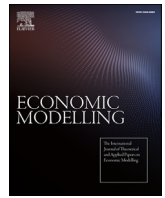




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A near real-time economic activity tracker for the Brazilian economy during the COVID-19 pandemic[☆]



Flavio Menezes^{a,*}, Vivian Figer^b, Fernanda Jardim^{b,c}, Pedro Medeiros^b

^a School of Economics, The University of Queensland, Brisbane, QLD4072, Queensland, Australia

^b Center of Studies in Infrastructure Regulation, Getulio Vargas Foundation, 22231000, Rio de Janeiro, Brazil

^c EPGE Brazilian School of Economics and Finance, Getulio Vargas Foundation, 22231000, Rio de Janeiro, Brazil

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ABSTRACT

During the COVID-19 pandemic, policymakers needed to assess the impact of large monetary and fiscal policy interventions in as close to real time as possible—yet existing survey-based indicators are usually released monthly or quarterly. The use of high-frequency data to track economic activity has become widespread. This paper constructs a near real-time economic activity indicator for the Brazilian economy during the COVID-19 pandemic. Brazil's integrated national electricity sector, which covers over 98% of the population, allows us to construct an economic activity indicator based solely on electricity consumption data that are available at near real time and accounts for activity in the large informal sector of the economy. We construct our indicator by isolating the variability in electricity consumption that is not related to economic activity, then measure how well monthly and quarterly versions of our indicator track against standard economic indicators. The results show strong correlation with standard indicators, notably during economic shocks.

1. Introduction

COVID-19 has had substantive economic and societal impacts across the world. Governments responded through both economic and public health levers. The latter included requirements for social distancing, quarantine, and lockdowns, while the former included financial assistance to businesses and workers. The magnitude of the economic response by governments has been unprecedented, with reports that over US\$10 trillion in financial assistance was announced by 54 countries in the first 2 months of the pandemic (Cassim et al., 2020). This assistance took the form of loan guarantees, loans, monetary transfers to firms and individuals, deferrals, and equity investments. Since then, governments have committed yet more resources to support businesses and communities. This continued commitment is illustrated by the US\$1.9 trillion relief plan in the US and the extension of a substantive cash transfer program in Brazil that had already exceeded US\$50 billion in 2020 and reached 67.9 million people (around one-third of the country's population).

The size and breadth of governments' response to the pandemic necessitates a near real-time understanding of the level of economic

activity and the impact of the various interventions. During rapidly moving economic shocks, as in the case of the pandemic, high-frequency economic indicators can provide valuable guidance for policymakers before the release of traditional, survey-based metrics indicators, which are usually available with a lag of weeks or months and often only provide a snapshot at the time the survey was conducted. To this end, this paper uses electricity consumption data, available with a 2- to 5-day lag, to track economic activity during the pandemic in Brazil. In contrast, the IBC-Br, a monthly indicator of activity published by the Brazilian Central Bank, is released within 45 days of the end of a month, and official GDP numbers are made available 60 days after the end of a quarter. Fig. 1 illustrates the difference in time between the release of these official macroeconomic indicators and the indicator estimated in this paper.

Although the use of high-frequency indicators to track economic activity dates to 1920s (Lourenço and Rua, 2021), only recently have data availability and the development of statistical methods allowed such indicators to assess short-run changes in economic activity as a response to shocks such as natural disasters or pandemics. The key

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* Corresponding author.

E-mail address: f.menezes@uq.edu.au (F. Menezes).

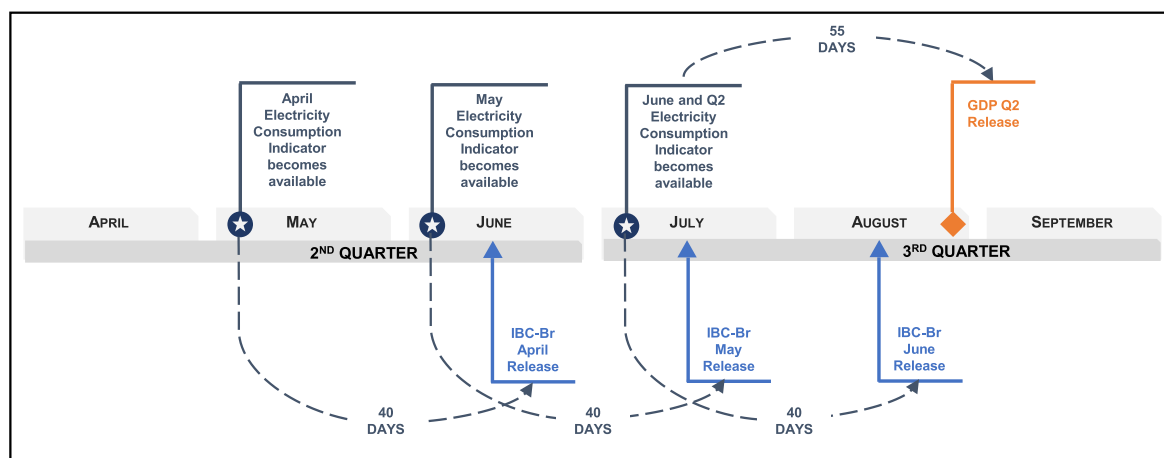


Fig. 1. Brazilian economic indicators' release schedule.

empirical challenge is to construct an appropriate counterfactual: What would have happened in the absence of the shock? While such a challenge exists in any empirical work, it is particularly acute in the case of high-frequency data, since short-term behavior is often noisier than longer-term trends.

By focusing on short-term electricity consumption in Brazil, we can construct such a counterfactual. In the electricity sector, demand and supply must be balanced in real time. This implies that consumption data are often available in real time or with short lags. It follows that, as shown in this paper, we may be able to track economic activity close to real time by using electricity consumption data—which is expected to be available for many developing countries, as is the case in Brazil. Moreover, while electricity consumption changes over time as a response to shifts in technology, prices, and other structural factors that may not be related to economic activity, the factors that impact short-run electricity consumption are more limited. For most consumers, there are no changes in retail electricity prices in the short run, consumers face volumetric charges in Brazil, and instantaneous (in this paper, hourly) electricity consumption is well understood to be a function of the temperature and whether it occurs during a workday. We can, therefore, measure the impact of COVID-19 on daily electricity consumption by estimating the variation of the load on a particular day with respect to the load in the previous 3 years, controlling for week of the year, day of the week, heat index (temperature), and holiday dummy variables. The data allow us to construct one indicator for each of the four regions. Brazil is a large country with significant regional differences, which renders the indicator also useful for understanding the differences in short-run economic activity across regions.

High-frequency electricity consumption data have been used to assess the economic impact of COVID-19 in the US and Europe (Blonz and Williams, 2020; Cicala, 2020; Chen et al., 2020; Janzen and Radulescu, 2020; and McWilliams and Zachmann, 2020). However, this paper is, to our knowledge, the first to use electricity consumption to assess the impact of COVID-19 in a developing country with a high level of income inequality (a 0.543 Gini index in 2019, according to IBGE (2020)) and a large informal sector (estimated at 38.4% of the economy in the 3rd quarter 2020). We chose of Brazil as a study case for three reasons. First, Brazil is a large, developing economy, ranked within the 10 largest world economies, renders it a relevant focus for our analysis. Second, access to electricity is nearly universal, with the National Integrated System (SIN) covering over 98% of the population. Third, the availability and coverage of the data enable us to develop a robust electricity consumption estimator for Brazil.

Prior research has used other high-frequency measures of economic activity (Glaeser et al., 2022; Diebold, 2020).¹ For example, data from Google mobility, restaurant reservation data, and movie releases and revenue have all been used to identify the determinants of social distancing and its impact on economic activity (Maloney and Taskin, 2020). The Federal Reserve's Weekly Economic Index (Lewis et al., 2020) is an index of 10 indicators of real economic activity, including electricity consumption, scaled to align with the four-quarter GDP growth rate. For the US, anonymized data from private companies have also been used to build a publicly available database² with the intent of disseminating daily statistics on consumer spending, business revenues, employment rates by ZIP code, industry, income group, and business size (Chetty et al., 2020). In a recent study, Lourenço and Rua (2021) developed a daily economic indicator to track economic activity in Portugal during the lockdown. These authors draw on a factor model and use 5 high-frequency data sources (electricity consumption, card-based payments, road traffic of heavy commercial vehicles, cargo and mail landed, and natural gas consumption) to estimate a latent factor. For the case of Brazil, however, electricity consumption is the only source of publicly available, high-frequency data that are released with a small lag.

In this paper, we estimate an hourly electricity consumption indicator and show that it fell 6.9% during the first 3.5 months of social distancing requirements—introduced on March 16—with the sharpest monthly decline of 10.05% occurring in April. By using monthly billing data, our electricity consumption indicator shows a decline of 17.27% and 25.52% for the industrial and commercial sectors, respectively. We confirm these findings by using consumption (rather than billing) data, as detailed in Section 5.1.

We then establish a link between economic activity and our electricity consumption indicator. The relationship between electricity consumption and economic activity is not a new idea. For example, the seminal paper of Kraft and Kraft (1978) used Grange causality tests to establish the relationship between energy consumption and GNP. More recently, Hirsh and Koomey (2015) describes adjusted trends in the relationship between growth in economic activity and electricity use. Moreover, Zhang et al. (2017) focus on the relationship between electricity consumption and economic growth in China (see Tiba and Omri (2017) and Ozturk (2010) for a review of empirical work on

¹ Night light intensity obtained from satellite data has been successfully used as a measure of economic activity, but its usefulness is in overcoming data reliability issues rather than temporal delay. See, for example, Henderson et al. (2012) and Galimberti (2020).

² The database is available at <https://tracktherecovery.org/>.

the relationship between these two variables). We note, however, that this literature concerns the long-run relationship between the two variables, whereas more recent literature, spurred by the need for real-time economic activity trackers, focuses on the very short-run relationship between electricity consumption (and other indicators) and economic activity. This new literature has focused on the short-term impact of an aggregate shock (demand or supply) in which data availability allows researchers to use indicators that are based on a variety of sources (e.g., electricity consumption and credit card data). Our focus is instead on an emerging economy with a large informal sector and is based on a single variable, a publicly available data source. Electricity-based indicators are especially useful in assessing the short-run impact of shocks, because it is difficult to substitute away from the use of electricity and especially in the very short run.

We start by estimating our indicator for the period that encompasses the global financial crisis (GFC) and compare it with standard economic indicators. As in the case of the pandemic, there is a well-defined date for the start of the GFC: September 15, 2008, the day Lehman Brothers filed for bankruptcy. The monthly electricity consumption indicator has correlation coefficients of 0.69 with IBC-Br and 0.75 with the actual GDP in its quarterly version. Second, we follow [Loureço and Rua \(2021\)](#) and run a regression of both IBC-Br and GDP on our indicator in its monthly and quarterly versions, obtaining R^2 values equal to 0.86 and 0.89, respectively.

Finally, our analysis shows that the impact of COVID-19 has differed from previous crises such as the global financial crisis and the 2014 recession. The COVID-19 pandemic is best thought of as having an effect similar to a natural disaster, with disruptions in supply leading to drops in income, which then feed into reduced aggregate demand. The lockdowns have clearly had a disproportionate impact on commercial activities such as retail and services. In contrast, the global financial crisis (and recessions more broadly) is associated with a reduction in aggregate demand reflected in industrial activity.

2. Data

Hourly electricity aggregate consumption data are collected for the four zones (Southeast/Midwest, South, Northeast, North) of the National Interconnected System (SIN) from January 1, 2004, to December 31, 2020. The consumption data represent system load, defined as the amount of energy withdrawn from the grid in addition to technical losses. The data do not account for load from isolated systems and self-consumption by consumers who have distributed generation systems (behind-the-meter consumption). Isolated systems, which are mainly located in the north of the country, represent less than 1% of total demand. Although distributed generation systems are expanding, they represent only 0.5% of the consumption load of captive consumers and around 2% of the installed capacity in Brazil. The data are available from the system operator (National System Operator - ONS) with a lag of 2–5 days.

Hourly consumption data by type of consumer (contestable and captive) are collected from the market operator (Chamber of Electric Energy Commercialization - CCEE) from January 2019 to December 2020. The data are available with a lag of around 3 months. The data on contestable consumers are available at firm level from the date a captive consumer, who does not have a choice of electricity supplier (Regulated Contracting Environment - ACR), migrates to become a contestable consumer, who can purchase electricity within the competitive contracting environment (Free Contracting Environment - ACL).

Monthly electricity billing data, disaggregated by sector, are collected from the Energy Research Office (EPE) for February 2004 to September 2020. These data are reported by distribution companies, self-producers, and contestable (large) consumers through the SIMPLES/SAM system (more information available at the EPE website). The data do not account for losses (either technical or non-technical) and are available with a lag of around 3 months. Also, during the months

of March to July of 2020, distribution companies were allowed by the regulator to refrain from meter reading and likely based bills on previous consumption data, which affects the accuracy of the data for non-contestable consumers.

There was also a data issue for the small state of Piauí (representing 0.7% of national consumption) in December 2018, for which commercial consumption, as reported in the EPE dataset (39.968 MWh), is almost 40% lower than the previous month. The data are clearly incorrect, since consumption within the regulated environment, as reported by the regulator (ANEEL, the National Agency of Electric Energy), is equal to 60.163 MWh. To correct the error, we replace the EPE data entry for December 2018 for the state of Piauí with the sum of the consumption within the regulatory environment and the consumption from the contestable consumers (2.810 MWh), as reported in the CCEE dataset.

Seven hourly heat index bins were built for each state in the four zones: 0–15 °C, 15–20 °C, 20–25 °C, 25–30 °C, 30–35 °C, 35–40 °C and over 40 °C. The bins acted as dummy variables to indicate whether the temperature was within the limits of the bin.³ The heat index was built using the methodology developed by [Rothfus \(1990\)](#) and with data on temperature and humidity scraped from Underground. We selected one weather station from each state, located at the state's capital (airport data when available), and for which historically hourly data were available. As there were no available stations for the two less populated states of Tocantins and Rio Grande do Norte, we used averaged data from neighboring weather states to replace it: Paraíba, Piauí, Pernambuco, and Ceará to replace Rio Grande do Norte, and Goiás, Distrito Federal, and Mato Grosso to replace Tocantins. Averaged data from weather stations in neighboring states were also used whenever data for an entire day were missing. When there were gaps in the hourly data, we interpolated the data from the adjacent hours.

We have also included dummies to capture the official national holidays, intra-holidays (IH) (i.e., Mondays or Fridays when holidays fall on Tuesdays or Thursdays, respectively), and long weekends (WLW). Although the Day for Black Awareness is not a national holiday, it is a holiday for the majority of states (including the largest ones), so we treated it as such. We only excluded this holiday in developing the Northeast Electricity Consumption Indicator, since most cities in that region do not consider it to be a holiday. We also used a separate dummy for Carnival and controlled for the week before and after. We also included dummies that capture holidays in the state of São Paulo for the Southeast/Midwest zone and two dummies interacted with weekend days to capture the different impacts a holiday has if it falls on a Sunday versus a Saturday.

3. Empirical approach

Our approach consists of three stages. In the first stage, we estimate a reliable indicator of electricity consumption by considering factors that can explain the majority of variability in consumption. The second stage is to test a longer series of the monthly and quarterly versions of the indicator against widely used economic indicators. The final stage analyzes electricity consumption by type of consumer (or sector of the economy) using two different datasets.

To estimate an electricity consumption indicator, we modify the approach of [Cicala \(2020\)](#) and estimate the following regression for

³ We have tested many other values for the bins, including a more complete specification with additional bins for 0–5 °C, 5–10 °C, and 10–15 °C. We note that negative temperatures are very rare, and there are very few observations below 10 °C. We have also undertaken robustness checks by including the heating and cooling degree variable specification as in [Cicala \(2020\)](#), in which the heating degree is the number of degrees the ambient temperature is below 18 °C and the cooling degree is the number of degrees the ambient temperature exceeds 18 °C.

each of the four zones of the SIN and for each hour of the day t :

$$\log C_{it} = \delta_{id,2020} + \Pi_i + X_i + Y_i + \text{Holidays}_i + \text{StateHI}_{it} + u_{it}. \quad (1)$$

In equation (1), C_{it} denotes the electricity consumption in MW for zone i at hour t . Our variable of interest is $\delta_{id,2020}$, which will be described below. The covariates are a set of dummies for each day of the week (Π_i), hour of the day (X_i), week of the year (Y_i), and the heat index (StateHI_{it}) for each state in the four zones, which was constructed as previously described. We also included a set of dummies (Holidays_i) to capture official national holidays (differentiating their impact, depending on whether they fall on a weekday, Sunday, or Saturday); intra-holidays (IH) (i.e., Mondays or Fridays when the holiday falls on Tuesdays or Thursdays, respectively); and long weekends (WLW). Holiday dummies also include a separate dummy for Carnival, controlling for the week before and after the event, and dummies to capture the holidays in the state of São Paulo for the Southeast/Midwest zone.

Error components are given by u_{it} and are clustered at the month level, since they may be serially correlated. A potential cause of autocorrelation could be measurement errors arising from the fact that the temperature of the capital cities of each state may not be perfectly representative of all cities in that zone. Omitted variables due to local events and holidays are another source of autocorrelation. It follows that there may be some residual demand variation captured by the error component.

In terms of our variable of interest, we estimate the daily mean $\delta_{id,2020}$ for each day d by pooling data from 2017 to 2020 and making the daily fixed effects an interaction between the day of the year and an indicator for the final year of the sample. Thus, $\delta_{id,2020}$ measures the variation of the load on day d with respect to the load in the previous 3 years, controlling for week of the year, day of the week, the heat index, and the various holiday dummy variables. We normalize the coefficients $\delta_{id,2020}$ with respect to the pre-pandemic months of January and February 2020.

We note that Chen et al. (2020) compare weekly electricity usage in 2020 with the same week in 2019 for 32 European countries (counting only workdays and excluding weekends). The authors proxy for weather conditions with the average temperature difference between 2020 and the same week of 2019, and capture the heterogenous sectoral composition of output by using either the share of manufacturing in national production or the expected GDP loss for a 6-week lockdown, as calculated by other authors.

We believe that our empirical approach (based on Cicala (2020)) is more robust than that of Chen et al. (2020). Increasing the granularity of the data (hourly rather than weekly, as in Chen et al. (2020)) and adding weekends and holidays ought to (weakly) generate better estimates of the impact of COVID-19 on electricity consumption. Moreover, the nature of our data allows us to analyze actual consumption by zone of the national electricity system and by sector of the economy, rather than by calculating the sectoral impact on electricity consumption using historical data on sectoral shares.

The second stage of our empirical analysis is to test a longer series of the monthly and quarterly version of the indicator against widely used economic indicators: the monthly GDP monitor, the quarterly GDP (official index by Brazilian Institute of Geography and Statistics – IBGE), and the Central Bank monthly indicator IBC-br. As with our hourly indicator, we employ Eq. (1) and a rolling-window analysis to estimate indicators from July 2007 to December 2020 by pooling data for years $y-3$, which means that we used data from year 2004 onward. The monthly and quarterly electricity consumption indicators are the mean of the daily fixed effects over the month or quarter. After constructing these monthly and quarterly indicators, we measure the correlation between the three standard indicators of economic activity, listed above, and our electricity consumption indicator.

The third stage of our empirical analysis considers electricity consumption across different sectors of the economy. Using monthly data from the EPE, we estimate the following regression:

$$\log C_{it} = \delta_{t,y} + \varphi_t + W_{it} + \rho_i + \tau_{it} + \text{StateHI}_{it} + u_{it}. \quad (2)$$

In Eq. (2), C_{it} denotes the electricity consumption in MWh for consumer of type i (industrial, commercial, or residential) in month t . The data are organized as a panel (state and month). Our variable of interest, $\delta_{t,y}$, measures changes in consumption in month t of the last year of the window y . The longer EPE monthly series allows us to include consumption data during the 2014 recession, which had no well-defined starting date.

We normalize $\delta_{t,y}$ by the period immediately before each of the three crises: January 2020 for the COVID-19, August 2008 for the subprime crisis, and March 2014 for the recession. φ_t and ρ_i are the month and state fixed effects, respectively. W_{it} is the number of working days in period t in state i , and τ_{it} is a time trend for states with nonstationary consumption series. StateHI_{it} are heat index bins, with temperature intervals 0–15 °C, 15–20 °C, 20–25 °C, 25–30 °C, 30–35 °C, 35–40 °C, and over 40 °C, with each containing the number of days in which the maximum temperature was within the particular range (adjusted by the number of total days of the month). We clustered standard errors at state level.

We conduct a further disaggregated analysis of hourly data available from the market operator (CCEE). The data contain hourly consumption for regulated and contestable (large) consumers from January 2019 to December 2020. Contestable consumers are classified by activity type: food industry; beverages; manufacturing; metallurgy and metals; extraction of metallic minerals; wood, paper and pulp; chemicals; textile; vehicles; sanitation; transport; telecommunication; and commerce and services. We exclude data from contestable consumers absent from the sample in January 2019. This prevents overestimating any increase in consumption in the contestable consumers contracting environment that only occurred due to migration from the regulated to the free contracting environment during the sample period.

We construct electricity consumption indicators for regulated consumer, and contestable industrial and commercial consumers. We estimate the following equation length:

$$\log C_{it} = \delta_{id,2020} + \Pi_i + X_i + \text{Holidays}_i + \text{StateHI}_{it} + u_{it}. \quad (3)$$

In equation (3), C_{it} denotes the electricity consumption in MW for class i at hour t . The variable of interest is $\delta_{id,2020}$ and the covariates are a set of dummies for each day of the week (Π_i), hour of the day (X_i), and the heat index (StateHI_{it}) for each state. Dummies for week of the year are not used for this specification due to the shorter time period for the analysis. The set of holiday dummies Holidays_i is the same used in equation (1), except we do not include a dummy for Carnival and its control for the week before and after, again due to the shorter time period used for the analysis as a consequence of data availability. The error component is given by u_{it} .

4. The impact of COVID-19 on electricity consumption

On February 26, 2020, Brazil was the first country to report a positive case of COVID-19 in Latin America. Because the pandemic reached Latin America later than Europe, it allowed more time for emergency preparedness and response. However, despite a significant economic response amounting to around USD\$880 per inhabitant and approximately 10% of GDP, the country was hit hard by the pandemic. Likely causes include the high degree of informality of the economy, the lack of ability to contact trace and test, and the lack of a nationally consis-

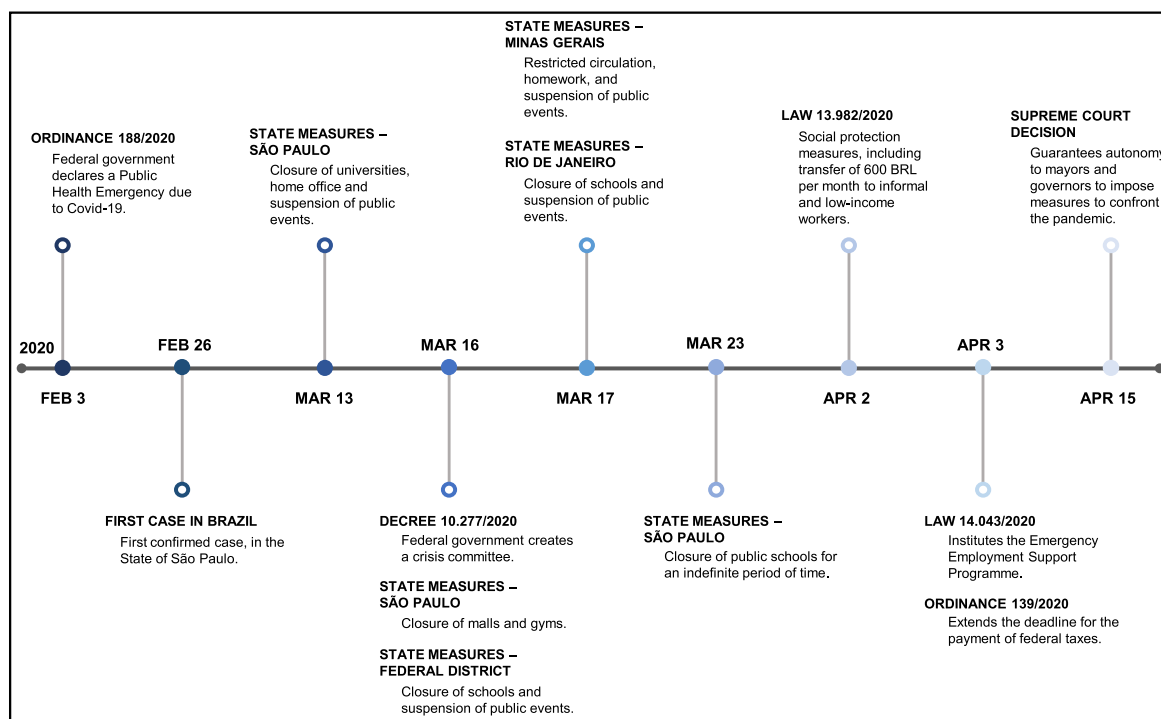


Fig. 2. Some key social and economic measures to address the pandemic's first wave in Brazil.

tent approach.⁴

Brazil's president famously dismissed COVID-19 as a "measly cold" at the end of March⁵ and later argued publicly with the Health Minister—who was subsequently fired—over the need for social distancing.⁶ The Brazilian government, likely influenced by Trump's approach in the US, left some of the heavy lifting to states and cities, with limited attempts to achieve a nationally consistent approach, as captured by Fig. 2. On March 16, the Federal Government declared a state of emergency and states and municipalities began imposing restrictions, starting with the closure of schools and universities and the suspension of public events. With the federal government refraining from coordinating a response to the crisis, state governments acted. The official quarantine in the states of São Paulo and Rio de Janeiro—the largest states—started on March 24 (initially for 15 days, though this was later extended), with the closure of nonessential businesses and other restrictions. The disagreement between federal and state governments was resolved by a Supreme Court ruling on April 15 whereby state and municipal governments had the power to determine rules on lockdowns. We consider March 16 as the start of the pandemic response by governments.

This timeline is important, since we want to identify what the electricity consumption would have been in the absence of COVID-19. We adjust consumption for variables that, under no COVID-19, would have explained more than 84% of the variation. We estimate the impact of COVID-19 using hourly electricity consumption data for each of the four

zones (Southeast/Midwest, South, Northeast, North) of the National Integrated System, which covers around 98% of the national electricity load. Our explanatory variables include hour of the day, day of the week, holidays, and week of the year. They also include an hourly heat index, which combines temperature and humidity data from a weather station in each state for each of the four zones. The heat index is classified into six bins: 0–15 °C, 15–20 °C, 20–25 °C, 25–30 °C, 30–35 °C, 35–40 °C, and over 40 °C. The difference between estimated consumption and actual consumption is our indicator for the impact of COVID-19, which is also an indicator for the impact on economic activity, as we will show in the next section.

Our indicator, which captures the impact of COVID-19 on electricity consumption, is depicted in Fig. 3 from March 16, the start of the pandemic response, through December 31. Our target coefficient is a set of daily dummies for the last 10 months of the last year in the sample (2020). They are an estimate of how much the electricity consumption on that specific day varied from the prior 3 years controlling for the week of the year, day of week, hour of day, and heat index. Our coefficients are normalized to the pre-COVID-19 months of January and February 2020. Fig. 3 shows that our electricity consumption indicator was down 4.33% from March to September 1 relative to the baseline, with a sharper decrease of 14.46% on April 20. We have added some key dates below, including the start of the pandemic response and the dates for the 5 rounds of income support payment: R\$600 (US\$106.07) or R\$1200 (US\$212.14) to informal workers and mothers in single-income families and additional rounds of payments of R\$300 (US\$53.04).

Fig. 4 displays the electricity consumption indicator relative to the baseline for the four zones of the SIN. While the general trend is similar across the four zones, peaks and troughs occur at different times, representing different local conditions. For example, Fig. 4 shows that electricity consumption started to fall in the Northeast region a week later than the rest of the country. This reflects the later start of the restrictions in that region.

⁴ See Benítez et al. (2020), who provide an analysis of the first 100 days of the COVID-19 pandemic in five Latin American countries, including Brazil.

⁵ *New York Times*. Bolsonaro isolated and defiant, dismisses Coronavirus threat. Press release 2020 [cited 2020 Jun 10]. Available from: <https://www.nytimes.com/2020/04/01/world/americas/brazil-bolsonaro-coronavirus.html>.

⁶ *Washington Post*. Brazil's Bolsonaro fires Health Minister Mandetta after differences over coronavirus response. Press release 2020 [cited 2020 Jun 10]. Available from: https://www.washingtonpost.com/world/the_americas/coronavirus-brazil-bolsonaro-luiz-henrique-mandetta-health-minister/2020/04/16/c143a8b0-7fe0-11ea-84c2-0792d8591911_story.html.

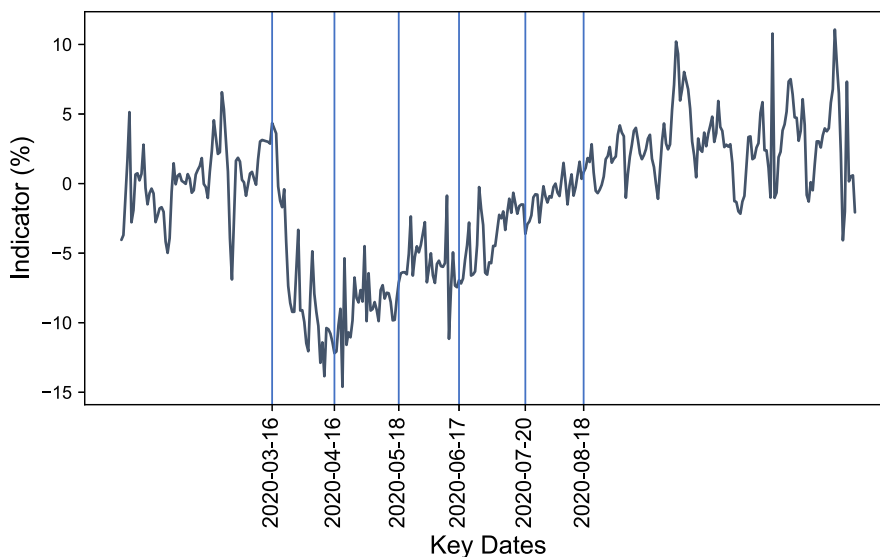


Fig. 3. Variation of normalized indicator of energy consumption for Brazil (%).

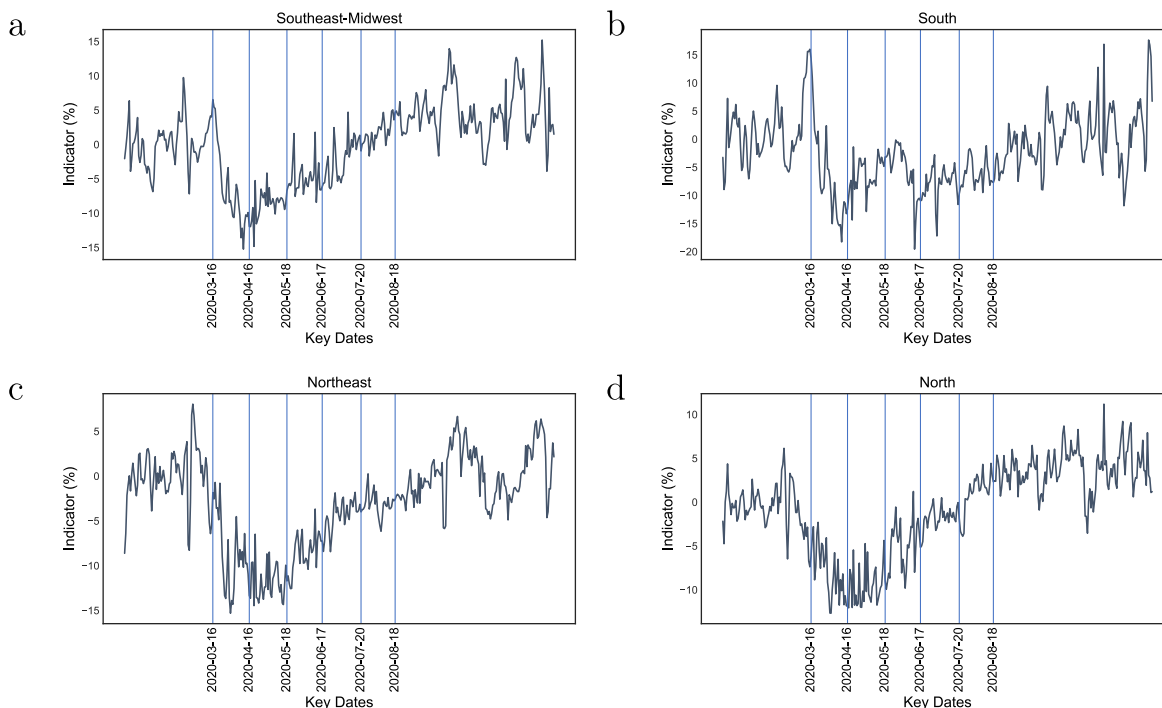


Fig. 4. Variation of normalized indicator of energy consumption for SIN Zones (%).

5. Electricity consumption and economic activity

In this section we compare our indicator of electricity consumption—aggregated on an hourly, monthly, and quarterly basis—with widely used indicators that are only available with a temporal lag of 1.5–2 months. As with our hourly indicator, we employ a rolling-window analysis to estimate indicators from July 2007 to December 2020 by pooling data for years $y-3$, meaning that data from years 2004 onward were used. The comparisons are depicted in Figs. 5 and 6.

Fig. 5 lends support for the use of our electricity consumption indicator as a short-term measure of economic activity. For both Brazil as a country and for the Southeast/Midwest Zone, the correlation between

our indicator (aggregated at quarter level) and the GDP is 0.75 and 0.70, respectively.

The comparison in Fig. 6 provides strong support for the use of our electricity consumption indicator, especially during the initial response to the GFC and the pandemic. The monthly series exhibits a correlation of 0.83 and 0.93 with the IBC-br for a period of 6 months from the beginning of each of the crises, respectively, whereas the correlation for the entire period is 0.69. The correlation between the entire series with the monthly GDP is 0.70, whereas the correlation for the Southeast Zone series (representing over 50% of total consumption) with the IBC-br and monthly GDP are 0.62 and 0.63. The correlation is considerably stronger the shorter the period of comparison. For example, the correlation between the two indicators is equal to 0.96 from February

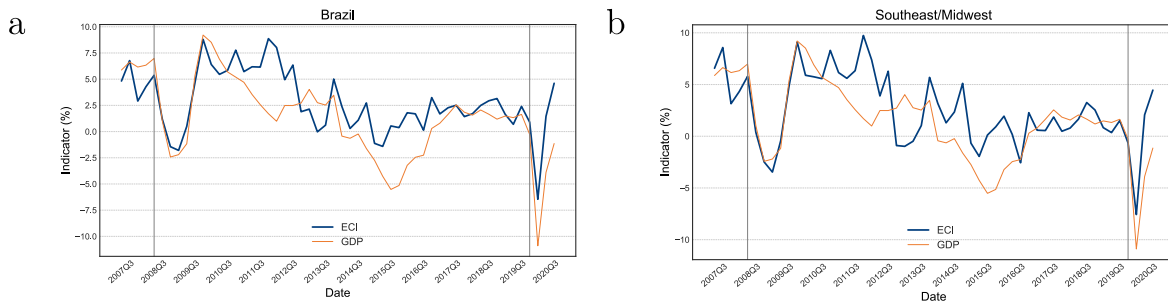


Fig. 5. Electricity consumption indicator and quarterly economic activity.

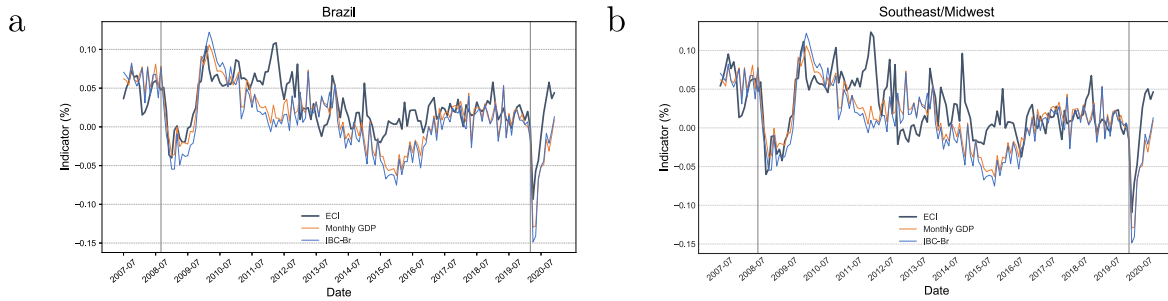


Fig. 6. Electricity consumption indicator and monthly economic activity.

2020 to May 2020, and this correlation becomes 0.95, 0.95, 0.91, 0.92, and 0.88 as we successively expand the period by 1 month from June to October.

Comparison of the monthly indicators also highlights the need for more timely indicators to assist policymakers in calibrating their response to a systemic crisis. According to our electricity consumption indicator, the recovery of economic activity started at least 1 month before being picked up by the IBC-br for both crises.

To provide additional evidence of the link between economic activity and our electricity consumption indicator, we followed Lourenço and Rua (2021) and ran a regression of both IBC-Br and GDP on our indicator in its monthly and quarterly versions, respectively. We added one lag for the dependent variable. Both IBC-Br and GDP are represented in their variation with respect to the previous 3 years—i.e., the same measurement as our indicator:

$$Y_t = \sum_{k=1}^K Y_{t-k} + \beta \text{Indicador}_t + u_{it}. \tag{4}$$

K was determined based on the Schwarz information criterion. The results suggest that our indicator does a good job of tracking economic activity, with R^2 values of 0.86 and 0.89 for the IBC-Br and GDP, respectively.

5.1. The heterogeneous impact of COVID-19 on the economy

While our electricity consumption indicator captures variation in short-term aggregate economic activity remarkably well, designing appropriate policy responses to crises requires an understanding of their impact across different sectors of the economy. In the case of COVID-19, for example, aggregate electricity consumption confounds increases in household consumption with the decreases in commercial and industrial consumption that arise from lockdowns and quarantines.

This section provides two different estimates for the short-term impact of different crises across distinct sectors of the economy by constructing appropriately designed electricity consumption estimators. First, we use monthly electricity billing data from EPE to estimate an indicator across the residential, commercial, and industrial sectors. This

longer time series allows us to test the usefulness of our estimator in tracking economic activity during the COVID-19 pandemic, the 2008 global financial crisis, and the 2014 economic recession (the last of which has no well-defined starting date).

Fig. 7 depicts our estimators across the three categories of consumers. Recall that our estimators measure the change relative to a previous base period. The industrial electricity consumption indicator shows a deep dive and recovery pattern for both the 2008 and 2020 crises. This conclusion is supported by the behavior of the IBC-Br index. For the 2014 recession, however, our indicator shows a much smoother reduction in industrial activity after March 2014, which continues for the following 2 years.

The commercial monthly electricity consumption indicator only shows a strong pattern of downturn and recovery for the COVID-19 pandemic, which demonstrates how the current crisis differs from previous crises. The lockdowns have clearly had a disproportionate impact on commercial activities, such as retail and services, differing from effects of the GFC. Disruptions in supply lead to drops in income, which then fed into reduced aggregate demand.

The impact on residential consumers is more difficult to assess, given that, as explained above, distribution companies were allowed by the regulator to refrain from meter reading, and likely based bills on previous consumption data. This would underestimate any increase in consumption for residential consumers during this period.

Next, we use hourly data from the market operator (CCEE) that disaggregates consumption between regulated and contestable (large) consumers from January 2019 to December 2020. The data further break consumption into activity types. We have constructed three indicators covering regulated, contestable industrial, and contestable commercial consumers, respectively. Regulated consumers are residential, rural, public lighting, commercial, and industrial consumers (among others). Households represent around 45% of regulated consumption. Commercial consumers make up around 20% of regulated consumption, which accounts for around 70% of the total consumption of the sector across both the regulated and contestable market environments. Industrial consumers represent 10% of regulated consumption, with the bulk of industrial consumers operating in the contestable market. Contestable industrial consumers include the food, beverage, manufactur-



Fig. 7. Sector analysis in recessions – Industrial, residential, and commercial.

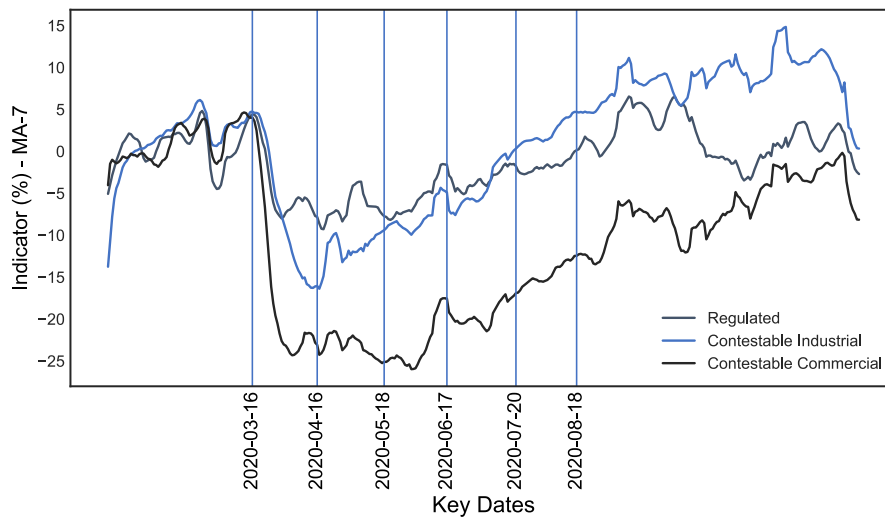


Fig. 8. Electricity consumption indicator for regulated and contestable consumers (%).

ing, and metallurgy industries, organic and inorganic material processing, and textile and vehicle manufacturing.

The CCEE sample is different from the EPE sample, with contestable commercial consumers including retail and wholesale but excluding services, and with disaggregated data for contestable service consumers. However, in order to align the comparison with the monthly indicator, we constructed a commercial electricity consumption indicator that aggregates both sectors. Fig. 8 depicts our three indicators, represented as a 7-day moving average, which capture the percentage change compared with pre-COVID-19 consumption. It shows a sharp decline in the electricity consumption indicator for the commercial and service sectors. Contestable industrial consumption also suffered a sharp decline of around 20%—twice the reduction in consumption by regulated consumers. Since the regulated environment includes residential (45% of

the total), commercial/services, and industrial consumers, it is not possible to directly test the previous result—that residential consumption remained stable throughout the pandemic—using billing data.

6. Conclusion

We constructed an electricity consumption indicator for short-run economic activity based on hourly electricity consumption data to measure the impact of both COVID-19 and various measures introduced by governments in Brazil. A key feature of our indicator is that it is based on 3-day-old data, as opposed to standard indicators that are based on data at least 1 month old.

In constructing the indicator, we considered what electricity consumption would have been in the absence of COVID-19. We do this by

considering variables that explain the variation between consumption on each day during the pandemic and consumption on the same day over the previous 3 years. These variables include temperature, humidity, holidays, and workdays versus weekends.

We use our indicator to track the impact of both lockdowns and Brazil's various income support measures introduced by Brazil's federal government. In addition, using hourly consumption data, we compare the behavior of our electricity consumption indicator with that of standard indicators available after much longer delays during the GFC and COVID-19. Our indicator does remarkably well in tracking economic activity during the two crises.

To further test the usefulness of electricity consumption as an indicator of economic activity, we used monthly electricity consumption data across the residential, commercial, and industrial sectors. We used electricity consumption to track economic activity during the COVID-19 pandemic, the 2008 global financial crisis, and the 2014 economic recession. While the first two crises had a well-defined start date, the 2014 recession has no well-defined starting date. Our results suggest very different behaviors across the different crises, and clearly show that the COVID-19 pandemic is best thought of as having an effect similar to a natural disaster, with disruptions in supply leading to drops in income, which then feed into reduced aggregate demand. The global financial crisis (and recessions more broadly), in contrast, is associated with a reduction in aggregate demand.

The key implication from this research is that a well-constructed electricity consumption indicator can provide useful, real-time insights into the economic impact of major crises. Such an indicator is particularly useful in crises with a well-defined starting date—such as a pandemic or a natural disaster—where the need for real-time monitoring is important for calibrating policy responses, particularly in countries such as Brazil with a large informal sector.

Declaration of competing interest

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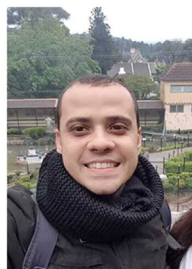
Flavio Menezes. Flavio Menezes is a Professor of Economics at the School of Economics at The University of Queensland. He joined The University of Queensland in June 2006 after more than a decade at the Australian National University, where he was the Foundation Director of the Australian Center of Regulatory Economics. Flavio was also a part-time Vice President with the Regulatory Economics and Public Policy Practice at CRA International in Canberra until May 2006 and a Senior Consultant until May 2007. He has published over 50 journal articles on the economics of auctions, competition and regulatory economics, industrial organization, and market design.



Vivian Figer. Vivian is a researcher at FGV CERI since 2016. She holds a PhD in Economics from New York University and a Master's degree in Economics from PUC-Rio and Production Engineering from the Federal University of Rio de Janeiro (2004). She worked at the Organization for Economic Cooperation and Development (OECD) as a consultant in the area of Economic Regulation and Governance. Her main research areas are Applied Theory, Industrial Organization and Antitrust.



Fernanda Jardim. Fernanda Jardim is a Ph.D. Candidate at EPGE Brazilian School of Economics and Finance (FGV EPGE). She holds master's and bachelor's degrees in Economics from the same institution. She is a researcher at the Center for Studies in Regulation and Infrastructure (FGV CERI) since June 2016 in the areas of economic regulation, infrastructure financing, applied economics, and energy economics. Previously she worked with applied research and customized price indexes at the Brazilian Institute of Economics (FGV IBRE).



Pedro Medeiros. Pedro Medeiros holds a Master's Degree in Applied Math from FGV EMap and a bachelor's degree in Economics from UFRJ. Previously he worked with business cycles and macroeconomic research at the Brazilian Institute of Economics (FGV IBRE) and in data science projects at the Center for Studies in Regulation and Infrastructure (FGV CERI). He currently works in the real estate industry as a data scientist.