Comovement of Economic Activity During the Covid Recession

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Danila Maroz
Department of Economics, Harvard University

James H. Stock
Department of Economics, Harvard University
and the National Bureau of Economic Research

and

Mark W. Watson*
Department of Economics and School of Public and International Affairs, Princeton University
and the National Bureau of Economic Research

Abstract

This paper asks whether the comovement of economic activity across different sectors in the United States was different during the Covid recession than during preceding recessions. A dynamic factor model fit to data for the pre-Covid period is used to characterize historical patterns of comovement. When extrapolated over the Covid period, the fitted values from this model show how the various sectors were predicted to evolve based on their pre-Covid correlations. The paper documents large deviations from these predicted patterns. Including an additional factor for the Covid period improves the fit substantially. This new 'Covid factor' takes on large values from March to June 2020, but was less important after June 2020. This Covid-factor augmented model provides a parsimonious representation of comovement during the Covid recession and its aftermath.

Key words: Dynamic factor model, pandemic, business cycles
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* Replication files are available at http://www.princeton.edu/~mwatson.

1. Introduction

Recessions are not all alike. They arise from different causes and evolve from different initial conditions. Sectors behave differently in different recessions. That said, there are well-documented regularities: consumption falls less than income; consumption of durables falls more than consumption of services; employment lags production, and so forth. This paper looks at comovement of different economic sectors during the Covid recession and asks whether these comovements were consistent with historical precedent. We find large, but relatively short-lived, deviations from regular patterns of comovement.

We carry out the analysis using a large cross section of real economic indicators. A small-dimensional dynamic factor model (DFM) estimated using pre-Covid data is used to measure the historical patterns of comovement. Extrapolating this pre-Covid DFM over the post February 2020 period shows how the sectors of the economy would have behaved had they followed their pre-Covid patterns. We find large deviations from these historical patterns for some sectors. Taken as a whole, these deviations are themselves well described by a DFM with one factor, and the resulting 'Covid factor' and factor loadings serve as a parsimonious representation of the special nature of comovement during the Covid recession and its immediate aftermath.

This paper is related to two strands of literature. First, it is motivated by the descriptive literature on business cycles going back to Burns and Mitchell (1946) and earlier, and the use of dynamic factor models to describe this comovement, notably Sargent and Sims (1977), Stock and Watson(1989, 2002), Forni and Reichlin (1998), and many others. (See Stock and Watson (2016) for a survey and Stock and Watson (2012) for an exercise like the one carried out here, but for the 2007-2009 recession). This paper is also related to a recent literature that investigates special methods to handle the unique features of the Covid recession. Examples include Carriero, Clark, Marcellino and Mertens (2021), Lenza and Primiceri (2020), Diebold (2020), Antolin-Diaz, Drwchsel and Petra (2021), and especially Ng (2021), which also modifies a pre-Covid DFM to better fit the Covid recession.

The plan of the paper is as follows. Section 2 describes the data, presents some initial descriptive statistics, and describes the pre-Covid factor model. Section 3 is the heart of the paper and discusses how the factor model fares during the Covid period and proposes a one-factor modification that captures many of the unique features of the Covid recession. Section 4 concludes.

2. Data, descriptive statistics, and pre-Covid DFM

We use data on 127 real economic indicators, observed at a monthly frequency over the sample period 1959:M3 through 2021:M10. The pre-Covid sample period is 1959:M3-2020:M2, and the Covid period is 2020:M3-2021:M10. The data cover different categories of personal consumption expenditures, personal income, housing starts, employment, and industrial production. Table 1 shows the number of series by category; a detailed list is given in the replication files. The data set includes 89 subaggregates together with 38 aggregates in the various categories. The factors from the DFM model are estimated using the subaggregates, and these estimated factors are then used to describe the comovement of all the variables in the full dataset.

We apply five transformations to the raw data. First, with two exceptions, the variables are converted to growth rates as the first difference of logarithms. The exceptions are the unemployment rates (overall, and by duration) and labor force participation rate, all of which are first differenced. Second, a handful of the series contain large idiosyncratic outliers in the pre-Covid period; these outliers are coded as missing values and dropped from the analysis. During the Covid period, outliers are omnipresent and are not removed. Third, we locally demean each series using a bi-weight weighted average with bandwidth of 100 months. These local means are computed over the pre-Covid period, and the local mean from 2020:M2 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 are standardized using standard deviations estimated over the pre-Covid period. Fifth, most of the series are pro-cyclical, but a few, like the unemployment rate, are countercyclical; countercyclical series are multiplied by -1. (A series is categorized as countercyclical if its 12-month moving average is negatively correlated with the 12-month moving average of the growth rate of Industrial Production over the pre-Covid period.) These transformations yield variables that have a mean of zero, are pro-cyclical, and are measured in pre-Covid standard deviation units.

We computed the cross-section distribution of these 127 series for each month in the sample, and Figure 1 plots selected quantiles of these distributions. Panel (a) shows the pre-Covid period. Recessions are easily recognized in the figure as they are associated with 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. 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.

Panel (b) shows the quantiles over the Covid period. It shows a similar negative shift and skew during the Covid recession, but the scale of the shift is an order magnitude larger than in the pre-Covid period. For example, during the Great Recession of 2007-2009 the lowest values of the median and 25th percentile of the cross-section distribution were -1.7 and -2.8 standard deviations; in the Covid recession these were -14.8 and -25.8.

As is widely documented for the pre-Covid sample, comovement of these real economic indicators is well captured by a small number of common factors in a DFM. (See Stock and Watson (2016) for a survey.) In our dataset of 89 sub-aggregates and over 1959:M3-2020:M2, one factor explains 14% of variability in the series (that is, the average R^2 across the 89 series is 0.14 for the one-factor model), and this increases to 22% using three factors. The Bai-Ng (2002) information criterion is roughly indifferent between one and two factors, and this result is robust to using the whole pre-Covid sample or beginning the sample in 1984. Stock and Watson (2016) use a three-factor model for a related dataset, and we will use three factors in the results presented here. Results with two factors are very similar and are available in the replication files.

Because we will extrapolate this model over the Covid period, it is useful to introduce some notation for the various factor weights, factor loadings, and so forth. Let Y_t denote the 127×1 vector of observations available at month t, F_t denote the 3×1 vector of factors, Λ the 127×3 vector of factor loadings, and u_t the sector-specific errors. The factor model is:

$$Y_t = \Lambda F_t + u_t \tag{2.1}$$

Partition Y_t as $(Y_{SA,t}{}'\ Y_{AG,t}{}')'$ where $Y_{SA,t}$ denotes the 89 subaggregates and $Y_{AG,t}$ denotes the remaining aggregate variables. Partition Λ analogously. Using the data from the pre-Covid sample, the estimated factors and factor loadings for the subaggregates solve the least squares problem

$$\min_{\hat{\Lambda}_{SA},\hat{F}} \sum_{i=1}^{89} \sum_{t=1959:M3}^{2020:M2} d_{i,t} (Y_{SA,i,t} - \hat{\Lambda}_{SA,i} \hat{F}_t)^2 \tag{2.1}$$

subject to $T^{-1}\sum_{t=1959:M3}^{2020:M2} \hat{F}_t \hat{F}_t' = I_3$, where $d_{i,t} = 0$ when $Y_{SA,i,t}$ is missing and $d_{i,t} = 1$ otherwise. (When the panel is balanced, that is $d_{i,t} = 1$ for all i and t, the least squares estimators coincide with the principal components estimators of F_t and Λ_{SA}.) The factor loadings for the aggregates are estimated by regressing $Y_{AG,t}$ onto $\hat{F}_t$ by OLS, again using the pre-Covid sample period. Denote the resulting estimated factor loadings by $\hat{\Lambda}$, the fitted values as $\hat{Y}_t = \hat{\Lambda}\hat{F}_t$ and the residuals as $\hat{u}_t = Y_t - \hat{Y}_t$.

Figure 2 plots selected quantiles of the month-to-month cross-section distribution of the residuals. Unlike Figure 1, there is little evidence of cyclicality in the cross section of $\hat{u}_t$. Evidently, after conditioning on the estimated factors, cyclical comovement in the series has been eliminated.

3. Comovement during the Covid recession

3.1 Out-of-sample fit of the 3-factor model

We extrapolate the 3-factor model over the Covid period as follows: First we estimate the factors using the pre-Covid estimators factor loadings $\hat{\Lambda}_{SA}$ together with the Covid-period values of $Y_{SA,t}$. These factors correspond to weighted averages of the data over the Covid period that summarize their pre-Covid patterns of comovement. We then compute the fitted values $\hat{Y}_t = \hat{\Lambda}\hat{F}_t$ which represent the values of Y_t over the Covid-period that are predicted by the patterns of comovement during the pre-Covid period.

We use two estimators for F_t during the Covid period. Both are computed using cross-sectional regressions of $Y_{SA,t}$ onto the pre-Covid estimated factor loadings. The first is the ordinary least squares (OLS) estimator: $\hat{F}_t^{OLS} = (\hat{\Lambda}_{SA}'\hat{\Lambda}_{SA})^{-1}\hat{\Lambda}_{SA}'Y_{SA,t}$, which is the estimator used in the pre-Covid period. The second estimator, $\hat{F}_t^{WLS}$, uses weighted least squares (WLS) to reduce the influence of outliers in the cross-sectional distributions during the Covid period.

To motivate the WLS estimator, consider the cross-section distribution of $Y_{SA,t}$ in 2020:M4. The median of the elements in $Y_{SA,\text{2020:M4}}$ is −10 (pre-Covid) standard deviations and the 25th percentile is −25 standard deviations. These large negative values indicate a dramatic *absolute* decline in economic activity in April 2020. But, some sectors experienced dramatic declines *relative* to the other sectors. For example, in 2020:M4 employment in *Accomodation and Food Service* sector experienced a drop of -275 standard deviations, *layoffs* increased by 140 standard deviations, and employment in *Arts and Entertainment* and *Healthcare and Social Assistance* showed similarly large changes. These sectors represent outliers relative to other sectors in the 2020:M4 cross section. In other months of the Covid-sample, relatively extreme changes in other sectors produce outliers. The WLS estimator of F_t downweights the outlying sectors that occur in month t.

We model outliers using the mixture-of-normals outlier distribution from Marron and Wand (1992). Specifically, the model assumes that

$$u_{SA,i,t} \sim iid \begin{cases} N(0,\sigma_t^2) \text{ with probability } 0.90 \\ N(0,(10\sigma_t)^2) \text{ with probability } 0.10 \end{cases} \tag{3.1}$$

so that the month t cross-section distibution is a mixture of random variables with standard deviations σ_t and $10\sigma_t$. While this is undoubtedly an over-simplified characterization of the evolution of u_t, it captures two important features of the cross-section distribution: time variation in the cross-sectional dispersion (through σ_t) and the presence of outliers. It also allows for a straightforward weighting scheme for estimating F_t: sectors that are outliers in month t are downweighted by a factor of 10 relative to other sectors.

Of course, whether a sector is an outlier (that is, is a draw from the $N(0,(10\sigma_t)^2)$ distribution) or not, is unknown and needs to be estimated from the data. We use Bayes calculations for this. Specifically, we suppose that $Y_{SA,i,t} = \Lambda_{SA,i}F_t + u_{SA,i,t}$, where $u_{SA,i,t}|(\Lambda_{SA}, \mathbf{F}, \boldsymbol{\sigma})$ has the outlier distribution (3.1) during the Covid period, and where $(\mathbf{F},\boldsymbol{\sigma})$ denotes the values of (F_t, σ_t) over the Covid period. We estimate the posterior for $\mathbf{F}$ using a diffuse prior for $(\mathbf{F},\boldsymbol{\sigma})$ and the plugin etimator $\Lambda_{SA} = \hat{\Lambda}_{SA}$ from the pre-Covid period. The mean of the posterior is the weighted least squares estimators, $\hat{F}_t^{WLS}$.

Figure 3 shows a scatter plot of Y_t against $\hat{Y}_t$; panel (a) shows the (in-sample) pre-Covid period, and panel (b) and (c) show the (out-of-sample) Covid period for the OLS and WLS estimates. Note that the scales are different in the pre-Covid and Covid period, consistent with the increase in variance during the Covid period. The three factors in F explain 27% of the variance in Y during the pre-covid period, so $R^2 = 0.27$ in panel (a). The R^2 is slightly *higher* in panel (b) ($R^2 = 0.30$) and slightly lower in panel (c) ($R^2 = 0.23$). That said, the RMSE increases by an order of magnitude in Covid period from 0.85 standard deviations in panel (a) to over 10 standard deviations in panels (b) and (c).

Figure 4 plots time series for eight series over the the 2019:M1-2021:M10 period, along with their fitted values from the factor model estimated by WLS. (The replication files contain analogous figures for all of the series for both the WLS and OLS fitted values.) The fitted values capture the historical pattern of comovement, and the figure indicate that these patterns explain some of the variability that occurred during the Covid period. That said, much of the variability is left explained. For example, the pre-Covid factor model predicts a 10-standard deviation increase in *layoffs* in 2020:M4 (panel (a)), but in fact layoffs increased by over 140 standard deviations. Moreover, the sudden increase in layoffs changed the typical pattern of unemployment duration (panel (e)), which is missed entirely by the factor model. The historical factors predicts that employment in the *Accomodations and Food Services* should have fallen 27 standard deviations in 2020:M4, but in fact employment in this sector fell by 275 standard deviations. PCE in *Healthcare* fell much more than predicted, while PCE in *Furnishing and Durable Household Equipment* fell by less. The plots for the 127 variables, which are available in the replication files, show similarly large differences from historical patterns in many of the sectors; this conclusion is robust to using the WLS or OLS fitted values.

3.2 A Covid factor model

These results indicate that the Covid recession was markedly different from other recessions, and it is useful to have a simple and convenient way to summarize the unique comovement during the Covid recession. One way to do this is to augment the three historical factors with an additional Covid factor, say G_t, where $G_t = 0$ during the pre-Covid period, but takes on non-zero values during the Covid period. The resulting factor model is:

$$Y_t = \Lambda F_t + \Gamma G_t + u_t \tag{3.2}$$

where Γ is a vector of factor loadings for the new Covid factor. In this formulation, ΛF_t measures variability in the series captured by the historical, pre-Covid comovement in the series, while ΓG_t measures variability captured by the residual comovement over the Covid period, and u_t captures sector-specific variability.

Three normalizations are imposed to identify the Covid factor. The first, $G_t = 0$ in the pre-Covid period has already been mentioned. The second is that $G_{2020:\mathrm{M4}} = -1$, which fixes the scale of the Covid factor. The third is that $\Lambda'\Gamma = 0$, which assigns all comovement in the column of space of Λ to F; only the remaining comovement is attributed G.

We estimate (3.2) using the subaggregates, $Y_{SA,t}$, using both OLS and a version of WLS. The OLS estimator is straightforward and amounts to estimating Γ_{SA} and G_t using principal components applied to $Y_{SA,t} - \hat{\Lambda}_{SA}\hat{F}_t^{OLS}$ over the Covid period.

The weighted least squares estimator uses the mixed-normal outlier model (3.1) for $u_{SA,t}$. As in the F-only model, the resulting estimator downweights outlying sectors in each monthly cross section when estimating the (F,G)-factors. In addition, because the cross-section standard deviation, σ_t, varies through time, the factor loadings in Γ_{SA} are estimated using values of $Y_{SA,t}$ with time-varying weights that are proportional to $1/\sigma_t$. As in Section 3.1, Bayes methods are used to construct a feasible estimator: we suppose that $Y_{SA,i,t} = \Lambda_{SA,i}F_t + \Gamma_{SA,i}G_t + u_{SA,i,t}$, where $u_{SA,i,t}|(\Lambda_{SA}, \mathbf{F}, \Gamma_{SA}, \mathbf{G}, \boldsymbol{\sigma})$ has the outlier distribution (3.1) during the Covid period. We compute the posterior for $(\mathbf{F}, \Gamma_{SA}, \mathbf{G}, \boldsymbol{\sigma})$ using diffuse priors for $(\mathbf{F}, \Gamma_{SA}, \mathbf{G}, \boldsymbol{\sigma})$ after imposing the constraints $G_{2020:\mathrm{M4}} = -1$ and $\Lambda_{SA}'\Gamma_{SA} = 0$, and use the plugin etimator $\Lambda_{SA} = \hat{\Lambda}_{SA}$ from the pre-Covid period. We use the posterior means as the weighted least squares estimators. Finally, we estimate Γ_{AG}, the factor loadings for the aggregates, using WLS after conditioning on (F_t, G_t, σ_t) – a convenient shortcut that ignores correlation between the aggregates and subaggregates.

Figure 5 plots the OLS and WLS estimates of G. Figure 6 presents a scatter plot of Y_t and its fitted value $\hat{Y}_t = \hat{\Lambda}\hat{F}_t + \hat{\Gamma}_t\hat{G}_t$ using WLS. (The replication files contain the scatter plot using the OLS fitted values.) Figure 7 plots the estimates of σ_t. We make four comments. First, the estimated Covid factor captures the sharp drop in real economic activity in April 2020 and the rebound in May and June. To a first approximation, the single Covid factor captures the unusual comovement of the various sectors in March-June 2020 but suggests that much of the comovement after June 2020 is captured by the historical factors F, without the need of the additional Covid factor. This result is robust to using OLS or WLS. Second, the fit of the model improves significantly when the Covid factor in included. In Figure 6 the $R^2 = 0.80$ compared to $R^2 = 0.23$ from Figure 3(c) which did not include the Covid factor. Third, from Figure 7, after controlling for the Covid factor, the cross-section standard deviation of u is higher in the Covid period, but far less than suggested when looking at the raw data in Figure 1(b). Fourth, at the end of the sample in 2021:M10, the estimated Covid factor is close to zero, and the estimated value of σ_t is only slightly larger than its value before the pandemic. This suggests that the real economy had nearly returned to pre-Covid comovement patterns by 2021:M10.

The value of Γ, the factor loadings on the Covid factor, provides a useful summary for the unusual comovement of each series during the Covid recession. Recall that the scale of G is chosen so that $G_{2020:\text{M4}} = -1$ and that the data are measured in pre-Covid standard deviation units. Thus, Γ_i shows the standard deviation decrease in $Y_{i,2020:4}$ associated with the Covid factor. Table 2 lists the values of Γ_i (estimated by WLS) for 34 of the sub-aggregates ordered by the value of Γ_i. (The online appendix includes the complete list and also includes the OLS estimates of Γ.) For example, the last entry in the table shows that $\Gamma_i = 226$ for employment in the *Accommodation and food service* sector, which indicates that the Covid factor explains 226 of the 275-standard deviation decline in April 2020 that was evident in Figure 4. Similarly (from the first entry in the table), the Covid factor explains 128 of the 140-standard deviation increase in *layoffs*.

Figure 7 plots the same series as in Figure 4, but now including the fitted values from the factor model augmented with the Covid factor. The fits are a marked improvement over those using on the pre-Covid factors, but there are noteworthy residuals for some series. For example, the Covid factor captures the large increase in government transfer payments in 2020:M4, but explains little of the large increase in at the end of 2020 and beginning of 2021; that is, the large movement in April 2020 coincided with large movement in other series, but the large increases later in the sample did not. And, from panel (e), the Covid factor does not explain the unusual (based on *F*) timing of the rise of the longer-term unemployment rate.

Table 3 shows the values of Γ_i for each of the aggregates in the data set. It shows, for example, that at the trough of the recession, the growth rate of real personal income associated with the unique features of the Covid recession (as measured by the Covid factor) was 68 standard deviations higher than was predicted its comovement during pre-Covid recessions. Similary, the growth rate of employment in the private service producing sector was 42 standard lower, the consumption of durable goods was 20 standard deviations higher, and so forth.

Figure 8 shows the corresponding plots for eight of the key aggregates in the data set. Each of the aggregates exhibited important deviations from the path predicted by *F*. The additional Covid factor improves the fit significantly during the tumultuous first months of the Covid period.

4. Conclusions and additional remarks

The Covid recession and its immediate aftermath differed markedly from previous recessions. It was deep and sharp, and had unusual sectoral effects. The qualitative features of the Covid recession in the United States – government transfers were large, activity in the service and health sectors fell precipitously, durable goods and industrial production fared better, the timing and duration of unemployment was unusual, etc. – are well known. The contribution of the calculations summarized here is to quantify these features.

A somewhat surprising result of the analysis is that a single Covid factor can explain much of the novel comovement during the Covid period. In the monthly data, this factor is large and important from March-June 2020, but after June 2020, this factor adds little to pre-Covid patterns of comovement in the sectors.

One interpretation of these results is that cause-and-effect patterns of the Covid recession were substantially different than previous recessions. This presents challenges for using data from the Covid recession to answer traditional questions in macroeconomics, such as the effect of productivity or policy shocks. A straightforward empirical approach is to ignore the Covid period when investigating these traditional questions. This raises the question of defining the `Covid period' and chosing which dates to exclude and include. The analysis presented here suggests that variations in the data from March-June 2020 were dominated by unique factors related to Covid, so that these data should be ignored when studying non-Covid questions. Historical covariation patterns seemed to have returned in the latter part of 2020.

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Table 1: Economic Activity Indicators

Category	Number	Number of sub-aggregates
Personal Consumption Expenditures	23	17
Personal income	14	8
Housing starts and permits	10	8
Employment CES	30	23
Employment/Unemployment CPS	14	10
Industrial Production	37	23
Total	**127**	**89**

Notes: See replication files for a detailed description of the data series.

Table 2: Values of $\hat{\Gamma}$ ranked from smallest to largest: 89 subaggregates

Rank	Series	Γ
1	CPS: Layoffs	-128.4
2	PI: Gov Transfers to Persons real	-59.9
3	CPS: Unemployment rate, less than 5 weeks	-46.3
4	CES: Finance and Insurance	-36.3
5	CES: Construction	-35.2
6	PCE: Furnishings and durable household equipment	-31.8
7	IP: Construction supplies	-31.6
8	PCE: Recreational goods and vehicles	-30.9
9	PCE: Other nondurable goods	-30.8
10	PI: Personal Income Receipts on Assets real	-24.8
11	CES: Wholesale Trade	-24.2
12	IP: Equipment parts	-22.7
13	IP: Chemicals	-22.0
14	CES: Real Estate	-20.1
15	CES: Transportation and wharehousing	-19.9
16	CES: Information	-19.8
17	PCE: Clothing and footwear	-18.8
⋮	⋮	⋮
73	CES: Education services	17.1
74	PCE: Other services	19.0
75	PCE: Gasoline and other energy goods	23.4
76	PCE: Transportation services	26.7
77	CPS: Unemployment rate, 27 weeks and greater	27.5
78	CPS: Unemployment rate, 15 to 26 weeks	29.3
79	PCE: Food services and accommodations	32.9
80	CPS: Job losers, not on layoff	35.0
81	IP: Consumer parts	35.4
82	IP: Transit	39.9
83	PCE: Recreation services	41.0
84	IP: Automotive products	48.5
85	PCE: Health care	52.8
86	CES: Arts entertainment recreation	93.4
87	CES: Other Services	107.9
88	CES: Health care and social assistance	111.4
89	CES: Accomodation and food services	226.1

Notes: The table shows the values of the weighted least squares estimates of Γ. The prefixes are: HO is housing starts/permits, PI is personal income, PCE is personal consumption expenditures, IP is industrial production and CES and CPS are employment. The series are measured in pre-Covid standard deviation units and counter-cyclical series are *not* multiplied by -1. The Covid factor, G_t, is normalized to equal -1 in 2020:M4.

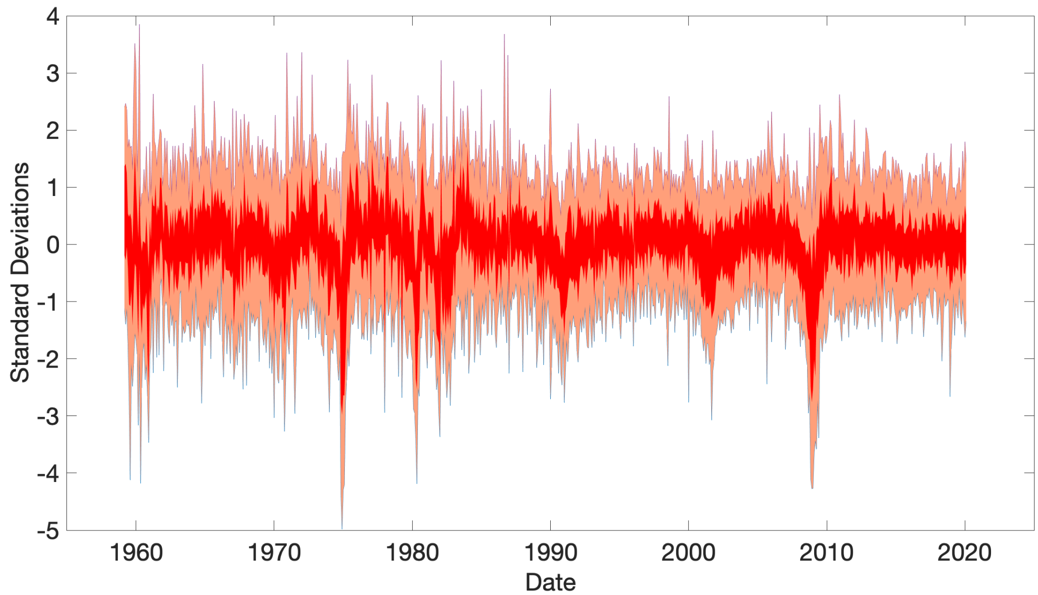
Table 3: Values of $\hat{\Gamma}$ ranked from smallest to largest: 38 aggregates

Rank	Series	Γ
1	PI: Personal current transfer receipts	-67.9
2	PI: Personal income	-55.9
3	CPS: Unemployed, job losers	-52.2
4	PI: Disposal Personal Income real	-46.7
5	CPS: Unemployment rate	-31.5
6	PCE: Goods	-26.2
7	CES: Goods producing	-25.6
8	PCE: Nondurable goods	-21.7
9	PCE: Durable goods	-20.5
10	PI: Real personal income excluding transfers	-17.0
11	PCE: Personal consumption expenditures	-14.3
12	PI: Wages and salaries	-12.0
13	HO: Housing starts	-11.8
14	IP: Non-energy materials	-10.9
15	IP: Nondurable manufacturing	-9.3
16	IP: Nondurable materials	-8.7
17	IP: Durable materials	-8.4
18	HO: Housing permits	-7.9
19	IP: Materials	-7.8
20	IP: Manufacturing (NAICS)	-5.9
21	PI: Proprietors income	-5.8
22	IP: Manufacturing (SIC)	-5.4
23	IP: Total index	-4.9
24	IP: Nondurable consumer goods	-3.6
25	IP: Final products and nonindustrial supplies	-3.0
26	IP:Durable manufacturing	-2.4
27	IP: Business equipment	-1.8
28	CES: State government	4.3
29	IP: Consumer goods	7.4
30	CES: Total private	11.3
31	CES: Government	12.1
32	CES: Local government	12.9
33	CES: Total nonfarm	13.6
34	CPS: Employment	24.4
35	IP: Durable consumer goods	25.0
36	PCE: Services	30.1
37	PCE: Household consumption expenditures for services	34.9
38	CES: Private service producing	42.1

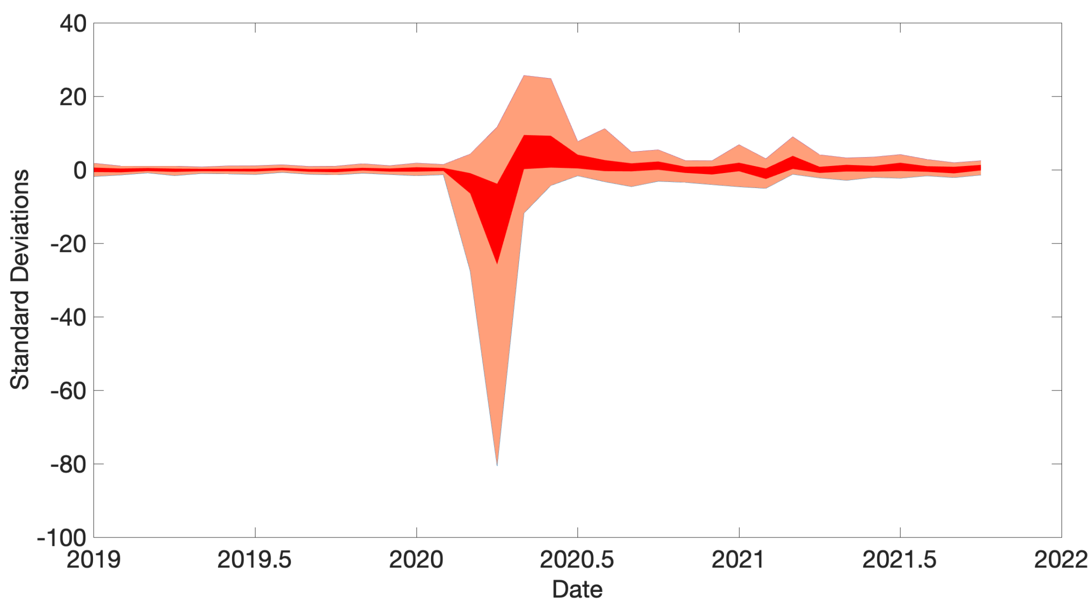
Notes: See notes to Table 2.

Figure 1: Cross-section quantiles of 127 activity variables
Dark Red: 25^{th} – 75^{th} quantile
Light Red: 5^{th} – 95^{th} quantile

(a) 1959:M3 – 2020:M2



(b) 2019:M1 – 2021:M10

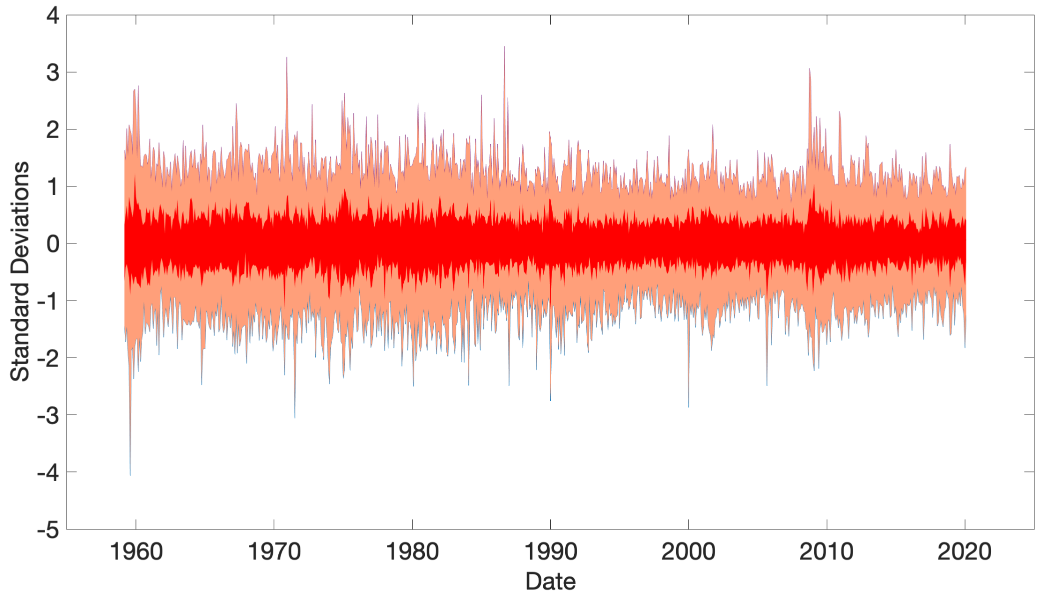


Notes: All variables are standardized using local-means and standard deviations over 1959:M3 – 2020:M2. Counter-cyclical series have been multiplied by –1.

Figure 2: Cross-section quantiles of $\hat{u}_t$ for 127 variables

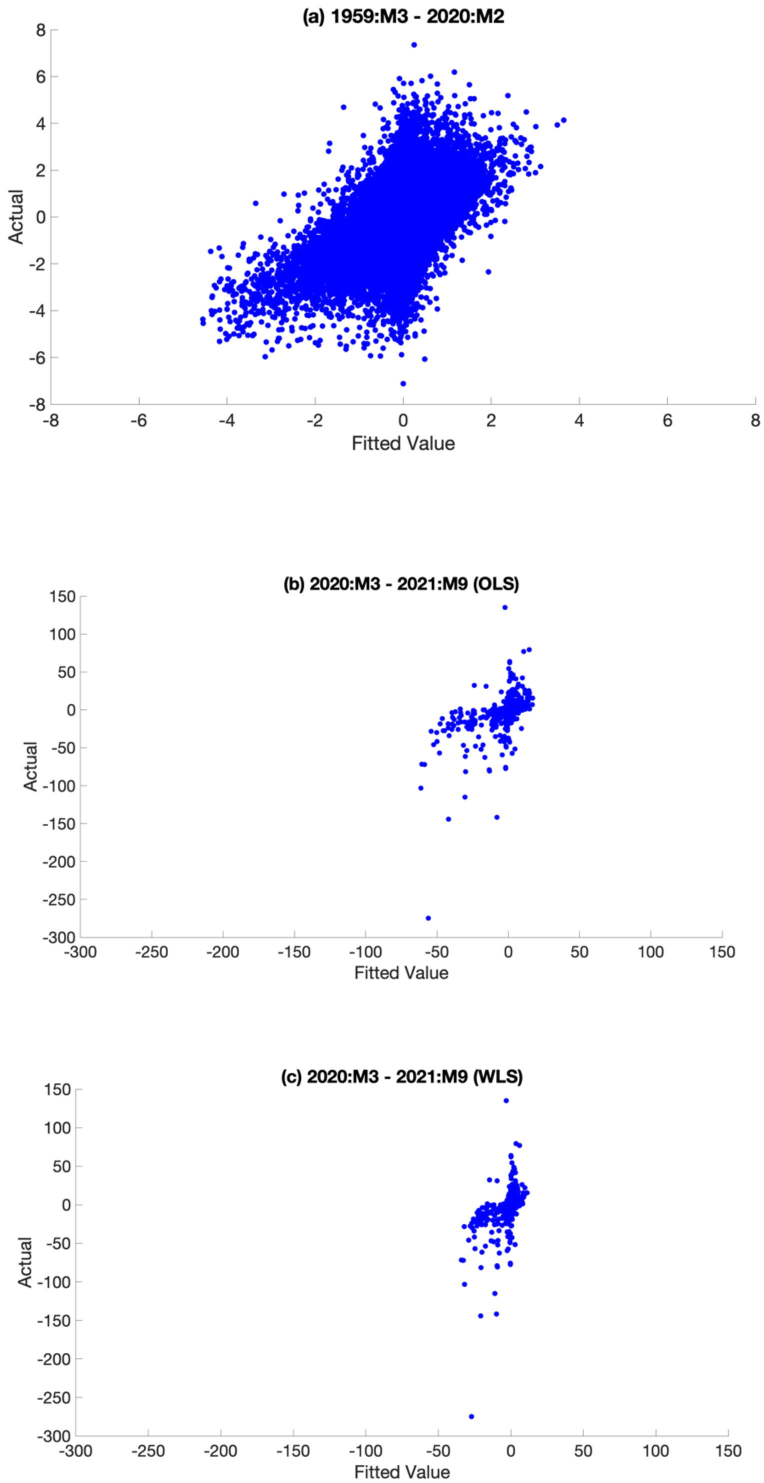
Dark Red: 25th – 75th quantile

Light Red: 5th – 95th quantile



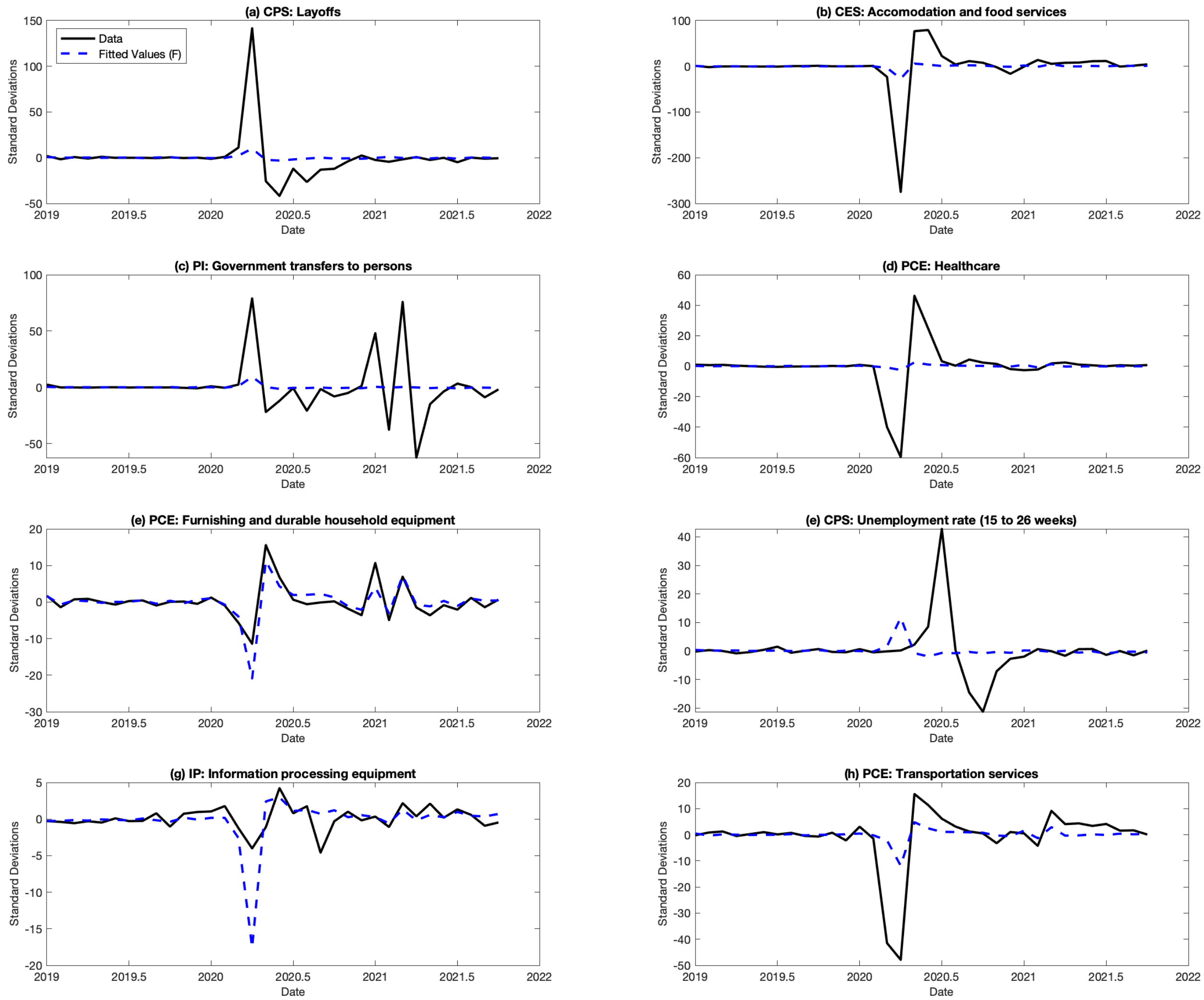
Notes: See notes to Figure 1.

Figure 3: Scatter plot of actual and fitted values from pre-Covid factor model



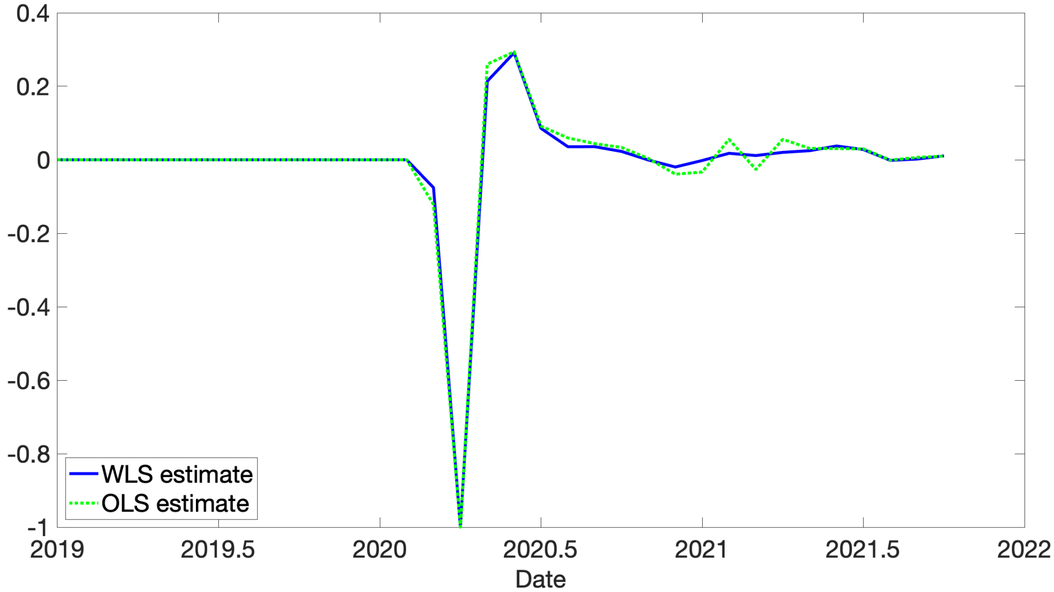
Notes: This is a scatter plot of $Y_{i,t}$ versus $\hat{Y}_{i,t} = \hat{\Lambda}_i{}'\hat{F}_t$ for all 123 series over the time periods shown.

Figure 4: Actual and (pre-Covid) fitted values for selected series



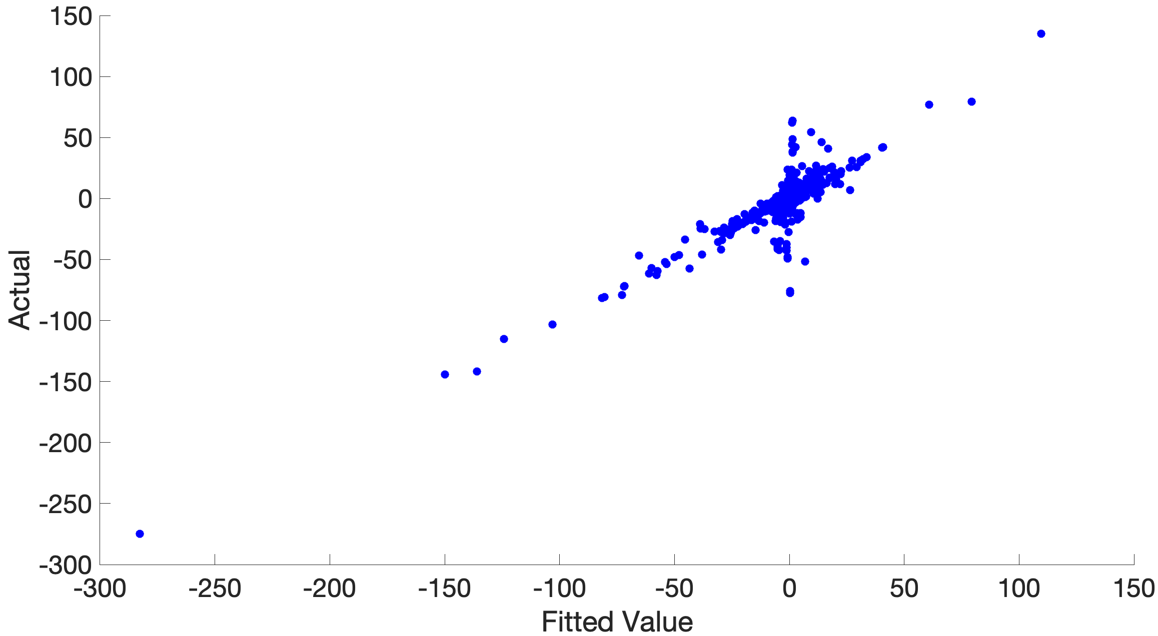
Notes: Series are standardized using in-sample values of (biweight) mean and standard deviation. Fitted values use the WLS estimates of F_t. The variables have their original sign, that is, countercyclical series are not Layoffs in (a) and the unemployment rate in panel (e) have their original counter-cyclical sign, that is, they are is not multiplied by -1.

Figure 5: Plots of Covid Factor, *G*



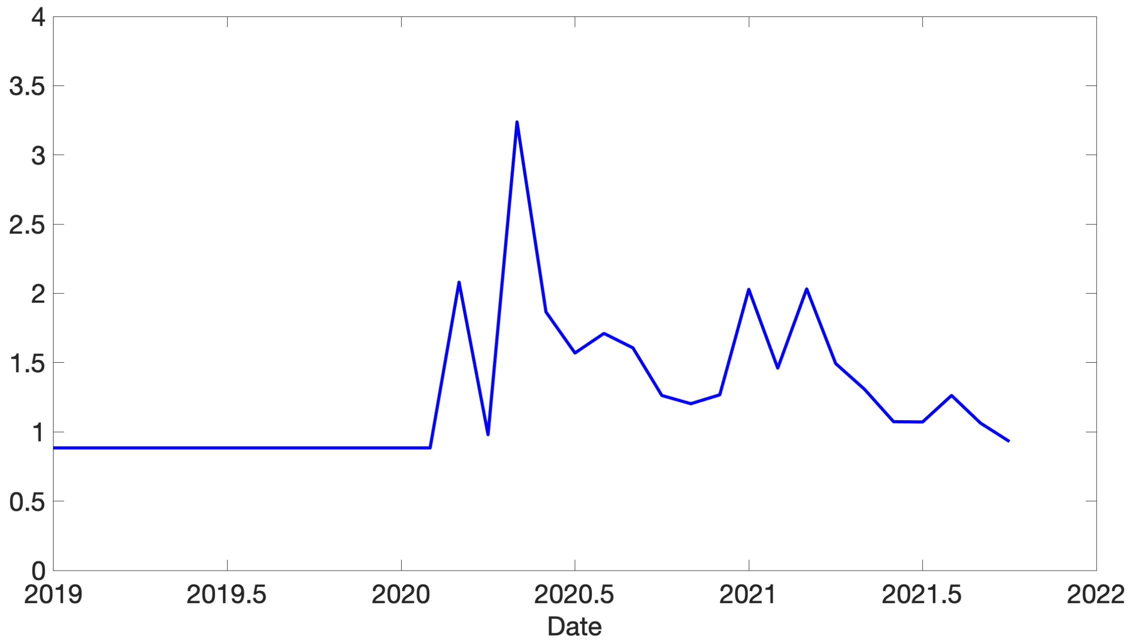
Notes: The factor is normalized so that $G_{2020:\mathrm{M4}} = -1$ and $G_t = 0$ in the pre-Covid period.

Figure 6: Actual versus fitted value from Covid-factor augmented model estimated by WLS: 2020:M3-2021:M10



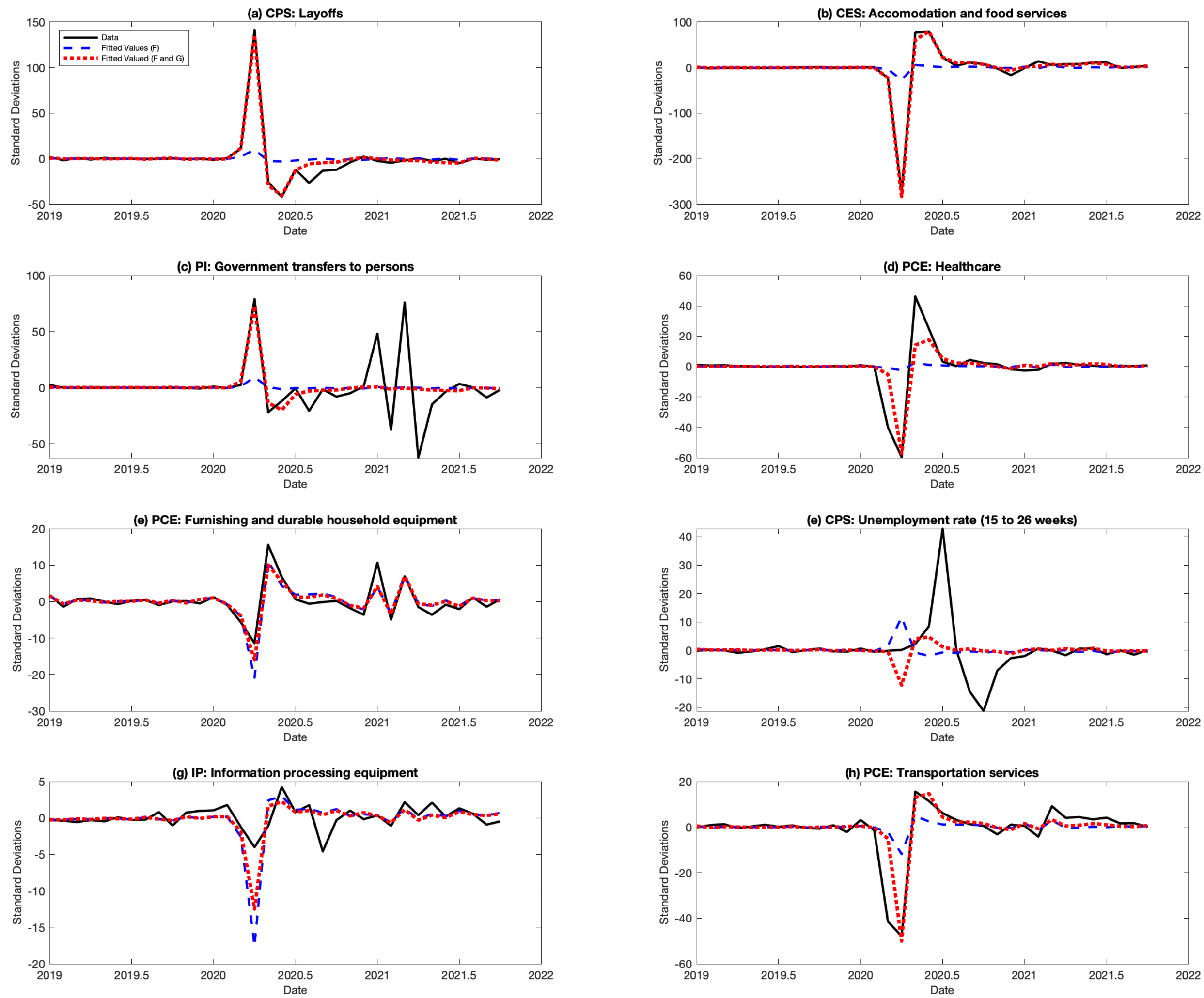
Notes: This is a scatter plot of $Y_{i,t}$ versus $\hat{Y}_{i,t} = \hat{\Lambda}_i'\hat{F}_t + \hat{\Gamma}_i\hat{G}_t$ for all 123 series over 2020:M3-2021:M10.

Figure 7: Cross-section variance, σ_t



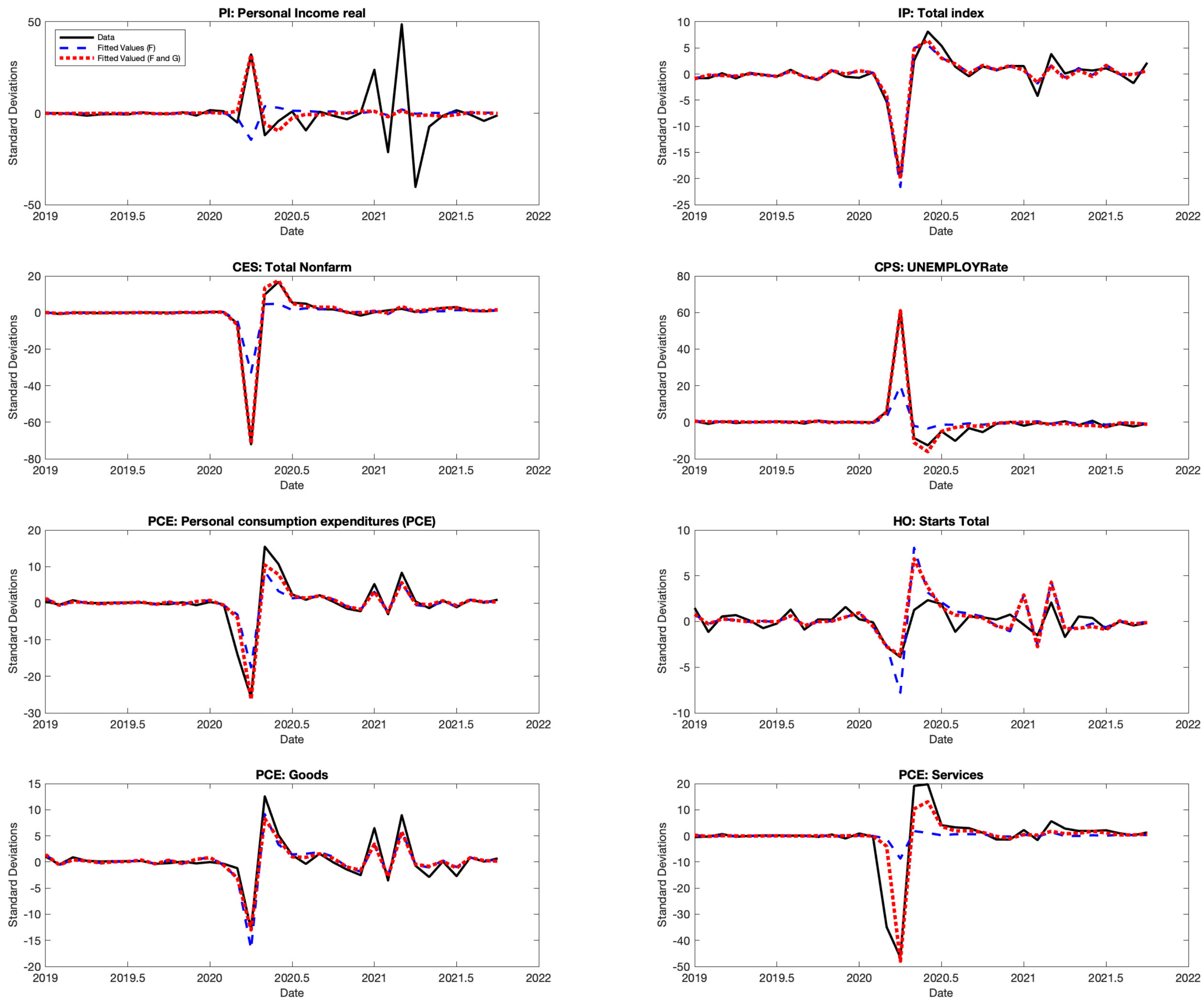
Notes: The pre-Covid value of σ_t is the pooled standard deviation in the cross-sections over 1959:M3-2020:M2.

Figure 7: Actual and fitted values for selected series



Notes: See notes the Figure 4.

Figure 8: Actual and fitted values for selected aggregate series



Notes: See notes to Figure 4