Applied Economics Letters

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rael20

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APPLIED ECONOMICS LETTERS
https://doi.org/10.1080/13504851.2021.1907278

Routledge
Taylor & Francis Group

ARTICLE

Nowcasting the trajectory of the COVID-19 recovery

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ABSTRACT

I develop a weekly coincident index of economic activity in the State of Hawaii. The purpose of the index is to nowcast the recovery from the COVID-19 induced downturn. The index is the first principal component extracted from 18 daily and weekly state-level time series, it captures about 80% of the variation in the sample, it is available with a four-day lag, and it predicts the changes in nonfarm payrolls, the Philadelphia Fed coincident index, and excise tax revenues.

KEYWORDS

Coincident index; principal component analysis; high-frequency data; nowcasting; COVID-19

JEL CODES

C22; C53; C55; C82; E27

I. Introduction

COVID-19 has brought the longest period of economic expansion in modern history to an abrupt halt. The pace and magnitude of decline in economic activity has been unprecedented, and the recovery ahead will likely be uneven. Decision making in such a rapidly-changing environment requires data and tools that support (nearly) real-time monitoring of conditions. With this in mind, I have developed a weekly coincident index of economic activity for the State of Hawaii. The index captures both the steep drop and sluggish recovery seen across many economic indicators in the wake of the COVID-19 outbreak. While similar indexes can be developed for any state, the choice of Hawaii is practical: Hawaii's economy is one of the hardest hit in the US due to its heavy reliance on tourism, dependence on air travel, and intensive service orientation. Hawaii is a small open economy that can serve as a good example of the method's usefulness for national, state and sub-state economies dominated by tourism. I am working on an extension of this analysis to every US state.

Traditionally, macroeconomic models have relied on time series reported at the monthly or quarterly frequency. Often this lower-frequency data is released with a substantial delay – especially for subnational regions – dramatically diminishing the timeliness of the information. However, as documented by Garboden (2020), the last two decades have seen a surge in data gathering occurring in real time. While a large share of the data collected by private entities remains unavailable to the public or is only reported at the national level, recognizing the need for timely information in the wake of the COVID-19 outbreak, some companies have begun sharing data that can be used to track economic conditions with a very short lag. This study takes advantage of daily and weekly data to nowcast the trajectory of the Hawaii economy.

There has been enormous progress in developing and adopting techniques to digest the ever-growing flow of information (Fuleky 2019). The type and extent of available data plays an important role in choosing an appropriate method to track economic fluctuations. Many techniques attempt to filter out the signal from the noise, that is to separate relevant from irrelevant information, contained in a large number of variables. Such synthesis – resulting in a coincident index – is useful if it summarizes the underlying conditions shared by many different facets of the economy and tracks the path of economic recovery, or relapse, in almost real time. At the most general level, an index is constructed as a weighted average of the observed time series, and a key area of inquiry has been the determination of optimal weights. The literature has embraced two frameworks in this respect.

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Table 1. Variable descriptions. Transformations of the variables are indicated in parentheses: yoy = year-over-year change, idx = indexed to the beginning of 2020, inv = inverted sign. The mei_dallas_fed variable is based on SafeGraph.com (2020) data. For additional information, see Atkinson et al. (2020), Chetty et al. (2020), Fitzpatrick, DeSalvo, and Karen (2020), OpenTable.com (2020), Waldmann (2020), and Warren and Skillman (2020).

Variable	Description	Source
air_passengers	Number of deplaning passengers in Hawaii (yoy)	http://dbedt.hawaii.gov/visitor/daily-passenger-counts/DBEDT
business_open	Businesses open % change relative to January, 2020 (idx)	https://joinhomebase.com/data/Homebase
cont_claims	Continuing claims of unemployment insurance benefits (yoy, inv)	http://labour.hawaii.gov/rs/home/unemployment/DLIR
empl_working	Employees working % change relative to January, 2020 (idx)	https://joinhomebase.com/data/Homebase
hours_worked	Hours worked % change relative to January, 2020 (idx)	https://joinhomebase.com/data/Homebase
job_postings	Average level of job postings relative to January 4–31 2020 (idx)	https://www.burning-glass.com/research-project/covid-19/Burning Glass
mei_dallas_fed	Deviation from normal mobility behaviours induced by COVID-19 (idx)	https://www.dallasfed.org/research/MEI.aspxDallas Fed
mobility_hi	Typical distance travelled in a day (idx)	https://github.com/descarteslabs/DL-COVID-19Descartes Labs
opentable_diners	Year-over-year % change in seated diners (yoy)	https://www.opentable.com/state-of-industryOpenTable
proc_payrolls	Volume of processed payrolls (yoy)	https://www.proservice.comProService Hawaii
search_covid	Search volume for "covid" in Hawaii (inv)	https://trends.google.com/trends/Google Trends
time_at_grocery	Time spent at grocery and pharmacy location relative to Jan 3-Feb 6 2020 (idx)	https://www.google.com/covid19/mobility/Google Mobility
time_at_parks	Time spent at parks relative to Jan 3-Feb 6 2020 (idx)	https://www.google.com/covid19/mobility/Google Mobility
time_at_resid	Time spent at residential locations relative to Jan 3-Feb 6 2020 (idx, inv)	https://www.google.com/covid19/mobility/Google Mobility
time_at_retail	Time spent at retail and recreation locations relative to Jan 3-Feb 6 2020 (idx)	https://www.google.com/covid19/mobility/Google Mobility
time_at_transit	Time at/inside transit stations relative to Jan 3-Feb 6 2020 (idx)	https://www.google.com/covid19/mobility/Google Mobility
time_at_work	Time spent at work places relative to Jan 3-Feb 6 2020 (idx)	https://www.google.com/covid19/mobility/Google Mobility
traffic_volume	Road traffic volume relative to the 2019 annual average (idx)	https://hidot.hawaii.gov/highways/covid-19-traffic-volume-comparison/DOT

The first one decomposes the observed time series into unobserved common and idiosyncratic components via a parametric state-space model, and uses the Kalman filter to extract a common factor from the data (Stock and Watson 1991). While the classical dynamic factor model has seen many extensions that relax the underlying assumptions (see the surveys by Stock and Watson 2012; Doz and Fuleky 2020), it is not suitable for short time series since the estimation of dynamics requires a reasonably long sample. In the present study, this requirement is binding because much of the relevant high frequency data has only been made available since the emergence of COVID-19.

The second approach for forming an index is nonparametric and it circumvents the long-sample requirement. It uses principal component analysis (PCA) to identify the margin of dominant variation in the data set. For surveys of PCA and its applications in macroeconomics see Bai and Serena (2008) and Cao, Gu, and Wang (2020). I use PCA to extract the common signal from 18 weekly state-level time series.

There are two existing high-frequency indexes of US economic conditions at the national level. The Aruoba, Diebold, and Scotti (2009) business conditions index is based on weekly initial jobless claims, four monthly variables, and quarterly real GDP. The Lewis, Mertens, and Stock (2020) weekly economic index is based on ten different daily and weekly series covering consumer behaviour, the labour market and production. At the sub-national level, the Federal Reserve Bank of Philadelphia produces a *monthly* coincident index for each of the fifty states (Crone and Clayton-Matthews 2005) but it is released with an approximately four-week lag (the Philadelphia Fed has suspended the release of state leading indexes due to the methodology's incompatibility with the current economic fluctuations). In contrast, the *weekly state level* index developed here is available with a four-day lag, increasing its usefulness in the current fast-paced environment.

II. Data

This paper highlights the abundance of high-frequency data at the state level. The data set contains 18 variables listed in Table 1. Chetty et al. (2020) used some of this data to track spending and employment in the wake of COVID-19 along various socio-economic dimensions. While most series only cover the period since early 2020, the few observations from

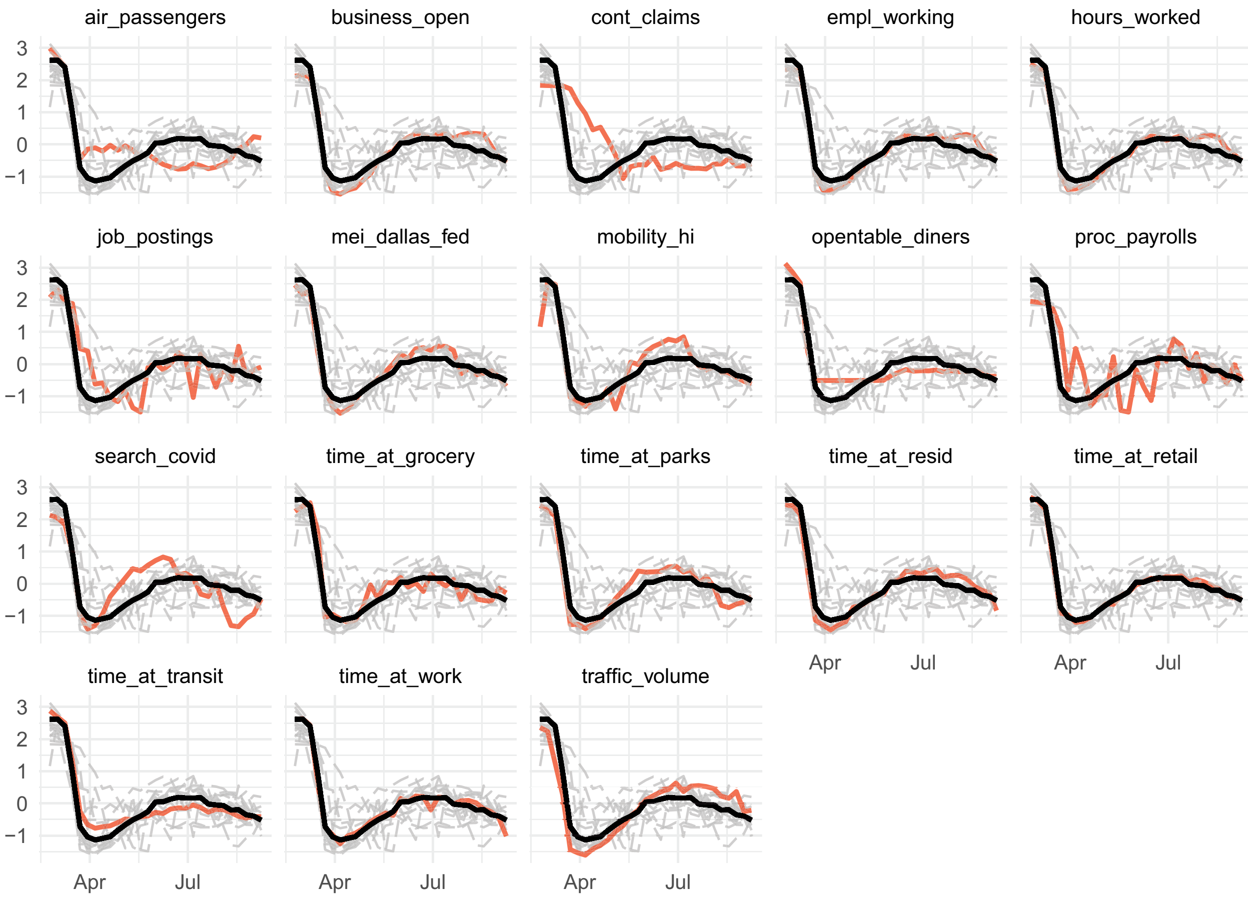

Figure 1. Each panel illustrates the evolution of the index (black) and the variable denoted in the panel heading (highlighted in red). The continuing_claims, search_covid, and time_at_resid variables are multiplied by −1 since they tend to be inversely related to the other variables.

before the COVID-19 outbreak ensure a reference point for comparison. The short release lag makes the data ideal for nowcasting the current state of the economy. Because PCA requires a balanced panel, the time period of analysis is determined by the variable with the shortest sample. As of 17 September 2020, the analysed sample contains 29 weekly observations between 24 February 2020 and 13 September 2020.

The input variables cover various facets of the economy, including the labour market, consumer behaviour, and locally important business conditions in the tourism and restaurant industries. In

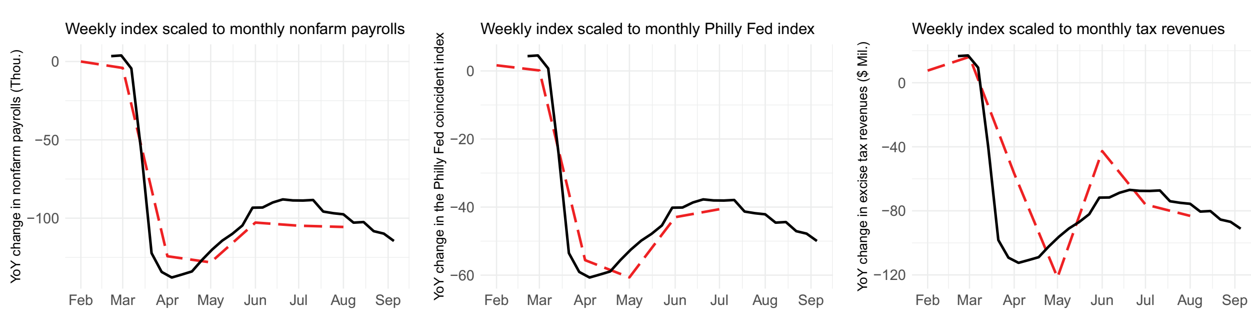

Figure 2. Time plot of the index (black) and year-over-year changes in nonfarm payrolls, the Philadelphia Fed coincident index, and general excise tax revenues (red). Because taxes are collected after the conclusion of the reference period, tax revenues are slightly lagging economic activity.

contrast to traditional approaches, the index developed here incorporates several measures of mobility that capture the impact of stay-at-home and physical-distancing behaviour that have followed the COVID-19 outbreak.

Since most variables have a short history, traditional seasonal adjustment – which requires multiple years of data – is not feasible. However, series with 2019 values are converted into year-over-year changes, which eliminates most of the seasonality in the data. Series with observations starting in early 2020 are indexed relative to the pre-pandemic period. Additional information about data collection and transformation is available on the websites of the sources linked in the third column of Table 1. Since PCA is sensitive to the unit of measurement, each variable is standardized to have zero mean and unit variance. Continuing unemployment claims, Google searches for 'COVID', and time spent at residential locations are inversely related to economic activity, and so these variables are inverted by multiplying their values by negative one. Principal component analysis is carried out with the R function prcomp, and the code is available from the author upon request.

III. Results and discussion

Figure 1 demonstrates the relationship between each series and the first principal component (PC1). PC1 captures 81% of the overall variation in the sample and exhibits statistically significant correlation with each underlying series; the weakest correlation, 0.45, occurs between PC1 and continuing claims. Since PC1 effectively consolidates the common signal about the business cycle, it is a useful summary measure of overall economic conditions. Due to its timeliness, PC1 – or the index – can be used to nowcast the recovery from the COVID-19 recession. When normalized, by setting its peak to 100% and the trough to 0%, the index represents the extent of recovery from the decline.

Figure 2 illustrates the relationship between the index and the year-over-year change in three monthly economic indicators: nonfarm payrolls, the Philly Fed coincident index, and general excise tax revenues. Although the short sample inhibits forecast evaluation, the index – available four days after the reference week – predicts the evolution of these broad-based economic measures – released 3–4 weeks after the reference month – more accurately than a random walk forecast. The index suggests that Hawaii's nascent and weak recovery began faltering in mid-July, just after the expiration of the Paycheck Protection Program and the onset of the second wave of COVID-19 infections.

Disclosure statement

No potential conflict of interest was reported by the author.

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