Brookings Papers
ON ECONOMIC ACTIVITY

BPEA Conference Draft, March 27-28, 2025

Recovering from COVID

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March 13, 2025

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Abstract

The COVID business cycle was unique. The recession was by far the deepest and shortest in the U.S. postwar record and the first several quarters of the recovery were remarkably rapid. The cycle saw an unprecedented reallocation of employment and consumption away from in-person services towards goods that can be consumed at home and outdoors. This paper provides a simple empirical model that attributes these and other anomalies in real economic activity to a single unobserved shock. That shock, which turns out to be closely connected to COVID deaths, diminishes in importance over the expansion, consistent with self-protective measures like masking, COVID fatigue, and eventually the availability of the vaccine. The COVID shock and anomalous COVID dynamics largely disappeared by late 2022. It appears that macrodynamics have returned to normal and that the structural shifts wrought by the pandemic have had limited effects on the underlying economic trends of key indicators, despite notable changes like the prevalence of remote work and the large increase in the debt-GDP ratio. Given the magnitude of COVID shock, it is remarkable how limited are its lingering effects on the real macroeconomy.

Acknowledgments: We thank Mark Gertler and Lucrezia Reichlin for helpful comments. This paper builds on unpublished work in Maroz, Stock and Watson (2021).

Five years ago from the date of this conference, the economy was collapsing at a breathtaking pace. In New York City, deaths from COVID were growing exponentially and the virus, about which much was still being learned, was spreading across the United States. Much of the country was in lockdown. Millions of workers had been laid off: initial weekly claims for unemployment insurance, which normally range between 200,000 and 300,000 and which peaked around 650,000 during the financial crisis recession, were nearly 6 million in the week ending March 28, 2020. As uncertainty mounted and consumers stayed home, real consumption fell by 6.6% in March and another 11% in April. Closer to home, this conference was for the first time held virtually using a technology new to most participants, a harbinger of broad social and technological changes to come.

Compared to other business cycles, the COVID recession was highly unusual. The NBER-dated recession lasted only two months, by far the shortest on record. The initial recovery was nearly as rapid as the collapse: in two months following the April trough, real PCE grew by 14% and the unemployment rate fell nearly two percentage points. The recession and recovery were associated with an unprecedented sharp shift in consumption away from in-person services like restaurants and towards goods, especially goods that can be consumed at home and outdoors.

Economists responded in real time, producing a corpus of work documenting the collapse and assessing the economic and public health programs launched in response; see for example the two COVID issues of the Brookings Papers in the Summer and Fall of 2020. Much less, however, has been written about the equally unusual recovery.

The purpose of this paper is to provide a comprehensive assessment of macroeconomic dynamics over the course of the COVID business cycle. To do so, we examine the joint behavior of more than 100 quarterly and monthly economic time series, focusing on measures of real economic activity. It has long been recognized that, prior to COVID, the comovements of macroeconomic time series are well-described by a small number of common macroeconomic factors in a dynamic factor model (DFM) (Sargent and Sims 1977; Forni and Reichlin 1998; surveyed in

Stock and Watson 2016). A DFM therefore provides a tractable starting point for studying the behavior of the economy over this period.

We reach three main conclusions.

First, the recovery was unprecedented in the postwar record in two main ways: its rapid speed, and its sectoral shifts in consumption, production, and employment. Formally, a pre-COVID DFM fails to describe the magnitude of the COVID recession, the speed of the recovery, and even the sign of the changes in many macroeconomic variables. This stands in contrast to the well-established finding that DFMs provide a reliable description of postwar U.S. business cycle dynamics, which in turn implies that the shocks driving business cycles are captured by the factors (or, with invertibility, are spanned by the space of the factor innovations). For example, a DFM with large conventional shocks, but no new factors, quantitatively explains the financial crisis recession (Stock and Watson 2012). This time *was* different.

Second, this anomalous behavior can all be traced to a single novel aggregate shock, the COVID shock. Although it is estimated using only economic data, the COVID shock traces out the waves of COVID deaths, diminishes as self-protective measures such as masking are adopted and COVID fatigue sets in, and largely disappears once individuals either are vaccinated or have decided against vaccination. From March 2020 through December 2021, the single COVID shock explained 95% of the variation in the unemployment rate, 97% of the variation in establishment employment growth, 75% of the variation in personal consumption, 73% of the variation in consumption of services, 37% of the variation in consumption of durables, and 56% of the variation in housing starts. It is sometimes said that the COVID recession was comprised of many shocks – uncertainty, aggregate demand, labor supply, reallocation, and perhaps others. In our empirical model, there is just one shock – the COVID shock – to which all these macroeconomic channels responded.

Third, although the post-COVID period is too short to draw firm empirical conclusions, it appears that the pre-COVID macroeconomic dynamics have returned or, more precisely, they never disappeared or changed, they were just masked by the massive COVID shock. As the

COVID shock dissipated, conventional dynamics took over, and by 2023 the expansion largely looked like a normal expansion.

Although there do not seem to be lingering long COVID effects on business cycle dynamics, an open question is whether COVID and the changes it induced have had long-term effects on core macroeconomic measures such as consumption, investment, labor force participation, and productivity. There are reasons to suspect that COVID introduced or accelerated structural change, including remote work, a persistent increase in the number of new businesses, increasing attention to supply chain resiliency, and the labor force effects of COVID deaths and long-COVID, especially on older workers. It also led to a persistent increase in the debt-GDP ratio. We provide some preliminary evidence on the effect of the COVID shock on trend economic growth and raise some puzzles for future study as more data become available.

Given the magnitude of COVID shock, it is remarkable how limited its lingering effects seem to have been, at least at the level of macroeconomic aggregates. One takeaway is how remarkably the U.S. economy is after being subjected to this level of stress. Another takeaway is that we need humility in our ability to see around the corner: like the financial crisis, the COVID shock was almost entirely unexpected, and there is no reason to believe that this unexpected shock will be the last.

I. Review of the COVID Recession and Recovery

I.A. The COVID Timeline

The 2019 Novel Coronavirus (COVID-19) originated in Wuhan, China, with initial cases reported in early December, 2019.[1] As shown in the COVID timeline in Figure 1, the first confirmed U.S. case of the 2019 Novel Coronavirus (COVID-19) detected on January 20, 2020. The SARS-CoV-2 virus spread rapidly, with lockdowns ordered in Wuhan on January 23 and in

[1] Unless otherwise noted, dates and information in this section is taken from the Center for Disease Control COVID Timeline (2023) and COVID Data Tracker (2025). Also see Tax Policy Center (2024).

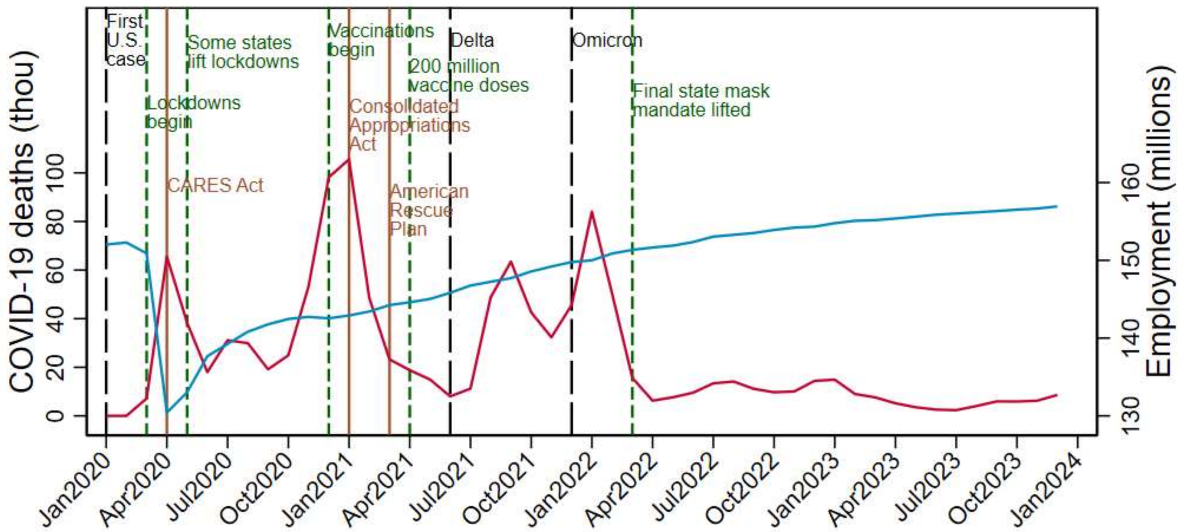


Figure 1: Monthly COVID Timeline

Italy on February 23. On March 11, the World Health Organization declared COVID-19 a pandemic, and on March 13 the U.S. Administration declared a national emergency. Tests for COVID were scarce in the first few months of the pandemic, and convenient rapid testing was not authorized until late August 2020. In December 2020, the Food and Drug Administration issued the first Emergency Use Authorizations for COVID-19 vaccines, less than one year after the SARS-CoV-2 virus was initially sequenced and eight months after the start of Operation Warp Speed to develop the vaccine. Vaccine administration began on December 14, 2020 and progressed as supply expanded, with half of the U.S. population receiving at least one dose by the end of May 2021. Vaccine hesitancy was widespread, however, so uptake slowed: by June 2022, only 67% of the population was fully vaccinated. Throughout the pandemic, the virus mutated, typically with increasingly transmissive variants superseding the prior dominant strain; these include the Gamma variant (January 2021), the Delta variant (June 2021), and the Omicron variant (November 2021). Infections and deaths occurred in waves, due in part to new variants, incomplete vaccination, changes in mandated non-pharmaceutical interventions (NPIs), and changes in voluntary self-protective behavior. By mid-February 2024, an estimated 1.19 million Americans had died from COVID. Atkeson and Kissler (2024) estimate that through that date, the vaccine saved approximately 800,000 U.S. lives.

The virus spread unevenly across the country. With some exceptions, such as air travel and transportation hubs, policies on NPIs were left to the States with the CDC issuing guidance but not regulations or orders. Accordingly, State NPIs, such as masking mandates, remote schooling, and so forth, varied substantially. Some states started lifting restrictions in late April 2020 while others kept them in place much longer; the last state to lift its universal indoor masking mandate, Hawaii, did so in in March 2022.

The combination of lockdowns, other mandatory NPIs, self-protective behavior, and widespread uncertainty resulted in a collapse of economic activity starting in the second week of March 2020 and accelerating in the third week of March as schools and businesses closed and laid off workers. From its peak on February 19 to its trough on March 23, the S&P 500 fell by 32%. From February 18 through March 16, economic uncertainty, as measured by the VIX, more than quintupled, reflecting deep unknowns about the virus and its economic consequences. Initial claims for unemployment insurance rose from 271,000 for the week ending March 14 to 2,914,000 for the weekend ending March 21, then to 6,137,000 for the week ending April 4, an order of magnitude greater than its peak weekly rate during any previous postwar recession.

Confronted with this collapse, fiscal and monetary authorities took extraordinary measures. In March 2020, the Federal Reserve Bank reduced the Federal Funds rate by 150bp to 0-0.25 bp and took additional emergency measures to ensure liquidity (see Gagliardone and Gertler 2024 for a quantification of monetary policy accommodation). Congress authorized three rounds of direct payments or tax rebates to individuals: up to $1200 for adults in the Coronavirus Aid, Relief, and Economic Security (CARES) Act, signed on March 27, 2020; $600 in the December 28, 2020 Consolidated Appropriations Act; and up to $1400 in the March 11, 2021 American Rescue Plan. Between executive and legislative actions, expenditures and tax expenditures through COVID-related programs totaled $6.8 trillion through February 2025.[2]

[2] Committee for a Responsible Federal Budget, "COVID Money Tracker," at https://www.COVIDmoneytracker.org/, updated February 12, 2025.

I.B. The COVID Recession and Recovery Compared to Prior Business Cycles

The COVID business cycle was unusual in many ways. We collect these key features into four stylized facts about the COVID cycle:

1. The recession was unusually steep and short. It was the deepest postwar recession, as measured by the peak-to-trough rise in the unemployment rate, and it was by far the shortest contraction in the 170-year NBER record, lasting only two months (the next-shortest is the 7-month contraction starting in March 1919).

2. The dynamics of the recovery were highly unusual. During the first six months after the April 2020 trough, the recovery was extraordinarily rapid. Establishment employment grew by 18% at an annual rate, compared to a 1% mean for this window in prior post-1960 recoveries. The next 12 months of the recovery (months 7-18) were also unusually strong. For example, employment grew by 4.2% compared to its mean of 2.1% for this window in prior post-1960 expansions. In contrast, months 19-36 exhibited growth generally within the range of prior post-1960 expansions.

3. The COVID cycle was accompanied by strongly expansionary fiscal policy: from the first to the third quarter of 2020, the debt-GDP ratio increased by 17.4 pp to 124%, a cyclical increase exceeded only during the financial crisis recession and early recovery.

4. The sectoral dispersion of the recession was unprecedented in the postwar record. Normally, services consumption and employment are less cyclical than goods, especially durable goods. In the COVID recession, however, services collapsed and took years to recover whereas, after the initial contraction in March and April 2020, consumption of durables soared and by June 2020 exceeded its February value by 10%.

The first three stylized facts are evident in Table 1 and Figure 2. Figure 2 plots the level of major macroeconomic aggregates over the COVID cycle to date and the previous seven business cycles, where all series are relative to their cyclical peak value. All series exhibit the sharp initial

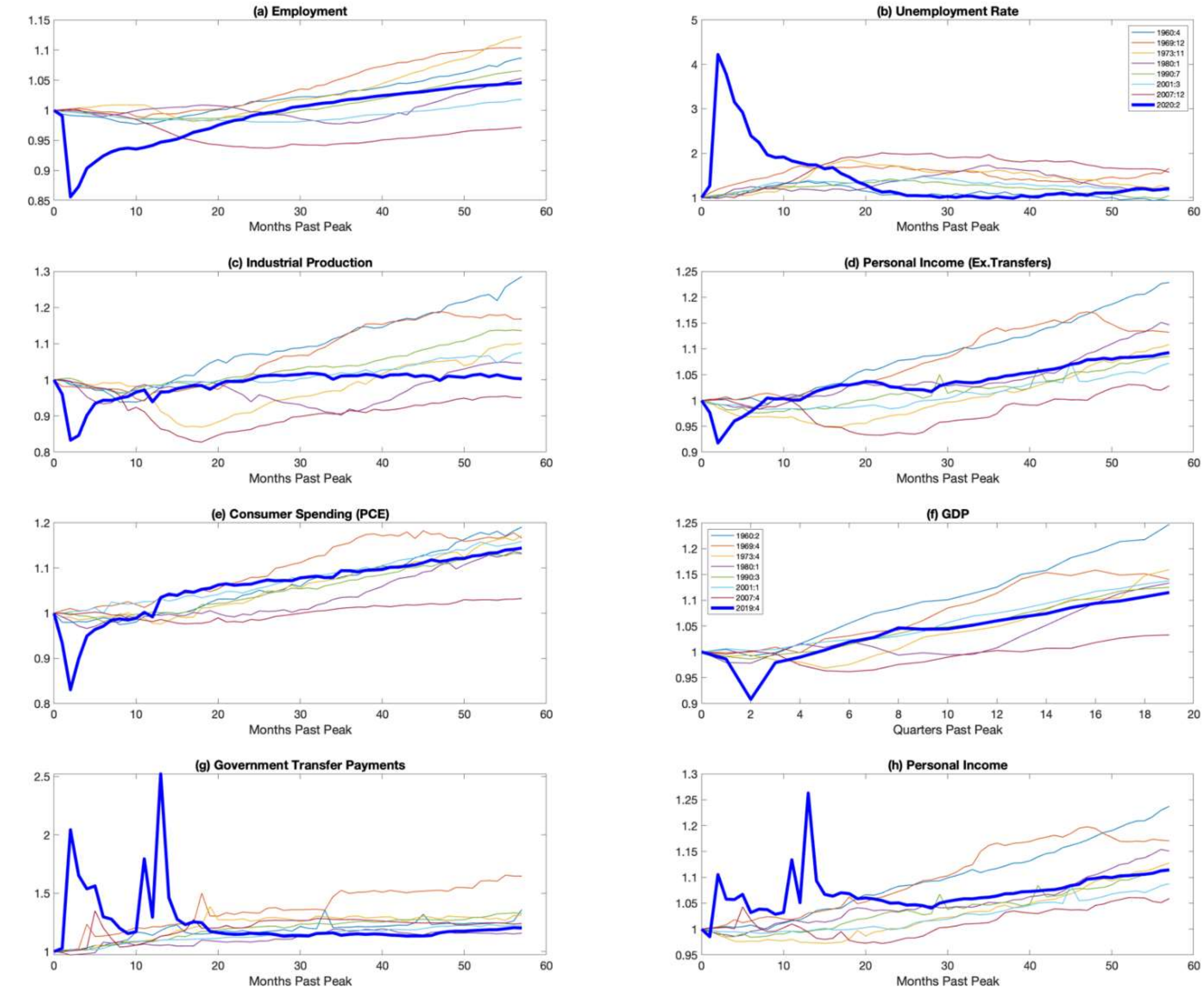
Table 1: Log point change (annual rate) of major economic indicators
in the early, middle, and late stages of cyclical expansions, 1960-2010 and 2020

	Months 1-6		Months 7-18		Months 19-36	
Indicator	**1960-2010**	**2020**	**1960-2010**	**2020**	**1960-2010**	**2020**
Unemployment rate	-0.016	-1.526	-0.073	-0.427	-0.086	-0.187
	(0.037)		(0.031)		(0.024)	
Personal income less transfers	0.030	0.181	0.041	0.031	0.039	0.008
	(0.006)		(0.004)		(0.008)	
Employment	0.010	0.177	0.021	0.042	0.027	0.030
	(0.004)		(0.003)		(0.002)	
PCE	0.037	0.346	0.042	0.073	0.037	0.020
	(0.009)		(0.006)		(0.006)	
Industrial production	0.082	0.262	0.057	0.039	0.044	0.019
	(0.012)		(0.008)		(0.005)	
Employment-goods	-0.005	0.148	0.015	0.030	0.021	0.030
	(0.008)		(0.005)		(0.003)	
Employment-services	0.014	0.225	0.025	0.051	0.032	0.032
	(0.003)		(0.003)		(0.002)	
PCE-goods	0.041	0.454	0.049	0.064	0.040	0.000
	(0.02)		(0.011)		(0.011)	
PCE-nondurable goods	0.023	0.284	0.032	0.067	0.026	-0.007
	(0.013)		(0.008)		(0.008)	
PCE-durable goods	0.090	0.803	0.087	0.060	0.073	0.012
	(0.051)		(0.024)		(0.025)	
PCE-services	0.031	0.293	0.037	0.078	0.036	0.030
	(0.006)		(0.004)		(0.003)	

Notes: Entries are log point changes of the indicator, at an annual rate, over the indicated window following a NBER-dated cyclical trough, with standard errors of the mean decline for the pre-COVID recessions in parentheses. Personal income and consumption are real. Shading: post-2020:4 trough growth exceeds 5x (dark) or 1.5x (light) pre-COVID growth for that post-trough window.

drop in March and April 2020 and a sharp initial recovery. After this first phase, growth slowed, but even during this second phase the recovery was unusually strong by historical standards. By the third phase – 18 months into the expansion – growth had returned to normal rates.

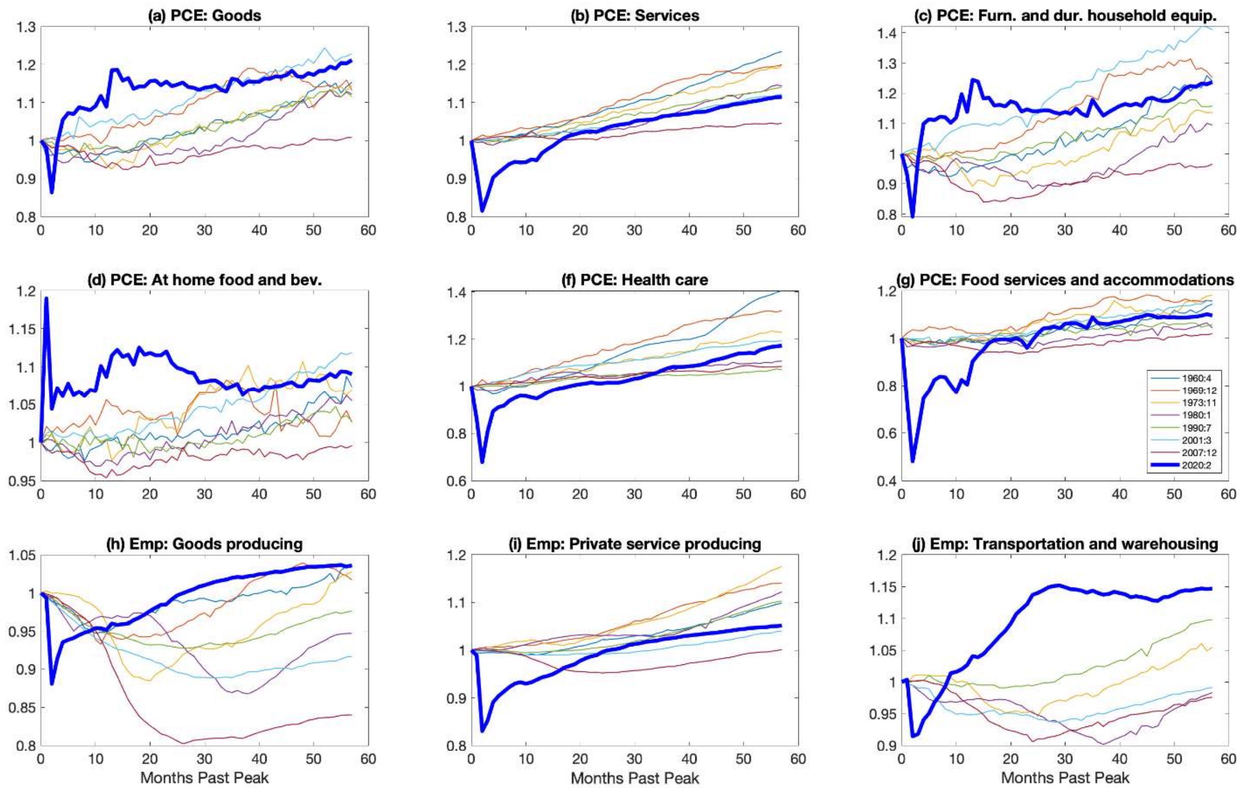
Table 1 quantifies the growth of selected monthly macroeconomic aggregates and sectoral activity measures over the three phases. The first two columns compare the log point changes in the first six months after the April 2020 trough to the first six months following the eight previous post-1960 troughs (peaks and troughs are dated using the NBER chronology). By



Notes: Recessions are labeled by their peaks. For this figure, the recession starting in July 1981 is included as a continuation of the recession that began in January 1980.

Figure 2: Aggregate time series over the COVID and prior business cycles

October 2020, the unemployment rate had fallen to 6.8% from its April peak of 14.8%, a decline of 7 pp or 1.53 log points, compared to just 0.02 log point decline in previous post-1960 recessions and an order of magnitude faster than Hall and Kudlyak's (2022) regularity of a 0.10 (SE = 0.02) log point decline in the unemployment rate during the full span of previous postwar recoveries. By this metric, growth was an order of magnitude stronger immediately following the COVID trough than the average over the same window for the eight prior troughs, for all the aggregates and sectoral measures in the table. A similar pattern emerges with quarterly flow variables (not shown). During the third and fourth quarter of 2020 (the first two quarters following the 2020:II trough), GDP grew at the extraordinary annual rate of 35%. GDP, personal income less transfers, nonresidential private investment, and consumption (PCE) each regained their 2019:IV cyclical peak value in 2021:I, boosted by the large transfer payments in March 2021 from the American Rescue Plan.



Notes: See the notes to Figure 2.

Figure 3: Selected sectoral time series over the COVID and prior business cycles

The second two columns in Table 1 document the less-noted strong growth during the second phase of the expansion (months 7-18). The recovery of the labor market was exceptionally strong for this phase of the recovery, both as measured by the unemployment rate and by aggregate and sectoral employment. The final columns document the general return of these indicators to normal growth rates over the third phase, months 19-36, although it is worth noting that the unemployment rate fell faster than usual – nearly twice as fast as the Hall-Kudlyak postwar norm – reaching 3.4% by April 2023, 36 months after the cyclical trough. This return to normal growth is also evident in Figure 2.

Figure 2 (g) and (h) illustrates the third stylized fact: the strength of the fiscal response, as shown here by government transfer payments, during the COVID recession into 2021 was unprecedented during prior postwar recoveries.

The fourth stylized fact is that the COVID cycle also saw sectoral dispersion unprecedented in the postwar business cycle record. Because of self-protection measures, both mandated and voluntary, consumption shifted sharply from in-person services to goods that can be used at home or outdoors. This shift is apparent in Figure 3. In-person services such as food services and accommodations and health care fell sharply and recovered slowly (many non-urgent health care needs were postponed during COVID). In contrast, demand for goods surged after an initial contraction, both durable goods such as recreational equipment and furniture and nondurables such as food at home. Services that were complementary with home consumption of goods, in particular transportation and warehousing, also surged as consumption shifted from in-person to at-home.

Figure 4 provides another visualization of the unprecedented dispersion of cyclical responses during the COVID recession and early expansion. The figure plots the 5%, 25%, 50%, 75%, and 95% percentiles of the cross-section distribution of 128 monthly time series from 1960-2024, where the data series are generally monthly growth rates, standardized using pre-COVID sample means and standard deviations and, if the series is countercyclical, multiplied by -1 (for more on the data, see Section III.A).

Panel (a) of Figure 4 shows the pre-COVID period. Recessions are easily recognized as a negative shift in the cross-section distribution leading to a downward shift in the quantiles plotted in the figure. Also evident is an increased negative skew in the distributions during recessions that leads the lower quantiles to shift down more than the upper quantiles.[3]

[3] Adrian, Boyarchenko and Giannone (2019) find the predictive distribution for U.S. GDP growth exhibits a similar pattern with a negative shift and negative skew during recessions.

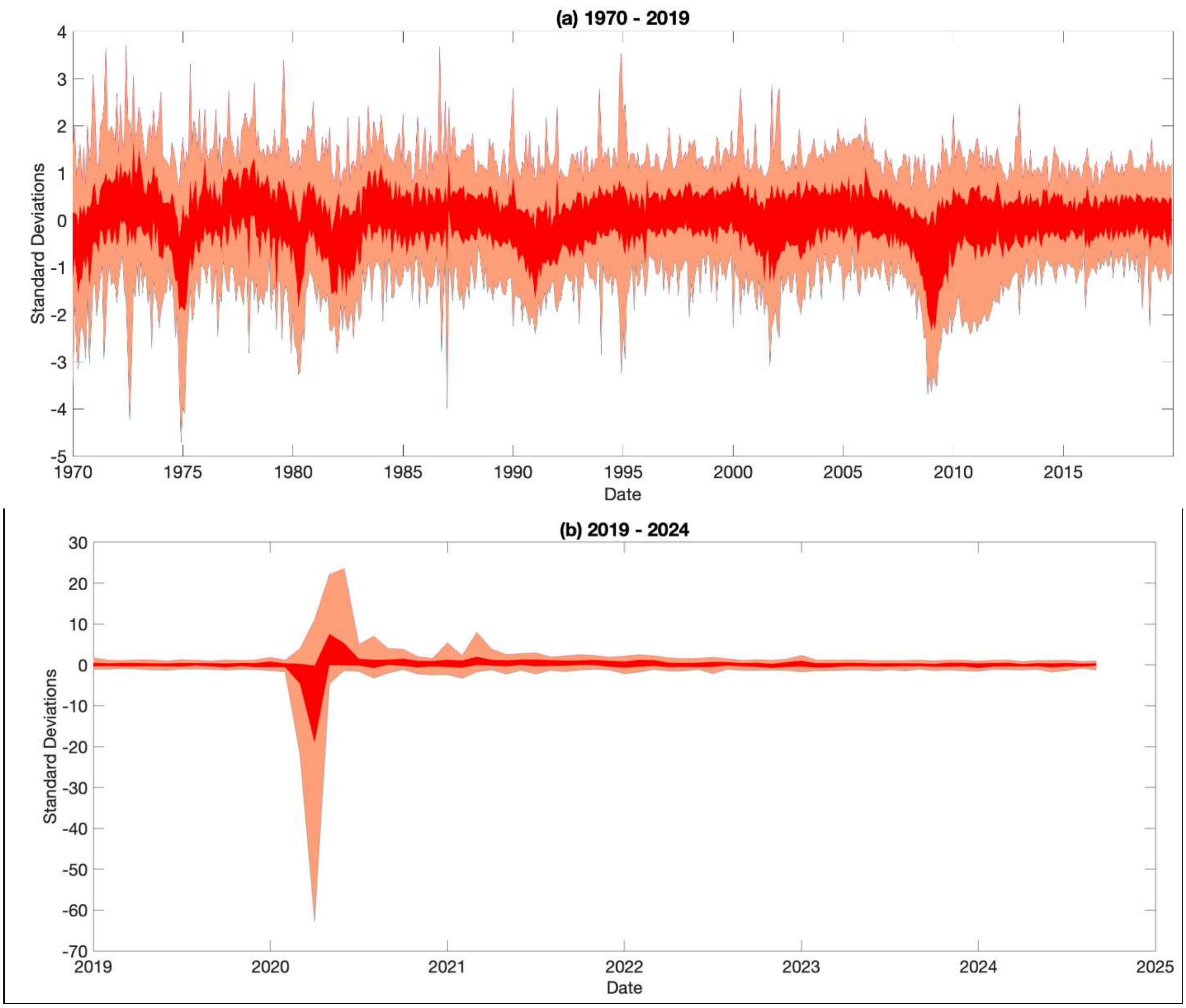


Figure 4: Time series of cross-section quantiles of 128 monthly activity variables over (a) the pre-COVID sample and (b) including the COVID period. All series are standardized over the pre-COVID sample. Counter-cyclical series such as the unemployment rate are multiplied by -1. Dark red: 25th – 75th quantile. Light red: 5th – 95th quantile.

Panel (b) shows the monthly quantiles over the COVID period. The COVID recession also exhibits a negative shift and skew, but the scale of the shift is an order magnitude larger than in the pre-COVID period. During the financial crisis recession of 2007-2009, the lowest values of the median and 25th percentile of the cross-section distribution were -1.2 and -2.0 standard deviations, whereas in the COVID recession they were -3.9 and -19.0.

I.C. Measurement issues

The abruptness of the shutdown raises a date alignment issue. The reference week for the Current Population Survey, the week containing the 12th, was in the second week of March as shutdowns were just starting, so the March unemployment rate increased only 0.9 pp from February to 4.4% in March, before jumping to 14.8% in April. Similarly, the reference period for the establishment survey is the pay period including the 12th. In contrast, NIPA flow data are obtained from surveys that typically cover the entire month, so NIPA series measure any collapse during the second half of March. For example, real personal consumption expenditures (PCE) fell 6.6% in March and another 11% in April. In reality, weekly employer data (Cajner and others 2020), initial claims for unemployment insurance (which skyrocketed in the third and fourth weeks of March), and daily spending data (Cox and others 2020) indicated that the collapse in employment and spending were temporally closely aligned and began in earnest in the second half of March. Thus, the apparent lag of employment relative to consumption in official data (see Figure 2) is an artifact of the survey dates.

There are other measurement issues arising from the COVID lockdowns. Surveys that are normally done in person or on site needed to shift to remote surveys, the enormous spikes caused problems for multiplicative seasonal adjustment, the volume of unemployment insurance claims overwhelmed state offices leading to backlogs and reporting problems, and there were potential misclassifications of Current Population Survey respondents; see Cohen (2020) and Davis and others (2023).

I.D. Related Literature

There is a large literature on the COVID recession. One strand augments SIR epidemiological models of infection with endogenous self-protective behavior, both voluntary (staying home) and policy responses such as lockdowns and mask mandates. In those models, the self-protective behavior reduces the frequency of social contacts and/or the probability of transmission given contact with an infected individual, so the transmission probability (β in the SIR model) is a function of some observable disease outcome such as the death rate. These models can be used to develop optimal policy given the infection externality (e.g. Eichenbaum, Rebelo, and Trabandt 2021) to evaluate public health interventions (e.g. Baqaee and others 2020), and to quantify COVID fatigue through time variation in the feedback (e.g., Droste and Stock 2021). Atkeson and Kissler (2024) show that a surprisingly simple version of a behavior-augmented SIR model, modified to allow for the evolution of different viral strains and seasonality, is able to match the complex evolution of deaths remarkably well; also see Atkeson, Kopecky, and Zha (2024).

Another strand focuses on tracking the high-frequency events of the recession (e.g. Chetty and others 2024; Diebold 2020; and Lewis and others 2021). A number of papers document the sectoral shift towards goods during the recession (e.g. Barrero, Bloom, and Davis 2020; Greenwood and others 2023) and the increase in uncertainty (e.g. Altig and others 2020). Other papers focus on empirical estimation of the causal effects of various interventions, including NPIs (e.g. Tian and others 2020; Chernozhukov, Kasahara, and Schrimpf 2020; Gupta and others 2020; Baek and others 2021), the Paycheck Protection Program (Hubbard and Strain 2020; Granja and others 2022), the individual payment and unemployment insurance programs (e.g. Auerbach and others 2022; Chetty and others 2024), and the Federal Reserve Bank's liquidity facilities (e.g. Goldberg 2022). The early literature on the COVID recession is reviewed by Brodeur and others (2021) and covered broadly in the papers in the Summer and Fall 2020 issues of the *Brookings Papers on Economic Activity*.

Given the intense study of the COVID recession, there are surprisingly few papers on the subsequent recovery. Some papers examine longer-term consequences of COVID-induced changes, such as working from home, on productivity (e.g., Bloom and others 2025), inequality (e.g., Stantcheva 2022), real estate values (e.g., Van Nieuwerburgh 2023), labor force participation (Abraham and Rendell 2023), and retirement (Davis and others 2023).

A few papers address the practical difficulties arising in estimating macroeconomic models using data that includes the COVID cycle; these include Carriero, Clark, Marcellino and Mertens (2024), Lenza and Primiceri (2023), Diebold (2020), Antolin-Diaz, Drechsel and Petrella (2024); at a technical level, this paper is closely related to Ng (2021), which modifies a pre-COVID DFM to better fit the COVID recession.

II. Analytical Framework

Our interest is in whether there is a parsimonious quantitative model that explains the anomalous behavior summarized in the stylized facts in Section I.B. The analytical framework we use is a dynamic factor model (DFM). For our purposes, DFMs have two virtues. First, the pre-COVID comovements of real economic indicators are well-described by a DFM with a small number of common factors (Sargent and Sims 1977; Forni and Reichlin 1998; for a survey see Stock and Watson 2016). Second, a fundamental empirical challenge in providing a comprehensive unifying empirical reconciliation of these anomalous macrodynamics is that they lasted perhaps 18 months or two years, a very short time span for any time series modeling, and DFMs provide a parsimonious way to investigate COVID dynamics across many series.

Because a shock like the COVID epidemic had not been seen in the postwar record, it is unsurprising that (as we will show) a pre-COVID DFM fails to explain the anomalous COVID macrodynamics. We therefore consider a DFM that consists of conventional, or preexisting, factors, F_t, and potentially one or more new COVID factors, C_t. Let Y_t denote a vector of many time series variables and let u_t denote a vector of error terms ("idiosyncratic disturbances") with limited dynamic- and cross-correlation. The augmented DFM is,

$$Y_t = \Lambda F_t + \Gamma C_t + u_t \tag{1}$$

$$\begin{pmatrix} C_t \\ F_t \end{pmatrix} = \begin{pmatrix} \Theta_{CC}(\mathrm{L}) & \Theta_{CF}(\mathrm{L}) \\ \Theta_{FC}(\mathrm{L}) & \Theta_{FF}(\mathrm{L}) \end{pmatrix} \begin{pmatrix} \varepsilon_t^C \\ \varepsilon_t^F \end{pmatrix}, \tag{2}$$

where Λ and Γ are factor loading matrices, ε_t^C are the structural COVID shocks, ε_t^F are structural preexisting shocks, the structural shocks are serially and mutually uncorrelated, $\Theta_{CC}(\mathrm{L})$ is the structural moving average relating the COVID shock to the COVID factor, i.e. the impulse response function (IRF) of the COVID shock to the COVID factor and so forth for the other elements of the structural moving average matrix $\Theta(\mathrm{L})$, and intercepts are suppressed.

Equation (1) relates the factors to observable variables, and equation (2) describes the dynamics of the factors in response to their structural shocks. Combined, these two equations provide a decomposition of Y_t into movements from conventional shocks, COVID shocks, and idiosyncratic movements:

$$Y_t = \Theta_{YF}(\mathrm{L})\varepsilon_t^F + \Theta_{YC}(\mathrm{L})\varepsilon_t^C + u_t, \tag{3}$$

where $\Theta_{YF}(\mathrm{L}) = \Lambda\Theta_{FF}(\mathrm{L}) + \Gamma\Theta_{CF}(\mathrm{L})$ and $\Theta_{YC}(\mathrm{L}) = \Lambda\Theta_{FC}(\mathrm{L}) + \Gamma\Theta_{CC}(\mathrm{L})$.

Because the factors and the shocks are unobserved, they are not identified without additional assumptions.

II.A. Identification and estimation of F and C

We identify the spaces spanned by $\{F_t\}$ and $\{F_t, C_t\}$ by assuming (i) $C_t = 0$ in the pre-COVID period, and (ii) Λ does not change between the pre-COVID and COVID periods. With these assumptions, we estimate the factors and factor loadings by first estimating F and Λ by principal components in the pre-COVID period, which yields estimates of the factor loadings $\hat{\Lambda}$ and estimates of the pre-COVID factors $\hat{F}_t = \left(\hat{\Lambda}'\hat{\Lambda}\right)^{-1}\hat{\Lambda}'Y_t$ for pre-COVID values of t.[4] During the COVID period, the C factor(s) and Γ are then estimated by principal components applied to $Y_t - \hat{\Lambda}\hat{F}_t$, where $\hat{F}_t = \left(\hat{\Lambda}'\hat{\Lambda}\right)^{-1}\hat{\Lambda}'Y_t$ is now computed over the COVID period. To avoid identities (e.g., sectoral components of employment that sum to total employment), the factors from the DFM model are estimated using only subaggregates. The predicted value of Y given the factors is then $\hat{Y}_t = \hat{\Lambda}\hat{F}_t + \hat{\Gamma}\hat{C}_t$.

[4] Because not all series are available over the full pre-COVID estimation sample, the estimates of Λ and F solve the principal components least squares problem, modified for missing observations; see Stock and Watson (2016).

These assumptions identify the space spanned by F_t and impose a particular normalization from using principal components. As discussed in the next section, we use three pre-COVID factors (so F_t is 3×1), and for expositional purposes we find it useful to rotate the factors using the named-factor normalization, where the first factor is associated with aggregate employment (the predicted value from regressing establishment employment growth on the factors), the second factor is associated with real personal consumption, and the third factor is a residual, uncorrelated with the first two factors that has a unit effect on industrial production.

II.B. Identification of factor shocks

As with structural vector autoregressions with observable variables, the structural IRFs $\Theta(L)$ are not identified without further assumptions. In the context of (2), the vast literature on structural macrodynamics focuses on identification of $\Theta_{FF}(L)$ (see for example Ramey 2016). In contrast, our interest is on the elements of $\Theta(L)$ that involve the novel COVID factor C_t: its dynamics $\Theta_{CC}(L)$ resulting from COVID shocks, the effect of COVID shocks on conventional factors, $\Theta_{FC}(L)$, and the effect of conventional shocks, if any, on the COVID factor, $\Theta_{CF}(L)$.

First, we discuss what is meant by a COVID economic shock. Our interest is the effect of the COVID pandemic on macroeconomic variables. It is not only the evolution of the virus itself that matters here – viruses, including serious ones, circulate all the time – it is also the perceptions of economic agents about the virus, which in turn induce changes in economic behavior. Like the seasonal flu, COVID has a direct effect on labor supply because the sick don't work; unlike the seasonal flu, the fear of contagion leading to severe illness and death induced changes in policy (lockdowns) and behavior (shopping less, shifting to at-home consumption) that had macroeconomic consequences. Once the vaccine became available, the vaccinated were far less susceptible to severe illness and death, so the continuing spread of the virus had reduced behavior effects. In addition, COVID fatigue potentially reduced the effect of the virus on economic activity, which in the context of (2) (in which $\Theta(L)$ is not time-varying) would manifest as smaller COVID shocks. Thus, the COVID shock comprises both direct effects (e.g., labor supply) and a shock to perceptions of COVID that induce behavioral change: news about deaths, transmissivity (new strains), treatment (antivirals), severity (availability of vaccines), and so forth. To the extent that the COVID shock induces sectoral reallocation, it also captures the costs of those reallocations which would weigh on overall performance, see Fujita, Ramey, and Roded (2024). Because COVID shocks have both direct and perception elements, in principle there could be multiple COVID shocks and factors, however we find that a single COVID factor suffices empirically, so our exposition focuses on the case of scalar C_t and ε_t^C.

To identify the COVID shock, we assume that (iiia) the COVID shock can affect the F factors within the month, but that (iiib) the conventional factor shocks ε_t^F do not affect the COVID factor C within the month. These assumptions impose a single restriction on $\Theta_{CF}(L)$, that $\Theta_{CF,0} = 0$, where $\Theta_{CF,0}$ is the contemporaneous effect of F_t on C_t.

Assumption (iiia) aligns with the actual course of events during the COVID cycle. The arrival of the virus in the United States, and in particular the exponentially increasing deaths in New York City – that is, a shock to C in March 2020 – induced uncertainty, abrupt lockdowns, and voluntary self-protective behavior, which reduced aggregate demand and labor supply through the withdrawal of many workers. The COVID shock also induced a large and immediate fiscal response in the signing of the CARES Act on March 27, 2020. Thus, within the month of March alone, the shock to C_t arguably induced movements in aggregate demand, aggregate supply, and fiscal policy that were contemporaneous at the monthly level. Consumer demand, labor supply, and fiscal policy are all conventional macroeconomic channels – that is, F's – through which the unforeseen and novel COVID shock ε_t^C immediately affected economic activity.

Assumption (iiib) aligns with the epidemiological-economics literature discussed in Section I.D and with the discussion of the two elements of C – direct and perception – discussed above. Because of the biology of the virus, there are lags between economic activity and exposure, to the perception of a change in risk and thus to self-protective behavior. Consistent with much of the epidemiological-economic literature, Atkeson and Kissler (2024) model self-protective behavior as depending on observed COVID deaths. For the initial strains, the latency period from exposure to symptomatic was estimated to be approximately 5 days (see the review in Baqaee and others 2020), there are additional delays between showing symptoms and hospitalization, and Atkeson and Kissler take the mean time from hospitalization to death to be 30 days although this varied over the pandemic as treatments changed. There were additional administrative delays of up to a week before a death was reported. If self-protective behavior relied on the infection rate instead of the death rate, the delays were shorter, but many problems remain with infection rates: early in the pandemic, tests were rationed so infections were under-reported, the time from infection to public reporting could be two weeks or more, and later in the pandemic home testing resulted in an unknown amount of underreporting of infections. Atkeson (2021) find a better fit using deaths than infections, which makes sense because of problems with reported infections and because the relevant shock to perceptions is the threat of severe harm (see the discussion in Atkeson and Kissler 2024). In short, a (daily) shock to economic activity affected COVID perceptions only with a delay, which, if deaths is the measure used, is on the order of four-six weeks after the interaction that eventually leads to death. This motivates assumption (iiib) in the monthly factor model.

Finally, we assume that (iv) the moving average $\Theta(\mathrm{L})$ is invertible. Under invertibility, (2) can be written as a structural DFM in vector autoregression (VAR) form,

$$\begin{pmatrix} C_t \\ F_t \end{pmatrix} = \begin{pmatrix} \mathrm{A}_{CC}(\mathrm{L}) & \mathrm{A}_{CF}(\mathrm{L}) \\ \mathrm{A}_{CF}(\mathrm{L}) & \mathrm{A}_{FF}(\mathrm{L}) \end{pmatrix} \begin{pmatrix} C_{t-1} \\ F_{t-1} \end{pmatrix} + \begin{pmatrix} \nu_t^C \\ \nu_t^F \end{pmatrix}, \text{ where } \begin{pmatrix} \nu_t^C \\ \nu_t^F \end{pmatrix} = \begin{pmatrix} \Theta_{CC,0} & 0 \\ \Theta_{CF,0} & \Theta_{FF,0} \end{pmatrix} \begin{pmatrix} \varepsilon_t^C \\ \varepsilon_t^F \end{pmatrix}, \tag{4}$$

where ν_t is the vector of VAR innovations (1-period ahead forecast errors) and where $\Theta_{CC,0,}$ $\Theta_{CF,0,}$ and $\Theta_{FF,0}$ are elements of the 0-lag matrix of $\Theta_{FF}(\mathrm{L})$.

Direct estimation of the VAR (4) is hampered because C_t, and thus the VAR, is defined only over the COVID sample, which has at most a few years of observations. We therefore adopt an indirect approach which assumes stability of $\mathrm{A}_{FF}(\mathrm{L})$ and Λ over the pre-COVID and COVID periods. To begin, ε_t^C be estimated (up to scale) by the residual from the regression of C_t onto lagged values of C and F. Then, given the predicted values $\hat{Y}_t$ from Section II.A and noting that ε_t^C and ε_t^F are uncorrelated, the contribution of ε_t^C to Y_t (the first term in (3)) can be estimated by the regression of $\hat{Y}_t$ on current and past values of $\hat{\varepsilon}_t^C$. The residual from this regression is an estimate of the contribution of ε_t^F (the second term in (3)), and $Y_t - \hat{Y}_t$ is an estimate of the idiosyncratic term u_t. This approach also permits direct estimation of $\Theta_{CC}(L)$ and $\Theta_{FC}(L)$ by direct regression of *C* and *F* on current and lagged values of $\hat{\varepsilon}_t^C$.

III. Evidence of a Single COVID Factor

We begin with some basic data description questions. First, was the COVID cycle really different than prior postwar cycles, as the discussion in Section I.B suggests? Second, if so, is there a concise numerical summary of those novel differences – one, or a small number, of series that explain the outliers in Figure 4? As it turns out, the answer to both questions is yes, where that series is a single COVID factor that initiates in March 2020 and dies out by February 2023.

III.A. Data and number of pre-COVID factors

The data set consists of 128 monthly real economic indicators, of which 77 are components used to estimate the factors (i.e. are not linked by identities) observed from 1970 through September 2024. For some calculations we additionally use 23 quarterly real indicators of economic activity. Taken together, these series include the major aggregate variables (GDP, NIPA components, employment, industrial production, consumption, housing starts, labor productivity) as well as sub-aggregates measuring components of consumption, employment and production. The NBER dates the 2020 recession peak as February 2020 (monthly) and 2019:IV (quarterly), so we use January 1970 – February 2020 (1970:I – 2019:IV) as the pre-COVID monthly (quarterly) sample and March 2020 – September 2024 (2020:I – 2024:III) as the COVID sample.

With few exceptions, the variables are transformed as first differences of logarithms, standardized using pre-COVID means and standard deviations, so they are monthly growth rates in pre-COVID standard deviation units. See Appendix A for a summary and the data transformations and the online documentation for the complete list of series.

In the monthly dataset, one factor explains 13% of variability in the series over the pre-COVID sample (that is, the average R^2 across the series is 0.13 for the one-factor model), and this increases to 25% using three factors. The Bai-Ng (2002) information criterion is indifferent between two and three factors, and these results are robust to using the whole pre-COVID sample or beginning the sample in 1984. Thus, we use three pre-COVID factors. We estimate both monthly and quarterly factors, where the quarterly factors are estimated using the quarterly data. When we discuss results for quarterly series, those results refer to quarterly estimates of the factors.

III.B. Results: A single COVID factor

We focus here on results for the factors and the C-augmented DFM in (1). The factor estimation results show that: (i) while the pre-COVID factors F have some explanatory role during the COVID recession, they fail to explain the movements of many sectoral variables; (ii) adding a single COVID factor C captures a great deal – for many series, nearly all – of the anomalous COVID dynamics that are unexplained by the pre-COVID factors; (iii) the COVID factor explains the unusual sectoral movements during the COVID cycle; and (iv) the COVID factor is well approximated as a factor measuring reallocation between goods and services.

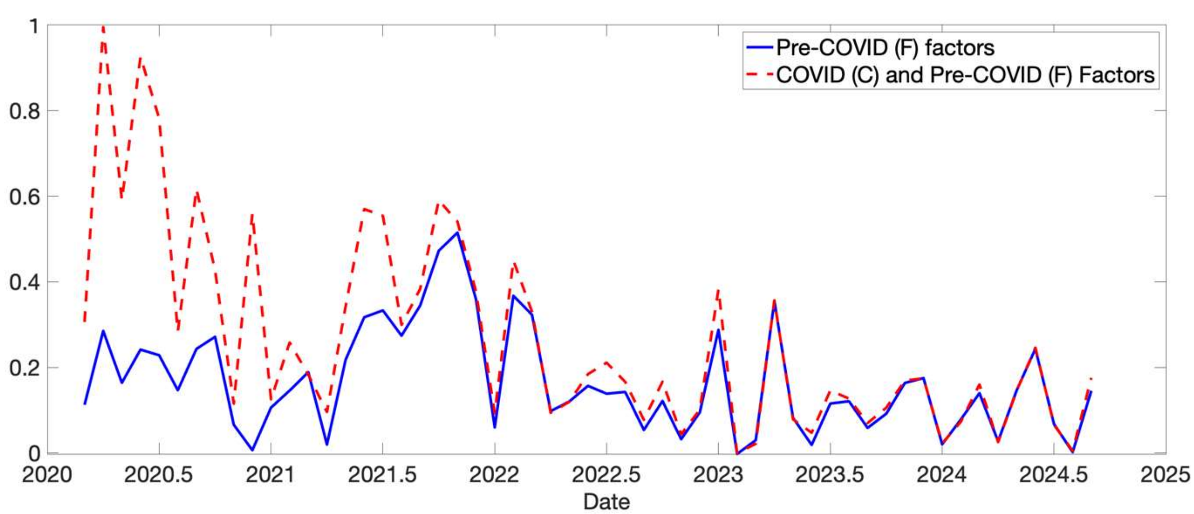


Figure 5: Cross-sectional R^2 by month, F and F & C factors

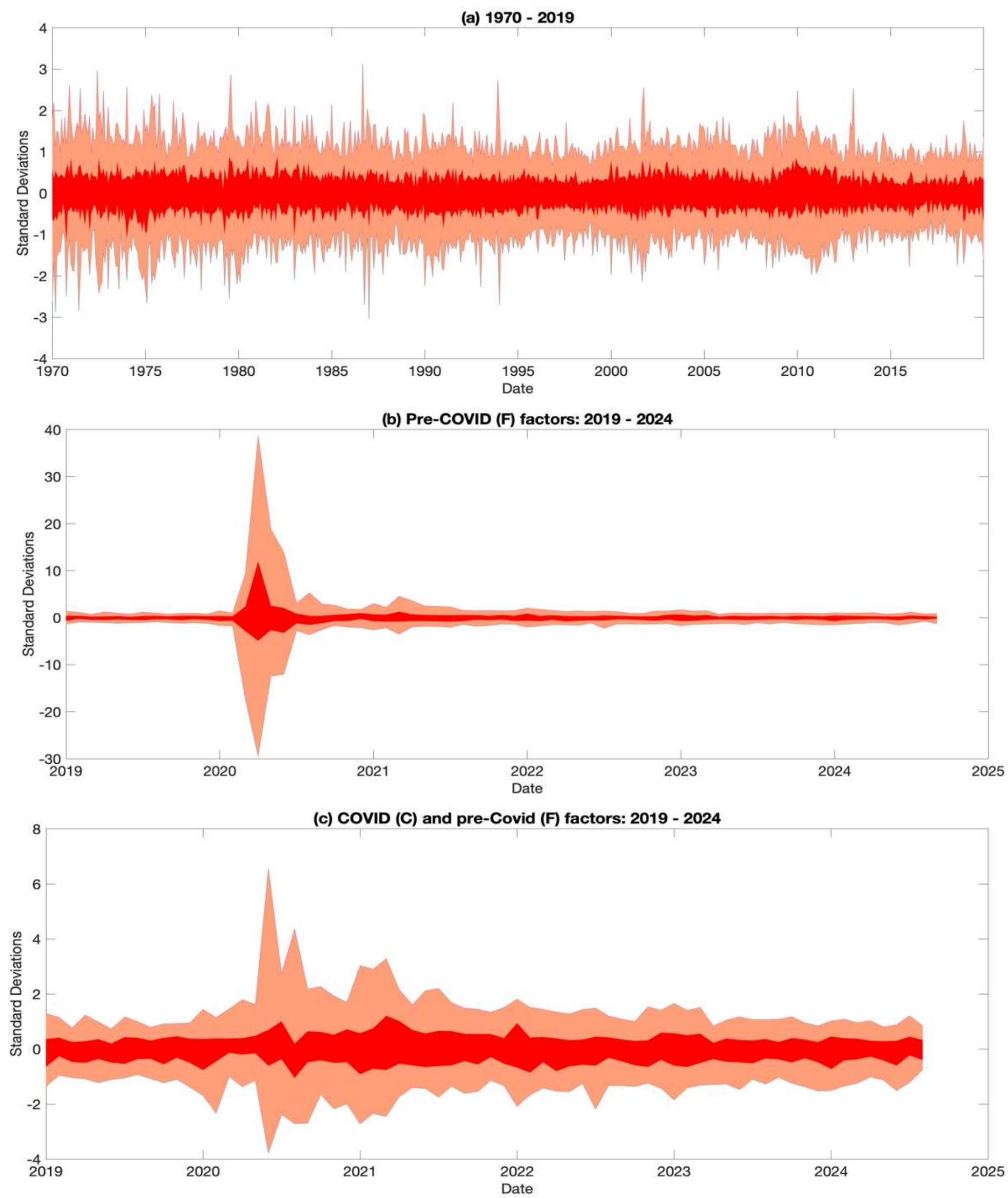


Figure 6: Time series of cross-section quantiles of residuals of 126 monthly activity variables. (a) and (b) control for three pre-COVID F factors, (c) additionally controls for the single COVID C factor. All series are standardized over the pre-COVID sample. Counter-cyclical series such as the unemployment rate are multiplied by -1. Dark red: 25^{th} – 75^{th} quantile. Light red: 5^{th} – 95^{th} quantile.

Figure 5 summarizes the cross-sectional R^2 of the F factors, and also of the combined F and C factors for each month from March 2023.[5] The pre-COVID factors explain only a fraction of this cross-sectional variation during the COVID cycle. In contrast, the COVID factor plays an outsize role during the first two years, especially from March to July 2020, when the marginal R^2 of the C factor exceeds 60%. This large effect subsides quickly, and marginal R^2 is less than 10% from 2022 on, however the C factor remains a marginally significant predictor in the cross-sectional regression through January 2023.

Figure 6 provides an alternative visualization of the cross-sectional explanatory power of the C factor. This figure is the counterpart of Figure 4 that displays the cross-sectional quantiles of the standardized residuals $\hat{u}_t$ from (1) using only the F factors (panels (a) and (b)) and using the F and C factors (panel (c)).[6] As can be seen in panel (a), the F factors remove the pre-COVID cyclic pattern evident in Figure 4, but as can be seen in panel (b), only partially reduce the cross-sectional dispersion early in the COVID cycle. In contrast, when the single COVID factor is added in panel (c), there is much less abnormal cross-sectional dispersion.

The quantitative importance of the C factor varies by series. Figure 7 plots actual and predicted values of percentage growth rates of various aggregates, where the predicted values are computed using only the F factors, and then using both the F and C factors. Figure 8 provides a similar plot for subaggregates, and the online appendix contains predicted-actual plots for all series. The growth of aggregate employment is well explained by the F factors over this period, with a negligible role for the C factor. In contrast, for employment in goods-producing sectors

[5] Specifically, for the F factors, the figure plots the R^2 of the regression for date t of the cross-sectional regression of Y_t on $\hat{\Lambda}$. The estimated coefficients on $\hat{\Lambda}$ in this regression are estimated factor loading $\hat{F}_t$ for that date, so the R^2 in that regression is the fraction of the cross-sectional variation in Y_t explained by $\hat{\Lambda}\hat{F}_t$. The R^2 of the (F, G) factors is computed from the regression of Y_t on $\left(\hat{\Lambda},\hat{\Gamma}\right)$. The marginal cross-sectional R^2 of the G factor is the difference between these two R^2's.

[6] Because of the timing misalignment between the survey period for the Current Employment Situation, the mid-March 2020 COVID shock, and flow series such as consumption and investment, the monthly residuals plotted in Figure 4(c) are from a regression of the series Y_{it} onto F_t, C_t, and one lead and one lag of C_t.

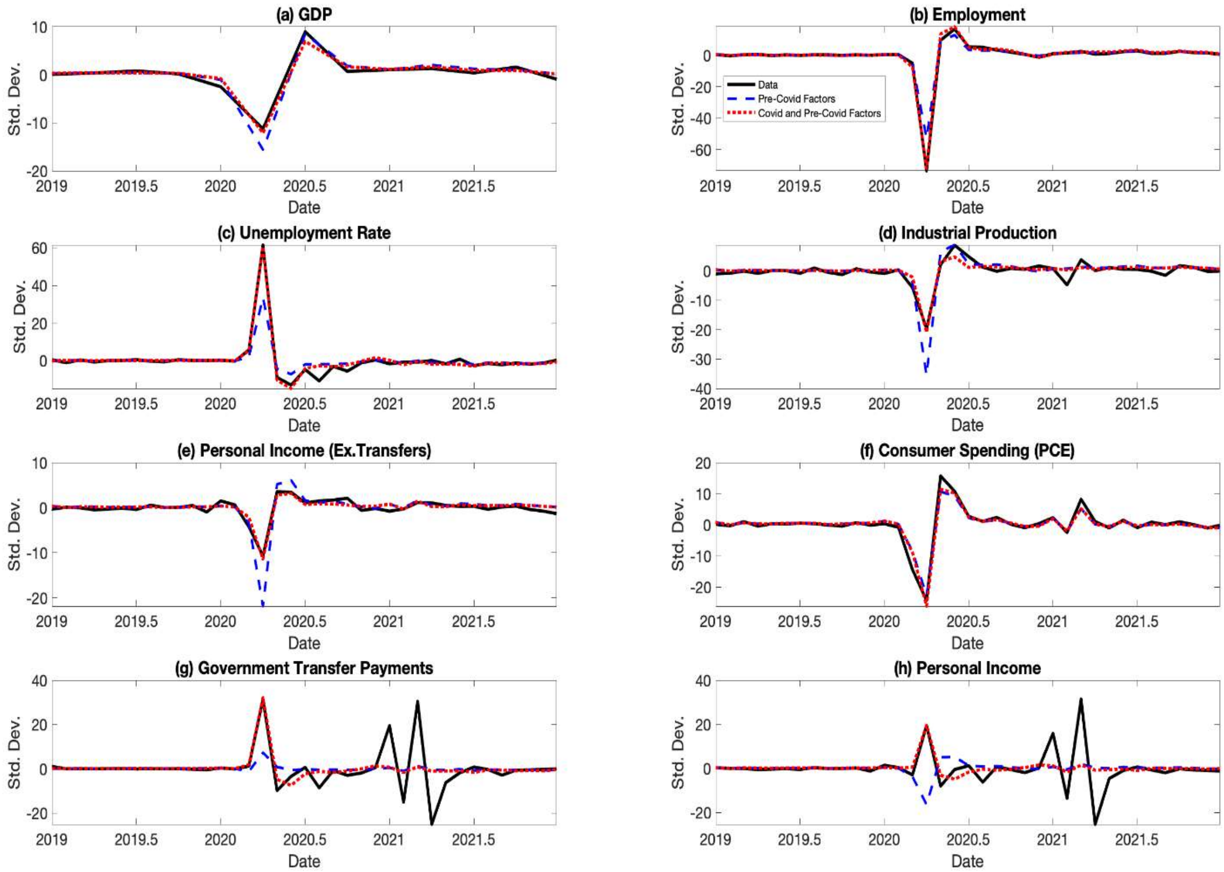
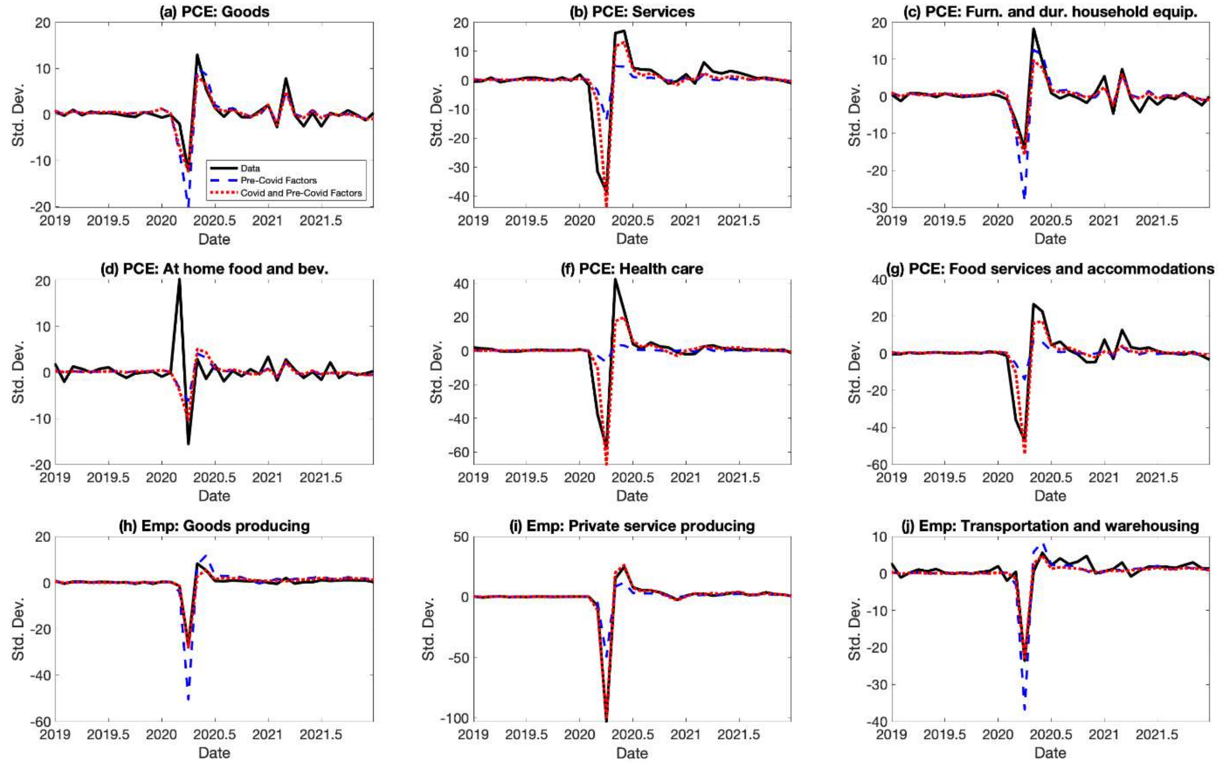


Figure 7: Factor model fits during COVID: monthly percentage growth (pre-COVID standard deviation units) of selected aggregate series, actual (black) and predicted using F (blue dashed) and F & C (red dots), aggregates.



Notes: Series are monthly growth rates, demeaned and standardized using pre-COVID means and standard deviations.

Figure 8: Factor model fits during COVID: monthly percentage growth of selected subaggregates, actual (black) and predicted using F (blue dashed) and F & C (red dots).

(including manufacturing, not shown) and in construction, the F factors dramatically overpredicted the decline and rebound, but those muted effects are captured by C. The opposite is true for services, including health care and social assistance, which are normally not cyclically sensitive so their large swings are unexplained by the conventional F factors but are nearly entirely explained by the COVID factor. The same sectoral patterns are evident in consumption broken down by component.

The marginal R^2 of the C factor for a given series depends on the value of Γ for that series. Table 2 presents estimates of Γ for selected variables, using the normalization that $C_t = 1$ in April 2020 for the monthly model or the first quarter of 2020 for the quarterly model, where the series are in pre-COVID standard deviation units; negative values of Γ indicate that the COVID shock

Table 2: Estimates of Γ for Selected Series

	Γ
(a) Monthly Model: PCE Components	
Total	-3.4
Goods	7.9
Durable goods	10.0
Motor vehicles and parts	6.6
Furnishings and durable household equipment	12.6
Recreational goods and vehicles	16.2
Other durable goods	-4.9
Nondurable goods	0.1
Food and beverages (home consumption)	-4.2
Clothing and footwear	-10.7
Gasoline and other energy goods	-13.9
Other nondurable goods	15.1
Services	-30.1
Health care	-60.4
Transportation services	-14.8
Recreation services	-34.6
Food services and accommodations	-40.3
Financial services and insurance	0.3
Other services	-3.9
Final cons exp of nonprofits (NPISHs)	11.5
Housing and utilites (excl. energy)	21.6
Housing and utilites (energy)	-5.9
(b) Quarterly Model: Output, Employment and Productivity	
GDP	3.5
Employment	-3.9
Labor Productivity	6.1
Unemployment Rate	8.4
Labor Force Participation Rate	-7.9

Notes: The table shows the value of Γ, the factor loading on the COVID factor (*C*), where *C* is normalized to +1 in April 2020, and each observable variable is in pre-COVID standard deviation units.

depresses the series. Panel (a) shows results from the monthly model for personal consumption expenditures. Evidently, the *C* factor captures the shift in consumption towards goods (positive Γ), especially goods that can be consumed at home and outside, away from goods involved with social interaction (clothing and footwear), and away from services, especially services involving contact with the general public (eating out, hotels, entertainment). Similar patterns are evident for sectoral employment (not shown). Panel (b) shows results for the quarterly model and focuses on output, employment and productivity. GDP fell less than it would have during a typical recession, given the large declines in F (positive Γ), while employment fell more (negative Γ), resulting in a COVID-induced increase in labor productivity. The COVID factor exacerbated the rise in the unemployment rate and, given the less-than-normal fall in GDP, resulted in a flattening of the typical GDP/unemployment relationship (Okun's law): see Fujita, Ramey and Roded (2024) for more discussion and the parallels with the aftermath of World War II.

The estimated factors are plotted in Figure 9, along with empirical counterparts. As discussed, the first factor is normalized to be the best factor predictor of employment growth pre-COVID, the second is the best factor predictor of PCE growth pre-COVID, and the third factor is the residual orthogonal to first two and with a unit effect on industrial production. Taken together, the three normalized factors span the space of the principal components factors. For comparison, monthly employment growth is plotted with the employment factor, and PCE growth is plotted with the PCE factor. Figure 9 reveals several key features. First, all the factors, not just the COVID factor, spike in the first months of the pandemic. Second, the employment and PCE factors fit employment and PCE, respectively, reasonably well, even though those normalizations are estimated in the pre-COVID period. Third, consistent with Figure 5 and Figure 6, the COVID factor is essentially zero after January 2023, providing additional evidence that the COVID component of the cycle ended within 36 months.

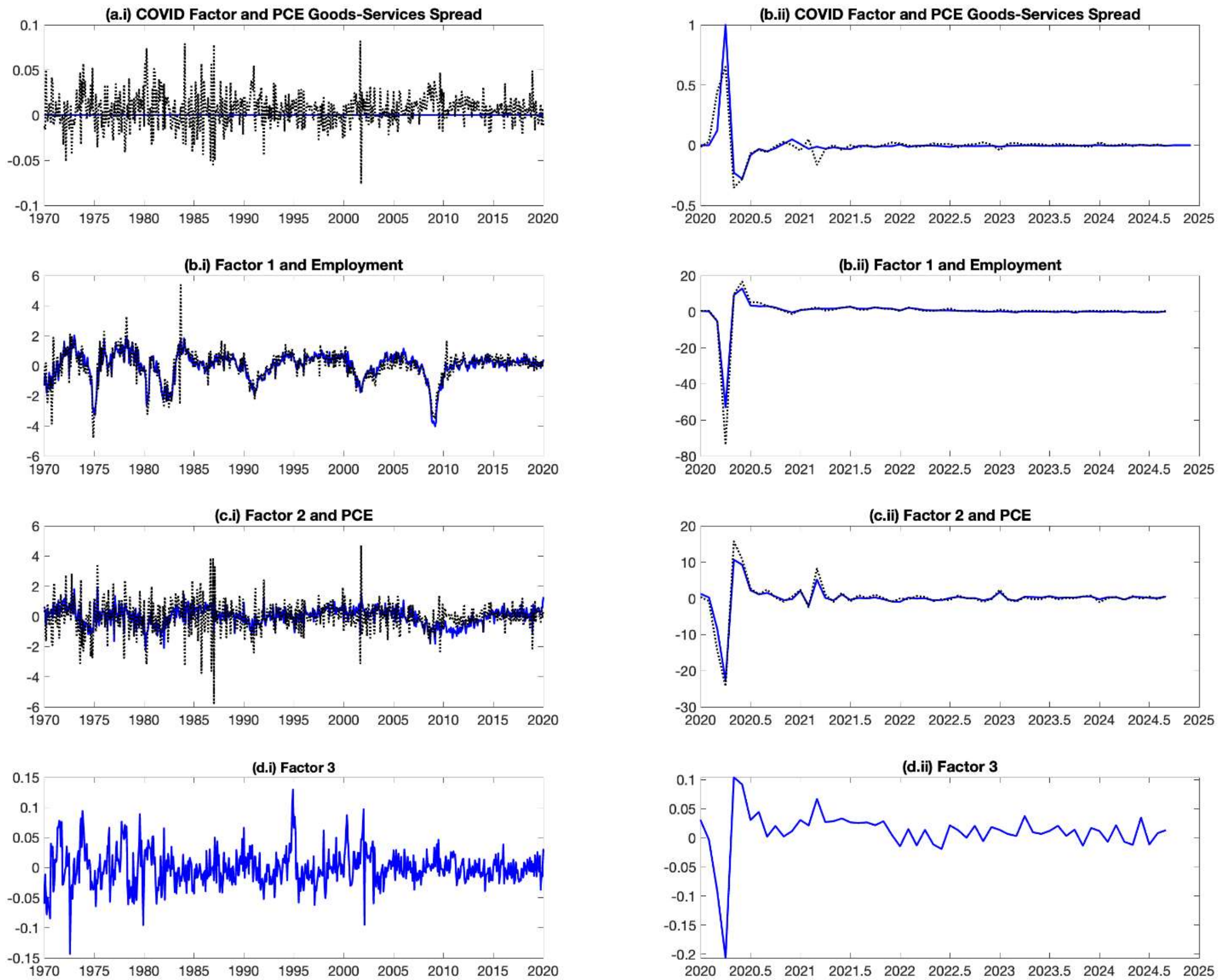


Figure 9: Monthly estimated factors observed approximations during (i) the pre-COVID period and (ii) the COVID period: (a) COVID factor and a weighted spread of goods vs. services consumption expenditures; (b) the employment factor and employment; (c) the PCE factor and PCE; (d) the residual factor.

A fourth feature shown in Figure 9 is that the COVID factor has a simple empirical counterpart, the weighted spread $\Delta\ln(PCE\text{-}goods) - 3.8\Delta\ln(PCE\text{-}services)$, where 3.8 is the ratio of the Γ coefficients (the factor loadings for C_t in the monthly factor model) for PCE-services to PCE-goods shown in Table 2. Evidently, the COVID factor directly summarizes the unprecedented reallocation of consumption during the COVID period. Notably, this spread exhibits only moderate cyclical behavior in the pre-COVID period. This finding is useful because this goods-services employment spread provides a high-fidelity and intuitive observable version of the COVID factor.[7]

IV. The COVID Timeline through the Lens of the DFM

We now turn to a discussion of the COVID shock, identified as described in Section II.B, and its ability to explain the anomalous macrodynamics over the COVID cycle.

IV.A. The COVID Shock

Figure 10 plots the COVID shock and monthly COVID deaths. It is striking how closely the COVID shock tracks deaths, given that the COVID shock is estimated solely from economic data. The magnitude of the movements in the shocks, relative to the deaths, falls over time: the coefficients in a regression of the COVID shock on COVID deaths over the four eight-month windows starting in March 2020 are 0.083, 0.027, 0.025, and 0.013. This decline in sensitivity of the economic shock to COVID deaths is consistent with pre-vaccine adaptations and methods of self-protection, such as masking, with COVID fatigue, and with the increasing availability of the vaccine over the winter and spring of 2021. This decline in the sensitivity of activity to deaths is qualitatively consistent with the estimates in Droste and Stock (2021) and the calibration in Atkeson and Kissler (2024). The decline in sensitivity estimated here is larger than in those papers, however the sample here is longer (extending into when the vaccine was available) and all the estimates are noisy because of the limited data (we refrain reporting standard errors for these 8-observation time series regressions).

The IRFs of the four factors to the COVID shock are provided in Table 3. In the notation of (2), these are estimates of $\Theta_{CC}(L)$ and $\Theta_{FC}(L)$. The COVID shock is slightly anti-persistent in its effect on the COVID factor – own-dynamics that are quite different than standard persistent

[7] Recall that the variables are measured in pre-COVID standard deviation units. In monthly growth rates, the PCE Good/Services spread is $\Delta\ln(\textit{PCE-goods}) - 13.5\Delta\ln(\textit{PCE-services})$.

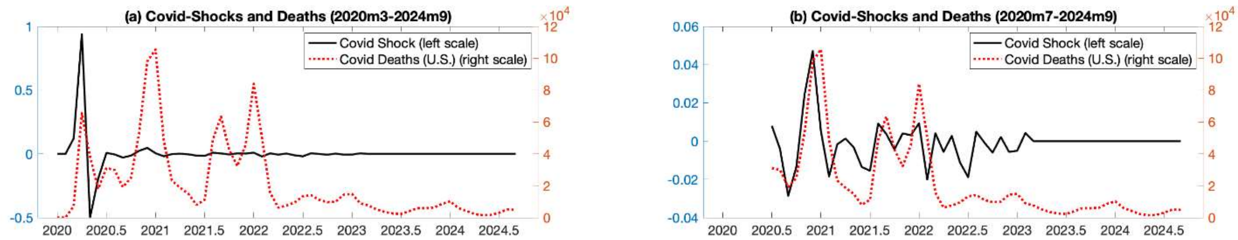


Figure 10: The COVID shock and monthly COVID deaths over the COVID period starting (a) January 2020 and (b) July 2020.

Table 3: Impulse response functions for the factors (2) with respect to the COVID shock.

Lag of ε_t^C	Variable			
	C_t	$F_{1,t}$	$F_{2,t}$	$F_{3,t}$
0	1.0	-53.9 (0.23)	-24.9 (0.73)	0.23 (0.01)
1	-0.038 (0.113)	-18.1 (0.30)	-2.55 (0.70)	0.02 (0.01)
2	-0.270 (0.070)	-6.92 (0.40)	2.45 (0.99)	-0.03 (0.01)
3	-0.162 (0.086)	-3.56 (0.45)	2.32 (1.10)	-0.03 (0.02)
4	-0.100 (0.070)	-0.68 (0.46)	1.74 (1.05)	-0.05 (0.02)

Notes: Estimated by local projection. HAC standard errors are shown in parentheses.

dynamics seen in impulse responses for conventional shocks (Ramey 2016). The effect of the COVID shock on the first two factors is large, negative, and also dies off quickly, within a month or two. This fast response has a natural interpretation in light of the COVID shock-deaths relationship: after deaths subside, the perceived risk of illness and death drops and the COVID factor rapidly falls. The COVID shock has a small positive contemporaneous impact on the third factor, however the third factor plays a negligible role in explaining the behavior of the series during the COVID period. In short, a positive (bad) COVID shock induces a sharp contraction in the conventional factors, however that effect is much less persistent than the effect of a conventional shock.

Figure 11 decomposes the four factors into their variation arising from the COVID shock and the conventional shocks; for example, the COVID shock contribution to the COVID factor is $\Theta_{CC}(L)\varepsilon_t^C$ in (2). During the spring of 2020, the large movements of the conventional factors

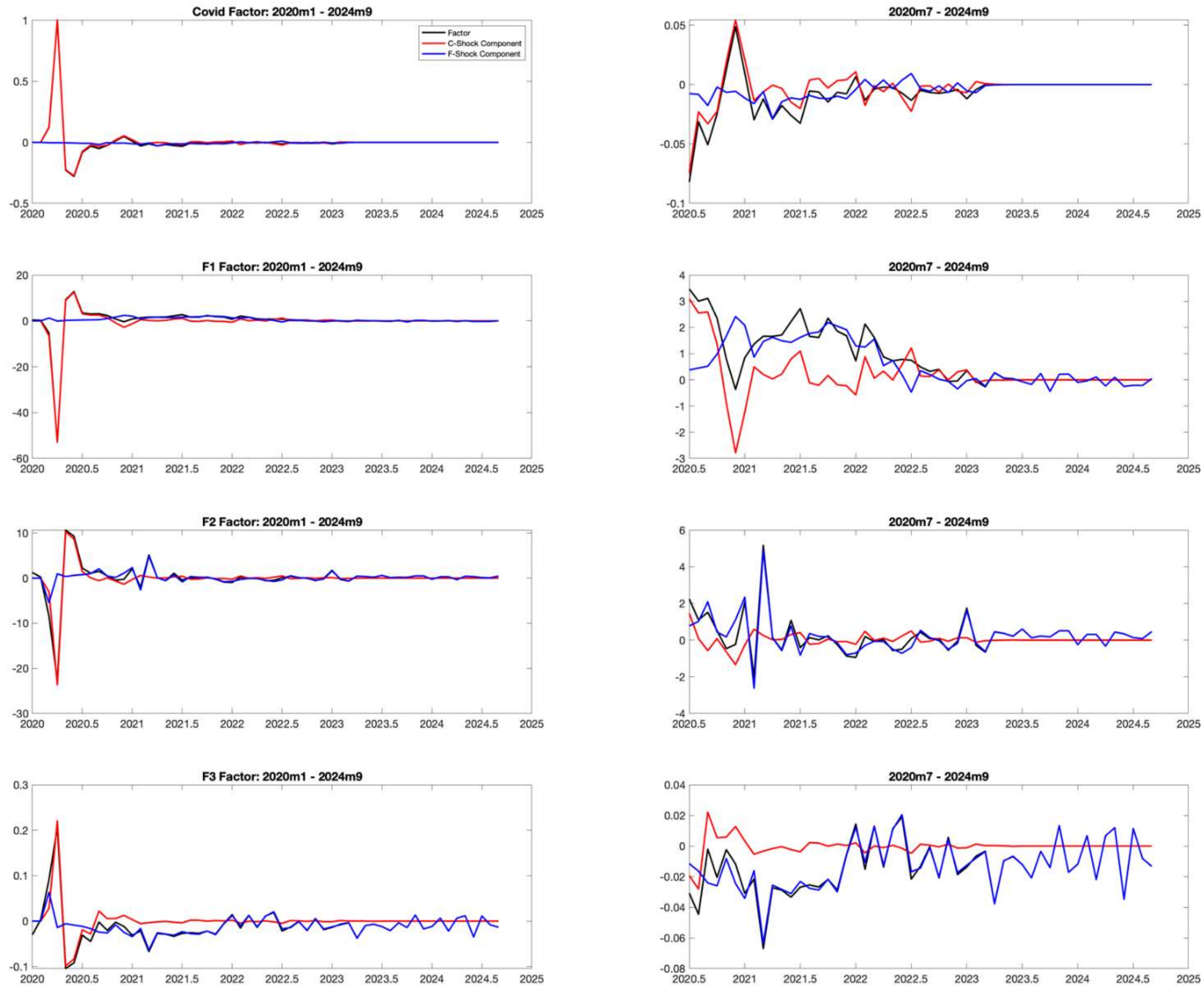


Figure 11: Decomposition of the COVID and conventional factors into variation driven by the COVID and conventional shocks.

were almost entirely driven by the COVID shock. Starting in 2021, the conventional factors are all largely driven by the conventional shocks. Notably, the two largest values of F_{2t} after the summer of 2020 occur in January and March 2021, coinciding with the personal payments under the Consolidated Appropriations Act and the American Rescue Plan, with the March 2021 shock being roughly 2.5 times the January 2021 shock, aligning quite closely with the relative size of the two stimulus checks (\$600 and \$1400). We do not attempt to interpret F_{3t}, which plays little role in explaining COVID fluctuations. Interestingly, feedback from the conventional shocks to the COVID factor has a small net effect.

Taken together, these results strongly suggest that the COVID economic shock is a response to perceived changes in risk of serious illness or death from COVID. This perceived risk, and the impact of that risk on economic behavior, decreased over time as more was learned about the virus, as self-protective measures come into use, as COVID fatigue set in, and as the vaccine became available. The large spikes in the conventional factors in Figure 9 are nearly entirely a consequence of the COVID shock, not the contemporaneous conventional shocks. The only large conventional shocks during the COVID period were those from the second and third pandemic stimulus payments.

IV.B. Historical Decompositions

Figure 12 presents historical decompositions of the monthly growth rate of payroll employment and some of its components into the contribution of the conventional factor shocks and the COVID shock, that is, the first and second terms on the right hand side of (3). Figure 13 presents this decomposition for the monthly growth rate of PCE, its primary components, some secondary components, and selected other series. Figure 14 presents these decompositions for selected series that are frequently analyzed in levels, such as the unemployment rate. Monthly growth rates are in pre-COVID standard deviation units, levels are in native units.

Looking across these series and the rest of the decompositions, which are available in the online Appendix, leads to several high-level conclusions.

First, the COVID shock explains, in a quantitative sense, the fast dynamics of the recession and the early stages of the recovery: the sharp jump of the unemployment rate (Figure 14) and its rapid decline through the fall of 2020, the sharp decline and rapid recovery of the labor force participation rate, and the sharp decline and rebound of total employment (Figure 12) and total PCE (Figure 13).

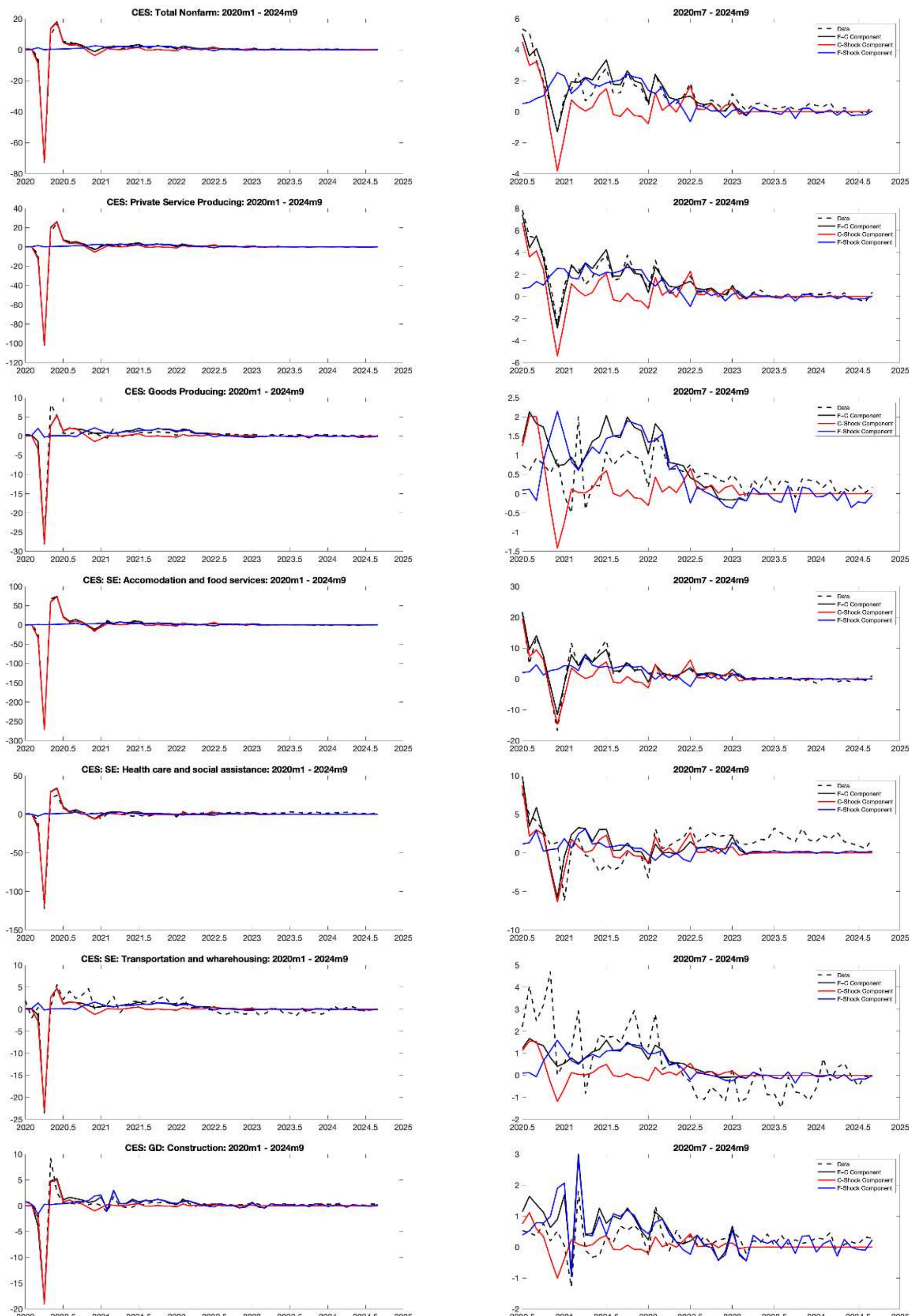


Figure 12: Historical decompositions of monthly growth into COVID (red) and conventional (blue) shocks: Employment.

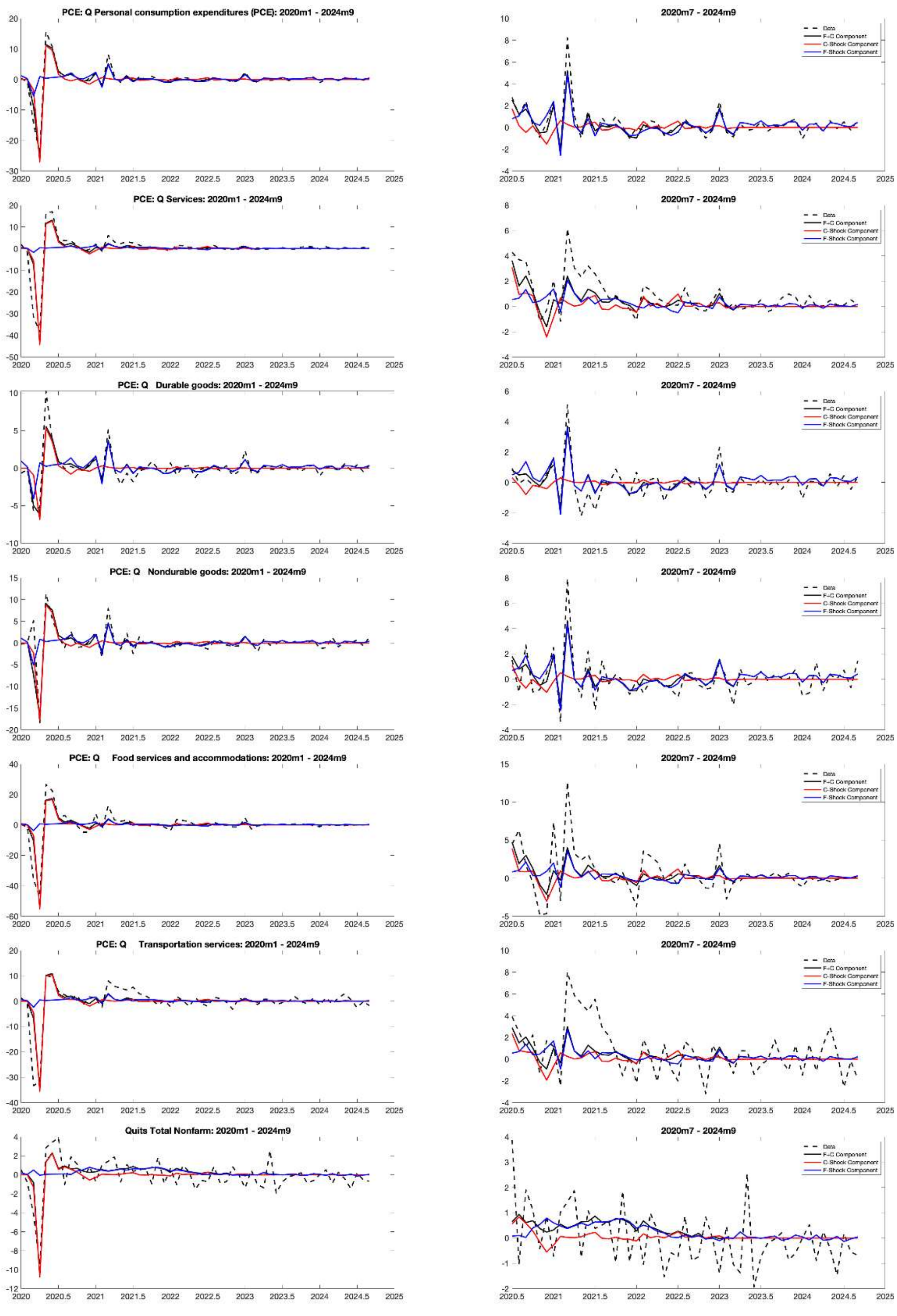


Figure 13: Historical decompositions of monthly growth into COVID (red) and conventional (blue) shocks: PCE and selected other series.

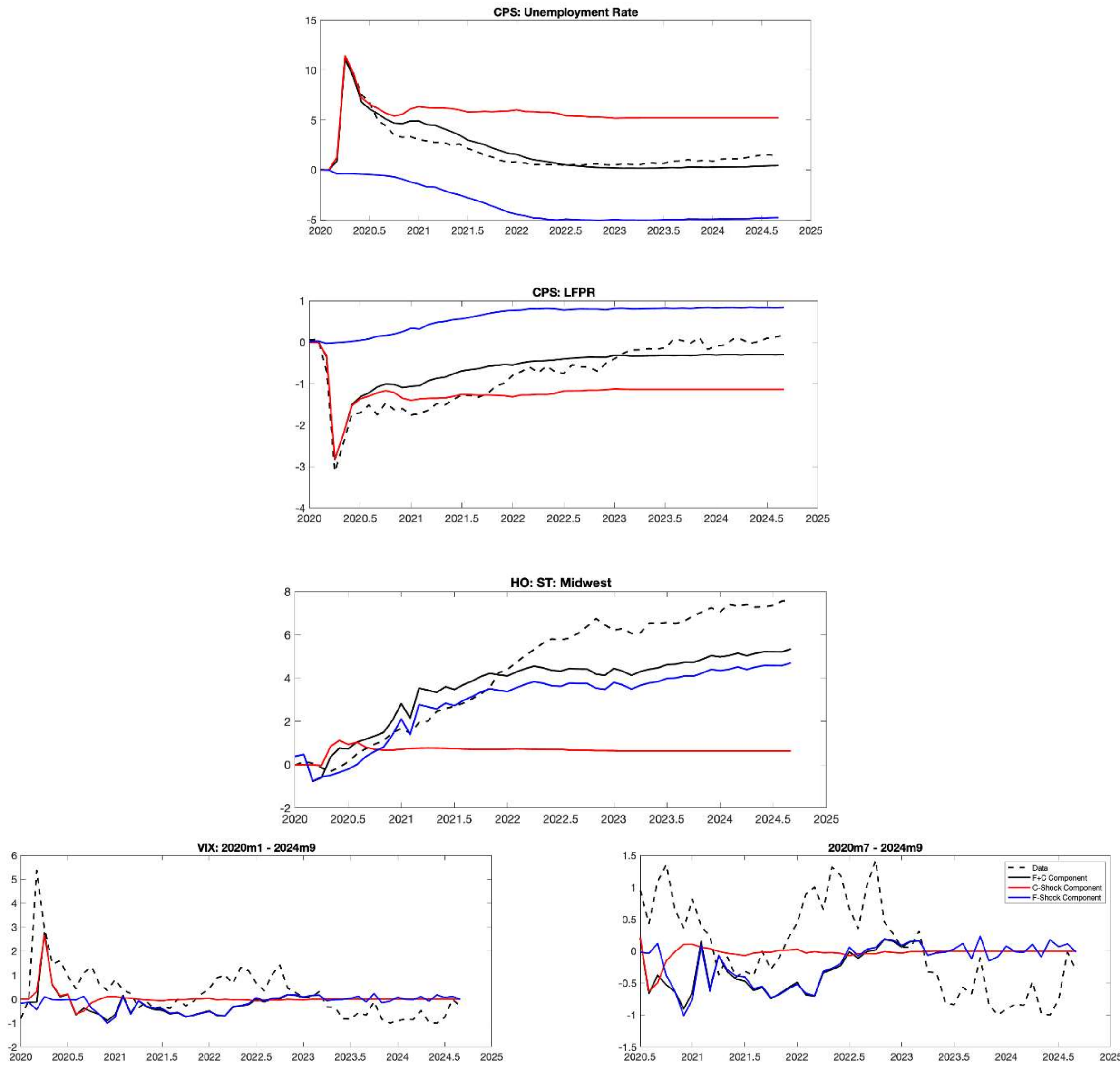


Figure 14: Historical decompositions of levels of selected series into COVID and non-COVID sources.

Second, the shock also explains the anomalous sectoral reallocation, notably the extraordinary decline in PCE-services, the smaller decline and large rebound of PCE nondurables, and the small decline and (to a lesser degree) the rebound of PCE-durables. This is also true for most PCE components such as food services and accommodations and transportation services.[8] The COVID shock also explains the anomalous behavior of sectoral employment through 2020, both

[8] For some consumption series, the COVID factor lags the initial March drop, however this is a consequence of the COVID factor putting considerable weight on employment series, which had only modest declines in March for the survey week reasons discussed in Section I.C.

at the primary disaggregated level of goods and private services and at the next level of disaggregation. For example, the COVID shock explains the collapse and slow recovery of employment in accommodations and food services and the smaller sharp contraction in health care employment.

Third, once 2021 is reached, for most series the conventional factor shocks take over and C shock ceases to be important. Notably, the conventional factors explain jumps in consumption in January and March 2021, the months of distribution of the personal transfers under the Consolidated Appropriations Act and the American Rescue Plan; see for example the growth rates of PCE, PCE durables, and PCE-food and beverages off premises, and the growth of employment in accommodation and food services and construction, both of which apparently responded to the additional income from these two transfers.

Fourth, in some cases the factor model explains the dynamics less well in the first half of 2021 than it does in 2020. Because the COVID shock had substantially subsided by 2021 (Figure 10), the dynamics in 2021 are largely driven by the conventional factors, so a failure of the DFM to match the 2021-2022 dynamics indicates a departure from pre-COVID dynamics upon which the prediction is based. A leading example is the unemployment rate, which declined more rapidly in late 2020 and early 2021 than predicted by the two factors, although it is interesting to note that total establishment employment is well described by the C and F shocks over 2021 and 2022. The faster-than-predicted decline in the unemployment rate over early 2021 thus seems to be driven not by unusual behavior of employment but rather by the slower-than-predicted recovery of the labor force participation rate (LFPR) (Figure 14). Note that for both the unemployment rate and the LFPR, these aberrations are transitory, and the predictions match the actuals by early 2022. Another example of a series with unexplained strong growth in the spring and summer of 2021 is consumption of transportation services. Air revenue passenger miles (not shown) were slow to recover during the pandemic, and did not restart strong growth until the vaccine was widely available. With the availability of the vaccine and, given the coincident timing, the second stimulus check, transportation services grew strongly through the spring and summer of 2021 in a way that appears as a residual. Plausibly, this residual actually reflects a modeling limitation in which the pent up demand for travel, released after the vaccine became available, is not captured by the relatively short lags in the projections on the shocks that we need to use because of the short time span. Indeed, this underprediction is present, but smaller, for food services and accommodation and for total services consumption, driven by these components.

Finally, there are a few series that are not well explained by the shocks, either because they have a large one-month error or because of a systematic trend mismatch. A leading example of a large one-month error is the spike in consumption of food and beverages off-premises (not shown) in March 2020. In part this is attributable to the consumption-employment data misalignment: purchases of alcohol and staples (toilet paper, etc.) surged in March then declined in April from their March peak, clearly driven by COVID but with a timing pattern not captured by the COVID shock which was relatively small in March and large in April. An example of a systematic shift in the trend is housing starts, shown for the Midwest in Figure 14 but true for all other housing start series, especially in the West and South, in which the strong demand for new homes in 2022 and beyond is not captured.

Another series that is not well fit by the COVID shock is the VIX (Figure 14), which was not used to estimate the factors because it is not a measure of real activity. The VIX experienced large movements but its was highest from mid-February through mid-March, a month ahead of the rise in deaths and the March-April initial spike of the COVID shock. The VIX is not well predicted by the F factors in the pre-COVID sample either (not shown), consistent with the R^2 of 31% found in Stock and Watson (2016) for the VIX using the first three factors in a mixed real/nominal quarterly factor model exercise. The fact that the VIX was not predicted by the F shocks suggests that either the F shocks do not incorporate uncertainty shocks or that many of the movements in the VIX do not stem from macroeconomic uncertainty. In any case, the uncertainty around COVID, as measured by the VIX, was in large part resolved when deaths started to climb, the nation went into lockdown, and Congress passed the CARES Act.

V. Did the Economy Catch Long COVID?

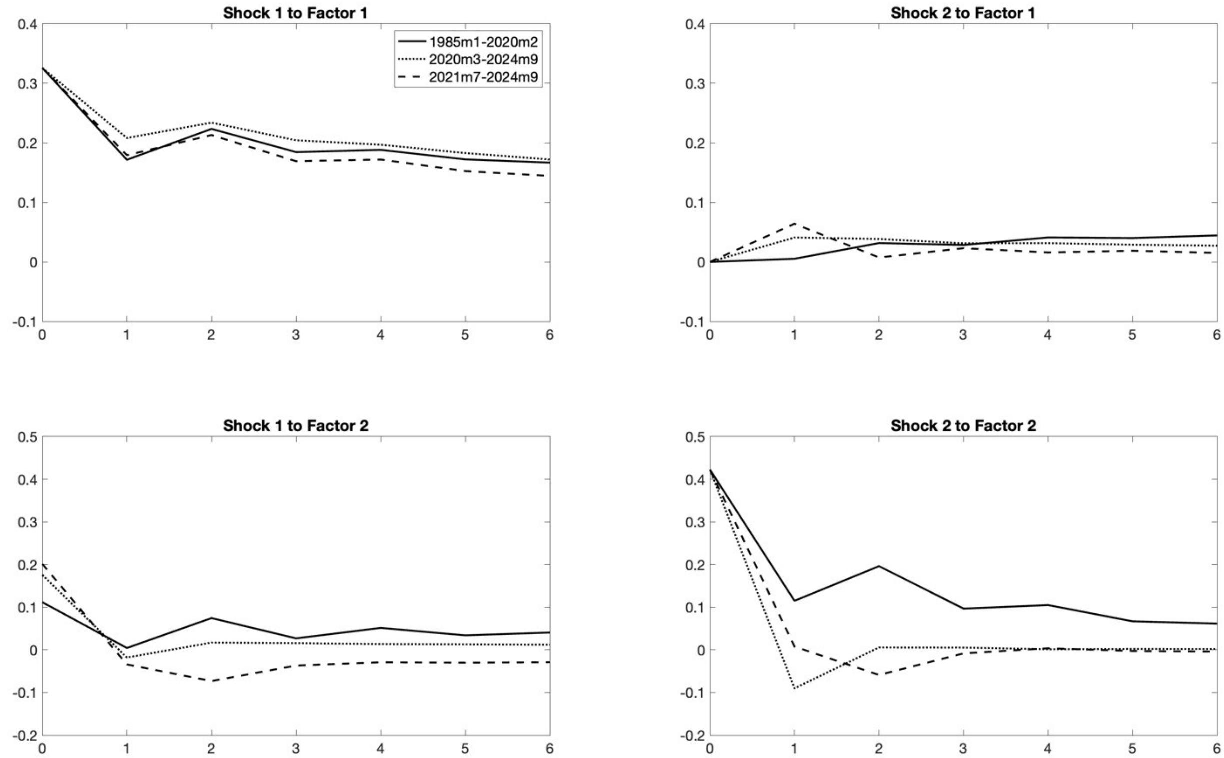
An open question is the extent to which the COVID recession and recovery wrought lasting structural changes in the economy. The pandemic introduced or speeded up some microeconomic structural changes, such as working remotely, and also induced some macroeconomic changes, notably the high debt-GDP ratio that is the legacy of the three COVID stimulus plans. Other structural shifts include deaths of a substantial number of workers, early retirements of older workers (Davis and others 2023), and a portion of the labor force having long COVID (Blanchflower and Bryson 2023). There are also less tangible effects, such as the loss of trust in government.

Only five years after the pandemic – and at most three years after the end of lingering effects of the COVID shock – it is too soon to say with certainty whether there are lasting changes in economic variables. With this caveat, we take an initial look, first at potential changes in business cycle dynamics, then at potential changes in long-term aggregate growth rates. In short, we find scant evidence of any long COVID effects at the level of macro dynamics or aggregate, and even sectoral, growth.

V.A. Macrodynamics

To assess the stability of the dynamics of the conventional factors, we estimated $\Theta_{FF}(L)$ for the first two factors over three periods: 1985-February 2020, March 2020-September 2024, and July 2021-September 2024.[9] The results are shown in Figure 15 and Table 4 We refrain from showing standard errors given the short samples for the second two VARs. Even without standard errors, there seems to be considerable stability for three of the four IRFs, although the IRF for shock 2 to factor 2 shows reduced persistence in the COVID period. Table 4 shows the standard deviation of the VAR shocks estimated over the three sample periods. While the standard deviations increased in 2020 through the first half of 2021, they returned to their pre-COVID values after the middle of 2021. The standard deviations of shocks 1 and 3 increased modestly by roughly 25%. Recalling that the second shock is the one that captures the three large COVID relief bills, it is perhaps not surprising that its standard error through the first half of 2021 is larger than in the pre-COVID sample.

[9] For the pre-COVID period, the estimates were obtained by estimating a VAR(2) for (F_1, F_2). For the COVID period, $\Theta_{FF}(L)$ was estimated using the residuals from a regression of the factors on current through four lags of the COVID shock.



Notes: Estimated using a VAR(2) on the first two F factors pre-COVID, and on the residuals from projecting F_1 and F_2 on the COVID shock for the COVID samples.

Figure 15: F-to-F impulse response functions $\Theta_{FF}(L)$ for the first and second F factors: Pre-COVID and COVID sample estimates

Table 4: Standard deviations of first and second F-shocks, pre-COVID and COVID samples

	1985m1-2020m2	2020m3-2024m9	2021m7-2024m9
Shock 1	0.33	0.43	0.34
Shock 2	0.42	1.24	0.42

V.B. Long-term Growth

We begin with a broad look at whether there is empirical evidence suggesting long-term effects of the COVID recession at the aggregate level. Table 5 presents evidence on whether there are changing trends associated with the COVID cycle, using quarterly data so we can examine NIPA aggregates. The first two columns provide mean growth rates over the two thirty-year periods

Table 5: Trend Growth Rates of Selected Series

	Average Growth Rate		**Smoothed Growth Rate**	
	1960-1989	**1990-2019**	**2019Q4**	**2023Q3**
Gross domestic product	3.49	2.49	2.66	2.72
Nonfarm Business Sector: Labor Productivity (Output per Hour) for All Wokers	1.96	2.02	1.91	1.69
Employment (CES)				
Employment (CES): Total Nonfarm	2.33	1.11	1.46	1.73
Employment (CES(: Goods Producing	0.7	-0.44	1.49	1.39
CES: GD: Manufacturing	0.78	-0.92	0.8	0.61
CES: Private Service Producing	3.1	1.68	1.64	1.86
CES: SE:Wholesale Trade	2.28	0.39	0.57	1.4
CES: SE: Retail Trade	2.88	0.56	-0.14	0.44
CES: SE: Prof and Bus Services	3.58	2.31	1.87	1.55
CES: Government	2.58	0.82	0.63	1.47
Personal Consumption Expenditures				
Total	3.67	2.69	2.56	2.91
PCE: Q Goods	3.4	3.26	3.55	2.99
PCE: Q Durable goods	5.21	5.2	5.39	4.33
PCE: Q Nondurable goods	2.62	2.21	2.63	2.29
PCE: Q Services	3.93	2.4	2.1	2.89
Industrial Production				
Total Index	3.18	1.67	0.27	0.48
Consumer goods	4.75	2.27	3.02	1.09
Materials	5.22	2.74	6	2.21
Manufacturing	5.17	3.14	5.63	2.09
Gross Private Domestic Investment	3.89	3.57	3.22	3.42
Government consumption expenditures and gross investment	2.64	1.27	2.35	2.44
Personal Income	3.71	2.62	2.76	2.1
Personal Income Excluding Transfers	3.49	2.41	2.8	2.28

Note: Smoothed growth at indicated dates is one-sided exponential average with discount factor 0.95.

prior to the pandemic. The final two columns are estimates of the instantaneous trend growth rate for 2019:IV and 2029:III, two quarters during which the unemployment rate was 4.1%, at or near full employment (so these two dates hold constant the stage of the cycle). The trend growth rate is estimated by one-sided exponential smoothing with a smoothing parameter of 0.95.

The most striking feature of Table 5 is how similar are these smoothed growth rates at the 2019:IV peak and nearly five years later, at least for the main aggregates. GDP growth is the same to one decimal point. There are sectoral differences, however, for example services consumption growth is substantially stronger in 2024:III than in 2019:IV (2.9% v. 2.1%) while goods consumption is weaker. Where there are discrepancies, the 2024:III growth rate is frequently closer to the 1990-2019 mean than the 2019:IV growth rate, except for a slowdown in the growth of industrial production which is consistent with a continuing decline in domestic goods production. Trend labor productivity growth in 2023:III is estimated to have fallen by 0.2pp, compared to 2019:IV and the prior two thirty-year periods, however productivity growth is very noisy making low-frequency variation quite difficult to measure with precision.

Figure 16 provides the comparison of the final two columns of Table 5 for multiple sectors of consumption, employment, and industrial production. For consumption and employment, the smoothed values in 2024:III v. 2019:IV are highly correlated and fall along the 45^{o} line, consistent with there being no substantial lingering changes. For industrial production, the correlation is also high but with a slope less than 1, reflecting the long-term slowdown of industrial production growth seen in Table 5.

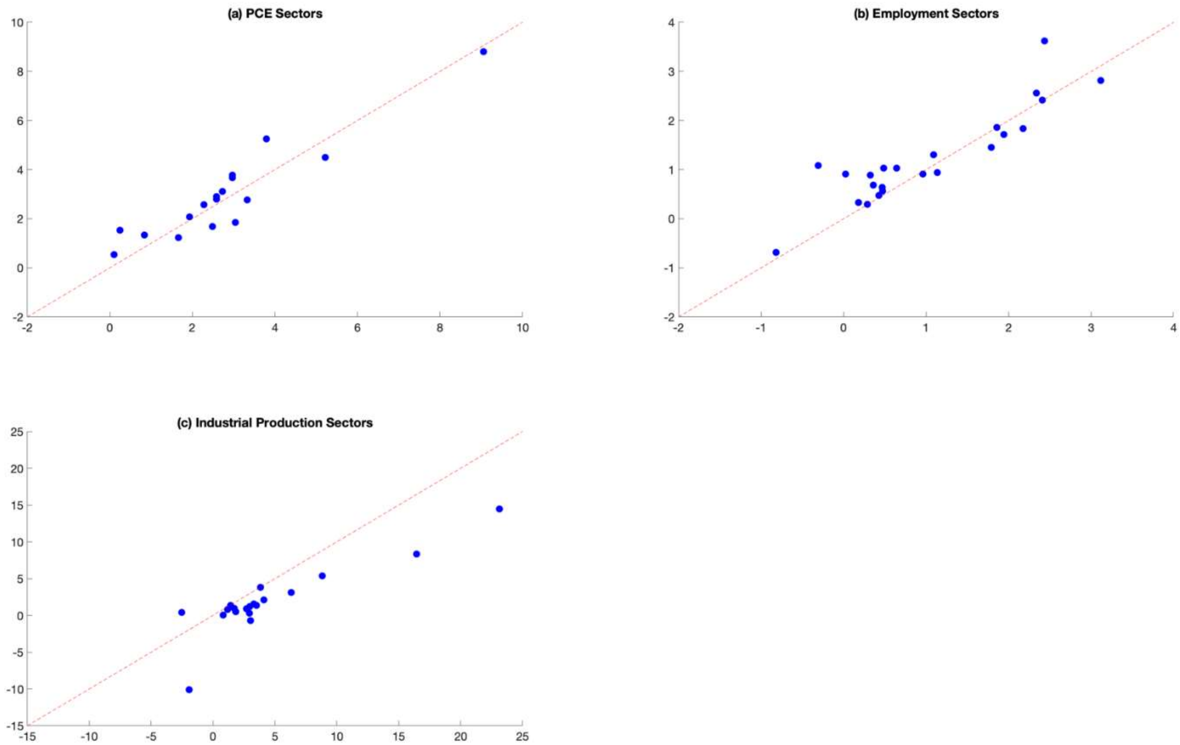


Figure 16**:** Smoothed growth rates of sectoral real activity for 2024:III v. 2019:IV, with 45º line.
Note: Smoothed growth at indicated dates is one-sided exponential average with discount factor 0.95.

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Appendix A. Data and Transformations

The macro data set is comprised of 128 monthly and 23 quarterly time series. Table A-1 summarizes the series by category; a complete list is given in the replication files. We apply five transformations to the raw data. First, with a handful of exceptions, the variables are converted to growth rates as the first difference of logarithms. Second, a few of the series contain large idiosyncratic outliers in the pre-COVID period; these outliers are replaced with the median of the five preceding values. During the COVID period, outliers are omnipresent and are not altered. Third, we locally demean each series using a bi-weight weighted average with bandwidth of 25 years. These local means are computed over the pre-COVID period, and the local mean from 2019::IV (quarterly model) or 2020:M2 (monthly model) is used to demean the data in the COVID period. The use of first-differenced data, together with local demeaning greatly reduces low-frequency variability in the time series and guards against the estimation of spurious factors of the sort described in Onatski and Wang (2021). Fourth, the data (after the first three transformations) are standardized using standard deviations estimated over the pre-COVID period. These transformations yield variables that have a mean of zero and are measured in pre-COVID standard deviation units. Finally, for constructing the plots in Figure 4 and Figure 6, countercyclical series are multiplied by −1. (Series were categorized as pro- or counter- cyclical based on the sign of the sum of coefficients from a regression of the series onto leads and lags of GDP (quarterly data) or Industrial Production (monthly data).)

For quarterly analysis, quarterly average of the monthly data were used.

The COVID deaths data in Figure 1 are from the U.S. Center for Disease Control (https://www.cdc.gov/nchs/nvss/vsrr/COVID19/index.htm, accessed February 16, 2025.

Table A-1: Summary of Monthly Economic Activity Indicators

Category	Number	Number of sub-aggregates
Quarterly variables		
NIPA (excluding PCE)	19	11
Productivity	4	2
Monthly variables		
Personal consumption expenditures	22	17
Employment	43	25
Industrial Production	33	19
Personal Income	13	6
Orders and Inventories	5	5
Housing starts and permits	10	4
Other Series	2	1
Total	**151**	**90**