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Business-Cycle Dynamics: An Empirical Assessment*

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Abstract

This study provides an empirical assessment of business cycle dynamics using a structural vector autoregressive (VAR) model that measures cyclical output and identifies business cycle shocks as the main drivers. Using the same data and reduced-form VAR setup as Angeletos et al. (2020, *American Economic Review*), we estimate the dynamic effects of this shock on the U.S. economy. The cyclical output indicated by the model closely tracked the standard measure of the output gap. The identified business cycle shock has long-lasting effects on both demand- and supply-side factors, permanently influencing output and affecting labor productivity and total factor productivity. These findings contradict the prevailing notion that business cycles are short-term phenomena and suggest that the forces driving them contribute to medium-term dynamics. This implies a pivotal connection between short-term stabilization and long-term growth.

JEL Classification: C32; E32.

Keywords: business-cycle shocks; structural vector autoregressive model; finite-horizon identification; cyclical output; medium-term dynamics.

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1 Introduction

The dynamics of business cycles have been the central focus of macroeconomic research. Understanding the underlying forces driving economic fluctuations and their complex relationships with long-term economic growth remains a critical challenge for both academic researchers and policymakers. This study contributes to the ongoing debate by developing a novel methodology for measuring and analyzing business cycle dynamics using a vector autoregressive (VAR) model.

A foundational question in business cycle research concerns the potential interdependence between cyclical fluctuations and the factors driving long-term economic growth. Traditional neoclassical perspectives often view these phenomena as fundamentally distinct, thereby leading to the separation of the analysis of short-run, primarily demand-side shocks that elucidate business cycles from the study of long-run supply-side factors within the framework of growth theory (Mankiw, 2022). These frameworks frequently assume that cyclical deviations are transient and exert minimal influence on an economy's long-term growth potential. However, a growing body of research challenges this strict dichotomy, suggesting that business cycle fluctuations can have persistent or even permanent effects on long-term growth. Determining whether cyclical fluctuations are truly independent of growth factors or whether they are interdependent is a critical empirical question that warrants further investigation.

While many studies examine the different ways in which business cycles can influence growth, relatively little focus has been placed on empirically identifying and quantifying the specific shocks responsible for these effects. An important contribution in this area is the work of Angeletos et al. (2020), which explores the role of "business-cycle shocks" that explain 6-quarter-to-32-quarter frequency domain variation in economic variables. However, their analysis, although insightful, may underestimate the importance of supply-side factors and the potential for business cycle shocks to exert longer-lasting effects on an economy's long-term growth path.

This study proposes a novel yet straightforward empirical framework for measuring business cycle dynamics and estimating the causal effects of business cycle shocks on the macroeconomy. The proposed approach uses a structural VAR model that specifies a system that includes the output and key macroeconomic time series relevant to the forecast output. We impose restrictions on the VAR model to identify business cycle shocks that best explain cyclical output movements. Building on the work of Angeletos et al. (2020), we employed the same dataset and reduced-form VAR specification for the U.S., allowing us to compare our results directly.

Our empirical analysis reveals two key findings. First, we show that our cyclical output measures, derived from the VAR model, closely track the output gap and accurately reflect the U.S. business cycle fluctuations. Second, and more importantly, we find that the identified business cycle shocks exert significant and persistent effects, impacting not only demand factors, such as consumption and investment, but also supply-side or growth factors, such as labor productivity and total factor productivity. This suggests that business cycle fluctuations can have long-term consequences on an economy's productive capacity and long-run growth potential. This result differs from previous findings, such as Angeletos et al. (2020), which suggested a limited impact of business cycle shocks on growth factors.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the econometric methodology used to measure cyclical outputs and identify business cycle shocks. Section 4 presents the empirical results by applying our framework. Finally, Section 5 concludes the paper by summarizing the main findings and discussing their implications.

2 Related literature

Our study builds upon and contributes to the vast literature that examines the dynamics of business cycles. The past studies focus on measuring business cycles, identifying the underlying forces that drive fluctuations, and analyzing the relationship between business cycles and long-term economic growth.

Measuring business cycles

Early work by Burns and Mitchell (1946) provided a foundational descriptive definition of business cycles, which they characterized as a type of fluctuation found in the aggregate economic activity of nations that organize their work, mainly in business enterprises. They emphasized that a business cycle consists of expansions occurring at approximately the same time, followed by similar general recessions, contractions, and revivals, which merge into the expansion phase of the next cycle. Crucially, Burns and Mitchell (1946) highlighted that this sequence of changes is recurrent but not periodic. Moreover, they noted that the duration of business cycles varies, typically ranging from more than one year to ten or twelve years.

Following Burns and Mitchell (1946), subsequent research focused on developing statistical methods to extract the cyclical components of economic time series. Common approaches include polynomial detrending, such as removing a quadratic trend, and the application of filters like the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997), the Baxter-King (BK) bandpass filter (Baxter and King, 1999), and the Hamilton filter (Hamilton, 2018). These methods differ in their assumptions regarding the nature of the trend and frequency range of cyclical fluctuations. Hodrick (2020) argues that when the output is close to a random walk, the Hamilton filter performs well; however, when it follows a more complex process, the HP or the BK filter is better. By contrast, Canova (2025) argued that simple polynomial detrending can be superior when assessing the consistency of cyclical measures with the output gap.

Identifying the forces driving business cycles

Identifying structural shocks that drive economic fluctuations is a key challenge in business cycle research. Blanchard and Quah (1989) pioneered the use of structural VAR models to distinguish between demand and supply shocks based on their long-run effects. King et al. (1991) and Galí (1999) extended this approach, using VAR models to analyze the effects of technology shocks, monetary shocks, and others on the business cycle.

More recently, Angeletos et al. (2020) proposed a different approach, identifying a "main business-cycle shock" as the single shock in the VAR model that explains the most variance in economic variables within the 6-quarter-to-32-quarter frequency domain, aligning with the BK filter cyclical output. They found that this shock mainly affects demand-side variables and has a limited impact on long-run growth and inflation, leading them to question the significance of supply-side factors and nominal rigidities in driving business cycles.

Business cycles and long-run growth

Another area of research examines the link between business cycle fluctuations and long-term economic growth. This field explores the various mechanisms through which cyclical activities can have lasting effects on growth, such as endogenous technological change driven by innovation (Stadler, 1990; Comin and Gertler, 2006), hysteresis effects from prolonged periods of unemployment that damage human capital (Blanchard and Summers, 1986), and financial market imperfections that amplify and spread cyclical shocks (Guerrón-Quintana and Jinnai, 2019; Guerrón-Quintana et al., 2023). Moreover, recent work by Furlanetto et al. (2025) identified a permanent output shock associated with inflation. They reported that although such shocks have a limited effect on labor productivity, they have economically significant and long-lasting impacts on output, investment, and employment.

Previous studies, particularly Comin and Gertler (2006), indicated that macroeconomic fluctuations include a *medium-term cycle* distinct from the typical short-term business cycle. They identified a component with periodicities spanning decades that exhibited notable output variations. Figure 1 shows the medium-term cycle alongside the Congressional Budget Office (CBO) GDP gap. Although the two series tend to move together at specific turning points, the medium-term cycle progress is slower, and the swings are larger and longer, while the output gap reflects short-term slack around the potential output. The authors underscored the significance of the mechanism driving these medium-term cycles in macroeconomic dynamics.

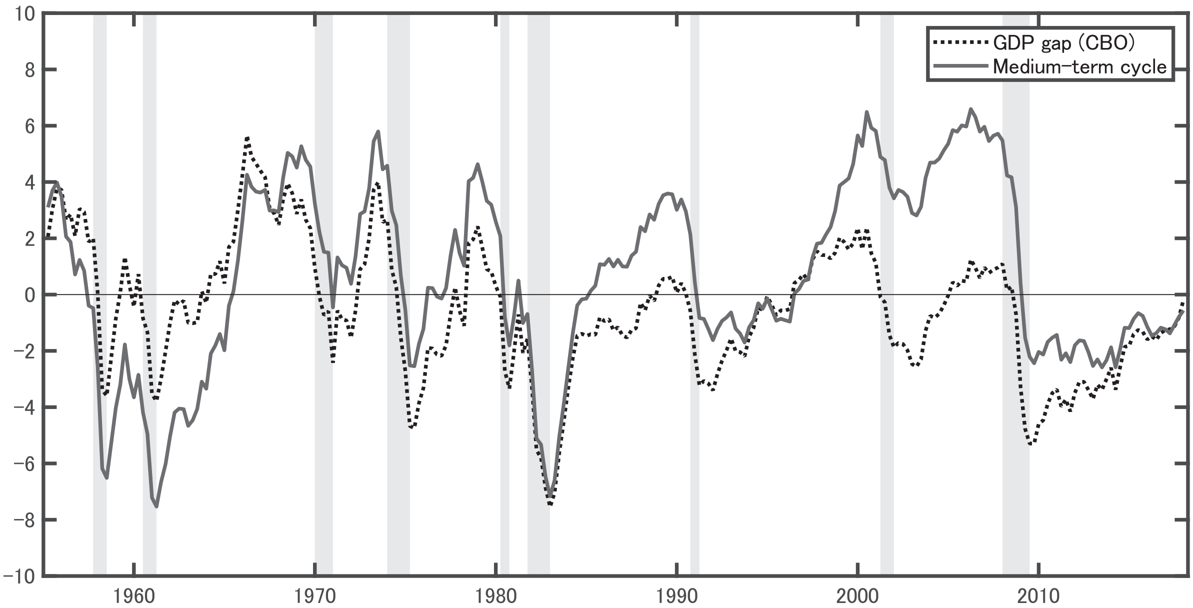

Figure 1: Medium-term cycle vs output gap

Notes: The shaded areas show periods of recession in the US, as defined by the NBER. The medium-term cycle is the variation in per capita real GDP at frequencies between 2 and 200 quarters. The output gap is the GDP gap measured by the Congressional Budget Office (CBO). Samples span from the first quarter of 1955 to the fourth quarter of 2017.

Contribution to the literature

This study contributes to the literature on business cycles in three ways. First, we propose a cyclical output measure using a VAR model. Second, in contrast to Angeletos et al. (2020), we identify the single business-cycle shock that best explains the dynamics of cyclical output using the VAR model. Third, we present evidence on the interdependence of cyclical fluctuations and growth factors by examining whether the shock has long-lasting effects on both demand-and supply-side factors and whether it creates a medium-term cycle in dynamics.

3 Econometric methodology

3.1 Modeling cyclical output

First, we introduce our concept of the cyclical component of output. Suppose that the variable y_t represents output in quarter t. Following Hamilton (2018), we define the cyclical component of output as the difference between the actual value in quarter $t+h$ and the expected value based on the information available at the beginning of quarter t,

$$y^c_{t+h} \equiv y_{t+h} - E_{t-1}(y_{t+h}), \tag{1}$$

where y^c_{t+h} denotes the cyclical component of output in quarter $t+h$ and $E_{t-1}(y_{t+h})$ is the expected output in quarter $t+h$ based on the information set at quarter $t-1$. Following Hamilton (2018), we set a horizon of $h = 8$ quarters to reflect the features of the business cycle movements in the output.

Our concept of the cyclical component can differ from that of a transitory component, which can be extracted by, for example, Beveridge and Nelson's (1981) decomposition.[1] We define the transitory component as the difference between the actual output and its long-run forecast,

$$y^t_t \equiv y_t - \lim_{h\to\infty} E_{t-1}(y_{t+h}), \tag{2}$$

where the long-run forecast of the output $\lim_{h\to\infty} E_{t-1}(y_{t+h})$ limit exists. The literature assumes that long-run forecasts reflect permanent and random walk components.

Stochastic shocks that cause cyclical and transitory components can have different long-

[1]Beveridge and Nelson (1981) refer to the transitory component as the "cyclical component."

term effects on output. Since deviations from the permanent component are stationary, shocks to the transitory component are assumed by construction to have no long-term influence on output. However, if the impact of the shocks to the cyclical component has not fully faded after a sufficiently long period, part of the stochastic trend would include the components explained by these shocks. In other words, cyclical shocks can notably influence output in the long term.

3.2 Identifying business-cycle shocks

First, we specify a reduced-form VAR model, in which the endogenous variables contain significant information on macroeconomic dynamics. Let X_t denote a $K \times 1$ vector of the time-varying observables in quarter t. The output is given by the first element of X_t, that is, $X_{1,t} = y_t$. We construct the following reduced-form VAR model:

$$A(L)X_t = e_t, \tag{3}$$

where $A(L) = I - A_1L - \cdots - A_qL^q$ is a qth order matrix lag polynomial in the lag operator, L, of a coefficient matrix $A_j (j = 1, \cdots, q)$, and e_t denotes the $K \times 1$ vector of the reduced-form VAR innovations with a zero mean of a covariance matrix of Σ_e.[2] This stochastic structure can be expressed in terms of the following infinite vector moving average (VMA) representation:

$$X_t = \Phi(L)e_t, \tag{4}$$

where $\Phi(L) = A(L)^{-1} = I + \Phi_1L + \Phi_2L^2 + \cdots$ is a matrix lag polynomial of the coefficient matrices $\Phi_\tau (\tau = 0, 1, \cdots), \Phi_0 = I$.

We then derive the time-series variations of the VAR variables attributed to structural shocks. Let the business cycle shocks ϵ_t^c be the first element of the $K \times 1$ vector of the structural shocks $\epsilon_t = (\epsilon_t^c, \epsilon_t^{o'})'$. The space spanned by business cycle shocks ϵ_t^c is disentangled from the other possible shocks in the following linear relationship between the reduced-form VAR innovations e_t and structural shocks ϵ_t:

$$e_t = R^c\epsilon_t^c + e_t^{\perp}, \tag{5}$$

[2]In practice, since the VAR variables X_t generally have non zero mean, the reduced-form VAR in (3) estimated in the empirical analysis contains a constant vector. In this subsection, to simplify the notation, we do not intercept the VAR without loss of generality.

where R^c represents the impact vector for the responses of the VAR variables X_t to business cycle shocks, and $e_t^{\perp}$ represents the residual of e_t consisting of a linear combination of other shocks. From (4) and (5), we can express the parts of the stochastic process of the VAR variables driven by business cycle shocks as the VMA, $\Phi(L)R^c\epsilon_t^c$.

We identify business cycle shocks in the VAR model in a way that aligns with the forces driving the dynamics of cyclical output, as described in Subsection 3.1. Specifically, we identify business cycle shocks as those that best explain the future movement of output over a horizon of 8 quarters. To this end, we employ the maximum forecast error variance (MFEV) approach introduced by Faust (1998), Uhlig (2004), and Francis et al. (2014).

To explain our MFEV approach, we begin by relating the covariance matrix Σ_e of VAR innovations to the impact vector R^c of a business cycle shock. First, we consider an arbitrary $K \times K$ orthogonalization matrix $\tilde{R}$ (e.g., Cholesky decomposition), such that it satisfies the condition, $\Sigma_e = \tilde{R}\tilde{R}'$. Suppose $\tilde{R}\gamma$ is a $K \times 1$ vector, which is interpreted as an impact vector R^c, where the $K \times 1$ vector γ has unit length, $\gamma'\gamma = 1$. Suppose we have a vector γ and an orthogonalization matrix $\tilde{R}$. In this case, we can generate the impulse responses of the VAR variables to business cycle shocks from the impact vector $R^c = \tilde{R}\gamma$.

Next, we consider the forecast error in output due to business cycle shocks. Using equation (4), we can express the cyclical output as the h-period-ahead forecast error in the output:

$$X_{1,t+h} - E_{t-1}(X_{1,t+h}) = \sum_{\tau=0}^{h} \Phi_{1,\tau} e_{t+h-\tau}, \tag{6}$$

where $\Phi_{1,\tau}$ is the first column of the matrix of MA coefficients Φ_τ. From equation (5), the h-period-ahead forecast error in output due to business-cycle shocks can be expressed as follows:

$$\sum_{\tau=0}^{h} \Phi_{1,\tau} R^c \epsilon_{t+h-\tau}^c = \sum_{\tau=0}^{h} \Phi_{1,\tau} \tilde{R}\gamma \epsilon_{t+h-\tau}^c. \tag{7}$$

We identify business cycle shocks by choosing the vector γ to maximize the forecast error variance of the output for h periods ahead. The share of the forecast error variance of the output attributable to business cycle shocks at horizon h is

$$\Omega_{1,c}(h) = \frac{\sum_{\tau=0}^{h} \Phi_{1,\tau} \tilde{R}\gamma E(\epsilon_{t+h-\tau}^c \epsilon_{t+h-\tau}^c)\gamma' \tilde{R}' \Phi_{1,\tau}'}{\sum_{\tau=0}^{h} \Phi_{1,\tau} \Sigma_e \Phi_{1,\tau}'} = \frac{\sum_{\tau=0}^{h} \Phi_{1,\tau} \tilde{R}\gamma\gamma' \tilde{R}' \Phi_{1,\tau}'}{\sum_{\tau=0}^{h} \Phi_{1,\tau} \Sigma_e \Phi_{1,\tau}'}, \tag{8}$$

where the variance of business cycle shocks is normalized to one. We choose the vector γ by solving the following restricted optimization problem:

$$\hat{\gamma} = \arg\max_{\gamma} \Omega_{1,c}(h), \tag{9}$$

s.t. $\gamma'\gamma = 1$.

In our empirical exercise, we elucidate the difference between our business cycle shocks and the shocks to the transitory component of output y_t^t. If the dichotomy between business cycles and economic growth holds in reality, we would expect transitory shocks to result in business cycles in the macroeconomy, independent of the permanent shocks that cause economic growth. Thus, we hypothesize that transitory shocks are both quantitatively and qualitatively similar to business cycle shocks: if business cycle shocks have zero or negligible impact on output in the long run, they would cover a similar space as spanned by transitory shocks. To validate this hypothesis, we compare the properties of business cycle shocks and transitory shocks. We follow the methodology proposed by Blanchard and Quah (1989) and identify the transitory shock ϵ_t^t as the residual of output innovations independent of the permanent shock, which accounts for output movement in the very long horizon of $h = 200$ quarters using the MFEV approach.[3]

3.3 Benchmark specification of reduced-form VAR model

We use the same U.S. dataset and reduced-form VAR specification as Angeletos et al. (2020), allowing for a direct comparison of the results. They used the following ten macroeconomic variables: the real per capita GDP (Output), investment (Investment), consumption (Consumption), hours worked per person (Worked hours), the unemployment rate (Unemployment), the labor share (Labor share), the nominal interest rate, measured by the federal funds rate (Nominal interest rate), the inflation rate, as measured by the change in the GDP deflator (Inflation), labor productivity in the nonfarm business sector (Labor productivity), and the level of utilization-adjusted factor productivity (TFP). We set the lag length q in the reduced-form VAR to two quarters. The sample period begins in the first quarter of 1955 and ends in the fourth quarter of 2017.

[3]Blanchard and Quah (1989) proposed the methodology to identify the shocks to the transitory component of output. Specifically, they imposed a long-run restriction on the VAR model consisting of real GDP growth and unemployment and identify the permanent shock as the shock that accounts for real output movements in the long run and the transitory shock as the residual of output innovation independent of the permanent shock.

4 Empirical results

This section presents the empirical findings from the VAR framework described in the previous section. First, we evaluated whether the cyclical output derived from the VAR model aligns with the standard output gap measures. Next, we identify business cycle shocks using the MFEV approach, which best explains the eight-quarter-ahead forecast error variance of output, and analyze their dynamic causal effects on the demand and growth variables. Finally, we compare these business cycle shocks with transitory shocks to clarify the differences.

4.1 Measuring cyclical output

This subsection analyzes the time series of the VAR-based cyclical output measure, $y_t^c \equiv y_t - E_{t-9}(y_t)$. To achieve this objective, it is helpful to compare this VAR measure with alternative measures other than the output gap. In particular, cyclical output is expected to satisfy two key criteria. First, business cycles should exhibit time-series features consistent with the output gap, which reflects deviations from potential output. Secondly, as cyclical elements, business cycles must show recurrent stationary patterns over time. Therefore, we examine the factors that specifically and quantitatively explain the observed differences among various cyclical output measures.

Figure 2 displays four cyclical output measures: the VAR-based series (VAR), the Hamilton filter (Ham), the BK bandpass filter with 6-32-quarter periodicity (BK), and a polynomial-detrended series (POLY), along with the CBO GDP gap. This figure enables direct comparison of the phase alignment (peaks and troughs), amplitude, and low-frequency persistence. Table 1 provides the descriptive statistics for these cyclical output measures: standard deviation, standardized long-run variance, and correlation and root mean squared errors (RMSE) with the GDP gap that quantify these visual patterns.[4]

The evidence shows that VAR accurately tracks the GDP gap in both timing and magnitude: the turning points and swing sizes in Figure 2 match well, and Table 1 indicates a comparable standard deviation (2.50), stationarity (0.22 standardized long-run variance), high correlation

[4]Cochrane (1988) proposed the ratio of far-future long-run variance of the *first difference* of the time-series variable of interest to its variance as a measure of the persistence of the series *level*. This ratio is referred to as *standardized long-run variance*. This measure is zero for a stationary time series, one for a pure random walk, greater than one for a series that continues to diverge following a shock, and between zero and one for a series that returns to a stochastic future trend. We estimate the long-run variance as 1/40 times the variance of the 40-quarter difference in the series.

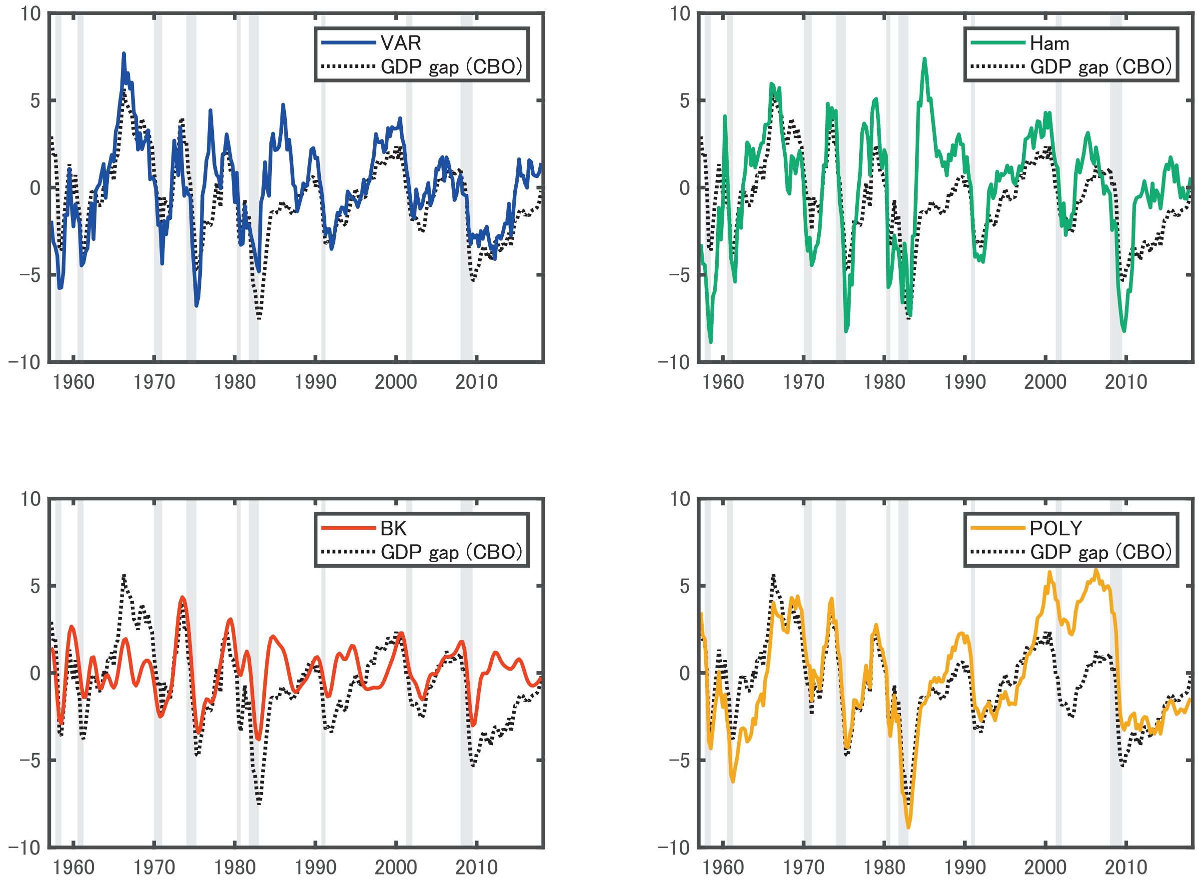

Figure 2: Cyclical output measure comparisons

Notes: Samples span from the first quarter of 1955 to the fourth quarter of 2017. VAR is the deviation of output from the 8-quarter-ahead forecast using the reduced-form vector autoregressive model with 2-quarter lags. Ham is the Hamilton filter, the residual of a regression of 8-quarter-ahead output on current output and up to 3 lags of output. BK is the Baxter-King bandpass filter with a 6-32-quarter periodicity. POLY is polynomial detrend, the residual of a regression on a quadratic polynomial. The shaded areas show periods of recession in the US, as defined by the NBER.

Table 1: Descriptive statistics for output gap and cyclical output measures

	GDP gap	Cyclical output measure			
	(CBO)	VAR	Ham	BK	POLY
Standard deviation	2.30	2.50	3.30	1.44	3.09
Standardized long-run variance	0.37	0.22	0.25	0.43	0.82
Correlation with GDP gap	–	0.73	0.67	0.57	0.77
RMSE compared with GDP gap	–	1.90	2.54	2.05	2.03

Notes: Samples span from the first quarter of 1955 to the fourth quarter of 2017. VAR is the deviation of output from the 8-quarter-ahead forecast using the reduced-form vector autoregressive model with 2-quarter lags. Ham is the Hamilton filter, the residual of a regression of 8-quarter-ahead output on current output and up to 3 lags of output. BK is the Baxter-King bandpass fitter with a 6-32-quarter periodicity. POLY is polynomial detrend, the residual of a regression on a quadratic polynomial. Standard deviation is the standard deviation of each measure. Standardized long-run variance is 1/40 times the variance of the 40-quarter difference of each measure divided by the variance of its first difference. The correlation is the coefficient between the GDP gap and each of the cyclical output measures. RMSE is the root mean square error, calculated as the root of the average squared difference between the GDP gap and each of the cyclical output measures.

(0.73), and relatively small RMSE (1.90) with the GDP gap. In contrast, Ham is overly volatile, with larger swings, as shown in Figure 2 a higher standard deviation (3.30), and a larger RMSE (2.54) with the GDP gap. This phenomenon reflects the tendency to include short-term noise as cycles because of limited predictive information compared to the VAR model, which incorporates additional variables relevant for predicting output. BK resulted in smaller fluctuations with subdued peaks and troughs, as illustrated in Figure 2. Table 1 shows a reduced standard deviation (1.44) and weaker correlation (0.57), suggesting dampening of the significant cyclical variation. POLY moves with the gap but exhibits stronger persistence, with prolonged deviations in Figure 2, especially from the late 1990s through the 2000s, with more low-frequency content (0.82 standardized long-run variance), making POLY resemble a medium-term cycle rather than an output gap.

Overall, these results support the VAR measure as the preferred option because of its balance between phase alignment and amplitude accuracy. While the other methods are still useful, they show consistent biases: Ham tends to exaggerate variations, BK tends to underestimate them, and POLY shows medium-term persistence, which may drift from the output gap over long periods.

4.2 Estimating the dynamics of business cycles

Dynamic causal effect of business-cycle shocks

We report the results of the dynamic causal effect and contribution of business cycle shocks ϵ_t^c to the macroeconomic dynamics using the estimated structural VAR model. Figure 3 summarizes the estimated impulse response functions for the business cycle shocks. We set the horizon in the identification problem at $h = 8$; that is, we identify the business cycle shock as the shock that best accounts for output movements over a two-year horizon. Business-cycle shocks are normalized to have unit variance and are signed to positively affect output in the four quarters ahead. The solid line indicates the estimated response of the VAR variables for up to 20 quarters. The shaded areas denote one-standard-error bands calculated using 1000 bootstrap samples. Table 2 presents the results of the forecast error variance decomposition. The entries are $\Omega_{k,c}(h)$ for $k = 1, \cdots, 10$, which show the percentage share of the variance in the forecast error by the VAR variable described in the upper header at a given horizon h as explained by the business cycle shocks.

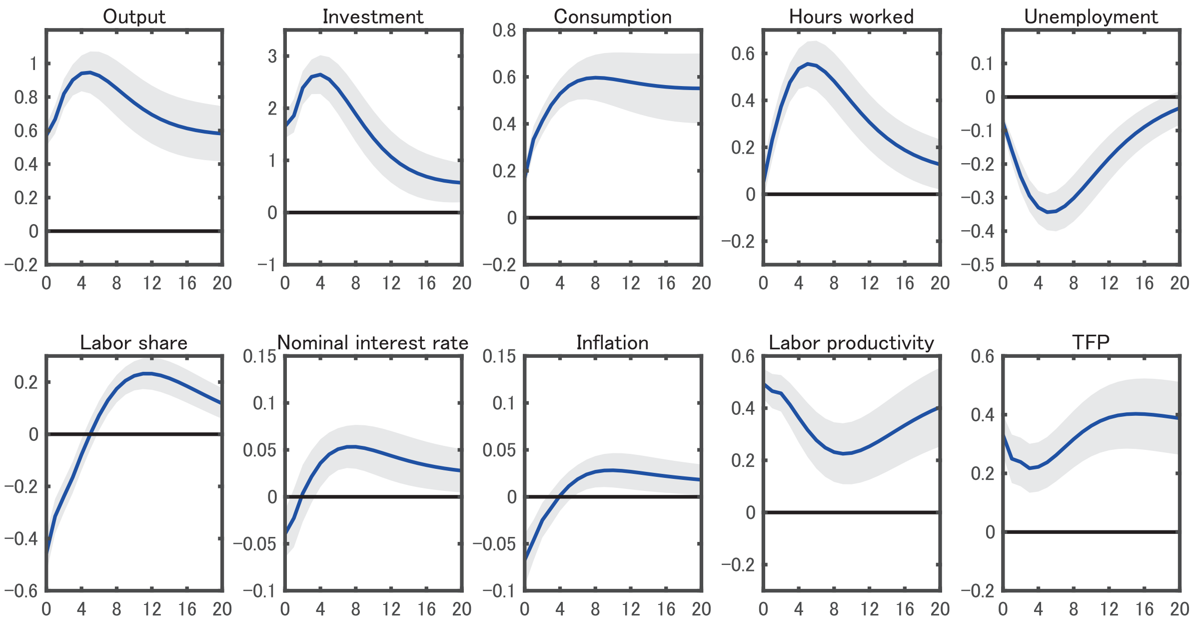

Figure 3: Estimated responses to a business-cycle shock

Notes: The solid line represents the point estimates of the impulse responses to one standard deviation business-cycle shock identified using the estimated structural VAR model described in Section 3 over the sample period from the first quarter of 1955 to the fourth quarter of 2017. The shaded areas denote one-standard-error bands, calculated using 1000 bootstrap samples. We set the lag length to two quarters in the reduced-form VAR estimation.

Table 2: The share of forecast error variance due to business-cycle shocks

h	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
0	67.3	46.5	15.8	0.8	12.1	30.7	4.5	7.6	48.8	21.7
8	86.9	64.0	65.2	45.2	56.0	26.8	6.1	7.1	34.2	22.5
20	79.3	55.1	68.3	39.9	52.3	34.6	9.5	9.0	29.1	38.6

[1] Output. [2] Investment. [3] Consumption. [4] Hours worked. [5] Unemployment. [6] Labor share. [7] Nominal interest rate. [8] Inflation. [9] Labor productivity. [10] TFP.

Notes: The entries are $\Omega_{k,c}(h)$ for $k = 1, \cdots, 10$, which show the percentage share of the variance of the forecast error made in the VAR variable described in the upper header at a given horizon h as explained by the business-cycle shocks. The results are computed from the structural VAR model over the sample period from the first quarter of 1955 to the fourth quarter of 2017. We set the lag length to two quarters in the reduced-form VAR estimation.

Business-cycle shocks have significant economic and statistical long-term effects on output. In Figure 3, a one-standard-deviation shock causes an initial increase in output of approximately 0.6%, peaks at approximately 1% within 4-8 quarters, and maintains a positive long-run level effect of 0.6%. This suggests that the business cycle shock influenced a portion of the stochastic trend. Table 2 confirms the economic importance of this lasting effect: the shock accounts for a large portion of the output's forecast error variance in the medium to long horizons (e.g., 86.9% at $h = 8$ and 79.3% at $h = 20$). These findings are inconsistent with purely transitory effects and point to level-shifting effects on output.

Business cycle shocks have long-lasting effects on other demand components around the same time. Investment responds strongly and persistently; consumption changes are moderate but long lasting; worked hours and unemployment show typical demand-driven patterns- worked hours increase, while unemployment decreases- with effects that last beyond the short term. Their contributions to these components are economically significant: business cycle shocks explain approximately 55%, 68%, 40%, and 52% of the fluctuations in investment, consumption, worked hours, and unemployment, respectively, over 20 quarters.

Shocks to the business cycle affect supply-side capacity and not just demand. Figure 3 illustrates notable medium-term improvements in labor productivity and TFP. This suggests that business cycle shocks are not solely temporary demand effects but also induce changes in supply-side capacity. Table 2 attributes substantial FEV shares to growth-related factors in the medium-term horizon (e.g., labor productivity at 29% and TFP at 39% at $h = 20$). In addition, as both supply and demand strengthen, labor share and inflation initially decline following the shock but then gradually increase over time. Furthermore, the nominal interest rate rises steadily and persistently slightly ahead of and more prominently than the inflation dynamics. These patterns create a mechanism that propagates effects through both the demand and supply aspects of the macroeconomy.

Identified business-cycle shock series

Next, we report the time-series patterns of the identified business cycle shocks $\hat{\epsilon}_t^c$ for $t = 1, \cdots, T$. Figure 4 shows the time series of business cycle shocks. The dotted line represents business cycle shocks identified using the estimated VAR model. The estimated shocks tend to be noisy because they are serially uncorrelated by construction. We also present the centered, 5-quarter moving average of the shocks-that is, $\sum_{\tau=-2}^{2} \hat{\epsilon}_{t-\tau}^c/5$-in Figure 4 for easier visual interpretation, as indicated by the bars. The shaded areas highlight the periods of recession in the US.

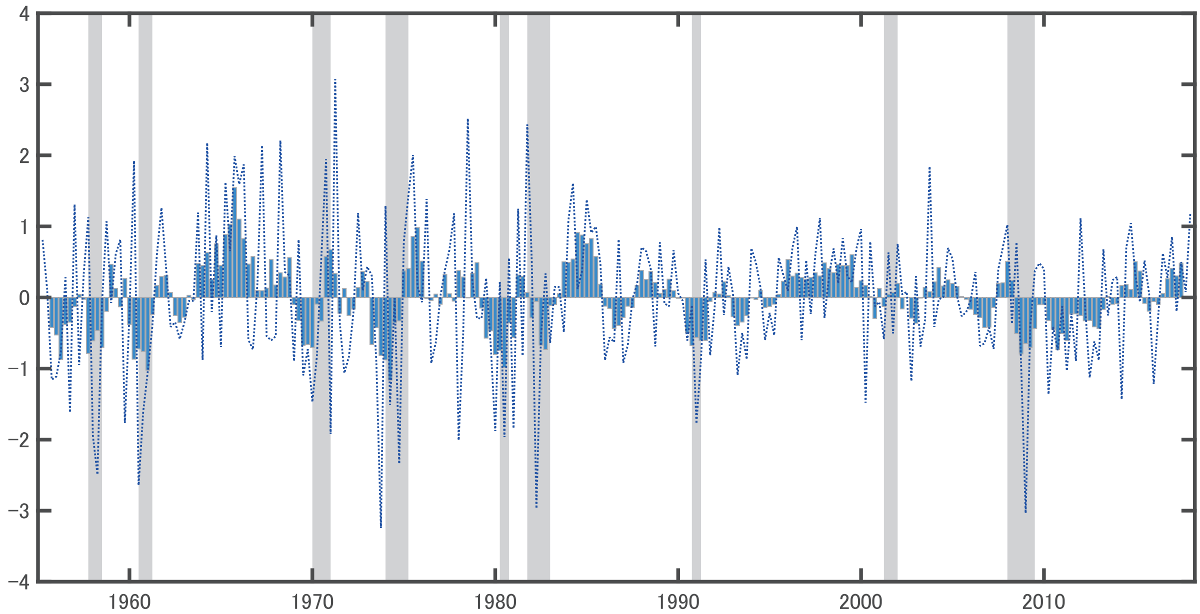

Figure 4: Identified business-cycle shocks

Notes: The dotted lines indicate the business-cycle shocks identified using the estimated structural VAR model described in Section 3 over the sample period from the first quarter of 1955 to the fourth quarter of 2017. The bars indicate the centered, 5-quarter moving average of the business-cycle shocks. The shaded areas show periods of recession in the US, as defined by the NBER.

Business-cycle shocks are not periodic but recurrent and random fluctuations that tend to reverse over approximately two to five years without exceeding a 10-year period. We can confirm that the estimated shock series naturally moves with the business cycle phases: positive during an expansion and negative during a recession.

Historical evolution of output due to business-cycle shocks

We analyze the historical evolution of output driven by the identified business cycle shocks using our structural VAR model. Specifically, we assess whether these shocks reflect medium-term cycles in dynamics. Although we do not explicitly model medium-term cycles in our structural VAR, we hypothesize that the identified shocks, which account for cyclical output variations, can also represent stochastic changes in output trends because they have substantial long-lasting impacts on output. To visualize the plausibility of this hypothesis, we decompose actual output into a series attributed to business cycle shocks.

Figure 5 plots the fitted values of the output from the VAR model for the identified business cycle shocks from the first quarter of 1957 to the fourth quarter of 2017. The blue solid and black dotted lines show the series explained by business cycle shocks and actual output, respectively. The left panel shows the decomposition series and actual cyclical output over 0-quarter-8-quarter lags using the estimated VAR model.[5] The right panel shows the decomposition series of past business cycle shocks and medium-term cycles proposed by Comin and Gertler (2006).[6]

Business-cycle shocks in the U.S. economy create medium-term cycles. When only considering shocks from zero to eight quarter lags, they produce a cyclical output that aligns with the identifying restrictions. However, the stochastic component explained by all past lags accounts for most of these medium-term cycles because business cycle shocks have long-lasting effects. This suggests that the main drivers of both business and medium-term cycles are analogous: shocks to the business cycle have persistent impacts on output through medium-term dynamics, resulting in these cycles.

4.3 How business-cycle shock differs from transitory and Angeletos et al. (2020) shocks

We present the results for the dynamic causal effects of the transitory shock ϵ_t^t in contrast with the business cycle shock ϵ_t^c. Figure 6 shows the estimated impulse response functions to a transitory shock, and Table 3 presents the forecast error variance decomposition results. As

[5]We calculate the decomposition series as $\sum_{\tau=0}^{8} \hat{\Phi}_{1,\tau} \hat{R}^c \hat{\epsilon}_{t-\tau}^c$, given the shock series $\hat{\epsilon}_t^c$ for $t = 1, \cdots, T$.

[6]We calculate the decomposition series as the first element of $\sum_{\tau=1}^{q=2} \hat{A}_\tau \tilde{X}_{t-\tau} + \hat{R}^c \hat{\epsilon}_t^c$ recursively, given the initial value of X_0, X_{-1} and the shock series $\hat{\epsilon}_t^c$ for $t = 1, \cdots, T$.

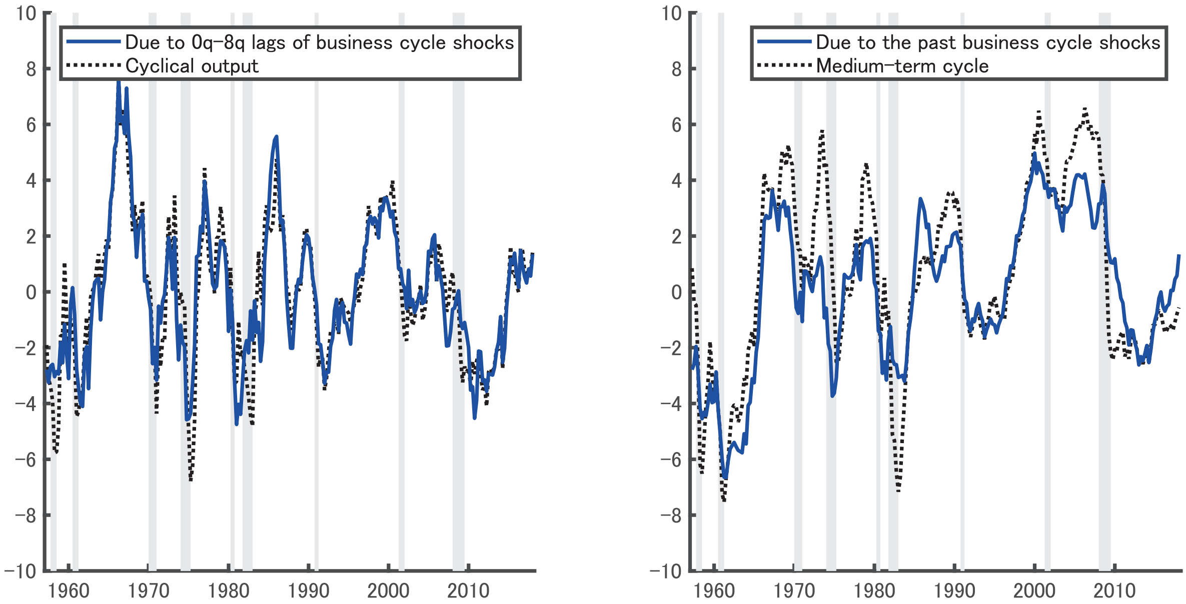

Figure 5: Historical output decompositions due to business-cycle shocks

Notes: Sample period from the first quarter of 1957 to the fourth quarter of 2017. The black dotted lines indicate the actual data. The blue solid lines show the series explained by the business-cycle shocks using the VAR model. We set the lag length to two quarters in the reduced-form VAR estimation. The gray-shaded areas show periods of recession in the US, as defined by the NBER.

expected, this shock produces short-lived effects on output, investment, and consumption with limited influence on labor productivity and TFP, explaining a modest part of the long-term output variation. Although transitory shocks capture some of the cyclical co-movements in demand-side factors, consistent with the results of Angeletos et al. (2020), they do not generate the persistent-level effects or growth responses observed in the case of business cycle shocks.

Transitory shocks generate only part of the business cycle, with peaks and troughs appearing less pronounced than those caused by business cycle shocks. Figure 7 depicts the fitted output values from the VAR model owing to the identified transitory shocks. The shocks produce only muted peaks and troughs of the business cycle, similar to the BK-filtered cyclical output reported in Figure 2.

Finally, we analyze the relationship among our identified business cycle shocks, transitory shocks, and the shocks identified by Angeletos et al. (2020). Following Angeletos et al. (2020), we use the MFEV approach to identify their shock as the one that maximizes the 4-quarter-ahead forecast error variance of unemployment.[7] Figure 8 presents scatter plots comparing

[7]Angeletos et al. (2020) report that their identified shock that accounts for most of the unemployment fluctuations in the frequency domain between 6 and 32 quarters is nearly identical to the one that targets 4 quarters in the time domain.

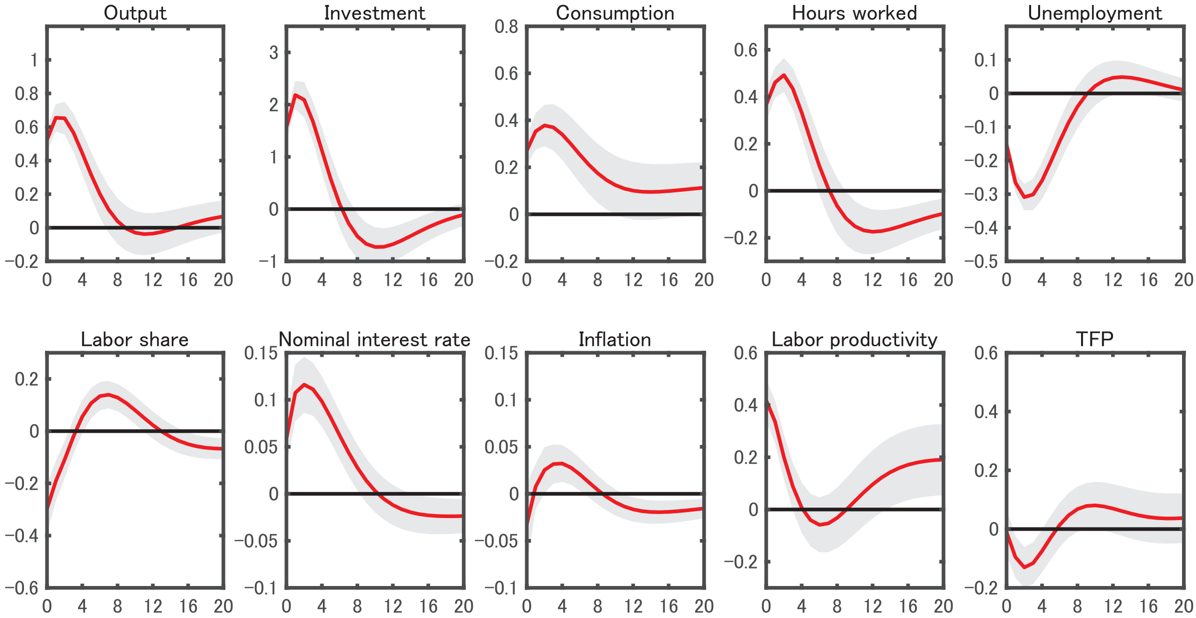

Figure 6: Estimated responses to a transitory shock

Notes: The solid line depicts point estimates of impulse responses to a one-standard-deviation transitory shock identified as the residual from output innovations that are independent of the permanent shock responsible for output movement at 200 quarters. These estimates are derived from the VAR model estimated over the sample period from the first quarter of 1955 to the fourth quarter of 2017. The shaded areas represent one-standard-error bands, which are calculated using 1,000 bootstrap samples. For the reduced-form VAR estimation, we set the lag length to two quarters.

Table 3: The share of forecast error variance due to transitory shocks

h	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
0	56.8	41.7	39.8	42.6	48.7	13.0	9.9	1.7	35.0	0.0
8	24.4	22.8	24.5	23.6	32.8	12.2	27.3	4.0	9.3	1.9
20	12.3	18.6	10.9	17.9	22.6	9.5	19.8	4.7	7.0	1.5

[1] Output. [2] Investment. [3] Consumption. [4] Hours worked. [5] Unemployment. [6] Labor share. [7] Nominal interest rate. [8] Inflation. [9] Labor productivity. [10] TFP.

Notes: The entries are $\Omega_{k,t}(h)$ for $k = 1, \cdots, 10$, which represent the percentage share of the variance of the forecast error in the VAR variable described in the upper header at a given horizon h as explained by the transitory shocks. The results are computed from the structural VAR model over the sample period from the first quarter of 1955 to the fourth quarter of 2017. We set the lag length to two quarters in the reduced-form VAR estimation.

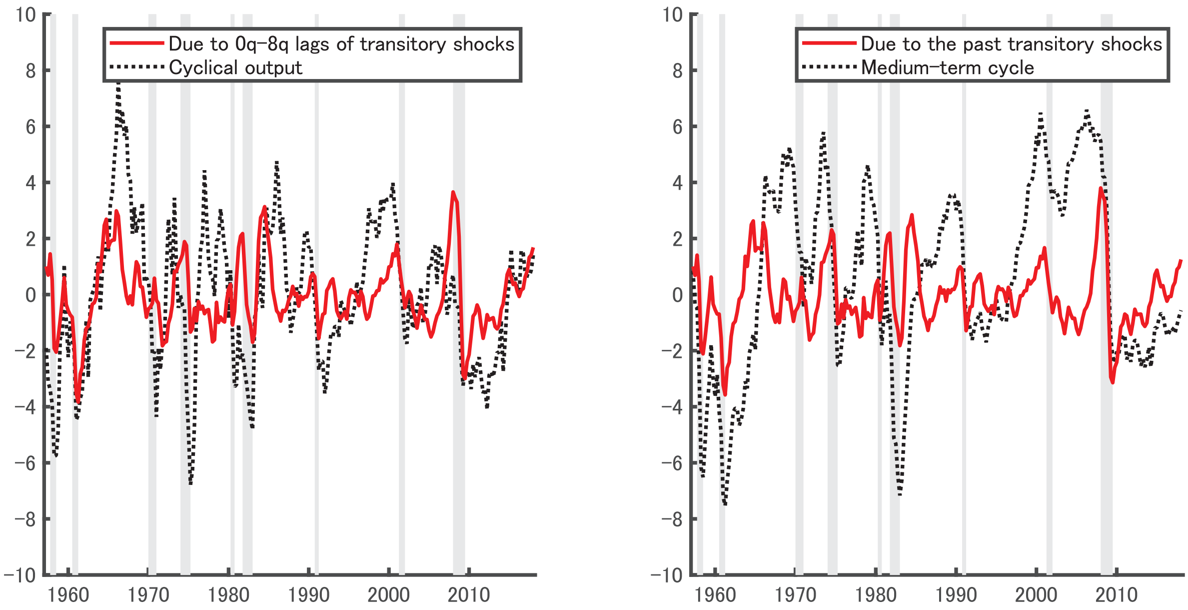

Figure 7: Historical output decompositions due to transitory shocks

Notes: Sample period from the first quarter of 1957 to the fourth quarter of 2017. The black dotted lines indicate the actual data. The red solid lines represent the series explained by the transitory shocks using the VAR model. The gray-shaded areas show periods of recession in the US, as defined by the NBER. We set the lag length to two quarters in the reduced-form VAR estimation.

transitory shocks with business cycle shocks in the left panel and those identified by Angeletos et al. (2020) in the right panel.

Our business cycle shocks differ markedly from transitory shocks. Although the figure shows a positive relationship between the two, their correlation is weak. This indicates that, while our business cycle shocks, which explain most business cycle fluctuations, are not entirely independent of transitory shocks, they remain distinct both quantitatively and qualitatively.

By contrast, the transitory shocks and shocks identified by Angeletos et al. (2020) exhibit a strong positive correlation. This suggests that their identified shocks -which, as they argue, explain the most variance in various economic variables at business cycle frequencies of 6 to 32 quarters- are in fact quite similar to transitory shocks, which only partially account for business cycles.

5 Concluding remarks

This study provides empirical evidence on business cycle dynamics using a structural VAR framework. This framework enables the direct measurement of cyclical output and the identi-

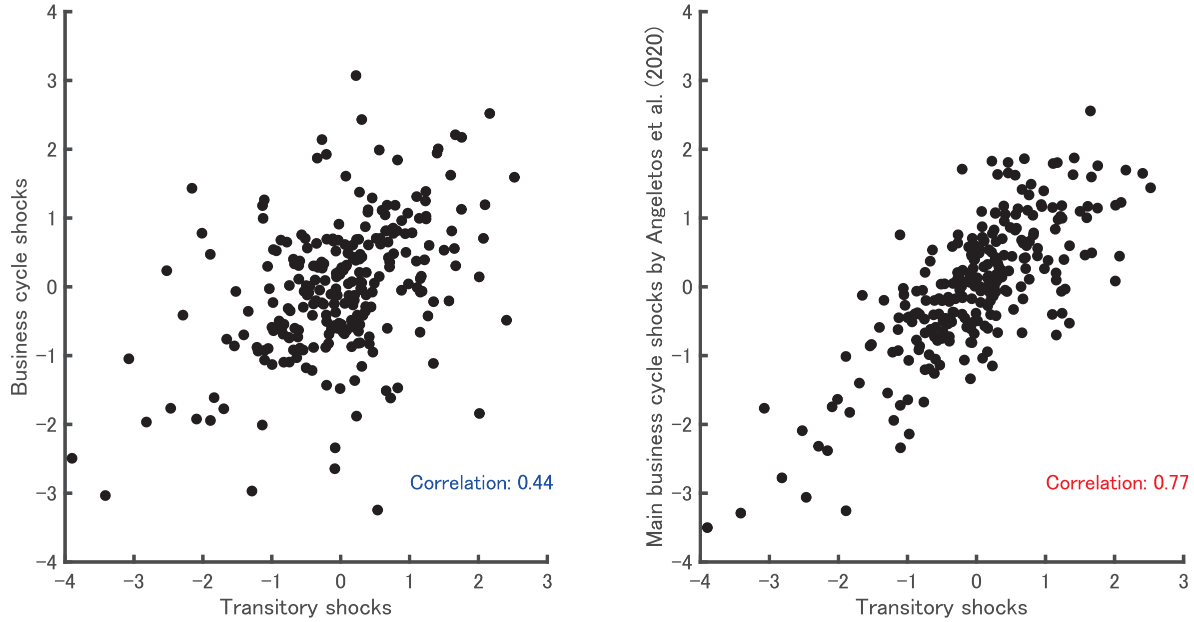

Figure 8: Scatter plot of transitory shocks and business-cycle shocks

Notes: The horizontal axis plots the transitory shocks. The vertical axis plots the business-cycle shocks in the left panel and the shocks that maximize the 4-quarter-ahead forecast error variance of the unemployment in the right panel. The sample period spans from the first quarter of 1955 to the fourth quarter of 2017. We set the lag length to two quarters in the reduced form-VAR estimation.

fication of the business cycle shock that best explains cyclical output movements. The cyclical output derived from the VAR model exhibited a close correspondence with the CBO output gap in both phase and amplitude. This characteristic prevents issues that frequently arise with Hamilton and bandpass filters, as well as polynomial detrending. The identified shock has significant, long-lasting effects on output and demand components and affects labor productivity and TFP in the medium term, suggesting that parts of the stochastic trend respond to business cycle innovations. These findings contradict the prevailing perspective that separates short-term cycles from long-term growth.

A comparison with transitory shocks reveals that business cycles are not merely short-term phenomena. Transitory shocks have been shown to generate only a modest proportion of cyclical movements, exhibit limited persistent effects on real activity, and exert minimal influence on labor productivity and TFP. However, business cycle shocks, which comprise the majority of cyclical movements, are responsible for a considerable portion of medium- to long-term output changes. This finding suggests that the forces driving short-term business cycle fluctuations contribute to the medium-term dynamics.

This study also elucidates the discrepancy with Angeletos et al. (2020). Utilizing their data and reduced-form specifications, it is evident that their shock, identified by maximizing the unemployment variance over short horizons, closely resembles a transitory shock. However, our business cycle shocks exhibit a positive yet weak correlation with transitory shocks, suggesting that they are fundamentally distinct from transitory shocks. This finding suggests the existence of distinct characteristics between business cycles and transitory shocks. This discrepancy underscores the significance of the identification targets, as evidenced by the observation that maximizing cyclical variation in output over a two-year horizon captures stochastic components with more complex propagation that are not reflected by a purely transitory shock.

The findings imply the need to revise the prevailing perspective that business cycles are merely short-lived, demand-driven fluctuations. The propagation mechanisms of business cycle fluctuations can extend beyond demand channels to encompass investment, innovation, and efficient resource utilization (see section 2 for a review of the relevant literature). Consequently, macroeconomic policies aimed at the short-term stabilization of the output gap and inflation should also consider the long-term impact on future supply capacity through medium-term dynamics. The relevance of these perspectives may differ, depending on the policy environment.

These implications give rise to three research themes within this empirical framework. First, the VAR can be expanded to include variables such as R&D, patenting, investment-specific technology proxies, and productivity to better trace how business cycle conditions influence long-term growth. Second, it can estimate systematic macroeconomic policy responses to business cycle shocks and run counterfactual simulations that compare policies to explore how macroeconomic policies stabilize and support growth. Third, the application of our empirical framework to other countries with analogous datasets facilitates the evaluation of business cycle growth across diverse contexts and serves to test the external validity of the U.S. findings.

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