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US economic activity during the early weeks of the SARS-Cov-2 outbreak[1]

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This paper describes a weekly economic index (WEI) developed to track the rapid economic developments associated with the response to the novel Coronavirus in the United States. The WEI shows a strong and sudden decline in economic activity starting in the week ending March 21, 2020. In the most recent week ending April 4, the WEI indicates economic activity has fallen further to -8.89% scaled to 4 quarter growth in GDP.

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1 Bi-weekly updates of the Weekly Economic Index are available at https://www.jimstock.org/. 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. We are grateful to Mihir Trivedi and Eric Qian for research assistance, to Tyler Atkinson for useful suggestions, and to Mark Booth for sharing the tax collections data.

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Economists are well-practiced at assessing real economic activity based on a range of familiar aggregate time series, such as the unemployment rate, industrial production, or GDP growth. However, these series represent monthly or quarterly averages of economic conditions, and are only available at a considerable lag, after the month or quarter ends. When the economy hits sudden headwinds such as the COVID-19 pandemic, conditions can evolve rapidly. How can we monitor the high-frequency evolution of the economy in “real time”?

To address this challenge, this paper develops a Weekly Economic Index (WEI) that measures real economic activity at a weekly frequency and that can be updated relatively quickly.[2] Few of the government agency data releases macroeconomists often work with are available at weekly or higher frequency. Our weekly series instead come mostly from private sources such as industry groups that collect data for the use of their members, or from commercial polling companies. Financial data, such as stock market prices and interest rates, are also available at high frequency. We do not use financial data in the construction of the WEI, as our objective is to obtain a direct measure of real activity, and not of financial conditions.

To compute our index, we extract the first principal component from 10 weekly time series, using the sample from January 2008 to present. We scale our baseline index to four-quarter GDP growth, such that a reading of 2 percent in a given week means that if the week’s conditions persisted for an entire quarter, we would expect, on average, 2 percent growth relative to a year previous.[3] The top panel in **Figure 1** plots the WEI based on data through April 9, 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 2019 to its most recent value. As is clear from the figure, developments

[2] The WEI builds on earlier work by Stock (2013). A preliminary version of WEI was presented in a NY Fed blog post, see Lewis, Mertens and Stock (2020).
[3] Specifically, the mean and standard deviation of the Weekly Economic Index have been adjusted so that they match the mean and standard deviation of the four-quarter growth of GDP from 2008 through the fourth quarter of 2019.

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related to the Coronavirus pandemic have led the index to fall to levels below those of 2008 in recent weeks. Specifically, the WEI registers a strong and sudden decline in economic activity starting in the week ending March 21, 2020, falling to -3.23%. For reference, the WEI stood at 1.58 for the week ending February 29. The week ending March 21 saw an unprecedented 3.28 million initial UI claims (seasonally adjusted), a sharp decline in consumer confidence and fuel sales, and a more modest decline in steel production. 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 fell to -6.75%. This further decline was driven by another sharp increase in unemployment insurance initial claims, which came in at 6.65 million (seasonally adjusted), far surpassing the prior week's record-setting release. The drop was reinforced by a 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 unemployment insurance claims (7.46 million seasonally adjusted), as well as modest decreases in electricity output, rail traffic, temporary and contract employment, and consumer confidence. In the most recent week ending April 4, the WEI fell to -8.89%. This week's decrease was again driven by initial unemployment insurance claims (6.61 million seasonally adjusted) and sharp decreases in fuel sales and steel production, and reinforced by falls in rail traffic, electricity output, and tax withholdings, while retail sales stalled.

To track the rapidly evolving economic fallout of the Coronavirus pandemic, the WEI is updated weekly every Tuesday and Thursday. The weekly updates contain preliminary estimates for the prior week based on the available data. The latter are based on estimated historical relationships between the WEI and the series available at the time of the update. The final values of the WEI are available after two weeks.

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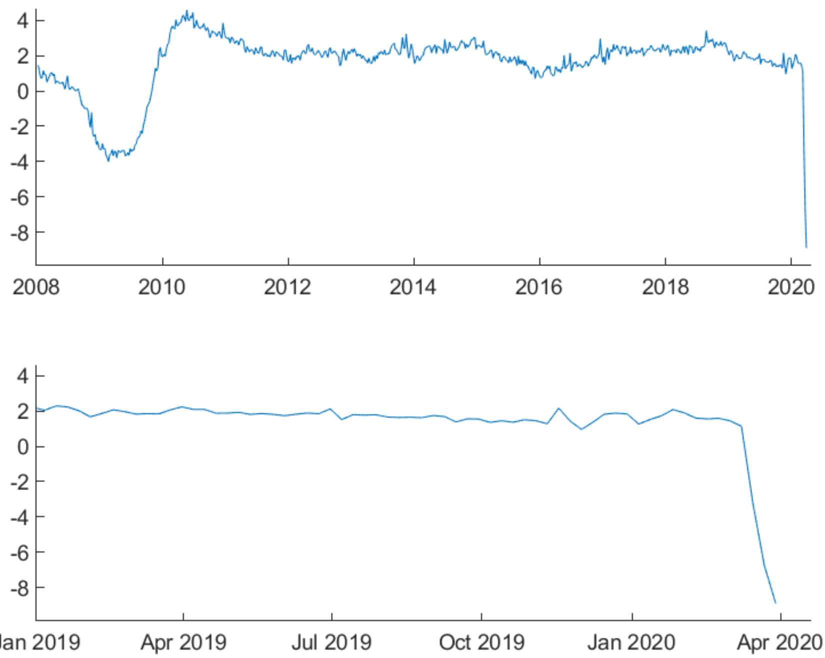
Figure 1: Weekly Economic Indicator (WEI)



Notes: Based on data available through April 9, 2020. The units are scaled to 4-quarter GDP growth.

The rest of this paper describes the underlying weekly data series as well as the details behind the construction of WEI. We also document the close relationship between the WEI and widely used lower frequency indicators of aggregate economic activity in the US, such as real GDP growth and industrial production.

I. The Weekly Data Series

Table 1 below lists the series we use to construct our baseline WEI. These include a measure of same-store retail sales, an index of consumer sentiment, initial and continued claims for unemployment insurance, an index of temporary and contract employment, tax collections from paycheck withholdings, a measure of steel production, a measure of fuel sales, a measure of railroad traffic, and a measure of electricity consumption. Unless

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the source already provides year-on-year growth rates, we transform all series to represent 52-week percentage changes, which also eliminates most seasonality in the data. **Figure 2** plots all the transformed series that serve as inputs to the index.

Table 1: Weekly Variables

Series	Native Units	Notes
Redbook Research: Same Store, Retail Sales Average, Y/Y % Chg.	NSA, Y/Y % Chg.	**The index is 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	**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.	**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.	**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	**The ASA Staffing Index tracks temporary and contract employment trends. Participants include a stratified panel of small, medium, and large staffing companies that together provide services in virtually all sectors of the industry. They account for about one-third of industry sales offices. https://americanstaffing.net/**
Federal Withholding Tax Collections	Y/Y % Chg.	**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/**

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Raw Steel Production	NSA, Thous. Net Tons	**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	**Weekly product supplied minus change in stock of finished gasoline and distillate fuels. This estimates wholesale gasoline + diesel sales to retailers and large end users (e.g., UPS). 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, units	**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**	**Total output for U.S. (excluding Alaska and Hawaii) investor-owned electric companies. https://www.eei.org/**

As can be seen in **Figure 2**, some of the weekly series exhibit considerable noise from week to week, such that gleaning broader trends from any one series can be difficult. The series, however, also display a clear cyclical pattern, which suggests that they might usefully be combined into a single index. The WEI is computed from these ten series using the method of principal component analysis. The first principal component of these ten series provides an estimate of a signal about the economy which is common to all variables. By construction, the Weekly Economic Index is a weighted average of the ten series. The mathematics of principal components analysis is summarized next.

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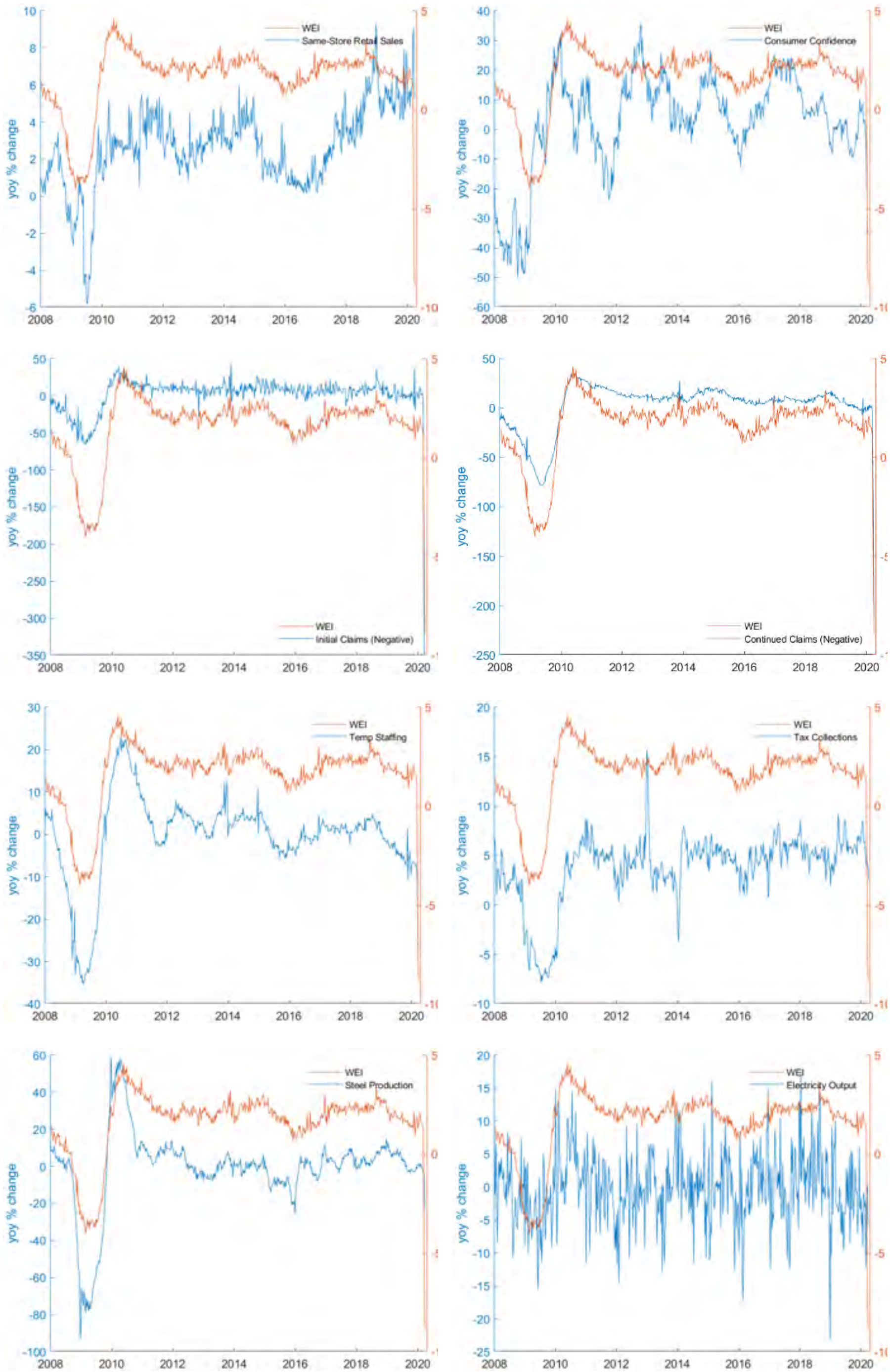
Figure 2 Weekly Variables and WEI



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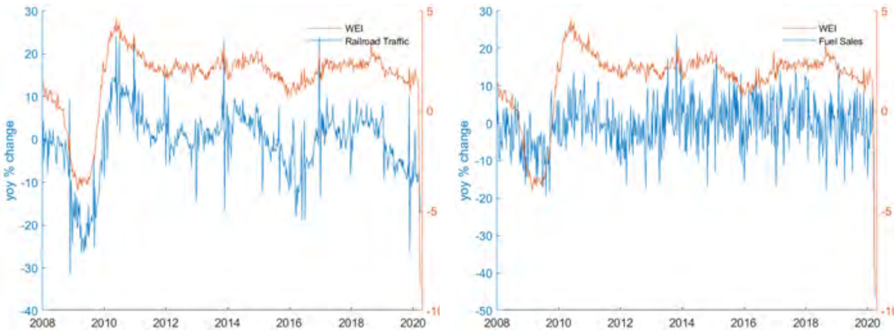

Notes: Based on data available through April 9, 2020. For sources, see **Table 1**.

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II. Construction of the Weekly Economic Index[4]

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). See Stock and Watson (2016) for a review.

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 is the sum of the dynamic effect of the common factor and an idiosyncratic disturbance, e_t, which arise from measurement error and from special features that are specific to an individual series:

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

[4] Parts of this section are adapted from the appendix in Stock (2013).

where L is the lag operator. The elements of the $N\times1$ vector of lag polynomials λ (L) are the dynamic factor loadings, and $\lambda_i(\mathrm{L})f_t$ 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 $\lambda(\mathrm{L})$:

$$X_t = \Lambda F_t + e_t \tag{2}$$

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

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 used both methods in developing the WEI, but found the results using the parametric DFM to be sensitive to specification details (lags, sample length, etc.), so principal components estimation is used in this paper.

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Table 2: PCA Results

Series	Weights Baseline	Weights Trimmed (ALS)
Same-Store Retail Sales	0.29	0.29
Consumer Confidence	0.23	0.21
Tax Collections	0.30	0.31
Initial Claims	-0.38	-0.38
Continued Claims	-0.41	-0.41
Temp Staffing	0.40	0.40
Steel Production	0.37	0.36
Fuel Sales	0.17	0.18
Electricity Output	0.12	0.13
Railroad Traffic	0.34	0.34
Total variance explained	54.4%	52.7%

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. In this case, the weights are estimated using alternating least squares, see for instance Stock and Watson (2002b).

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

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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. Removing outliers overall has little effect on the weights, and for WEI we therefore use the full-data weights. We find that WEI explains 54% of the overall variance of the underlying series.

Robustness The WEI is robust to changes in the details of its construction. Subtracting or adding individual series has little effect on the overall path; the same is true for estimating the weights on each series using only more recent data. The left panel of **Figure 3** compares our baseline index to one with a subset of 7 variables (omitting railroad traffic, tax withholdings and continuing claims). The middle panel plots a version in which we omit consumer sentiment. Both figures illustrate that the common signal is not driven by the precise choice of series. The right panel of **Figure 3** plots the baseline WEI against a series computed with weights estimated using only data from 2015 onward, showing that the relationship between these series has been fairly constant during and after the Great Recession.

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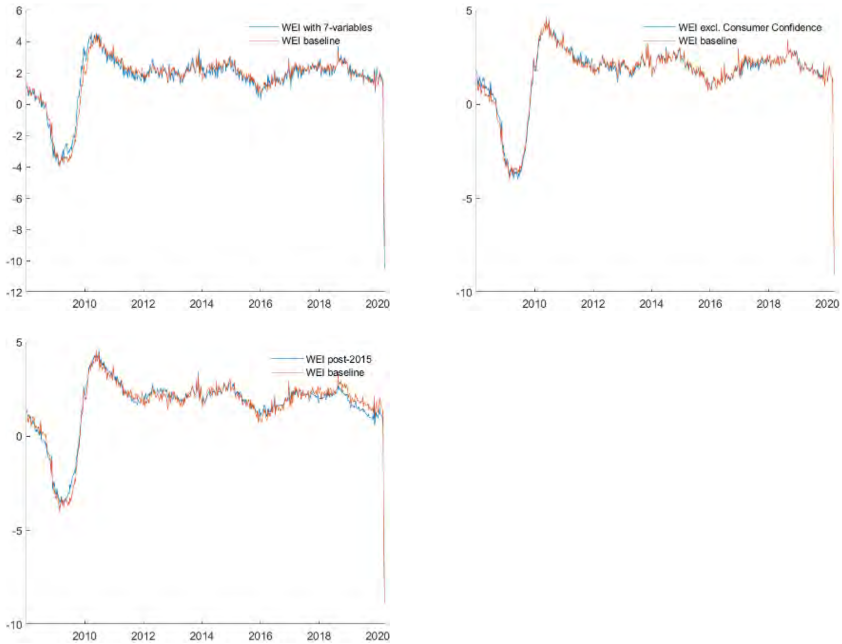
Figure 3: Robustness Checks



Notes: Based on data available through April 9, 2020.

Real Time Updating The WEI is published every Tuesday and Thursday following the releases of the underlying weekly data. Each WEI release reports a preliminary estimate for the prior week based on the data available at that point. The Tuesday update reflects incoming data on retail sales, consumer confidence and steel production for the prior week, as well as data on temp staffing for the week before the prior week. The Thursday update reflects incoming data on fuel sales, tax collections, initial claims, electricity use, and railroad traffic for the prior week, as well as data on continued claims for the week before the prior week. Final values for the WEI are available with a two-week lag.

Our procedure to produce the preliminary values is based on forecasting regressions for the WEI on two lags of WEI as well as the non-missing data. For example, in the Thursday update, where we miss the latest data points for two series, we use the estimated value from the forecasting regression of the WEI on its lags and the current values of the eight available series. The

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forecasting regressions use the same estimation sample (Jan 2008 to Feb 2020) as the one used to estimate weights in **Table 2**. The Tuesday update misses observations of two consecutive weeks of continuing claims. In that case, we first produce a preliminary WEI for two weeks prior based on this procedure, and subsequently repeat the forecasting step for the latest week using the preliminary WEI as input for the forecast.

III. Relationship Between the Weekly Index and Lower Frequency Measures

Figure 4 plots the WEI together with the four-quarter growth rate of real GDP. The latter series is used to scale the baseline index. A reading of 2 percent in a given week indicates that if the week's conditions persisted for an entire quarter, real GDP would be 2 percent greater than the same quarter a year ago. The panels in the first row of **Figure 5** plots the index against the monthly change in nonfarm payrolls and the twelve-month percentage change in industrial production (IP). The figure shows that the index tracks both payroll changes and IP growth closely. The bottom panels of **Figure 5** plot the index against two additional monthly activity indicators: capacity utilization and the ISM manufacturing index. The index also tracks these series relatively well. 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.

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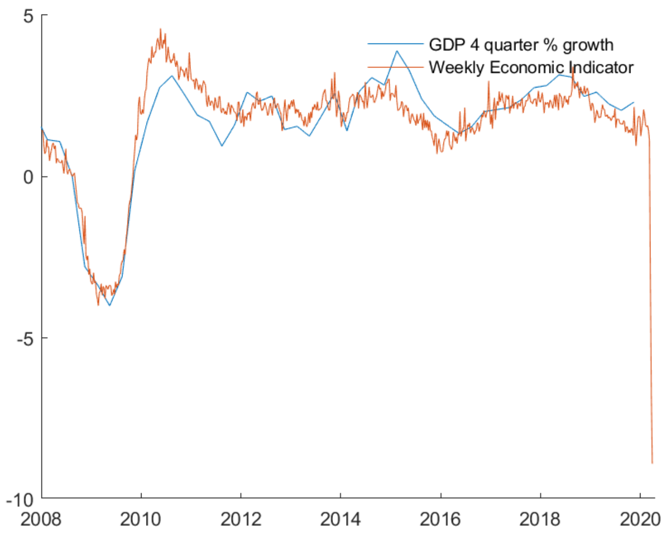
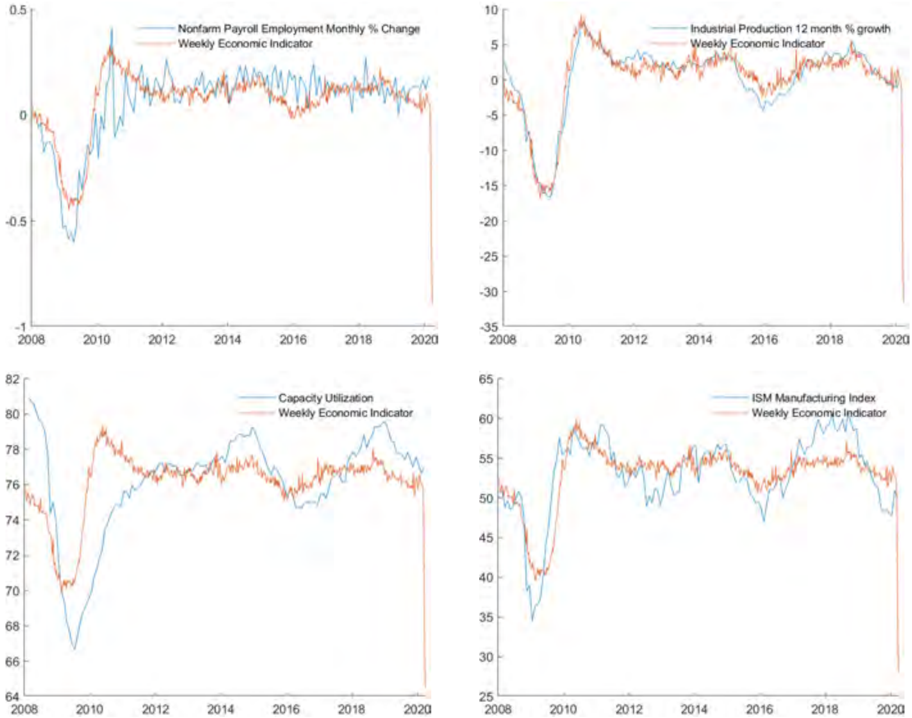
Figure 4: WEI and GDP growth



Notes: Based on data available through April 9, 2020.

Figures 4 and 5 help to illustrate two important differences between our index and a nowcast, like those for GDP growth produced by the Federal Banks of New York, Atlanta or St. Louis. 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—both are important to get a sense of real activity. Second, most nowcasts (including those of the New York, Atlanta and St Louis Feds) 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.

Figure 5: Relationship Between WEI and Other Monthly Activity Measures



Notes: Based on data available through April 9, 2020.

This said, it is useful to examine the predictive content of the WEI for relevant lower frequency activity indicators. A complication in comparing weekly and monthly data is the non-alignment of the calendar. To address this non-alignment, we introduce the concept of "pseudo-weeks", which 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 22^{nd} through final day of the month (so including between 7 and 10 days). Each day of the month naturally falls into a calendar week of the original WEI, so 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. We also calculate a monthly WEI by computing the average WEI for all constituent days.

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Payroll Employment We first explore predictive power for changes in payroll employment. Specifically, we begin by computing a monthly regression,

$$\Delta Y_t = c + \beta WEI_t^{monthly} + \sum_{s=1}^{2} \gamma_s \Delta Y_{t-s} + u_t, \qquad (4)$$

where Y_t is monthly private payroll employment. We compute heteroskedasticity and autocorrelation robust standard errors using the EWC estimator recommended by Lazarus et al (2018). Column (I) of **Table 3** reports the results; the WEI is a highly significant predictor of employment changes, with an R^2 of 0.83 (regressing on WEI alone gives 0.66).

We run an additional regression, reported in column (II), adding the change in employment from the ADP release as a control. The ADP release, which precedes the official payroll numbers by two days, is known to be highly informative for the eventual BLS release. We find that despite this strong relationship, the WEI provides additional information, above and beyond the ADP release.

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

$$\Delta Y_t = c + \sum_{i=1}^{\overline{w}} \beta_i WEI_t^{w_i} + \sum_{s=1}^{2} \gamma_s \Delta Y_{t-s} + u_t, \ \overline{w} = 1,2,3,4\,; \qquad (5)$$

where $WEI_t^{w_i}$ is the average WEI for the i^{th} pseudo-week of month t. For employment, since the payroll survey is conducted during the second week of the month, we consider the last two pseudo-weeks of the prior month and the first two pseudo-weeks of the current month. The results are reported in columns (III) to (VI). In regression (VI), we find that the second pseudo-week of the month, that on which the payroll survey is focused, is a significant predictor of employment changes. Moreover, from the last week of the prior month onwards, the weekly information provided by the WEI is jointly significant (from the F-test that all weekly coefficients are zero).

Industrial Production The WEI also helps to nowcast industrial production (IP). 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. We regress this first on the monthly WEI and lagged IP

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growth according to (4), where Y_t is monthly log IP. Column (I) of **Table 4** shows that the monthly average WEI (and lags) explains 17% of variation in IP growth, about two weeks before the official release (still 16% dropping lags of IP growth). We then proceed with the weekly nowcasting regressions, following (5). 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 15% to 28%. The most recent week is 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.

Table 3: Employment Regression Results

Regressors	(I)	(II)	(III)	(IV)	(V)	(VI)
$WEI_t^{monthly}$	21.90***	10.54*				
	(6.78)	(6.05)				
ΔADP_t		0.84***				
		(0.09)				
WEI week 2, current month						111.51*
						(60.87)
WEI week 1, current month					51.13	-46.11
					(39.06)	(62.10)
WEI week 4, past month				54.02	-2.32	8.64
				(42.37)	(67.83)	(68.51)
WEI week 3, past month			10.77	-42.09	-33.66	-56.13
			(10.30)	(49.64)	(50.62)	(54.78)
F-test: weekly coefficients = 0			1.09	6.41	6.55	3.61
			(0.32)	(0.01)	(0.01)	(0.05)
F-test: weekly coefficients equal				0.50	0.79	0.76
				(0.62)	(0.53)	(0.58)
SER	96.42	73.20	97.84	97.01	96.40	94.39
Adjusted R^2	0.83	0.90	0.83	0.83	0.83	0.84

*Notes: HAR standard errors computed using the EWC estimator of Lazarus et al (2018). Results starred at the 1%, 5%, and 10% levels, ***,**,*.*

GDP growth Finally, the WEI also aids in nowcasting GDP growth. To show this, we first regress GDP growth on the quarterly WEI, following (4), where ΔY_t is 4-quarter GDP growth (percent) and we replace the monthly average

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WEI with the quarterly average WEI. The results in Column (I) of **Table 5** show that the quarterly WEI is a significant predictor of GDP growth, with 89% of variation explained (85% 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

$$\Delta GDP_t = c + \sum_{i=1}^{\overline{m}} \beta_i WEI_t^{m_i} + \sum_{s=1}^{2} \gamma_s \Delta GDP_{t-s} + u_t,\ \overline{m} = 1,2,3\ ; \qquad (6)$$

where ΔGDP_t is 4-quarter GDP growth (percent). 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 0.86 to 0.92. 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.

IV. Conclusion

In normal times, familiar macroeconomic aggregates provide accurate descriptions of economic conditions with a modest delay. When conditions evolve rapidly from day to day and week to week, as is the case in the current environment, less familiar sources of data can provide an informative and timely signal of the state of the economy. The WEI provides a parsimonious summary of that signal.

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Table 4: Industrial Production Regression Results

Regressors	(I)	(II)	(III)	(IV)	(V)
$WEI_t^{monthly}$	0.17 (0.11)				
WEI week 4, current month					0.99** (0.36)
WEI week 3, current month				0.57* (0.31)	-0.11 (0.26)
WEI week 2, current month			0.76** (0.31)	0.18 (0.33)	-0.05 (0.27)
WEI week 1, current month		0.14 (0.10)	-0.60** (0.28)	-0.57** (0.26)	-0.63** (0.25)
F-test: weekly coefficients = 0		1.94 (0.19)	2.99 (0.09)	1.92 (0.19)	2.78 (0.09)
F-test: weekly coefficients equal		0.00	2.50 (0.13)	1.84 (0.20)	1.80 (0.21)
SER	0.67	0.68	0.66	0.65	0.62
Adjusted R^2	0.17	0.15	0.18	0.20	0.28

*Notes: HAR standard errors computed using the EWC estimator of Lazarus et al (2018). Results starred at the 1%, 5%, and 10% levels, ***,**,*.*

Table 5: GDP Regression Results

Regressors	(I)	(II)	(III)	(IV)
$WEI_t^{quarterly}$	0.70** (0.22)			
WEI month 3				0.25 (0.57)
WEI month 2			1.66*** (0.45)	1.25 (0.86)
WEI month 1		0.64* (0.28)	-1.12** (0.42)	-0.97** (0.37)
F-test: weekly coefficients = 0		5.42 (0.06)	12.81 (0.01)	8.14 (0.04)
F-test: weekly coefficients equal			4.28 (0.08)	2.87 (0.17)
SER	0.55	0.63	0.48	0.48
Adjusted R^2	0.89	0.86	0.92	0.91

*Notes: HAR standard errors computed using the EWC estimator of Lazarus et al (2018). Results starred at the 1%, 5%, and 10% levels, ***,**,*.*

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