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Two Main Business Cycle Shocks are Better than One*

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Abstract

This paper challenges the claim of a recent authoritative study that identifies a single shock as the main driver of business cycle fluctuations. We argue that the VAR used in that study is informationally insufficient, i.e., it is unable to recover the true structural shock driving business cycle fluctuations. Using a large-dimensional Structural Dynamic Factor model, we present an alternative view of US business cycles, more in line with classical AD-AS theory. This underscores the multivariate nature of cycles and challenges the existence of a Main Business-Cycle shock.

JEL subject classification: E32, C32.
Key words: Frequency Domain, Structural Dynamic Factors Models, Business Cycle

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1. Introduction

In their quest for a parsimonious explanation of business cycles, Kydland and Prescott (1982) put forward an appealing idea: cyclical fluctuations could be explained by a single shock.[1] In their model this shock is the technology shock. A recent authoritative paper, Angeletos et al. (2020), ACD henceforth, revives this idea but from a completely different perspective. The authors provide a comprehensive anatomy of the U.S. macroeconomy. The core of this anatomy is a set of five shocks, each of which accounts for the maximal volatility of a given macroeconomic variable (unemployment, output, hours worked, consumption and investment, respectively) over the business-cycle frequency band (6-32 quarters). These shocks share a common propagation mechanism, that is, they produce the same impulse-response functions (IRFs), and can be considered as the same shock, named the "Main Business Cycle" shock (MBC). The MBC shock accounts for the bulk of cyclical fluctuations in economic activity and has very special and well-defined features that challenge existing theories. On the one hand, it has no long-run effects; in that, it resembles a demand shock. On the other hand, it is disconnected from inflation; in that, it differs from a standard inflationary demand shock, of the New Keynesian variety. This is at odds with both the idea of news-driven cycles proposed by Beaudry and Portier (2006), and the view put forward by Christiano et al. (2014) that risk shocks are the dominant factors in cyclical fluctuations.[2] Most importantly, the picture that emerges is in sharp contrast with the standard AD-AS textbook theory, partly inspired by Blanchard and Quah (1989), where cyclical fluctuations are driven by two main shocks, a standard supply shock and a standard demand shock. This new perspective therefore lends support to theories that aspire to explain the bulk of the observed business cycles with a single demand shock, while posing a significant challenge to conventional New-Keynesian paradigm.

From a methodological point of view, ACD proposes a frequency-based identification method in the context of SVAR models. The method allows for the identification of the shock which maximizes the explained variance of a particular

[1] This perspective is reminiscent of the original idea of Burns and Mitchell (1946), who argued that a reference cycle, or a one-dimensional latent cause of variation, drives the fluctuations of all macroeconomic variables.

[2] In general, it is incompatible with all those estimated New-Keynesian DSGE models that assume nominal rigidities or "sticky prices". In addition to Christiano et al. (2014), see also Smets and Wouters (2007) and Justiniano et al. (2010).

variable in a given frequency band.[3] The approach of identifying dominant shocks in the frequency domain, starting from a VAR, is drawing increasing interest. This is because it allows isolating cyclical and long-run features without imposing economic conditions that could invalidate any conclusions about the sources of fluctuations (DiCecio and Owyang, 2010; Giannone et al., 2019; Dieppe et al., 2021; Basu et al., 2021). However, this method is not immune to the well-known problems that affect VAR models. (1) Due to the so called "curse of dimensionality", VAR systems could be informationally deficient. This means that the variables used by the econometrician may not contain enough information to recover the structural shocks driving the economy and the related IRFs.This problem, known as "non-fundamentalness" or "non-invertibility" of Moving Average (MA) representations, is discussed among others in Sargent and Hansen (1991), Lippi and Reichlin (1993, 1994), Fernández-Villaverde et al. (2007), Alessi et al. (2011), Soccorsi (2016), Forni et al. (2019). (2) Many of the macroeconomic variables used in SVAR models are affected by measurement errors and/or small residuals of no economic interest. These can dynamically contaminate the estimated VAR shocks, potentially leading to misleading results even when information seems sufficient to correctly recover the IRFs (Lippi, 2019; Giannone et al., 2006; Forni et al., 2020). Due to the potential bias introduced by the lack of information and the presence of measurement errors, the results of SVAR analysis can be quite unstable, depending on the variables included in the vector.

This raises a fundamental question: Is ACD's VAR informationally sufficient to recover the MBC shock? It appears not. We test for sufficient information by using the "orthogonality" test proposed by Forni and Gambetti (2014).[4] The test results suggest that informational sufficiency is rejected, as the estimated MBC shock can be predicted by the lags of the principal components (PCs) of a large dataset (the testing procedure is explained in Section 2). Since PCs reflect virtually all available macroeconomic information, it implies that the VAR used by ACD lacks some data that could be useful in predicting the shock of interest. The lack of information can lead to a misleading interpretation of what drives economic cycles, making it difficult to distinguish between "fact and fiction". This is our key insight.

Building upon this, our paper provides empirical evidence that challenges

[3]This approach is essentially the frequency domain version of the max-share identification pioneered by Uhlig (2004). See also Barsky and Sims (2011), Francis et al. (2014), among others.

[4]Specifically, we investigate whether the 10-variable VAR considered by ACD contains enough information to recover the MBC shock obtained by targeting business cycle frequencies variation in unemployment, which is the baseline shock in ACD's anatomy.

the existence of a single shock or a dominant propagation mechanism explaining the bulk of business cycle fluctuations, as suggested by ACD. We argue that this mechanism is not a robust feature of the data. Instead, it appears to be a product of the well-documented instability of VAR results. Working in an environment that is free from the limitations of VARs enables us to draw an alternative anatomical template for the transmission mechanisms of the business cycles, that well fits into the traditional AD-AS narrative, contrary to what claimed by ACD. In this sense, large-dimensional Structural Dynamic Factor models (SDFM) offer a solution.

Just like ACD, we use the frequency domain identification method described above to compile a collection of reduced-form shocks. Each shock maximizes the volatility of a different macroeconomic variable over either business cycle (6-32 quarters) or long run frequencies (80-∞). In contrast to ACD, we assume that U.S. macroeconomic series follow a large-dimensional SDFM, as introduced by Forni et al. (2009) and Stock and Watson (2005). Our positive argument is that the availability of a large dataset, when combined with factor model techniques, helps in solving both problems affecting SVAR analysis. These models can be used for structural economic analysis in the same way as VAR models. However, unlike VARs, they include a large amount of information, so that insufficient information is unlikely.[5] Moreover, they allow us to study the effect of structural shocks on the common components, which are the observed macroeconomic series cleaned of measurement error. To this end, we built a dataset for high dimensional macroeconomic analysis of 114 quarterly US time series, covering the period 1961-I to 2019-IV.

As suggested by factor model literature, we do not believe that a single shock is the sole driver of business cycles.[6] Therefore, in our collection, we consider the possibility that there exist at least two important cyclical shocks. First, for each of the target variables, we identify the shock that has the largest contribution to the business-cycle volatility of that variable, which is equivalent to ACD's MBC.

[5] Large factor models, as shown in Forni et al. (2009), are generally unaffected by non-invertibility issues. Typically, the vector of the factors is singular, meaning it is driven by a number of shocks that is smaller than its dimension. In such cases, achieving fundamentalness becomes easier as it satisfies a less demandig condition.

[6] Studies by Sargent and Sims (1977), Giannone et al. (2005) and Watson (2004) show that two shocks account for a significant portion of US data volatility. Similarly, Onatski (2009) cannot reject the null hypothesis of two shocks against an alternative of 3 to 7 shocks. The subsequent factor literature has repeatedly confirmed this insight. More recently, Avarucci et al. (2021) proposed a new consistent estimator for the number of shocks, suggesting that the US business cycle is driven by two common shocks.

Next, we identify the shock that is orthogonal to the first one and has the second largest contribution, in order of importance, referred to as the "secondary" business cycle shock (SBC). This process generates ten reduced-form shocks (two for each variable, respectively) that target any of the following real activity quantities over the business cycle frequencies: output, unemployment, hours worked, consumption, and investment. This forms the core of our anatomy.[7]

Armed with this equipment, in the first part of our analysis, we examine the IRFs and the variance contribution of the five MBC shocks. Our goal is to determine whether our rich information setup provides evidence of a common propagation mechanism that supports the idea of a single, dominant business-cycle shock. However, our findings suggest otherwise. Firstly, unlike ACD, a single shock that target any one of GDP, unemployment, consumption, investment, and hours worked is not sufficient to explain the bulk of business cycle fluctuations across all these variables. Most importantly, the shock that targets consumption is neither correlated nor interchangeable in terms of IRFs with the other identified shocks which, in contrast, appear to share roughly the same propagation mechanism. The former has significant permanent effects and accounts for only a quarter of the cyclical fluctuations in the remaining variables. It also induces a negative covariance between GDP growth and inflation changes. In terms of both IRFs and variance contributions, this reduced form shock closely resembles a standard deflationary supply shock. On the other hand, the remaining shocks are purely cyclical. They are disconnected from the long-run of real activity, and contribute minimally to consumption volatility. Specifically, the shocks obtained by targeting GDP, investment, and unemployment are highly correlated with each other and induce a positive covariance between GDP growth and inflation changes. In terms of both IRFs and variance contributions, each of these reduced form shocks closely resembles a standard inflationary demand shock.[8] It follows that our results not only argue against the hypothesis of a single dominant business cycle shock, but also challenge the distinctive features of ACD's business cycle anatomy. Specifically, we question the two disconnects between the short and the long run, and between real activity and cyclical inflation. The

[7]Other important elements of our collection include shocks that target output, consumption, investment, TFP, and labor productivity over long-run frequencies, and the shock that targets inflation over business cycle frequencies.

[8]The hours worked shock is quite similar to the latter in terms of the IRFs it produces. However, it is quite different in terms of variance contribution: it turns out to be disconnected from inflation. This rules out the possibility of interpreting this shock as standard inflationary demand.

shock that targets consumption is permanent and deflationary, interpretable as a standard supply shock, while the GDP, unemployment, and investment shocks are transitory and inflationary, interpretable as a standard demand shock.[9]

Building on these findings, we proceed to the second part of our study. Here, we enhance our anatomical analysis with the five "secondary" business cycle shocks and present our parsimonious representation of the observed business cycles. We find that, regardless of the target variable, two cyclical shocks are sufficient to account for most of the business cycle fluctuations in real activity variables and, to a somewhat lesser extent, in inflation. Then we look at the long-run. Our two shocks together also account for most of the long-run variance.[10] Specifically, the SBC shock, obtained by targeting any one of GDP, unemployment, investment, and hours worked, explains more than half of the long-run volatility in real activity and induces a negative covariance between GDP growth and inflation changes. This shock behaves as an aggregate supply shock of the textbook-type. Thus, for each of these variables, while the MBC shock fits the profile of a demand shock, the SBC shock fits the profile of a supply shock.[11] On the other hand, the SBC shock, obtained by targeting consumption, accounts for a small fraction of long-run volatility and induces a positive covariance between GDP growth and inflation changes. For private consumption, while the MBC shock behaves as a generic supply shock, the SBC shock transmits a demand shock.

In essence, our empirical template of observed business cycles seems to fit the traditional AD-AS narrative. Two main forces are at play: demand shocks of the standard New Keynesian variety, which raise output and inflation, and supply shocks, which raise output but lower inflation and map to long-run movements in TFP. The business cycle of consumption is largely supply-driven, consistent with the permanent income hypothesis, while that of GDP, investment, and unem-

[9] As for inflation, the shock that targets unemployment (GDP) accounts for about 36% (20%) of the business cycle variation in inflation. Symmetrically, the shock that targets the cyclical variance of inflation explains 32% (22%) of the business cycle variation in unemployment (GDP), as against a scant 4% in ACD's template.

[10] Symmetrically, the shocks identified by targeting any one of GDP, investment, consumption, TFP or labor productivity at the long-run frequencies (referred to as main long run shock, MLR), make a non negligible contribution to the business cycle, particularly with respect to consumption cyclical fluctuations. This result is in sharp contrast to ACD, where the same shock has a small footprint on the business cycle.

[11] Compared with the corresponding MBC, each of these SBC shocks significantly contributes to consumption volatility at business cycle frequencies, accounting for approximately half of fluctuations. Indeed, they are strongly correlated with the consumption-targeted MBC shock, reflecting shared supply dynamics.

ployment is mainly demand-driven, supporting the New Keynesian perspective. Hence, one may advance the concept of the "Two Main Business-Cycle" shocks as the main drivers of business cycle movements in real activity.

2. Is ACD's VAR Informationally Sufficient?

We address this question using the "orthogonality" test proposed by Forni and Gambetti (2014).[12] This test checks for the orthogonality of the estimated shock of interest with respect to the past of the PCs of a large macroeconomic dataset. The key insight is that the PCs encapsulate virtually all available information. Therefore, if the shock of interest is correlated with the past of available information (i.e., if orthogonality is rejected), it indicates that the VAR is informationally deficient. In this scenario, VAR results can be misleading: changing the variables may change the information set and therefore the estimated shock of interest.

The testing procedure unfolds as follows: First, we estimate the 10-variable VAR model, as proposed by ACD, with two lags, spanning the period from 1955:Q1 to 2017:Q4, and identify the shock that targets the unemployment rate at business-cycle frequencies.[13] Second, we regress this shock on the past values of a set of variables that reflect agents' information, and perform an F-test for the significance of the regression. We use the first $r = 6, 7, \ldots, 11$, PCs of the variables in our large dataset as regressors, where $\hat{r} = 11$ is the number of factors driving the panel. This number is determined using the criterion of Bai and Ng (2002) with the penalty modification proposed in Alessi et al. (2010).[14]

The top panel of Table 1 shows the p-values of the test for different choices of PCs and number of lags. We find that informational sufficiency is rejected, since the estimated MBC shock is predicted by the lags of the PCs. This implies that

[12] For our purposes, the relevant issue is not to establish whether the VAR is globally sufficient or not, but whether it can correctly recover a single shock of interest. Forni and Gambetti (2014) show that even if the VAR lacks sufficient information to capture all of the structural shocks (i.e., the MA representation of the variables in the vector is non-fundamental), it can still be informationally sufficient for a single shock. For this purpose, we use a less demanding test than the Granger causality test proposed in the same paper.

[13] As detailed in Section 2 of ACD, the data consist of quarterly observations on the following macroeconomic variables: the unemployment rate; the per-capita level of GDP, investment (inclusive of consumer durables), consumption (of non-durables and services), and total hours worked; labor productivity in the non-farm business sector; utilization-adjusted TFP; the labor share; the inflation rate (GDP deflator); and the federal funds rate.

[14] For the testing procedure, we adjusted the shock size by removing the initial six observations to align the start date with 1961:Q1 instead of 1955:Q1. This adjustment ensures that the period matches our sample for this specific exercise, which spans from 1961:Q1 to 2017:Q4, instead of extending to 2019:Q4 as in the rest of the analysis.

by enlarging the information set, the estimated MBC shock could be different while maintaining the same identifying assumptions. In other words, the causal interpretation of the MBC shock is questioned. We perform the test for any of the other shocks that make up the main business cycle template (GDP, consumption, investment and hours worked) obtaining the same result.[15]

Orthogonality				
Principal Components	1 lags	2 lags	3 lags	4 lags
r=6	0.00	0.00	0.00	0.03
r=7	0.01	0.00	0.00	0.00
r=8	0.01	0.00	0.00	0.01
r=9	0.01	0.00	0.00	0.01
r=10	0.02	0.01	0.00	0.04
r=11	0.02	0.02	0.01	0.08
Variables	1 lags	2 lags	3 lags	4 lags
Baa-GS10 spread	0.06	0.02	0.01	0.01
S&P500	0.00	0.00	0.00	0.01
JLN Uncertainty 3M	0.06	0.01	0.01	0.01
BC12M	0.01	0.03	0.03	0.02

Table 1: p-values of the orthogonality F-test, with 1, 2 3 and 4 lags, for the MBC shock that targets the unemployment rate, estimated with ACD's VAR specification. r = number of principal components used in the test.

We also try to provide some insight into the missing information. To do this, we regress the estimated MBC shock on the past values of some forward-looking variables and on the past values of other variables that are widely used in business cycle analysis. These include the Shiller's real S&P stock price index (S&P500), the University of Michigan's confidence index on expected business conditions for the next year (BC12M),[16] a measure of the risk spread (Baa-GS10 spread) and the Jurado et al. (2015)'s measure of macroeconomic uncertainty over a three-month horizon. The bottom panel of Table 1 shows that orthogonality of the estimated MBC shock with respect to the past of any of these variables is clearly rejected.

In conclusion, we believe that the potential lack of information in VAR analysis, can lead to a mis-characterization of the business cycle anatomy. In this sense, large-dimensional SDFMs offer a solution. These models are free from this

[15] Available upon request.

[16] BC12M summarize responses to the following forward-looking question:"Turning to economic conditions in the country as a whole, do you expect that over the next year we will have mostly good times, or periods of widespread unemployment and depression, or what?". The anticipation properties of this variable on future movements in economic activity are widely discussed in Barsky and Sims (2012) and Beaudry and Portier (2006).

drawback by design; in fact, they use a large amount of data by enlarging the information set available to the econometrician.

3. Model and Method

3.1. Structural Dynamic Factor Model

Let x_t be a n-dimensional, stationary vector of observable economic variables. The vector x_t is part of an infinite-dimensional panel of time series. Each variable x_{it}, $i = 1, \ldots, n$, is decomposed into the sum of two mutually orthogonal unobservable components, the common component, χ_{it}, and the idiosyncratic component, ξ_{it}:

$$x_{it} = \chi_{it} + \xi_{it}. \tag{1}$$

The idiosyncratic components are interpreted as sources of variation that are specific to one or just a small group of variables, like regional or sectoral shocks, plus measurement error. In particular, for macroeconomic variables like GDP, investment or consumption, in which all local and sectoral shocks have been averaged out, the idiosyncratic part can be interpreted essentially as only containing measurement error. The ξ's are allowed to be mildly cross-sectionally correlated, thus they have a covariance matrix which is not necessarily diagonal (see Forni et al., 2009, Assumption 5).The χ's, on the contrary, account for the bulk of the co-movements among macroeconomic variables. This is because they are different linear combinations of the same $r < n$ common factors, not depending on i, i.e. they span a r-dimensional vector space (see Stock and Watson, 2002a,b; Bai and Ng, 2002). Then there exist an r-dimensional weakly stationary vector process $F_t = (F_{1t} \ldots F_{rt})'$, orthogonal to $\xi_t = (\xi_{1t} \ldots \xi_{nt})'$, and loadings λ_{ij}, $j = 1, \ldots, r$, such that

$$\chi_{it} = \lambda_{i1} F_{1t} + \ldots + \lambda_{ir} F_{rt} \quad \text{or} \quad \chi_t = \Lambda F_t. \tag{2}$$

The unobservable coordinates of F_t are called the static factor and Λ, the factor loading matrix, is of size $n \times r$. We require the factors to be pervasive i.e. to have non-negligible effects on most of the variables x_{it} (see Forni et al., 2009, Assumption 4). Combining (1) and (2), we get a static equation linking the n

observable variables x_{it} to the r factors and the idiosyncratic components

$$x_{it} = \lambda_{i1} F_{1t} + \ldots + \lambda_{ir} F_{rt} + \xi_{it} \quad \text{or} \quad x_t = \Lambda F_t + \xi_t. \tag{3}$$

Equation (3) is the static factor representation, where the factors have only contemporaneous effect on the common components. The dynamic nature of the model comes from the fact that the static factors F_t follow a VAR(p) driven by a q-dimensional vector of orthonormal structural white noise, or common shocks $u_t = (u_{1t}, \ldots, u_{qt})'$, with $q \leq r$. Precisely:

$$x_t = \Lambda F_t + \xi_t \tag{4a}$$

$$C(L) F_t = \epsilon_t \tag{4b}$$

$$\epsilon_t = R u_t \tag{4c}$$

where ϵ_t is the residual of the VAR on F_t, $E(\epsilon_t \epsilon_t') = \Sigma_\epsilon$, $C(L)$ is an $r \times r$, stable polynomial matrix and R is $r \times q$ and has maximum rank q. As a consequence, R has a left inverse and the vector u_t belongs to the space spanned by $F_{t-s},\ s \geq 0$, that is, u_t is fundamental for F_t. By inverting the matrix $C(L)$ we get $F_t = C(L)^{-1} \epsilon_t = C(L)^{-1} R u_t$, so that the dynamic relationship between u_t and the common components is

$$\chi_t = \left[\Lambda C(L)^{-1} R\right] u_t = B(L) u_t. \tag{5}$$

Then, by merging (1) and (5), we have the structural dynamic representation

$$x_{it} = b_i(L) u_t + \xi_{it} \quad \text{or} \quad x_t = B(L) u_t + \xi_t, \tag{6}$$

where the macroeconomic variables are represented as driven by a few pervasive structural shocks, loaded with the IRFs in $B(L)$, plus measurement error. We are interested in the effect of structural shocks on the common components χ_t of some key series, i.e. on the variables obtained by removing idiosyncratic errors. Notice that representation (6) is not unique, since the IRFs are not identified. Forni et al. (2009) (Proposition 2), show that identification is achieved up to orthogonal rotations, just like in structural VAR models.

Let us consider the linear mapping in (4c), $\epsilon_t = R u_t$. We define $R = SH$, where S is the Cholesky factor of Σ_ϵ, such that $SS' = \Sigma_\epsilon$, and H is an orthonormal matrix, namely a matrix such that $H^{-1} = H'$. We can then rewrite (5) as

$$\chi_t = \left[\Lambda C(L)^{-1} S\right] H u_t = D(L) H u_t = B(L) u_t \tag{7}$$

where $D(L) = \Lambda C(L)^{-1} S$ encapsulates the Cholesky IRFs and $B(L) = D(L)H$ collects the structural IRFs. To identify the shocks, we must impose additional restrictions on the rotation matrix H. This is usually done as in standard SVAR analysis, which mainly employs an appropriate number of exclusion or sign restrictions motivated by specific economic theories. Here we implement an alternative approach: identification of dominant shocks in the frequency domain.

3.2. Identification of dominant shocks in the Frequency Domain

Our identification strategy follows ACD's spectral method. In this approach, a shock is identified as the one that explains the dominant fraction of the variance of a particular variable within a specific frequency band, such as the business cycle (6-32 quarters) or long-run (80-∞ quarters) frequencies. In this section, we show how to use spectral decomposition to target the variance of a specific variable within a defined frequency domain. We also illustrate how to isolate the shocks that dominate this objective variance.

Consider representation (7). The effect of the j-th structural shock on the k-th common-component is given by the (k, j) element of the matrix $B(L)$, that is $D^{[k]}(L)h$, where $D^{[k]}(L)$ is the k-th row of $D(L)$ and h is the j-th column of H. On the other hand, the structural shocks are related to the VAR residuals by the relation $u_t = R^{-1}\epsilon_t = H' S^{-1}\epsilon_t = H'\eta_t$, η_t being the vector of the Cholesky shocks. Hence the j-th structural shock is given by the product of the j-th row of H' and η_t, that is $h'\eta_t$. Now, let $\left[\underline{\theta}, \overline{\theta}\right]$ be a band of frequencies, such that $0 \leq \underline{\theta} \leq \overline{\theta} \leq \pi$. In the frequency domain, the contribution of the j-th structural shock $h'\eta_t$ to the spectral density of the k-th variable over the frequency band $\left[\underline{\theta}, \overline{\theta}\right]$ is given by

$$\begin{aligned} \Psi\left(h; k, \underline{\theta}, \overline{\theta}\right) &= \int_{\underline{\theta}}^{\overline{\theta}} \left(D^{[k]}\left(e^{i\theta}\right)' h' D^{[k]}\left(e^{-i\theta}\right) h\right) \, d\theta \\ &= h' \left[\int_{\underline{\theta}}^{\overline{\theta}} \left(D^{[k]}\left(e^{i\theta}\right)' D^{[k]}\left(e^{-i\theta}\right)\right) d\theta\right] h \end{aligned} \tag{8}$$

where the matrix

$$V\left(k, \underline{\theta}, \overline{\theta}\right) = \int_{\underline{\theta}}^{\overline{\theta}} \left(D^{[k]}\left(e^{i\theta}\right)' D^{[k]}\left(e^{-i\theta}\right)\right) d\theta$$

captures the entire frequency band variace of the k-th variable in terms of the contributions of all Cholesky shocks. The contribution of the j-th structural shock can then be re-written as

$$\Psi\left(h; k, \underline{\theta}, \overline{\theta}\right) = h' V\left(k, \underline{\theta}, \overline{\theta}\right) h. \tag{9}$$

Our approach is to identify the largest contributors to the variance of a particular variable k over a specific frequency band $\left[\underline{\theta}, \overline{\theta}\right]$, ordered in decreasing order of importance: First, the shock with the largest contribution to the target variance, then the shock orthogonal to the first with the second largest contribution, and so on. Suppose, without loss of generality, that the shocks $u_{1t}, u_{2t}, \ldots, u_{qt}$ have to be identified. The solution is given by the first q eigenvectors $h = [h_1, h_2, ..., h_q]$ corresponding to the q largest eigenvalues of the matrix $V\left(k, \underline{\theta}, \overline{\theta}\right)$ and provides the shocks $h_1'\eta_t, h_2'\eta_t \ldots, h_q'\eta_t$ ordered in terms of their contribution to the target. This strategy allows for the identification of a collection of shocks by systematically varying the target variable and/or frequency band.

We show below that two shocks are enough to explain the bulk of cyclical variance in the main macroeconomic aggregates, while the long run is explained by only one shock.

4. Empirical Analysis

4.1. Data

Coming to the empirical application, we collect a quarterly dataset for high dimensional macroeconomic analysis.

Our $N \times T$ dataset consists of 114 US quarterly series, spanning from 1961-I to 2019-IV. The majority of these series are sourced from FRED-QD.[17] TFP data series are obtained from John Fernald's website (Fernald, 2012), while the Confidence data are accessible on the Michigan Survey of Consumer website.[18] Lastly, the macroeconomic uncertainty series (Jurado et al., 2015) are retrieved from Sydney C. Ludvigson's website. Some series have been constructed by ourselves as transformation of the original ones. Following standard practice in macroeconomic analysis, consumption includes non-durables and services, while

[17]FRED-QD is a large quarterly macroeconomic database with 248 series, developed by McCracken and Ng (2020).

[18]http://www.sca.isr.umich.edu/

investment has been broadly defined to include consumer durables. Both measures are taken in real terms. Monthly data, like the macroeconomic uncertainty series, have been aggregated to get quarterly figures. Finally, it is worth noting that most series are expressed in per capita terms, dividing by population aged 16 years or more (civilian non-institutional population series) and stock market data have been deflated by the GDP deflator. We transform each series to reach stationarity. As for the transformations, we deviate from those suggested by McCracken and Ng (2020) for the interest rates, which are taken in levels rather than in differences; furthermore, we take prices and other nominal variables in log-differences, rather than in double differences of the logs. This avoids potential over-differentiation, which could enhance high frequencies of little interest for business cycle analysis. The complete list of variables and transformations is provided in Appendix (B).

To conclude this section, let us look at the common-idiosyncratic variance decomposition of the key variables above with $\hat{r} = 11$ static factors, shown in table 8. The common variance of the main macroeconomic aggregates like GDP, consumption, investment and unemployment rate are 94, 82, 90 and 94 percent of total variance, respectively. These numbers seem compatible with the measurement error interpretation of the idiosyncratic components.

4.2. Identification Strategy

We use the techniques discussed in Section (3.2) to compile a collection of shocks, in a way that is similar to, but somewhat distinct from, ACD. Just as in that paper, the core of our collection consists of shocks targeting any one of unemployment, output, consumption, investment, and hours worked over business cycle frequencies. The difference is that, as we show below, a single shock is not sufficient to provide an accurate description of business cycles in real activity variables. Therefore, we place a second business cycle shock at the center of our analysis, while ACD relegates it to the appendix.

Thus, for each of these five variables, we identify the $q = 2$ dominant shocks that explain the majority of business cycle fluctuations. They are selected in decreasing order of importance. First, we identify the shock with the largest contribution to the business cycle volatility, equivalent to ACD's shock. Then, we identify the shock orthogonal to the first one with the second-largest contribution, referred to as SBC shock. To do this, for $j = 1, \ldots, q$, we solve the maximization problem (3.2) in the frequency interval $[\underline{\theta}, \overline{\theta}] = [2\pi/32, 2\pi/6]$, corresponding to cycles with periodicity between 18 months and 8 years. Repeating this process for each of the aforementioned variables produces a collection of ten reduced-form shocks. Mimicking ACD's approach, in the first part of the analysis our focus is exclusively on the five MBC shocks. The aim is to determine whether our rich information setup provides evidence of a single, dominant business cycle shock. In the second part, we enhance our anatomical analysis with the five "secondary" business cycle shocks and present our parsimonious (two shocks) representation of the observed business cycles. A second, important but auxiliary subset comprises the shocks identified by targeting any one of GDP, investment, consumption, TFP, or labor productivity at long-run frequencies. For each of these variables, we find the shock that accounts for the bulk of long run fluctuations, referred to as MLR shock. In this case, we solve the maximization problem (3.2) by setting $q = 1$ and in the frequency interval $[\underline{\theta}, \overline{\theta}] = [0, 2\pi/80]$, corresponding to periodicities greater than 20 years. These auxiliary shocks, along with other elements comprising our data anatomy, help us to characterize the properties of the business cycle picture we aim to provide. In doing so, we delve deeper into potential connections or disconnections with the nominal side, technology, and the long run.

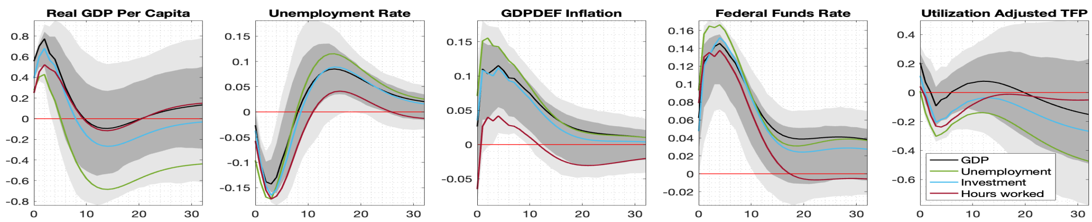
5. Results

5.1. Questioning the Existence of a "Main Business-Cycle Shock"

The first part of the results aims to establish the existence of a single, dominant business-cycle shock. Following ACD's approach, we focus on the MBC shocks that target any one of GDP, unemployment, consumption, investment and hours worked. A key finding in ACD is that these shocks turn out to be interchangeable, in the sense that they produce essentially the same IRFs, or the same propagation mechanism. Moreover, any one of them not only explains approximately three-quarters of the business-cycle volatility in the targeted variable but also accounts for more than one half of the business-cycle volatility in the remaining variables. These findings serve as the foundation, outlining necessary requirements for establishing the existence of a singular driver of the business-cycle. Is there comparable evidence in our data?

Consider the first requirement: the interchangeability of these shocks in terms of IRFs. Figure 1, Panel A, compares the responses of selected variables to the shocks targeting output, unemployment, investment and hours worked. Meanwhile, Panel B reports the responses to the shock targeting consumption.[19] It is clear from this figure that targeting consumption produces a shock with a different propagation mechanism from the others. The former (Panel B) has a large permanent effect on real economic activity variables and generates a temporary hump-shaped response of unemployment and hours worked (see Figure 3). GDP increases immediately by around 0.2%, peaks around the 10th quarter, and converges to 1.2% in the long run. Unemployment behaves countercyclically, reaching a minimum of about -0.2% around the 8th quarter. This shock generates a negative comovement between the inflation rate and output growth. The former immediately falls by around 0.15%, after which the effect relatively quickly vanishes. Monetary policy, as proxied by the federal funds rate, reacts very weakly. The response of TFP follows an S shape, featuring a relatively small impact effect and a much larger long-run effect (about 1.1). In terms of IRFs, this shock is essentially an aggregate supply shock of the textbook-type.

(a) GDP, Unemployment, Investment and Hours worked shocks



(b) Consumption shock

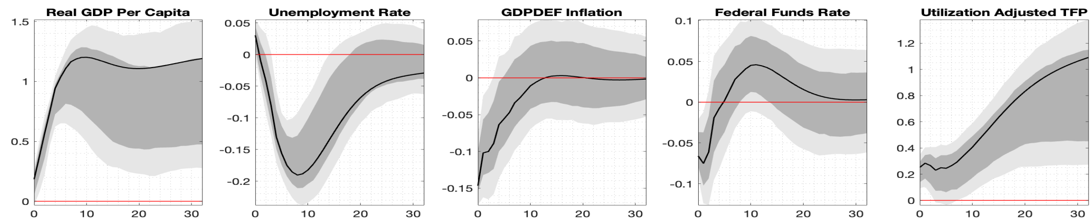


Figure 1: Impulse response functions of the MBC shock obtained by targeting different variables. The dark gray and light gray areas are the 68% and 90% confidence bands, respectively, for the shock that targets GDP (Panel A) and consumption (Panel B).

Conversely, the other shocks are purely cyclical. Moreover, they seem to share roughly the same propagation mechanism. This is the first piece of evidence suggesting that at least two shocks with distinct propagation mechanisms are

[19]For a comprehensive view of the responses of all the variables to these shocks, please refer to Figure 3.

needed to explain business-cycle movements in real activity. Consider the shock that targets GDP (Panel A, black line). The responses of output and investment are temporary and hump-shaped, peaking in the 2nd quarter. The effects are no longer statistically significant after about one year. GDP exhibits a positive impact effect of 0.6% and a peak of about 0.8%. For consumption the effect is positive but very short-lived, being barely significant only on impact (0.3%, see Figure 3). Unemployment reaches a minimum of around -0.15% after a few quarters. Then show a very short-lived rebound effect, with a peak of about 0.1%. This shock generates a positive comovement between the inflation rate and output growth. Inflation and the interest rate move in tandem. The former increases on impact, peaks just above 0.1%, and converges to zero afterward. TFP does not react, with the effect not being statistically significant. In terms of IRFs, this shock is essentially an aggregate demand shock of the textbook-type. As is evident from the figure, GDP, investment and unemployment shocks are highly interchangeable, suggesting that they represent multiple facets of the same inflationary demand shock.[20] The hours worked shock is very similar to the latter in terms of IRFs it produces. However, it differs in that the inflation response is nearly zero and lacks statistical significance.

Now, turning to the second necessary requirement: our goal is to assess whether each of these shocks can effectively explain the bulk of business-cycle fluctuations in real activity variables. Table 2 reports, for each variable, the percentage of variance explained by the MBC shocks at business-cycle frequencies (top panel) and in the long run (bottom panel). From the top panel of Table 2, it is evident that a single shock targeting any one of the aforementioned variables is not sufficient to explain the majority of business-cycle fluctuations in all of these variables. For example, the shock that targets GDP explains about 61% of the business-cycle volatility in GDP and only 36% of that in unemployment, compared to 80% and 56% in ACD. Similarly, the shock that targets unemployment explains 58% of the cyclical volatility in unemployment and only 39% of that in GDP, as opposed to 73% and 59% in ACD. Consistent with previous findings, the shock that targets consumption explains 66% of the cyclical volatility in consumption and only a quarter of that in the remaining variables. Symmetrically, the other shocks account for only 11% to 21% of the business-cycle fluctuations

[20]The observed responses of both GDP and its components to the unemployment shock show a rebound effect followed by a long-run decline. Nevertheless, this effect is consistently not statistically significant. The transitory nature of this shock is confirmed in terms of its contribution to the long-run variance (see the next section). The IRFs of this shock with the corresponding confidence bands are available upon request.

in consumption. This constitutes the second piece of evidence suggesting that a single shock is not sufficient to explain the bulk of fluctuations in real activity over the business cycle, contrary to what is claimed by ACD.

Finally, Table 3 corroborates the findings presented so far, showing the correlation coefficients between the identified shocks. The shock that targets consumption shows very weak or almost no correlations with the other shocks, ranging from 0.04 to 0.22. Conversely, the shock obtained by targeting any one of GDP, investment, and unemployment are highly correlated with each other, with coefficients ranging from 0.78 to 0.92.

Main Business Cycle Shock					
Percentage of Explained Cyclical Variance					
	GDP	Unemp	Cons	Invest	Hours
GDP	60.6	39.3	26.9	52.3	29.5
Unemployment	36.0	57.7	26.9	45.6	42.1
Consumption	19.0	17.5	66.0	21.0	11.8
Investment	52.8	48.1	24.8	61.6	35.6
Hours Worked	26.7	40.1	29.9	33.5	57.5
TFP	9.8	15.4	10.9	12.5	12.2
Inflation	19.5	36.0	22.1	19.2	5.8
FFR	36.5	53.6	14.8	40.3	35.7
S&P500	14.5	14.3	23.3	23.9	21.5
Labor	45.9	31.3	18.6	37.4	22.5
Percentage of Explained Long Run Variance					
	GDP	Unemp	Cons	Invest	Hours
GDP	0.5	11.8	65.7	0.6	0.5
Unemployment	5.3	9.6	58.1	4.2	5.5
Consumption	1.1	10.5	68.9	2.3	0.2
Investment	1.0	16.9	55.6	0.8	0.3
Hours Worked	2.0	1.1	58.1	2.8	28.0
TFP	2.2	10.3	55.7	3.5	0.2
Inflation	10.3	14.8	2.2	7.3	1.0
FFR	22.1	23.6	0.6	17.0	7.4
S&P500	1.3	3.2	22.6	0.3	3.4
Labor	0.5	7.3	49.2	1.0	4.9

Table 2: Percentage of variance explained by the main business cycle shock for a few selected variables, by frequency bands. The columns correspond to different targets in the construction of the shock.

Main Business Cycle Shock					
	GDP	Unemp	Cons	Invest	Hours
GDP	1	0.78	0.17	0.92	0.67
Unemployment	0.78	1	0.04	0.87	0.80
Consumption	0.17	0.04	1	0.20	0.22
Investment	0.92	0.87	0.20	1	0.75
Hours Worked	0.67	0.80	0.22	0.75	1

Table 3: Correlation between the shocks obtained by targeting GDP, Unemployment, Consumption, Investment, and Hours worked

5.2. Nature and (Dis)connections of our MBC Shocks

The results discussed so far exclude the existence of such thing as a "Main Business Cycle" shock. First of all, a single shock is not enough to explain most of the business-cycle fluctuations in real activity. More importantly, the shock that targets consumption is neither correlated nor interchangeable in terms of IRFs with the other identified shocks which, in contrast, appear to share roughly the same dynamic comovements. Therefore, our results do not support the hypothesis of a main, unifying propagation mechanism, as at least two distinct mechanisms are at play. Before moving on to the second part of the analysis, where we enhance our collection with the five "secondary" business-cycle drivers, we now examine more in detail the properties of our MBC shocks. Although the timing and magnitude of the responses in Figure 3 provide valuable insights into the nature of the shocks identified, they alone may not be exhaustive to offer a comprehensive interpretation. From this perspective, Table 2 provides additional information in terms of variance contributions, which help us to better understand potential connections or disconnections with the nominal side and the long run. This understanding is crucial to determine whether the nature of these shocks aligns with what the observed co-movements (IRFs) have previously suggested.

Let us turn our attention to the long run. From the lower panel of Table 2, we see that previous insights are confirmed. While the shocks that dominate the business cycle of GDP, unemployment, investment, and hours are largely disconnected from the long run of real economic activity, the shock that dominates the business cycle of consumption is far from being disconnected. Indeed, it explains over half of the long-run fluctuations in real activity variables, accounting for approximately 66% and 56% of the long-run variance in GDP and TFP, respectively. This is an early indication that what drives the long run of output and TFP has a non-negligible footprint on the business cycles. This point is further corroborated later. Conversely, the remaining shocks explain almost nothing, or very little (unemployment-shock), of the long-run variance in real activity, that is, they have a transient nature.

We now turn attention to the relation between inflation and real activity over the business cycle. First, as shown in Table 4 (which repeats a portion of the top panel of Table 2), all identified MBC shocks, except for the one that targets hours worked, have significant effects on the nominal side of the economy. In particular, differently from ACDs findings, the unemployment shock that we identify account for 36% of the business-cycle variation in inflation, as against a scant 7% in ACD. This is consistent with what has been observed in terms of co-movements, that is, the inflation rate seems to behave as suggested by the New-Keynesian framework: it increases when the unemployment rate is low (during expansion), and then converges to zero when the economy stabilizes. This result is largely in line with the figures reported in Bianchi et al. (2023).[21] Shocks targeting GDP, investment and consumption also explain about 19% to 22%. These are relatively high shares, when considering that the identified shocks explain "only" about 60% of the business cycle fluctuations in the targeted variables. On the other hand, the hours worked shock turns out to be disconnected from inflation, in that it explains close to nothing of the business-cycle variation in inflation (6%).

Inflation and the business cycle						
Percentage of Explained Cyclical Variance						
	GDP	Unemp	Cons	Invest	Hours	Inflation
GDP	60.6	39.3	26.9	52.3	29.5	21.8
Unemployment	36.0	57.7	26.9	45.6	42.1	32.1
Consumption	19.0	17.5	66.0	21.0	11.8	21.2
Investment	52.8	48.1	24.8	61.6	35.6	23.7
Hours Worked	26.7	40.1	29.9	33.5	57.5	12.3
Inflation	19.5	36.0	22.1	19.2	5.8	86.6
FFR	36.5	53.6	14.8	40.3	35.7	40.1

Table 4: Percentage of business cycle variance explained by the MBC shocks for a few selected variables. The columns correspond to different targets in the construction of the shock.

Second, the shock that targets the business cycle variance of inflation explains approximately 21% to 32% of the business cycle variation in unemployment,

[21] In that paper, a Trend-Cycle VAR is used to identify the shock that explains most of the cyclical component of unemployment. This shock accounts for approximately 30% of the inflation cycle.

GDP, investment, and consumption. This result is in sharp contrast to ACD, where the same shock has a very small footprint on the business cycle of real economic activity (4 to 8%). Thus, business cycle fluctuations in inflation seem to co-move with real activity, at least to some extent. It follows that our results not only argue against the hypothesis of a single dominant business cycle shock, but also challenge the distinctive features of ACD's business cycle anatomy. To make a long story short, the interpretation of shocks obtained by targeting any one of GDP, unemployment and investment is in line with a demand shock in a textbook version of the New Keynesian model.[22] Conversely, in terms of both IRFs and variance contributions, the interpretation of the shock that target consumption is in line with an aggregate supply shock, which raises output but lowers inflation, and maps to long run movements in productivity. However, neither categories of shock/mechanism alone is able to explain the bulk of the observed business cycles. In what follows, we enrich our collection with the five "secondary" business cycle shocks.

5.3. The two Main Business-Cycle Shocks

Are two shocks sufficient to explain the majority of business cycle fluctuations in real activity variables? And if yes, what are they and what are their effects? For each of the five macroeconomic quantities, we now identify two shocks. The first, already reported in the Part I, is the MBC shock of that specific variable. The second, referred to as the SBC shock, is identified by maximizing its contribution to the residual business cycle volatility of that variable, after the effect of the MBC shock has been filtered out. Table 5 reports the percentage of variance jointly explained by the two shocks at business cycle frequencies and in the long run. Our hypothesis is broadly confirmed: two shocks are enough to provide an accurate description of the observed business cycle in real activity. Depending on the target variable, the percentage of cyclical volatility explained by the two shocks varies between 65 and 91 for GDP, 62 and 95 for unemployment, 66 and 95 for consumption, 68 and 96 for investment, 50 and 76 for hours worked. As for the relation between inflation and real activity at business cycle frequencies, while it is tenuous for the hours worked, it is still evident for the other variables, as the corresponding shocks explain between 44% and 62% of the variation in inflation. Then we look at the long-run. In principle, both shocks could be

[22] As for the hours worked shock, despite its transitory nature, the disconnect with inflation rules out the possibility of interpreting this shock as a standard inflationary demand shock.

disconnected from long term real activity, since they are selected as those shocks maximizing cyclical variance. But this is not the case: our two shocks together account for most of the long-run variance in both output and productivity.

The Two Main Business Cycle Shocks										
	Percentage of Business Cycle Variance					Percentage of Long Run Variance				
	GDP	Unemp	Cons	Inv	Hours	GDP	Unemp	Cons	Inv	Hours
GDP	91.5	69.7	65.2	83.0	58.3	60.8	63.7	76.6	47.8	52.6
Unemployment	73.0	95.0	62.1	82.4	76.0	76.8	77.5	74.2	72.8	63.1
Consumption	74.7	66.9	95.2	68.3	65.4	56.4	54.9	81.0	46.1	54.1
Investment	86.1	82.7	67.5	95.8	66.5	70.9	77.8	67.8	65.1	66.2
Hours	61.1	75.6	50.4	66.2	92.5	66.0	68.5	62.7	55.8	70.4
TFP	22.2	27.2	19.8	25.0	27.9	56.2	56.0	74.8	52.1	51.9
Inflation	51.5	61.9	43.7	51.9	33.1	18.9	22.2	7.5	18.1	6.2
FFR	56.0	67.7	50.0	62.2	59.7	22.7	23.8	7.7	19.4	8.0
S&P500	56.4	65.3	32.5	69.7	54.3	43.9	47.8	27.3	48.5	39.9
Labor	63.7	47.7	42.7	53.5	41.9	55.2	57.2	61.6	50.4	49.0

Table 5: Percentage of variance explained by the two main shocks for a few selected variables, by frequency band. The columns correspond to different targets in the construction of the shock.

The Two Main Business Cycle Shocks										
Percentage of Explained Cyclical Variance										
	GDP		Unemp		Cons		Invest		Hours	
	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC
GDP	60.6	30.9	39.3	30.4	26.9	38.3	52.3	30.6	29.5	28.8
Unemployment	36.0	37.0	57.7	37.2	26.9	35.2	45.6	36.9	42.1	33.9
Consumption	19.0	55.7	17.5	49.4	66.0	29.3	21.0	47.2	11.8	53.6
Investment	52.8	33.4	48.1	34.6	24.8	42.7	61.6	34.2	35.6	30.9
Hours	26.7	34.4	40.1	35.5	29.9	20.5	33.5	32.7	57.5	35.0
TFP	9.8	12.4	15.4	11.8	10.9	8.9	12.5	12.5	12.2	15.7
Inflation	19.5	32.0	36.0	25.9	22.1	21.7	19.2	32.7	5.8	27.3
FFR	36.5	19.4	53.6	14.1	14.8	35.2	40.3	21.9	35.7	24.0
S&P500	14.5	41.9	14.3	50.9	23.3	9.2	23.9	45.8	21.5	32.8
Labor	45.9	17.8	31.3	16.4	18.6	24.1	37.4	16.2	22.5	19.4
Percentage of Explained Long-Run Variance										
	GDP		Unemp		Cons		Invest		Hours	
	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC
GDP	0.5	60.3	11.8	51.9	65.7	11.0	0.6	47.2	0.5	52.2
Unemployment	5.3	71.5	9.6	67.9	58.1	16.1	4.2	68.6	5.5	57.6
Consumption	1.1	55.4	10.5	44.4	68.9	12.1	2.3	43.8	0.2	53.9
Investment	1.0	69.9	16.9	60.9	55.6	12.2	0.8	64.3	0.3	65.9
Hours	2.0	63.9	1.1	67.4	58.1	4.7	2.8	53.0	28.0	42.4
TFP	2.2	54.0	10.3	45.7	55.7	19.1	3.5	48.6	0.2	51.7
Inflation	10.3	8.6	14.8	7.4	2.2	5.3	7.3	10.8	1.0	5.2
FFR	22.1	0.6	23.6	0.2	0.6	7.1	17.0	2.4	7.4	0.7
S&P500	1.3	42.7	3.2	44.6	22.6	4.7	0.3	48.2	3.4	36.5
Labor	0.5	54.6	7.3	49.9	49.2	12.4	1.0	49.4	4.9	44.1

Table 6: Percentage of variance explained by the MBC shock and the SBC shock for a few selected variables, by frequency band. The columns correspond to different targets in the construction of the shock.

The key to understanding this representation lies in the SBC shock. Table 6 reports the percentage of variance explained by the MBC shock and the SBC shock at business cycle frequencies (top panel) and in the long run (bottom panel). From the bottom panel of the table, it can be observed that the SBC shock, obtained by targeting any one of GDP, unemployment, investment, or hours worked, accounts for 42 to 60% of the long-run fluctuations in GDP, and 46 to 54% in TFP, that is, it has long-lasting effects on economic activity.[23] When we turn our attention to the explained variance at business cycle frequencies (top panel), we find that the secondary shock, which targets any of these variables, is not only important in explaining long-run fluctuations, but also plays a crucial role in the business cycle. Its importance is almost comparable to that of the corresponding MBC shock. In particular, it is found to be dominant for consumption, in that it explains about one-half of its cyclical variance, while the corresponding MBC shock explains between 12 and 21%.[24] This finding reinforces the previous insight: shocks that account for the long-run of output and productivity also make a significant contribution to the business cycle. Finally, depending on the target variable, this shock also accounts for about 26-33% of the fluctuations in inflation. Figure 2, Panel A, compares the IRFs of selected variables to the SBC shocks of output, unemployment, investment and hours worked.[25] As is evident from the figure, these shocks are nearly indistinguishable and share the typical features of a supply shock. The degree of matching is very high, with correlation coefficients ranging from 0.90 to 0.98 (Table 9). Therefore, for each of these variables (GDP, unemployment, investment and, to a somewhat lesser extent, hours worked), while the corresponding MBC shock fits the profile of an aggregate demand shock, the SBC shock fits the profile of an aggregate supply shock.

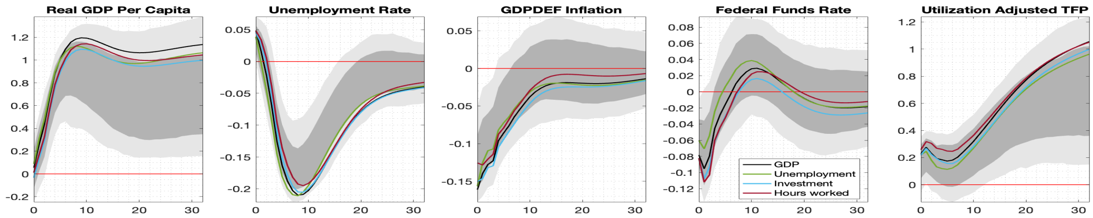
Building on the previous discussion, it's worth noting that each of these secondary shocks not only produces the same comovements/IRFs as the MBC shock of consumption, as detailed in section 5.1, but also exhibits a high correlation with it. This correlation is quantified by coefficients ranging from 0.80 to 0.90. Based on this, we can conclude that they represent interchangeable facets of the same aggregate supply shock.

[23]It also accounts for 58 to 72% of the fluctuations in unemployment, 44 to 55% in consumption, 61 to 70% in investment, and 42 to 67% in hours worked.

[24]Note that the contribution of these shocks to the cyclical variance of consumption is left unrestricted.

[25]For a comprehensive view of the responses of all the variables to these shocks and the shock that targets consumption, please refer to Figure 4.

(a) GDP, Unemployment, Investment and Hours worked shocks



(b) Consumption shock

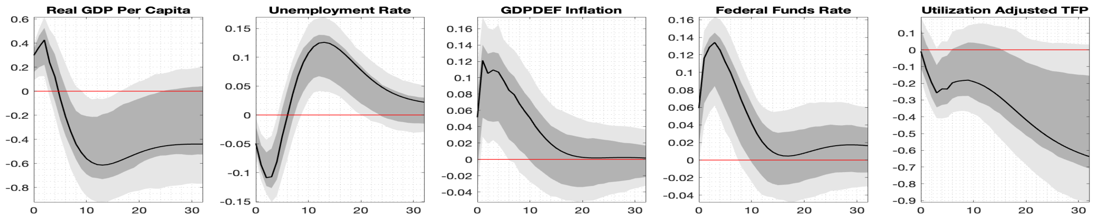


Figure 2: Impulse response functions of the SBC shock obtained by targeting different variables. The dark gray and light gray areas are the 68% and 90% confidence bands, respectively, for the shock that targets GDP (panel A) and consumption (Panel B).

What about the SBC shock obtained by targeting consumption? Unsurprisingly, while the corresponding MBC shock turns out to be a permanent supply shock, the SBC shock turns out to be a transitory shock, as the percentage of long-run fluctuations in GDP, consumption, and investment accounted for by this shock is negligible (Table 6, bottom panel).[26] Going back to the top panel of the table, it can be seen that this shock accounts for about 38, 35, and 43% of the business cycle fluctuations in GDP, unemployment, and investment, respectively, whereas the corresponding slow-moving MBC shock accounts for about 27% and 25%. This is consistent with previous results: transitory shocks are the most important factors in explaining the business cycle of output, unemployment and investment. Regarding cyclical inflation, this shock appears to be fairly connected with it, accounting for approximately 22%. Given these observations, it is very tempting to interpret this shock as a standard demand shock, in line with the interpretation given to the MBC shock that targets any one of GDP, unemployment, and investment. This interpretation finds some support in Panel B of Figure 2, which reports the IRFs of selected variables to this shock. The observed response of output growth shows a positive impact and a peak of about 0.4% at horizon 2, followed by a rebound and a substantial decline in the

[26]However, note that this shock explains a non-negligible fraction of long-run fluctuations in TFP (about 19%).

long run. However, this long-lasting effect is not statistically significant.[27] The inflation rate increases on impact, peaks at 0.12% in the second quarter, and converges to zero afterward. This is consistent with what we would expect from a demand shock. The interest rate follows a similar dynamic, increasing in a hump-shaped pattern and reaching a maximum of about 0.13%. Therefore, for private consumption, while the corresponding MBC shock fits the profile of an aggregate supply shock, the SBC shock fits the profile of an aggregate demand shock.

Once again, it's important to note that this shock is closely related to each of the MCB shocks that target GDP, unemployment, and investment, displaying correlation coefficients near 0.8.[28] This suggests that they share roughly the same propagation mechanism and represent different facets of the same aggregate demand shock.

Summing up, considering a sample from 1962 to 2019, the observed business cycles of GDP, investment, consumption, unemployment and, to a lesser extend hours worked, appears to be well described by two common factors/mechanisms of a different nature: a demand shock having only transitory effects (or vey small long-term impacts) and a generic supply shock having long-lasting effects on output and productivity. Hence, one may advance the concept of the "Two Main Business-Cycle shocks" as the main drivers of business cycle movements in real activity.

5.4. The Main Long-Run Shock and the Business Cycle

One of the main findings emerging from our analysis is that, although the long-run is left unrestricted, our two main business cycle shocks togheter account for more than half of the long-run fluctuations in both output and productivity. This suggests that what drives the long run also leaves a nontrivial footprint on the business cycle. In what follows, we further corroborate this finding. A second, important subset of our anatomy indeed comprises the shocks identified by targeting any one of GDP, investment, consumption, TFP, or labor productivity at long-run frequencies. This subset allows us to answer two questions. First,

[27]The same applies to the response of TFP in the long run, which is never statistically significant. Note that these objects are still reduced-form shocks, the interpretation of which is inherently delicate, as also pointed out by ACD. This is the price of following an agnostic approach.

[28]The correlation coefficient between the SBC shock of consumption and the MBC shock of hours worked is 0.51, indicating a slightly weaker connection.

is a single shock sufficient to account for the bulk of long-run fluctuations in real activity? If yes, how much of the business cycle variance in real activity is accounted for by this shock?

Table 7 and Figure 5 show that these shocks produce essentially the same results in terms of both IRFs and variance contributions, as well as being highly correlated with each other (Table 10). Furthermore, any one of them accounts for almost all of the long-run variance in the targeted variables and for more than one half of the long run variance in the remaining variables. For example, the shock that targets GDP explains about 97% of the long run volatility in GDP and 70% of that in TFP. Similarly, the shock that targets TFP explains 91% of the long run volatility in TFP and 74% of that in GDP. Therefore, we can assume the existence of a single main long-run shock. From the figure, it is evident that this shock has the typical features of a supply shock that reflects long-run movements in productivity: it has a large permanent effect on real activity variables, and induces a negative covariance between GDP growth and inflation changes. In response to this shock, unemployment and hours worked exhibit a temporary hump-shaped pattern. Note that TFP and labor productivity, after a relatively modest impact effect, slowly increase toward their new long run level, suggesting that the various facets of this shock include an important technological component related to news about future productivity.

Now, let us turn our attention to the explained variances at business cycle frequencies (Table 7, top panel). Despite the fact that the short-run is left unrestricted, we find that the main long-run shock has considerable effects on the business cycle. This shock, represented by the shock that targets TFP, explains 21% of the business cycle volatility for GDP and investment, 25% for unemployment, and 24% for hours worked. Moreover, consistent with previous findings, it accounts for approximately 46% of the business cycle volatility in consumption. These results support the thesis that private consumption fluctuations are mostly explained by supply shocks and therefore, to best describe the observed business cycles in real activity, both demand and supply shocks should be taken into account. Overall, our main long-run shock does not seem to be disconnected from short-term economic activity, just as our empirical template of the business cycle does not seem to be disconnected from the long run. The emerging picture stands in stark contrast to ACD, where the same shock presents a profound disconnect with the short run. At the same time, is clearly incompatible with both the standard RBC model and the view proposed by Beaudry and Portier (2006) that TFP news is the main driver of cyclical fluctuations in real activity.

To conclude, there is a nontrivial connection between the short run and the long run of real economic activity, which theoretical models should take into account.

Main Long Run Shock					
Percentage of Explained Cyclical Variance					
	GDP	Cons	Invest	Labor	TFP
GDP	21.8	19.8	23.1	19.2	20.5
Unemployment Rate	27.1	23.7	33.0	24.3	25.1
Consumption	48.2	51.5	41.3	38.5	46.2
Investment	18.2	17.7	23.5	19.1	20.6
Hours Worked	20.3	21.2	24.0	20.0	20.8
Labor	24.6	14.7	24.5	24.3	26.0
TFP	16.2	8.4	14.9	21.2	29.2
Inflation	33.0	17.4	47.8	46.8	28.8
FFR	17.1	19.5	24.4	15.1	23.8
S&P500	9.0	5.9	15.3	11.9	7.3
Percentage of Explained Long Run Variance					
Target	GDP	Cons	Invest	Labor	TFP
GDP	96.7	80.1	71.3	72.2	74.1
Unemployment Rate	57.7	50.0	59.9	74.9	61.4
Consumption	78.9	95.3	47.7	52.3	72.8
Investment	70.8	47.2	96.4	66.7	51.9
Hours Worked	64.1	59.0	45.4	66.9	53.1
Labor	69.4	50.7	64.4	93.0	73.4
TFP	69.9	69.5	49.8	72.2	90.8
Inflation	5.5	1.0	23.2	23.1	2.8
FFR	0.2	5.9	8.7	5.8	0.4
S&P500	18.7	12.7	28.6	22.0	14.6

Table 7: Percentage of variance explained by the main long run shock for a few selected variables, by frequency bands. The columns correspond to different targets in the construction of the shock.

5.5. Robustness

In this section we conduct a robustness check for the shocks that make up our business cycle anatomy. Specifically, we explore the robustness of our findings for the main and secondary shocks identified by targeting GDP or consumption. Firstly, we estimate the model with four lags instead of three. Secondly, we test the robustness to different numbers of static factors. Specifically, we compare the results of our baseline specification ($r = 11$) with two alternatives: $r = 8, 12$. The third robustness exercise serves a complementary objective. We take into account that economic expansions have become progressively longer, as suggested by Beaudry et al. (2020).[29] As a result, we adjust our approach to the business

[29] The authors show that many macroeconomic aggregates appear to have a peak in their spectral densities at periodicities between 32 and 50 quarters and that the implied movements

cycle by using a different frequency band. Instead of the conventional range of 18 months to 8 years, $[\underline{\theta}, \overline{\theta}] = [2\pi/32, 2\pi/6]$, we now consider cycles with periodicity between 18 month and 12 years, $[\underline{\theta}, \overline{\theta}] = [2\pi/48, 2\pi/6]$. Finally, we constrain the sample to 1961-2007, excluding the Great Recession and the Zero Lower Bound.

For each robustness exercise, Table 11 reports the contributions of both the MBC and SBC shocks, identified by targeting GDP growth, to the cyclical (top panel) and long-run (lower panel) variance. The first two columns correspond to our baseline specification, while the remaining are for the alternative specifications. Similarly, Table 12 provides the same information but for the main and secondary business cycle shocks identified by targeting consumption. As we move across specifications, we observe that the contribution of the identified shocks to the cyclical and long-run variances of the main macroeconomic aggregates remains almost unchanged. The main conclusions are all confirmed. Interestingly, in the third exercise, when considering cycles with a periodicity slightly longer than what is traditionally associated with business cycles, the relative importance of shocks with long-lasting effects/supply in explaining cyclical fluctuations in real activity appears to increase, although it remains true that the cyclical fluctuations in GDP are mostly explained by a transitory/demand shock.

Finally, the same robustness is found when considering the IRFs. Figures 6 and 7 plot the IRFs for the MBC and the SBC shocks that target GDP, respectively, for both the baseline and alternative specifications. The solid black lines and confidence bands are those obtained in the baseline. Likewise, Figures 8 and 9 display the IRFs for shocks targeting consumption. Although there are some differences when we set a lower number of static factors compared to the benchmark, or when we narrow the sample, the dynamic responses overall are reasonably similar to those obtained in the baseline exercise.

6. Discussion and Concluding Remarks

In this paper we challenge the ACD's hypothesis that most of the business cycle fluctuations in real economic activity can be explained by just one shock. We argue that the VAR used in their work is informationally deficient, rendering the causal interpretation of the "Main Business Cycle" shock untenable. By using a large-dimensional Structural Dynamic Factor model along with ACD's

coincide with NBER cycle dating. For this reason, they argue that the traditional definition of business cycle may have become slightly too narrow and should be modified accordingly.

frequency-domain method, we propose an alternative anatomical template for the transmission mechanisms of business cycles. The picture emerging from our empirical analysis is as follows. It is possible to account for the majority of the business-cycle fluctuations in GDP, investment, consumption, unemployment, and, to a somewhat lesser extent, hours worked, using a parsimonious two-shock model. These reduced-form shocks, which we refer to as the "Two Main Business Cycle" shocks, align with the traditional AD-AS narrative in terms of their characteristics. Both mechanisms are important factors of business cycle fluctations. Private consumption fluctuations are almost entirely explained by supply dynamics, whereas GDP growth fluctuations are mainly explained by demand dynamics. The last result is consistent with the standard New Keynesian narrative that the bulk of the business cycle in output is due to shifts in aggregate demand. The result on consumption can be explained in light of the Permanent Income Hypothesis: at the aggregate level, private consumption largely follows expectations about future income, and thus would be more responsive to permanent shocks than transitory ones (Quah, 1990).

Our conclusions are in line with those of Francis and Kindberg-Hanlon (2022), even though the model and the method used here are different. In that paper, a VAR is used, and the variance-maximizing method is coupled with additional theoretical constraints, to identify the dominant driver of US GDP at business cycle frequencies. In contrast, we use a SDFM and follow ACD's spectral method to identify a collection of reduced-form shocks, without imposing additional constraints. As noted above, our findings regarding the joint dynamics of inflation and real activity over the business cycle align with the evidence presented in Bianchi et al. (2023), which instead employs a Trend-Cycle VAR model. To conclude, the reduced-form shocks contained in our collection, the interpretation of which is inherently delicate, suggest that a simplified yet fairly complete representation of the US macroeconomy can be provided by only two shocks. In that, our paper can be regarded as complementary to Forni et al. (2023). In that paper, our evidence serves as a starting point to provide a comprehensive and stylized structural description of the US macroeconomy, focusing on both the business cycle and the long run.

Tables

	χ	ξ
GDP	94.33	5.67
Unemployment Rate	94.17	5.83
Consumption	81.62	18.38
Investment	89.54	10.46
Hours Worked	83.53	16.47
TFP	80.91	19.09
Inflation	90.47	9.53
FFR	97.92	2.08
S&P500	94.47	5.53
Labor Productivity	89.31	10.69

Table 8: Percentage of the variance explained by the estimated common and idiosyncratic components. Baseline specification: $r = 11$ static factors.

Secondary Business Cycle Shock					
	GDP	Unemp	Cons	Invest	Hours
GDP	1	0.98	-0.26	0.98	0.95
Unemployment	0.98	1	-0.22	0.96	0.90
Consumption	-0.26	-0.22	1	-0.38	-0.30
Investment	0.98	0.96	-0.38	1	0.95
Hours Worked	0.95	0.90	-0.30	0.95	1

Table 9: Correlation between the SBC shocks obtained by targeting GDP, Unemployment, Consumption, Investment, and Hours worked

Main Long Run Shock					
	GDP	Unemp	Cons	Invest	Hours
GDP	1	0.91	0.86	0.86	0.88
Consumption	0.91	1	0.70	0.74	0.87
Investment	0.86	0.70	1	0.83	0.73
Labor	0.86	0.74	0.83	1	0.89
TFP	0.88	0.87	0.73	0.89	1

Table 10: Correlation between the MLR shocks obtained by targeting GDP, Consumption, Investment, Labor productivity and TFP

Robustness: The Two Main Business Cycle Shocks (GDP)												
Percentage of Explained Cyclical Variance												
	Baseline		[1] p=4		[2] r=8		[3] r=12		[5] 6-48		[6] 1961-2007	
	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC
GDP	60.6	30.9	63.5	28.9	59.5	35.0	61.2	29.9	55.4	34.4	51.4	35.7
Unemployment	36.0	37.0	39.1	35.2	35.6	42.3	37.1	36.2	33.9	39.1	39.5	34.9
Consumption	19.0	55.7	22.4	56.7	18.6	71.6	18.4	58.9	17.7	61.2	22.7	51.9
Investment	52.8	33.4	56.5	31.2	47.9	42.5	52.5	32.9	50.3	34.8	47.0	38.5
Hours	26.7	34.4	27.5	33.3	31.9	36.9	25.0	34.7	23.0	41.7	38.3	29.9
TFP	9.8	12.4	8.3	15.7	14.2	15.5	6.8	12.9	9.7	13.9	3.3	9.8
Inflation	19.5	32.0	25.8	27.8	18.7	32.6	21.0	29.8	24.2	30.0	20.7	40.6
FFR	36.5	19.4	43.1	17.3	41.6	23.6	36.8	20.0	36.4	17.7	46.1	16.9
S&P500	14.5	41.9	19.2	34.1	17.0	39.1	16.5	37.2	14.1	36.4	18.0	37.2
Labor	45.9	17.8	46.0	19.7	42.9	18.9	45.7	19.6	42.7	20.8	34.8	26.8
Percentage of Explained Long-Run Variance												
	Baseline		[1] p=4		[2] r=8		[3] r=12		[5] 6-48		[6] 1961-2007	
	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC
GDP	0.5	60.3	0.5	76.4	1.7	68.2	0.5	66.3	0.2	74.6	2.5	66.4
Unemployment	5.3	71.5	8.8	70.4	6.1	75.1	5.8	71.8	6.3	72.5	3.0	49.9
Consumption	1.1	55.4	1.2	68.4	1.4	71.5	1.2	62.4	1.6	65.3	0.3	70.7
Investment	1.0	69.9	1.8	78.7	2.4	78.3	1.9	69.8	1.5	76.2	0.4	69.4
Hours	2.0	63.9	1.7	65.6	5.1	71.4	0.8	60.2	1.5	65.1	0.4	17.1
TFP	2.2	54.0	2.7	66.0	2.5	59.1	2.2	62.4	2.9	63.3	1.8	44.3
Inflation	10.3	8.6	13.6	7.1	21.1	5.5	14.5	6.2	11.5	7.6	2.0	16.0
FFR	22.1	0.6	30.2	0.2	36.8	0.3	24.9	0.2	23.2	0.4	20.2	21.3
S&P500	1.3	42.7	2.6	34.9	1.2	38.0	2.1	43.4	1.5	37.3	0.7	36.2
Labor	0.5	54.6	0.8	63.8	1.4	42.2	0.8	57.9	1.0	61.1	0.9	33.3

Table 11: Percentage of variance explained by the MBC shock and the SBC shock, obtained by targeting GDP, by frequency band. The columns correspond to different robustness exercises. Business cycle frequency band [5]: $[2\pi/48 \leq \omega \leq 2\pi/6]$ corresponding to cycles with periodicity between 18 months and 12 years.

Robustness: The Two Main Business Cycle Shocks (Consumption)												
Percentage of Explained Cyclical Variance												
	Baseline		[1] p=4		[2] r=8		[3] r=12		[5] 6-48		[6] 1961-2007	
	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC
GDP	26.9	38.3	26.1	42.9	33.2	52.0	27.4	38.0	30.9	37.5	32.4	34.9
Unemployment	26.9	35.2	28.3	36.9	37.8	44.5	30.3	33.9	35.2	31.9	31.0	41.7
Consumption	66.0	29.3	62.6	33.8	75.7	21.4	64.5	29.6	68.4	26.5	57.4	34.7
Investment	24.8	42.7	24.6	47.8	37.7	53.0	27.2	42.6	28.1	42.9	33.0	38.0
Hours	29.9	20.5	30.9	22.2	33.0	34.9	30.5	18.3	36.8	19.3	27.5	37.5
TFP	10.9	8.9	13.9	5.3	14.4	17.9	9.3	7.9	11.0	8.8	13.7	4.7
Inflation	22.1	21.7	24.0	23.9	31.1	31.0	23.7	19.2	28.5	18.3	42.0	28.2
FFR	14.8	35.2	15.9	39.0	21.5	52.1	17.1	32.4	18.9	31.2	12.3	49.2
S&P500	23.3	9.2	21.2	14.5	26.0	23.4	23.1	9.9	20.6	13.9	23.3	14.9
Labor	18.6	24.1	19.3	26.7	20.5	32.8	17.5	25.2	18.2	25.5	24.9	24.7
Percentage of Explained Long-Run Variance												
	Baseline		[1] p=4		[2] r=8		[3] r=12		[5] 6-48		[6] 1961-2007	
	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC	MBC	SBC
GDP	65.7	11.0	69.0	6.7	81.3	0.6	74.7	4.3	76.1	2.8	76.4	0.9
Unemployment	58.1	16.1	61.1	17.0	80.2	8.9	64.5	10.4	67.2	5.9	57.8	4.9
Consumption	68.9	12.1	71.5	7.2	86.5	2.3	77.1	5.3	80.2	3.0	88.8	0.6
Investment	55.6	12.2	55.6	12.4	78.1	4.2	63.1	8.0	64.5	3.7	65.1	0.7
Hours Worked	58.1	4.7	57.0	1.7	79.8	5.4	61.6	2.2	59.0	0.5	21.5	0.2
TFP	55.7	19.1	62.7	12.2	68.6	3.3	62.6	12.2	67.7	7.0	53.7	1.1
Inflation	2.2	5.3	3.9	7.2	4.7	39.6	2.2	8.2	4.4	4.9	20.8	2.3
FFR	0.6	7.1	0.1	13.6	0.4	56.7	0.9	10.0	0.2	9.6	23.8	18.5
S&P500	22.6	4.7	22.2	6.3	25.7	1.3	27.3	3.4	24.1	0.9	27.5	1.4
Labor	49.2	12.4	53.3	7.1	57.4	9.0	54.9	6.2	58.2	4.0	37.8	0.1

Table 12: Percentage of variance explained by the MBC shock and the SBC shock, obtained by targeting Consumption, by frequency band. The columns correspond to different robustness exercises. Business cycle frequency band [5]: $[2\pi/48 \leq \omega \leq 2\pi/6]$ corresponding to cycles with periodicity between 18 months and 12 years.

Figures

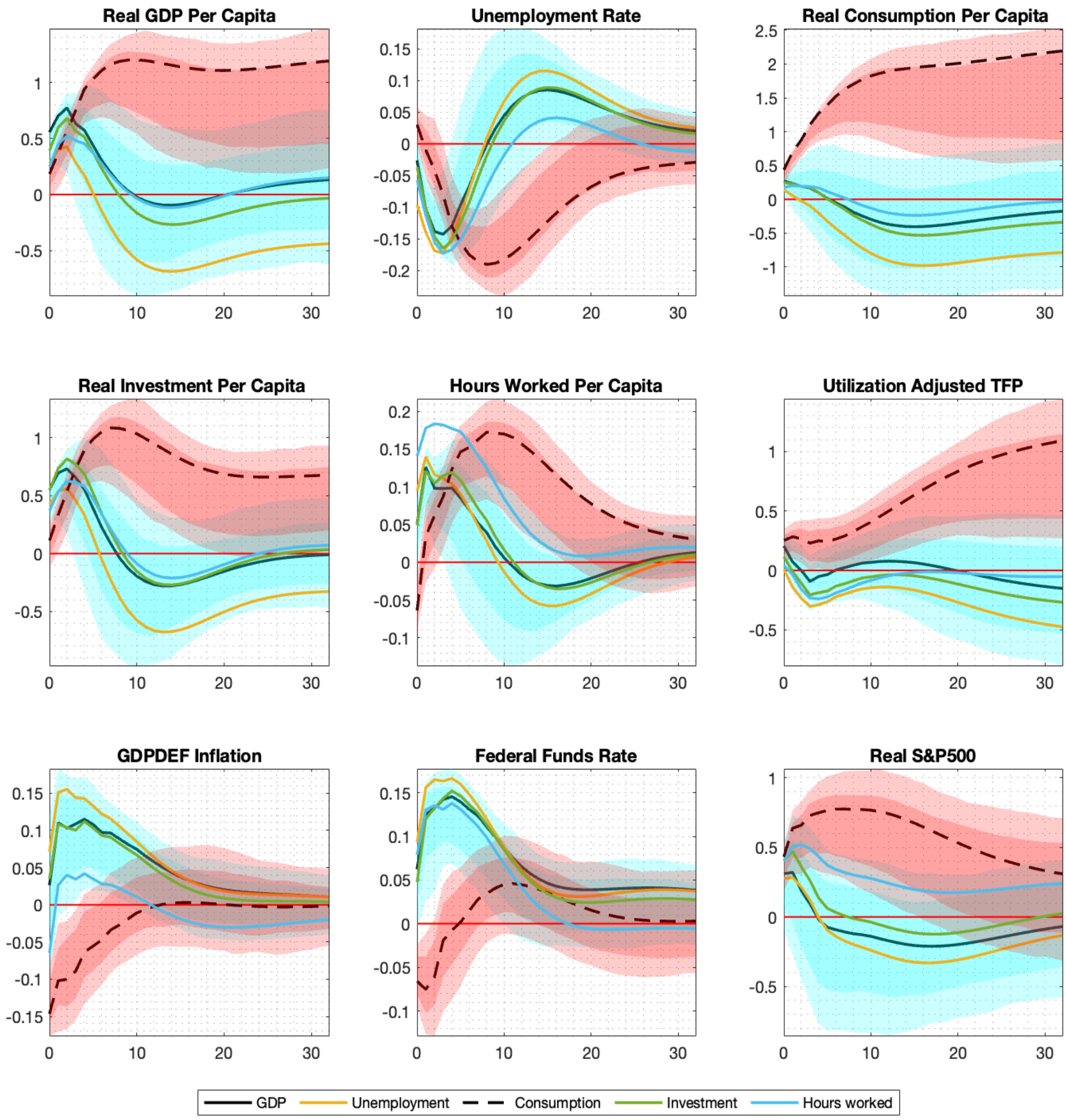


Figure 3: Impulse response functions of the MBC shock obtained by targeting different variables. The dark red (dark blue) and light red (light blue) areas are the 68% and 90% confidence bands, respectively, for the shock that targets GDP (consumption)

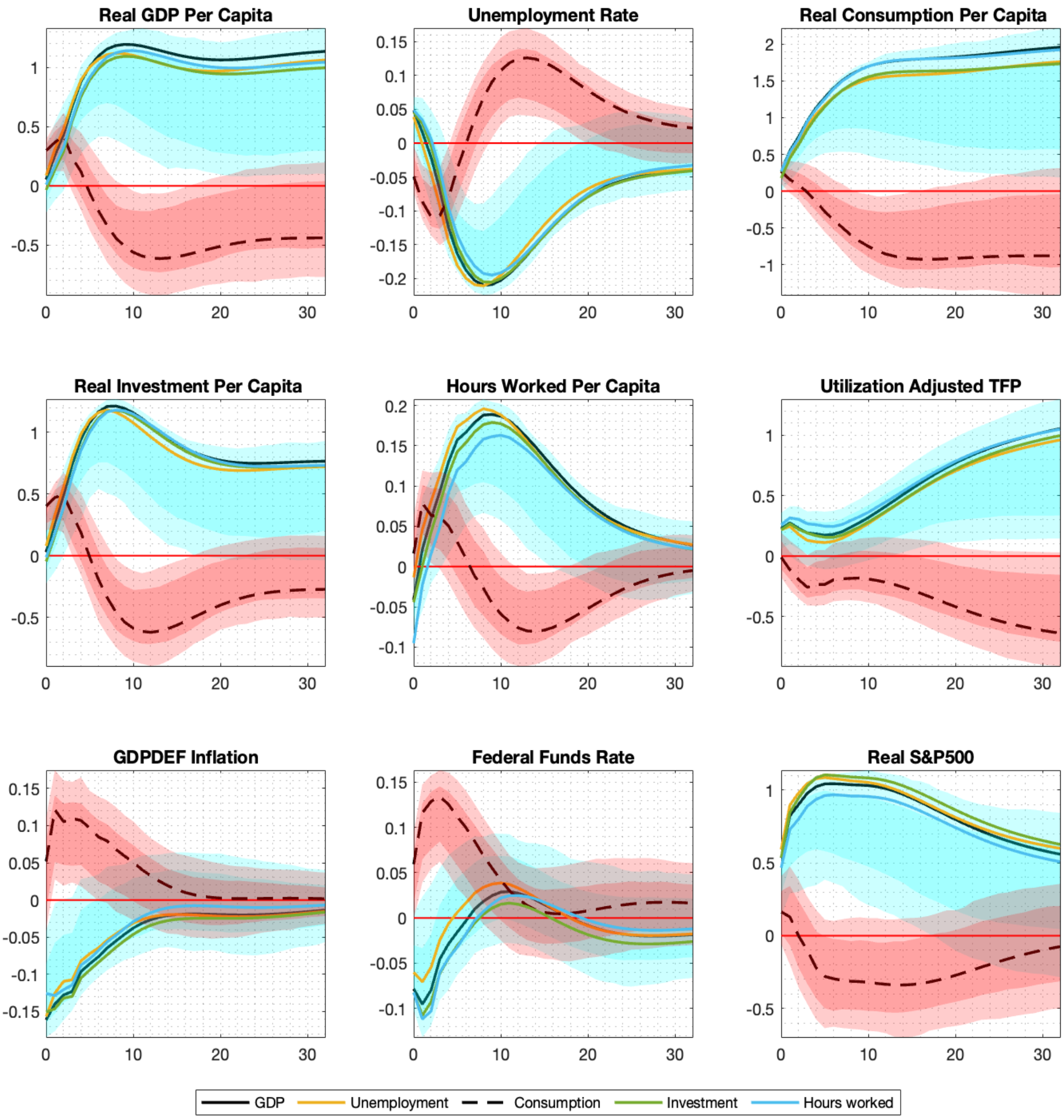


Figure 4: Impulse response functions of the SBC shock obtained by targeting different variables. The dark red (dark blue) and light red (light blue) areas are the 68% and 90% confidence bands, respectively, for the shock that targets GDP (consumption)

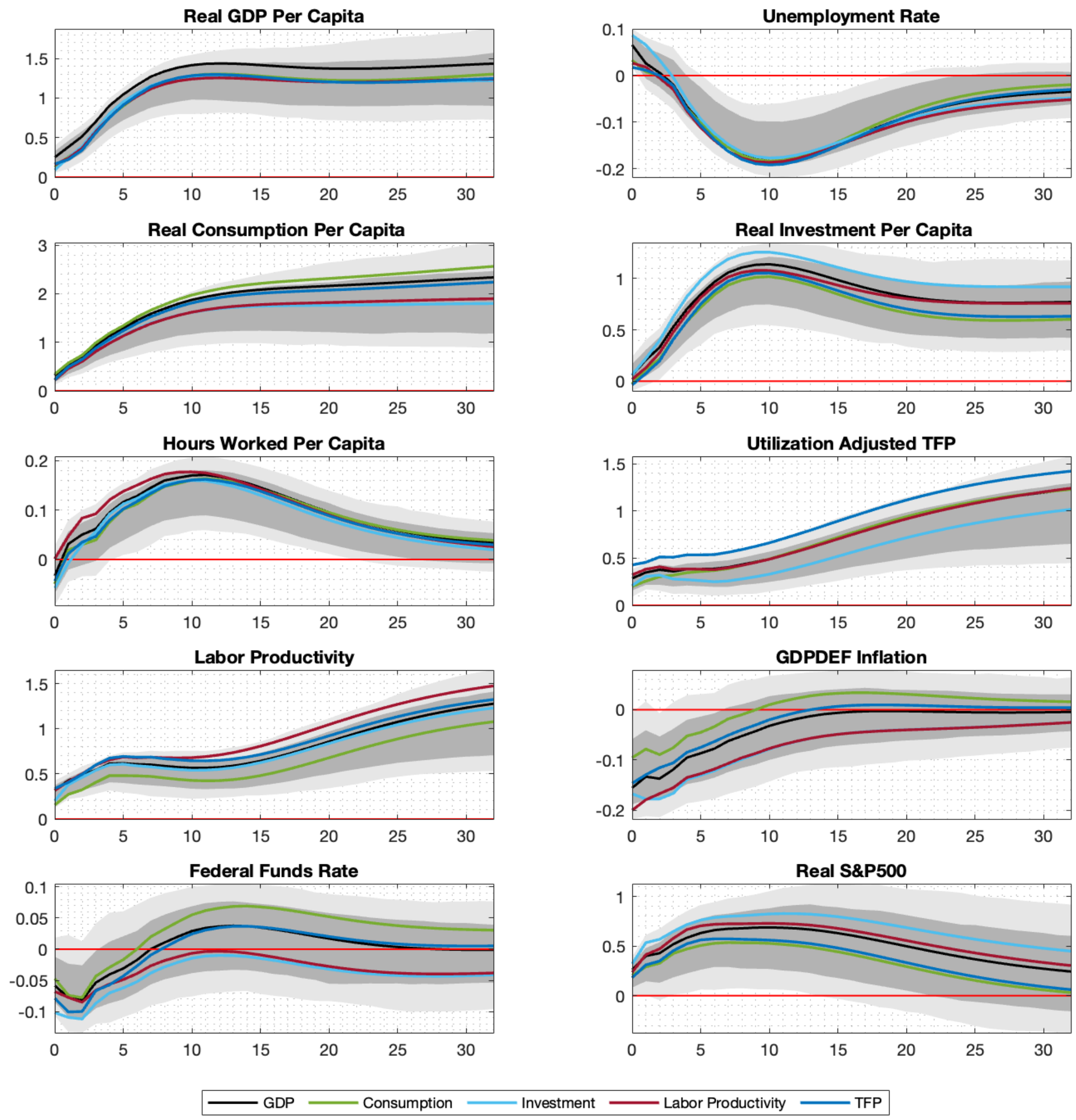


Figure 5: Impulse response functions of the MLR shock obtained by targeting different variables. The dark gray and light gray areas are the 68% and 90% confidence bands, respectively, for the shock that targets GDP.

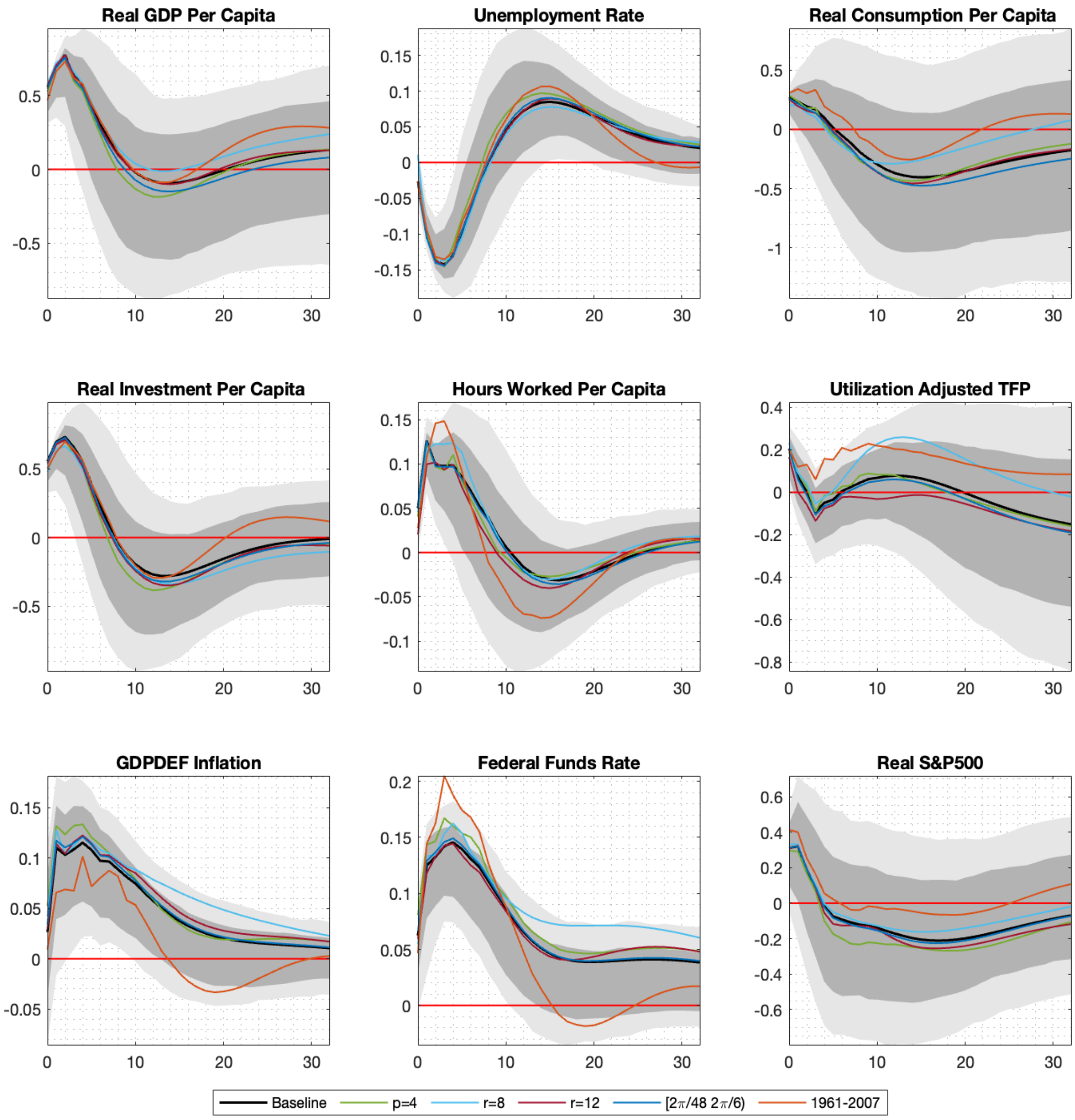


Figure 6: Impulse Response Functions of the MBC shock obtained by targeting GDP. The solid lines represent the point estimates for different robustness exercises. The dark gray and light gray areas are the 68% and 90% confidence bands, respectively. Black line and confidence bands: baseline specification.

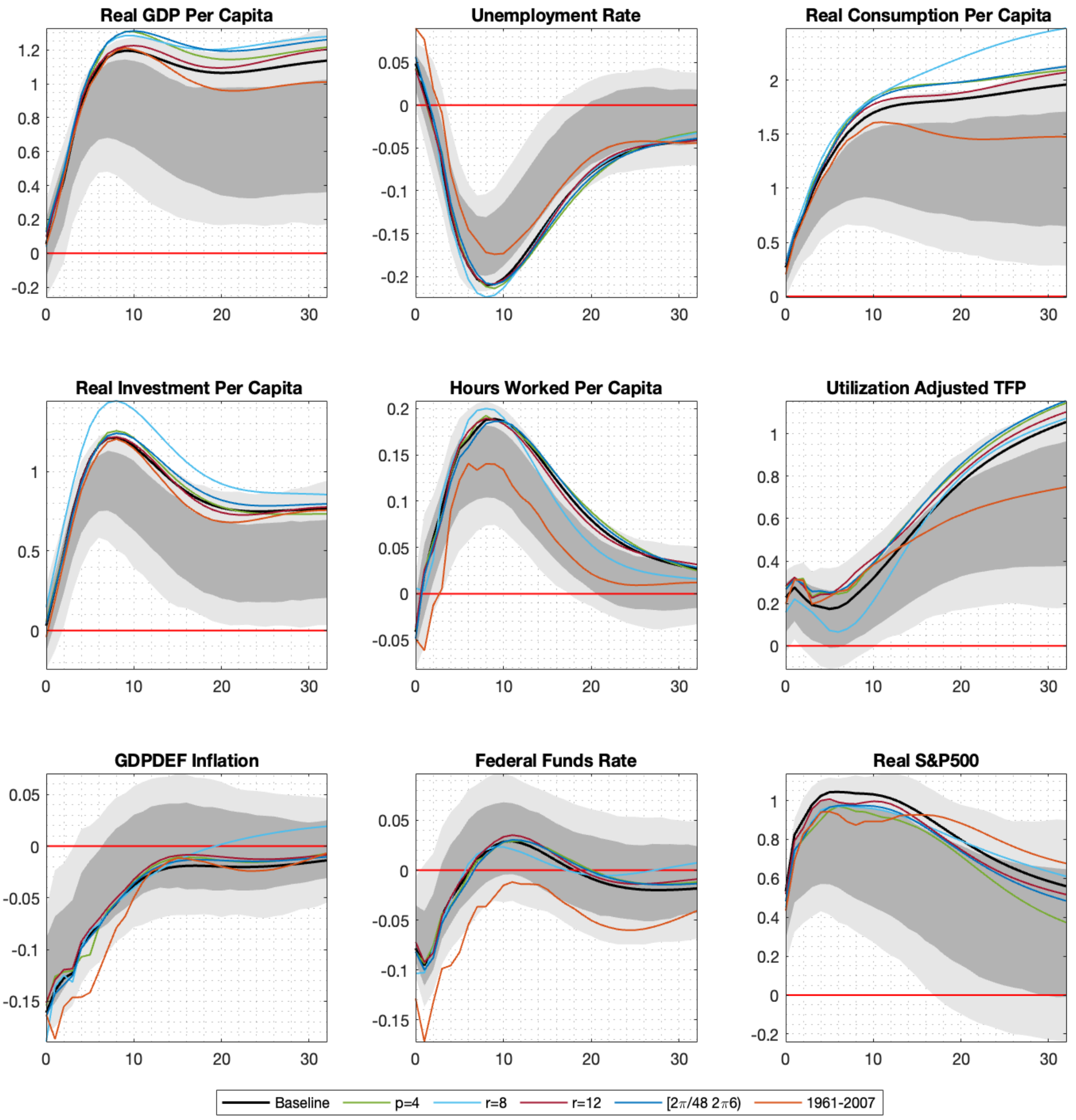


Figure 7: Impulse Response Functions of the SBC shock obtained by targeting GDP. The solid lines represent the point estimates for different robustness exercises. The dark gray and light gray areas are the 68% and 90% confidence bands, respectively. Black line and confidence bands: baseline specification.

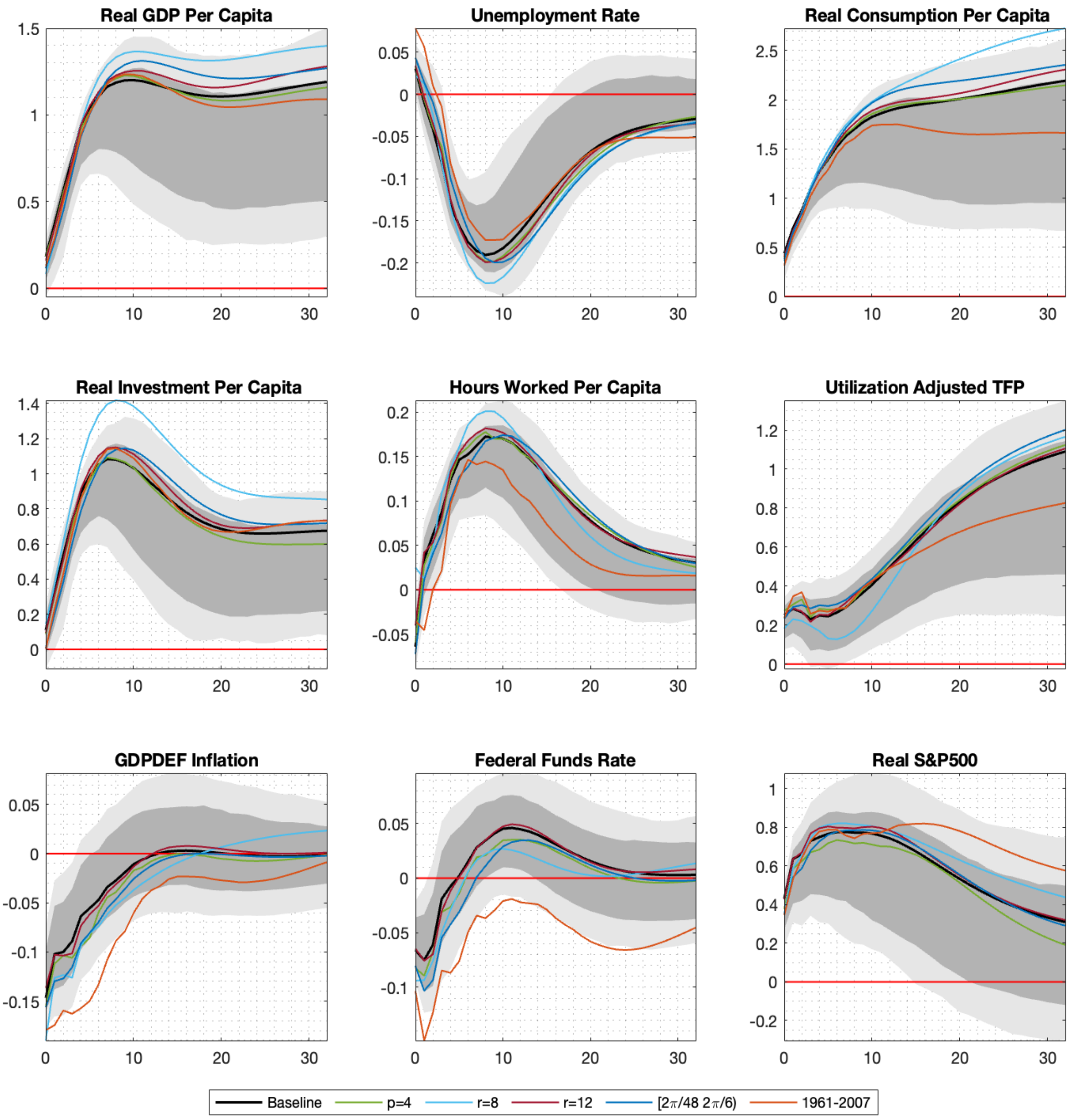


Figure 8: Impulse Response Functions of the MBC shock obtained targeting consumption. The solid lines represent the point estimates for different robustness exercises. The dark gray and light gray areas are the 68% and 90% confidence bands, respectively. Black line and confidence bands: baseline specification.

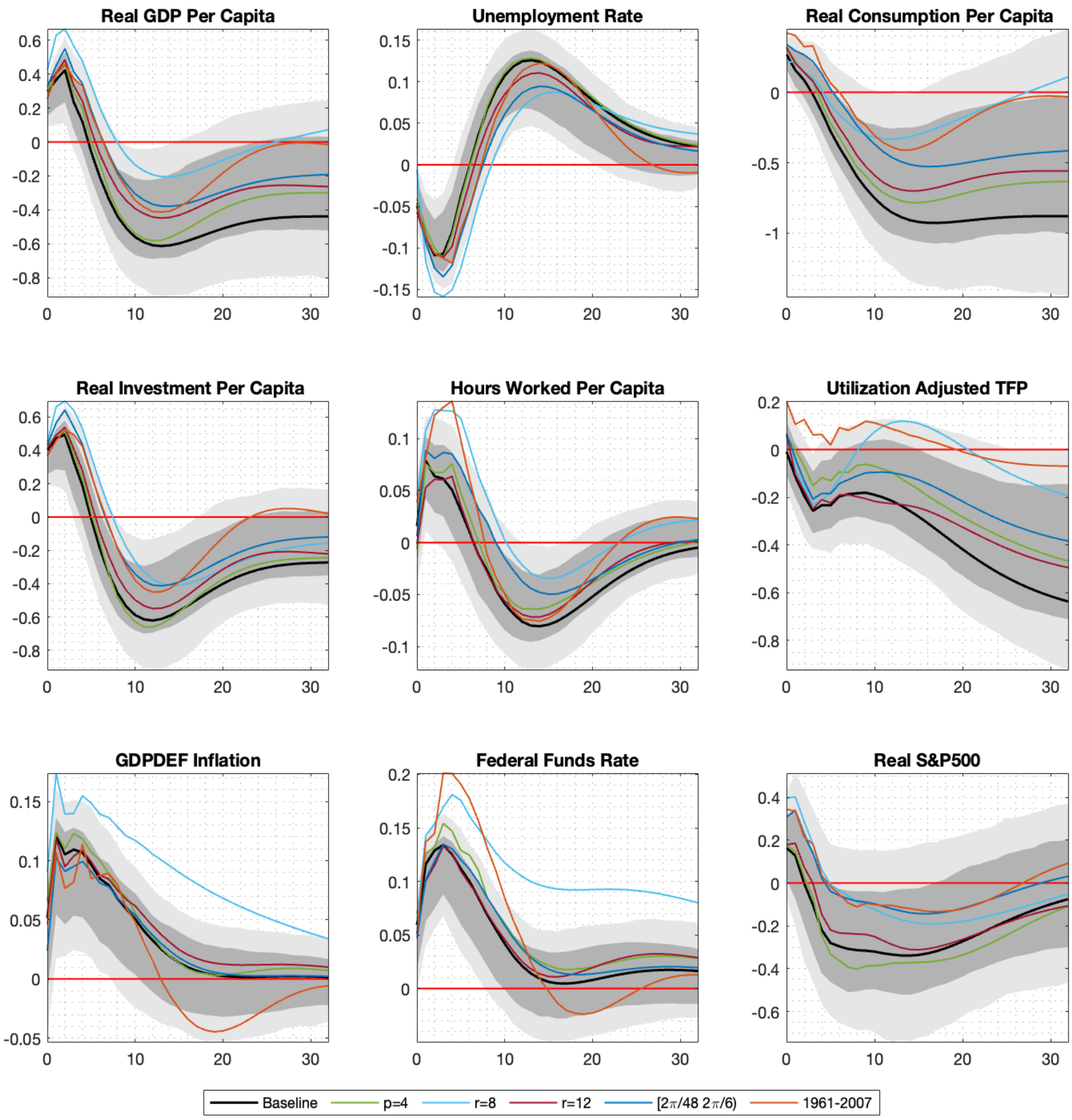


Figure 9: Impulse Response Functions of the SBC shock obtained by targeting consumption. The solid lines represent the point estimates for different robustness exercises. The dark gray and light gray areas are the 68% and 90% confidence bands, respectively. Black line and confidence bands: baseline specification.

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Appendix

A. Estimation Procedure

In order to compute the spectra and the objective function we proceed as follows. We estimate the first two equations (4a)-(4b) using the two step estimation technique discussed in Forni et al. (2009), which we briefly review here. First Step. We set a value for the number r of the static factors, using the criterion by Bai and Ng (2002) with the penalty modification proposed in Alessi et al. (2010), finding a number of static factors $\hat{r} = 11$. In the robustness section, we take into account the uncertainty in estimating the number of static factors, and repeat the analysis with different specifications of $\hat{r}$. The static factors $F_t = (F_{1t} \dots F_{rt})'$ are estimated by the first $\hat{r}$ principal components of the variables in our dataset, and the factor loadings, λ_{ij}, $j = 1 \dots r$, by the associated eigenvectors. Thus, the estimated loading matrix, $\hat{\Lambda}$, is the $n \times \hat{r}$ matrix having on the columns the normalized eigenvectors corresponding to the $\hat{r}$-largest eigenvalues of the sample covariance matrix of the data, $\hat{\Sigma}_x$. The estimated common component vector is given by $\hat{\chi}_t = \hat{\Lambda}\hat{F}_t$. Second Step. We run a VAR(p) for the estimated factors $\hat{F}_t$ to get estimates $\hat{C}(L)$ and $\hat{\epsilon}_t$ of $C(L)$ and the VAR innovations ϵ_t. The estimated MA representation is $\hat{F}_t = \hat{C}(L)^{-1}\hat{\epsilon}_t$. The number of lags p is determined according to the AIC criterion ($\hat{p}_{AIC} = 3$). The Cholesky IRFs of the common components are obtained according to (7) as $\hat{D}(L) = \hat{\Lambda}[\hat{C}(L)^{-1}\hat{S}]$. From this matrix we estimate the spectral density of the common components at the Fourier frequencies $\theta = 2\pi s/T$, $s = 1, \dots, T$. Finally, we compute $V\left(k, \underline{\theta}, \overline{\theta}\right)$ by replacing the integral with the simple average of the spectral density matrix, across the frequencies belonging to the relevant interval. We do not apply the rank reduction step as this will be part of the identification strategy discussed below.

B. Data Description and Data Treatment

For the description of each variable see McCracken and Ng (2020). For variables not in the FRED-QD dataset, refer to the Mnemonic and note. Treatment codes: 1 = no treatment; 2 = first difference, Δx_t; 4 = $\log(x_t)$; 5 = log of the first difference, $\Delta \log(x_t)$.

The analysis presented in the main text focuses on a subset of 10 macroeconomic series of interest: (1) the log difference of the real per capita GDP [ID 1]; (2) the log difference of real per capita consumption [ID-21]; (3) the log difference of real per capita investment [ID-22]; (4) the unemployment rate [ID-37]; (5) the log of real per capita hours worked [ID-44]; (6) the inflation rate, defined as the log difference of the GDP deflator [ID-50]; (7) labour productivity [ID-62]; (8) the cumulated sum of the utility-adjusted total factor productivity [ID-68]; (9) the Federal Funds rate [ID-73] and the (10) Shiller's real S&P500 stock price index [ID-107].

ID	FRED-QD ID	Mnemonic	Treatment code	Note
1	1	GDPC1/CNP16OV	5	
2	2	PCECC96/CNP16OV	5	
3	3	PCDGx/CNP16OV	5	
4	4	PCESVx/CNP16OV	5	
5	5	PCNDx/CNP16OV	5	
6	6	GPDIC1/CNP16OV	5	
7	7	FPIx/CNP16OV	5	
8	8	Y033RC1Q027SBEAx/CNP16OV	5	
9	9	PNFIx/CNP16OV	5	
10	10	PRFIx/CNP16OV	5	
11	11	A014RE1Q156NBEA	1	
12	12	GCEC1/CNP16OV	5	
13	13	A823RL1Q225SBEA	1	
14	14	FGRECPTx/CNP16OV	5	
15	15	SLCEx/CNP16OV	5	
16	16	EXPGSC1/CNP16OV	5	
17	17	IMPGSC1/CNP16OV	5	
18	18	DPIC96/CNP16OV	5	
19	19	OUTNFB/CNP16OV	5	
20	20	OUTBS/CNP16OV	5	
21		(PCESVx+PCNDx)/CNP16OV	5	
22		(PCDGx+FPIx)/CNP16OV	5	
23	22	INDPRO/CNP16OV	5	
24	23	IPFINAL/CNP16OV	5	
25	24	IPCONGD/CNP16OV	5	
26	25	IPMAT/CNP16OV	5	
27	28	IPDCONGD/CNP16OV	5	
28	30	IPNCONGD/CNP16OV	5	
29	31	IPBUSEQ/CNP16OV	5	
30	35	PAYEMS/CNP16OV	2	
31	36	USPRIV/CNP16OV	2	
32	38	SRVPRD/CNP16OV	2	
33	39	USGOOD/CNP16OV	2	
34	51	USGOVT/CNP16OV	2	
35	57	CE16OV/CNP16OV (EMRATIO)	2	
36	58	CIVPART	2	
37	59	UNRATE	1	
38	60	UNRATESTx	1	
39	61	UNRATELTx	1	
40	62	LNS14000012	1	
41	63	LNS14000025	1	
42	64	LNS14000026	1	
43	74	HOABS/CNP16OV	4	
44	76	HOANBS/CNP16OV	4	

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ID	FRED-QD ID	Mnemonic	Treatment code	Note
45	77	AWHMAN	1	
46	79	AWOTMAN	1	
47	81	HOUST/CNP160V	5	
48	95	PCECTPI	5	
49	96	PCEPILFE	5	
50		GDPDEF	5	GDP: Implicit Price Deflator
51	97	GDPCTPI	5	
52	98	GPDICTPI	5	
53	120	CPIAUCSL	5	
54	121	CPILFESL	5	
55	122	WPSFD49207	5	
56	123	PPIACO	5	
57	124	WPSFD49502	5	
58	126	PPIIDC	5	
59	129	WPU0561	5	
60	130	OILPRICEx	5	
61	135	COMPRNFB	5	
62	138	OPHNFB	5	
63	139	OPHPBS	5	
64	140	ULCBS	5	
65	142	ULCNFB	5	
66	143	UNLPNBS	5	
67		dtfp	1	Fernald's TFP growth
68		dtfp util	1	Fernald's TFP growth CU adjusted
69		dtfp I	1	Fernald's TFP growth - Inv
70		dtfp C	1	Fernald's TFP growth - Con
71		dtfp I util	1	Fernald's TFP growth CU - Inv
72		dtfp C util	1	Fernald's TFP growth CU - Con
73	144	FEDFUNDS	1	
74	145	TB3MS	1	
75	146	TB6MS	1	
76	147	GS1	1	
77	148	GS10	1	
78	150	AAA	1	
79	151	BAA	1	
80	152	BAA10YM	1	
81	156	GS10TB3Mx	1	
82		BAA-AAA	1	
83		GS10-FEDFUNDS	1	
84		GS1-FEDFUNDS	1	
85		BAA-FEDFUNDS	1	
86	158	BOGMBASEREALx/CNP16OV	5	
87	160	M1REAL/CNP16OV	5	
88	161	M2REAL/CNP16OV	5	
89	163	BUSLOANSx/CNP16OV	5	
90	164	CONSUMERx/CNP16OV	5	
91	166	REALLNx/CNP16OV	5	
92	168	TOTALSLx/CNP16OV	5	
93	188	UMCSENTx	1	
94		Business Condition 12 Months	1	Michigan Consumer Survey
95		Business Condition 5 Years	1	Michigan Consumer Survey
96		Current Index	1	Michigan Consumer Survey
97		Expected Index	1	Michigan Consumer Survey
98		News Index: Relative	1	Michigan Consumer Survey
99	197	UEMPMEAN	1	
100	201	GS5	1	
101	210	CUSR0000SAC	5	
102	211	CUSR0000SAD	5	
103	212	CUSR0000SAS	5	
104	213	CPIULFSL	5	
105	245	S&P 500	5	
106	246	S&P: indust	5	
107		S&P 500/GDPDEF	5	
108		S&P: indust/GDPDEF	5	
109		JLN Macro Unc 1-month	1	Jurado, Ludvigson and Ng Uncertainty
110		JLN Macro Unc 3-month	1	Jurado, Ludvigson and Ng Uncertainty
111		JLN Macro Unc 12-month	1	Jurado, Ludvigson and Ng Uncertainty
112		DPCCRC1Q027SBEAx/CNP16OV	5	Real PCE Excluding food and energy
113		DFXARC1M027SBEAx/CNP16OV	5	Real PCE: Food
114		DNRGRC1Q027SBEAx/CNP16OV	5	Real PCE: Energy goods and services

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