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Recovering from COVID

ABSTRACT The COVID business cycle was unique. The recession was by far the deepest and shortest in the U.S. postwar record and the recovery was 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 is closely connected to COVID deaths, and 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. The greatest macroeconomic legacy of the COVID business cycle has been on the national debt.

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

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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 high-quality body 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 128 monthly and 23 additional quarterly 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 four main conclusions.

First, the COVID business cycle was unprecedented in the postwar record in the depth and speed of the collapse, its sectoral shifts in consumption, production, and employment, the speed of the recovery, and – unlike all other expansions since 1960 – the return of GDP to its pre-recession trend. A pre-COVID DFM utterly fails to describe this episode, even getting the sign of the changes in many variables wrong. This stands in contrast to the well-established finding that DFMs provide a reliable description of postwar U.S. business cycle dynamics, which, with the additional assumption of invertibility, implies that the shocks driving business cycles are captured by (spanned by) the factors. 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 be traced to a single novel aggregate shock, the COVID shock. Although we estimate it using only economic data, the COVID shock traces out the waves of COVID deaths. It diminishes as self-protective measures such as masking are adopted and COVID fatigue sets in in the summer and fall of 2020, and largely disappears once individuals either are vaccinated or have decided against vaccination. Remarkably, the diminishing link from deaths to the COVID shock and its timing matches the diminishing behavioral effect from deaths to reduced contacts estimated by Atkeson, Kopecky, and Zha (2024) solely from epidemiological data. 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 and too recent to draw firm empirical conclusions, it appears that the pre-COVID macroeconomic dynamics have returned or, more precisely, conventional macrodynamics never disappeared or changed, they were just masked by the massive COVID shock. As the COVID shock dissipated, conventional dynamics resurfaced, 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. The COVID recession accelerated remote work, drove a persistent increase in the number of new businesses, increased attention to supply chains, and changed the labor force through COVID deaths, long-COVID, and accelerated retirements. It also led to a persistent increase in the debt-GDP ratio. At the moment, however, growth rates of macroeconomic aggregates are largely what they were pre-COVID.

Fourth, the root problem was the COVID shock, and the most effective macroeconomic policy was to diminish then extinguish that shock directly, which was ultimately accomplished by Operation Warp Speed and the development and free distribution of the vaccine. Within a year of the vaccine's introduction, the economy was in most regards back to normal. The CARES Act of March 2020 provided social insurance, especially in the extensions and innovations in unemployment insurance benefits, and preserving job matches. The stimuli later in the pandemic, however, largely addressed the aggregate demand symptoms of the COVID shock. By the time the American Rescue Plan and its FY2021 stimulus of 5.2% of GDP were enacted in March 2021, vaccine distribution was in full force, the COVID shock was waning, and the unemployment rate stood at 6.1%. This stimulus supercharged the remaining recovery but added significantly to the national debt and contributed to the post-COVID inflation.

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.[2] As shown in the COVID timeline in Figure 1, the first confirmed U.S. case of the 2019 Novel Coronavirus (COVID-19) was detected on January 20, 2020. The SARS-CoV-2 virus spread rapidly, with lockdowns ordered in Wuhan on January 23 and in 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 rapid testing was not authorized until late August 2020 and even then tests were rationed. The virus spread unevenly. With some exceptions, such as air travel and transportation hubs, policies on non-pharmaceutical interventions (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.

On December 11, 2020, the Food and Drug Administration issued an Emergency Use Authorizations for the Pfizer-BioNTech COVID-19 vaccine, the first such authorization, 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 commenced on December 14, 2020 and expanded with supply; by the end of May 2021, half of the U.S. population had received at least one dose. Vaccine hesitancy was widespread, however, so uptake slowed: by June 2022, only 67% of the population was fully vaccinated. Throughout the

[2] 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), CEA (2022), and Tax Policy Center (2024). See Zelikow and the COVID Crisis Group (2023) and Macedo and Lee (2025) for more fulsome narratives.

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, changes in mandated NPIs, and changes in self-protective behavior. Because of incomplete vaccination, deaths from the Delta and Omicron variants were high, with 475,000 COVID deaths occurring between August 2021 and December 2022. 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 sum of which is remarkably close to Ferguson and other's March 16, 2020 estimate of 2.2 million U.S. deaths from an uncontrolled COVID-19 pandemic.

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 Kashyap and others 2025 and 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 per person (including dependents) in the March 11, 2021 American Rescue Plan (ARP). Between executive and legislative actions, federal expenditures and tax expenditures through COVID-related programs totaled $6.8 trillion through February 2025 (Committee for a Responsible Federal Budget 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. Sectoral dispersion during the cycle 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 fully, whereas, after the initial contraction in March and April 2020, consumption of durables soared and by June 2020 exceeded its February value by 10%.

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 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. This was followed by a slower phase through February 2021, in which growth rates were comparable to historical norms, then by a faster phase starting in March or April 2021 through the end of 2021. By the end of 2021, the economy was near or at full employment.

5. The COVID business cycle was the first trend-stationary business cycle since 1960, that is, it was the first in which the level of GDP reattained its pre-recession trend.

The first four stylized facts are evident in Figure 2, which plots the logarithms of selected activity variables for the COVID cycle and for the previous seven business cycles, relative to their value at the NBER business cycle peak. All series exhibit a precipitous but very short collapse in March and April, which turns around in May (the first stylized fact).

The second stylized fact – the unprecedented sectoral shift – is evident in Figure 2(c)-(f) and in the full set of figures in the online appendix (also see Council of Economic Advisers [CEA] 2022). Because of voluntary and mandated self-protection measures, consumption shifted sharply from high-contact services such as dining out, air travel, non-urgent health care, and concerts to goods that can be used at home or outdoors. High contact services, such as food services and accommodations (Figure 2(f)) and health care, fell sharply and recovered slowly, both because of a fall in demand and a decline in supply (e.g., low-density restaurant seating). 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, surged as consumption shifted from in-person to at-home. The run on nondurable home goods and off-premises alcoholic beverages in March 2020 is also clearly visible.

Figure 3 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).

Figure 3(a) 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]

Figure 3(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, 25th and 5th percentile of the cross-section distribution were -1.2, -2.4 and -3.6

[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.

standard deviations, whereas in the COVID recession they were -3.9, -19.0 and -62.7.

The third stylized fact – the extraordinary fiscal response – is evident in Figure 2(h). Clearly, the amount of government transfer payments during the COVID recession into 2021 was unprecedented during prior postwar recoveries.

The fourth stylized fact – the rapid recovery – is especially striking in the labor market. Figure 4 plots the natural logarithm of the unemployment rate over expansions relative to its series-specific cyclical peak (here, the month of the maximal unemployment rate following the NBER-dated cyclical trough). This figure is a variation on Figure 1 in Hall and Kudlyak (2022a), who document that, during pre-COVID postwar expansions, the unemployment rate consistently fell by 0.10 log points per year (SE = 0.02). The Hall-Kudlyak regularity is evident in Figure 4 in the tightly-clustered paths during the pre-COVID expansions.

The COVID path is dramatically different. During the COVID expansion, the fall in the log unemployment rate had three distinct phases. The first, lasting six months through October 2020, saw a remarkable drop of 0.76 log points from a rate of 14.8% in April to 6.9% in October. The second phase, lasting approximately another six months to April 2021, was much slower (but still faster than the Hall-Kudlyak rate), with the unemployment rate declining 0.12 log points. In the third phase, roughly May-December 2021, it fell another 0.45 log points, a rate of decline nearly three times its October 2020-April 2021 rate and six times the Hall-Kudlyak benchmark. By the end of 2021, the unemployment rate stood at 3.9%, arguably full employment.

As can be seen in Figure 2 and in the full set of charts in the online appendix, many other indicators follow this three-phase expansion, although the dates of these phases can differ by a month or two from the unemployment rate (consumption tends to lead employment).

This unusual pattern of an extremely rapid, moderate, then rapid phase is quantified for selected series in Table 1. The first two columns compare the log point changes in the first six months after the April 2020 trough (month 0) to the first six months following the eight previous post-1960 NBER cyclical troughs; the other pairs of columns examine the post-trough months corresponding to November 2020 – February 2021 and March – December 2021.[4] Growth rates are typically in a normal range during the second phase, then unusually strong in the third phase.

[4] Although most series exhibit this three-phase structure, the precise dating varies slightly from series to series, with the unemployment rate and labor market variables lagging consumption by a month or two. The dates used in Table 1 represent a compromise between the phase dates for the labor market and consumption variables.

The fifth stylized fact – the unique trend stationarity of the COVID recovery – is evident in Figure 5. The failure of post-1960 expansions to reattain the prior trend reflects multiple factors, including the underlying unit root behavior of GDP and a long-term slowing of the underlying trend growth rate in GDP in the United States and indeed among developed economies globally. Notably, the trend stationarity of the COVID recession was unique to the U.S. and did not obtain in the Euro Area (Giannone and Primiceri 2024).

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(a) and (b)) 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 and Atkeson, Kopecky, and Zha 2021, 2024). 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.

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), how targeted fiscal policy can be effective if such a shift is driven by sectoral supply (Guerrieri and others 2022), 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), and Diebold (2020); 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

Given the unprecedented macrodynamics of the COVID cycle, it is tempting to declare that everything about COVID was different so that one should adopt a modeling strategy with, say, structural breaks and widespread nonstationarity. But while COVID *was* unique, the virus did not change the fundamental features of economic behavior that underpin macrodynamics: consumers partially smooth income, investment decisions and price-setting relies on expectations of future conditions, it takes time to design, make and ship products, to find a job, to adjust to a change in interest rates, and so forth. We therefore adopt a parsimonious approach to modeling the COVID cycle, in which conventional business cycle dynamics do not change: there is but one thing new, the virus. The virus both can affect economic activity in new ways, such as shifting consumption patterns. It also can manifest through conventional channels, for example by increasing uncertainty and restraining both aggregate demand and aggregate supply.

The analytical framework we use is a dynamic factor model (DFM). For our purposes, DFMs have three 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 DFM provides a highly parsimonious way to introduce a single new feature – the COVID shock – which introduces new dynamics and responses but does not change conventional macrodynamics. Instead of everything about the economy changing, COVID is simply layered on top. Third, this highly parsimonious approach introduces relatively few new parameters to estimate from the time series data, a useful feature given that the entire COVID episode lasted perhaps two years.

Specifically, we consider a DFM that consists of conventional, or preexisting, factors, F_t, and potentially one or more new COVID factors, C_t. It will turn out (Section III) that a scalar factor C_t suffices to explain the COVID period, and our discussion in this section incorporates this assumption. 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 is the structural COVID shock, ε_t^F are conventional structural 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 factor to the COVID shock 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.

Pre-COVID, only the F elements of equations (1) and (2) are present, that is, $Y_t = \Lambda F_t + u_t$ where $F_t = \Theta_{FF}(\mathrm{L})\varepsilon_t^F$. We impose that Λ and $\Theta_{FF}(\mathrm{L})$ do not change from the pre-COVID to COVID periods, however this assumption is testable (we test it in Section V.A).

This augmented DFM introduces multiple channels in which the COVID shock can affect the macroeconomy. It induces changes in the COVID factor C_t, which can induce new comovements in observables (through different column spaces of Λ and Γ). The COVID shock can induce changes in F (through $\Theta_{FC}(\mathrm{L})$) that manifest in the same way as conventional shocks, for example by reducing aggregate demand. Conventional shocks can in turn affect the COVID shock (through $\Theta_{CF}(\mathrm{L})$), for example a positive shock to aggregate demand can increase economic activity thereby increasing infections. This feedback from conventional shocks to the COVID factor can be seen as the counterpart of the behavioral feedback equation in a behavioral SIR model, in which ε_t^C captures COVID deaths and the behavioral response to deaths and ε_t^F reflects the effect of economic activity on contacts, augmented for lagged effects.[5]

[5] For example, the behavioral component of the SIR model in Atkeson and Kissler (2024) is $\ln\beta(t) = \ln\overline{\beta} - \kappa(t)\dot{D}(t) + \psi(t)$, where $\beta(t)$ is the SIR transmisivity parameter, $\kappa(t)$ is the semi-elasticity of transmission with respect the the current death rate, and $\psi(t)$ is a shifter of transmissibility. Given the infection-fatality rate, over which an individual has little control, $\beta(t)$ is a direct measure of an individual's risk so aligns with our interpretation of C_t. The parameter $\beta(t)$ subsumes the biological transmissibility of the virus given a contact ($\overline{\beta}$), any protective measures to reduce that transmissibility (e.g., masking), and any measures to reduce

Combined, equations (1) and (2) 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. 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. The predicted value of Y given the factors is then $\hat{Y}_t = \hat{\Lambda}\hat{F}_t + \hat{\Gamma}\hat{C}_t$.[6]

These assumptions identify the space spanned by F_t. As discussed in the next section, we use three pre-COVID factors. We normalize the F factors by making the first F factor be the best factor predictor of employment growth pre-COVID (the "employment factor") and making the second F factor be the best factor predictor of PCE growth pre-COVID (the "PCE factor"). The third factor is the residual orthogonal to first two and with a unit factor loading on industrial production. These normalizations are only used for a stability test in Section V.A and a

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the frequency of contacts (e.g., working at home, closing schools). In terms of (2), the innovation in $\kappa(t)\dot{D}(t)$ corresponds to the COVID shock ε_t^C, lags of ε_t^C enter as linear predictors of $\kappa(t)\dot{D}(t)$, and economic activity enters by increasing contacts through $\psi(t) = \Theta_{CF}\varepsilon_t^F$.

[6] 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. Principal components estimation was modified for missing observations, see Stock and Watson 2016.

counterfactual calculation in Section VI.A

II.B. Identification of factor shocks

As with structural vector autoregressions with observable variables, the structural IRFs Θ(L) are not identified without further assumptions. In the context of (2), the vast literature on structural macrodynamics focuses on identification of $\Theta_{FF}(\mathrm{L})$ (see the survey in Ramey 2016). In contrast, our interest is on the elements of Θ(L) that involve the novel COVID shock ε_t^C.

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 just 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 Θ(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 those 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.

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

Assumption (iiia) stems from our interpretation of the COVID factor as virus-induced, behavior-altering perceptions of risk and COVID biology. Economic activity, both consumption of services and production, exposes people to the virus, but there are lags from the date of an economic shock (say, receiving a stimulus check) to exposure (going out to dinner and becoming infected) to becoming symptomatic to hospitalization to death. For the initial strain, the latency period from exposure to symptomatic was estimated to be approximately 5 days (see the review in Baqaee and others 2020). There were additional delays between showing symptoms and hospitalization, and Atkeson and Kissler (2024) take the mean time from hospitalization to death to be 30 days although this varied as treatments changed. There were additional administrative delays of up to a week before a death was reported. In principle, self-protective behavior could be triggered by observing an increase in infections, in deaths, or both. Infection rates, however, had significant reporting problems: the time from infection to public reporting could be more than a week, early in the pandemic tests were rationed so infections were under-reported, and later in the pandemic home testing resulted in an unknown amount of underreported infections. Atkeson (2021) finds a better fit in a behavioral epidemiological model if the feedback from observed COVID risks to self-protective behavior relies on reported deaths rather than infections, which makes sense both because of problems with reporting of infections and because the relevant shock to perceptions is the threat of severe harm. Atkeson and Kissler (2024) model self-protective behavior as depending on observed COVID deaths. 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 to eight weeks after the interaction that eventually leads to death. This motivates assumption (iiia).

Assumption (iiib) 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, the COVID shock of early- to mid- March 2020 – induced uncertainty, abrupt lockdowns, and voluntary self-protective behavior, which reduced aggregate demand and labor supply. The COVID shock also induced a large and immediate fiscal response in the signing of the CARES Act on March 27, 2020, with disbursements beginning immediately. Thus, within the month of March alone, the COVID shock induced shifts in aggregate demand, aggregate supply, and fiscal policy that were contemporaneous at the monthly level. These are all conventional macroeconomic channels – that is, F's – through which the unforeseen and novel COVID shock immediately affected economic activity.

Finally, we assume that (iv) the moving average $\Theta(L)$ is invertible, so that (2) can be written as a structural vector autoregression (VAR), where under (iiia), ε_t^C is the innovation in the C_t equation (up to scale), and ε_t^F can be recovered (up to a non-singular transformation) from the vector of innovations in F_t after conditioning on ε_t^C.

Estimation of the decomposition (3) and counterfactuals for the F shocks (done in Section VI) requires estimation of the shocks and parameters in the DFM (1) and (2). This would be straightforward if the COVID period were long, but in fact the COVID period is short while the pre-COVID period is long. Moreover the dimension of the DFM switches over the COVID boundary. We therefore use a hybrid structural VAR-local projection estimation method which uses the full sample where possible – in particular, in estimating $\Theta_{FF}(L)$, which is assumed constant over the COVID boundary – and the COVID sample where necessary, for example, by estimating ε_t^C as the residual from the regression of $\hat{C}_t$ onto a single lag of $\left(\hat{C}_t, \hat{F}_t\right)$ per (2). The stability of $\Theta_{FF}(L)$ is examined in Section V.A by estimating $\Theta_{FF}(L)$ during the COVID sample as well. The details are given in the online appendix.

III. Evidence of a Single COVID Factor

This section further quantifies how the COVID cycle differed from previous cycles and shows that a standard DFM, augmented with a single COVID factor, provides a concise numerical summary of those differences and of the COVID business cycle dynamics.

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

The data set consists of 128 monthly real economic indicators comprised of aggregate consumption and its components (22 series), employment (43 series), industrial production (33), personal income (13), housing starts and permits (10), orders and inventories (5), and other series (2). Some calculations additionally use 23 quarterly real indicators of economic activity. Some outliers were removed from the pre-COVID sample but not from the COVID sample. With a few exceptions, the variables are transformed to be first differences of logarithms. All series are demeaned and standardized using pre-COVID means and standard deviations, so they are mainly monthly growth rates in pre-COVID standard deviation units. See the online appendix for the complete list of series and data preprocessing details.

The NBER dates the 2020 recession peak as February 2020 (quarterly, 2019:IV). Not all of our monthly series are consistently available before 1970, 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. The results are generally robust to starting the pre-COVID sample instead in 1960 (using missing data methods) or in 1984.

The factors are estimated using the 77 monthly series (of the 128 total) that are not linked by identities and are observed from January 1970 through September 2024. In the monthly dataset, a single 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), which increases to 25% using three factors. The Bai-Ng (2002) information criterion is indifferent between two and three factors, so we use three pre-COVID 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 6 summarizes the cross-sectional R^2 of the *F* factors, and also of the combined *F* and *C* factors for each month from March 2020.[7] The pre-COVID factors explain only a fraction of this cross-sectional variation early in the COVID cycle, whereas from March to July 2020 the marginal R^2 of the *C* factor exceeds 60%. This importance of the *C* factor subsides quickly: its marginal R^2 is less than 10% from 2022 on and is essentially zero in 2023.

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[7] At date *t*, the cross-sectional R^2 of the *F* factors is the R^2 of $\hat{\Lambda}\hat{F}_t$ as a predictor of vector Y_t. For the combined factors, it is the cross-sectional R^2 of $\hat{\Lambda}\hat{F}_t + \hat{\Gamma}\hat{C}_t$ for Y_t. The marginal cross-sectional R^2 of the *C* factor is the difference between these two R^2's.

Figure 7 provides an alternative visualization of the cross-sectional explanatory power of the C factor. Figure 7 displays 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)).[8] As can be seen in Figure 7(a), the F factors remove the pre-COVID cyclic pattern evident in Figure 3(a), but as can be seen in Figure 7(b), only partially reduce the cross-sectional dispersion early in the COVID cycle. In contrast, when the single COVID factor is added in Figure 7(c), there is much less excess cross-sectional dispersion.

The quantitative importance of the C factor varies by series. Figure 8 plots actual and predicted values of percentage growth rates of the series in Figure 2, where the predicted values are computed using only the F factors, and then using both the F and C factors (see the online appendix for these predicted-actual plots for all series). The growth of aggregate employment and consumption is well explained by the F factors over this period, with a negligible role for the C factor. In contrast, for consumption (Figure 8(c)) and employment in goods-producing sectors and in construction, the F factors overpredicted the decline, while for services consumption and employment (including services components), the F factors substantially underpredict the decline. These prediction errors are nearly all resolved by including the COVID factor.

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 depresses the series. Part (a) shows results from the monthly model for consumption. 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 used for work or social occasions (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

[8] 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 7(c) are from a regression of the series Y_{it} onto F_t, C_t, and one lead and one lag of C_t.

the large declines in F (positive Γ), while employment fell more (negative Γ), yielding a COVID-attributed 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 discussion of parallels with the aftermath of World War II.

The estimated COVID factor, normalized to +1 in April 2020, is plotted in Figure 9 Consistent with Figure 6, the COVID factor is small after June 2021 and essentially zero after January 2023. It turns out that the COVID factor has a simple empirical counterpart, the weighted spread $\Delta\ln(\textit{PCE-goods}) - 13.5\Delta\ln(\textit{PCE-services})$, where 13.5 is the ratio of the Γ coefficients for PCE-services to PCE-goods in Table 2, rescaled from pre-COVID standard deviation units to growth rates. This spread, which exhibits only moderate cyclical behavior in the pre-COVID period, is potentially useful for future time series applications as an observable version of the COVID factor, cf. Ng (2021) and Lenza and Primiceri (2023).

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 *F* factors spiked in the spring of 2020 – that is, it appeared that there were large conventional shocks – but those spikes were in fact almost entirely driven by the COVID shock. This is shown in Figure 11, which 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). The effect of the COVID shock on *F* dies out, however, and by mid-2021 the conventional factors are largely driven by the conventional shocks. Notably, the two largest values of F_{2t} (the PCE *F*-factor) 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). 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 PCE 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 equation (3). Figure 13 presents these decompositions for the levels of payroll employment and 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 in the online Appendix, leads to several high-level conclusions.

First, the COVID shock 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.[9] The COVID shock also explains the anomalous behavior of sectoral employment through 2020, both 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.

Second, 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 13) 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 total PCE.

Third, there are a few series that are not well explained by the shocks, either because they have a large one-month error, plausible lagged effects, or because of a systematic trend mismatch. One example of a large one-month error is the spike in consumption of food and beverages off-premises (not shown) in March 2020. This is partly attributable to the consumption-employment data misalignment, but is also attributable to the anticipatory shifting forward of purchases for April into March, which occurred for alcohol and household staples (toilet paper, disinfectant, etc.) but not for other goods, and which is not captured by the COVID shock timing which peaked in April. The demand for transportation services, a major component of which is air travel, also is not well-fit in 2021, arguably because of unmodeled lags. Air revenue passenger miles (not shown) plummeted during the pandemic and did not see strong growth until the vaccine was widely available. With the availability of the vaccine and the ARP stimulus checks, transportation services grew strongly through the spring and summer of 2021 in a way that appears in the DFM as a residual. Plausibly, this residual reflects a limitation of our using only four lags, because air travel has built-in delays from vacation planning to ticketing to travel. A similar but smaller underprediction is present for food services and accommodation and for total services consumption, driven by these components. An example of a systematic shift in

[9] 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.

the trend is housing starts, especially in the West and South, in which the DFM does not capture the growth in demand for new homes in 2022-2023.

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. Clearly 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 a 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), a portion of the labor force having long COVID (Blanchflower and Bryson 2023), and many American children missing a year of in-person school. 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 the COVID shock – it is too soon to conclude 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

We assess the stability of conventional business cycle dynamics pre- vs. post-COVID by examining the stability first of Λ and $\Theta_{FF}(\mathrm{L})$.

To assess the stability of Λ, we apply Andrews' (2003) end-of-sample stability test, which allows for non-Gaussian errors, to each of the 128 monthly series. We compare estimates of Λ from the pre-COVID period to those from the post-COVID period (March 2023-September 2024). Of the 128 series, five reject at the 5% level, and 11 reject at the 10% level (see the online appendix for details). Among those that reject stability of Λ, there are no clear patterns. Although the short post-COVID period means that the power of the test will be low, these results are consistent with Λ not changing after the COVID episode.

To assess the stability of $\Theta_{FF}(\mathrm{L})$, we estimated $\Theta_{FF}(\mathrm{L})$ for the first two factors over three periods: 1985-February 2020, March 2020-September 2024, and July 2021-September 2024.[10] The results, displayed in Figure 14, show considerable stability for three of the four IRFs, except that the IRF for shock 2 to factor 2 shows reduced persistence in the COVID and post-COVID period. The standard deviation of the innovation to factor 2, the PCE factor, was much larger during 2020 through the middle of 2021 than before or after, consistent with this factor capturing the three large fiscal stimuli of March 2020 and January and March 2021. The standard deviations of the innovation to factor 1 increased modestly during March 2020-June 2021, then returned to pre-COVID levels.

These results are consistent with the macroeconomy returning to normal rather quickly: business cycle dynamics pre-COVID and post-vaccine are quite similar.

V.B. Trend Growth Rates and Sectoral Shares

We now turn to the question of whether there have been long-term shifts in aggregate and sectoral growth rates as a result of COVID, using quarterly data so we can examine NIPA aggregates. The first two columns of Table 3 provide mean growth rates over the two thirty-year periods prior to the pandemic. The final two columns are estimates of the instantaneous trend growth rate for 2019:IV and 2024:III, two quarters during which the unemployment rate was 4.1%, at or near full employment. The trend growth rate is estimated by one-sided exponential smoothing with a smoothing parameter of 0.95.

The most striking feature of Table 3 is how similar are the 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 (2.5% v. 2.0%) while durable goods consumption is weaker. Industrial production growth has slowed, consistent with a continuing decline in domestic goods production. Figure 15 provides the comparison of the final two columns of Table 3 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,

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[10] Estimation is described in Section II.B. Only the first two factors are used because the third factor is quantitatively unimportant during the COVID sample.

reflecting the long-term slowdown of industrial production growth seen in Table 3.

VI. Assessment and Lessons

VI.A. How Well Does the DFM Explain the Five Anomalies?

The addition of a single COVID factor and its COVID shock to a conventional DFM provides a parsimonious explanation of the five stylized facts about the COVID cycle in Section I.B across the 128 monthly and additional quarterly real economic time series we consider.

The COVID shock explains the first stylized fact, the sharp and deep initial contraction in March and April. As shown in Figure 7(c), the COVID shock also explains nearly all of the unprecedented sectoral shifts, with a few exceptions such as the run on alcohol and home sanitary products in March 2020 and the pent-up demand for air travel in the late spring and summer of 2021. With the benefit of the new literature on epidemiological-economic models, the economics of these anomalies are well understood as manifestations of self-protective behavior and mandated NPIs prior to the vaccine. What is noteworthy is not why they occurred, but that there is a parsimonious statistical explanation – the single COVID shock – that captures this behavior empirically.

In a statistical sense, the DFM explains the final two anomalies, the rapid recovery and trend reversion of GDP. These explanations raise a number of economic questions about mechanisms, so we discuss them in some detail, including how they relate to the unprecedented fiscal expansion (the third anomaly).

The rapid recovery (the fourth anomaly) occurred in three phases: very fast (roughly the first five months, or May through September 2020), moderate (months 6-10, or October 2020 – February 2021), and fast (roughly months 11-20, or March through December 2021). The DFM attributes the fast first phase to a large negative COVID shock. Over the late spring of 2020, employers and consumers adapted to the new environment by adopting self-protection measures such as social distancing, masking, and Plexiglas protections at retail establishments. These adaptations, combined with the end of the spring wave of deaths, appear in the DFM as a negative COVID shock, that is, good news about the ability to continue economic activity despite the virus. In addition, the summer wave of COVID deaths was substantially smaller than the spring wave which, in conjunction with adaptation to COVID, led to small COVID shocks in the summer and early fall.

These adaptations and outcomes – the negative then small COVID shocks – facilitated reopening of businesses from May 2020 through the early fall. Arguably, a number of factors contributed to the rapidity of the reopening. First, as Hall and Kudlyak (2021, 2022b) stress, the preponderance of workers were on temporary layoff so they could return to their prior job and avoid time-consuming searching by workers and employers. Second, Autor and others (2022a,b) and Granja and others (2022) estimate that the Paycheck Protection Program (PPP), part of the CARES Act of March 2020, also made a modest contribution to the rehiring during this period because it paid for workers to return to the firm's payroll (from layoff and unemployment insurance) even if they were not actually working. Using the estimates in Autor and others (2022a,b), this contributed perhaps 1-2 percentage points to the decline in the unemployment rate over this period, although the literature on the PPP (also including Hubbard and Strain 2020) suggests that these gains were at considerable fiscal cost. Third, as documented and discussed by Decker and Haltiwanger (2023) and Kwan and others (2024), there was a surge in new business formations, facilitated in part by tools (such as Zoom) that make working from home more productive and facilitate labor market entry, for example for the disabled (Bloom, Dahl, and Rooth 2024) and home caregivers. Fourth, and running counter to these labor market tailwinds, Hornstein and others (2024) estimate that generous pandemic unemployment insurance programs under the CARES Act, such as the Pandemic Unemployment Assistance program, held back the recovery of aggregate employment by 3.4 percentage points from April through December 2020.

The DFM attributes the second, slower phase of the expansion (months 6-10 of the expansion), with its growth rates comparable to prior expansions, to the positive COVID shocks in December 2020 and January 2021 (Figure 10), which correspond to the winter deaths peak from the Beta variant; in fact, the December 2020 COVID shock was second in size only to the much larger March 2020 shock. Leaning against this COVID shock were the transfers, disbursed in January 2021, in the Consolidated Appropriations Act; that Act also extended many of the expiring CARES Act pandemic unemployment benefits, further stimulating demand but, per Hornstein and others (2024), tempering an expansion of labor supply. According to the decompositions, for many series including aggregate employment and PCE, these factors largely offset over this phase, resulting in much slower economic growth than in April-September 2020.

The third phase of the expansion, from March 2021 to December 2021, saw a return to above-normal growth, although less strong than during the first phase. By then, the vaccine was widely available. Despite the surge in COVID deaths in September 2021 (Delta variant) and January-February 2022 (Omicron) among the unvaccinated, by mid-spring the COVID shock was essentially zero (Figure 10), consistent with the widespread availability of the vaccine for those who wanted it or a lack of economic dampening from COVID by those who did not. With the COVID shock essentially gone, the conventional factors drove growth during this phase.

The most prominent of those drivers was the second and third rounds of stimulus checks under the Consolidated Appropriations Act of 2021 and especially the American Rescue Plan, which were disbursed in January and March 2021, along with other provisions that affected tax year 2021 (including expansions of the Child Tax Credit and the Earned Income Tax Credit). The shock decompositions (Figure 12) provide some circumstantial evidence linking the strong recovery to the ARP. The conventional factors explain the jumps in consumption in January and March 2021. In addition, the decline in the unemployment rate largely tracks its predicted value, and starting in the spring of 2021 the decline is attributed to the conventional shocks (Figure 13).

We refine these observations by conducting a counterfactual that removes this fiscal stimulus. In the context of the DFM, the space of the F shocks includes the fiscal shock. Inspection of the three conventional factors (see the online appendix) and of Figure 12 suggest that the fiscal shocks of January-March 2021 appear in the PCE factor. We therefore treat the shock to PCE as including these fiscal shocks, where the PCE shock is identified as the first shock in a Cholesky factorization of the F factors. As a counterfactual, we set the PCE shock to zero in January-March 2021. One justification for this approximate method for identifying the fiscal shock is that there were no other notable non-COVID economic surprises during this period (CEA 2022, Chapter 2).

Figure 16 presents the actual and counterfactual values of the unemployment rate and overall, goods, and services PCE under the no-additional-stimulus counterfactual. According to these estimates, the second and third round of stimulus pulled forward the decline of the unemployment rate from its March 2021 value of 6.1% to 5% by approximately 2 months. Absent these two stimulus programs, we estimate that the unemployment rate would have fallen at an annual rate of 0.37 log points/year over this third phase, from March 2021 to December 2021, still faster than the Hall-Kudlyak (2022a) rate but slower than the actual rate of 0.53 log points/year. Given our approximate way of identifying the fiscal shock, these estimates are best viewed as suggestive, and the results are somewhat sensitive to alternative identifying schemes.

Still, they do suggest that the two stimulus plans contributed substantially to speed of the third phase of the expansion.

The final anomaly is the COVID trend reversion of GDP. The estimates of the decomposition of the levels of PCE in Figure 12 provide an estimate of the cumulative effect of the COVID and conventional shocks on the levels of these series. For all these series, the return to zero of the COVID shock by mid-2021 accounts for most but not all of the series regaining its prior trend value; that is, the COVID shock alone would have produced unit root behavior (base drift) in the series. The no-additional-stimulus counterfactual estimates for PCE in Figure 16 suggest that the two final stimulus plans raised the level of PCE by roughly 5.3% by the end of 2022. This is a plausible contribution, given that the two stimulus plans combined amounted to 8.5% of GDP in fiscal year 2021 and 2.5% in fiscal year 2022 (CEA 2022, Table 2-1).

Although this explanation of the third, fast phase of the expansion and of the trend-reversion has focused on the expansionary effect of the two stimulus plans, especially the ARP, there are other complementary explanations. Because temporary layoffs had returned to normal levels by the end of 2020, the Hall-Kudlyak (2021, 2022b) and PPP explanations do not explain the fast third phase. Instead, one candidate explanation is the improvement in technology for working at home, along with the increased access it provides to pull some potential workers into the labor force, which could have led to a persistent increase in entrepreneurial activity (Decker and Haltiwanger 2023). If so, this would have important implications for a long-lasting shift to faster labor market dynamics. In any event, more work remains to sort out the economics of the fast third phase and trend reversion of GDP.

VI.B. Lessons

The COVID business cycle was triggered by just one thing: the novel coronavirus and COVID-19. The threat of severe illness and death triggered a macroeconomic shock that was the macroeconomic manifestation of the epidemiological shock. In our identified DFM, the macroeconomic shock, which is estimated solely from aggregate and sectoral economic data, turns out to be tightly linked to COVID deaths, with the linkage declining over time as individuals and governments deploy self-protective measures, as COVID fatigue sets in, and ultimately as the vaccine becomes widely available. The macroeconomic COVID shock affected the economy both directly through new channels and indirectly through conventional channels, including reducing both aggregate demand and aggregate supply and sowing uncertainty.

Because the source of the disturbance was the COVID shock, from a macroeconomic perspective the most important policy measures were those that reversed then eliminated the shock. Early in the pandemic this was done through self-protection, mandatory NPIs, and by initiating Operation Warp Speed.

Public health policy, especially around NPIs, was divisive and broadly distrusted. The economic costs of NPIs were often ignored by public health officials, public health information and communication was chaotic, non-experts suddenly became experts and injected noise, and citizens were left alienated and confused (e.g., Macedo and Lee 2025). There have been several retrospectives, and while all agree that the pre-vaccine public health measures were rife with failures, they disagree on the lessons. Zelikow and the COVID Crisis Group (2023) draw on interviews with experts and their own experience to conclude that the top-down expert-driven approach was the right one, but failed because of incomplete information, rigidity of the public health system, insufficient central authority, and inconsistent communication. In contrast, Macedo and Lee (2025) draw on empirical evidence to conclude that the command-and-control approach to public health was bound to fail based on pre-COVID evidence. They point to the small effects of mandated NPIs during the crisis (e.g., Goolsbee and Syverson 2021a,b) and the persistence of certain NPIs with high costs but low public health benefits, like school closures, to conclude that the pre-vaccine public health policy significantly diminished trust in government and science. The *Lancet* COVID-19 Commission (Sachs and others 2022) also criticizes the simplistic views of social behavior that underlaid divisive public health measures. In any event, the decline in trust in scientists (Algan and others 2021) contributed to misinformation and vaccine hesitancy: from August 2021 through December 2022, a period during which the vaccine was widely and freely available, there were more than 475,000 COVID deaths.

From a macroeconomic perspective, the novel COVID macroeconomic shock effectively disappeared when the perceived threat of COVID subsided with the widespread availability of the vaccine. A key lesson is: When faced with a novel shock, take effective policy actions to address that shock directly. Operation Warp Speed and the free availability of the vaccine did so.

Most of federal spending during the pandemic was not, however, on measures that directly addressed the COVID shock; rather, it was on measures designed to dampen the macroeconomic impact of the COVID shock. Given the magnitude of the spending, we believe that additional research on the effects and cost of these policies is needed, however that research must recognize interactions with the pandemic. As usual, labor market policies such as PUA or PPP provided social insurance; uniquely during COVID, by keeping workers out of the labor market, they reduced exposure and deaths, thereby diminishing the COVID shock.

From a fiscal perspective, the largest pandemic-era program was the American Rescue Plan. The ARP was signed on March 11, 2021, by which time more than 50 million doses of the vaccine had been administered and one month before all Americans adults became eligible for vaccination. The Congressional Budget Office scored the ARP as adding $1,164B to the deficit through September 2021, and another $528B in fiscal year 2022, of which $93B was for public health (Kates 2021). Because the macroeconomic COVID shock was nearly vanquished by the date of its enactment, in hindsight the ARP is best viewed as conventional deficit-financed fiscal stimulus applied to an economy with an unemployment rate of 6.1%. Because of the vaccine rollout, the ARP also coincided with pent-up demand for consumption that had been postponed during the pandemic, such as air travel to visit now-vaccinated parents, vacations, and entertainment services.

With no COVID shock to retard growth, we estimate that the ARP expedited the final phase of the recovery, contributed to a decline of the unemployment rate from 6.1% in March 2021 to 3.9% in December 2021 (a decline of .45 log points that would have taken four years at the Hall-Kudlyak (2022a) rate), and raised employment and output to their prior trend levels. These benefits, however, came at significant costs, adding 8pp to the debt-GDP ratio, thereby reducing future fiscal headroom. Although the jury remains out, recent studies point to the ARP stimulus as being a source of excess demand pressures that contributed to the pandemic-era inflation.[11] With these observations, one could reasonably conclude that the ARP was too much, too late. Given the magnitude of this policy experiment, more work is needed to better understand labor market dynamics during the third, fast phase of the COVID recovery, the role of the ARP, and the ARP's subsequent consequences.

[11] Dynan and Elmendorf (2025) make the case for the ARP stimulus being the key driver of this inflation. There are, however, other factors and views: the energy price increases in late 2020 through early 2022 (Bernanke and Blanchard 2023), supply chain disruptions and the inability of sectoral supply to keep up with sectoral demand shifts (di Giovanni and others 2025), and the role of energy prices in driving short-run inflationary expectations (Beaudry and others 2024).

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Figure 1: COVID Timeline

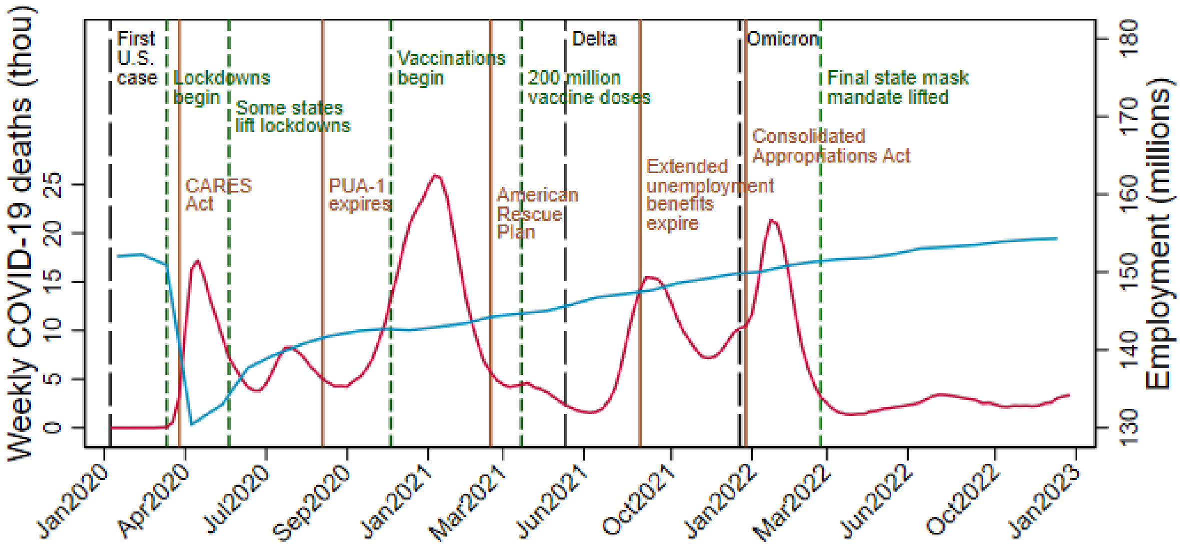
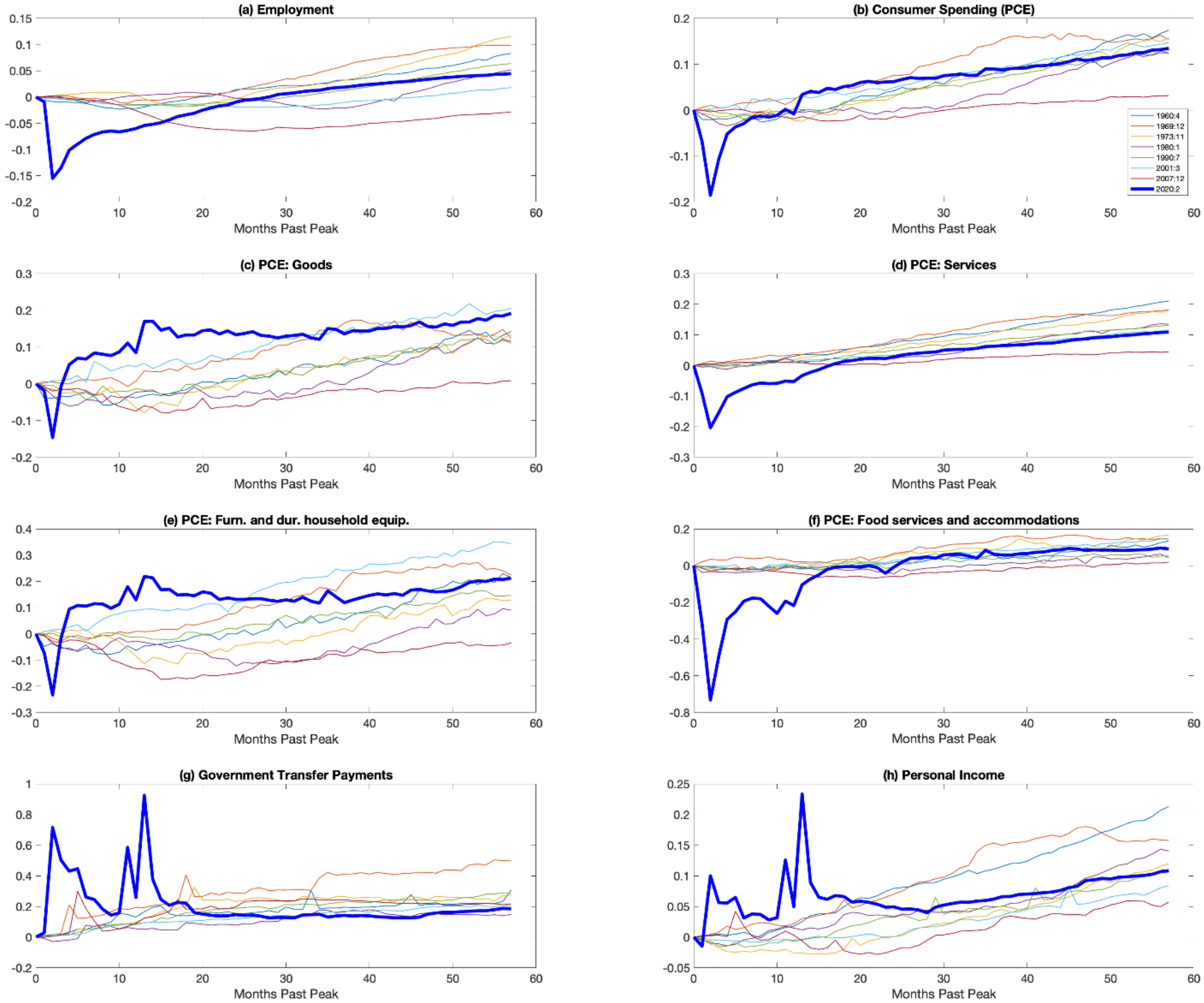
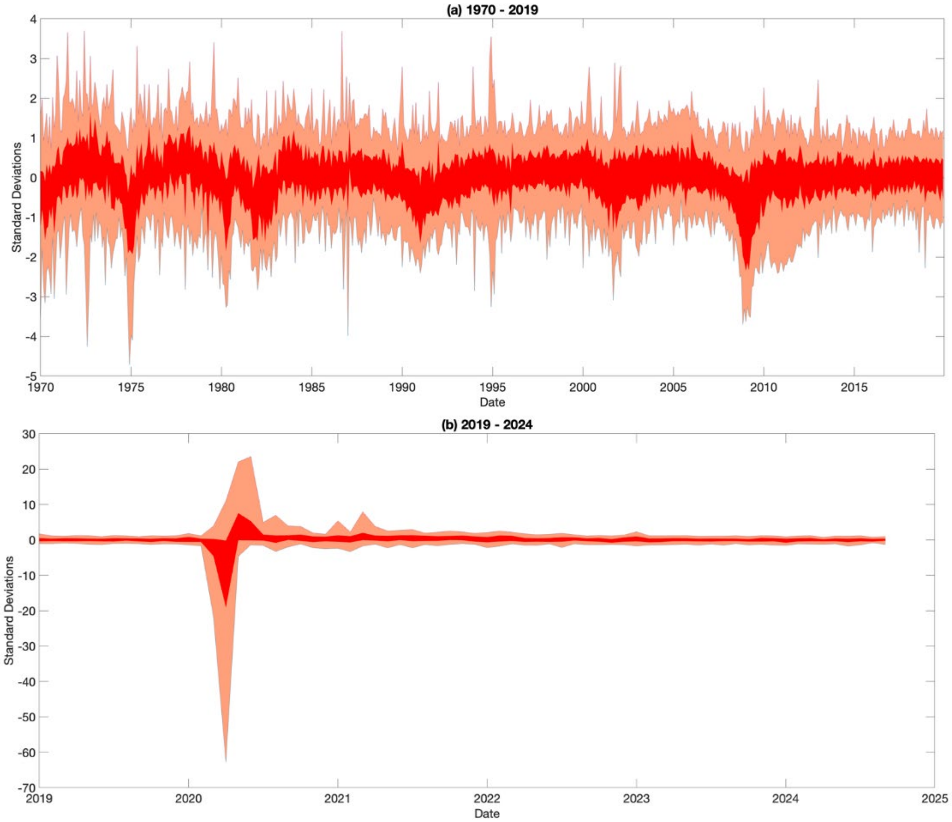


Figure 2: Aggregate time series over the COVID and prior business cycles



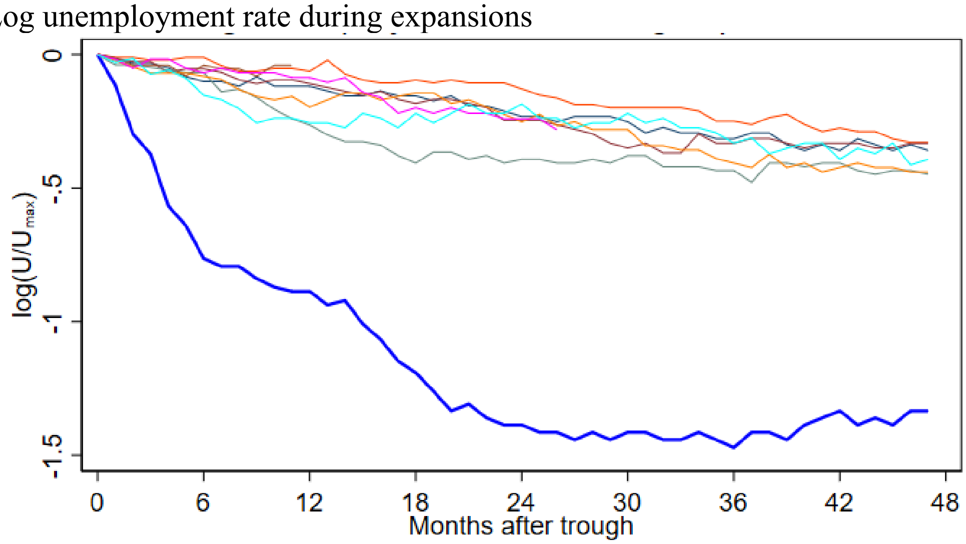
Notes: Lines are logarithms of the indicated series, relative to its value on the NBER-dated peak, over all U.S. business cycles since 1960. The COVID cycle data are bolded. The business cycles starting in January 1980 and July 1981 are combined.

Figure 3: Time series of cross-section 25%-75% (dark) and 5%-95% (light) quantiles of 128 monthly activity variables.



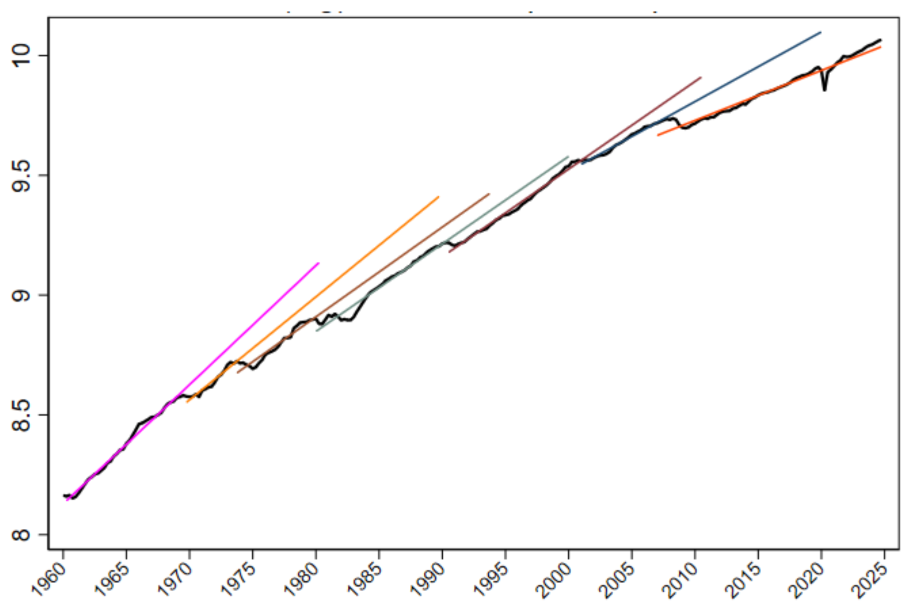
Notes: Units are pre-COVID standard deviations. Counter-cyclical series such as the unemployment rate are multiplied by -1.

Figure 4. Log unemployment rate during expansions



Notes: The unemployment rate is relative to its value at its series-specific peak, taken to be the month of its maximal value on or following each NBER-dated cyclical trough.

Figure 5. Log real GDP and peak-to-peak trends



Notes: Straight lines are linear time trends estimated over a given business cycle using NBER dates. The business cycles starting in January 1980 and July 1981 are combined.

Figure 6: Cross-sectional R^2 by month, F and F & C factors

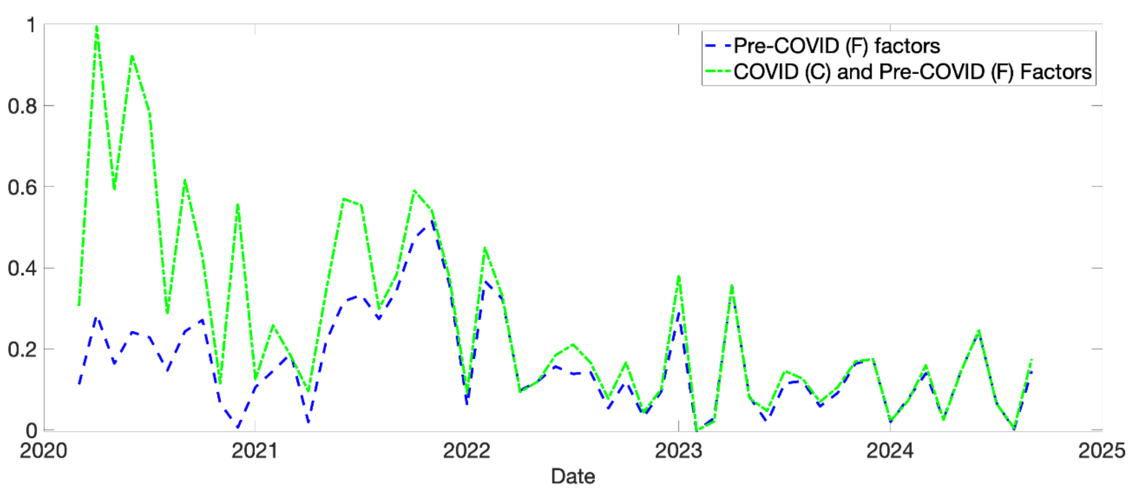
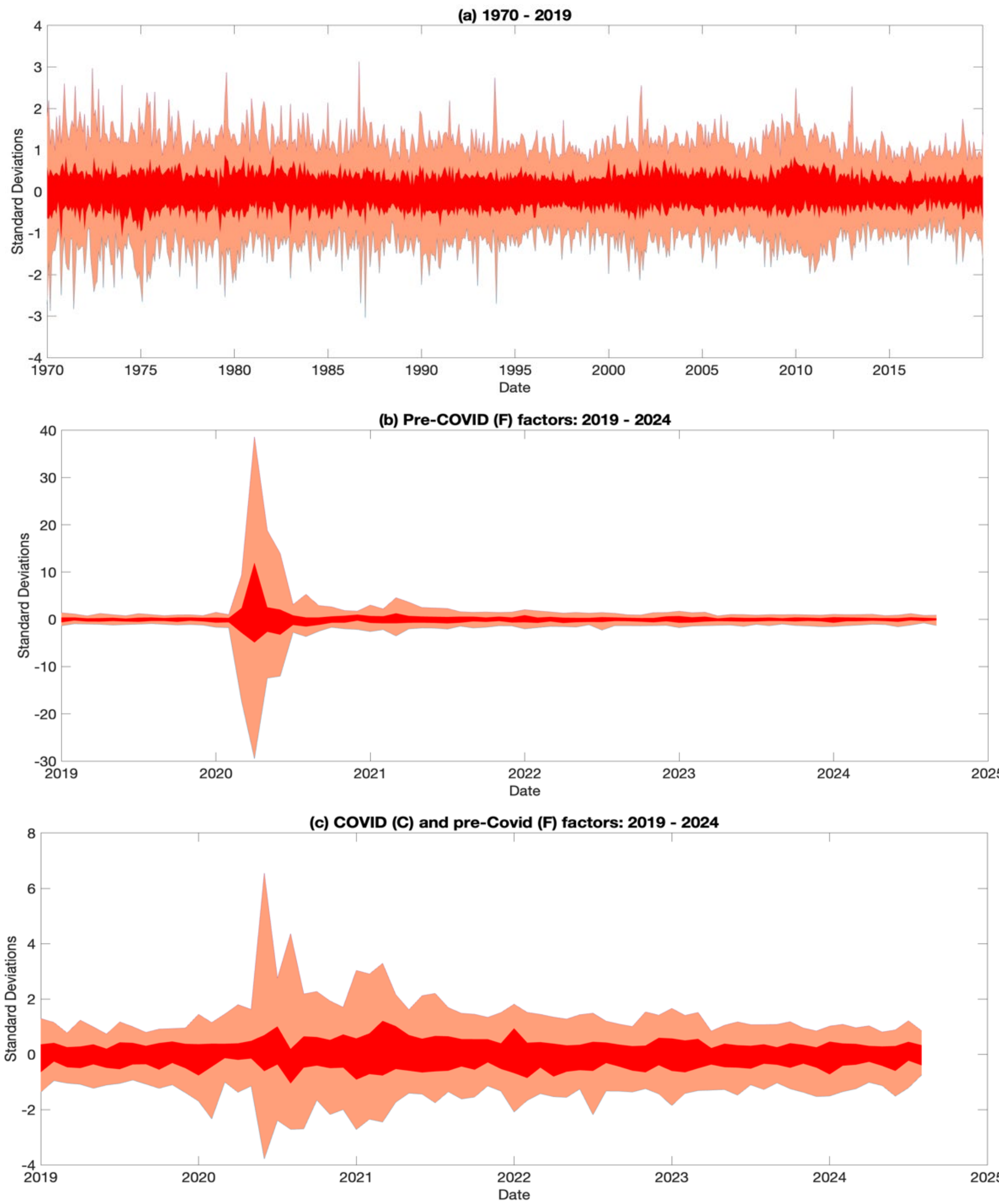
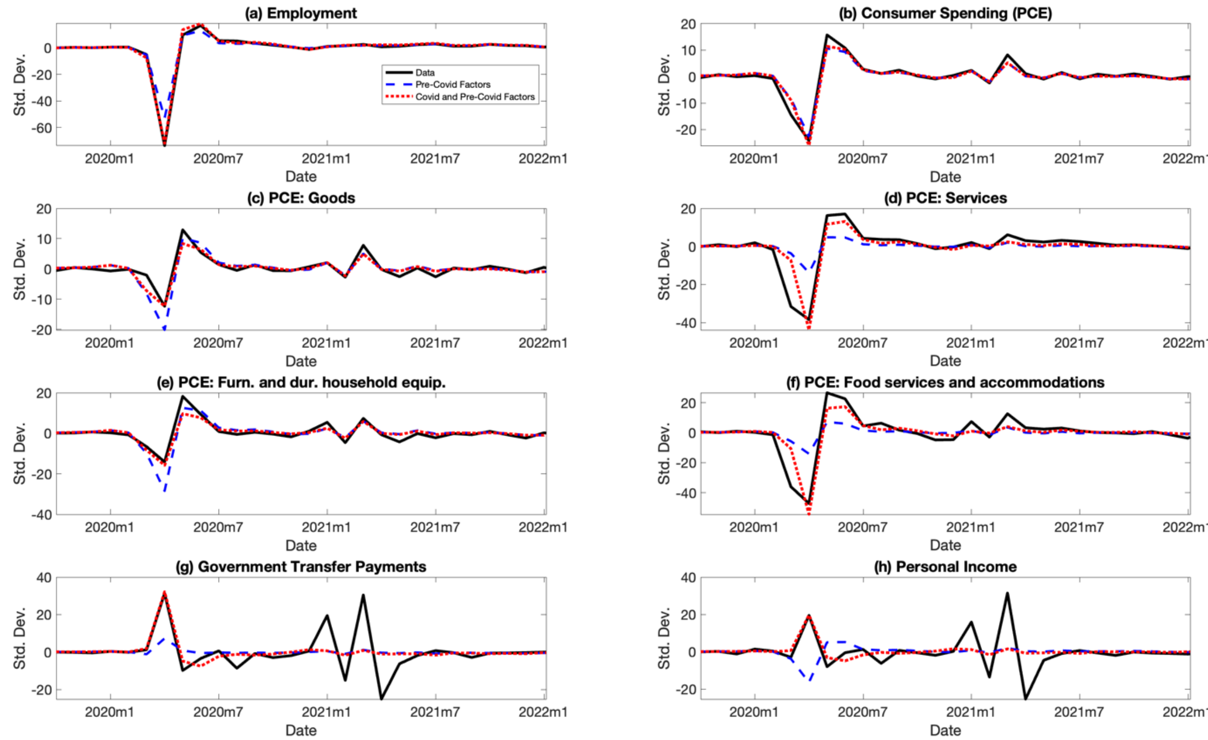


Figure 7: Time series of cross-section quantiles of residuals of 128 monthly activity variables, controlling for three pre-COVID F factors ((a) and (b)) and additionally controlling for both F and C factors ((c)).



Notes: See the notes to Figure 3.

Figure 8: Factor model fits during COVID



Notes: Series are monthly growth rates (quarterly for GDP), demeaned and standardized using pre-COVID means and standard deviations. Key: Actuals (bold), predicted using F (dashed), and predicted using both F and C (dots).

Figure 9: COVID factor and the weighted goods-services consumption spread.

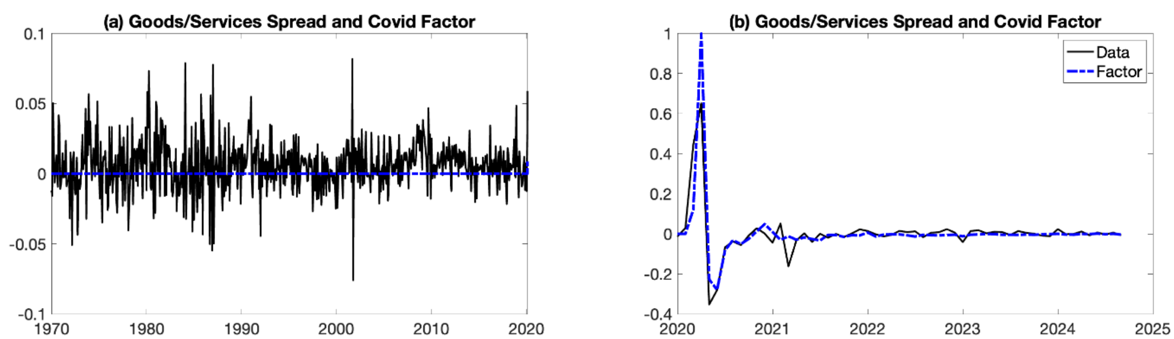


Figure 10: The COVID shock and monthly COVID deaths over the COVID period starting (a) January 2020 and (b) July 2020.

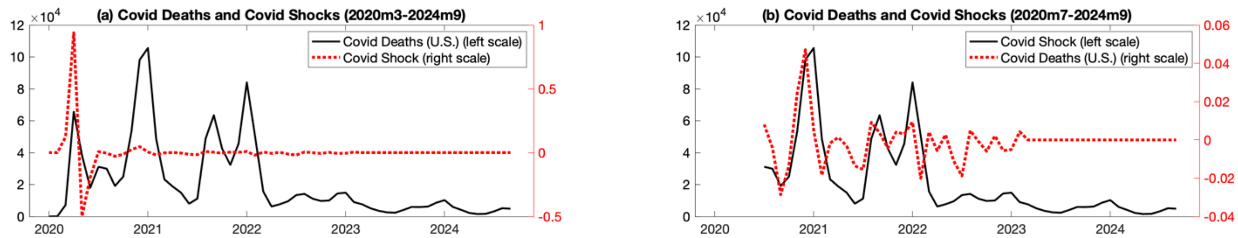


Figure 11: Decomposition of the COVID and conventional factors into COVID and conventional shock components

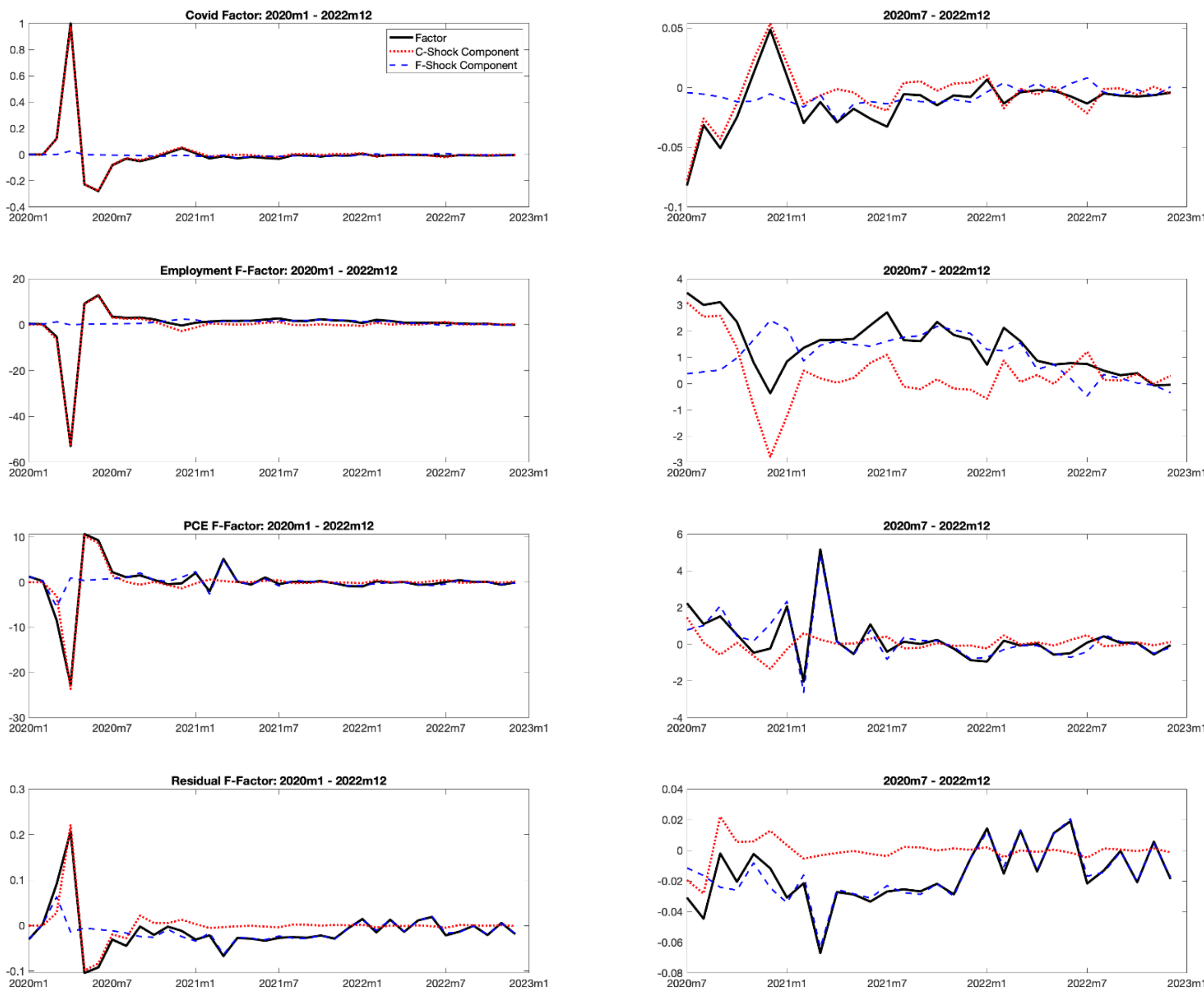


Figure 12: Decomposition of monthly growth of consumption and selected components into COVID and conventional shock components

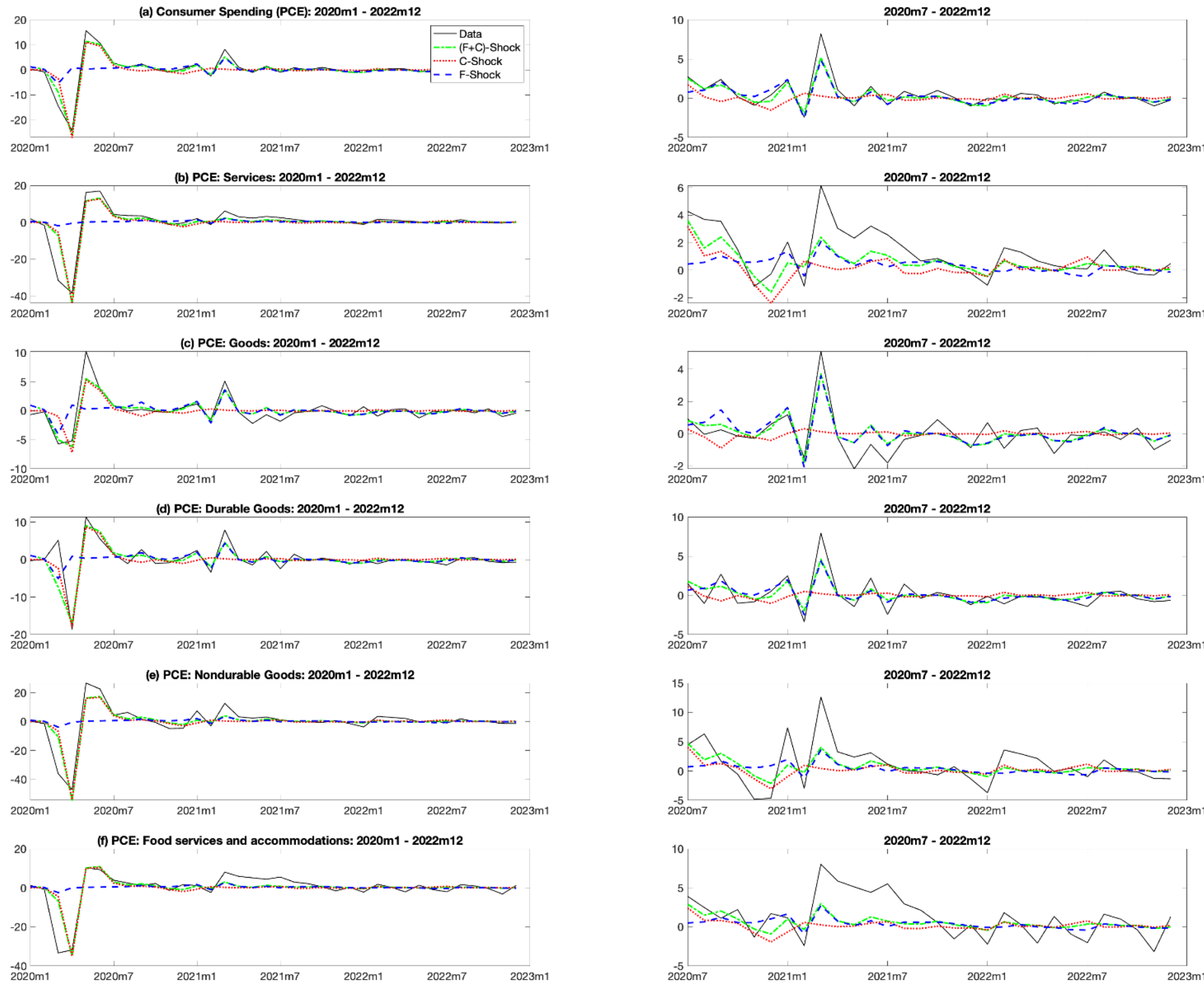
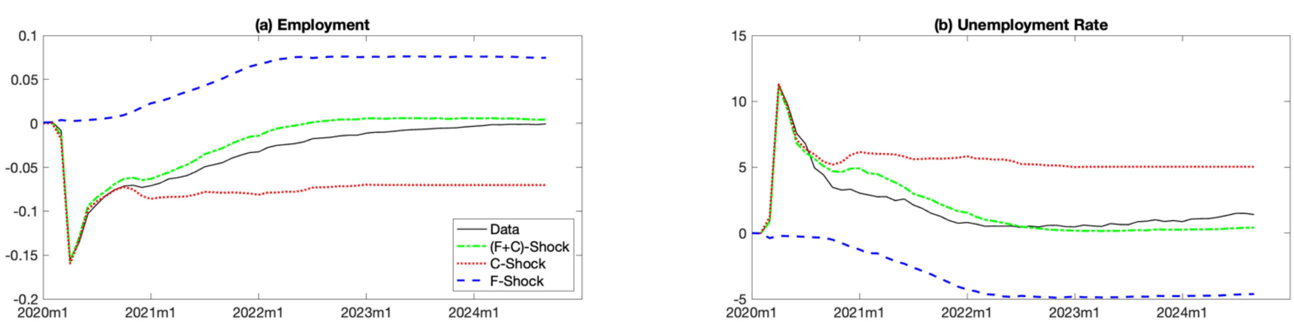
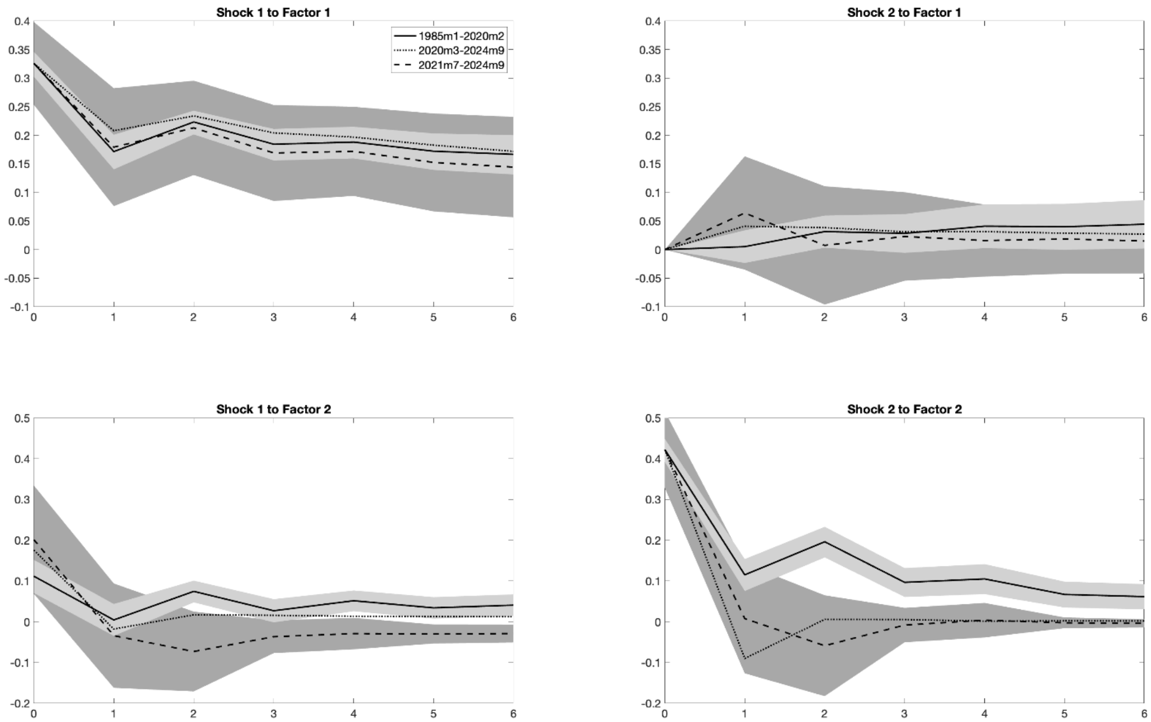


Figure 13: Decompositions of payroll employment and the unemployment rate (levels) into COVID and conventional shock components



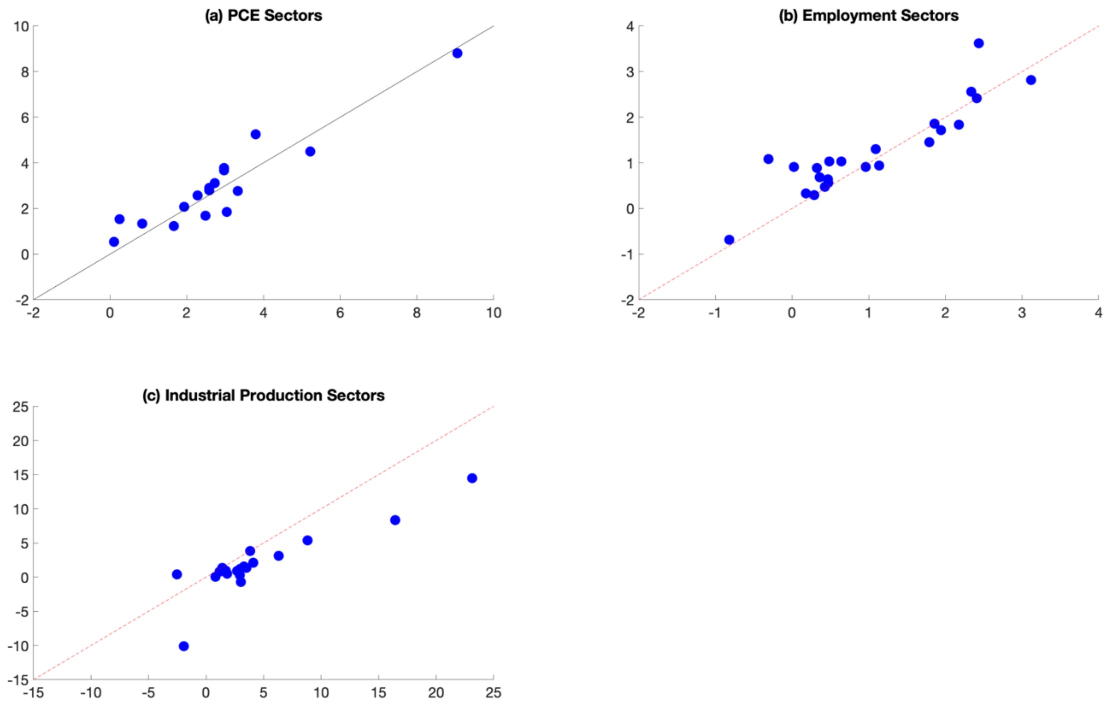
Notes: Values are differences from their values in 2020m1. The logarithm of employment is shown in panel (a) and the level of the unemployment rate in panel (b).

Figure 14: F-to-F impulse response functions $\Theta_{FF}(L)$ for the first and second F factors: Pre-COVID and COVID sample estimates



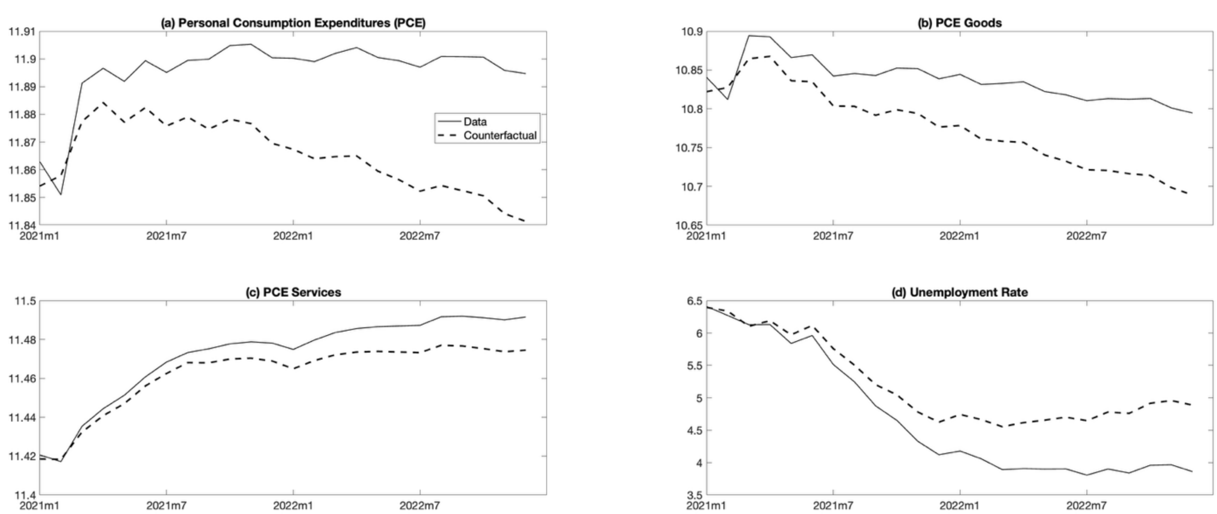
Notes: Impulses use Cholesky factorization with the employment factor ordered first and the PCE factor ordered second. Shading denotes 95% error bands for the pre-COVID (light) and 2021m7-2024m9 (dark) samples. Shock standard deviations over the periods 1985m1-2020m2, 2020m3-2024m9, and 2021m7-2024m9 are respectively 0.33, 0.43, and 0.34 for the first shock and 0.42, 1.24, and 0.42 for the second shock.

Figure 15: Smoothed growth rates of sectoral real activity for 2024:III v. 2019:IV, with 45º line.



Note: Smoothed growth rate at indicated dates is one-sided exponential average with discount factor 0.95. Values for 2019:IV are shown on the x-axis and values for 2024:III are on the y-axis.

Figure 16: Counterfactual prediction for GDP and the unemployment rate absent the fiscal stimulus of January – March 2021.



Note: Logarithms of PCE are shown in panels (a)-(c)

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 7-10		Months 11-20	
Indicator	**1960-2010**	**2020**	**1960-2010**	**2020**	**1960-2010**	**2020**
Unemployment rate	-0.016	-1.526**	-0.073	-0.321*	-0.031	-0.556**
	(0.037)		(0.051)		(0.035)	
Personal income less transfers	0.030	0.181**	0.033	-0.011	0.041	0.038
	(0.006)		(0.008)		(0.005)	
Industrial production	0.082	0.262*	0.058	-0.032	0.040	0.069*
	(0.012)		(0.015)		(0.01)	
Employment	0.010	0.177**	0.020	0.02	0.017	0.052*
	(0.004)		(0.006)		(0.003)	
Employment-goods	-0.005	0.148**	0.014	0.01	0.006	0.041**
	(0.008)		(0.009)		(0.006)	
Employment-services	0.014	0.225**	0.024	0.028	0.024	0.062*
	(0.003)		(0.008)		(0.002)	
Emp-accomodations & food ser	-0.009	0.86**	0.013	-0.053*	0.020	0.167**
	(0.007)		(0.006)		(0.004)	
PCE-goods	0.041	0.454**	0.056	0.013	0.039	0.061*
	(0.02)		(0.02)		(0.011)	
PCE	0.037	0.346**	0.047	0.013	0.035	0.082*
	(0.009)		(0.01)		(0.006)	
PCE-nondurable goods	0.023	0.284**	0.033	-0.004	0.029	0.075*
	(0.013)		(0.014)		(0.009)	
PCE-durable goods	0.090	0.803**	0.109	0.043	0.058	0.036
	(0.051)		(0.05)		(0.025)	

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. Month 0 is the cyclical trough. Personal income and consumption are real. Post-April 2020 trough absolute growth exceeds **5 or *1.5 times the mean pre-COVID growth for the comparable pre-COVID expansion window.

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 utilities (excl. energy)	21.6
Housing and utilities (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.

Table 3: 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	2.42	2.51
Nonfarm Business Sector: Labor Productivity (Out	1.96	2.02	1.68	1.67
Employment (CES)				
Employment (CES): Total Nonfarm	2.33	1.11	1.32	1.43
Employment (CES(: Goods Producing	0.70	-0.44	0.95	1.09
CES: GD: Manufacturing	0.84	-0.92	0.42	0.47
CES: Private Service Producing	3.10	1.68	1.64	1.63
CES: SE:Wholesale Trade	2.28	0.39	0.49	1.03
CES: SE: Retail Trade	2.88	0.56	0.18	0.33
CES: SE: Prof and Bus Services	3.58	2.31	1.94	1.71
CES: Government	2.54	0.78	0.51	0.92
Personal Consumption Expenditures				
Total	3.67	2.69	2.42	2.73
PCE: Q Goods	3.40	3.26	3.35	3.30
PCE: Q Durable goods	5.21	5.20	5.27	4.89
PCE: Q Nondurable goods	2.62	2.21	2.40	2.49
PCE: Q Services	3.93	2.40	1.97	2.47
Industrial Production				
Total Index	3.18	1.67	0.56	0.49
Consumer goods	4.75	2.27	2.79	1.53
Materials	5.22	2.74	5.05	2.68
Manufacturing	5.17	3.14	4.94	2.55
Gross Private Domestic Investment	3.89	3.57	3.50	3.41
Government consumption expenditures and gross	2.64	1.27	1.54	1.87
Personal Income	3.71	2.62	2.62	2.30
Personal Income Excluding Transfers	3.49	2.41	2.59	2.31

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