Measuring the Effects of the COVID-19 Pandemic on Consumer Spending Using Card Transaction Data

Authors   Abe Dunn, Kyle Hood, and Alexander Driessen[1]
U.S. Bureau of Economic Analysis

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Abstract   We evaluate the economic effects of the COVID-19 pandemic on consumer spending using daily card transaction data. Overall, we find large effects of this pandemic on sectors such as accommodations and restaurants, which by the second week of March, show declines of around 80 percent and 70 percent, respectively. However, these declines were partly offset by the large 100 percent immediate increase in food and beverage store sales. For select goods and services in our data, we find an aggregate decline in spending of around 13.7 percent for March, and we estimate an aggregate "pandemic effect"—the effect of the pandemic on consumer spending after mitigation measures have had time to take hold—of around –27.8 percent.

Keywords   Economic Measurement, Event Study, Pandemic, Card Transaction Data

JEL Code   E01, E21, Q54

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1.   Introduction

Since it started in March 2020, the COVID-19 pandemic has dramatically impacted the U.S. economy. In the month after its declaration, as social distancing policies have taken effect, businesses have closed,[2] and over 22 million workers have sought unemployment benefits.[3] To help policymakers develop a course for economic recovery, it is important to use the most timely and accurate economic information available. This is especially pertinent given that pandemic-driven economic changes are measurable in days and weeks, rather than months and years.

We present estimates of consumer spending using card transaction data that are updated daily with a lag of about 3 days. The underlying data used to construct these series are collected by Fiserv, one of the largest card intermediaries in the country. Each observation in the data corresponds to a single card swipe (for example, debit card, credit card, or gift card), although all data are aggregated to the state and national levels and thus anonymized. While alternative data cannot offer a replacement for carefully conducted surveys, these data offer an important complementary source of information to traditional survey source data.

The method used to produce the card spending data series studied here was first developed by staff at the Board of Governors of the Federal Reserve System, along with data scientists from Palantir, a technology company specialized in managing and analyzing big data.[4] The methodology is described by Aladangady and others (2019). This data source has been used in conjunction with machine learning to obtain improved measures of the services sector of the U.S. economy (Chen and others (2019)) as well as to study the effects of hurricanes on state-level spending (Aladangady and others (2019)). The result of applying the methodology of Aladangady and others (2019) is a stable series of card spending intended to be representative at both the national and state levels and for each industry. The series have been shown to be highly correlated to national retail trade categories, restaurants, and accommodations.

We use daily card data from the Fiserv series to measure the reduction in revenue around the time of the pandemic. This includes both the immediate effects of the pandemic and measures of the total effects for March. Overall, we find the largest effects of this pandemic for sectors such as accommodations and restaurants, which by the second week of March, show declines of around 80 percent and 70 percent, respectively. However, these declines were partly offset by the 100 percent immediate increase in food and beverage store sales (likely a result of households stocking up on goods in early March).

In aggregate, for the month of March, we find about a 5 percent decline for the combined retail and food services sector, roughly matching the estimates of the advance MRTS for March for similar categories. The decline for March appears to be even larger for other nonretail categories, including categories like accommodations, recreation, and ambulatory health care. However, the effects for spending in March understate the full effect of the pandemic, as the main effects didn't occur until the middle of the month. We estimate an aggregate "pandemic effect"—the effect of the pandemic on consumer spending after mitigation measures have had time to take hold—of around –27.8 percent.

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2.   See *30 of America's iconic businesses that closed due to coronavirus*.

3.   See *U.S. Jobless Claims Top 20 Million Since Start of Shutdowns*.

4.   Palantir partnered with First Data (later acquired by Fiserv) and worked with federal agencies, including the Census Bureau, the Bureau of Economic Analysis, and the Federal Reserve Board, to explore ways to provide more timely and relevant information regarding national and local trends in the economy.

2.   Literature

A few recent papers have used near real-time data to look at the effects of the COVID-19 pandemic. Alexander and Karger (2020) examine the effects of stay-at-home orders on travel and spending using both cell phone data and card transaction data. They find that stay-at-home orders lead to significantly less travel and significantly fewer sales and that the response to stay-at-home orders depends on factors such as demographics and political affiliation. They are able to parse out these heterogeneous effects using county-level data. Baker and others (2020) use a panel of household-level transaction data to investigate the effects of the pandemic on spending. They find evidence of stockpiling, followed by a reduction in spending near the end of March. Similar to Alexander and Karger (2020), they find heterogenous effects, including variation in responsiveness depending on the shelter-in-place orders, political affiliation, demographics, and income. Lewis, Mertens, and Stock (2020) use near real-time data based on a variety of weekly indicators to obtain timely estimates of the economic effects of the pandemic. Consistent with our paper and others in the literature, they find a significant downturn in economic activity starting in mid-March. Finally, Bartik and others (2020) use a small-business survey to find that around 43 percent of small businesses have closed in response to the pandemic.

While the daily data source used in this paper is most similar to Alexander and Karger (2020) and Baker and others (2020), the focus of our paper is different, as we are specifically interested in measurement around the pandemic at the national level, rather than state-specific responses. While we provide some analysis of the heterogenous patterns of response depending on the state for the restaurant sector—a sector particularly affected by the pandemic—the point of this exercise is to consider the relationship between state-level and national responses. Although state-specific patterns are clearly distinct, we show that a majority of states generally follow the broad national trend. Finally, we note that none of these papers uses the same data as we do here. All of these data sets are subject to tradeoffs in terms of coverage and representativeness. Thus, it is important to get a read on the economy from several distinct real-time sources.

3.   Data

The merchants included in the aggregate Fiserv card series studied here include those merchants that utilize Fiserv for managing card intermediary services. Once a merchant uses Fiserv services, all associated card transactions (for example, credit card, debit card, and gift cards) go through their system, where the number of transactions and the full amount of each transaction is recorded. However, not all merchants that contract with Fiserv are included in the series, as some merchants opt out or are excluded due to limited coverage in a particular industry or area. All series are highly aggregated to the state or national level, so neither merchants nor individuals can be identified in the data. The location is based on the state in which the merchant resides, which is not necessarily the same as the consumer's location. As outlined in Aladangady and others (2019), the series is built around a rolling sample of merchants, in which all merchants are in the data over the past 13 months in which the estimate is formed. The focus on a panel of merchants is implemented to eliminate the confound introduced by merchants changing card intermediary services. However, the use of a panel also eliminates some actual economic activity from business entry and exit. Estimates are weighted to be representative of sales either at the national or state level based on the 2012 Economic Census. The development of the methodology in Aladangady and others (2019) was not only a substantial contribution to the economics literature, but it literally created a new source of economic information that provides a much clearer picture of economic trends and greatly increases the value of the data for economic interpretation. Indeed, Aladangady and others (2019) shows that the raw card transactions are practically impossible to interpret, as new merchants enter and exit the sample for a variety of reasons that are unrelated to the economic environment. Additional details regarding the data are discussed in Aladangady and others (2019).

Limitations. There are some important limitations to this analysis. First, the data set is a convenience sample, which is not necessarily representative of the associated industries, even after reweighting and applying adjustments to the series based on the method described by Aladangady and others (2019). This is an important distinction from official statistics, which are structured to be nationally representative. Second, the data cover primarily brick-and-mortar merchants.[5] However, e-commerce sales will appear in these data for merchants that are primarily brick and mortar but also sell through an e-commerce platform. The nonstore retail category is intended to capture firms that have a majority of their business comprised of e-commerce transactions, but it is unclear how well this category is represented in this series. Third, since the estimates are built around merchants that continually contribute to the data over a 13-month period, merchants that exit the sample entirely are not included in the sample, and so our analysis will miss the decline in overall sales associated with exits. This issue may be particularly problematic at this time, as we observe a sharp downturn in the economy. For this reason, the estimates shown here may understate the true declines observed in many sectors, as business exits may not fully be reflected in these estimates. Overall, the estimates should be viewed with caution and as an attempt to develop more accurate estimates and inform the public

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5.   The industry categories depend on the Merchant Category Code (MCC) in the card data that is then mapped to North American Industry Classification System (NAICS) codes through a crosswalk. There is not an explicit category for e-commerce, but MCC codes that seem to indicate a nonstore retailer are placed into the NAICS code 454 indicating a nonstore retailer.

and policymakers more quickly. These estimates are not a substitute for official series that are grounded in well tested and proven methodologies.

Correlation. Historically, the data from Fiserv and data from official surveys have shown a tight correlation, especially for the aggregate retail trade sector (correlation of 98 percent for the not seasonally adjusted series). The level of correlation varies by industry, but it is relatively higher for the components of retail trade, accommodations, and restaurants, which are all industries heavily impacted by the 2020 COVID-19 pandemic.

Figure 1. Growth Rates for Retail Based on the Fiserv Series and the Monthly Retail Trade Survey
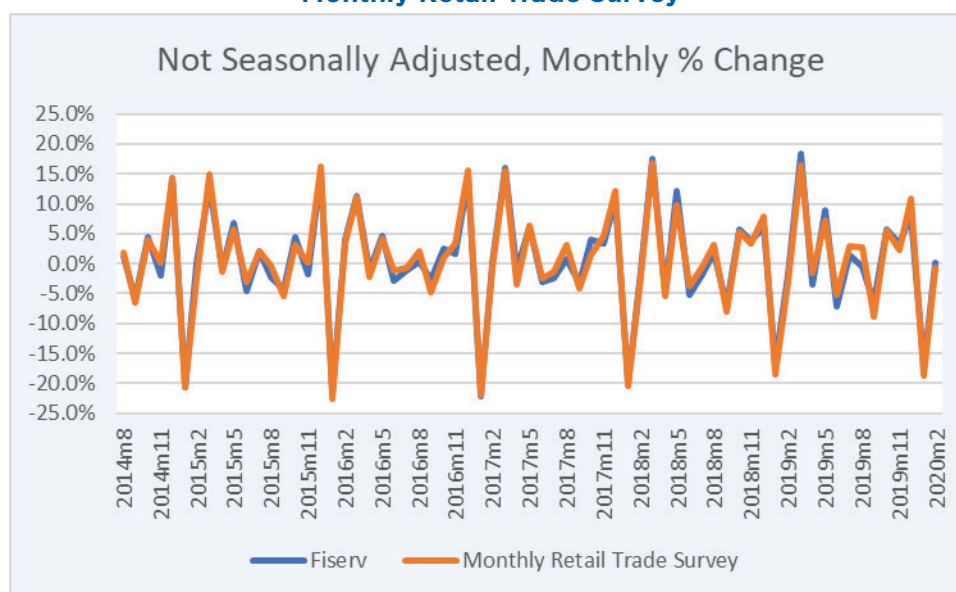
Note. The aggregate retail and food service category for Fiserv specifically includes North American Industry Classification System categories 4413, 442, 443, 445, 446, 448, 451, 452, 453, 454, and 722.

The strength of the series for predicting small changes in growth may be limited, as there is likely both noise in the official survey series as well as measurement limitations in the Fiserv series (Chen and others (2019)). However, we think the close historical correlation between the Fiserv series and the official series makes these estimates more useful for tracking large changes in the economy, especially for the retail sector.[6]

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6. There is not a single version of the Fiserv series, as the data is revised on a daily basis as new information rolls in and transactions are fully executed through the card network. However, the analysis presented here has been repeated on multiple revised versions of the data, and the basic findings presented in this paper remain stable across revisions.

4.   Event Analysis

Using the Fiserv series, we model the recent downturn in the economy during March and the beginning of April using an event study starting March 11, 2020, the day the World Health Organization (WHO) declared COVID-19 a pandemic. The event study controls for other seasonal factors and broad economic growth in the economy or specific industry using daily data, in order to isolate the effects of the pandemic around the March 11 date. A similar model was applied to the analysis of hurricane-related crises by Aladangady and others (2019), using the same data feed but for a previous time period. The basic model is specified as follows:

$$\log(spend_t) = \delta_t \cdot (date > event\ date) + \beta X_t + \varepsilon_t$$

The model includes a fixed effect for every day around the event, δ_t. The controls in the model capture seasonal effects and growth in the economy or North American Industry Classification System (NAICS) sector prior to the event. The specific controls include day-of-week effects, month effects, year effects, and holidays.[7] We look at a short time span starting in 2017 (the last 3 years and 3 months only) to avoid drift in the monthly and daily behavior, but the estimates are robust to choosing longer time horizons. A key difference with Aladangady and others (2019) is that we focus on the national effects, while their analysis took a panel approach, as U.S. states are differentially affected by hurricanes. Later in this paper, we will briefly discuss some panel analysis that was conducted to look at the COVID-19 pandemic.

4.1   Aggregate Effects

The event analyses show plots of the daily indicator variables, δ_t, and standard errors. Because these indicator variables are the residual level of spending for an industry category on a logarithmic scale after correcting for seasonal factors and broad trends in economic growth (the information contained in X_t), they are converted into percent terms for easier interpretation.[8] As noted above, we show economic trends just a few days prior to March 1, while the red line highlights March 11, the date WHO declared a pandemic. Figure 2 shows the plot associated with aggregate retail sales for all retail categories, excluding nonstore retailers (for example, e-commerce firms). The event study controls for all growth and seasonal factors leading up to the event, so that absent any major changes in the economy, we would expect the coefficients, δ_t, to not deviate significantly from 0. Deviations away from 0 indicate the change in the sector associated with the timing of the event. Prior to the March 11 event, we see no major changes, as the coefficient does not significantly deviate from 0. However, post March 11, the figure shows an initial growth in the aggregate retail sectors, followed by a decline beginning on March 16. The decline near the end of the month is approximately 30 percent, relative to expected sales, which continues into April.

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7.   Similar results are obtained when dummy variables for all 365 days of the year are included. We also ran panel versions of the model controlling for state-specific growth rates leading up to the events with similar results for the nation-wide trends. Dates for holidays were compiled by Jennifer Von Hagel.

8.   These coefficients, δ_t, are almost, but not precisely, the residuals if the model were run without including δ_t.

Figure 2. Event Study for Aggregate Retail and Food Services Sales Exluding Nonstore Retail
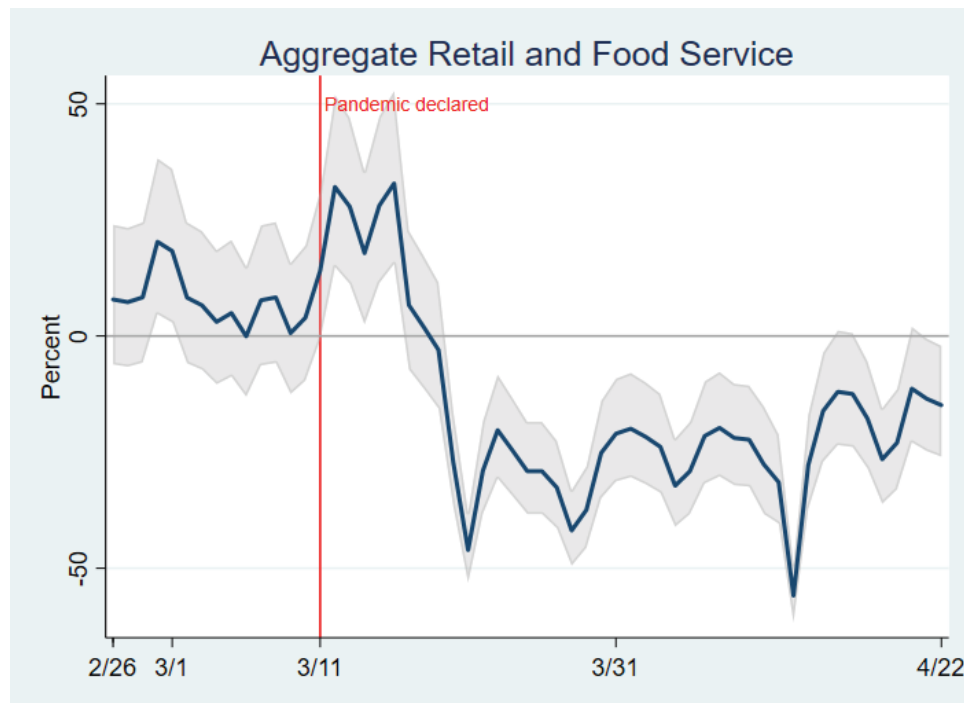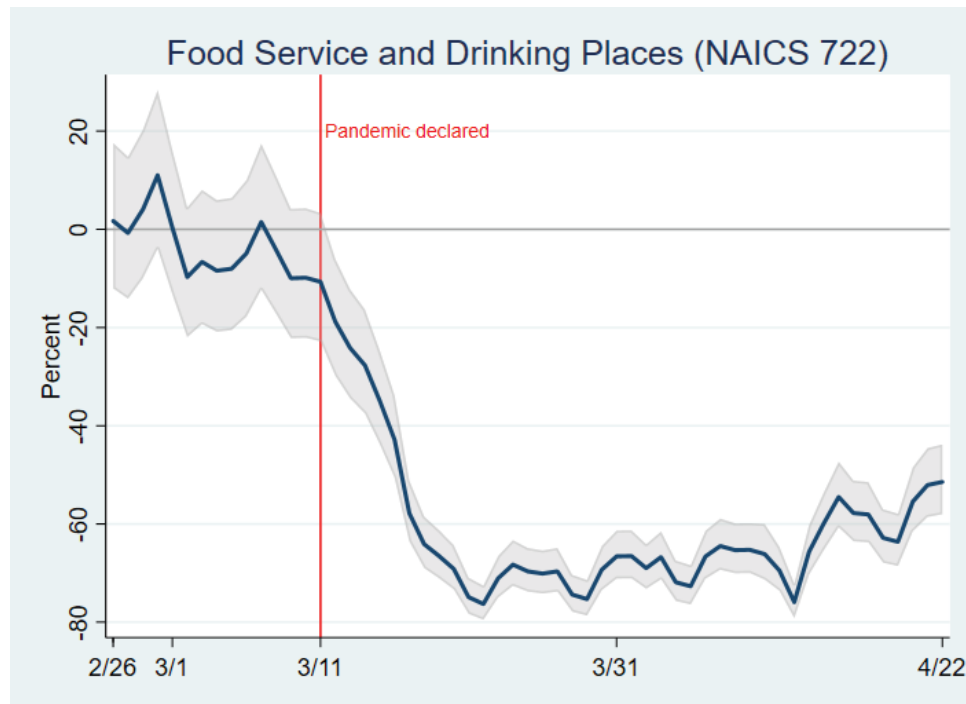

Notes. The estimates shown here have been transformed from log scale to percentages by using the exponential of the point estimate minus one, multiplied by 100. The vertical red line represents March 11, the date on which WHO declared a global pandemic. Deviations away from 0 indicate the change in the sector associated with the timing of the event. The area around the line represents the 95 percent confidence interval bands. The aggregate retail and food service category specifically includes North American Industry Classification System categories 4413, 442, 443, 445, 446, 448, 451, 452, 453, and 722.

4.2 Hardest Hit Industries

Figures 3 and 4 show the effects on restaurants and accommodations, which are two industries hit particularly hard by the COVID-19 pandemic. Near the end of March, the full decline in sales is around 70 percent for restaurants and around 80 percent for accommodations. A feature that stands out for the restaurant category is a post-pandemic weekend effect. Prior to the pandemic, there was a spike in sales over the weekend, which is removed by our day-of-week controls. However, post-pandemic, these weekend sales fall flat, relative to pre-pandemic levels, leading the counterfactual change in sales to fall over the weekends. This pattern is observed for some other retail categories (for example, clothing) and can be observed in the aggregate retail estimates (Figure 2).

Figure 3. Event Study for Restaurants

Food Service and Drinking Places (NAICS 722)

Notes. The estimates shown here have been transformed from log scale to percentages by using the exponential of the point estimate minus one, multiplied by 100. The vertical red line represents March 11, the date on which WHO declared a global pandemic. Deviations away from 0 indicate the change in the sector associated with the timing of the event. The bars represent the 95 percent confidence interval bands around the point estimate.

Figure 4. Event Study for Accommodations
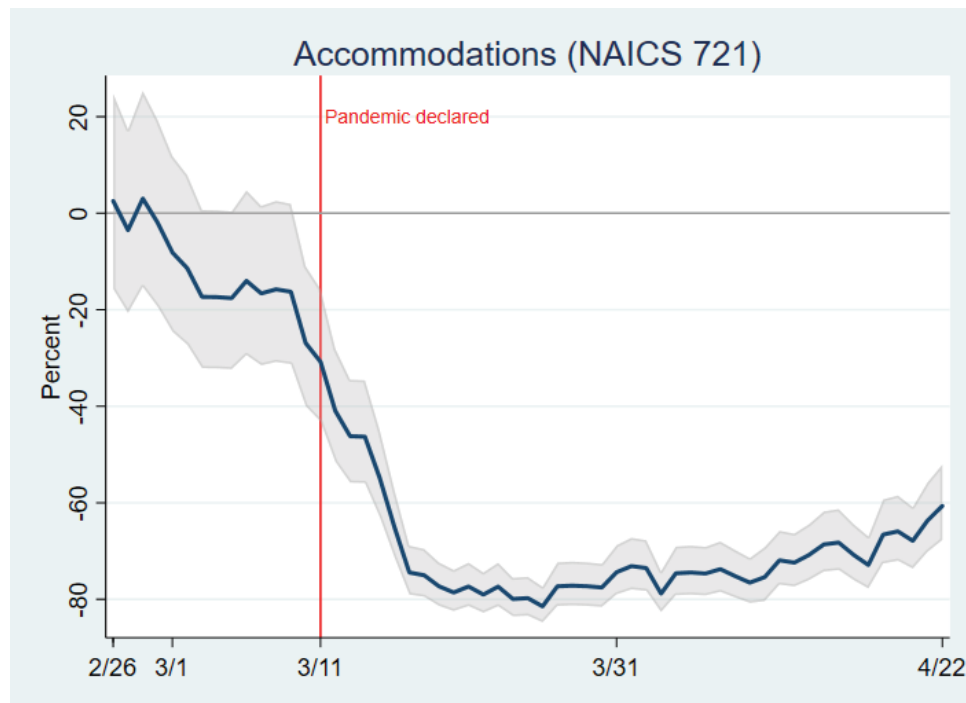
Accommodations (NAICS 721)

Notes. The estimates shown here have been transformed from log scale to percentages by using the exponential of the point estimate minus one, multiplied by 100. The vertical red line represents March 11, the date on which WHO declared a global pandemic. Deviations away from 0 indicate the change in the sector associated with the timing of the event. The bars represent the 95 percent confidence interval bands around the point estimate.

4.3   Other Relevant Sectors

Not every industry was subject to declines such as those observed in restaurants and accommodations. The food and beverage sector (Figure 5), which includes grocery stores, experienced a particularly large increase in sales of about 100 percent around the time of the event, followed by a rapid fall, with sales falling below expectations the last few days of March. The effects on gas stations are more nuanced (Figure 6) and appear to be marginal immediately following the pandemic, followed by a decline around a week after March 11, with lows of around 40 percent. About half of this decline is likely due to declining gas prices of around 20 percent in March, but the remaining decline is likely due to a reduction in travel, as more individuals remained home.[9]
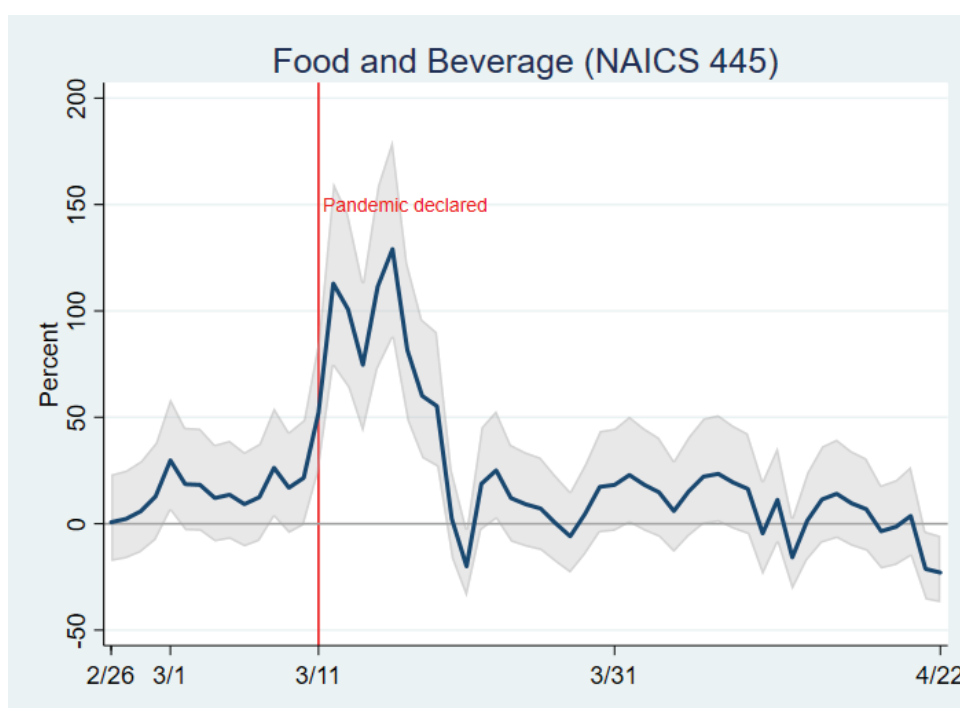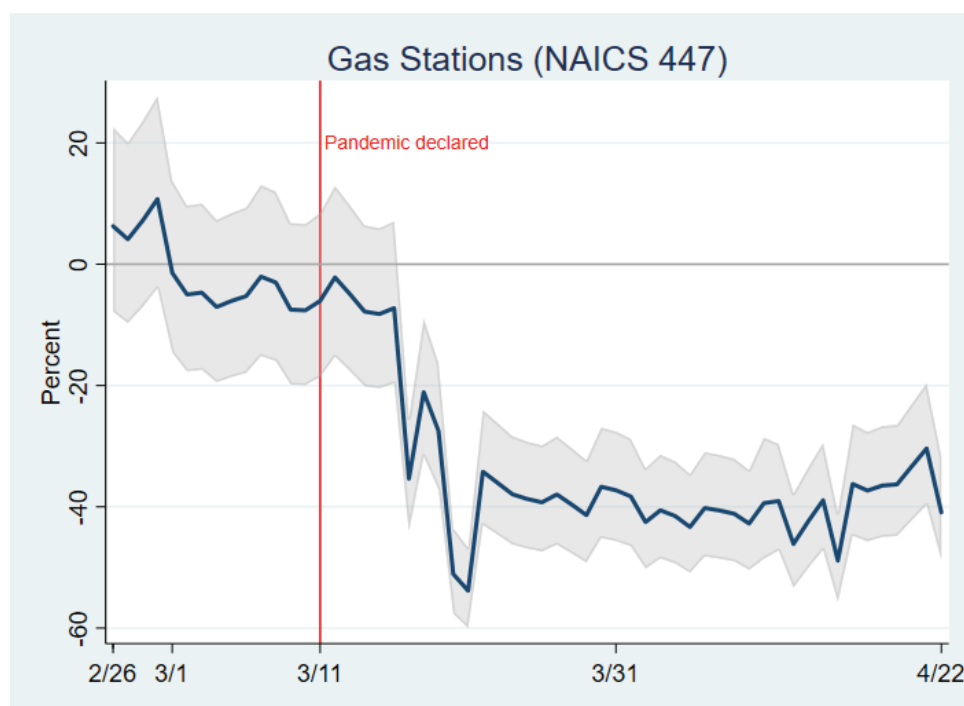
Figure 5. Event Study for Food and Beverage

Notes. The estimates shown here have been transformed from log scale to percentages by using the exponential of the point estimate minus one, multiplied by 100. The vertical red line represents March 11, the date on which WHO declared a global pandemic. Deviations away from 0 indicate the change in the sector associated with the timing of the event. The bars represent the 95 percent confidence interval bands around the point estimate.

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9.   Gasoline price data are from the U.S. Energy Information Administration and downloaded from the St. Louis Fed. Prices declined from $2.46 a gallon at the end of February to $2.00 a gallon at the end of March.

Figure 6. Event Study for Gas Stations

Notes. The estimates shown here have been transformed from log scale to percentages by using the exponential of the point estimate minus one, multiplied by 100. The vertical red line represents March 11, the date on which WHO declared a global pandemic. Deviations away from 0 indicate the change in the sector associated with the timing of the event. The bars represent the 95 percent confidence interval bands around the point estimate.

Finally, another area in which the Fiserv data set may be of some interest is health care. This includes ambulatory care services, such as physician offices, but also services such as dentists and physical therapy (Figure 7). Here, there appears to be a large decline that begins several days after the event, perhaps as patients defer elective care, consistent with underlined recent news reports.

Estimates for ambulatory services contrast to estimates for the hospital sector (Figure 8). Broadly, the trends for the hospital sector are consistent with those for ambulatory services, but only for the weekdays, where there is a clear decline in services. For hospitals, we find no decline in services over the weekend, but in fact an increase in services over the 2-day period. We identify this pattern, despite the inclusion of day-of-week effects, which account for day-of-week differences in hospital expenditures estimated based on the data for the periods prior to the pandemic. One potential explanation is that hospital services over the weekend tend to be nondeferrable emergency services, which are not likely to decline during the pandemic (Card, Dobkin, and Maestas 2009). If patients defer nonessential services that would typically have been scheduled only on weekdays but are unable to defer essential services (such as emergencies and trauma), we would see a pattern in which weekday consumption of hospital services drops, as deferable nonessential services consumption drops, but weekend consumption of hospital services increases, as weekday and weekend consumption of essential, nondeferrable services remains constant (or potentially increases as a result of the pandemic). As such, this figure could indicate that nonessential deferable services, those more likely to occur during

weekdays, have declined significantly, while nondeferable services have held relatively constant or even increased. Thus, while the event study methodologies for hospitals and retail categories such as restaurants and food services are identical, we find the weekend effects of these two categories move in opposite directions. Nevertheless, each of these movements are consistent with patterns we may expect in response to the pandemic.

There are some important limitations for the health care sector estimates, as they are a bit noisier than for other categories, and card transactions are only a fraction of the payments at doctor offices and even a smaller fraction at hospitals (around 15 percent and 3 percent, respectively[10]), so these estimates should be interpreted with some caution. In addition, it should be noted that the category 621 also includes dental services, which have disproportionately high out-of-pocket payments. While these numbers may move in the expected direction, they may not properly reflect the magnitude of the shift in consumption for these sectors and additional research may be necessary.

Figure 7. Event Study for Ambulatory Services
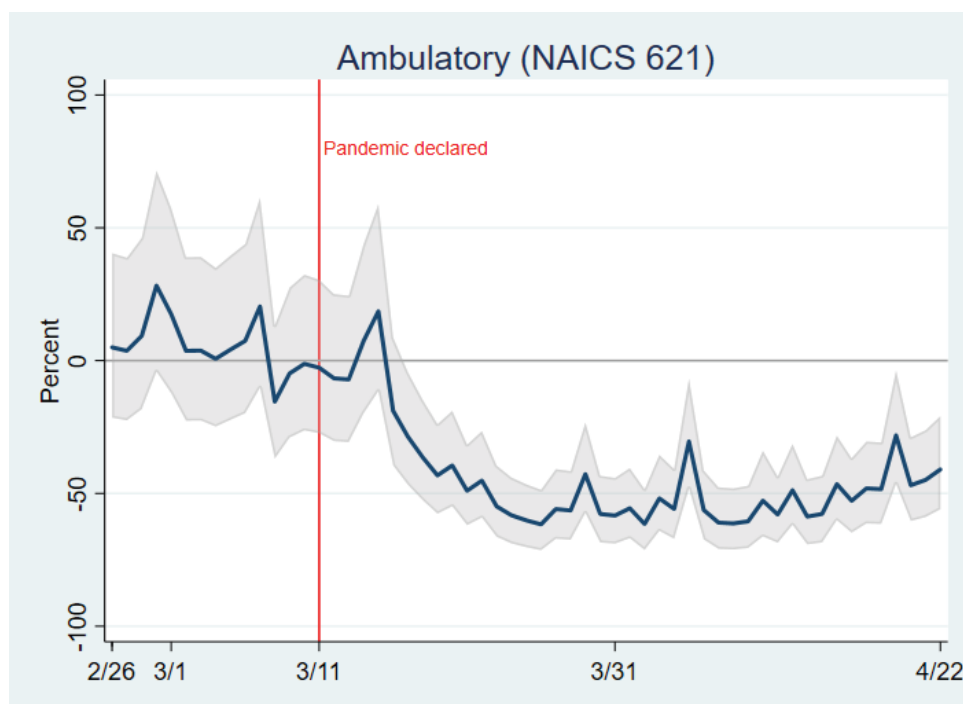
Notes. The estimates shown here have been transformed from log scale to percentages by using the exponential of the point estimate minus one, multiplied by 100. The vertical red line represents March 11, the date on which WHO declared a global pandemic. Deviations away from 0 indicate the change in the sector associated with the timing of the event. The bars represent the 95 percent confidence interval bands around the point estimate.

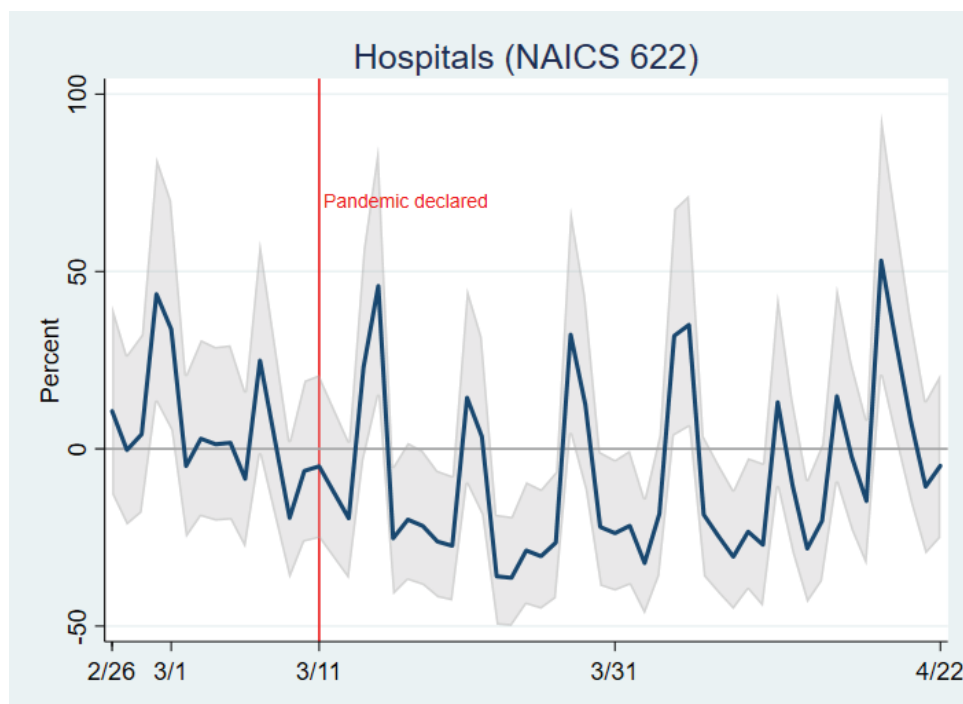10. These estimates are from the National Health Expenditure Accounts.

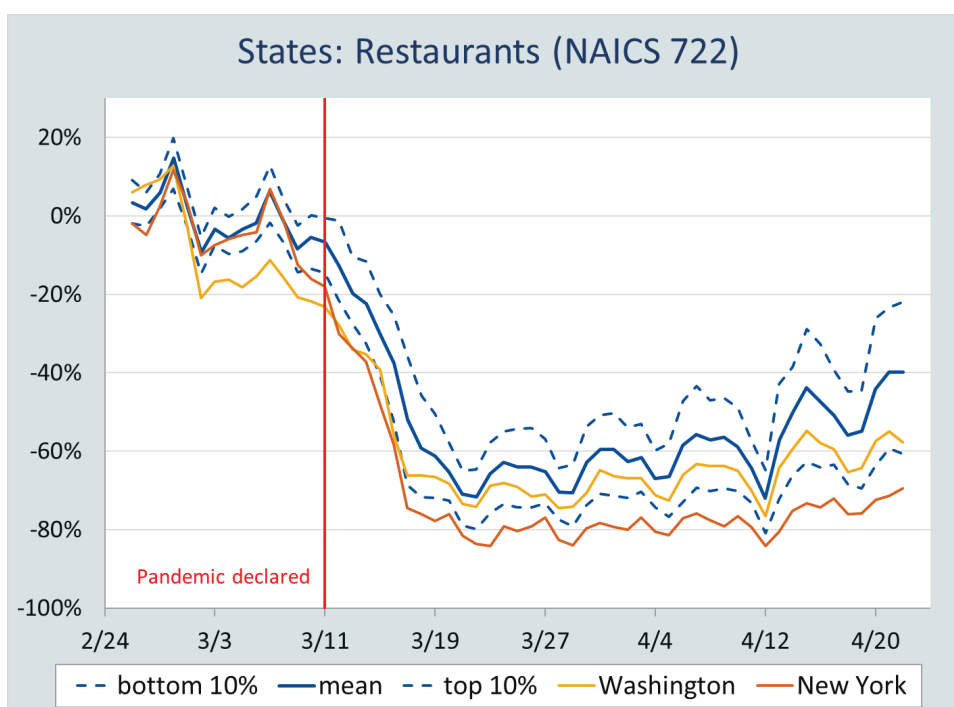**Figure 8. Event Study for Hospital Services**

Notes. The estimates shown here have been transformed from log scale to percentages by using the exponential of the point estimate minus one, multiplied by 100. The vertical red line represents March 11, the date on which WHO declared a global pandemic. Deviations away from 0 indicate the change in the sector associated with the timing of the event. The bars represent the 95 percent confidence interval bands around the point estimate.

4.4 State-Level Estimates

The Fiserv series also includes state-level data by industry. Using the state-level data, we can look at how consumer spending in the different states has been affected by the pandemic. To do this, we repeat the same procedure that we used for the national data but at the state level for each state independently.[11] We have chosen to study NAICS industry 722 (restaurants), which showed large declines after the beginning of the COVID-19 pandemic at the national level (Figure 3). We cannot show point estimates and standard errors for each state in a convenient format, so instead, we show the average of the point estimates across all states for each period from February 23 to the most recent date for which we have data available. We also show the 10th and 90th percentiles across states for each time period (noting that the approximately 40 states in which estimates fall between these two lines may change from day to day). Finally, Washington and New York, two states known to have been affected by the COVID-19 pandemic more than other states, but at different times, are shown for reference (Figure 9).

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11. Because we want to allow different states to have independent trends and seasonal behavior, estimation across states separately is equivalent to a simultaneous approach.

Figure 9. State-Level Event Studies (Food Service and Drinking Places)

States: Restaurants (NAICS 722)

Legend: -- bottom 10% — mean -- top 10% — Washington — New York

Notes. The estimates shown here have been transformed from log scale to percentages by using the exponential of the point estimate minus one, multiplied by 100. The vertical red line represents March 11, the date on which WHO declared a global pandemic. Deviations away from 0 indicate the change in the sector associated with the timing of the event. The two dark blue dashed lines are the 10 percent and 90 percent percentiles across states for the date on the horizontal axis (40 states fall between the two dashed lines). Washington and New York are shown separately.

Figure 9 demonstrates two things. First, it demonstrates how a majority of states in the country follow a similar pattern to the average state, as the 10th and 90th percentiles are relatively close to the mean. This pattern coincides with a dramatic increase in news coverage on the topic across several states in the country starting around March 11 (Baker and others 2020). Second, it shows how states such as New York and Washington differ from national trends. These states are of particular interest for different reasons. For Washington state, we may expect the economic impact of the pandemic to precede the impact on the rest of the country, as Washington was the first state to report a COVID-19 case. New York, on the other hand, is a high-density area that has been particularly hard hit by the pandemic, but it was not affected at a notably early date. Our preliminary findings are consistent with these patterns. Focusing on food service and drinking places, we find the dollars spent for these industries declined in Washington state prior to the rest of the country. The initial downturn in Washington state starts immediately after February 29, a date in which schools in the Seattle area of Washington state began to close in response to news of community spread in the area as well as a substantial increase of media coverage on the topic in the area (see Baker and others 2020). The effects on restaurants in New York are particularly large relative to the rest of the country in the latter portion of the period. Dollars spent in this industry eventually normalized to just below the national average in Washington state, while they are still lower for New York.[12]

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12. A panel analysis of the effects of different state policies (for example, stay-at-home orders and school closures) showed little effect of these policies on aggregate sales after incorporating the national trend. It is likely that other heterogenous factors, such as consumer expectations and beliefs, the rate of infection in the state, and other variables also contribute to this heterogeneous response of states. Additional regional analysis is necessary to sort out these effects.

5.   Aggregate Effects Using Daily Data

We move on to an analysis of changes to industry sales, first on a month-on-month basis (February 2020 to March 2020), and then a "pandemic effect" that averages together the days after the adjustment to industry sales that followed the pandemic announcement. The daily data above tell a story about when and to what extent the COVID-19 pandemic has affected certain industries. In contrast, averaged daily data converted to monthly growth rates and to the pandemic effect pull this information together to provide an early and independent picture of how the COVID-19 pandemic may impact aggregate economic statistics on consumer spending.

We elected to "split" the average effects in these two ways for two reasons. First, the monthly data provide a number that can be used for an apples-to-apples comparison against official statistics that are released at a monthly frequency, such as the Census Bureau Monthly Retail Trade Survey (MRTS). Second, the daily data over March, while useful for comparison purposes, do not tell the complete story, because there were many changes to industry sales happening within March 2020. Based on eyeballing the event studies for most industries negatively affected by the COVID-19 pandemic, March 2020 can roughly be divided into three periods: (1) the period before the WHO announcement on March 11, during which sales were relatively normal; (2) the period between March 11 and March 21, in which sales were declining rapidly; and (3) the period beginning around March 21, in which the decline halted and sales were again relatively flat but exhibiting a different level than the average level before March 11. An average over March will encompass all three of these rough periods. Thus, we take an average of the daily levels of spending by industry category over the final period beginning on March 21, 2020, to provide an estimate of the extent to which the COVID-19 pandemic has affected overall daily spending after mitigation measures have had sufficient time to take hold, and thus spending declines have leveled off.

5.1   Methods

Month-on-Month Growth. Rather than applying seasonal adjustment to the daily data, we can use the same month, year, and day-of-week fixed effects to remove some seasonality and trend from the data. By slightly modifying the event-study model, we can predict month-on-month percent changes for each industry. This is done by first predicting the error associated with each day in February and March. Because this model is in logs, February and March monthly means are computed by exponentiating and averaging. The ratio then gives the month-on-month growth rate, adjusted for day of week, year, and month.[13]

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13. To produce confidence intervals, we estimate the model with a dummy for each day in February and March of 2020. These coefficients, as well as the variance-covariance matrix of the coefficients, are then used to produce a confidence interval around the transformed monthly growth rates using a Monte Carlo simulation method (as several nonlinear transformations are required) with 10,000 iterations.

It should be noted that the month-on-month growth of the total may not correspond to a weighted average of the components, because the total is directly seasonally adjusted and detrended. No attempt is made to reconcile the seasonally adjusted total and its components.

Pandemic Effect. We compute the pandemic effect by averaging, for each industry, the daily levels of industry spending, computed as a percent deviation from the predicted baseline based on the model parameters; this baseline adjusts for seasonal factors and trends. We compute standard errors and averages using the same method that is used above for month-on-month growth rates. We start the averaging on March 21, 2020, until the final day we have data. As noted above, by March 21, 2020, all industries in the event studies above appear to have adjusted to a new level.

5.2 Discussion

Month-on-Month Growth. Table 1 shows the results of this exercise for a selection of categories that are included in the retail sales group, with the addition of food services. We will start by focusing on the month-on-month growth based on the daily data estimates. We see increases in a few categories, namely, food and beverage stores and health and personal care stores. We see decreases, however, in most other categories, with a particularly large decline of 40.5 percent for food services.[14] For the retail sales aggregate (excluding nonstore retailers), we see that the negative values dominate in the total, for a decline of 4.8 percent, based on the daily estimates.

Our estimates are broadly consistent with what the advance MRTS shows. The MRTS suggests that spending was lower for some categories (clothing and electronics retailers, for example) and higher for others (the drop in restaurants and food service spending is only 26.5 percent in the MRTS, while it is estimated to be 40.5 percent in the Fiserv data). As noted above, the nonstore retailer category in Fiserv has unknown coverage, and its Fiserv monthly estimate has the opposite sign as spending growth in this category in the MRTS, which shows positive growth of 3.1 percent. Excluding nonstore retailers, the total growth in spending across all categories is very close in both series, −4.8 percent for Fiserv and −4.4 percent for MRTS.

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14. One retail category that may not fully reflect economic activity is the nonstore retail sector, which shows an 8 percent decline. Based on both coverage in this sector in the data and its correlation with the official series, we believe that this estimate may not fully reflect the shift toward nonstore retailers, such as Amazon. Recent estimates from Adobe Analytics data from online transactions show a 25 percent increase in e-commerce sales.

Table 1. Predicted Month-on-Month Growth from February to March 2020
Based on Daily and Monthly Data, Retail and Food Service
[Seasonally adjusted]

Industry name	NAICS code	Daily data (month-on-month growth)[1]			Census data[2]
		Lower confidence interval[3]	Median growth	Upper confidence interval[3]	Monthly growth
Retail and restaurants					
Automotive parts, accessories, and tire stores	4413	−17.2%	−6.4%	5.7%	n/a[4]
Furniture and home furnishings stores	442	−30.7%	−22.5%	−13.3%	−26.8%
Electronics and appliance stores	443	−12.8%	−5.2%	3.1%	−15.1%
Building material and garden equipment and supplies	444	−14.9%	3.5%	26.3%	1.3%
Food and beverage stores	445	24.3%	31.3%	39.0%	25.6%
Health and personal care stores	446	−4.9%	8.0%	22.3%	4.3%
Gasoline stations	447	−23.7%	−20.4%	−17.1%	−17.2%
Clothing and clothing accessories stores	448	−44.7%	−39.5%	−33.6%	−50.5%
Sporting goods, hobby, musical instrument, and book stores	451	−10.8%	−2.9%	5.7%	−23.3%
General merchandise stores	452	−9.0%	−1.8%	5.8%	6.4%
Miscellaneous store retailers	453	−16.0%	−8.8%	−1.2%	−14.3%
Nonstore retailers	454	−13.6%	−7.3%	−0.4%	3.1%
Food services and drinking places	722	−43.4%	−40.5%	−37.5%	−26.5%
Total retail and food service[5]	**–**	**−10.3%**	**−5.3%**	**0.1%**	**−3.1%**
Total retail and restaurants, excluding nonstore retailers	**–**	**−10.0%**	**−4.8%**	**0.7%**	**−4.4%**

NAICS   North American Industry Classification System

1. Monthly growth rates from February 2020 to March 2020 computed after adjusting for day-of-week, month, and year effects, based on daily data.
2. Preliminary Monthly Retail Trade Survey (MRTS), March 2020 release. Seasonally adjusted growth rate, February to March 2020.
3. Confidence interval methodology described in paper.
4. Preliminary MRTS data do not report industry 4413 (auto parts).
5. The retail total for Fiserv is based on Aladangady and others (2019) and excludes gasoline stations, although we include gasoline stations as a line in the table because they are part of the official MRTS. Specifically, the total includes NAICS categories 4413, 442, 443, 445, 446, 448, 451, 452, 453, 454, and 772. The retail total for the Census data includes all of the same industries except 4413 (auto parts) because it is not available in the preliminary release.

Table 2 shows estimates for additional categories that do not fall under MRTS categories listed in Table 1. The estimates are ordered roughly in terms of the level of coverage and how well the category likely represents the associated three-digit category. For example, for professional and scientific services, it is not clear that credit card transactions in that category are representative, so we've included that near the bottom of the table. For ambulatory services, while the coverage is decent and the category shows a strong correlation, we are likely observing just the co-payments and coinsurance, so it is also included further down the list.

Table 2. Predicted Month-on-Month Growth from February 2020 to March 2020
Based on Daily and Monthly data, Other Industries
[Seasonally adjusted]

Industry name	NAICS code	Daily data (month-on-month growth)[1]			Consistency[2]
		Lower confidence interval[3]	Median growth	Upper confidence interval[3]	Historical R[2]
Other industries					
Accommodations	721	−55.0%	−52.3%	−49.3%	97.1%
Repair and maintenance	811	−29.7%	−16.8%	−1.4%	95.0%
Amusement, gambling, and recreation	713	−41.5%	−38.0%	−34.5%	93.0%
Personal and laundry service	812	−42.8%	−36.1%	−28.7%	97.9%
Ambulatory health care services	621	−36.7%	−24.7%	−10.7%	98.4%
Hospitals	622	−20.7%	−10.5%	0.8%	97.3%
Social assistance	624	−39.0%	−28.7%	−17.0%	97.3%
Performing arts, spectator sports, and related	711	−51.3%	−47.1%	−42.6%	87.5%
Transit and ground passenger transportation	485	−51.0%	−46.9%	−42.3%	19.9%
Motion picture and sound recording	512	−58.0%	−51.5%	−44.1%	0.3%
Rental and leasing services	532	−33.8%	−28.7%	−23.3%	44.5%
Professional, scientific, and technical services	541	−15.2%	−6.4%	3.5%	84.2%
Administrative and support services	561	−30.2%	−23.2%	−15.2%	95.8%
Educational services	611	−27.7%	−19.8%	−11.3%	90.5%
Museums, historical sites, and similar	712	−53.3%	−45.6%	−36.6%	29.8%

NAICS   North American Industry Classification System

1. Monthly growth rates from February 2020 to March 2020 computed after adjusting for day-of-week, month, and year effects, based on daily data.
2. Historical comparison with corresponding seasonally adjusted Quarterly Services Survey (QSS) series, log levels, based on the R^2 from a regression of Fiserv data aggregated to quarters on QSS data.
3. Confidence interval methodology described in paper.

Among the first several categories listed in Table 2, we see declines for accommodations and recreation related categories (NAICS 721 and 713), which fell around 40–50 percent for the month. The category for repair and maintenance and personal laundry services also showed declines of 17 percent and 36 percent, respectively. Both hospitals and ambulatory services show declines, but with hospitals showing a more modest 11 percent decline, relative to ambulatory services, which fell by 25 percent.

The categories listed below health care services in Table 2, where the representativeness of the estimates is less certain, also show declines across nearly every category. The largest declines are for transit and services categories associated with arts and entertainment (NAICS 711 and 712), which all fell by around 40 to 50 percent.

To provide an indication of what this suggests for the official series, we also include a measure of "consistency," which is the R-squared of the data, converted to a quarterly frequency and seasonally adjusted, when used to predict the corresponding official seasonally adjusted series, the Quarterly Services Survey (QSS). Most of the series show an R-squared above 0.80, indicating a fairly high degree of correlation in levels.[15]

To arrive at a full weighted-average effect of the decline for industries covered by these data, we focus on the median monthly change based on the daily data in Tables 1 and 2. We weight the monthly change in each three-digit category listed in Table 1 based on the latest MRTS release,[16] and we weight a subset of select categories listed in Table 2 (for example, categories in which data quality appears reasonably high, including NAICS 621, 622, 624, 711, 713, 721, 811, and 812) based on the latest QSS figures.[17] Combined, we find a weighted average decline for the month of March to be 13.7 percent.

Pandemic Effect. Table 3 shows the pandemic effect on restaurants and retail establishments. One thing that immediately stands out is that while food and beverage stores continue to show the bump in sales noted above (albeit an attenuated 8.5 percent), sales at health and personal care stores have reversed course, declining by 27.6 percent from baseline. Furniture, clothing, and restaurants have all experienced large reductions in sales of about 50 to 70 percent. Overall, we see a decline of about 26 percent from baseline, excluding non-store retailers from the calculation.

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15. We implicitly assume across all of our estimates that there is a one-to-one relationship between the estimates based on Fiserv and the associated category in the official series from MRTS or QSS. Based on a simple regression of the log of the official series on the corresponding log estimate from Fiserv, we find that the coefficient may deviate from 1, although the estimates do tend to center around this value. For instance, the log regression for aggregate retail services has a significant coefficient of 0.86. Using cross-validation, we found that for some series, assuming a one-to-one proportional relationship performed better than a log linear fitted value measured by mean squared errors of a hold-out sample, while for other series the fitted value performed better. As neither method clearly dominated, we chose the simple assumption of proportional growth to form our prediction.

16. The listed categories account for 76 percent of retail spending according to the Census Bureau's February MRTS. This excludes sales at motor vehicle and parts dealers (NAICS 441), sporting goods, hobby, musical instrument, and bookstores (451), and miscellaneous store retailers (453).

17. Estimated industries account for 21 percent of services spending according to the Census Bureau's latest QSS.

Table 3. Predicted Effects of Pandemic Based on Daily Data, Retail and Food Service
[Seasonally adjusted]

Industry name	NAICS code	Effects of pandemic[1]		
		Lower confidence interval[2]	Median growth	Upper confidence interval[2]
Retail and restaurants				
Automotive parts, accessories, and tire stores	4413	−16.8%	−6.6%	5.2%
Furniture and home furnishings stores	442	−48.3%	−42.5%	−36.2%
Electronics and appliance stores	443	−8.1%	−0.7%	7.7%
Building material and garden equipment and supplies	444	−6.7%	12.2%	35.1%
Food and beverage stores	445	3.2%	8.5%	14.3%
Health and personal care stores	446	−35.5%	−27.6%	−18.7%
Gasoline stations	447	−42.9%	−40.6%	−38.3%
Clothing and clothing accessories stores	448	−67.0%	−64.1%	−61.0%
Sporting goods, hobby, musical instrument, and book stores	451	−29.0%	−23.1%	−16.7%
General merchandise stores	452	−19.4%	−13.3%	−7.0%
Miscellaneous store retailers	453	−35.3%	−30.3%	−24.9%
Nonstore retailers	454	−14.5%	−8.7%	−2.5%
Food services and drinking places	722	−68.0%	−66.5%	−64.9%
Total retail and food service[3]	**–**	**−27.8%**	**−24.0%**	**−20.0%**
Total retail and restaurants, excluding nonstore retailers	**–**	**−29.7%**	**−25.9%**	**−21.9%**

NAICS   North American Industry Classification System

1. Effects of pandemic, starting March 21, 2020, computed by average daily effects after adjusting for day-of-week, month, and year effects.
2. Confidence interval methodology described in paper.
3. The retail total for Fiserv is based on Aladangady and others (2019) and excludes gasoline stations, although we include gasoline stations as a line in the table because they are part of the official Monthly Retail Trade Survey. Specifically, the total includes NAICS categories 4413, 442, 443, 445, 446, 448, 451, 452, 453, 454, and 772.

Table 4 shows the pandemic effect for other industries. Among the industries for which we believe these data most reliably match up with services measured by the Census Bureau (those near the top of the table), we see significant reductions in all categories excluding hospitals, which show only a slight decline in sales. Most other industries show a decline of 50–80 percent from baseline, except repair and maintenance, which seems to make some sense, as many repairs cannot easily be delayed.

Table 4. Predicted Effects of Pandemic Based on Daily Data, Other Industries
[Seasonally adjusted]

Industry name	NAICS code	Effects of pandemic[1]		
		Lower confidence interval[2]	Median growth	Upper confidence interval[2]
Other industries				
Accommodations	721	−74.7%	−73.3%	−71.8%
Repair and maintenance	811	−39.3%	−29.3%	−17.2%
Amusement, gambling, and recreation	713	−50.2%	−47.4%	−44.6%
Personal and laundry service	812	−74.8%	−72.1%	−69.1%
Ambulatory health care services	621	−57.3%	−49.9%	−41.4%
Hospitals	622	−14.5%	−4.4%	6.9%
Social assistance	624	−63.6%	−58.0%	−51.7%
Performing arts, spectator sports, and related	711	−53.1%	−49.2%	−45.0%
Transit and ground passenger transportation	485	−73.6%	−71.5%	−69.4%
Motion picture and sound recording	512	−83.8%	−81.2%	−78.1%
Rental and leasing services	532	−47.3%	−43.5%	−39.6%
Professional, scientific, and technical services	541	−12.7%	−3.9%	5.7%
Administrative and support services	561	−33.0%	−26.5%	−19.1%
Educational services	611	−22.5%	−15.0%	−6.5%
Museums, historical sites, and similar	712	−64.0%	−58.7%	−52.6%

NAICS   North American Industry Classification System

1. Effects of pandemic, starting March 21, 2020, computed by average daily effects after adjusting for day-of-week, month, and year effects.
2. Confidence interval methodology described in paper.

As before, to arrive at a full weighted-average effect of the decline for industries covered by these data, we focus on the median monthly change based on the daily data in Tables 3 and 4. We weight the monthly change in each three-digit category listed in Table 3 based on the latest MRTS release, and we weight a subset of select categories listed in Table 2 (for example, categories in which data quality appears reasonably high, including NAICS 621, 622, 624, 711, 713, 721, 811, and 812) based on the latest QSS figures. Combined, we find a weighted average "pandemic effect" of –27.8 percent.

6.   Conclusion

The daily Fiserv series offer new opportunities for measuring consumer spending during the current pandemic. Our estimates indicate a downturn in spending in the month of March and also provide early point estimates for that downturn across several important categories. The aggregate retail category shows a decline of around 5 percent, matching the advance MRTS for March, but declines are much larger for several service categories. The combined weighted average decline for March is around 13.7 percent based on the Fiserv estimates. The estimates for the month of March understate the full effect of the pandemic. When we compare the pre-March 11 period to the period after March 21, when most containment policies had taken effect, the weighted-average decline in spending is even larger, around 27.8 percent. The results also indicate the reduced level of spending has continued forward to the first part of April.

There is more work to be done in this area. First, while the correlations between the Fiserv series and official series are strong in many cases, the fit is imperfect. It may be useful to apply more flexible models to fit more closely with official series, similar to the approach of Chen and others (2019). Second, more work needs to be done to explain the regional patterns of decline across states, which may also help in understanding patterns of economic recovery. Third, the coverage of nonstore retail (e-commerce firms) may be limited in this data source, and it may be useful to investigate alternative sources. These estimates likely miss an offsetting source of spending increases from consumers switching to e-commerce.

While there is more to be done to establish the accuracy of these estimates, we think that timely data sources, such as those analyzed here, should be considered in combination with other series to help update our understanding of economic trends as we wait for more traditional data sources to arrive. Timely, alternative data sources may be especially useful now, as households, businesses, and policymakers attempt to assess and respond to the economic effects of the COVID-19 pandemic.

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