Federal Reserve Bank of New York
Staff Reports

Measuring Real Activity Using a Weekly Economic Index

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Staff Report No. 920
April 2020
Revised September 2020

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JEL classification: C51, E01, E66

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. We document how the WEI responded to key events and data releases during the first six months of the pandemic.

Key words: weekly economic index, high frequency, measurement of economic activity, forecasting

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To view the authors' disclosure statements, visit https://www.newyorkfed.org/research/staff_reports/sr920.html.

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.

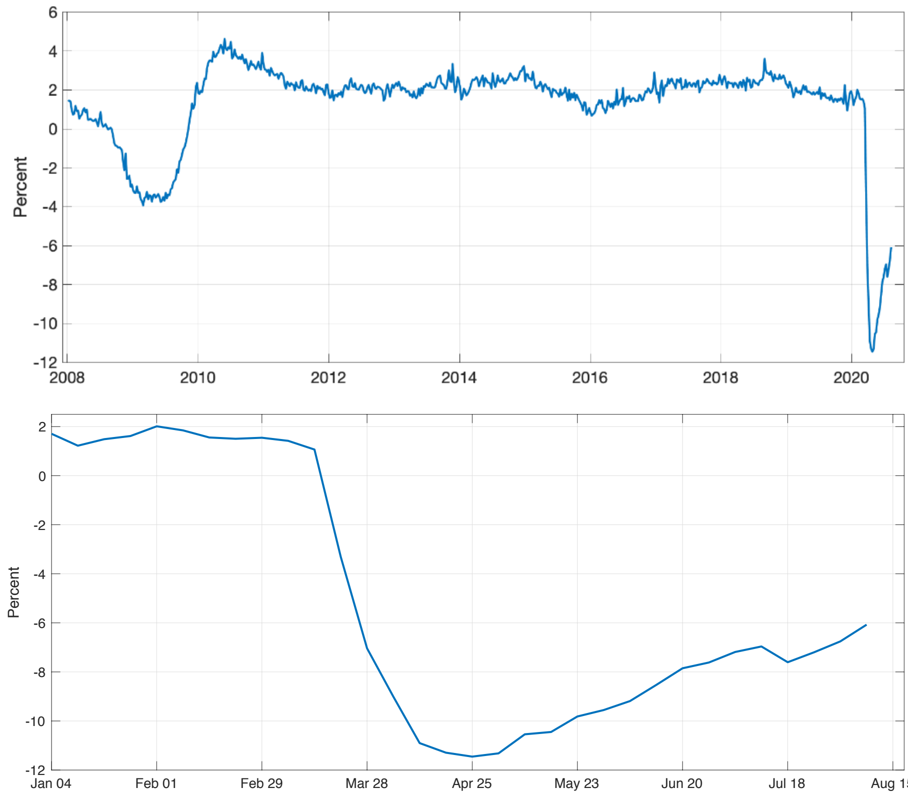
This paper describes a weekly index of economic activity (the Weekly Economic Index, or WEI) computed as the first principal component of ten weekly measures of real economic activity, including consumption, labor input, and production. The index measures the change in overall macroeconomic activity during the reference week, which runs Sunday through Saturday, relative to the corresponding week one year earlier. The index is normalized to match the mean and standard deviation of four-quarter GDP growth. 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 primary purpose of the WEI is to provide a weekly index of real activity, something a monthly or quarterly series cannot do. That said, a secondary use of the WEI is as a nowcast of monthly and quarterly activity series. We show that the WEI has useful nowcasting properties for 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 second release, available 58 days after the end of the quarter, Q2 GDP fell by 31.7 percent at an annual rate.

The top panel in **Figure 1** plots the WEI based on data through the reference week of August 8, 2020. 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.

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. 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. Coinciding with a resurgence in confirmed COVID-19

Figure 1: Weekly Economic Index (WEI)



Notes: Based on data available through the August 8, 2020 reference week. The units are scaled to 4-quarter GDP growth.

cases, the week of July 18 registered the first decline in the WEI since the April trough. In the subsequent weeks up to its most recent value at the time of writing (August 8), the WEI has resumed an upward trajectory, however as of August it remained well below its 2009 trough.

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 in the index 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.[2]

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.

Second, we include four labor market series. These are initial claims for unemployment insurance (UI), 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 more directly capture output. 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 measure both consumption and the sale of intermediate inputs. All four series provide alternative channels to capture broad industrial activity.

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

[2] 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/

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. These features, criteria for selecting the underlying data, are important to ensure that each constituent series provides a signal of the common component and that the weights may be appropriately estimated throughout the sample.

We considered but opted not to use a number of alternative data sources. Debit and credit card spending have been used fruitfully to measure daily consumption during the pandemic (e.g., Chetty et al, 2020), however coverage for those data, which come from individual firms, has changed over time, raising concerns about stationarity; that said, perhaps with some adjustment those data could fruitfully augment those used here. Other studies of activity during the pandemic have focused on industries hit particularly hard by the lockdowns and self-protection, such as air traffic, box office sales, mobility, and restaurant reservations. Those series have two disadvantages for our purpose. First, they tend to have short time series histories so are not amenable to estimating weights for inclusion in the index, especially after weekly seasonal adjustment. Second, those series are selected because they focus on the hardest-hit industries; while that is of separate interest, such selection based on poor outcomes would tend to provide an overly pessimistic index during the current pandemic.

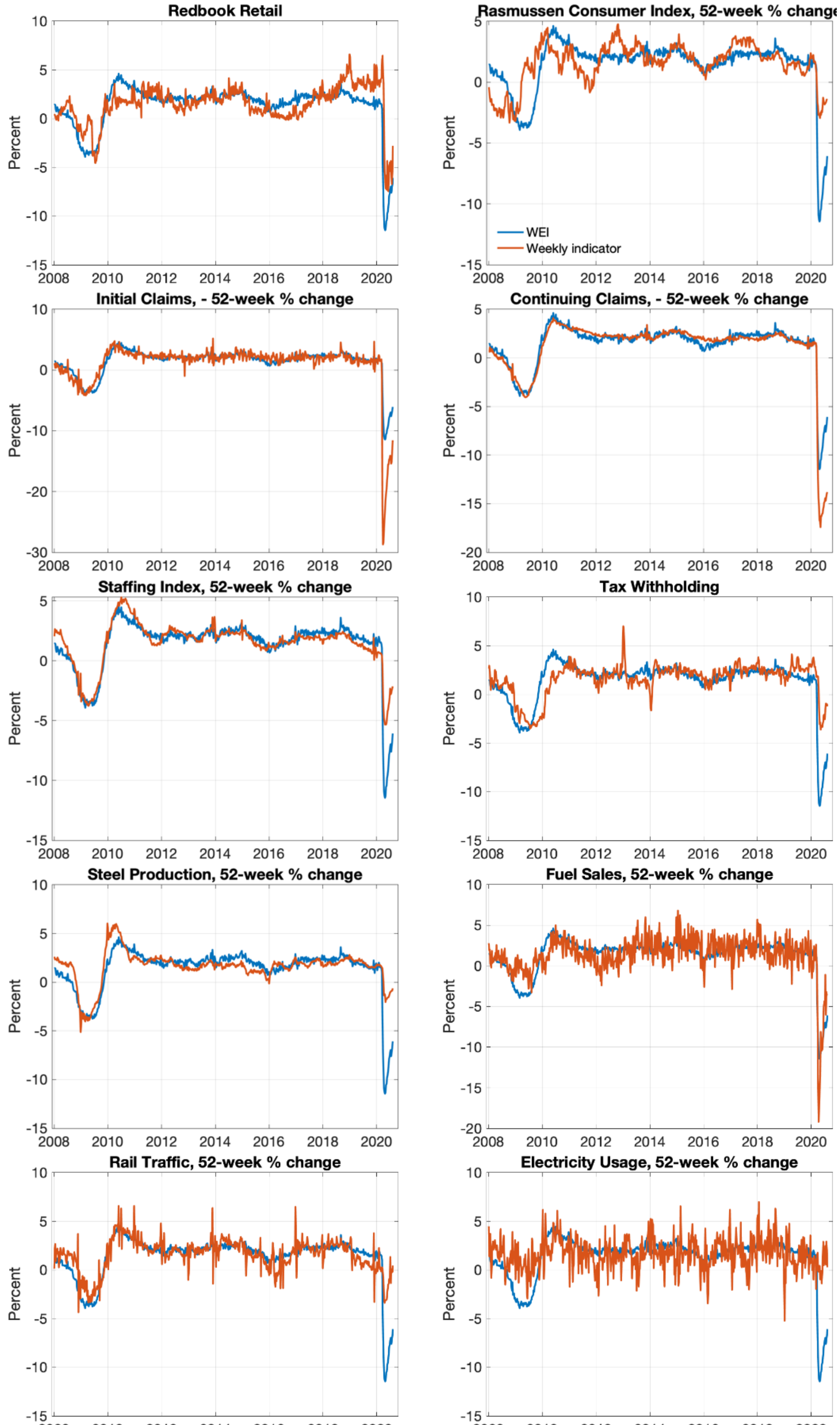
III. Construction of the Weekly Economic Index

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 can be 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

Figure 2: Weekly Variables and WEI



Notes: Based on data available through August 8, 2020. 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	0.20
Initial Claims	-0.37	-0.38
Continued Claims	-0.41	-0.41
Staffing Index	0.40	0.39
Tax Withholding	0.30	0.32
Steel Production	0.36	0.36
Fuel Sales	0.22	0.22
Railroad Traffic	0.34	0.36
Electricity Output	0.12	0.12
Total variance explained	55.4	56.6

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).

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 $N\times1$ 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 and using state space methods, where the factor is estimated by the Kalman filter. 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.).

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 February, 2020. The second column shows the weights over the same sample period, but after treating outliers in the weekly series as missing observations.[3] Removing outliers overall has little effect on the weights, and for the WEI we therefore use the full-data weights. We find that 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,

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

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

Sensitivity to changes in specification

The WEI is robust to changes in the details of its construction. **Figure 3** plots the alternative index under a series of different specifications against 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 discussed above coincides almost exactly with the baseline WEI. We also considered a parametric DFM, as described above. In particular, we estimate a model with one lag in the transition equation and i.i.d. idiosyncratic and factor innovations. The filtered estimates appear to be simply a smoother version of the baseline WEI (the smoothed estimates are very similar) with the exception of a smaller decline during 2015-2016 mini-recession and lower values during the pandemic; the

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

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.

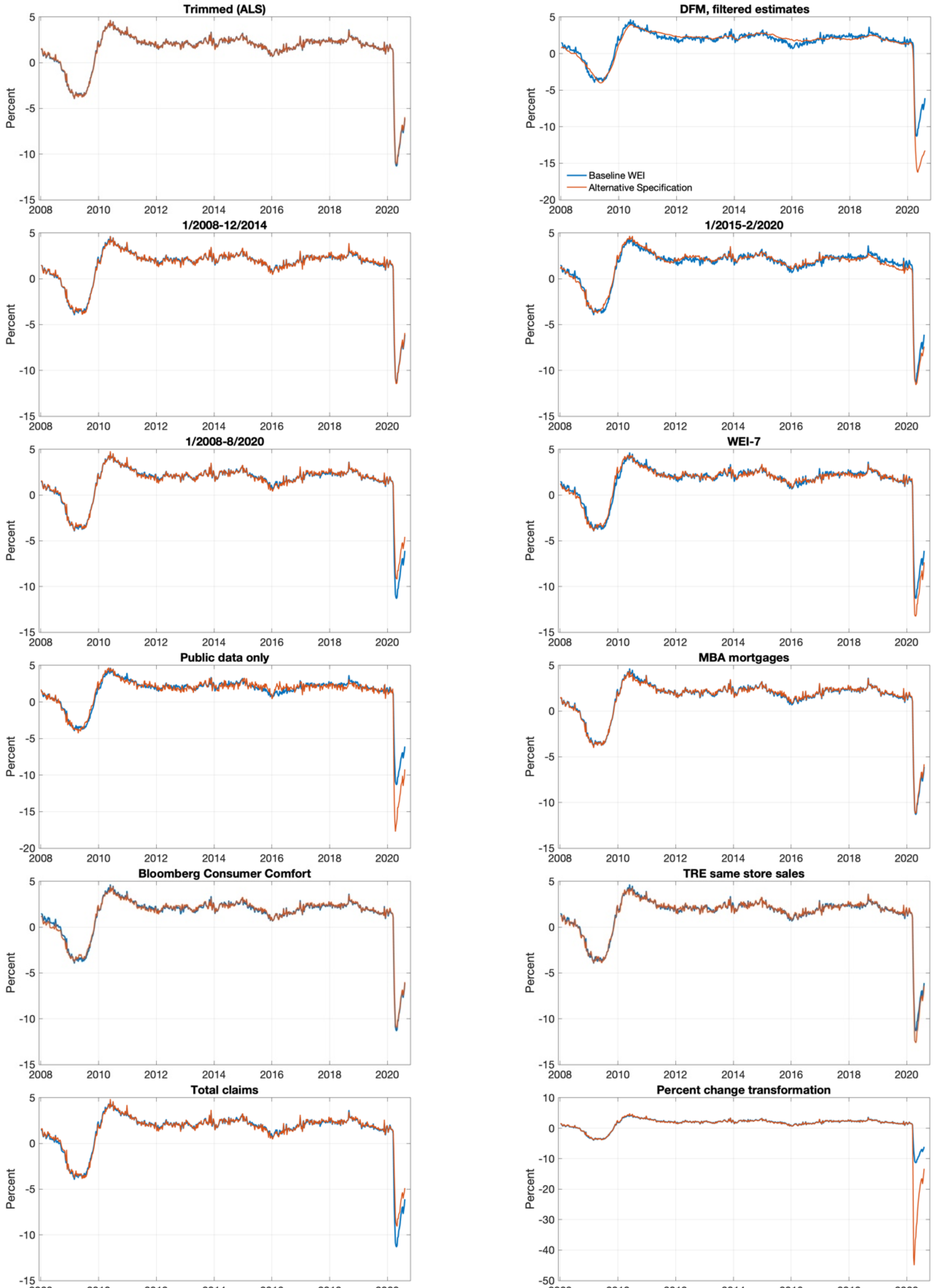
We next examine the stability of weights over time. We consider splitting the data into two estimation samples, 1/2008-12/2014 and 1/2015-02/2020. Essentially, the former captures the Great Recession and recovery period, while the latter does not include a major downturn, but rather a period of sustained growth. The index based on the earlier sample is virtually identical to the baseline, and the latter is very similar, with the main difference being that the weight on retail sales is essentially 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. We also consider extending the baseline estimation sample to include recent data from the pandemic. The weights are essentially unchanged relative to the baseline, and the only notable discrepancy is the depth reached at the worst of the pandemic, which is likely driven by updating the parameters of the scaling regression.

Next, we consider 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, we consider 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.

We also consider including three additional variables, one by one: the Mortgage Bankers of America (MBA) mortgage applications for purchase, the Bloomberg Consumer Comfort Index, and The Retail Economist same store sales 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.

Finally, we also consider alternative transformations of underlying series. First, we estimate a model where initial and continuing UI claims are summed and enter as single variable, measuring the stock of those receiving unemployment benefits at any one time (relative to release week *t*,

Figure 3: Alternative Specifications



Notes: Based on data available through August 8, 2020 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.

continuing claims pertain to claims in week t-2 and new claims pertain to week t-1).[4] The WEI is relatively unchanged by this modification, although the decline during the pandemic is less severe. Second, 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. We therefore estimated 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 index deviates markedly 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).

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

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

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

[4] 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.

Table 3: Relationship between WEI updates

	Panel a.: 1/5/2008 to 2/29/2020						Panel b.: 3/28/2020 to 8/8/2020					
	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	1.22	1.48	1.39	0.86	0.83	0.83
First revision	–	0.08	0.10	–	1.00	1.00	–	0.56	0.48	–	0.99	0.99
Second revision	–	–	0.06	–	–	1.00	–	–	0.72	–	–	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 8/8/2020, using the published values for each WEI update.

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).[5] 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 to the

[5] 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 interim values has no impact on the final WEI.

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.

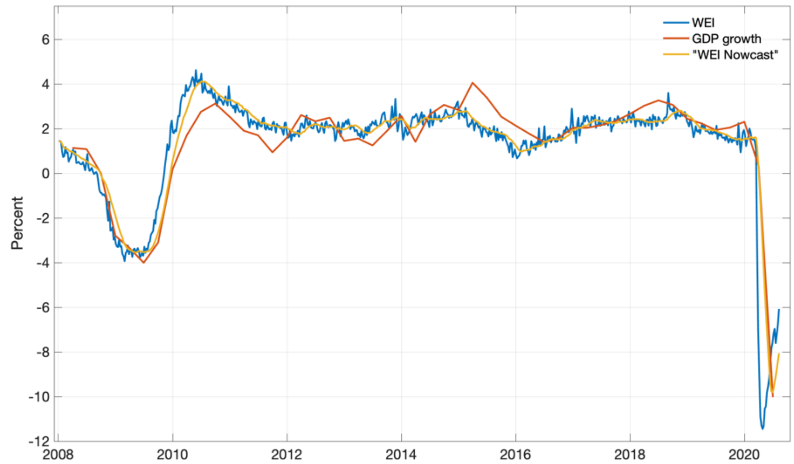
IV. Narrative Timeline

In this section, we briefly outline key events in the trajectory of the WEI over the first six months of the Coronavirus pandemic; a more detailed account will follow in a companion paper. 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%.[6] 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

[6] 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 4: WEI and GDP growth



Notes: Based on data available through August 8, 2020.

of UI benefits. This drop coincided with simultaneous falls in retail and fuel sales as well as increases in initial and continuing UI claims, all of which had been improving. Subsequently, the recovery has continued, leaving that week as a seeming blip for the time being, with initial UI claims notably falling below one million (NSA) for the first time since early March in the week of August 1. As of August 8, the WEI stood at -6.07%.

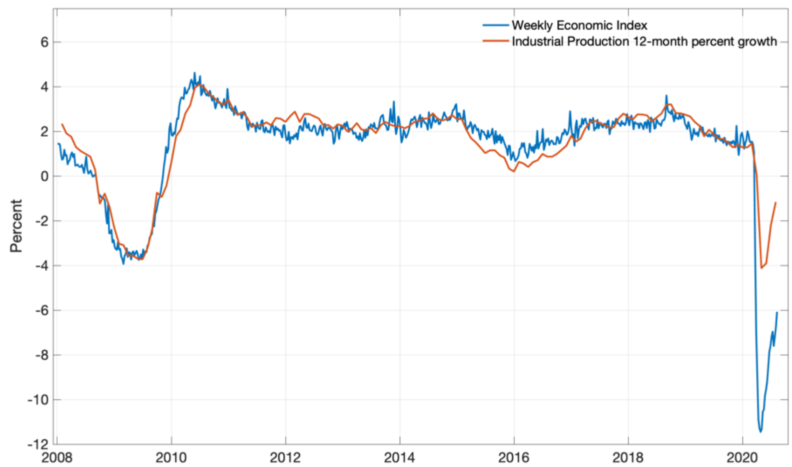
V. Relationship Between the WEI and Real Activity

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 4** 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 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 5** 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.

Figures 4 and **5** 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,

Figure 5: WEI and Industrial Production



Notes: Based on data available through August 8, 2020.

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, which are very informative about the economy. 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). The goal of these nowcasts is only to predict average variation in the target series over thirteen weeks, which they generally do well.

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. As noted in the discussion of the scaling of the WEI, the weeks of the WEI do not naturally correspond to months and quarters. Instead, we compute the monthly and quarterly average WEI by assigning each day a WEI value based on the week to which it belongs, and averaging those values over the days of a month or quarter. For the industrial production regressions below, we also make use of "pseudo-weeks" to address the non-alignment of the calendar. These divide the month into four weeks, the first starting on the first day of the month, the first three having seven days (and thus 5 weekdays and 2 weekend days), and the final pseudo-week running from 22nd through final day of the month (so including between 7 and 10 days). We compute the pseudo-week WEI as an average of the WEI of the constituent days. With these pseudo-weeks, we have an approximate measure of the signal provided by the index after the first, second, third, and fourth weeks of the month.

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 5** 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. Forecasting

Table 4: GDP regression results

Regressors	(I)	(II)	(III)	(IV)
$WEI_q^{quarterly}$	0.57***			
	(0.13)			
WEI month 3				-0.14
				(0.36)
WEI month 2			1.07***	1.24**
			(0.32)	(0.51)
WEI month 1		0.51***	-0.55*	-0.59*
		(0.13)	(0.32)	(0.33)
F-test: weekly coefficients = 0		15.01 (0.00)	15.02 (0.00)	9.94 (0.00)
F-test: weekly coefficients equal			3.25 (0.05)	1.94 (0.14)
SER	0.51	0.54	0.48	0.48
Adjusted R^2	0.89	0.88	0.90	0.90

*Notes: All regressions include 2 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)
$WEI_m^{monthly}$	0.04				
	(0.08)				
WEI week 4, current month					0.86*** (0.25)
WEI week 3, current month				0.42 (0.30)	-0.06 (0.26)
WEI week 2, current month			0.58* (0.33)	0.15 (0.34)	-0.09 (0.32)
WEI week 1, current month		-0.02 (0.06)	-0.56* (0.31)	-0.54* (0.30)	-0.61** (0.30)
F-test: weekly coefficients = 0			1.70 (0.19)	1.36 (0.26)	3.08 (0.02)
F-test: weekly coefficients equal			1.64 (0.20)	1.35 (0.26)	3.07 (0.02)
SER	0.64	0.64	0.64	0.63	0.60
Adjusted R^2	0.24	0.24	0.25	0.26	0.32

*Notes: All regressions include 2 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	2.318	0.32	2.03	0.88	2.02
2018:Q2	3.33	3.02	2.33	2.70	4.060	1.28	2.05	-1.22	1.61
2018:Q3	3.12	3.13	2.66	2.12	3.500	1.63	4.57	0.33	4.32
2018:Q4	2.48	3.02	2.62	1.32	2.588	0.99	3.34	1.88	3.67
2019:Q1	2.27	3.21	2.00	2.93	3.171	-1.60	0.04	1.85	1.24
2019:Q2	1.96	2.67	1.91	1.49	2.055	-0.97	3.13	1.26	2.32
2019:Q3	2.08	2.31	1.64	2.57	1.919	-0.71	1.83	0.83	1.03
2019:Q4	2.34	2.33	1.54	2.37	2.081	-1.03	0.70	-0.78	0.93
2020:Q1	0.32	0.32	0.15	-4.96	-4.783	-5.44	-2.51	-5.61	-2.67
2020:Q2	-9.14	-9.71	-9.77	-31.70	-32.90	-33.10	-32.69	-33.59	-33.07
RMSE	–	0.56	0.70	–	1.33	2.37	2.32	2.77	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.*

In this section we illustrate the forecasting performance of the quarterly average WEI for GDP growth since 2018. 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 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. The WEI has so far been particularly successful when faced with the challenge of the pandemic; it missed 2020:Q1 and Q2 growth by only about 20 basis points. However, it is important to note that the WEI is not always this accurate; it 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

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

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

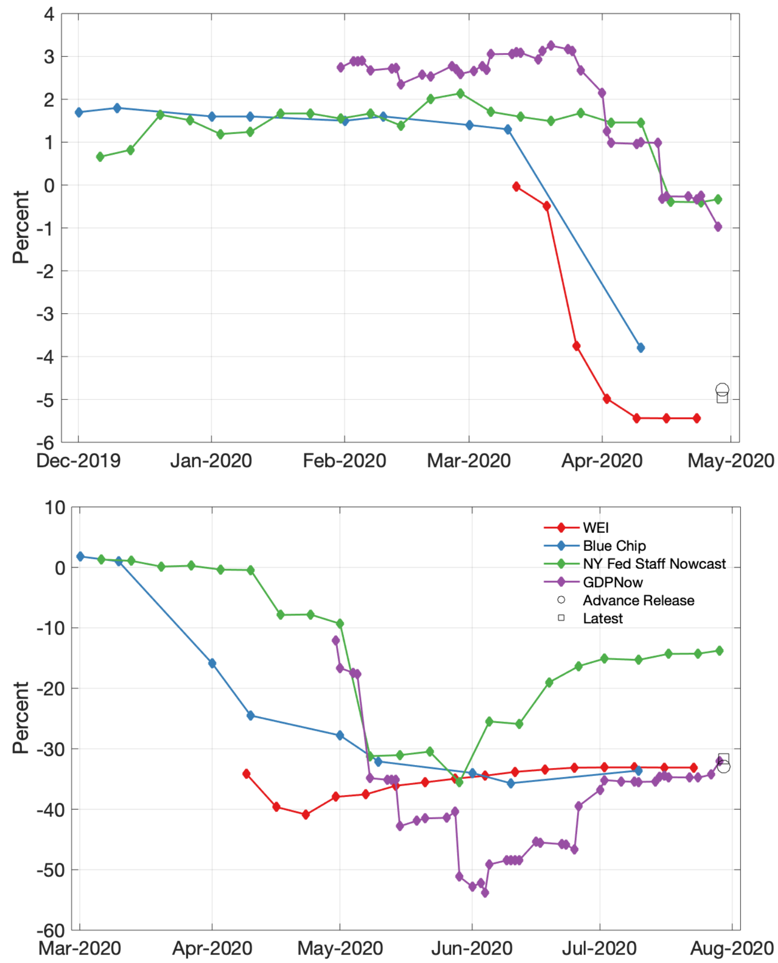
$$\left(1+\hat{g}_q\right)^{1/4} = 1 + (WEI_q - WEI_{q-1})/100 + \ln GDP_{q-4} - \ln GDP_{q-5}. \qquad (10)$$

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. So far during 2020, the WEI has 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, performing slightly worse for Q1 using method 2. However, the performance in 2019 is far weaker for method 1, 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, 0.56. For 1-quarter growth, Methods 1 and 2 have RMSEs of 2.37 and 2.32 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 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.

Figure 6: 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. 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 second panel repeats the exercise for 2020:Q2.

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. **Figure 6** presents progression plots for each forecast for 2020 Q1 (top panel) and Q2 (bottom panel) GDP growth. They report how each forecast evolved over time as additional data became available or a new survey was conducted. 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.

VII. Conclusion

Over the first six 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. The WEI has also proven to be a valuable forecasting 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. Over this period, it outperformed alternative statistical models, such as the New York Fed Staff Nowcast or the Atlanta Fed GDPNow, and was closely comparable to Blue Chip and Bloomberg Consensus professional forecasts. While the historical exercises we conduct are promising, only time will tell if this strong forecasting performance continues.

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Appendix

Table 7: Sensitivity of weights

Series	Baseline	DFM	2008-2014	2015-2/2020	2008-present	WEI-7	Public only	MBA	BB CC	TRE	Total claims	% change
Retail Sales	0.28	0.29	0.33	-0.05	0.31	0.31	–	0.28	0.27	0.28	0.31	0.28
Con. Conf.	0.23	0.24	0.20	0.42	0.26	0.28	–	0.23	0.25	0.22	0.23	0.23
IC	-0.37	-0.43	-0.36	-0.24	-0.35	-0.44	-0.54	-0.37	-0.37	-0.37	–	-0.38
CC	-0.41	-0.47	-0.39	-0.46	-0.39	-0.45	-0.56	-0.41	-0.40	-0.40	–	-0.41
Staffing	0.40	0.41	0.38	0.53	0.39	0.44	0.14	0.39	0.38	0.38	0.43	0.40
Withholding	0.30	0.33	0.29	0.02	0.29	–	–	0.30	0.29	0.29	0.33	0.30
Steel	0.36	0.37	0.35	0.16	0.33	0.41	0.51	0.35	0.34	0.35	0.39	0.34
Fuel Sales	0.22	0.22	0.26	0.16	0.31	0.25	0.34	0.22	0.22	0.22	0.25	0.22
Electricity	0.34	0.35	0.36	0.45	0.33	–	–	0.33	0.32	0.33	0.37	0.34
Railroads	0.12	0.12	0.15	0.13	0.12	–	–	0.12	0.11	0.12	0.14	0.13
Mortgage	–	–	–	–	–	–	–	0.16	–	–	–	–
BB CC	–	–	–	–	–	–	–	–	0.26	–	–	–
TRE	–	–	–	–	–	–	–	–	–	0.25	–	–
Total claims	–	–	–	–	–	–	–	–	–	–	-0.44	–
Total variance explained (%)	55.4	52.0	62.4	30.1	58.0	63.1	57.7	51.4	53.6	53.3	53.4	53.3
Correlation with baseline	–	1.00	1.00	0.99	0.99	0.99	0.97	1.00	1.00	1.00	0.99	0.89

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 inverse 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 6-8. Columns 9-10 consider alternative transformations of the data.