Real-Time Economics: A New Platform to Track the Impacts of COVID-19 on People, Businesses, and Communities Using Private Sector Data*

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Abstract

We build a new, publicly available economic tracker that measures economic activity at a high-frequency, granular level. Using anonymized data from several large businesses – credit card processors, payroll firms, job posting aggregators, and financial services firms – we construct statistics on consumer spending, employment rates, incomes, business revenues, job postings, and other key indicators. We report these statistics in real time using an automated pipeline that ingests data from these businesses and reports statistics publicly on the data visualization platform, typically with a lag of three days or less since the relevant transactions occur. We present fine disaggregations of the data, reporting each statistic by county and by industry and, where feasible, by initial (pre-crisis) income level and business size. We illustrate how the tracker can be used by measuring the economic impacts of the COVID-19 crisis on people, businesses, and communities and estimate the causal effects of recent local policy decisions. Going forward, we hope this tracker will serve as a public good that facilitates more precise targeting of policies and rapid diagnosis of the root causes of economic crises.

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I Introduction

Economic policy decisions have traditionally been made based on employment and business activity data collected from national surveys of households and businesses. Although such statistics have great value in understanding the economy, they have two limitations that have become apparent in the face of the fast-moving COVID-19 pandemic. First, such data are often available only with a significant time lag. For instance, the Employment Situation Summary (i.e., jobs report) released by the Bureau of Labor Statistics on May 8 presents information on employment rates as of the week ending April 12; the next update will not come for another month. Second, due to limitations in sample sizes, such statistics typically cannot be used to assess granular variation across geographies or subgroups; most statistics are typically reported only at the state level and breakdowns by demographic subgroups or sectors are often unavailable.

In this paper, we address these challenges by building a new, freely accessible platform that tracks economic activity in real time at a granular level. Using anonymized and aggregated data from several large businesses – credit card processors, payroll firms, job posting aggregators, financial services firms – we construct statistics on consumer spending, employment rates, incomes, business revenues, job postings, and other key indicators. We report these statistics in "real time" using an automated pipeline that ingests data from these businesses and reports statistics publicly on the data visualization platform, typically with a lag of three days or less since the relevant transactions occur. We present fine disaggregations of the data, reporting each statistic by county and by industry and, where feasible, by initial (pre-crisis) income level and business size.

Many firms already analyze their own data internally to make business decisions and some firms have begun sharing aggregated data with policymakers and researchers in the current crisis. Our contribution is to (1) collect these disparate data sources into a single, publicly accessible platform that eliminates the need to write contracts with specific companies to access relevant data; (2) systematize these data sources by documenting the samples they cover and adjusting for selection biases, seasonal fluctuations, and other statistical issues; and (3) provide the combined series in an interactive data visualization tool that facilitates comparisons across outcomes, areas, and subgroups. The key technical problem that our platform solves is that it allows companies to share data without disclosing sensitive information about their business or clients by combining data from multiple sources into a single series. Hence, the platform serves as a coordination device for the use of private sector data to inform public policy, one that we hope will expand over time and be a useful resource for economic policy in this crisis and beyond.

We illustrate the value of the tracker by analyzing the impacts of recent policy decisions in the COVID-19 crisis, focusing in particular on state shutdowns and re-openings. Perhaps surprisingly, we find these policies have little or no impact on economic activity. The decline in economic activity – consumer spending, the number of small business open, employment – occurred in most cases *before* states "shut down," consistent with other recent work examining data on hours of work and movement patterns (Bartik et al. 2020, Villas-Boas et al. 2020). Moreover, we show that recent policies ending these shut-downs in certain states such as Georgia and South Carolina have not been associated with significant increases in economic activity. These findings suggest that the primary barrier to economic activity is the threat of COVID-19 itself as opposed to legislated economic shutdowns. This simple analysis illustrates the utility of the tracker: this finding would not be evident in traditional government survey data for several months, but is easily observed in private sector data a few days after policy changes are made.

Our work builds on and contributes to a rapidly evolving literature on the economic impacts of COVID-19 as well as a long literature in macroeconomics on the measurement of economic activity at business cycle frequencies. Several recent papers have used private sector data analogous to what we assemble here to analyze labor market trends (e.g., Bartik et al. 2020, Kahn, Lange, and Wiczer 2020), spending patterns (e.g., Alexander and Karger 2020, Baker et al. 2020, Chen, Qian, and Wen 2020), business revenues (e.g.,), and social distancing (e.g., Allcott et al. 2020, Chiou and Tucker 2020, Goldfarb and Tucker 2020, Mongey, Pilossoph, and Weinberg 2020). These papers have identified a number of important patterns that we observe in our data as well, such as larger reductions in income and employment for lower-income workers and concentrated impacts in certain industries such as food and accommodation (e.g., Cajner et al. 2020). Each of these papers typically analyzes one or two of these data sources, obtained through a data use agreement with the relevant firm. We combine many of these datasets into a unified, freely accessible platform that is automatically updated to pull the most recent data from companies' internal databases. This approach eliminates the need to obtain specific permissions to use data from each company, thereby providing a public good that we hope will support the work of researchers, policy makers, and the general public.[1]

1. Additionally, building on work by Gupta et al. (2020), we build a systematic, quantitative list of key policy changes made in the COVID-19 crisis at the federal, state, and local levels that can be used by researchers and policymakers to identify causal effects of policy changes and uncover mechanisms underlying economic outcomes.

Going forward, we envision two roles for such a platform to support macroeconomic policy. First, the data can permit precise targeting of policies to subgroups and areas that are most affected by a crisis by directly revealing which groups have been impacted most. Second, the data can be used to learn rapidly from heterogeneity across areas – which are often hit by differential shocks and pursue different local policy responses. This approach can permit rapid diagnosis of the root factors underlying an economic crisis, potentially facilitating more effective macroeconomic policy responses.

The paper is organized as follows. The next section describes our data and the methods we use to construct the indices. In Section 3, we illustrate how the tracker can be used by presenting some simple illustrative event studies of key outcomes around legislated shutdowns and re-openings at the state level. Section 4 concludes by discussing policy implications and potential future applications of the tracker. Technical details on data, methods, and supplementary analyses are available in an online appendix. This paper will be updated to include further analysis as we obtain and analyze more data, both from the data providers described below and other companies whose data are currently being incorporated into the platform.

II Data and Methods

In this section, we describe the data sources and methods we use to construct the aggregated series in the Economic Tracker. We organize the section around the central outcomes we study: employment and earnings, consumer spending, business activity, education, and public health outcomes related to the COVID-19 crisis. For each of these outcomes, we describe the underlying data sources in turn, characterizing their samples and variable definitions to the extent permissible by the data providers.

II.A Employment and Earnings

II.A.1 Homebase

We form our series for Hourly Employment and Hours Worked at small businesses using data from Homebase. Homebase is a company that provides virtual scheduling and time-tracking tools, focused on small businesses in sectors such as retail, restaurant, and leisure/accommodation (Table 1 discussed below provides precise industry compositions). For our purposes, they have information on hours worked as well as wages of employees.

We receive de-identified data on employees at Homebase clients at the establishment-worker-day level. We then aggregate to the county-day, metro-day, state-day, national-day level. Individuals who work at multiple establishments are treated as distinct employees. We exclude firms that began using Homebase in 2020 and salaried employees. We suppress estimates for geographies with fewer than 10 Homebase clients in January 2020. The series runs from January 5, 2020 to the present.

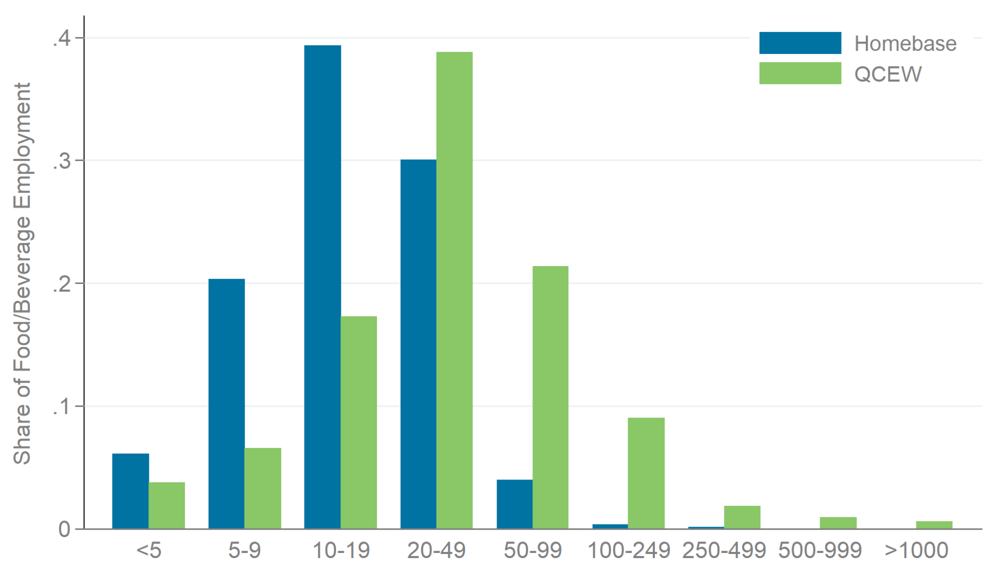
Hourly Employment Our Hourly Employment measure is constructed as a seven-day moving average percent change in number of hourly employees relative to January 2020. We construct this by taking the sum of the previous six days of number of hourly employees at an establishment and the current day's number of hourly employees at an establishment, and then dividing by 7. We then index each location relative to their pre-COVID-19 employment by dividing each moving average value by their mean value during the January indexing period. We then subtract 1 to center the series around 0. We aggregate across establishments to produce estimates at county, state and national geographies, weighting by number hours worked in January at the establishments. We assign location based on the zip code of establishment and crosswalk to counties and metros.

Comparison to QCEW In order to understand the context for this series, we compare coverage rates to the distribution of employees and employers in the Quarterly Census of Employment and Wages (QCEW). Table 1 compares the Homebase average monthly employees by industry distribution to the QCEW for the period January 2018-September 2019. Figure 1 compares the Homebase and QCEW distribution of firm sizes in the food and beverage industry for the period January-March 2019. We can see that Homebase clients are not representative of the national employment distribution, primarily consisting of small food and beverage and retail establishments and their employees.

TABLE 1: Distribution of Average Number of Monthly Employees by Industry, QCEW and Homebase

Industry	QCEW (%)	Homebase (%)	Homebase/QCEW
Beauty & Personal Care	1.91	1.10	0.58
Charities, Education, & Membership	5.33	2.78	0.52
Food & Drink	15.02	69.01	4.59
Health Care and Fitness	22.94	4.57	0.20
Home and Repair	3.72	1.51	0.41
Leisure and Entertainment	2.86	2.54	0.89
Professional Services	22.73	2.18	0.10
Retail	19.79	15.75	0.80
Transportation	5.71	0.56	0.10

FIGURE 1: Comparing Average Employment Share by Establishment Size (Food & Drink)



When examining trends in employment in its key industries, Homebase patterns generally track with the QCEW. Figure 2 and Figure 3 compare the national aggregate series of month-to-month employment change in the food and beverage industry and retail industry, respectively. Homebase employment change is calculated as establishment employment change at the weekly level then averaging to the month, weighted by firm size in the prior month; QCEW employment growth is computed nationally.

FIGURE 2: Month-to-Month Employment Growth (Food & Drink)

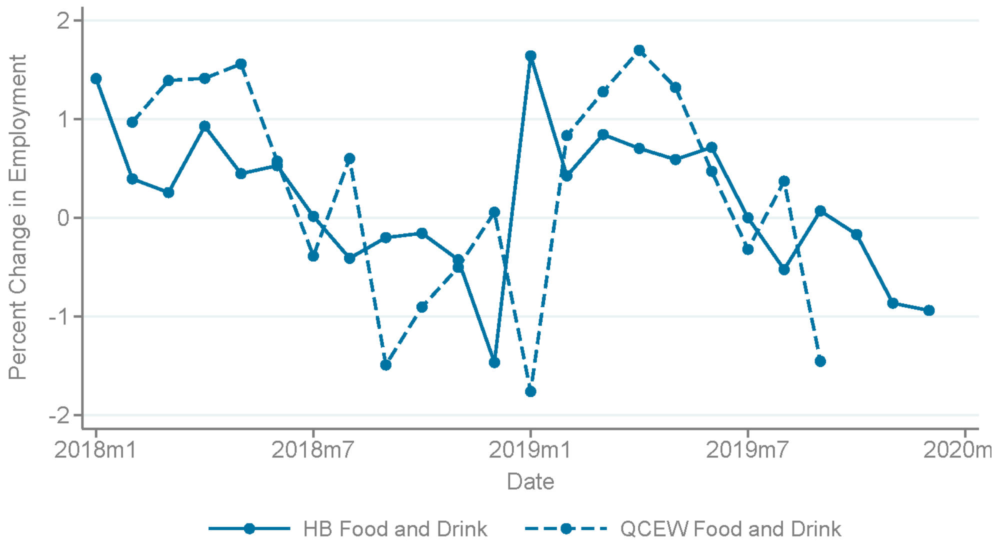


FIGURE 3: Month-to-Month Employment Changes (Retail)

Additionally, we compare Homebase wage distributions to the Current Population Survey (CPS), which reports surveyed hourly earnings that exclude tips and overtime pay. The Homebase data excludes tips but could include overtime pay. All wage data has been inflated to October

2019 levels. Figure 4 compares that national distributions of hours worked by wage level in the food and beverage industry, for the period August-October 2019 (the most recent three months of the CPS). The distributions appear quite similar; the wages offered by food and beverage firms in the Homebase data reflect the national distribution in the industry. Figures 5 and 6 show that national aggregate time trend in hours worked by wage bin in the food and beverage industry for CPS and Homebase respectively. Both sets show relatively stability in hours worked by wage bin and Homebase appears reflective of national wage trends.

FIGURE 4: Share of Total Hours Worked by Wage (Food & Drink)

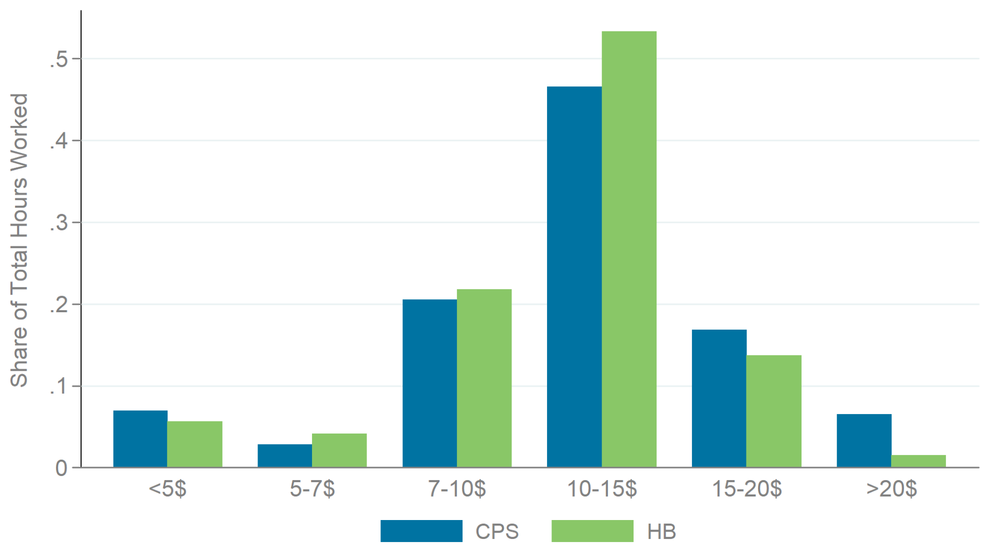


FIGURE 5: CPS Share of Hours Worked by Wage Over Time (Food & Drink)

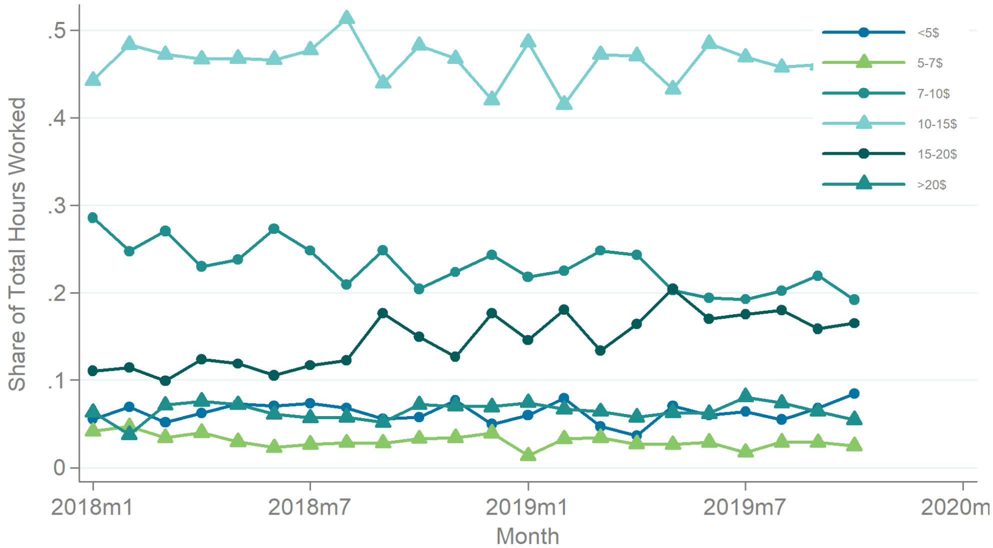
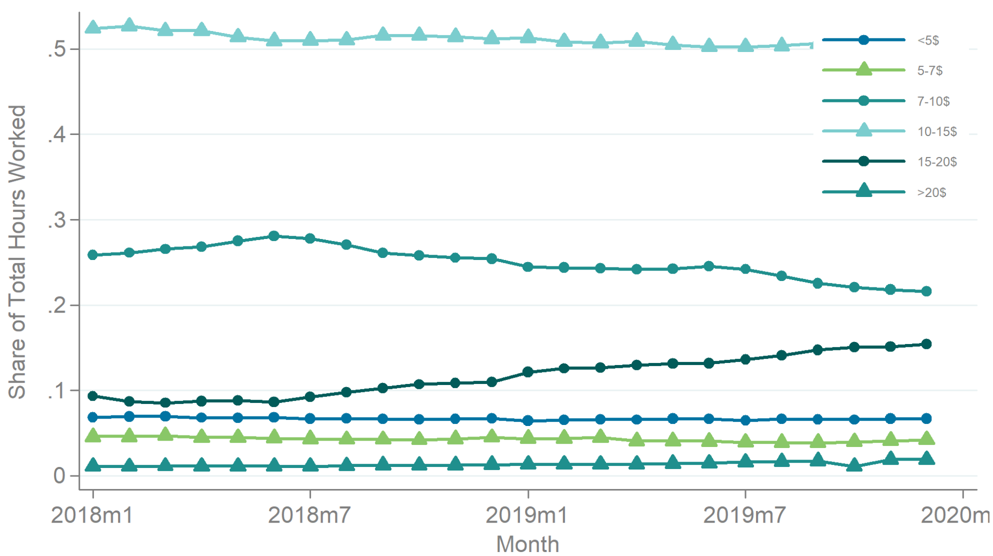


FIGURE 6: Homebase Share of Hours Worked by Wage Over Time (Food & Drink)



Hours Worked The key measure is the seven-day moving average percent change in total hours worked relative to January 2020. We construct daily values as a 7-day moving average by taking the sum of the previous six days of total hours worked at an establishment and the current day's total hours worked at an establishment, and then dividing by 7. We then index each location relative to their pre-Covid-19 employment by dividing each moving average value by their mean value during the January indexing period. We then subtract 1 to center the series around 0. We aggregate across establishments to produce estimates at county, state and national geographies, weighting by number hours worked in January at the establishments. We then produce metro-level estimates for select large metros.

Average Hourly Wages The key measure is change in individuals' hourly wages rates by week relative to the second week of January 2020. We produce week-on-week change by comparing hourly wages to the prior week for individuals who are observed in both time periods. We restrict the sample to individuals making at least $1 above the state minimum wage (since it would not be possible to see downward wage movement for individuals already at a lower bound). We aggregate across individuals to produce estimates at county, state, metro, and national geographies.

Individual Earnings The key measure is the seven-day moving average percent change in total earnings relative to January 2020. We construct daily values as a 7-day moving average by taking the sum of the previous six days of total employee earnings at an establishment and the current day's total employee earnings at an establishment, and then dividing by 7. We then index each location relative to their pre-Covid-19 employment by dividing each moving average value by their mean value during the January indexing period. We then subtract 1 to center the series around 0. We aggregate across establishments to produce estimates at county, state and national geographies, weighting by number hours worked in January at the establishments. We then produce metro-level estimates for select large metros.

II.A.2 State Unemployment Benefit Claims

We download and display claims data from the Office of Unemployment Insurance at the Department of Labor at the state-week level and national-week level. Future versions will provide information at the county-week level. Location is defined by the county and state of the filer's reported residence.

Unemployment Claims We provide both new employment claims and total employment claims. Total claims are the count of new claims plus the count of people receiving unemployment insurance benefits in the same period of eligibility as when they last received the benefits.

Unemployment Claims Rate We also construct an unemployment claims rate per 100 people by taking the total number of claims filed, multiplying by 100, and dividing by the 2019 Census population estimates[2]

II.B Consumer Spending

II.B.1 Affinity

We receive anonymized aggregate consumer spending data from Affinity Solutions Inc. Affinity Solutions is a company that collects consumer purchasing information from card-based transactions and uses this data to provide marketing insights. Information collected via Affinity is on the purchaser side of the market and therefore provides a measure of consumer spending.

All Consumer Spending We receive and present data on credit and debit transactions at the at the county-merchant category code-day level. We then crosswalk the MCCs to industry codes and then aggregate up to the metro-industry-day, state-industry-day, and national-industry-day levels.

We mask all observations for county-industry combinations that have an average of less than $XX in spending per day between January 4 and January 31. The series runs from January 7, 2020 to the present.

We construct daily values as a 7-day moving average as the sum of the previous six days spending and the current day's spending divided by 7. We then seasonally adjust the series by dividing each calendar date's 2020 value by its corresponding value from 2019. For the 29th of February, we use an average between the 28th and the 1st of 2019 to adjust. We then index the seasonally adjusted series relative to pre-Covid-19 spending by dividing the seasonally adjusted series by the mean seasonally adjusted 7-day moving average from January 4-31.

Industry is received as merchant category codes (MCC), which crosswalk to categories to Apparel & General Merchandise; Arts, Entertainment & Recreation; Grocery; Health Care; Restaurant & Hotels; and Transportation. These categories do not sum to total spending.

Location is assigned to a county by Affinity using the address of the cardholder.

Comparison to CEX (And Womply Small Business Spending Below) In order to understand the representativeness of this series, we compare the Affinity aggregate spending distri-

2. See the variable "popestimate2019" available here.

butions to the Consumer Expenditures Survey (CEX) from the Bureau of Labor Statistics. Figure 7 compares aggregate spending during the 2019, across NAICS codes. We crosswalk the Universal Classification Codes (UCCs) in the CEX to NAICS using an internally generated crosswalk. Affinity aggregate spending is skewed towards retail spending and has an overrepresentation of finance and insurance; food and construction spending are underrepresented.

To understand how the spending series reflects national spending trends, we compare the national aggregate spending series to the Monthly Retail Trade Survey (MRTS), a national survey of retailers and food service providers. Figure 8 compares the MRTS and Affinity month-to-month spending series for the period January- December 2019, indexed to January 2019; Figure 9 is the same but for the retail industry. Overall, Affinity data closely mirrors national patterns in food and drink and retail spending over time.

FIGURE 7: Aggregate Spending by Industry (2019), Womply, Affinity, and CEX

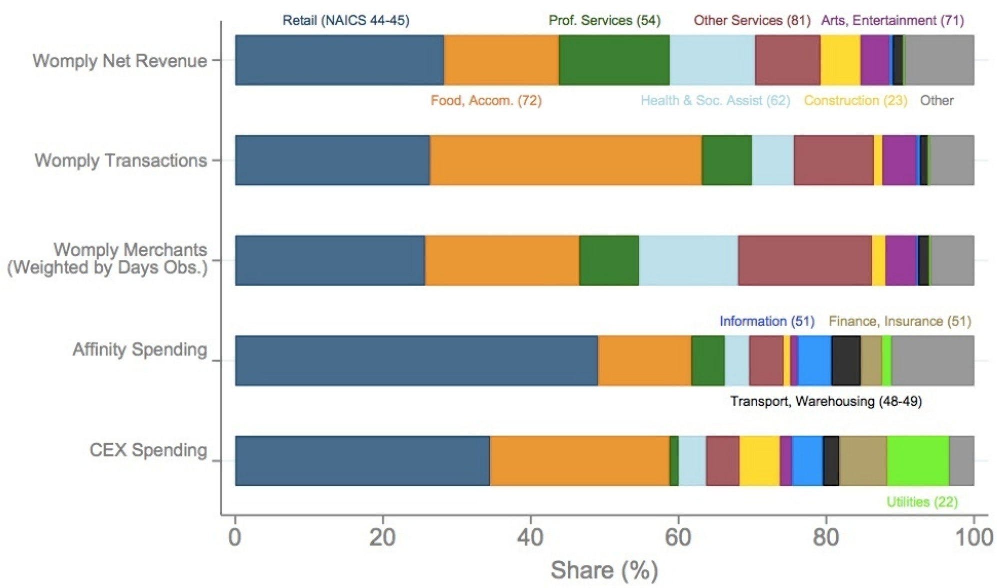


FIGURE 8: Month-to-Month Spending Change, Affinity and MRTS (Food & Drink)

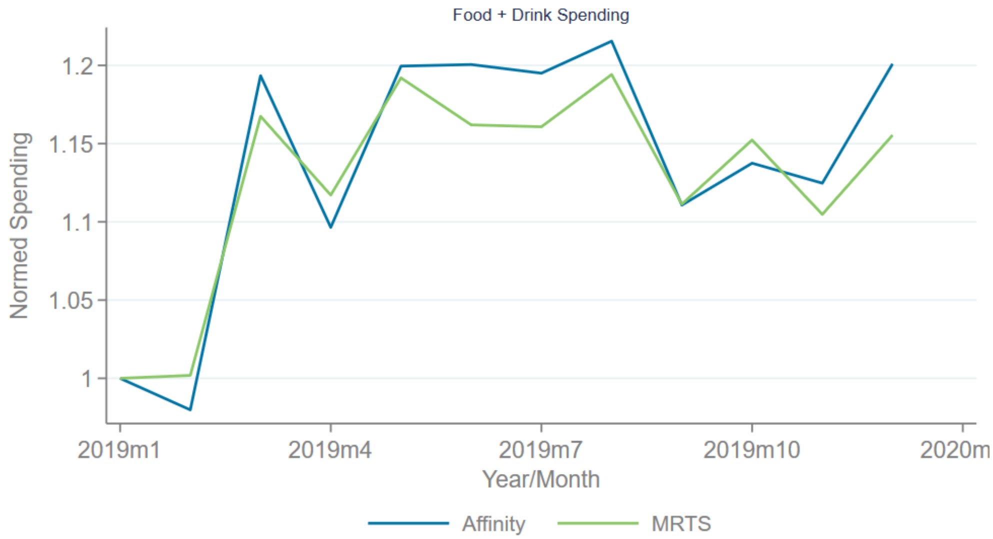
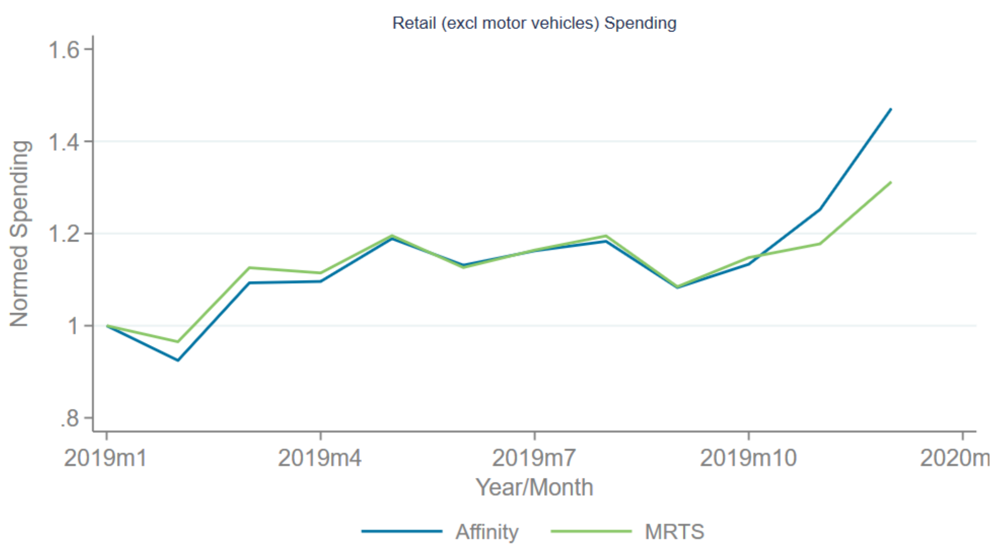


FIGURE 9: Month-to-Month Spending Change, Affinity and MRTS (Retail)



II.C Business Activity

II.C.1 Burning Glass

We receive job posting data at the geography-week level from Burning Glass which sources job posting data from approximately 40,000 online job boards in the United States.

Job Postings We construct a measure of job postings by aggregating to the county-week, metro-week, state-week, and national-week levels, with industry and qualification cuts at each level. Burning Glass removes duplicate postings in the data and assigns postings to geographic areas using an internal algorithm. Postings with or without associated employers are included. The dates used for the sample are January 1, 2020 to present.

Pooled estimates at all geographic levels are derived directly from the Burning Glass data, as are industry and qualification cuts at the state level and for the largest 200 counties. For other counties we impute industry postings as follows: we first use the state-industry data to get the share of postings in each industry in a given week and state. As the county total posts include posts that are missing an industry classification, we create a county-level variable that is number of posts that are not missing industry. We then multiply this number by the state-industry shares to get county-industry imputations.

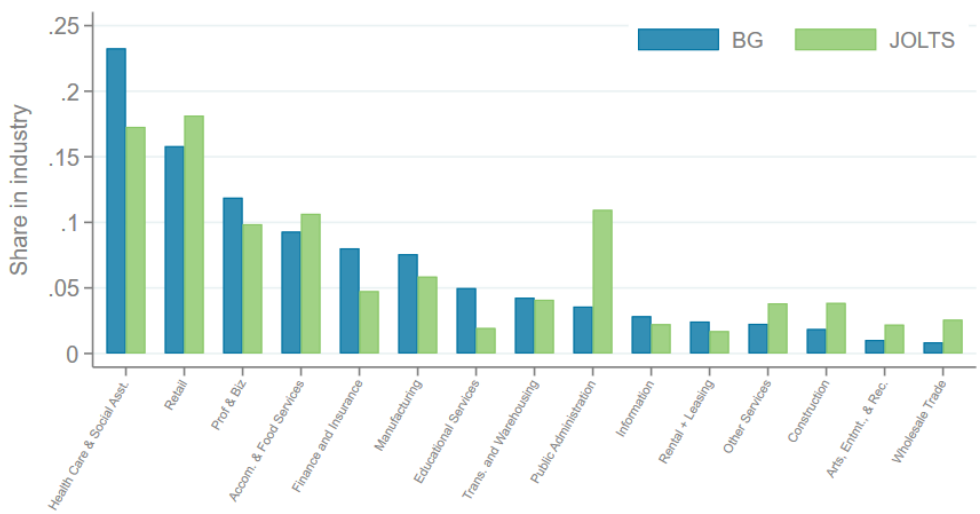
We use this data to construct the number of job postings relative to January 2020. We index to pre-COVID-19 job posting levels by dividing a count of the week's unique job postings by the average weekly postings from January 4-31, 2020 for each geography-industry and geography-qualification cell, with the exception of the imputed county-industry values (for counties outside the largest 200). For values in those counties, we compare the imputed value to the average weekly imputed postings from January 4-31, 2020.

Qualifications required are defined by ONET Job Zones, which are mutually exclusive categories describing occupations as needing little or no preparation, some preparation, medium preparation, considerable preparation or extensive preparation. A Burning Glass algorithm defines the ONET Job Zone. In the tracker ONET Job Zones are referred to "required education" for brevity. See this link for further details about this classification.

Industry is defined using select NAICS supersectors, which are aggregated from 2-digit NAICS classification codes assigned by a Burning Glass algorithm. We include Construction (20); Education & Heath Services (65); Leisure & Hospitality (70); Manufacturing (30); Transportation & Trade (40). Note that these categories are not exhaustive and therefore do not sum to total postings.

Comparison to JOLTS Burning Glass constructs a fairly comprehensive scan of online job postings, but may miss certain job postings that do not appear online or are not captured by their web scanning. In order to understand the representativeness of this series, we compare the occupation distributions to the Bureau of Labor Statistics' Job Openings and Labor Market Turnover (JOLTS) survey. Figure 10 compares the national aggregate industry distributions of the Burning Glass data and JOLTS categorized 2-digit NAICS codes for January 2020. The distributions are quite similar in general.

FIGURE 10: Industry Distributions for JOLTS and Burning Glass



II.C.2 Womply

We receive data on purchases at small businesses from Womply. Womply is a company that collects commercial transactions data. Information collected via Womply is on the seller side of the market and therefore provides a measure of small business revenue and activity.

We receive aggregate business sales data at the county-industry-day and state-industry-day level. Womply aggregates this data up from deidentified credit card transaction level data at businesses served by its payment processing partners. Prior to aggregation, they restrict to businesses meeting the following criteria:

- A businesses with 30 or more transactions in a quarter and more than on transaction in 2 to 3 months.

- A business must have annual revenue that is less than the SBA thresholds by industry AND within 2x the IQR (interquartile range) of the revenue Womply observes.

We aggregate data to the county-industry-week, metro-industry-week, state-industry-week and national-industry-week level. We drop counties with less than 25,000 residents, as defined by the 2019 Census population estimates. At the state and national levels we include breakdowns for the level of poverty of the zip codes of Womply businesses (i.e. for a given state, you can view data separately for businesses located in high/middle/ low income zip codes as defined by the bottom 25%/middle 50%/top 25% of 2010 poverty levels in the national distribution). The series runs from January 7, 2020 to the present.

Small Business Revenue The Small Business Revenue statistic measures the net businesses revenue relative to January 2020. Net business revenue is the sum of all credits (generally purchases) and debits (generally returns). We construct daily values as a 7-day moving average as the sum of the previous six days of net revenue and the current day's net revenue divided by 7. We then seasonally adjust the series by dividing each calendar date's 2020 value by its corresponding value from 2019. For the 29th of February, we use an average between the 28th and the 1st of 2019 to adjust. We then index the seasonally adjusted series relative to pre-Covid-19 net revenue by dividing the seasonally adjusted series by the mean seasonally adjusted 7-day moving average from January 4-31.

Industry is received as Womply transaction categories, which are based on MCCs and include some amount of additional Womply data on online business categories. We crosswalk these categories to two-digit NAICS codes, using an internally generated Womply category-NAICS crosswalk, and then aggregate to selected NAICS Supersectors: Construction (20); Education & Heath Services (65); Leisure & Hospitality (70); Manufacturing (30); Transportation & Trade (40). Note that these categories do not sum to total businesses.

Location is assigned by Womply as the county and state of the business at which the transaction occurred.

Comparison to CEX In order to understand the context for this series, we compare the Womply aggregate spending distributions to the Consumer Expenditures Survey (CEX) from the

Bureau of Labor Statistics. Figure 7 compares aggregate spending during the 2019, across NAICS codes. We crosswalk the Universal Classification Codes (UCCs) in the CEX to NAICS using an internally generated crosswalk. Womply total revenue, which is a proxy for spending, is somewhat skewed towards non-retail and food industries.

Small Businesses Open We construct a measure of changes in the number of businesses open relative to January 2020. Businesses are tagged as not open if have had no transactions for 3 consecutive days. We construct daily values as a 7-day moving average as the sum of the previous six days open businesses and the current day's open businesses divided by 7. We then seasonally adjust the series by dividing each calendar date's 2020 value by its corresponding value from 2019. For the 29th of February, we use an average between the 28th and the 1st of 2019 to adjust. We then index the seasonally adjusted series relative to pre-Covid-19 businesses openings by dividing the seasonally adjusted series by the mean seasonally adjusted 7-day moving average from January 4-31.

II.D Education

II.D.1 Zearn

We construct information on education outcomes from Zearn Inc. Zearn is an online education company that partners with schools to provide online lessons. Zearn is directly integrated into school curriculums and therefore provides a measure of the extent to which students of different backgrounds are engaged in classroom activities throughout the COVID-19 shutdown. For more information on Zearn see: https://about.zearn.org/

We receive data at the school-week level and aggregate to the county-week, city-week, state-week, and national-week level. At the state and national levels we include breakdowns for the level of poverty of the zip codes of Zearn schools (i.e. for a given state, you can view data separately for students who attend schools located in high/middle/ low income zip codes as defined by the bottom 25%/middle 50%/top 25% of 2010 poverty levels in the national distribution).

We drop schools who did not use Zearn for at least one week from January 6th-Feburary 7th and schools that never have more than 5 students using Zearn during our analysis period. We winsorize any values reflecting an increase of greater than 300% at the school level and cap all points in the final series to a maximum 150% increase in student participation and a 300% increase in badges. To reduce the effects of school break weeks and large fluctuations, we set any week for a given school that reflects a 50% decrease (increase) greater than both points on either side of it to the average of those three points The data are masked such that any county with fewer than 2 districts, fewer than 3 schools, or fewer than 50 students on average using Zearn during the pre-period is excluded. We fill in these masked county statistics with the commuting zone average whenever possible. The series runs from January 6, 2020 to the present.

Online Math Participation The key outcome is change in student participation relative to January 2020. Student participation is the number of students using Zearn in a given week.

We index to pre-COVID student participation by dividing weekly participation at the school level by average weekly participation during the base period January 6th-February 7th and then subtract 1 to center the data around 0% change. We aggregate school level-estimates to county, state and national level, weighting by the average number of students using the platform at each school during the base period.

Location is defined by the zip code of the school. When a zip code corresponds to multiple counties, we assign the school to the county with the highest business ratio, as defined by HUD-USPS ZIP Code Crosswalk Files. We generate city values for a selection of large cities using a custom city-county crosswalk, available in data downloads. We assigned cities to counties and ensured that a significant portion of the county population was in the city of interest. Some large cities share a county, in this case the smaller city was subsumed into the larger city.

To better understand the context for this series, Figure 11 states' true poor shares to the poor shares calculated when weighting by the number of students in the zip codes of schools using Zearn. Overall the relationship is strong, suggesting the locations of Zearn schools are reflective of state economic characteristics.

FIGURE 11:Actual Poor Share Versus Zearn Zip-Code-Weighted Poor Share, by State

Student Progress in Math We also construct a measure of student progress in math using the number of badges students earn from reaching milestones in a given week. We index to pre-COVID student progress by dividing weekly total badges at the school level by average weekly badges during the period January 6th-February 7th and then subtract 1 to center the data around 0.

II.E Public Health

II.E.1 COVID Cases

We construct this series using New York Times publicly available data available daily at the county, state and national level. Their series attempts to count only lab-confirmed cases, but states have differing reporting standards. See the NYTimes data description for a complete discussion of methodology and definitions.

We generate metro values for a selection of large metros using the custom metro-county crosswalk, with the exception of Kansas City which uses cases Kansas City proper rather than mapping directly from counties. The NYTimes counts all New York City counties as one entity. For these counties we instead use case data from New York State Department of Health data. The New York specific data is available starting March 22nd.

They key outcome is number of newly confirmed cases per day per 1,000 people. We use the Census Bureau's 2019 population estimates to define population. We suppress data where new counts are negative due to adjustments in official statistics. Data is for January 21 to present

II.E.2 COVID Death Rate

We construct this series using New York Times publicly available data available daily at the county, state and national level. Their series attempts to count only lab-confirmed COVID deaths, but states have differing reporting standards. This series is constructed identically to "COVID cases", but the key outcome is number of newly confirmed deaths per day per 1,000 people. See the description for that series and NYTimes data description for a complete discussion of methodology and definitions. Data is for January 21 to present.

II.E.3 COVID Tests

We construct this series using The COVID Tracking Project publicly available data on number of total number of tests, available daily at the state and national level. Details on reporting by state are available on their site.

The key outcome is new tests performed per day per 1,000 people. We use the Census Bureau's 2019 population estimates to define population. We suppress data where new counts are negative due to adjustments in official statistics.

II.E.4 Time Outside Home

We construct this series using data from Google's "Google COVID-19 Community Mobility Reports." We download and present data at the county-day, state-day and national-day level. We also generate metro-day values for a selection of large metros using the metro-county crosswalk.

The key outcome is time spent outside of residential locations relative to January 2020. At each geographic level, we provide breakdowns of time spent at parks, retail and recreation, grocery and transit locations. Details on these place types and additional information about data collection is available from Google. As described, indexing is done relative to median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020, and place type is assigned by Google.

In order to construct the "Time Outside Home" variable, we use the Google provided data that describes changes in amount of time spent as residential locations, and invert it to describe time spent outside. As there are no base hours in the dataset, we use the American Time Use survey to get the mean time spent inside the home (excluding time asleep) and outside the home in January 2018 for each day of the week. We multiply time spent inside the home in January with Google's residential percent change to get an estimate of time spent inside the home for each date. The remaining waking hours in the day are our estimate for time spent outside the home. We then use the average time spent outside the home in January to get the percent change outcome.

Note that Google Mobility trends do may not precisely reflect time spent at locations but rather "show how visits and length of stay at different places change compared to a baseline". We call this time spent at a location for brevity.

III Illustrative Application: Government Shut-Downs

We illustrate the value of the tracker by analyzing the impacts of state shutdowns and re-openings in the COVID-19 crisis, using event studies around these events to analyze their impacts.

Figure 12 plots several outcome around the day in which a state-level shutdown was implemented. Figure 12A plots the average series for states that shut down "early," defined as those that issued a stay-at-home order and non-essential business closure in the week of March 19-26. Figure 12B plots the average series across states that issued stay at home orders after this period. Consistent with previous analyses (Bartik et al. 2020, Villas-Boas et al. 2020), hours of work begins to fall prior to the formal date of the state-level shut-down. We also see similar declines in other series such as consumer spending, small business spending, and time spent at work well before the shutdowns. Broadly, these patterns suggests that the decline in economic activity was not driven directly by the formal shut-downs themselves, but rather a general response to the onset of the national COVID-19 epidemic.

FIGURE 12: Change in Consumer Spending, Small Business and Hours Worked Measures Around Stay-At-Home Order

A. States Issuing Stay-at-Home Order and Business Closure Order on Same Day in Week 19-26 March

B. States Issuing Stay-at-Home Order or Business Closure Order After 26 March

Several states began efforts to "re-open" their economies by ending shut-down orders in late April and early May. Figure 13 evaluates the early impacts of these policy changes by plotting the same set of outcomes shown in Figure 12 for 4 states that have implemented re-opening policies: Georgia, Oklahoma, South Carolina, and Alaska.

FIGURE 13: Change in Consumer Spending, Small Business and Hours Worked Measures Around Partial Re-Opening

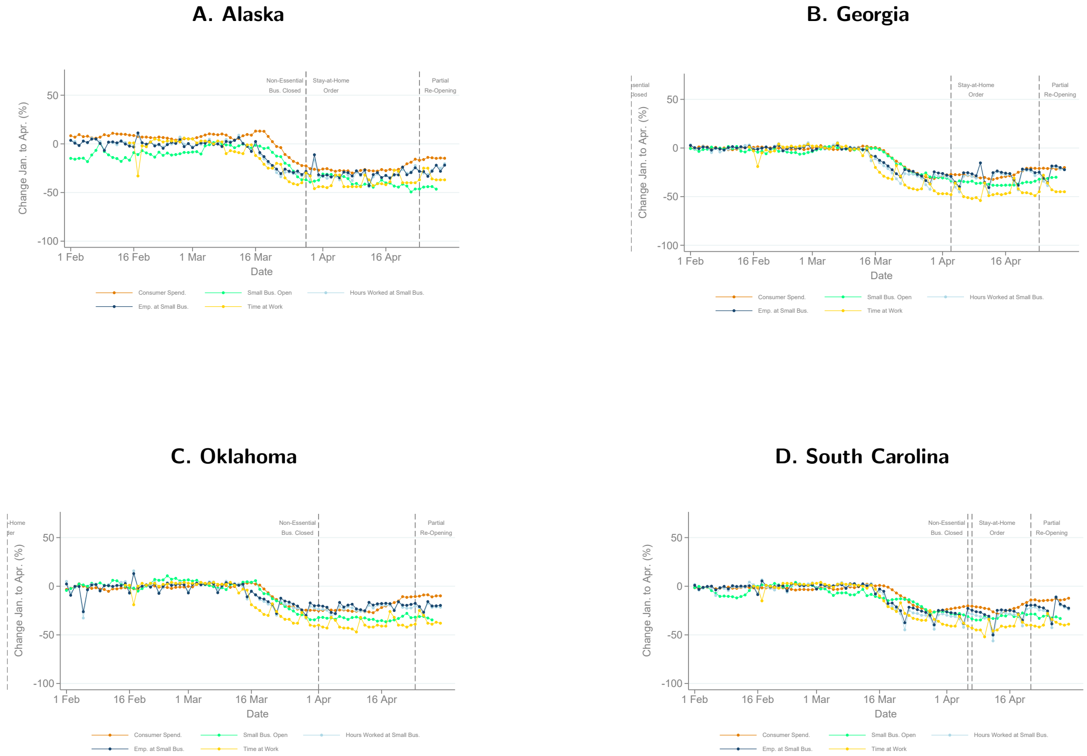


Figure 13A shows that we do not see an increase in economic activity in Georgia after it lifted its stay-at-home order on April 24. Consumer spending, employment and hours at small businesses, the number of small businesses that are open, and time spent at work all remain relatively similar to their levels prior to April 24. We find similar patterns in other states as well, as illustrated in Panels B-D. This suggests the primary factor limiting economic activity are choices being made by individuals and businesses in response to the threat of COVID-19 itself, as opposed to government policies that impose restrictions on economic activity.

The simple analysis in Figures 12 and 13 illustrates the utility of the tracker. These findings would not be evident in traditional government survey data for several months, but are easily observed in private sector data a few days after policy changes are made.

IV Conclusion

Modern data held by private companies provide an unprecedented capacity to measure economic activity at a granular level very rapidly. These data have become increasingly integral for corporations in improving business decisions. In this paper, we have constructed a freely available platform that harnesses the same data with the aim of supporting policymakers, non-profits, and the public seeking to make better decisions.

In these uncertain and unprecedented times, we hope this real-time economic tracker provides valuable information for understanding the state of the economy and facilitating the national recovery. We look forward to expanding upon this tracker as additional companies contribute data and reporting analyses that emerge from these data. More broadly, we hope the approach proposed here will serve as a template to permit real-time responses to changes in economic conditions going forward.

Supplementary Appendix

In this appendix, we describe additional details about information reported in the tracker: key dates in the COVID-19 crisis and geographic definitions.

Key Dates for COVID-19 Crisis. The Economic Tracker also includes information about key dates relevant for understanding the impacts of the COVID-19 crisis. At the national level, we highlight three key dates:

- First U.S. COVID-19 Case: 1/20/2020
- National Emergency Declared: 3/13/2020
- CARES Act Signed in to Law: 3/27/2020

At the state level we highlight dates when:

- Schools closed statewide: Sourced from COVID-19 Impact: School Status Updates by MCH Strategic Data, available here. Compiled from public federal, state and local school information and media updates.
- Nonessential businesses closed: Sourced from the Institute for Health Metrics and Evaluation state-level data (available here), who define a non-essential business closure order as: ”Only locally defined 'essential services' are in operation. Typically, this results in closure of public spaces such as stadiums, cinemas, shopping malls, museums, and playgrounds. It also includes restrictions on bars and restaurants (they may provide take-away and delivery services only), closure of general retail stores, and services (like nail salons, hair salons, and barber shops) where appropriate social distancing measures are not practical. There is an enforceable consequence for non-compliance such as fines or prosecution.”
- Stay-at-home order goes into effect: Sourced from the New York Times stay at home order data, available here.
- Stay-at-home order ends: Sourced from the New York Times reopening data, available here. Defined as the date at which the state government lifted or eased the executive action telling residents to stay home.
- Partial business reopening: Sourced from the New York Times reopening data, available here. Defined as the date at which the state government allowed the first set of businesses to reopen.

These dates are updated as of 5/4/2020.

Geographic Definitions. For many of the series we convert from counties to metros and zip codes to counties. Unless mentioned as otherwise the crosswalks are as follows:

ZIP Codes to County We use the HUD-USPS ZIP Code Crosswalk Files to convert from zip code to county. When a zip code corresponds to multiple counties, we assign the entity to the county with the highest business ratio, as defined by HUD-USPS ZIP Crosswalk.

County to Metro Areas We generate metro values for a selection of large cities using a custom metro-county crosswalk, available in Appendix Table 1. We assigned metros to counties and ensured that a significant portion of the county population was in the metro of interest. Some large metros share a county, in this case the smaller metro was subsumed into the larger metro.

Appendix Table I: Metro-County Crosswalk

Metro	County	State	County FIPS Code
Albuquerque	Bernalillo	NM	35001
Atlanta	Fulton	GA	5049
Austin	Travis	TX	48453
Bakersfield	Kern	CA	6029
Baltimore	Baltimore	MD	24005
Boise	Ada	ID	16001
Boston	Suffolk	MA	25025
Charlotte	Mecklenburg	NC	37119
Chicago	Cook	IL	17031
Cleveland	Cuyahoga	OH	39035
Colorado Springs	El Paso	CO	8041
Columbus	Franklin	OH	39049
Dallas	Dallas	TX	48113
Denver	Denver	CO	8031
Detroit	Wayne	MI	26163
El Paso	El Paso	TX	48141
Fort Worth	Tarrant	TX	48439
Fresno	Fresno	CA	6019
Honolulu	Honolulu	HI	15003
Houston	Harris	TX	48201
Indianapolis	Marion	IN	18097
Jacksonville	Duval	FL	12031
Kansas City	Jackson	MO	29095
Las Vegas	Clark	NV	32003
Los Angeles	Los Angeles	CA	6037
Louisville	Jefferson	KY	21111
Memphis	Shelby	TN	47157
Miami	Dade	FL	12025
Milwaukee	Milwaukee	WI	55079
Minneapolis	Hennepin	MN	27053
Nashville	Davidson	TN	47037
New Orleans	Orleans	LA	22071
New York City	New York	NY	36061
New York City	Kings	NY	36047
New York City	Queens	NY	36081
New York City	Bronx	NY	36005
New York City	Richmond	NY	36085
Oakland	Alameda	CA	6001
Oklahoma City	Oklahoma	OK	40109
Omaha	Douglas	NE	31055
Philadelphia	Philadelphia	PA	42101
Phoenix	Maricopa	AZ	4013
Portland	Multnomah	OR	41051
Raleigh	Wake	NC	37183

Sacramento	Sacramento	CA	6067
Salt Lake City	Salt Lake	UT	49035
San Antonio	Bexar	TX	48029
San Diego	San Diego	CA	6073
San Francisco	San Francisco	CA	6075
San Jose	Santa Clara	CA	6085
Seattle	King	WA	53033
Tampa	Hillsborough	FL	12057
Tucson	Pima	AZ	4019
Tulsa	Tulsa	OK	40143
Virginia Beach	Virginia Beach City	VA	51810
Washington	District Of Columbia	DC	11001
Wichita	Sedgwick	KS	20173

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