively unchanged, confirming that our findings are not driven by omitted macroeconomic conditions.[17]
- **Alternative Non-Linear Model 12** adjusts the baseline specification by estimating the transition function using a lower smoothness parameter ($\gamma = 0.5$). The corresponding IRFs and transition function are reported in the Appendix in Figs. 32 and 33, respectively.
- **Alternative Non-Linear Model 13** similarly adjusts the baseline specification by estimating the transition function using a higher smoothness parameter ($\gamma = 3$). The corresponding IRFs and transition function are reported in the Appendix in Figs. 34 and 35, respectively.

Overall, all fourteen VAR-LP non-linear models consistently demonstrate that there is an asymmetry with the state of the economy. Accordingly, the non-linear VAR-LP models indicate that a sentiment shock is more stimulative in the short-term (i.e., increases output and TCU) during high EPU periods.

3.4. Discussion of results

This section situates our findings within the literature on sentiment-driven fluctuations and uncertainty amplification, and clarifies how our results refine existing interpretations of confidence shocks and their macroeconomic relevance.

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[13] COVID-19 emerged as a pandemic in December 2019 and quickly spread across the world, with far-reaching consequences including higher deaths, stagnation of economic growth and elevated uncertainty, which resulted in lock-downs and other precautions to reduce the spread of the virus. U.S. Infectious Diseases Equity Market Volatility Tracker is included as a way to capture the prolific and persistent influence that COVID-19 has had on the economic conditions (Dufrénot et al., 2024a).

[14] Considering the sample period overlaps with the U.S. federal funds rate was at the zero lower bound between 2008:Q4 until 2015:Q4, we use the shadow federal funds rate (Wu and Xia, 2016) to reflect the stance of U.S. monetary policy.

[15] We use the 1-Year expected inflation (FRED mnemonic EXPINF1YR) provided by the Federal Reserve.

[16] Although EPU may already capture much of the variation in these variables, this specification serves as an alternative model to test robustness.

[17] The contemporaneous correlation between the VAR derived sentiment shock in the Baseline and Alternative Non-Linear Model 11 is 0.98 (statistically significant at the 1% level). Furthermore, the contemporaneous correlation between the first principle component of the derived sentiment shock compared to the VAR based on the alternative sentiment shock and GMM is 0.98 and 0.98 (both statistically significant at the 1% level), respectively. We also report that the first eigenvalue from the PCA is 95.8%.

Empirical studies based on linear frameworks often conclude that confidence innovations exert limited independent effects on real activity (Barsky and Sims, 2012; Blanchard et al., 2013). Our linear VAR–LP estimates are consistent with this view: average responses of output, utilization, and monetary policy to sentiment shocks are modest and often statistically insignificant.

However, the linear model masks substantial state dependence. The empirical findings from the nonlinear VAR-LP state dependent model consistently show that when EPU is elevated, consumer confidence shocks generate economically meaningful and statistically significant increases in capacity utilization and the output gap. In contrast, during low-uncertainty periods, the same shocks produce weaker, less persistent, and frequently insignificant responses. This finding accordingly extends the literature by demonstrating that the macroeconomic relevance of sentiment shocks is conditional on the prevailing uncertainty environment.

By conditioning on uncertainty states, our results extend the information-based view of sentiment shocks. Even after orthogonalizing confidence innovations with respect to policy uncertainty and news, sentiment can have sizeable effects when uncertainty is high. This conditional amplification mechanism is consistent with recent evidence showing that sentiment shocks matter primarily when informational frictions or belief dispersion are elevated (Boeck et al., 2025). Linear models that average across regimes therefore tend to underestimate the importance of sentiment-driven fluctuations.

A key contribution of our analysis is the identification of capacity utilization as the primary transmission channel through which sentiment shocks affect real activity. In high-uncertainty states, positive confidence shocks lead to a rapid and persistent increase in utilization, followed by improvements in the output gap. This pattern is consistent with real-options and "wait-and-see" mechanisms, whereby heightened uncertainty raises the option value of delaying irreversible investment and hiring decisions (Bernanke, 1983; Bloom, 2009; Baker et al., 2016). Such behavior generates economic slack that can be quickly reactivated once expectations improve.

This mechanism aligns closely with the "vulnerability paradox" proposed by Hallegatte and Ghil (2008), which argues that economies operating below capacity may be more resilient to disasters than economies near full utilization. In recessions or high-uncertainty environments, idle resources provide adjustment margins that allow shocks — whether real or expectational — to translate more easily into changes in production. Empirical evidence supporting this paradox for the U.S. economy is documented in Ginn (2022). Our results extend this logic to sentiment shocks: when uncertainty is elevated and economic slack is greater, confidence shifts have larger effects; when uncertainty is low and capacity constraints bind, sentiment shocks are rather muted.

Importantly, this asymmetry suggests that sentiment shocks primarily operate through the intensive margin of production rather than through permanent changes in productive capacity. Uncertainty thus acts as a state variable that amplifies short-run sensitivity to expectation shifts, while leaving longer-run supply fundamentals comparatively unaffected.

Our robustness exercises allow for a direct comparison between different dimensions of uncertainty. While the state-dependent amplification of sentiment shocks is robust, important differences emerge between economic policy uncertainty and financial uncertainty.

When EPU is used as the transition variable, confidence shocks mainly affect real activity through capacity utilization and the output gap, while the interest rate response remains weak and statistically insignificant. This suggests that policy uncertainty primarily operates through expectations and demand-side channels, without triggering a systematic monetary policy reaction. This finding is consistent with the view that reacting to transitory sentiment movements may be undesirable when inflationary consequences are limited (Bloom, 2009; Baker et al., 2016).

A comparison with the alternative uncertainty measures yields broadly similar conclusions. The JLN macroeconomic uncertainty and LMN financial uncertainty indices are both one-month-ahead (horizon-specific) measures, in contrast to EPU, which does not embed a specific forecast horizon. When these measures are used as transition variables, we continue to observe state-dependent effects, particularly during periods of elevated uncertainty. The magnitudes of the responses are broadly comparable to those obtained under EPU. Accordingly, the similarity of the impulse responses across alternative uncertainty measures reinforces the broader conclusion that it is the uncertainty state itself that matters for the propagation of sentiment shocks.

4. Conclusion

This paper investigates the macroeconomic effects of consumer confidence shocks with a particular emphasis on the role of economic policy uncertainty and state dependence. Using monthly U.S. data, we develop an empirical framework that jointly accounts for news, uncertainty, and nonlinear transmission mechanisms in order to reassess when and how sentiment may matter for economic activity. By combining modern identification strategies with local projections, our analysis helps reconcile mixed evidence in the literature and suggests that any macroeconomic relevance of sentiment is likely to depend on the prevailing uncertainty environment.

Our first contribution concerns the identification of sentiment shocks. We document a Granger-causal relationship running from economic policy uncertainty (EPU) to consumer confidence. Building on this result, we construct a sentiment shock that is orthogonal to both EPU and news by extracting confidence innovations from GMM and VAR models and combining them using principal component analysis. This orthogonalized sentiment innovation is then employed as an external shock in the VAR–Local Projections framework, allowing us to examine the dynamic responses of macroeconomic variables without imposing strong structural restrictions.

Our second contribution is to trace the macroeconomic effects of the externally identified sentiment shock using a linear VAR–LP framework. The linear results suggest that positive sentiment shocks are associated with modest increases in output and capacity utilization and a temporary rise in inflation. However, these responses are generally small and often not statistically distinguishable from zero, and we do not find robust evidence of a systematic monetary policy response. Taken together, the linear estimates indicate that, on average, the macroeconomic effects of sentiment shocks are limited and likely transitory.

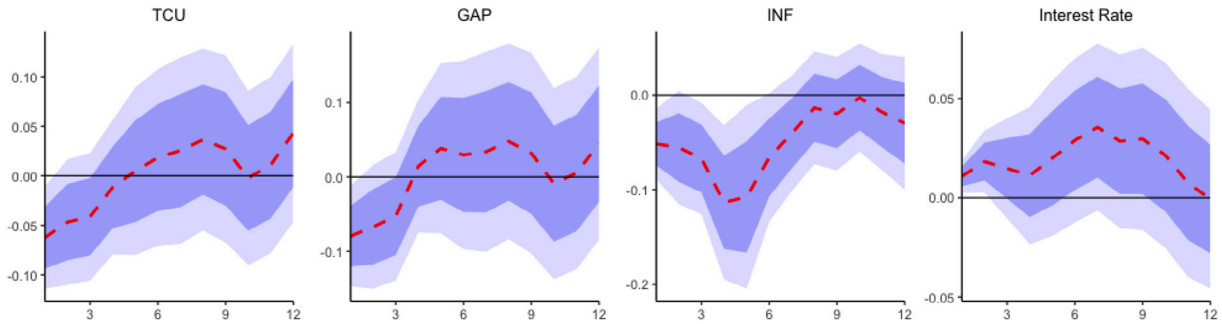

Fig. 9. Linear model impulse response functions to a sentiment shock.
Note: Impulse response functions from the linear VAR-LP model estimated over the pre-pandemic period (1997:09–2019:12). Responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Our third and central contribution is to explore whether the transmission of sentiment shocks varies across uncertainty states. Extending the VAR–LP framework to a smooth-transition specification conditioned on a continuous, one-sided Kalman-filtered measure of EPU, we find evidence consistent with state dependence in the propagation of sentiment shocks. While the estimated responses remain imprecise, the impulse responses in Fig. 6 suggest that sentiment shocks tend to be more pronounced and contemporaneous during periods of elevated uncertainty, particularly for output and capacity utilization. In contrast, during low-uncertainty states, the responses are muted, delayed, and largely indistinguishable from zero. These patterns are consistent with the interpretation that uncertainty may condition the transmission of sentiment through variations in economic slack. However, the magnitude of these effects should be interpreted with caution: while point estimates indicate stronger and more immediate responses during high-uncertainty periods, the associated confidence intervals frequently overlap across states. Accordingly, the evidence should be viewed as suggestive of economically meaningful state dependence.

Overall, our findings highlight the dual role of economic policy uncertainty as both a predictor of consumer sentiment and a moderator of its macroeconomic effects. Intuitively, policymakers should interpret a one-standard-deviation sentiment shock as an unexpected shift in households' confidence or expectations that is orthogonal to observable news and policy uncertainty, but whose macroeconomic effects may be amplified under conditions of elevated uncertainty. While the estimated impulse responses are often imprecise, the results suggest that sentiment is most relevant during periods of elevated uncertainty, when economic slack is greater and adjustments are less constrained. In such environments, shifts in consumer confidence are more likely to translate into short-run movements in output and capacity utilization, whereas during low-uncertainty periods sentiment shocks have weaker and more delayed effects and contain limited information beyond standard macroeconomic indicators. From a policy perspective, these findings imply that sentiment-driven fluctuations are unlikely to warrant a systematic monetary policy response. Although sentiment shocks can affect real activity — particularly under heightened uncertainty — their effects on inflation are transitory, and monetary policy operates with non-negligible transmission lags. As a result, reacting to short-lived movements in sentiment may risk amplifying noise rather than stabilizing the economy.

Appendix 5

5.1. Alternative linear VAR-LP models

See Fig. 9

5.2. Alternative non-linear VAR-LP model (with external shock)

See Figs. 10–35

Data availability

Data will be made available on request.

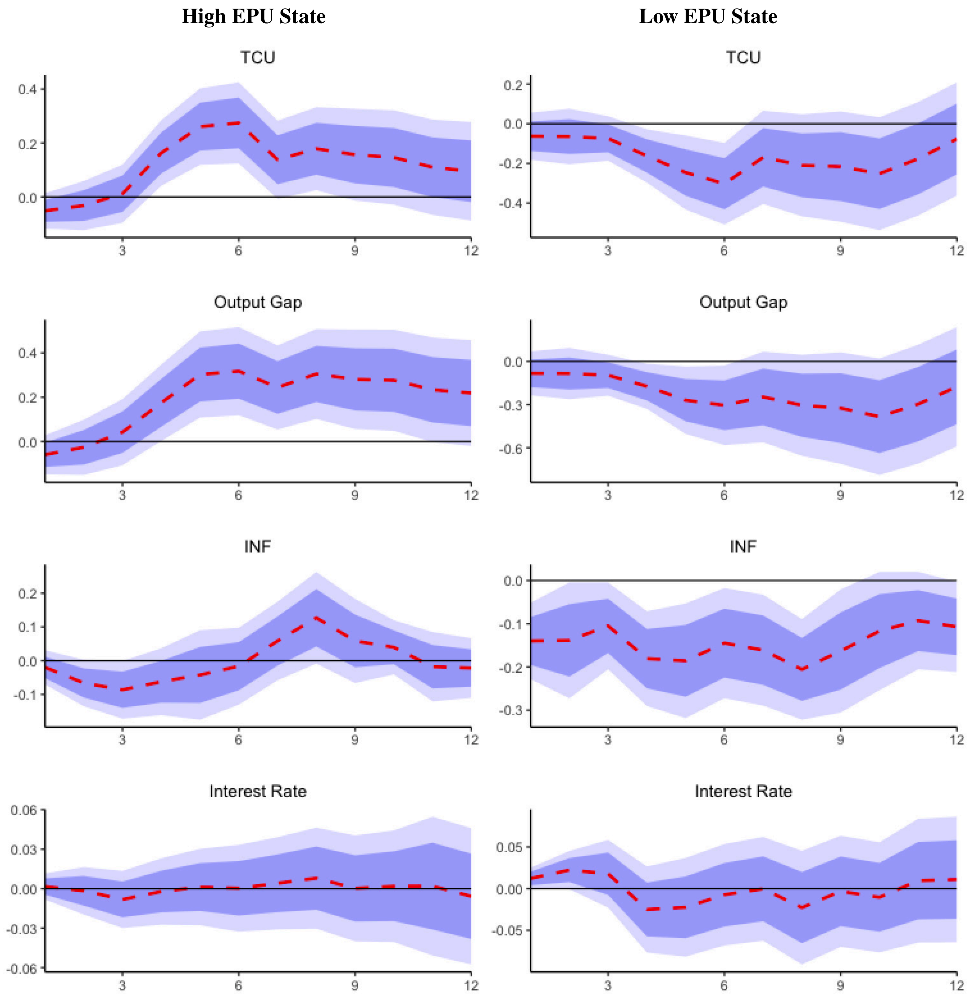

Fig. 10. Alternative Non-Linear Model 1 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 1 is estimated prior to the global pandemic (i.e., 1997:09 to 2019:12). "High EPU State'' (''Low EPU State'') represents periods of elevated (subdued) filtered EPU. Responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

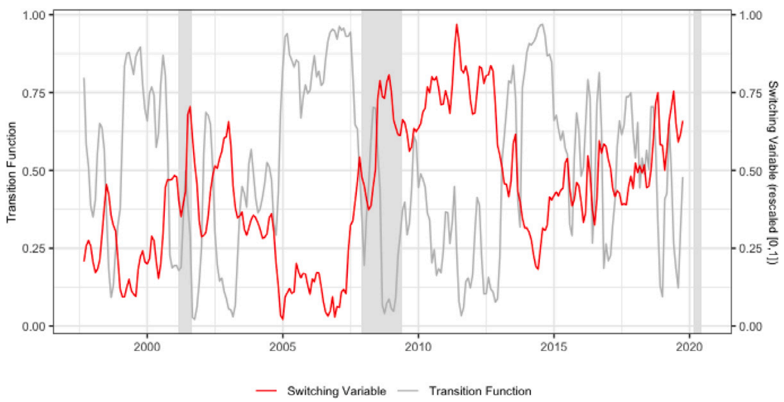

Fig. 11. Transition function non-linear model (Alternative Non-Linear Model 1).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

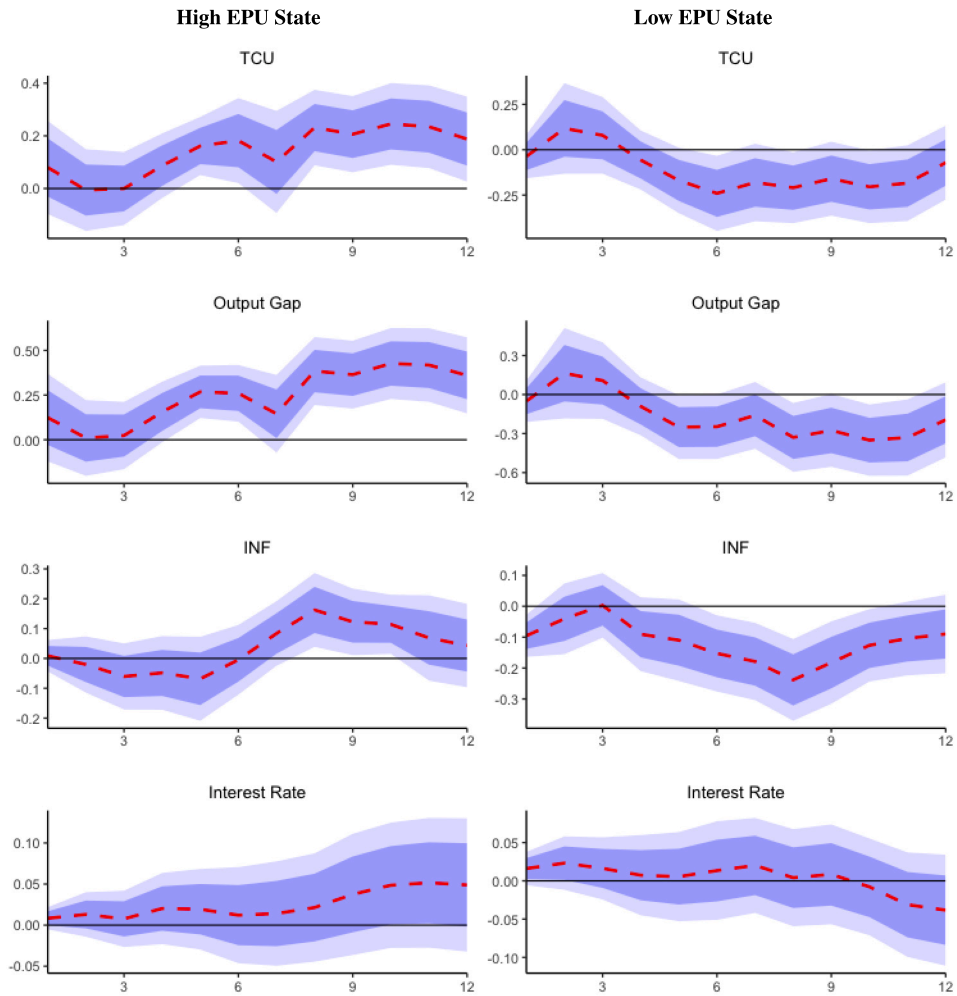

Fig. 12. Alternative Non-Linear Model 2 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 2 is estimated by replacing the EPU derived by the Kalman filter with the EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

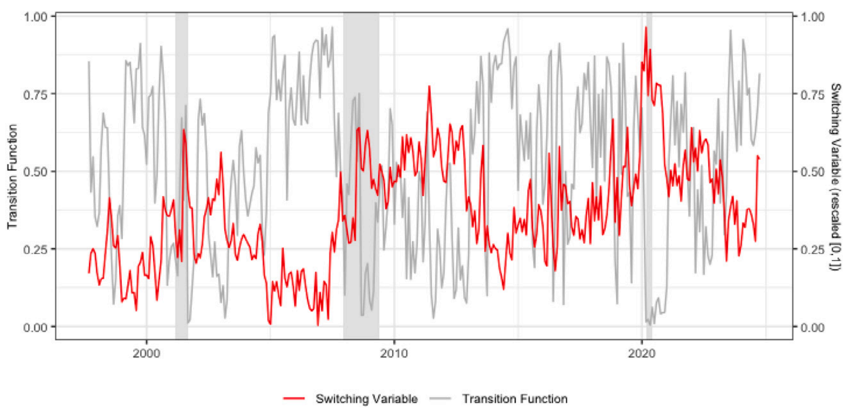

Fig. 13. Transition function non-linear model (Alternative Non-Linear Model 2).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

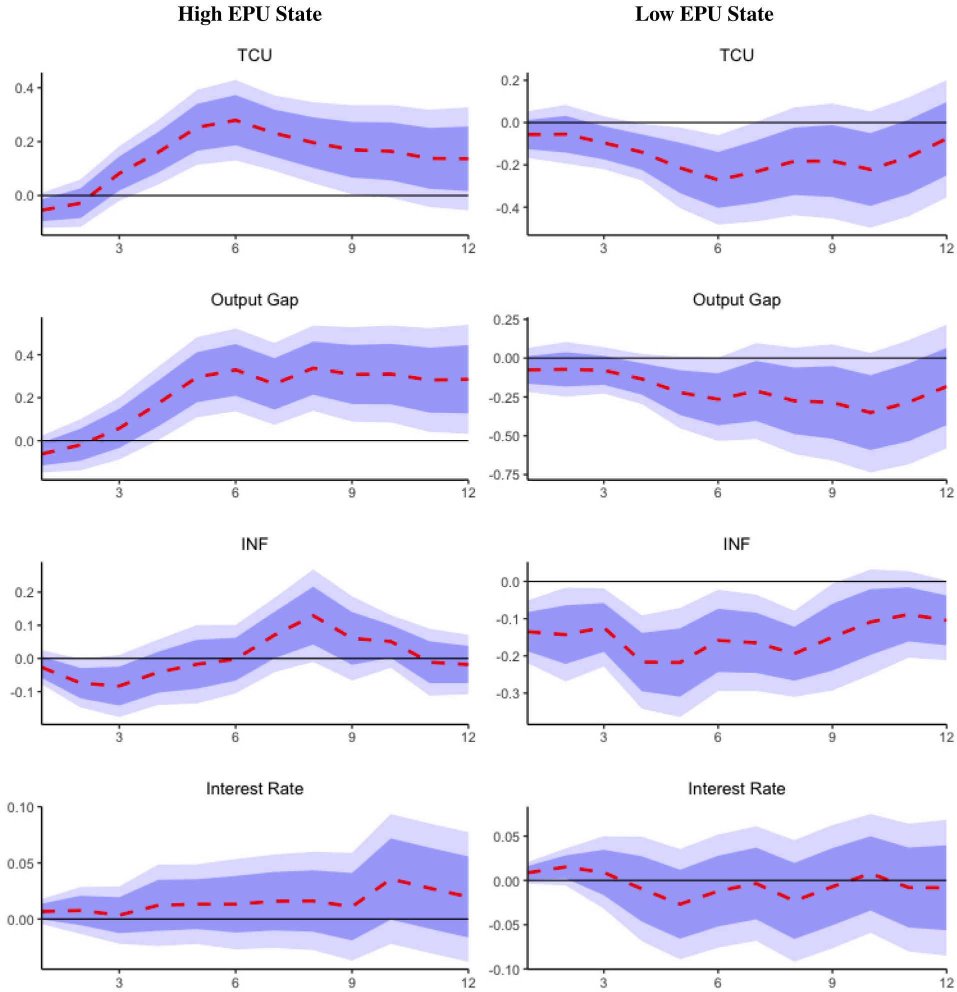

Fig. 14. Alternative Non-Linear Model 3 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 4 replaces the output gap in the Baseline Non-Linear Model with output growth. "High EPU State'' (''Low EPU State'') represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

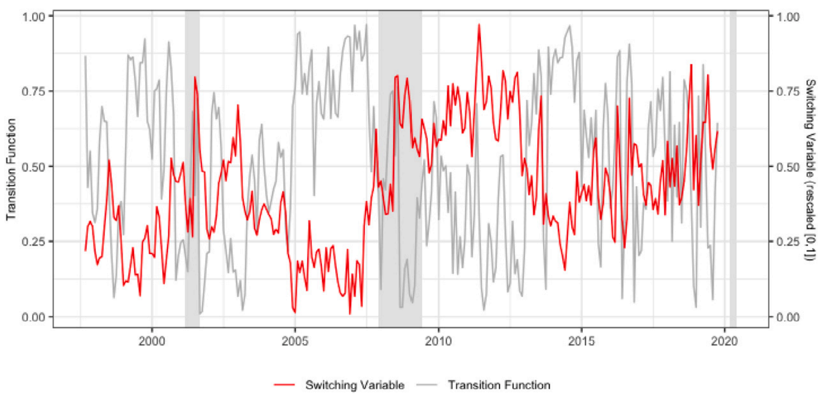

Fig. 15. Transition function non-linear model (Alternative Non-Linear Model 3).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

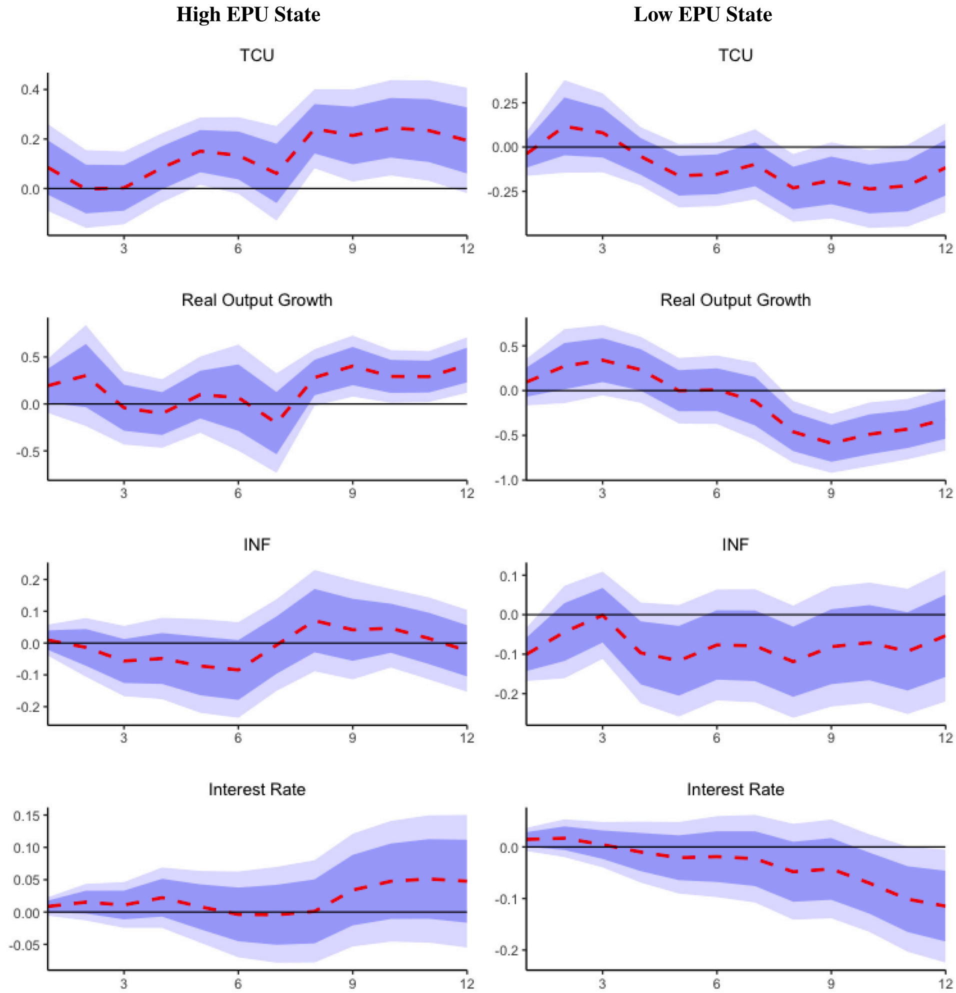

Fig. 16. Alternative Non-Linear Model 4 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 3 is estimated by replacing the EPU derived by the Kalman filter with the EPU and estimated prior to the global pandemic (i.e., 1997:09 to 2019:12). "High EPU State'' (''Low EPU State'') represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

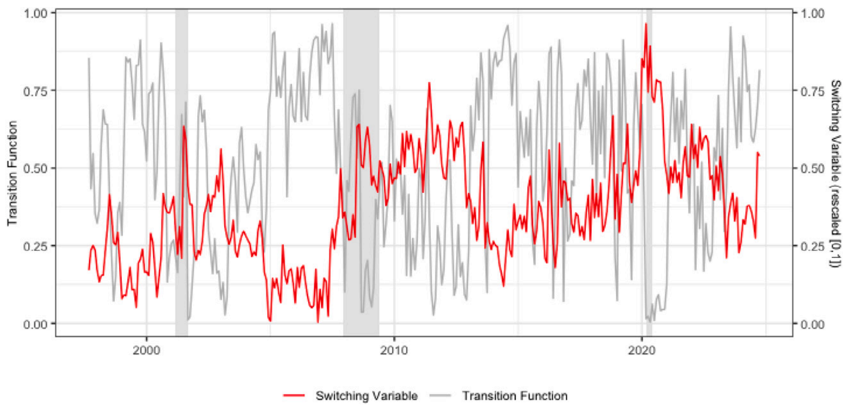

Fig. 17. Transition function non-linear model (Alternative Non-Linear Model 4).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

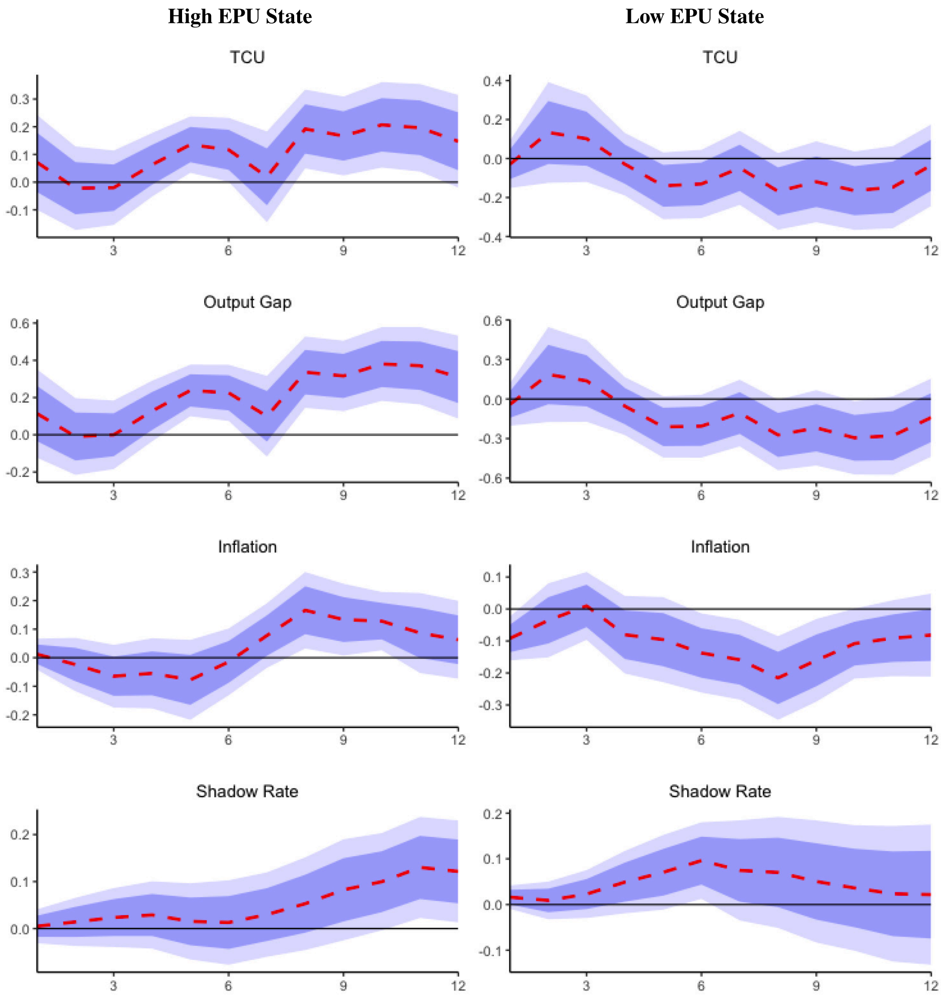

Fig. 18. Alternative Non-Linear Model 5 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 5 replaces GSCPI used as a control variable in the Baseline Non-Linear Model with U.S. Infectious Diseases Equity Market Volatility Tracker (Baker et al., 2019). "High EPU State" ("Low EPU State") represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

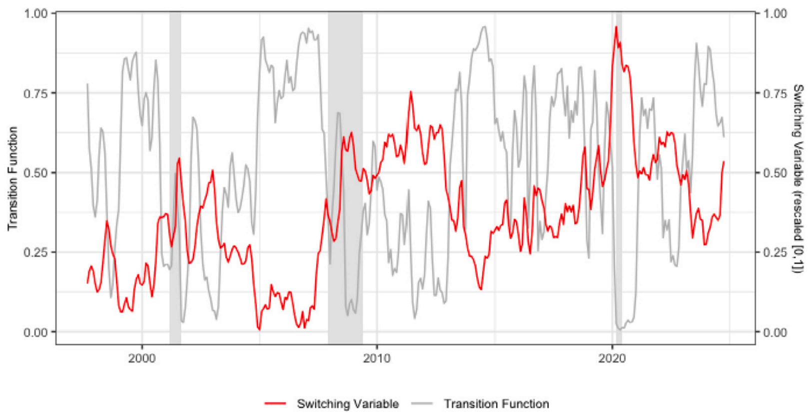

Fig. 19. Transition function non-linear model (Alternative Non-Linear Model 5).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

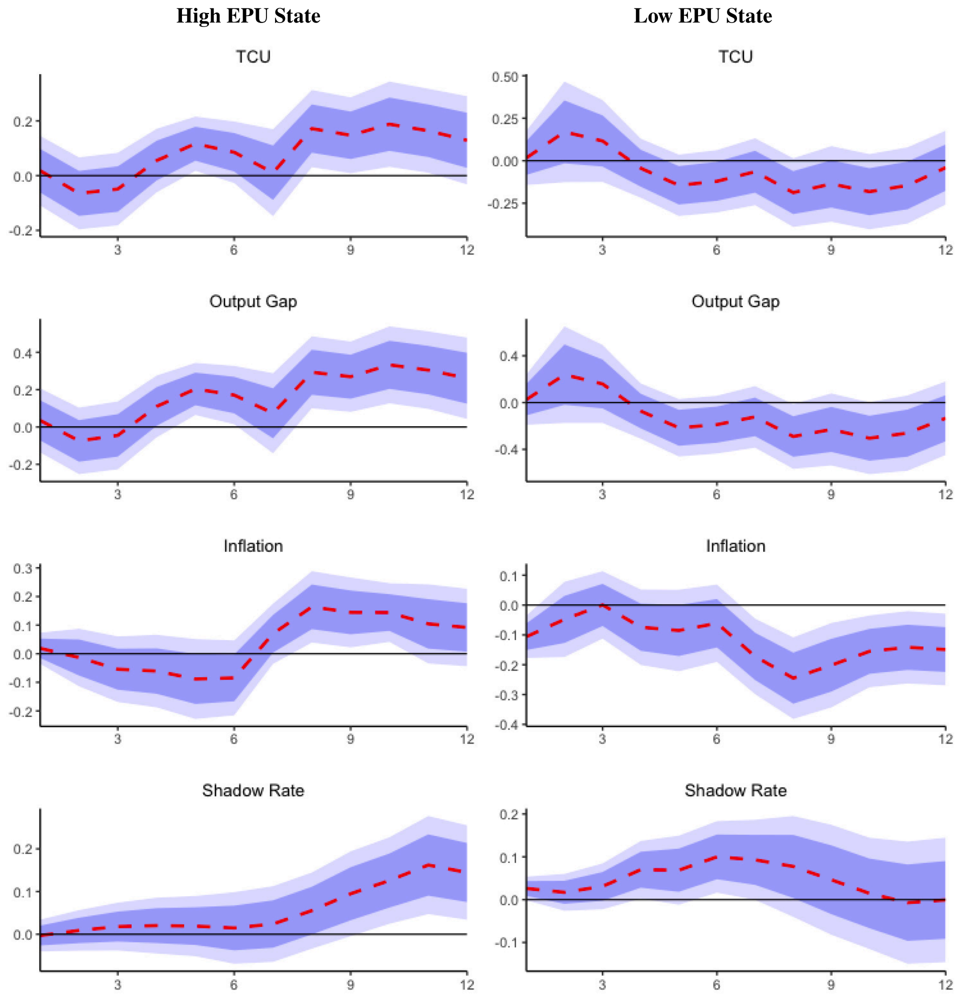

Fig. 20. Alternative Non-Linear Model 6 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 6 replaces the interest rate (Fed Funds) variable in the Baseline Non-Linear Model with the U.S. shadow interest rate. "High EPU State" ("Low EPU State") represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

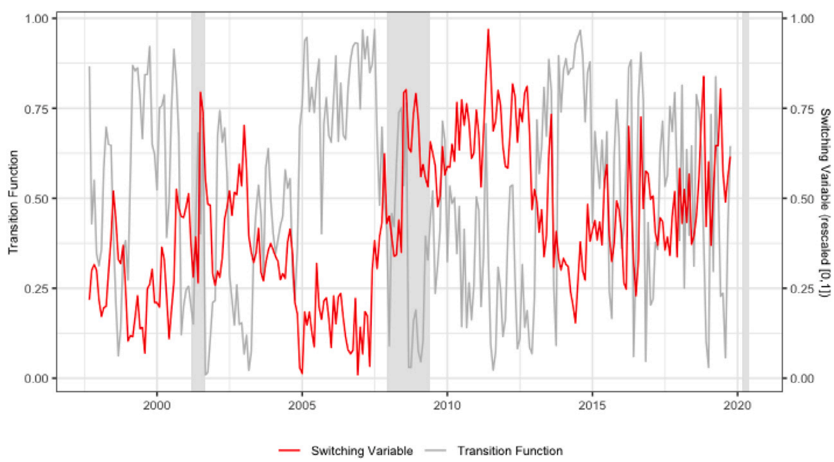

Fig. 21. Transition function non-linear model (Alternative Non-Linear Model 6).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

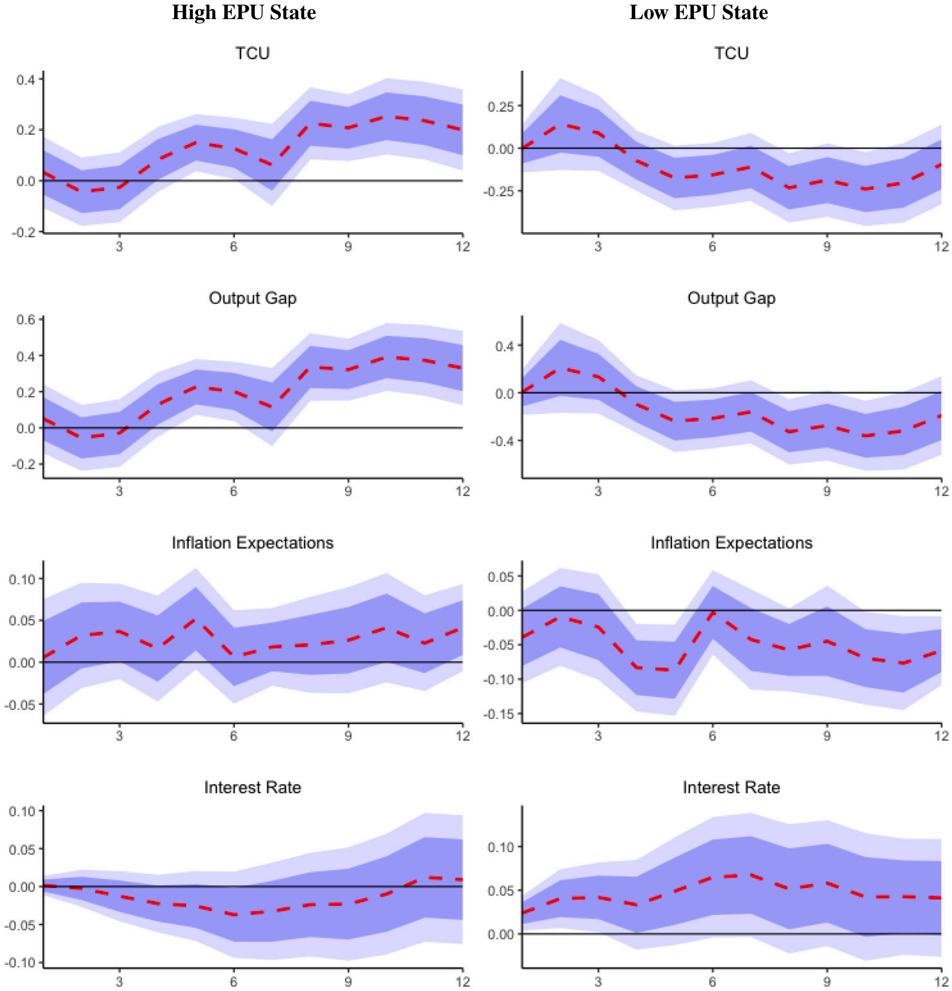

Fig. 22. Alternative Non-Linear Model 7 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 7 replaces inflation variable in the Baseline Non-Linear Model with inflation expectations. "High EPU State'' (''Low EPU State'') represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

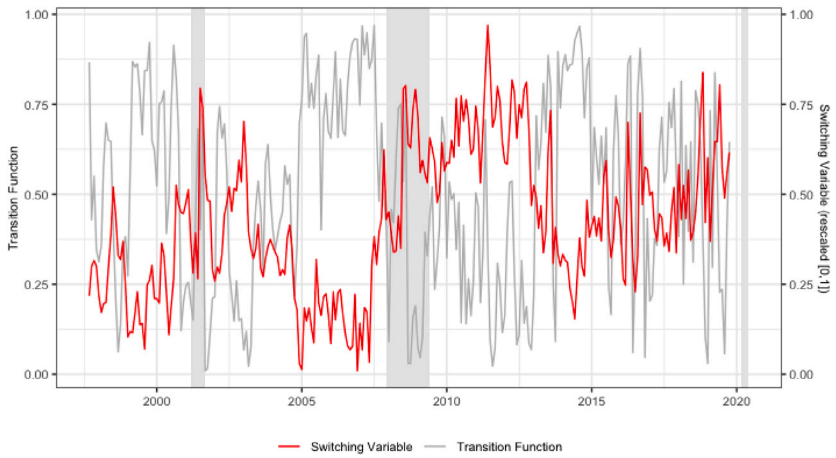

Fig. 23. Transition function non-linear model (Alternative Non-Linear Model 7).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

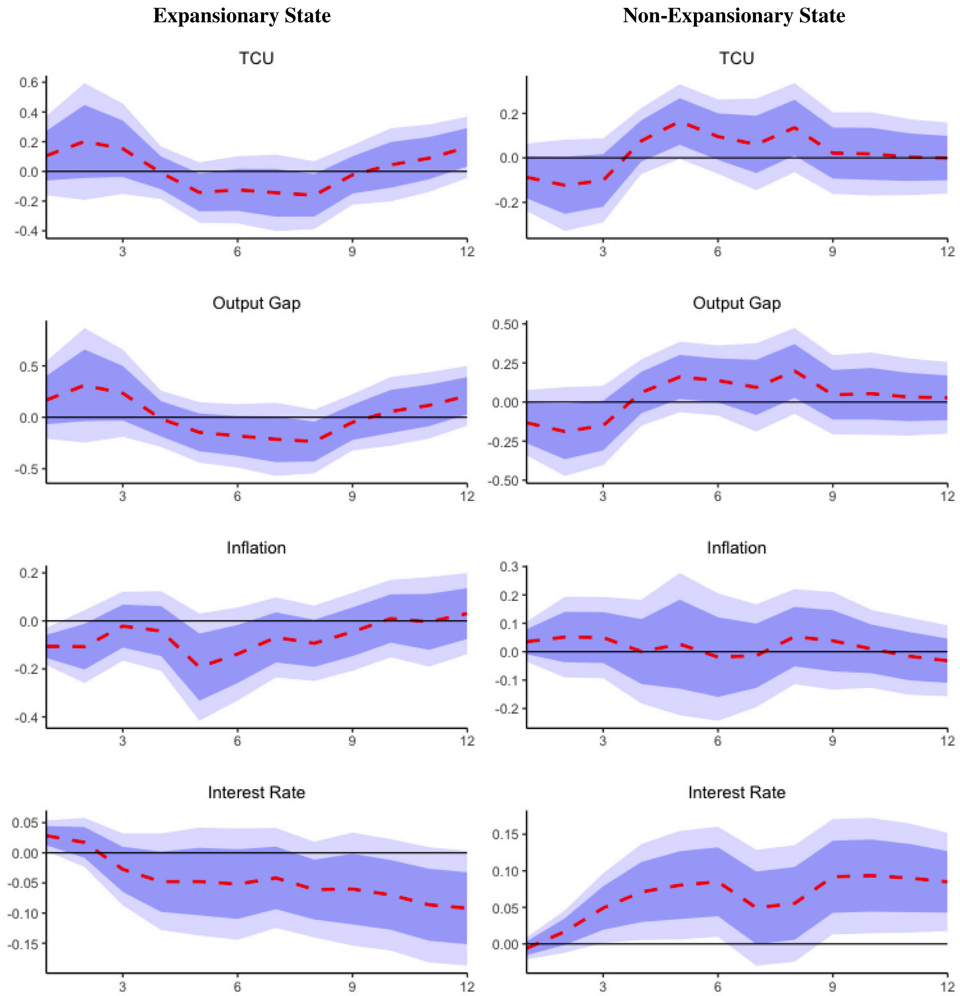

Fig. 24. Alternative Non-Linear Model 8 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 8 replaces inflation variable in the Baseline Non-Linear Model with inflation expectations. "Expansionary State" ("Non-Expansionary State") refers to periods in which the filtered output gap is positive (negative). Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

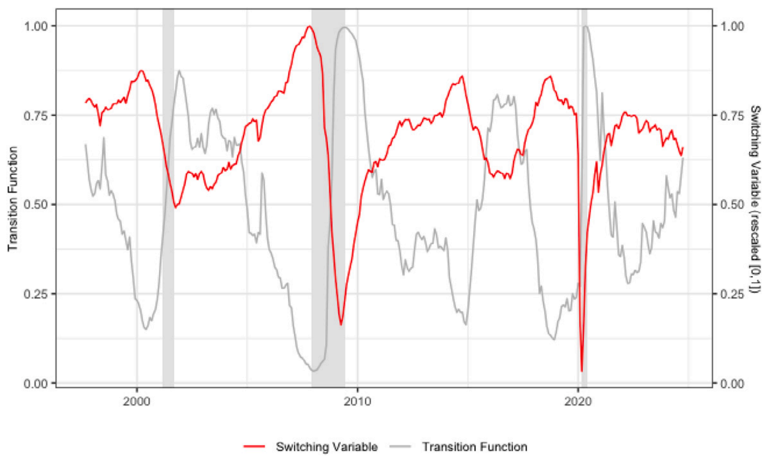

Fig. 25. Transition function non-linear model (Alternative Non-Linear Model 8).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

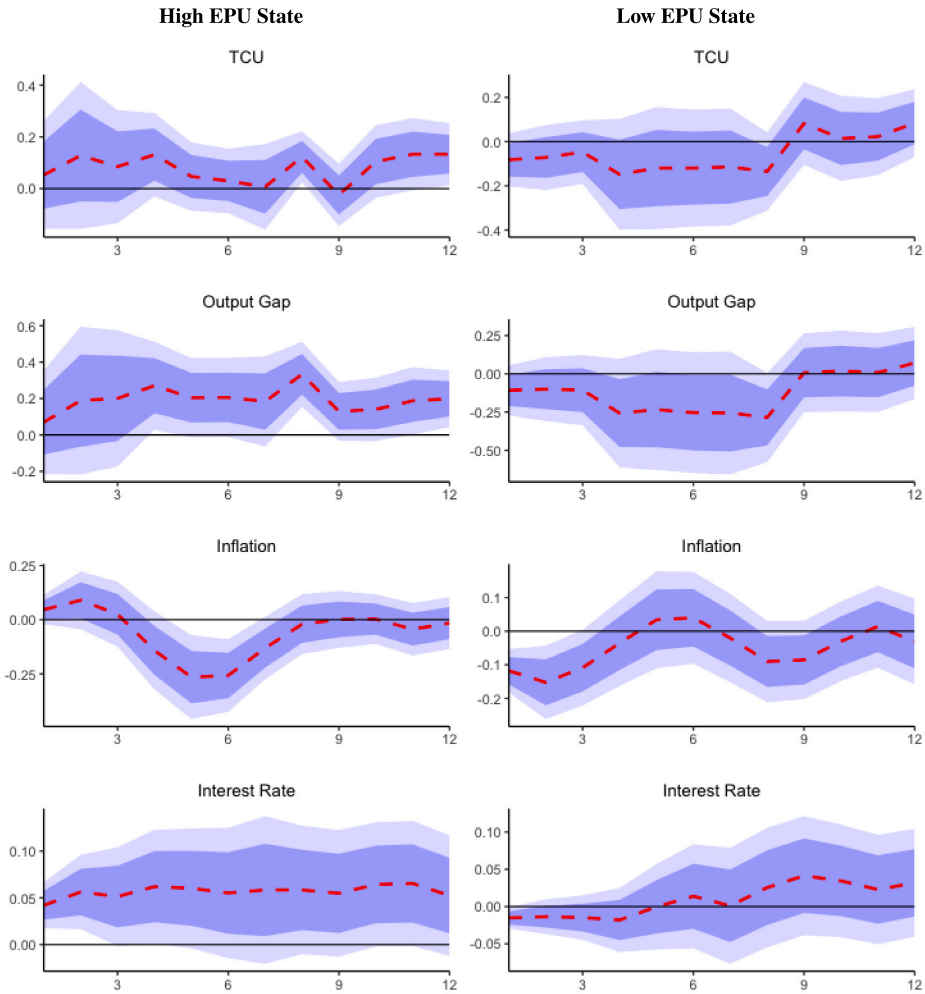

Fig. 26. Alternative Non-Linear Model 9 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 9 replaces EPU variable in the Baseline Non-Linear Model with the JLN Macroeconomic Uncertainty data. "High EPU State'' ("Low EPU State'') represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

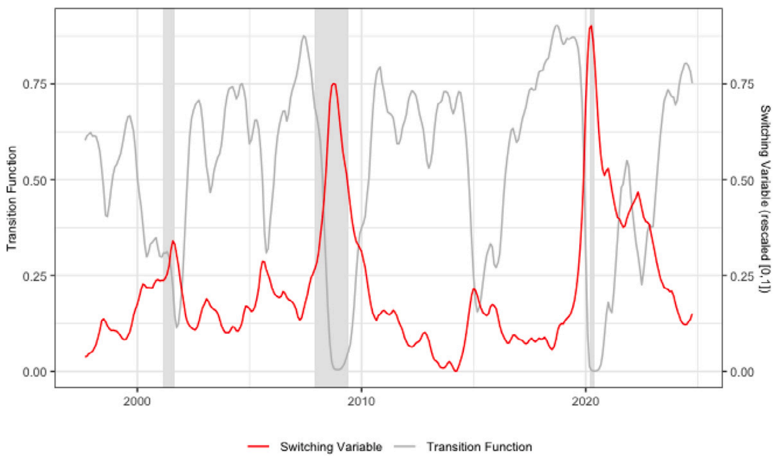

Fig. 27. Transition function non-linear model (Alternative Non-Linear Model 9).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

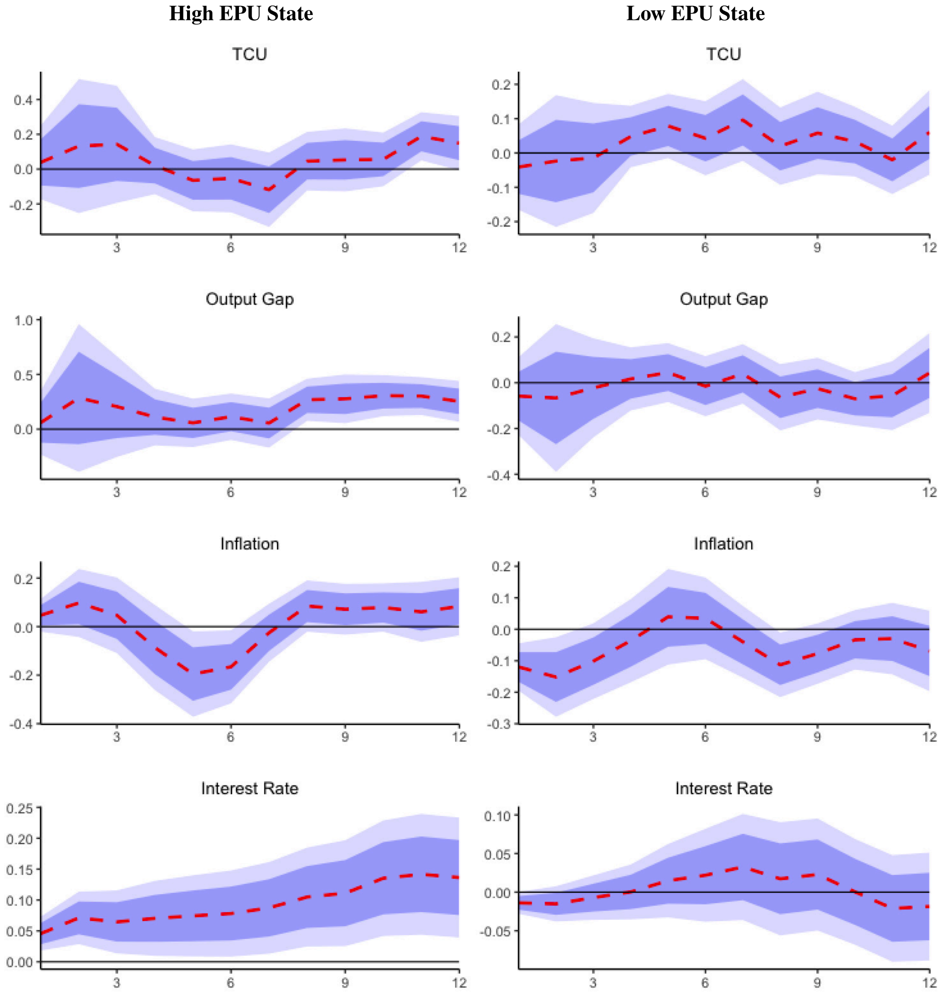

Fig. 28. Alternative Non-Linear Model 10 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 10 replaces EPU variable in the Baseline Non-Linear Model with the LMN Financial Uncertainty data. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

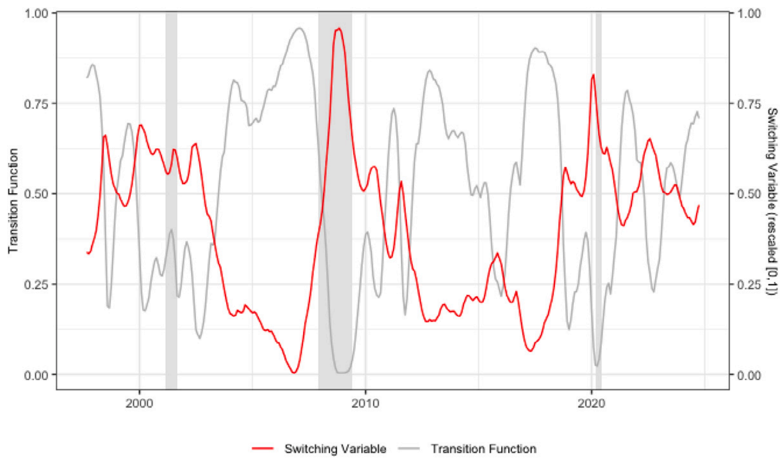

Fig. 29. Transition function non-linear model (Alternative Non-Linear Model 10).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

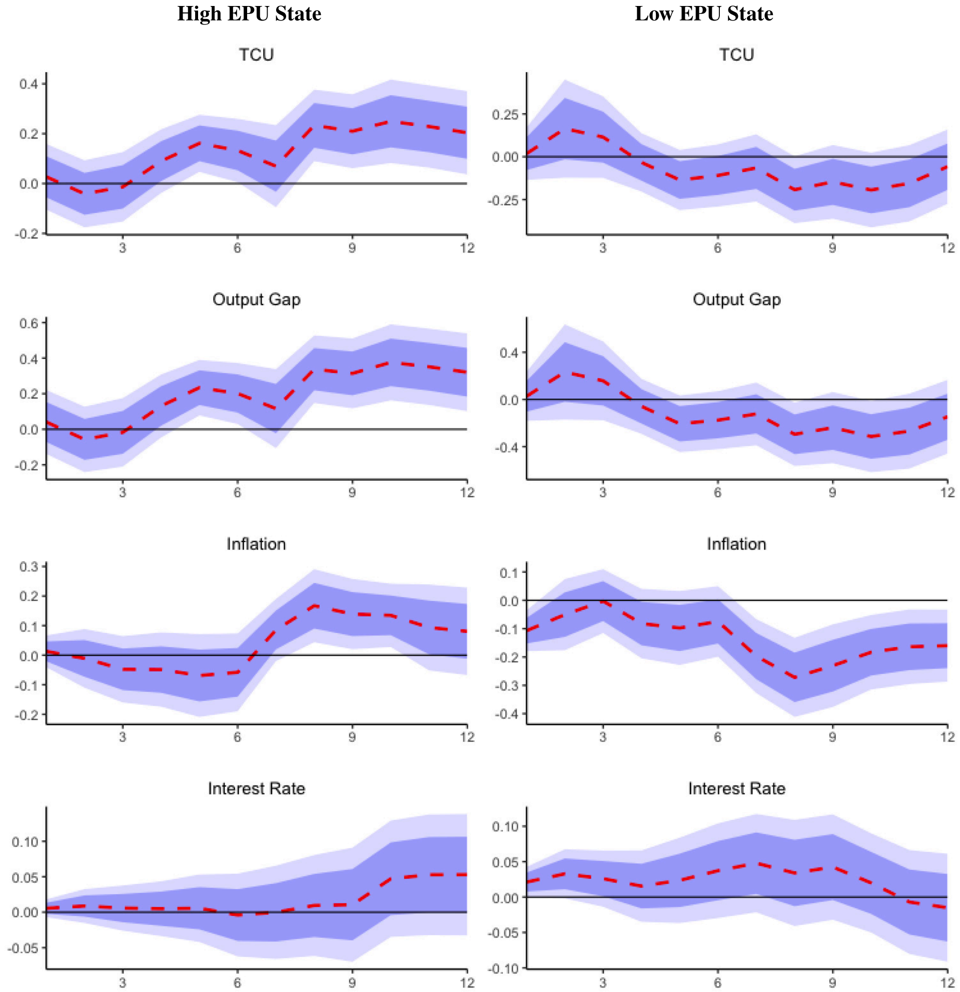

Fig. 30. Alternative Non-Linear Model 11 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 11 we extend the baseline sentiment shock by adding additional economic data to construct the sentiment shock term. "High EPU State'' (''Low EPU State'') represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

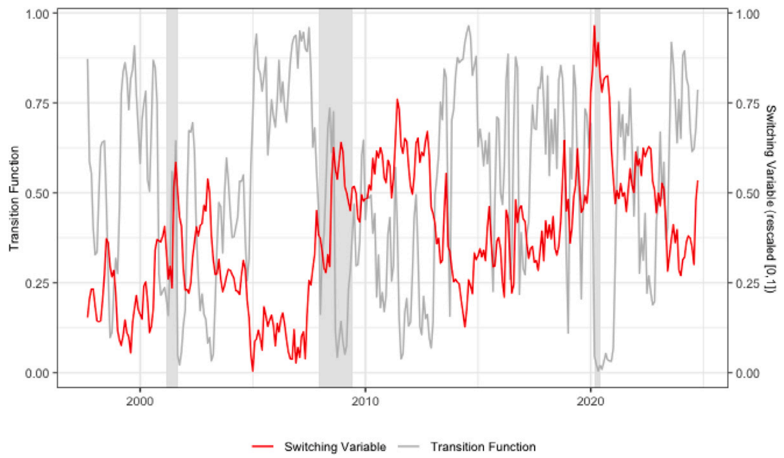

Fig. 31. Transition function non-linear model (Alternative Non-Linear Model 11).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

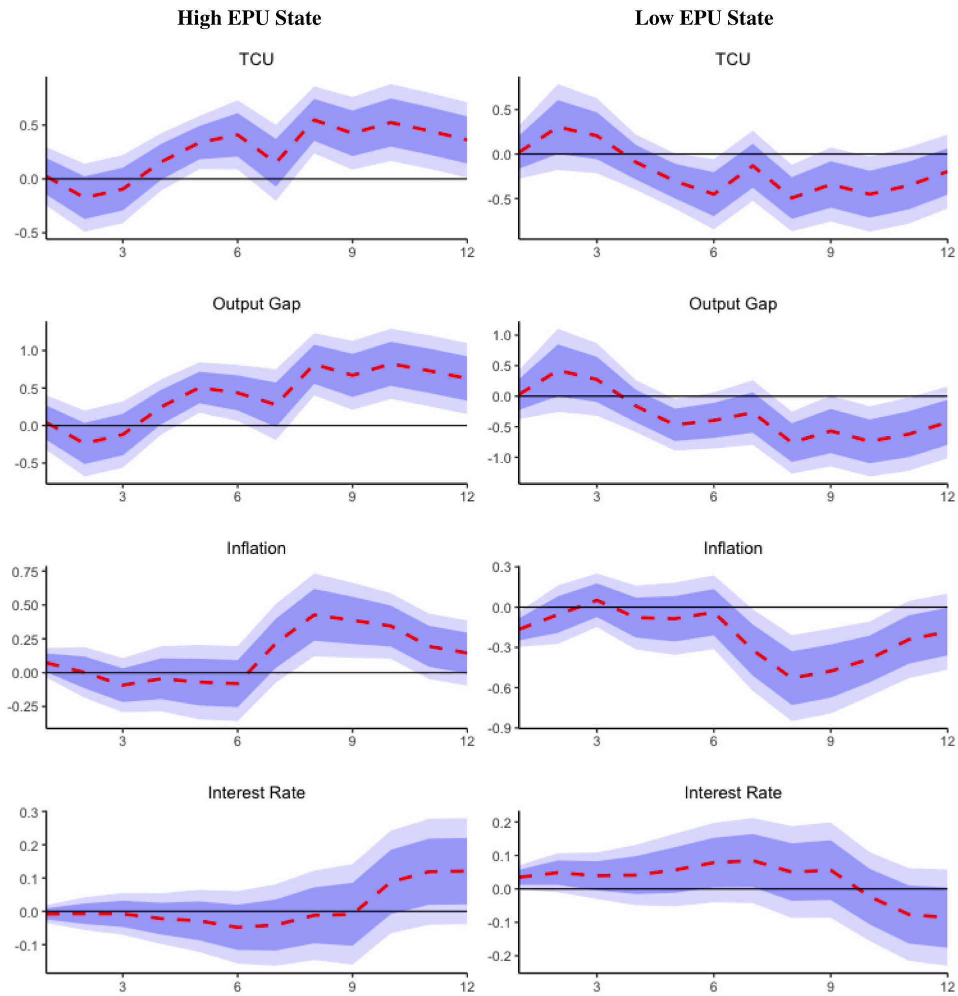

Fig. 32. Alternative Non-Linear Model 12 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 12 adjusts the baseline specification by estimating the transition function using a lower smoothness parameter (γ = 0.5). "High EPU State'' (''Low EPU State'') represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

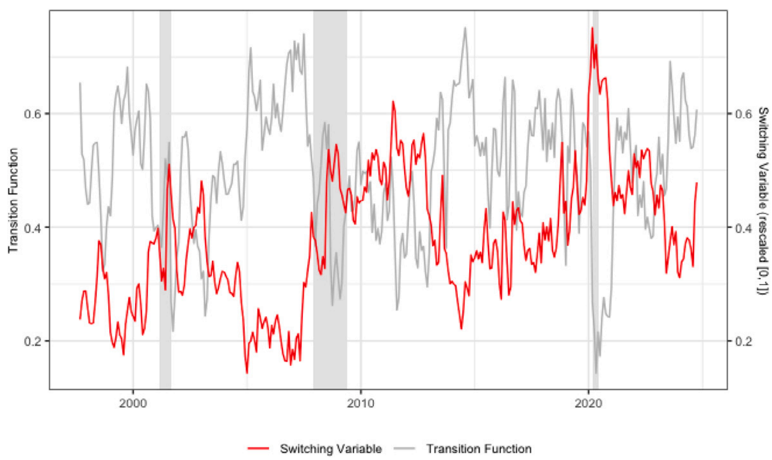

Fig. 33. Transition function non-linear model (Alternative Non-Linear Model 12).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates.

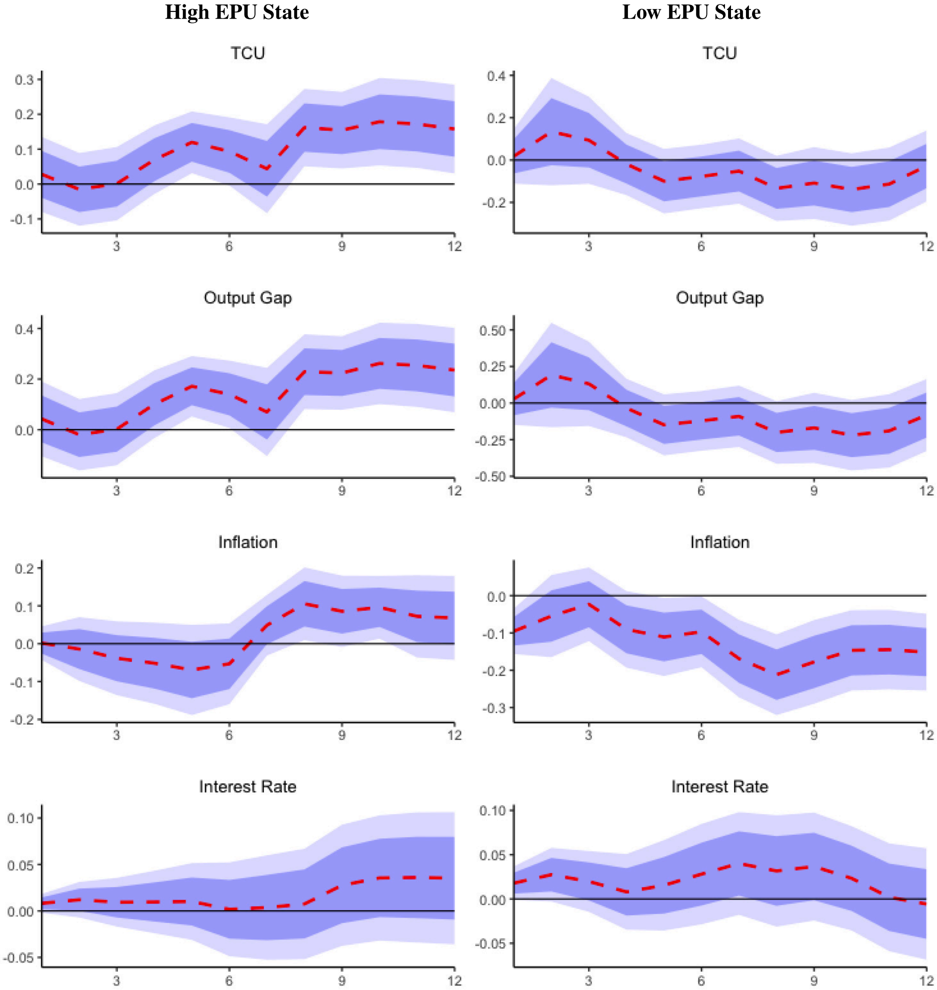

Fig. 34. Alternative Non-Linear Model 13 impulse response functions to a sentiment shock.
Note: Alternative Non-Linear Model 12 adjusts the baseline specification by estimating the transition function using a higher smoothness parameter ($\gamma = 3$). "High EPU State" ("Low EPU State") represents periods of elevated (subdued) filtered EPU. Impulse responses correspond to a one-standard-deviation consumer sentiment shock. Shaded areas denote 68 and 90 percent confidence intervals computed using Newey–West robust errors. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

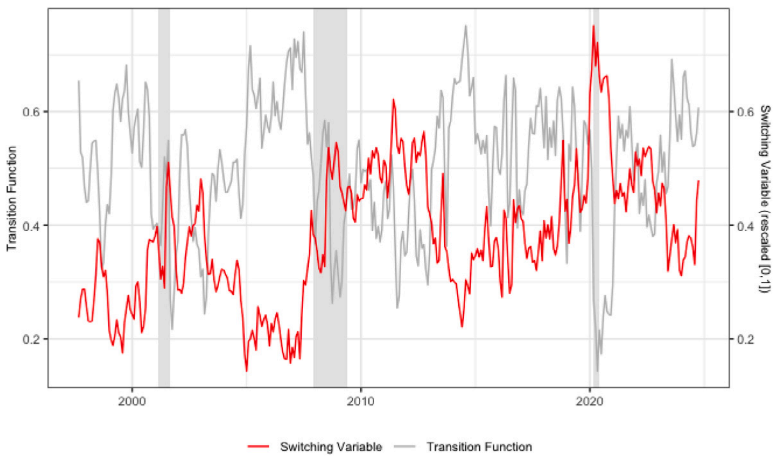

Fig. 35. Transition function non-linear model (Alternative Non-Linear Model 13).
The figures shows the weighted regime (i.e., F(z)). Shaded areas indicate NBER recession dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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