Measuring Real Activity Using a Weekly Economic Index[1]

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Abstract: This paper describes a weekly economic index (WEI) developed to track the rapid economic developments associated with the onset of and policy response to the novel Coronavirus in the United States. The WEI is a weekly composite index of real economic activity, with eight of ten series available the Thursday after the end of the reference week. In addition to being a weekly real activity index, the WEI has strong predictive power for output measures and provided an accurate nowcast of current-quarter GDP growth in the first half of 2020, with weaker performance in the second half. We document how the WEI responded to key events and data releases during the first 10 months of the pandemic.

JEL: E01, E66, C51

Keywords: Weekly Economic Index, High Frequency, Measurement of Economic Activity, Forecasting

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[1] Bi-weekly updates of the Weekly Economic Index are available at https://www.newyorkfed.org/research/policy/weekly-economic-index. The views expressed are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York, the Federal Reserve Bank of Dallas or the Federal Reserve System. Trivedi's contribution to the paper was completed prior to the author joining Amazon, while an employee of the Federal Reserve Bank of New York. We are grateful to Eric Qian and Christopher Simard for research assistance, to Tyler Atkinson for useful suggestions, and to Mark Booth for sharing the tax withholding data.

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I. Introduction

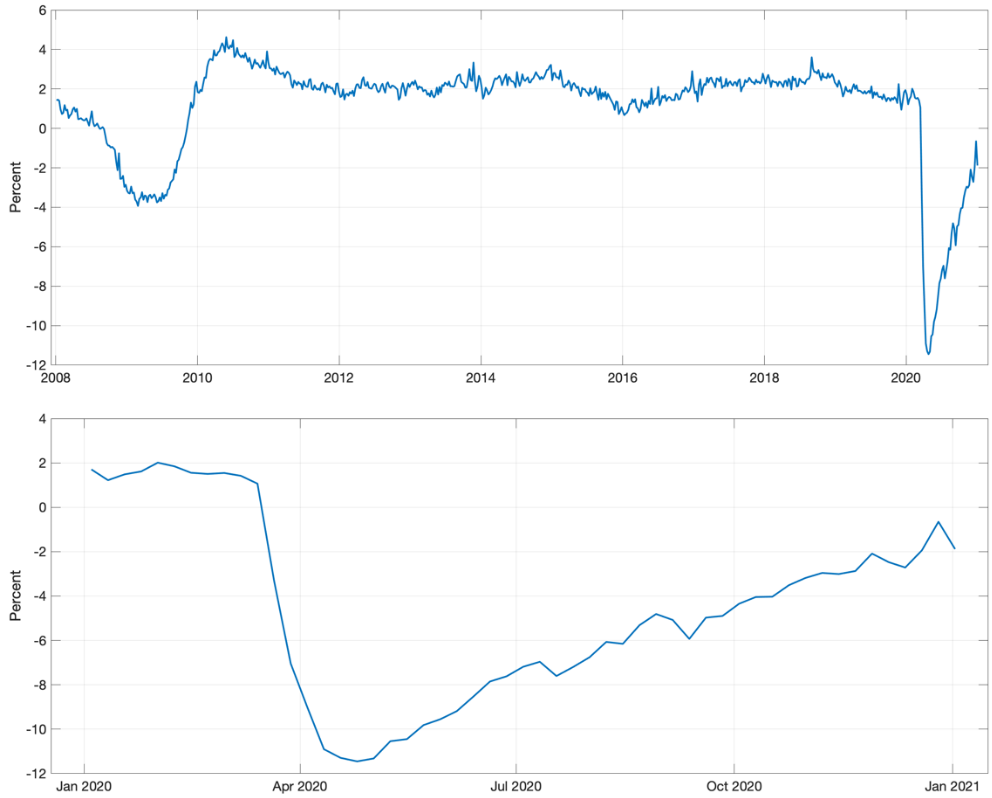
In normal times, real activity moves sluggishly so familiar monthly and quarterly macroeconomic data provide information on a time scale that is sufficiently granular for macroeconomic monitoring and forecasting. But when macroeconomic conditions instead evolve rapidly – on a time scale of weeks or even days, as was the case during the first half of 2020 – it is important to have a systematic measure of real economic activity available at higher frequencies to inform the policy and business communities.

This paper describes a weekly index of economic activity (the Weekly Economic Index, or WEI) computed as the first principal component of ten weekly measures of real economic activity, including consumption, labor input, and production. The goal of the WEI is two-fold: to measure fluctuations in real economic activity from week to week, and to provide a timely signal of real activity before conventional lower-frequency measures become available. With respect to the first goal, the index measures the change in overall macroeconomic activity during the reference week, which runs Sunday through Saturday, relative to the corresponding week one year earlier. For interpretability, the index is normalized to match the mean and standard deviation of four-quarter GDP growth. With respect to the second goal, eight of the ten constituent series are available by Thursday of the week following the reference week, five days after the end of the reference week. This index, and its fully revised version, which is available the next Thursday (12 days after the end of the reference week), provide a timely signal of the state of the economy.

The WEI aims to provide a weekly index of real activity, something a monthly or quarterly series – or existing mixed-frequency indices like the Aruoba, Diebold, and Scotti (2009) (ADS) index – cannot do. That said, as an ancillary benefit, the WEI can also be used to construct a nowcast of monthly and quarterly activity series. We show that the WEI contains useful information for nowcasting the monthly growth in industrial production and the quarterly growth in GDP. For example, in the second quarter of 2020, the WEI nowcast of second-quarter GDP growth, available 16 days after the end of the quarter, was for GDP to fall by 33.1 percent at an annual rate. According to the advance estimate released 30 days after the end of the quarter, Q2 GDP fell by 32.9 percent at an annual rate. According to the third release, available 93 days after the end of the quarter, Q2 GDP fell by 31.4 percent at an annual rate. The performance in Q3 was worse, considerably understating growth, although in Q4 the nowcast was off by only about 1 percentage point.

The top panel in **Figure 1** plots the WEI based on data through the reference week of January 2 2021. The trough of the Great Recession is clearly visible, as well as the subsequent recovery. The WEI index also shows a modest decline during the 2015-2016 mini-recession, during which the energy and agricultural sectors as well as certain segments of the manufacturing economy experienced substantial slowdowns in growth.

Figure 1: Weekly Economic Index (WEI)



Notes: Based on data available through the January 2, 2021 reference week. The units are scaled to 4-quarter GDP growth.

The bottom panel in **Figure 1** shows the evolution of the WEI from January 2020 to its most recent value. As is clear from the figure, developments related to the Coronavirus pandemic in March and April caused the index to fall to levels far below those of 2009 over the course of just a few weeks. The WEI reached a low point in the last week of April at a level of economic activity that was 11.5 percent below the level one year prior. The weekly turning points correspond to key developments in the pandemic and ensuing policy responses. Between early May and mid-July, the WEI recovered at a robust pace of roughly 40 basis points per week on average, pointing to a relatively fast pace of recovery in economic activity. Occasional reversals have coincided with resurgence in virus cases, renewed lockdowns, and the expiration of fiscal measures. Not until the week of October 24th did the WEI surpass -3.93, the value at the trough of the financial crisis recession.

The WEI is computed as the first principal component of the ten constituent weekly seasonally-adjusted real activity time series, using the sample from January 2008 through February 2020. Weekly seasonal adjustment is implemented by taking 52-week differences or log differences, depending on the series (for two series, the native units are 52-week percent changes). All ten series receive substantial weight and no one series dominates the index. As we show below, the values of the WEI are robust to many changes, including estimation method and addition or subtraction of constituent series.

During the Coronavirus pandemic, the WEI is updated every Tuesday and Thursday. The weekly updates contain estimates for the past two weeks based on the available data. The formulation of the WEI presented here (constituent series, weights, real-time updating methods, etc.) is that put in place for the March 28, 2020 reference week of the WEI. Thus, data postdating March 28, 2020 provide a true out-of-sample evaluation of the WEI.[3]

Since its launch at the end of March 2020, the WEI has inspired several indices taking similar approaches around the world. These include the Deutsche Bundesbank Weekly Activity Index (Erasland and Götz, 2020), the Swiss State Secretariat for Economic Affairs' index of Weekly Economic Activity (Wegmueller, 2020), the Central Bank of the Republic of Turkey's Weekly Economic Conditions Index for Turkey (Celgin and Gunay, 2020), the Banco de Portugal's Daily Economic Indicator (Laurenço and Ruo, 2020), the Banque de France's World GDP Nowcast (Jardet and Meunier, 2020), ING's Weekly Economic Activity Index for the Eurozone (Konings and Spakman, 2021), a Guatemalan Indice Economico Semenal (Leiva, 2020), and the Weekly UHERO Economic Pulse for Hawaii (Fuleky, 2020).

The paper proceeds as follows. Section II outlines the underlying data series and their relationship to the WEI. Section III describes the methodology used to estimate the WEI and compute the bi-weekly updates, and also explores the sensitivity to alternative specifications. Section IV documents the major movements in the WEI during the pandemic and the developments in the underlying data that drove them. Section V examines the historical predictive power of the WEI for output measures. Section VI presents the WEI-implied forecasts for growth for 2018 to present. Section VII concludes.

II. The Weekly Data Series

In this Section, we outline the underlying data series used in the WEI. We describe transformations used for each variable and show the historical relationship between each series and the WEI.

Table 1 lists the series used to construct the baseline WEI. The variables can broadly be divided into three categories. First, we include two consumer-focused series. These are the Redbook Research same-store retail sales measure and the Rasmussen Consumer Index, which tracks consumer sentiment.

[3] Estimation of weights and parameters in updating regressions are based on data through the February 29, 2020 reference week. The only non-real-time feature are the parameters of the scaling regression, which we re-estimated following the July 2020 re-benchmarking of the past 5 years of GDP; quantitatively, this change amounts to at most a few basis points.

Table 1: Weekly Variables

Series	Native Units	Time available EST, (days from reference week)	Notes
Redbook Research: Same Store, Retail Sales Average, Y/Y % Chg.	NSA, Y/Y % Chg.	1st Tuesday, 9:00am (3 days)	Sales-weighted, year-over-year same-store sales growth for a sample of large US general merchandise retailers representing about 9,000 stores. By dollar value, the Index represents over 80% of the "official" retail sales series collected by the Department of Commerce. **http://www.redbookresearch.com/**
Rasmussen Consumer Index	Index	Friday of reference week, 6:00pm (0 days)	Daily survey of 1500 American adults Sun-Thurs. Index is a 3-day moving average based on five questions about the current state of both the economy and personal finances, whether the economy and personal finances are getting better or worse, and whether the economy is in a recession. https://www.rasmussenreports.com/
Unemployment Insurance: Initial Claims	NSA, Thous.	1st Thursday, 8:30am (5 days)	Number of claims filed by unemployed individuals after separation from an employer. Data collected from local unemployment offices. https://oui.doleta.gov/unemploy/
Insured Unemployment (Continued Claims)	NSA, Thous.	2nd Thursday, 8:30am (12 days)	Number of continued claims filed by unemployed individuals to receive benefits. Data collected from local unemployment offices. https://oui.doleta.gov/unemploy/
American Staffing Association Staffing Index	NSA, Jun-12-06=100	2nd Tuesday, 8:30am (10 days)	The ASA Staffing Index tracks temporary and contract employment trends. Participants include a stratified panel of small, medium, and large staffing companies. https://americanstaffing.net/
Federal Withholding Tax Collections	Y/Y % Chg.	1st Tuesday, 4:00pm (5 days)	Treasury receipts of income and payroll taxes withheld from paychecks. The series is filtered for daily volatility patterns and adjusted for tax law changes. https://taxtracking.com/
Raw Steel Production	NSA, Thous. Net Tons	1st Monday, 4:00pm (2 days)	Weekly production tonnage provided from 50% of the domestic producers combined with monthly production data for the remainder. https://www.steel.org/industry-data
US Fuel Sales to End Users	NSA, EOP, Thous. barrels/ day	1st Wednesday 10:30am (4 days)	Weekly product supplied of finished gasoline and distillate fuels. This estimates wholesale gasoline, diesel, and aviation fuel sales to retailers and large corporate end users (e.g., airlines, truck fleets). Published by the U.S. Energy Information Administration in the Weekly Petroleum Status Report. https://www.eia.gov/petroleum/supply/weekly/
U.S Railroad Traffic	NSA, car-loads	1st Wednesday, 9:00am (4 days)	Total carloads and intermodal units reported by railroad companies to the Association of American Railroads https://www.aar.org/data-center/
Electric Utility Output	NSA, Gigawatt Hours	1st Wednesday, 1:00pm (4 days)	Total output for U.S. (excluding Alaska and Hawaii) investor-owned electric companies. https://www.eei.org/

Second, we include four labor market series. These are initial claims for unemployment insurance (UI) (the one weekly series included in the ADS index), continuing claims for UI, the American Staffing Association Staffing Index, and a smoothed and policy-adjusted measure of federal withholding tax collections. While the first three capture the extensive margin of employment, the latter can also offer some measure of the intensive margin.

Finally, we include four industrial series to measure output more directly. These are raw steel production, U.S. fuel sales to end users, U.S. railroad traffic, and electric utility output. Railroad traffic and steel production measure intermediate inputs to production. Fuel sales and electricity sales include both sales to individuals and to firms, such as jet fuel to airlines, so these series measure both consumption and the sale of intermediate inputs.

The native units of two data series (retail sales and tax withholdings) are year-over-year percentage changes. As discussed in Section III, we choose to target the year-over-year percentage change in real economic activity. We accordingly transform all remaining series to represent 52-week percentage changes, using the 52-week log-difference. This transformation has the added benefit of eliminating most seasonality in the data, which is otherwise a challenging problem for weekly data. All series are standardized before the index is estimated. **Figure 2** plots the transformed series that serve as inputs to the index, normalized to match the scale of the WEI.

As can be seen in **Figure 2**, some of the weekly series exhibit considerable weekly noise. All of the variables, however, also display a clear cyclical pattern. This preliminary visual evidence shows that each constituent series comoves with the WEI, and that the relationships between the series and the WEI appear stable over time.[4] These features are criteria for selecting the underlying data. They ensure that each constituent series provides a signal of the common component and that the weights can be reliably estimated throughout the sample.

We considered but opted not to use several alternative high frequency series that became available during the pandemic. Some of these novel series could offer better coverage of activity in service sectors that were hit particularly hard during the pandemic, such as airport passenger traffic, box office sales, mobility, and restaurant reservations. Information on debit and credit card spending from new private sources have also been used fruitfully to measure daily consumption during the pandemic (e.g., Chetty et al, 2020). For our purpose, these new series currently have several disadvantages. First, their short sample histories make it difficult to estimate reliable weights for inclusion in the index, especially after weekly seasonal adjustment. Second, sample coverage tends to be inconsistent (as online platforms are adopted over time, for example). Finally, many of these series are widely followed because they focus specifically on the hardest-hit industries; while extremely useful for that purpose, their inclusion in the WEI would not necessarily lead to a reliable signal for overall economic activity during the current pandemic. In a companion paper, Lewis et al (2021), we compare the trajectory of the WEI to many of these alternative indicators in detail. We find that the timing of the downturn in the WEI

[4] The one series that does not show a clear decline during the pandemic is electricity output; Cicala (2020) shows that the decline in commercial consumption has been offset by an increase in residential consumption.

is generally very similar to that in popular alternative data sources. The WEI's recovery starts slightly later and proceeds at a slower pace, but has been much steadier throughout the year; as more direct signals of sectors that are sensitive to the health situation, most alternative indicators instead have stagnated since the summer.

III. Construction of the Weekly Economic Index

In this section, we describe the methodology used to estimate the WEI. We report the weights placed on each series, showing that all constituent data play a relevant role in measuring real activity. We document extensive sensitivity analysis to demonstrate that the WEI is robust to alternative specifications. Finally, we explain how the WEI is updated using the real time data flow.

Methodology

A leading framework for the construction of an economic index from multiple time series is the so-called dynamic factor model, developed by Geweke (1977) and Sargent and Sims (1977). The dynamic factor model posits the existence of a small number of unobserved or latent series, called factors, which drive the co-movements of the observed economic time series. Application of dynamic factor models to estimating economic indexes range from the construction of state-level indexes of economic activity (Crone and Clayton-Matthews, 2005) to large-scale indexes of economic activity (for example, the Chicago Fed National Activity Index, or CFNAI). Stock and Watson (2016) provide a review of these methodologies.

The premise of a dynamic factor model is that a small number – in our application, a single – latent factor, f_t, drives the co-movements of a vector of N time-series variables, X_t. The dynamic factor model posits that the observed series are the sum of the dynamic effect of the common factor and vector of idiosyncratic disturbances, e_t, which arise from measurement error and from special features that are specific to an individual series:

$$X_t = \lambda(L) f_t + e_t \qquad (1)$$

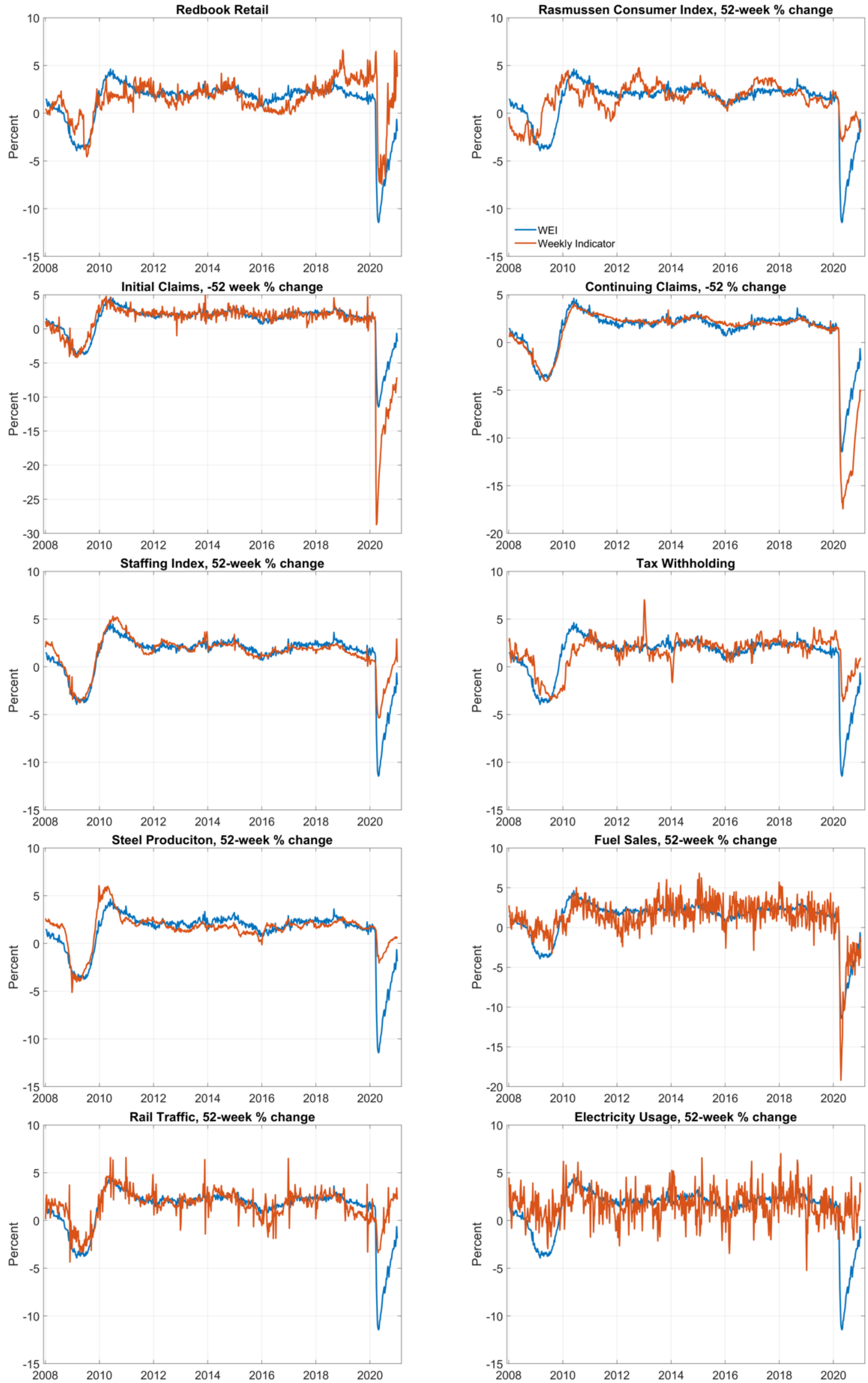
where L is the lag operator. The elements of the $N \times 1$ vector of lag polynomials $\lambda(L)$ are the dynamic factor loadings, and $\lambda_i(L) f_t$ is called the common component of the i^{th} series. The dynamic factor can be rewritten in static form by stacking f_t and its lags into single vector F_t, which has dimension up to the number of lags in $\lambda(L)$:

$$X_t = \Lambda F_t + e_t \qquad (2)$$

where Λ is a matrix with rows being the coefficients in the lag polynomial $\lambda(L)$.

The two primary methods for estimating the unobserved factor f_t are by principal components

Figure 2: Weekly Variables and WEI



Notes: Based on data available through January 2, 2021. For sources, see **Table 1.**

Table 2: PCA Results

Series	Weights Baseline	Weights Trimmed (ALS)
Same-Store Retail Sales	0.28	0.27
Consumer Confidence	0.23	0.22
Initial Claims	-0.37	-0.39
Continued Claims	-0.41	-0.41
Staffing Index	0.40	0.38
Tax Withholding	0.30	0.32
Steel Production	0.36	0.37
Fuel Sales	0.22	0.22
Railroad Traffic	0.34	0.34
Electricity Output	0.12	0.14
Total variance explained	55.4	51.5

Notes: Estimation sample is first week of 2008 through last week of February 2020. The first column uses all observations. The second column is based on a trimmed sample in which outliers were removed so those observations were treated as missing. In this case, the weights are estimated using alternating least squares, see for instance Stock and Watson (2002b).

and using state space methods, where the factor is estimated by the Kalman filter.[5] Broadly speaking, early low-dimensional applications used parametric state-space methods and more recent high-dimensional applications tend to use nonparametric principal components or variants. We adopt the principal components approach to estimate the WEI. We consider an alternative parametric DFM specification below; we find that results broadly align with our non-parametric baseline using this approach but suffer from sensitivity to specification details (lags, sample length, etc.). For our purposes, DFMs also have the drawback that the lag structure in $\lambda(L)$ imposes temporal smoothing, which may mask week-by-week fluctuations.

An alternative approach to using high-frequency data for real time monitoring ("nowcasting") is to focus on forecasting a specific economic release, such as the monthly change in employment, and to construct a model that updates those forecasts as new data comes in. The dynamic factor model and its state space implementation is useful for this purpose because a single model automatically adapts to new data becoming available to estimate the variable of interest. For applications of dynamic factor models to nowcasting, see Giannone, Reichlin and Small (2008) and Aruoba, Diebold and Scotti (2009).

Table 2 provides the weights associated with the first principal component, as well as the total variance explained based on the 10 weekly series described above. The first column provides the weights using the full sample between the first week of January 2008 and the last week of

[5] Recent work considering missing data and mixed-frequency data include Jungbacker et al (2011), Doz et al (2012), Banbura and Modugno (2014), Jungbacker and Koopman (2015), for example.

February, 2020. The second column shows the weights over the same sample period, but after treating outliers in the weekly series as missing observations.[6] Removing outliers overall has little effect on the weights, and for the WEI we therefore use the full-data weights. The WEI explains 54% of the overall variance of the underlying series.

After estimating the WEI weights based on the standardized constituent series, we rescale the common component to endow the index with interpretable units. In particular, we scale the WEI to 4-quarter GDP growth. The choice of GDP growth is natural, since it is of wide macroeconomic interest. The choice of 4-quarter growth aligns with the 52-week differencing used for weekly seasonal adjustment. The scaling and shift coefficients are estimated using the regression,

$$\Delta^{4q} GDP_q = \alpha + \gamma WEI_q^{raw} + u_q, \quad (3)$$

where $\Delta^{4q} GDP_q$ is 4-quarter GDP growth and WEI_q^{raw} is the average raw principal component value over the days of the quarter, and compute the WEI as $WEI_q = \hat{\alpha} + \hat{\gamma} WEI_q^{raw}$.

In constructing the WEI, we deliberately opt to work exclusively with daily and weekly data. We do not include lower-frequency data as in mixed-frequency models such as those of Aruoba et al (2009), Mariano and Murasawa (2003), Brave et al (2019), or Bok et al (2017). The goals of the WEI are different – and complementary – to those existing indices. We aim to capture fluctuations in real activity from week to week in periods when economic conditions are changing rapidly, not to provide a nowcast of GDP growth or track some other lower-frequency measure. Thus, the intertemporal smoothing typically introduced by models that include lower-frequency data is undesirable for our purposes.[7] We also want to finalize the index within the following two weeks. Data series included in the WEI must therefore be available in a timely manner, and lower-frequency series are necessarily stale for real-time tracking of weekly conditions when they become available. Moreover, later revisions of past index values as new monthly or quarterly data become available may be undesirable from a public communication standpoint. Finally, the asynchronicity of weekly and monthly calendars introduces a challenging, though not insurmountable, modeling problem, as discussed in Aruoba et al (2009).

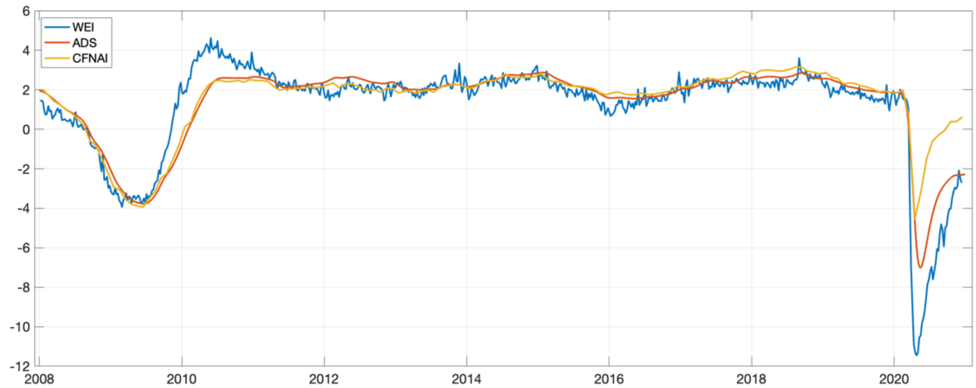
To illustrate the relationship between the WEI and existing mixed- and lower-frequency indices, **Figure 3** plots the WEI against suitably transformed and rescaled versions of the Aruoba, Diebold, and Scotti (ADS) index and the Chicago Fed National Activity Index (CFNAI). It is clear that despite the inclusion of a weekly series in the ADS index, the ADS index is more similar to the monthly CFNAI than to the WEI. Neither captures the weekly fluctuations the WEI is designed to measure.[8]

[6] We define outliers as observations for which the magnitude of the first difference is greater than three scaled median absolute deviations, the Matlab default.

[7] One argument for the inclusion of lower-frequency data would be the potential reduction of noise in measuring weekly activity, although we think the first principal component achieves the same purpose in the cross-section through purging idiosyncratic noise.

[8] For a discussion of the performance of the ADS index during the pandemic, see Diebold (2020).

Figure 3: WEI and Alternative Indices



Notes: Based on data available through January 2, 2020. ADS is transformed by computing the 365-day sum and and CFNAI is transformed by taking the 12-month sum; both are then rescaled to 4-quarter GDP growth using the same scaling regression as is used in the construction of the WEI.[9]

During the pandemic, the inclusion of monthly and quarterly series, some of which have recovered more strongly than weekly indicators, tempers the decline in the ADS.

Sensitivity to changes in specification

The WEI is robust to changes in the details of its construction. **Figure 4** plots the alternative index under a series of different specifications together with the baseline WEI. **Table 7** in the Appendix additionally reports the weights for each specification, along with the share of variance explained by the index and the correlation with the baseline WEI. The trimmed version of the WEI shown in the top left panel coincides almost exactly with the baseline WEI. The top right panel shows a version of the index based on a parametric DFM. In particular, we estimate a model with one lag in the transition equation and i.i.d. idiosyncratic and factor innovations. The filtered estimates produce a smoother version of the baseline WEI that is otherwise very similar, with the exception of a smaller decline during 2015-2016 mini-recession and lower values during the pandemic; the latter is driven by higher weight on UI claims data. The filtered DFM version is somewhat sensitive, however, to the number of lags used in the DFM specification. In addition, the principal components version is a transparent current-value weighted average which has substantial virtues in terms of communication and transparency of the index.

We next examine the stability of weights over time by splitting the data into two estimation samples, 1/2008-12/2014 and 1/2015-02/2020. Essentially, the former captures the Great Recession and recovery period, while the latter does not include a major downturn, but rather a period of sustained growth. The index based on the earlier sample (left panel, second row) is virtually identical to the baseline. The index based on the later sample (right panel, second row) is also very similar, with the main difference being that the weight on retail sales is essentially

[9] The WEI measures the percentage change in activity relative to a year prior. For ADS, which approximately represents a daily growth rate, the 365-day sum approximates growth relative to a year ago. For CFNAI, which represents a monthly log-change in activity, the 12-month sum is equivalent to $\ln x_t - \ln x_{t-12}$.

zero (with additional weight being placed on consumer confidence). Overall, the covariance structure of the constituent series does not appear to change substantially over the business cycle. In the next panel, the baseline estimation sample is extended to include recent data from the pandemic. The weights are generally similar to the baseline, and the only notable discrepancy is the depth reached at the trough, which is likely driven by updating the parameters of the scaling regression and decreased weight on claims data.

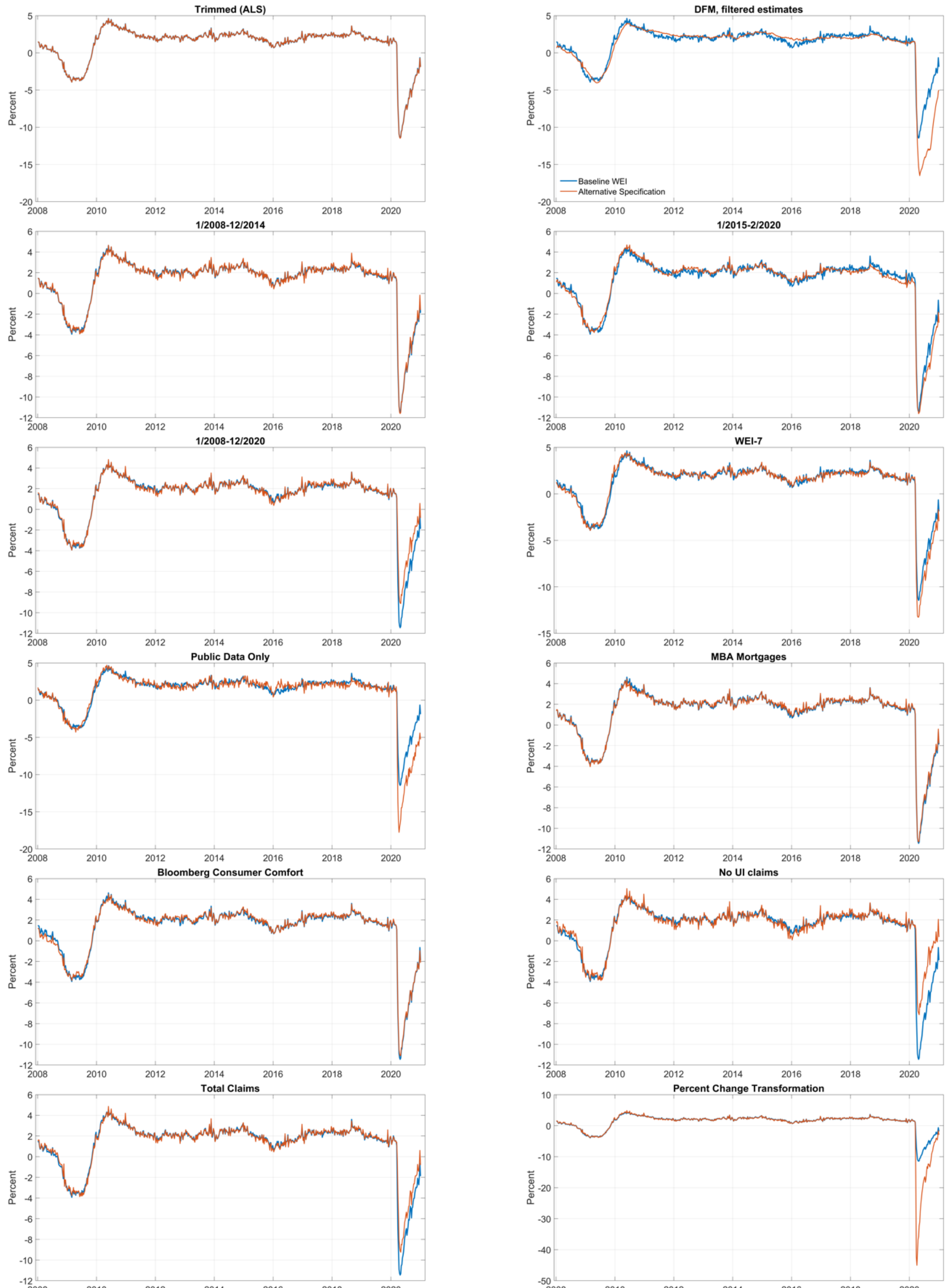
The left panel in the fourth row of **Figure 4** shows the index from a 7-variable specification, as in the earlier model described in Lewis, Mertens, and Stock (2020a), omitting railroad traffic, tax withholdings and electricity output. While the weights for the baseline model suggest that these three series do provide valuable signals, the path of the WEI is largely unchanged by their omission. The index falls slightly further than the baseline, since the weights on UI claims and steel production are larger, and those series showed particularly severe declines. In the spirit of providing an index that is easily replicable based on publicly available data, the next panel considers a specification dropping proprietary series. In particular, we include five variables: initial and continuing UI claims, an unadjusted version of federal tax withholdings, steel production, and fuel sales. The resulting index closely follows the baseline, with a correlation of 0.97. It does fall substantially further during the pandemic, again due to greater wait on UI claims and fuel sales.

The next two panels consider versions that include two additional variables, one by one: the Mortgage Bankers of America (MBA) mortgage applications for purchase and the Bloomberg Consumer Comfort Index. These inclusions leave the index largely unchanged, with pre-COVID correlations of 1.00 between the WEI and the "WEI plus one" indexes. Including these series leads to some differences during the pandemic, but those differences are not systematic.

The role and reliability of UI claims data during the pandemic has been widely discussed, with issues surrounding access, reporting lags, take-up rates, and fraud (e.g., Cajner et al (2020)). The next panel thus considers an 8-variable index omitting both claims series. The historical performance is very similar, although the depth of the decline during the pandemic is less severe when the UI variables are excluded. The fact that this index provides a similar signal overall also demonstrates that non-claims weekly series contain information beyond that included in the ADS index, for example. The next panel considers a model where initial and continuing UI claims are summed and enter as a single variable, measuring the stock of those receiving unemployment benefits at any one time (relative to release week t, continuing claims pertain to claims in week t-2 and new claims pertain to week t-1).[10] The WEI is relatively unchanged by this modification, although the decline during the pandemic is less severe. **Figure 8** in the Appendix also examines the effect of re-estimating PCA weights including the pandemic sample in the baseline WEI and

[10] At any time, this sum is an imperfect measure of the stock of UI claimants because it ignores the outflow out of UI recipients. In the pandemic, several additional factors distort the interpretation of this sum (e.g., long processing lags, high denial rates and interactions with the federal emergency UI programs). See Rinz (2020) for further details.

Figure 4: Alternative Specifications



Notes: Based on data available through January 2, 2021 reference week. First two panels based on DFM described in the text. Dated panels specify alterantive estimation samples. WEI-7 is the model of Lewis et al (2020a). Public data uses only publicly available series. The next three panels add the indicated series. The final two panels use the alternative transformations noted.

the specification omitting claims data. Remarkably, for the index dropping UI claims, the index is essentially unchanged; the correlation of these 8 series is virtually constant. However, the relationship of claims data with the other series is less stable, another indication of some nonstationarity in the claims series during the pandemic.

In the baseline WEI we follow standard practice and use 52-week differences of logarithms of the non-seasonally adjusted constituent series. The pandemic was a rare moment when the log approximation to percentage changes of macroeconomic variables broke down. The final panel in **Figure 4** shows a version of the WEI where all variables enter in 52-week percentage changes instead of 52-week changes of logs. Since the weights are estimated on the pre-pandemic sample, where the log approximation is almost exact, they are essentially identical. However, the "percentage" index deviates markedly from the WEI during the pandemic, falling about four times as far in percentage changes as log changes; the use of log-changes in the WEI evidently incorporates a robustness to outliers like the extreme movements in initial claims.

Real Time Updating

As can be seen in **Table 1**, the WEI components are reported with varying lags, and the final series, continuing UI claims, is released 12 days after the end of the reference week. To handle this ragged-edge inflow, we report three versions of the WEI: an initial estimate the Tuesday after the reference week (3 day delay from the Saturday ending the reference week), a second estimate the Thursday following the reference week (5 days), a third estimate the next Tuesday (10 days), and a final value that Thursday (12 days). These updates are published every Tuesday and Thursday at 11:30am EST through the Federal Reserve Banks of New York and Dallas, and subsequently distributed via data services such as FRED, Bloomberg and Haver.

The first estimate (3 days) uses same store retail sales, steel production, and consumer confidence data. The second estimate (5 days) adds initial UI claims, federal tax withholding, fuel sales, electricity output, and railroad traffic. The third estimate (10 days) adds the staffing index. The final value (12 days) adds continuing UI claims. Subsequent revisions are typically small and only due to revisions in the underlying inputs made by the data providers (or, alternatively, revisions of GDP data used in the scaling regression). This speed and ease of obtaining final estimates stands in contrast to mixed-frequency models, which would provide only preliminary estimates until low-frequency data is available (up to several months after the end of the reference period), and involve near-constant revision if a smoothed factor was used as the index.

When only partial data are available, we update the WEI by estimating its conditional expectation based on available data, implemented by separate OLS regressions for each of the three preliminary updates. For update date *d* (e.g., the first Tuesday following the reference week), these regressions take the form

$$WEI_t = \mu^d + \theta_1^d WEI_{t-1}^d + \theta_2^d WEI_{t-2} + \sum_{j \in J^d} \delta_j^d X_{jt} + v_t^d, \qquad (4)$$

Table 3: Relationship between WEI updates

	Panel a: 1/5/2008 to 2/29/2020						Panel b: 3/28/2020 to 1/2/2021					
	RMSE			Correlation			RMSE			Correlation		
	First revision	Second revision	Final	First revision	Second revision	Final	First revision	Second revision	Final	First revision	Second revision	Final
Initial estimate	0.23	0.25	0.26	0.99	0.99	0.99	0.92	1.21	1.04	0.96	0.95	0.95
First revision	–	0.08	0.10	–	1.00	1.00	–	0.55	0.43	–	1.00	0.99
Second revision	–	–	0.06	–	–	1.00	–	–	0.73	–	–	0.99

Notes: For the estimate indicated in each row, the table reports the RMSE with respect to the subsequent estimate indicated in the columns and the pairwise correlations for each pair of estimates. Panel a considers the pre-pandemic sample, 1/5/2008 to 2/29/2020, based on infeasible historical estimates computed using the baseline weights and update regression coefficients. Panel b considers the pandemic sample, 3/28/2020 to 1/2/2021, using the published values for each WEI update.

where J^d is the set of variables available at update day *d* for reference period *t.* Note that WEI_{t-1}^{d} denotes the latest estimate of the prior week's WEI available at *d.* In the regression for the initial estimate of the WEI (first Tuesday) this value will be the second revision of the prior week's WEI, not the final estimate (since continuing UI claims is not yet available for the prior week).[11] We experimented with alternative approaches, such as computing univariate forecasts for each pending release and computing an index using the full-date weights with these estimated values. We found the results to be qualitatively similar, with the weights on the lagged WEI in (4) generally quite low. Our chosen approach, based on a single equation, has the benefit of parsimony. We explore the performance of our updating procedure in **Table 3**. We report the RMSE of each preliminary estimate relative to subsequent revisions and the correlations between estimates, for the pre-pandemic period (Panel a) and the pandemic period (Panel b). As an in-sample exercise, Panel a shows that both first and second revisions (5 and 10 days after the end of the reference week) are very good indicators of the final value during normal times, with all three preliminary estimates very well-correlated with the final WEI. The sample for Panel b begins with the March 28, 2020 reference week, when we introduced the 10-variable WEI, and represents a real-time exercise. The RMSEs are naturally larger, since the magnitude of the WEI is much higher. There is considerable variation from one estimate to the next, but the first revision (5 days after the end of the reference week) provides the best approximation to the final value of the WEI. The weaker relationship between the second revision and the final WEI is due

[11] Especially during the early weeks of the pandemic, when most of the movement in the WEI was driven by UI claims data, the initial estimates (1st Tuesday) calculated in this way without any UI claims data were unrealistically high. We opted to include forecasts for UI claims data as observed releases in preliminary WEI estimates to avoid drastic revisions when those releases became available. The use of such forecasts to compute initial values has no impact on the final WEI.

to the fact that the staffing index, added at the second revision, has provided a more positive signal of recovery than the other constituent series over recent months. Both first and second revisions remain nearly perfectly correlated with the final WEI.

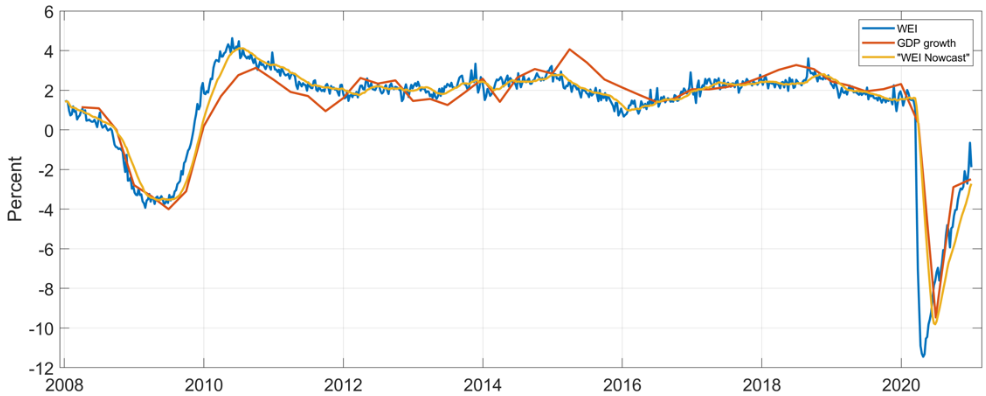
IV. Narrative Timeline

In this section, we briefly outline key events in the trajectory of the WEI over the first six months of the Coronavirus pandemic; we provide a decomposition into contributions from each series in Lewis et al (2021). On March 11, 2020, the WHO made the assessment that the virus outbreak has become a global pandemic, and on March 13 the U.S. President declared a national emergency. California issued the first stay-at-home order in the U.S. on March 19, 2020, following increased concern over the spread of the Coronavirus since mid-February. Accordingly, the WEI first registered a strong and sudden decline in economic activity in that same week (ending March 21), falling from 1.07% to -3.31%.[12] For reference, the WEI stood at 1.58 for the week ending February 29. The week ending March 21 saw initial UI claims easily break the million mark for the first time in history at 2.92 million (NSA), a sharp decline in consumer confidence and fuel sales, and a more modest decline in steel production. However, there was also a countervailing surge in retail sales, as consumers took to stores to stock up on consumer staples. In the week ending March 28, the WEI plunged further to -7.04%, easily eclipsing the lowest value during the Great Recession, -3.93%. This further decline was driven by another sharp increase in initial UI claims, which came in at 6.02 million (NSA), far surpassing the prior week's record-setting release. The drop was reinforced by another major decline in fuel sales in response to stay-at-home orders and other restrictions, a fall in steel production, and a surge in continuing UI claims (8.17 million NSA). The next week, the WEI fell further to -9.01%, again driven by a new record for initial UI claims (6.21 million NSA) and sharp decreases in fuel sales and steel production, while retail sales also began to stall after their initial surge.

The WEI continued to fall through the week of April 25, when it bottomed out at -11.45%, generally led by the four labor market series, slumping fuel sales, depressed retail sales, and plunging consumer confidence. In late April, states began to implement reopening plans. Starting the week of May 2, the WEI inched upward, even as continuing UI claims reached a record high in the week of May 9 at 22.79 million (excluding claims under the Pandemic Unemployment Assistance program). For the most part, the recovery was led by initial UI claims and fuel sales, and to a lesser extent consumer confidence, the staffing index, and income tax withholding. The recovery continued smoothly for eleven weeks until the week of July 18, when the WEI fell from -6.96% to -7.60%. The reversal came as several states were forced to suspend or backtrack on reopening plans in the face of surging Coronavirus cases, as well as speculation over the expiry of UI benefits. This drop coincided with simultaneous falls in retail and fuel sales as well as

[12] We reference values of the WEI following the re-benchmarking of GDP data in July 2020. As a result, the numbers noted here may differ slightly from those reported in real time or in previous versions of this paper.

Figure 5: WEI and 4-quarter GDP growth



Notes: Based on data available through January 2, 2021.

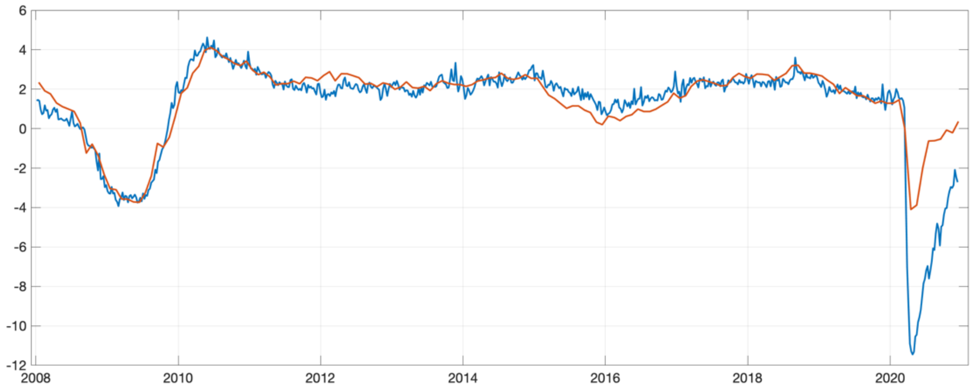
increases in initial and continuing UI claims, all of which had been improving. Subsequently, the recovery continued, with initial UI claims notably falling below one million (NSA) for the first time since early March in the week of August 1. A two-week reversal occurred in early September, coinciding with the expiry of pandemic assistance programs, the so-called "second wave," and renewed lockdowns in Europe. The recovery has since returned to a steady path, passing the nadir of the Great Recession in the week of October 24th. Fluctuations in the weeks between Thanksgiving and year's end are at least partially due to difficulty conducting complete seasonal adjustment over the holiday season.

V. Relationship Between the WEI and Real Activity

While the WEI is designed to capture weekly variation in real economic activity, such a measure should also provide an early indicator of movements in lower-frequency aggregates. In this section, we document the predictive relationship between the WEI and two output measures, real GDP and industrial production. We focus on these two series since they are of primary macroeconomic interest, but similarly strong relationships exist with other series, for example the ISM manufacturing index and capacity utilization.

To illustrate the relationship between the WEI and GDP growth, **Figure 5** plots the WEI together with the 4-quarter growth rate of real GDP and the 13-week moving average of the WEI. Since the WEI is scaled to pre-pandemic 4-quarter GDP growth, the 13-week moving average of the WEI represents expected GDP growth for a hypothetical quarter ending in a given week. The strong comovement of the series is clear, particularly for the moving average of the WEI. **Figure 6** plots the index against the twelve-month percentage change in industrial production (IP). This figure shows that the index also tracks IP growth closely, despite the inclusion of several non-industrial series. The close relationship with the lower frequency measures indicates that, despite the noise inherent in the raw high-frequency data, our methodology to combine these data into a weekly index produces an informative and timely signal of real economic activity.

Figure 6: WEI and 12-month Industrial Production growth



Notes: Based on data available through January 2, 2021.

Figures 5 and **6** help to illustrate two important differences between our index and a traditional nowcast, like those for GDP growth produced by the Federal Banks of New York or Atlanta. First, a nowcast focuses on a single important target series, and uses the information contained in intermediate data to predict that series. In contrast, while we report the WEI in GDP growth units, this is simply an *ex post* normalization; the WEI does not focus on a single outcome by targeting either a consumption variable or a production variable. Forecasts for other series (like industrial production) can be obtained by simply using an alternative re-scaling. Second, most nowcasts (including those of the Federal Reserve Banks of New York, Atlanta and St. Louis) focus on lower-frequency targets like GDP growth. But, since GDP is a quarterly variable, such models are not equipped to highlight variation from one week to the next (see also McCracken, 2020).

We now explore what predictive relationships do exist between the WEI and lower-frequency real activity measures, since such forecasts are a natural application of the WEI. The weeks of the WEI do not naturally correspond to months and quarters. We thus work with monthly and quarterly average values of the WEI, taken by assigning weekly WEI values to each constituent day, and computing averages over the days in each longer time period. Our regression samples run from 2008 to 2019.

GDP growth

To explore the nowcasting ability of the WEI for GDP growth, we first regress 4-quarter GDP growth on the quarterly WEI, following

$$\Delta^{4q} GDP_q = c + \beta WEI_q^{quarterly} + \sum_{s=1}^{4} \delta_s \Delta^{4q} GDP_{q-s} + e_q, \qquad (5)$$

where $\Delta^{4q} GDP_q$ is 4-quarter real GDP growth in quarter q and $WEI_q^{quarterly}$ is the quarterly average WEI*.* The results in Column (I) of **Table 4** show that the quarterly WEI is a significant predictor of GDP growth, with 89% of variation explained (84% without lagged GDP growth), nearly a month before the advance release. We then regress the 4-quarter growth rate on the flow of information from the WEI, starting with the WEI for just the first month of the quarter, and so on, following

$$\Delta^{4q} GDP_q = c^{\overline{m}} + \sum_{i=1}^{\overline{m}} \beta_i^{\overline{m}} WEI_q^{m_i} + \sum_{s=1}^{4} \delta_s^{\overline{m}} \Delta^{4q} GDP_{q-s} + e_q^{\overline{m}},\ \overline{m} = 1,2,3. \qquad (6)$$

Columns (II) to (IV) report the results. For the first two months of the quarter, the most recent month's WEI is a significant (positive) predictor of growth, with the adjusted R^2 rising from 0.88 to 0.90. Data on the final month does not appear to add much additional information, although the coefficients on monthly WEI are jointly significant for all specifications. We conclude that a strong signal of GDP growth is available from the WEI from the second month of the quarter, nearly two months before the advance release.

Industrial Production

While **Figure 6** shows a clear relationship between 12-month percentage changes in IP and the WEI, we now consider the more conventional monthly percentage change. Specifically, we begin by computing a monthly analog of (5),

$$\Delta IP_m = c + \beta WEI_m^{monthly} + \sum_{s=1}^{4} \delta_s \Delta IP_{m-s} + u_m, \qquad (7)$$

where ΔIP_m is monthly growth in industrial production in month *m* and $WEI_m^{monthly}$ is the monthly average WEI. Column (I) of **Table 5** shows that the monthly average WEI (and lags) explains 24% of variation in IP growth, about two weeks before the official release (still 17% dropping lags of IP growth).

Next, we turn to intra-month regressions. Week by week, we run "nowcasting" regressions based on the information flow from the WEI. These take the form

$$\Delta IP_m = c^{\overline{w}} + \sum_{i=1}^{\overline{w}} \beta_i^{\overline{w}} WEI_m^{w_i} + \sum_{s=1}^{4} \delta_s^{\overline{w}} \Delta IP_{m-s} + u_m^{\overline{w}},\ \overline{w} = 1,2,3,4\,; \qquad (8)$$

where $WEI_m^{w_i}$ is the average WEI for the i^{th} pseudo-week of month *m*. The results are reported in columns (II) to (V). We find that, from the second week of the month onwards, the flow of information from the WEI is a significant predictor of monthly IP growth; the explained variation rises from 24% to 32%. The most recent week is often a significant positive predictor of IP growth, while the first week is a negative predictor, since it is closely related to production in the prior month.

VI. Nowcasting

In the previous section, we illustrated how the weekly variation captured by the WEI provides an early signal of movements in GDP. In this section, we explore the potential auxiliary use of the quarterly average WEI to nowcast GDP growth in more detail. We begin by considering 4-quarter GDP growth, before presenting two approaches for computing the quarterly growth rate implied by the WEI.

Given the scaling of the WEI, the quarterly average WEI provides a natural nowcast of 4-quarter GDP growth. The first column of in Panel a of **Table 6** reports the latest vintage of 4-quarter GDP

Table 4: GDP regression results

Regressors	(I)	(II)	(III)	(IV)
$WEI_q^{quarterly}$	0.74***			
	(0.14)			
WEI month 3				-0.12
				(0.47)
WEI month 2			1.54***	1.21**
			(0.28)	(0.51)
WEI month 1		0.68***	-0.99***	-0.88***
		(0.17)	(0.31)	(0.30)
F-test: weekly coefficients = 0		15.86	29.12	23.34
		(0.00)	(0.00)	(0.00)
F-test: weekly coefficients equal			9.46	5.41
			(0.00)	(0.14)
SER	0.54	0.62	0.48	0.48
Adjusted R^2	0.89	0.85	0.91	0.91

*Notes: All regressions include 4 lags of four-quarter GDP growth as in (5) (column (I)) and (6) (remaining columns). Results starred at the 1%, 5%, and 10% levels, ***, **, *. Estimation sample is 2008:Q1-2019:Q4 using the latest vintage of WEI and GDP data. Standard errors are given in parentheses for coefficients and p-values are given in parentheses for F-statistics.*

Table 5: Industrial Production regression results

Regressors	(I)	(II)	(III)	(IV)	(V)
$WEI_m^{monthly}$	0.03				
	(0.07)				
WEI week 4, current month					0.83***
					(0.23)
WEI week 3, current month				0.44	-0.05
				(0.30)	(0.26)
WEI week 2, current month			0.55*	0.10	-0.10
			(0.33)	(0.33)	(0.31)
WEI week 1, current month		-0.01	-0.53*	-0.51*	-0.59**
		(0.06)	(0.31)	(0.30)	(0.30)
F-test: weekly coefficients = 0			1.52	1.26	3.24
			(0.22)	(0.29)	(0.01)
F-test: weekly coefficients equal			1.45	1.24	3.21
			(0.24)	(0.30)	(0.01)
SER	0.64	0.64	0.63	0.62	0.60
Adjusted R^2	0.23	0.23	0.24	0.25	0.31

*Notes: All regressions include 4 lags of four-quarter IP growth as in (7) (column (I) and (8) (remaining columns). Results starred at the 1%, 5%, and 10% levels, ***, **, *. Estimation sample is 1/2008-2/2020 using the latest vintage of WEI and industrial production data. Standard errors are given in parentheses for coefficients and p-values are given in parentheses for F-statistics.*

Table 6: Nowcasting GDP growth with the WEI

	Panel a: 4-quarter growth			Panel b: 1-quarter growth					
	Latest	Advance	WEI	Latest	Advance	Method 1 (real- time)	Method 2 (real time)	Method 1 (latest)	Method 2 (latest)
2018:Q1	3.08	2.86	2.35	3.78	2.32	0.33	0.99	0.91	2.03
2018:Q2	3.33	2.85	2.32	2.70	4.06	1.27	2.94	-1.19	1.61
2018:Q3	3.12	3.04	2.66	2.12	3.50	1.99	4.19	0.35	4.32
2018:Q4	2.48	3.08	2.62	1.32	2.59	0.77	2.11	1.91	3.68
2019:Q1	2.27	3.21	2.00	2.93	3.17	-1.60	-0.29	1.88	1.24
2019:Q2	1.96	2.29	1.91	1.49	2.06	-0.97	3.76	1.29	2.32
2019:Q3	2.08	2.03	1.64	2.57	1.92	0.37	1.83	0.85	1.03
2019:Q4	2.34	2.32	1.54	2.37	2.08	-1.00	0.71	-0.75	0.94
2020:Q1	0.32	0.32	0.15	-4.96	-4.78	-5.44	-2.51	-5.57	-2.66
2020:Q2	-9.03	-9.54	-9.77	-31.38	-32.90	-33.10	-32.69	-33.52	-33.03
2020:Q3	-2.85	-2.91	-5.96	33.44	33.08	17.15	18.91	17.15	18.91
2020:Q4	-2.46	-2.46	-2.79	4.01	4.01	2.61	15.88	2.61	15.88
RMSE	–	0.46	0.70	–	1.33	2.36	2.24	2.76	2.27

Notes: "Latest" values correspond to the most recent vintage of GDP growth. "Advance" values correspond to the Advance GDP release. "Method 1" values are calculated using equation (9) *and "Method 2" using equation* (10)*; "real time" calculations use the latest vintage available in real time for GDP growth in past quarters, and "latest" use the most recent available vintage of GDP growth. RMSE calculated relative to the latest available GDP values over the sample 2010:Q1 to 2019:Q4.*

growth for each quarter since 2018:Q1. The second column reports the advance GDP release for each quarter, which is itself essentially a nowcast of the final value. The third column reports the quarterly average WEI. At first glance, the WEI provided a reliable nowcast of both the advance and final GDP values. Notably, from 2018:Q4 to 2019:Q2, it actually provided a better indication of the final value than the official advance release. With the exception of Q3, the WEI has been remarkably successful when faced with the challenge of the pandemic; it missed 2020:Q1, Q2, and Q4 growth by only about 20-30 basis points. However, it missed Q3 growth by nearly 3 percentage points. We hypothesize that measurement issues with UI claims data, leading to an exaggerated negative signal (e.g., Cajner et al 2020) are largely responsible; a lack of sectoral coverage in areas most affected by fiscal stimulus may also have played a role. The WEI also repeatedly underestimated growth in early 2018 and late 2019.

However, more attention is often paid to quarterly GDP growth. Of course, the 4-quarter readings from the WEI naturally imply a quarterly growth rate. We consider two approaches; many more are possible. The first, "Method 1", primarily relies on past GDP releases to back out the quarterly growth rate. The 4-quarter growth rate implies a quarterly growth rate from the simple formula

$$\left(1+\frac{WEI_q}{100}\right) = (1+\hat{g}_q)^{\frac{1}{4}}(1+g_{q-1})^{\frac{1}{4}}(1+g_{q-2})^{\frac{1}{4}}(1+g_{q-3})^{\frac{1}{4}}, \qquad (9)$$

where $\hat{g}_q$ is the estimated annualized quarterly growth rate for quarter q, and g_{q-s} are the released values for annualized quarterly GDP growth (in decimal points) in recent quarters.

The second, "Method 2", minimizes the role of GDP data in the calculation, which may be desirable, as we discuss below. Since the ratio of the current 4-quarter growth rate and the previous quarter's is closely related to the ratio of the current quarterly growth rate and that four quarters ago, the second formulation is

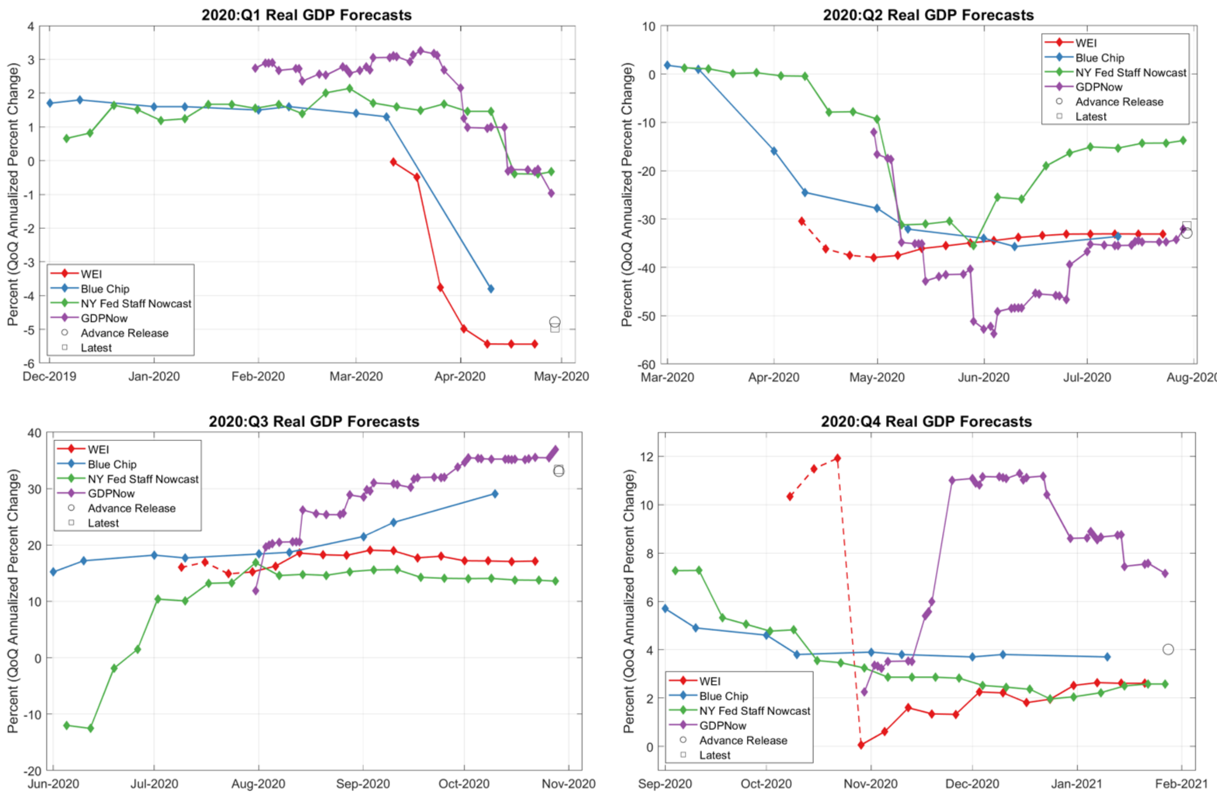
$$\left(1+\hat{g}_q\right)^{1/4} = 1 + (WEI_q - WEI_{q-1})/100 + \ln GDP_{q-4} - \ln GDP_{q-5}. \quad (10)$$

The first two column of Panel b of **Table 6** reports the latest vintage of GDP growth for each quarter. The next two columns present the quarterly growth rates implied by each formula using the latest vintages of GDP data available in real time. During early 2020, the WEI provided an accurate nowcast for quarterly GDP growth, missing Q1 by about 50 basis points and the advance release for Q2 by 20 basis points under Method 1. The performance in Q4 and particularly Q3 was weaker, as must be the case given the errors in 4-quarter growth rates, missing by about 1.4 and 16 percentage points, respectively. The same explanations offered for the 4-quarter rates also apply here.

Although performance using Method 2 was weaker during 2020 than that using Method 1, Method 1 performs far worse during 2019, with the WEI seemingly implying a recession, while actual growth was strongly positive. However, this is largely the result of limitations of the GDP data available in real time, not the WEI. In particular, the third revision values for GDP were substantially inflated relative to the latest vintage in 2018:Q2 to 2019:Q2. These erroneously high "real time" values for growth in recent quarters means that the WEI-implied quarterly growth computed based upon them is mechanically forced downwards, as it is simply a residual between the 4-quarter WEI and these official quarterly numbers. Given the frequency of substantial revisions in GDP, there is a strong case to be made for Method 2, which decreases the role of such data; note that while performance for Method 2 is also weaker in 2019, it does not perform nearly as badly as Method 1. The fourth and fifth columns in Panel b of **Table 6** compute the implied growth rates using the latest vintage of GDP data for past quarters. The quality of the implied quarterly estimates is substantially better for Method 1, with now only one quarter of negative growth in 2019. While not feasible in real time, this exercise serves to illustrate that, to some extent at least, it is indeed the GDP data holding the WEI back, since these calculations are based on exactly the same WEI values as the prior columns.

We report the RMSE for advance GDP releases and our WEI-based nowcasts in the final row of Table 6 over the sample 2010:Q1 to 2019:Q4. For 4-quarter growth, the RMSE of the WEI, 0.70, is only slightly worse than the advance release, 0.46. For 1-quarter growth, Methods 1 and 2 have RMSEs of 2.36 and 2.24 respectively, about a percentage point higher than the advance release (1.33), due to the compounding of both WEI and GDP release errors in the equations (9) and (10). Recall, however, that the WEI is strongly oriented towards 4-quarter growth, due to the challenges posed by noise and seasonality in the weekly data, and its performance on that metric

Figure 7: Progression of WEI and GDP nowcasts in 2020



Notes: The first panel plots the progression of the WEI-implied nowcast for 2020:Q1 annualized quarterly GDP growth, constructed using Method 1 and an average of the WEI over the course of the quarter, assuming that the latest WEI reading persists for the remainder of the quarter. The dashed line represents the period before the prior quarter's advance release is available, and prior GDP is proxied using the WEI. A combination of the Blue Chip Economic Indicators and Financial Forecasts consensus measures, the New York Fed Staff Nowcast, and the Atlanta Fed GDPNow are plotted for comparison, as well as the advance and latest release values. We plot the WEI from March 12 onwards, the first date that full data was available to estimate weights through 2/2020. The subsequent panels repeat the exercise for Q2-Q4.

is encouraging. Moreover, the main goal of the WEI is to provide a weekly reading of real activity, and its nowcasting ability when aggregated does not detract from its validity as weekly indicator. Finally, the nowcasting performance of the WEI can be compared to other GDP forecasts over the first half of 2020. In particular, we consider the New York Fed Staff Nowcast, the Atlanta Fed GDPNow, and the Blue Chip Economic Indicators/Financial Forecasts consensus forecast. The panels of **Figure 7** present progression plots for each forecast for GDP growth for each quarter of 2020. They report how each forecast evolved over time as additional data became available or a new survey was conducted. After it was launched in Q1, the WEI nowcast was consistently lower than the three other nowcasts, falling markedly in mid-March, along with the Blue Chip. While it overshot the contraction in GDP slightly, it finished closer to the latest GDP release than the other nowcasts, especially the NY Fed Staff Nowcast and GDPNow, neither of which fell below -1%.

For Q2, the WEI again fell in tandem with (or slightly ahead of) Blue Chip in April, and led the NY Fed Staff Nowcast and GDPNow, both of which must wait for lower-frequency releases to signal contraction. The WEI nowcast declined until late April, before recovering slightly, as did the other nowcasts, and converging towards its final value in June. The final nowcasts from the WEI, Blue Chip, and GDPNow are all very similar, while the New York Fed Staff Nowcast increased dramatically in June and July.

For Q3, the WEI-implied nowcast fluctuated between 15 and 20% throughout the quarter, never registering the improvement that appeared in all other forecasts. While it finished about 15% percentage points below the eventual release, it still outperformed the purpose-built New York Fed Staff Nowcast.

Once the advance estimate of Q3 GDP became available (and could be incorporated into the formula to compute the Q4 nowcast), the WEI-implied nowcast settled into the 0 to 2 percentage point range, from where it grew steadily to its eventual value, a little over 1 percentage point shy of the advance release. It outperformed GDPNow and the NY Fed Staff Nowcast, the former of which overshot substantially.

VII. Conclusion

Over the first ten months of the Coronavirus pandemic and the ensuing economic downturn, the WEI provided a real-time measure of weekly economic activity. It measured quantitatively the decline in real activity and subsequent recovery consistent with the narrative of health, policy, and economic developments. While not its goal, the WEI has also proven to be a valuable nowcasting tool for output. Indeed, the GDP growth implied by the WEI for both 2020:Q1 and 2020:Q2 were very close to the actual releases, with solid performance in Q4, but considerably weaker in Q3. Over this period, it regularly outperformed alternative statistical models specifically designed as nowcasts, such as the New York Fed Staff Nowcast or the Atlanta Fed GDPNow, and was at times closely comparable to Blue Chip and Bloomberg Consensus professional forecasts. The WEI has spurred the development of a family of related measures of high-frequency fluctuations of economic activity, not captured by traditional lower-frequency indices. We view the promising forecasting performance as a coincidental benefit, but only time will tell if the results for the first or second half of 2020 are representative of its ability.

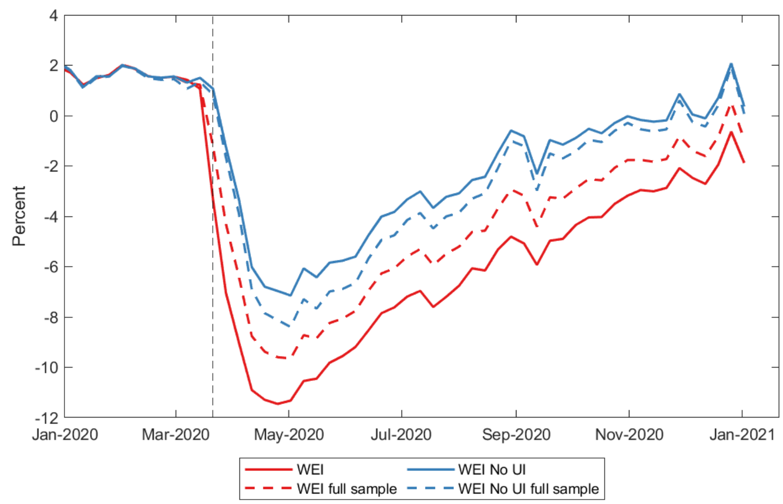
Appendix

Table 7: Sensitivity of weights

Series	Baseline	DFM	2008-2014	2015-2/2020	2008-present	WEI-7	Public only	MBA	BB CC	No claims	Total claims	% change
Retail Sales	0.28	0.27	0.33	-0.05	0.30	0.31	–	0.28	0.27	0.34	0.31	0.28
Con. Conf.	0.23	0.22	0.20	0.42	0.27	0.28	–	0.23	0.25	0.25	0.23	0.23
IC	-0.37	-0.39	-0.36	-0.24	-0.35	-0.44	-0.54	-0.37	-0.37	–	–	-0.38
CC	-0.41	-0.44	-0.39	-0.46	-0.38	-0.45	-0.56	-0.41	-0.40	–	–	-0.41
Staffing	0.40	0.41	0.38	0.53	0.39	0.44	–	0.39	0.38	0.47	0.43	0.40
Withholding	0.30	0.32	0.29	0.02	0.31	–	0.14	0.30	0.29	0.36	0.33	0.30
Steel	0.36	0.35	0.35	0.16	0.33	0.41	0.51	0.35	0.34	0.43	0.39	0.34
Fuel Sales	0.22	0.20	0.26	0.16	0.32	0.25	0.34	0.22	0.22	0.28	0.25	0.22
Electricity	0.12	0.10	0.15	0.13	0.13	–	–	0.12	0.11	0.16	0.14	0.13
Railroads	0.34	0.33	0.36	0.45	0.31	–	–	0.33	0.32	0.42	0.37	0.34
Mortgage	–	–	–	–	–	–	–	0.16	–	–	–	–
BB CC	–	–	–	–	–	–	–	–	0.26	–	–	–
Total claims	–	–	–	–	–	–	–	–	–	–	-0.44	–
Total variance explained (%)	55.4	51.8	62.4	30.1	57.5	63.1	57.7	51.4	53.6	49.0	53.4	53.3
Correlation with baseline	–	0.95	1.00	0.99	0.99	0.99	0.97	1.00	1.00	0.95	0.99	0.90

Notes: Unless otherwise noted, the estimation sample is first week of 2008 through last week of February 2020. The first column reports the baseline. The second column reports factor loadings (rescaled to match the sum of the baseline), as opposed to PCA weights, explained variance is based on filtered estimates. Columns 3-5 consider alternative estimation samples. Columns 6-7 consider additional series. Columns 8-9 consider alternative treatments of UI claims data. Column 10 considers and alternative transformation of the data.

Figure 8: The relationship between claims and re-estimation



Notes: The solid red line plots the baseline WEI with parameters estimated based on data through 2/29/2020. The dashed red line plots the 10-variable WEI with parameters estimated over the full sample, through 1/2/2021. The solid blue line plots an alternative index omitting both UI claims series with parameters estimated based on data through 2/29/2020. The dashed blue line plots this 8-variable index with parameters estimated through 1/2/2021.

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