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Using electricity consumption to predict economic activity during COVID-19 in Brazil
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Using electricity consumption to predict economic activity during COVID-19 in Brazil

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ABSTRACT — COVID-19 has led to substantial societal and economic changes. Social distancing, both voluntary and government-mandated through quarantine or lockdowns, became necessary to reduce the speed of transmission. Governments responded with substantive policies to support businesses that had to shut down and workers who were unable to work from home. Here, we show how hourly electricity consumption data, available with a 2-to-5-day lag, can be used to track economic activity during the pandemic in Brazil. Our electricity consumption indicator fell 6.9% during the first three and a half months since the introduction of social distancing requirements on March 16$^{\mathbf{th}}$, with the sharpest decline of 14.61% occurring in April. By using monthly consumption data, our electricity consumption indicator shows a decline of 17.27% and 25.52% for the industrial and commercial sectors, respectively, while there is no significant effect in the residential sector over the same period.

The emergence of the Coronavirus disease (COVID-19) in late 2019 has had substantive economic and societal impacts across the world. Social distancing, both voluntary and government-mandated through quarantine or lockdowns, became necessary to reduce the speed of transmission. Governments responded with substantive policies to support businesses that had to shut down and workers who were unable to work from home. The magnitude of the response by governments has been unprecedented, with reporting that over US$10 trillion in responsive measures was announced by 54 countries in the first two months of the pandemic. These responses included loan guarantees, loans, monetary transfers to companies and individuals, deferrals, and equity investments. Since then, governments have committed yet more resources to support businesses and communities. This continued commitment is illustrated by the US$ 1.9 trillion relief plan in the US [1] , and by consideration being given to extending for another four months a substantive cash transfer program in Brazil that has already exceeded US$ 50 billion in 2020, reaching 67.9 million people assisted (around one third of the country's population of 211.755.692 - The Brazilian Institute of Geography and Statistics - IBGE, 2020).

The size and breath of the response of governments to the pandemic necessitates a near real-time understanding of the level of economic activity and the impact of the various interventions. This

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paper uses electricity consumption data, available with a 2-to-5-day lag, to track economic activity during the pandemic in Brazil. During rapidly moving economic shocks, as in the case of the pandemic, such high-frequency economic indicator can provide valuable guidance to policymakers before 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, are released. For example, 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; while the official GDP numbers are made available 60 days after the end of a quarter. Figure 1 illustrates the difference in time between the release of these official macroeconomic indicators and the indicator estimated in this paper.

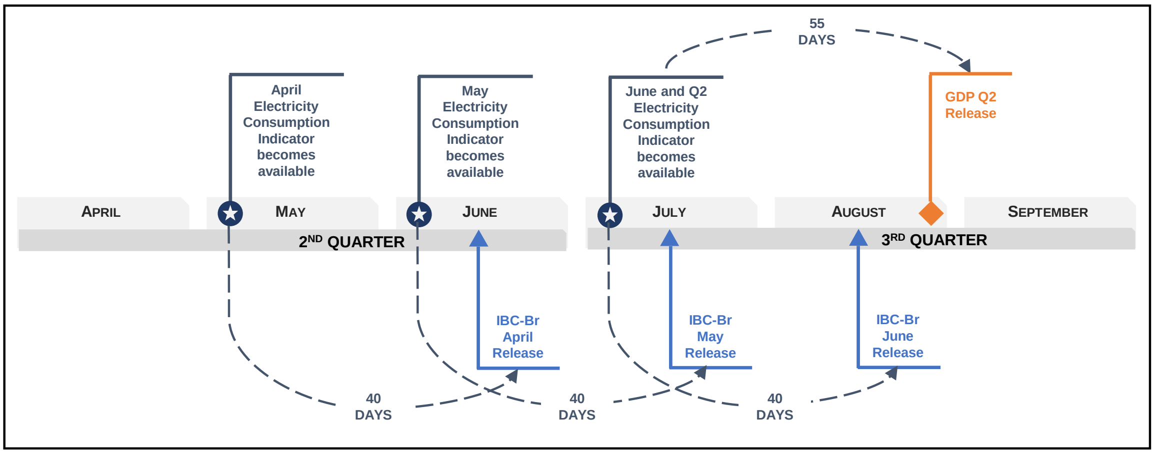

Figure 1: **Brazilian economic indicators' release schedule.**

Existing research has also used other high-frequency measures of economic activity [2]. 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 [3]. For the US, anonymized data from private companies have also been used to build a publicly available database with the intent of disseminating daily statistics on consumer spending, business revenues, employment rates by ZIP code, industry, income group, and business size [4]. While such high-frequency indicators can provide insights into specific segments of the economy [5], a key challenge is to determine how they would relate to overall economic activity statistics such as GDP. 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 [6] [7]. We note that electricity consumption indicators also have the additional advantage of capturing both the formal and informal sectors of the economy, which is particularly important in the case of Brazil where it is estimated that 40% of workers are in the informal sector.

We emphasize that electricity-based economic activity indicators are not substitutes for established metrics, which provide a more comprehensive view of the economy. Moreover, 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. Electricity indicators, however, are useful in assessing the short-run impact of shocks, when electricity consumption varies in a more predictable way across weekdays, weekends, during holidays, and as temperature changes.

While high-frequency electricity consumption data has been used to assess the economic impact of COVID-19 in the US [8] [9] [10] [11]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 large informal sector, estimated at 38.4% of the economy in the 3rd quarter 2020 and exhibiting a high level of income inequality (a 0.543 Gini Index in 2019) [12]. One of the key advantages of electricity consumption data is its availability across locations and sectors.

Our hourly electricity consumption indicator fell 6.9% during the first three and a half months since the introduction of social distancing requirements on March 16th, with the sharpest monthly decline of 10.14% occurring in April. By using monthly consumption data, our electricity consumption indicator shows a decline of 17.27% and 25.52% for the industrial and commercial sectors, respectively, while there is no significant effect in the residential sector over the same period. We validated our electricity consumption indicator by estimating it for the period of the global financial crisis (GFC) and comparing it to the standard economic indicators. In both instances, there are well-defined starting dates, with September 15th, 2008 being the day when Lehman Brothers filed for Bankruptcy. The monthly electricity consumption indicator has correlation coefficients of 0.69 with IBC-Br, and 0.77 with the actual GDP in its quarterly version. Moreover, the coefficient of correlation between electricity consumption and the actual GDP using annual data from 1990 and 2018 is equal to 0.99, indicating an extremely strong linear covariation in the long run. Research using the same data sources (International Energy Agency and World Bank) for Italy, estimates the correlation coefficient between GDP and electricity consumption at 0.88 [13].

We extend our analysis to study the impact of COVID-19 by sector of the economy. We show that this impact has been different from previous crises such as the global financial crisis and the 2014 recession. The COVID-19 pandemic is best thought of as having a similar effect of a natural disaster, with disruptions in supply leading to drops in income, which then feeds into reduced aggregated demand. The lockdowns have clearly had a disproportional impact on commercial activities such as retail and services. The global financial crisis (and recessions more broadly), in contrast, is associated with a reduction in aggregated demand with reflections in industrial activity.

The impact of COVID-19 on electricity consumption

On the 26th of February 2020, Brazil was the first country to report a positive case of COVID-19 in Latin America. As the pandemic reached Latin American countries later than European nations, it allowed more time for the emergency preparedness and response. However, despite a significant economic response, amounting to around USD$ 880 per inhabitant and accounting for approximately 10% of GDP, the country was hit hard by the pandemic. Likely causes include the high degree of informality, lack of ability to contact trace and test, and a lack of a nationally consistent approach [14].

Brazil's president famously dismissed COVID-19 as a 'measly cold' at the end of March [15] and later argued publicly with the Health Minister (who was subsequently fired) over the need for social distancing [16]. 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 Figure 2. On the 16th of March, the Federal Government declared a state of calamity and states and municipalities began imposing restrictions, starting with the closure of schools and universities, and the suspension of public events. Since the federal government refrained from coordinating a response to the COVID-19 crisis, State governments acted. The official quarantine in the States of São Paulo and Rio de Janeiro - the largest states - started on

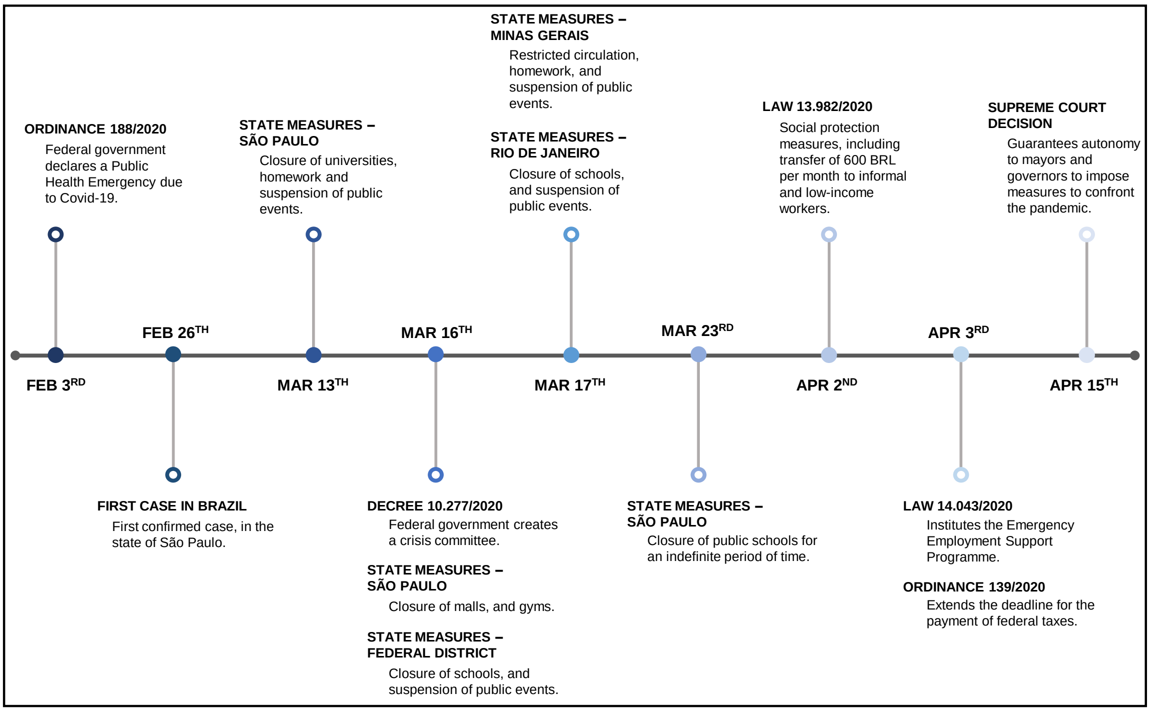

Figure 2: **Some key social and economic measures to address the pandemic's first wave in Brazil.**

the 24$^{\text{th}}$ of March (initially for 15 days, which was then extended), with the closure of non-essential businesses and other restrictions. The disagreement between federal and states governments was resolved by a Supreme Court ruling on April 15$^{\text{th}}$ endorsing that state and municipal governments also have the power to determine rules on lockdowns. We consider the 16$^{\text{th}}$ of March as the start of the pandemic response by governments.

This timeline is important as we want to identify what would have been the electricity consumption in the absence of COVID-19. That is, we adjust consumption for the variables that, under non-COVID-19, would have explained more than 84% of the variation. We estimate the impact of COVID-19 by using hourly electricity consumption data for each of the four zones (Southeast/Midwest; South, Northeast, North) of the National Integrated System, covering 99% of 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 four bins: less than 25°C, 25-30°C, 30-40°C or over 40°C. The difference between the estimated consumption and the actual consumption is our indicator of 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, capturing the impact of COVID-19 on electricity consumption, is depicted in Figure 3 from March 16$^{\text{th}}$, the start of the pandemic response, through December 31$^{\text{st}}$. 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

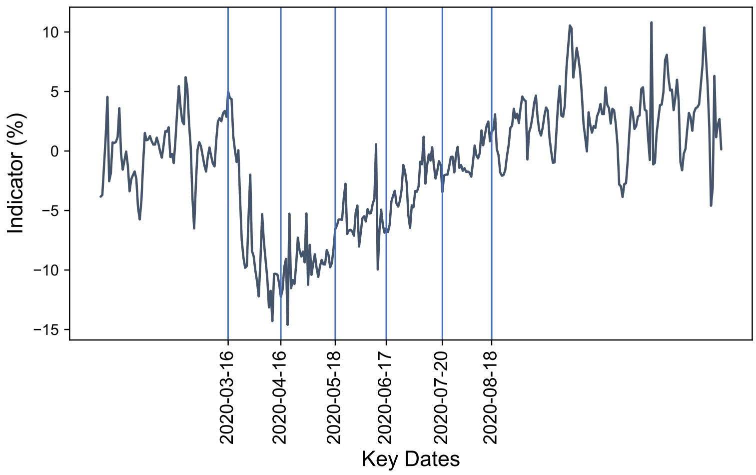

Figure 3: **Variation of Normalized Indicator of Energy Consumption for Brazil (%).**

prior three years within the same week of the year, day of week, hour of day and heat index. Our coefficients are normalised to the pre-COVID-19 months of January and February 2020. Figure 3 shows that our electricity consumption indicator was down 4.19% from March to September 1$^{\text{st}}$ relative to the baseline, with a sharper decrease of 14.61% in the April 20$^{\text{th}}$. We have added some key dates below, including the start of the pandemic response, and the dates for the five rounds of income support payment: R$600,00 (US$106,07) or R$ 1.200,00 (US$212,14) to informal workers and mothers in single income families, and additional rounds of payments of R$300,00 (US$ 53,04).

Figure 4 displays the electricity consumption indicator relative to the baseline for the four zones of the National Integrated System (SIN). While the general trend is similar across the four zones, peaks and troughs occur at different times, representing different local conditions. For example, Figure 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.

Electricity Consumption and Economic Activity

In this section we report the comparison of our indicator of electricity consumption, aggregated from an hourly basis to both monthly and quarterly basis, with widely used indicators that are only available with a temporal lag of 1.5 to 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* (which means we used data from years 2004 onwards). The comparisons are depicted in Figure 5 and 6 below.

Figure 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 the quarter level) and the GDP is 0.77 and 0.70, respectively.

The comparison in Figure 6 provides very strong support for the use of our electricity consumption indicator, especially during the initial response to the GFC and the pandemic. The monthly series

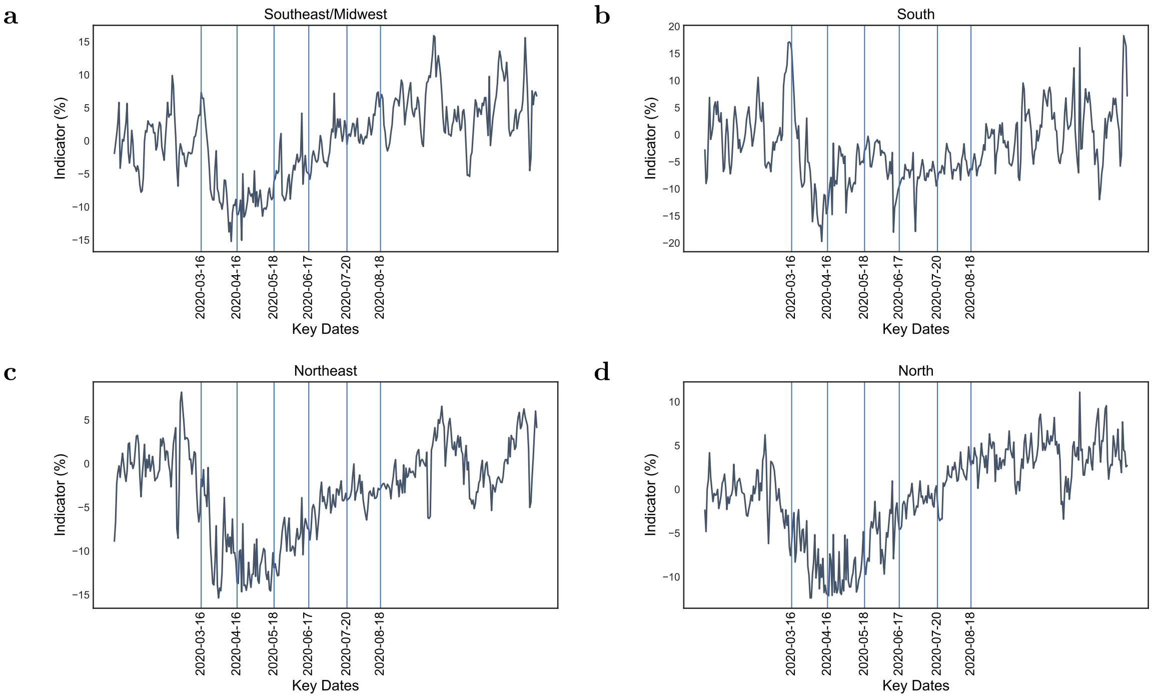

Figure 4: **Variation of Normalized Energy Consumption Indicator for SIN Zones (%).**

exhibits a correlation of 0.81 and 0.94 with the IBC-br for a period of 6 months from the beginning of each of crises, respectively, whereas the correlation for the entire period is 0.69. The correlation between the entire series with the monthly GDP is 0.71, whereas the correlation for the Southeast Zone (representing over 50% of total consumption) series with the IBC-br and the monthly GDP are both 0.62. The correlation is considerably stronger the shorter the period of comparison. For example, the correlation between the two indicators is equal to 0.98 from February 2020 to May 2020, and this correlation becomes 0.98, 0.96, 0.93, 0.93 and 0.90, as we expand the period by one month from June to October. The comparison of the monthly indicators also highlights the need for more timely indicators to assist policy makers in calibrating their response to a systemic crisis. According to our electricity consumption indicator, the recovery of economic activity started at least a month before being picked up by the IBC-br for both crises.

The Heterogenous Impact of COVID-19 on the economy

While our electricity consumption indicator captures variation in the short run aggregated 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, aggregated electricity consumption confounds increases in household consumption with decreases in commercial and industrial consumption arising from lockdowns and quarantines.

This section provides two different estimates of the short run impact of different crises across distinct sectors of the economy by constructing appropriately designed electricity consumption esti-

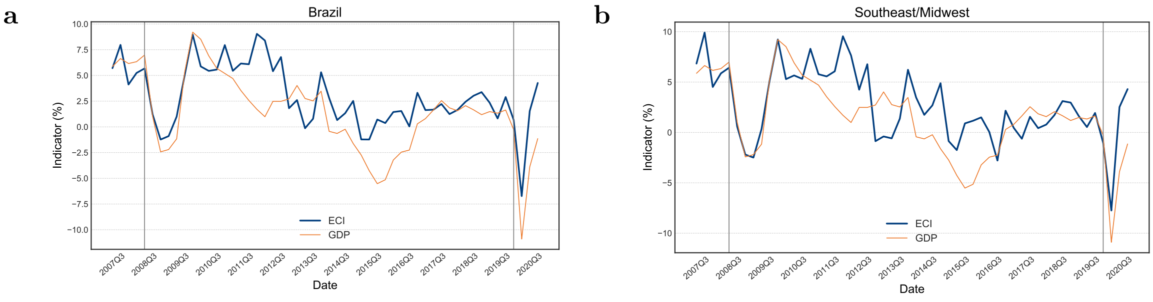

Figure 5: **Electricity consumption indicator (ECI) and quarterly economic activity.**

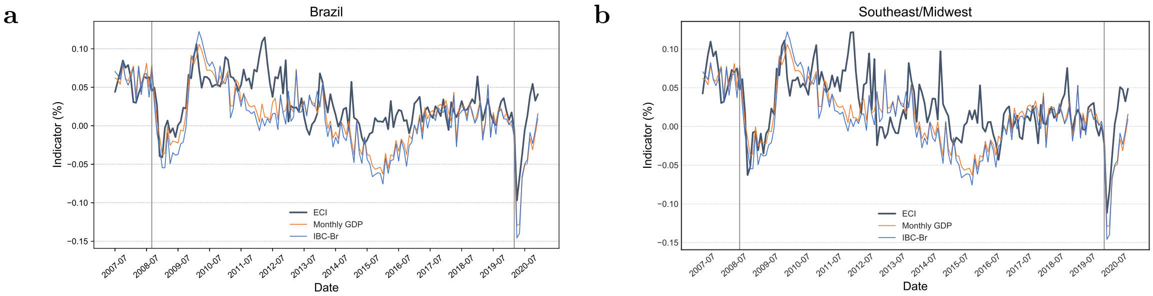

Figure 6: **Electricity consumption indicator (ECI) and monthly economic activity.**

mators. First, we use monthly electricity consumption data from the Energy Research Agency (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 to track 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.

Figure 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 both for the 2008 and 2020 crises. This conclusion is supported by the behaviour 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 next 2 years. The commercial monthly electricity consumption indicator only shows a strong pattern of downturn and recovery for the COVID-19 pandemic, illustrating how the current crisis is different from previous crises. The COVID-19 pandemic is best thought of as having a similar effect of a natural disaster, with disruptions in supply leading to drops in income, which then feeds into reduced aggregated demand. The lockdowns have clearly had a disproportional impact on commercial activities, such as retail and services. The global financial crisis (and recessions more broadly), in contrast, is associated with a reduction in aggregated demand. As expected, the residential sector shows a sharp increase in electricity consumption during the pandemic, reflecting the effect of working from home and lockdowns.

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. This data

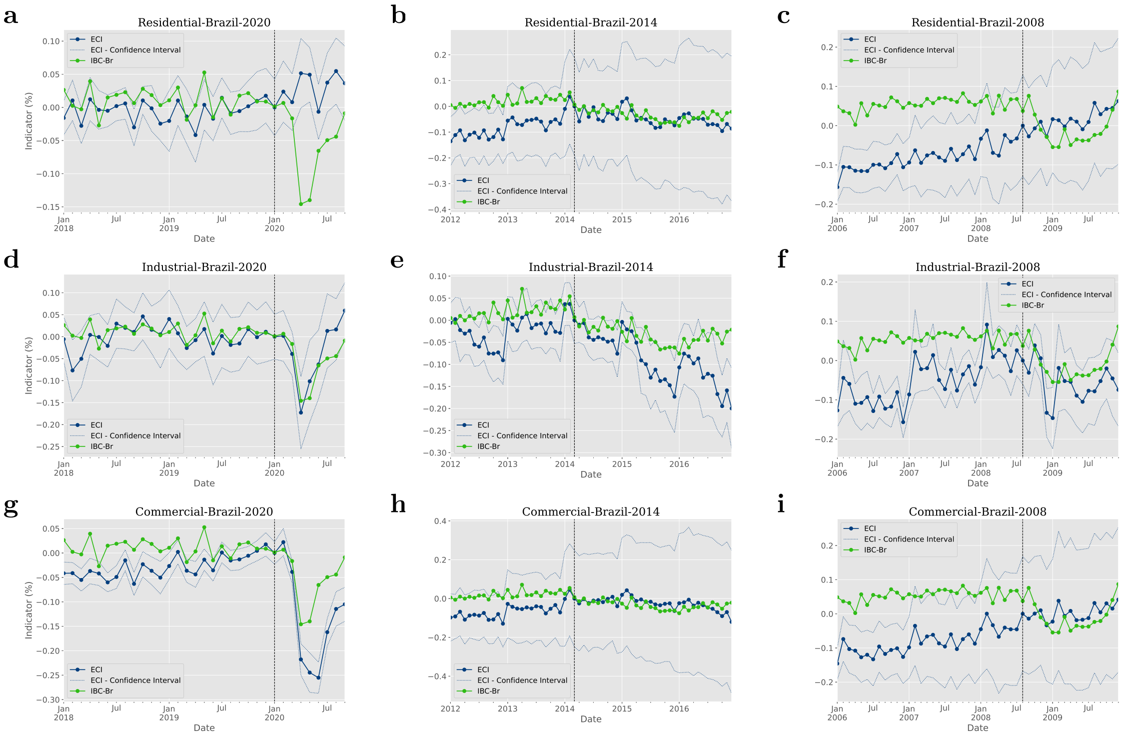

Figure 7: **Sector Analysis in Recessions – Electricity Consumption Indicator (ECI) for Residential, Industrial and Commercial.**

further breaks down consumption into activity types. We have constructed three indicators covering regulated, contestable industrial, and contestable commercial consumers, respectively. Regulated consumers are comprised of residential, rural, public lighting, commercial, and industrial consumers (among others). Households represent around 45% of regulated consumption. Commercial consumers make up around 20% of the regulated consumption, which accounts for around 70% of the total consumption of the sector across 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, manufacturing, and metallurgy industries, organic and inorganic material processing, and textile and vehicle manufacturing. The sample from the CCEE is different from the EPE, with Contestable Commercial consumers including retail and wholesale, but excluding services, and disaggregated data for contestable service consumers. However, in order to align the comparison with the monthly one, we built a commercial electricity consumption indicator aggregating both sectors. Figure 8 depicts our three indicators, represented as a 7-day moving average, capturing the percentage change compared to the pre-COVID-19 consumption. It shows a sharp decline in the commercial electricity consumption indicator, twice the reduction in the consumption by regulated and contestable industrial consumers.

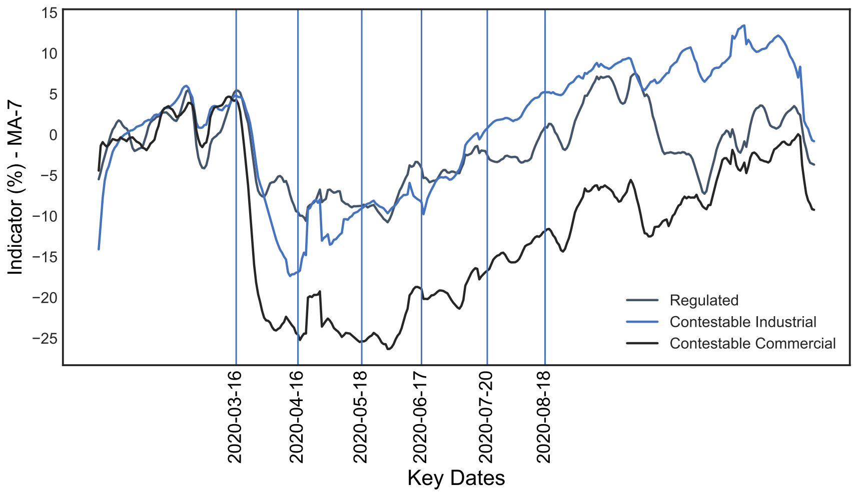

Figure 8: **Electricity consumption indicator for regulated and contestable consumers (%).**

Discussion

We have carefully constructed a electricity consumption indicator for short-run economic activity based on hourly electricity consumption data to allow us to measure the impact of COVID-19 and of the 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 that is at least a month old.

In constructing the indicator, we had to consider what would have been the electricity consumption in the absence of COVID-19. We do this by considering variables that explain the variation between consumption at each day during the pandemic with consumption on the same day over the previous three years. These variables include temperature, humidity, and workdays versus weekends and holidays.

We use our indicator to track the impact of lockdowns and of the various income support measures introduced by the Brazilian Federal government. In addition, using the hourly consumption data, we compare the behaviour of our electricity consumption indicator with that of standard indicators, available with 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 last of these crisis has no well-defined starting date. Our results suggest very different behaviours across the different crises. It clearly shows that the COVID-19 pandemic is best thought of as having a similar effect of a natural disaster, with disruptions in supply leading to drops in income, which then feeds into reduced aggregated demand. The global financial crisis (and recessions more broadly), in contrast, is associated with a reduction in aggregated demand.

The key implication from this research is that a well-constructed electricity consumption indicator can provide useful real-time insights on 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 like Brazil with a large informal sector.

Methods

Data

Hourly electricity aggregated consumption data are collected for the four zones (Southeast/Midwest; South, Northeast, North) of SIN from January 1st, 2017 to December 31st, 2020. The consumption data represents system load, defined as the amount of energy withdrawn from the grid in addition to technical losses. This data does not account for load from isolated systems and the self-consumption from consumers who have distributed generation systems (behind the meter consumption). Isolated systems, mainly located in the north of the country, represent less than 1% of total demand. While 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. This data is available with a lag of two to five days from the system operator (ONS).

Monthly electricity consumption data, disaggregated by sector, are collected from the Energy Research Agency (EPE) from 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 does not account for losses (neither technical nor non-technical) and are available with a lag of around three months. There was a data issue for the small state of Piaui (representing 0.7% of the national consumption) in December 2018, where commercial consumption as reported in the EPE dataset (39,968 MWh) is almost 40% lower than that of the previous month. The data is clearly incorrect as consumption only within the regulated environment, as reported by the regulator (ANEEL, the Brazilian Electricity Regulatory Agency), is equal to 60.163 MWh. To correct the error, we replaced the EPE data entry for December 2018 for the state of Piaui with the sum of the consumption within the regulatory environment, and the consumption from the contestable consumers (2.810 MWh) as reported by the CCEE dataset.

Hourly consumption data by type of consumer (contestable and captive) are collected from the market operator (CCEE) from January 2019 to December 2020. The data is available with a lag of around three months. The data on contestable consumers are available at firm level and the date of migration from a captive consumer who does not have a choice of electricity supplier (ACR) to a contestable consumer who can purchase electricity within the competitive contracting environment (ACL).

Hourly heat index binds were built for each state in the four zones. There are four bins: 0-25°C, 25-30°C,30-40°C, and over 40°C. The heat index was built using the methodology developed by Rothfusz (1990) [17] and with data on temperature and humidity scraped from Wunderground. We selected one weather station from each state, located at the state's capital (airport data when available), and for which historically hourly data was available. As there were no available stations for the two less populated states of Tocantins and Rio Grande do Norte, we used data from neighboring weather states and use the mean to replace it: Paraiba, Piaui, Pernambuco and Ceara to replace Rio Grande do Norte and Goias, Distrito Federal and Mato Grosso to replace Tocantins. When data for an entire day was missing, we used data from weather stations in neighboring states and took the average. When there were gaps in the hourly data, we interpolated the data from the adjacent hours.

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

Empirical Strategies

In a first step, we estimate a reliable indicator of electricity consumption by considering factors that can explain the majority of variability in consumption. We adapt the approach in Cicala (2020) [9] and estimate the following regression for each of the four zones of the SIN and for each hour t of the day:

$$\log C_{it} = \delta_{id,2020} + \Pi_i + X_i + Y_i + Holidays_i + StateHI_{it} + u_{it} \tag{1}$$

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 described previously. We have also included a set of dummies ($Holidays_i$) capturing the official national holidays (differentiating its impact weather it is on a weekday, a Sunday or a Saturday), intra-holidays (IH) (i.e., Mondays or Fridays when the holiday falls on, respectively, Tuesdays or Thursdays), and long weekends (WLW). The holidays dummies also include a separate dummy for Carnival (we also control for the week before and the week after), and dummies capturing the holidays in the state of São Paulo for the Southeast/Midwest zone. The error components are given by u_{it}, which were clustered at the month level, given they may be serially correlated. A potential cause of autocorrelation could be measurement errors attributed to the reason that the temperature of the capital cities of each state may not be perfectly representative for all cities in each 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 employ a rolling window of analysis and estimate the daily mean $\delta_{id,2020}$, for each day d by pooling data from 2017 to 2020, making the daily fixed effects an interaction between 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 three years controlling for week of the year, day of the week, 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.

The second step 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 The Brazilian Institute of Geography and Statistics – IBGE) and the Central Bank monthly indicator IBC-br. As with our hourly indicator, we employ equation 1 and a rolling window analysis to estimate indicators from July 2007 to December 2020 by pooling data for years *y-3* (which means we used data from years 2004 onwards). 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.

To further test the usefulness of our electricity consumption indicator to predict economic activity in the short run, we extend the analysis to consider different sectors of the economy. Using monthly data from the EPE, we estimate the following regression:

$$\log C_{it} = \delta_{t,y} + \phi_t + W_{it} + \rho_i + \tau_{it} + StateHI_{it} + u_{it} \tag{2}$$

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

We normalise $\delta_{t,y}$ by the period immediately before each of the three different 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 at period t in state i, and τ_{it} is a time trend for states with non-stationary 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, 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 the standard error u_{it} at the state level.

We conducted a further disaggregated analysis of hourly data available from the market operator (CCEE). The data contains 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 excluded data from contestable consumers absent in the sample in January 2019. This prevents overestimating the increase in consumption in the contestable consumers contracting environment due to migration from the regulated to the free contracting environment during sample period.

We construct electricity consumption indicators for regulated consumers, contestable industrial and commercial consumers. We also built an indicator aggregating the industrial, commercial, and service contestable consumers (denominated the ACL indicator). We estimate the following equation length:

$$\log C_{it} = \delta_{id,2020} + \Pi_i + X_i + Holidays_i + StateHI_{it} + u_{it} \tag{3}$$

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. The dummies for week of the year are not used for this specification due to the shorter time period for the analysis. The set of holidays dummies $Holidays_i$ is the same used in equation 1 except we do not include a dummy for Carnival and the control for the week before and the week after again due to the shorter time period for used for the analysis given data availability. The error component is given by u_{it}.

Data availability

All data used are available from publicly available sources. Zonal hourly electricity consumption data are obtained from the National System Operator at `http://www.ons.org.br/paginas/resultados-da-operacao/historico-da-operacao`. Monthly electricity consumption data for each state are collected from the Energy Research Agency (EPE) at `https://www.epe.gov.br/pt/publicacoes-dados-abertos/publicacoes/consumo-de-energia-eletrica`. Hourly and daily consumption data by type of consumer are available from the market operator (CCEE) at `http://ccee.org.br/`. The temperature and humidity data from Weather Underground are available at `https://www.wunderground.com/`.

Code availability

Data and models run in Python 3.9. The figures are produced in Python 3.9 and Microsoft Excel for Microsoft 365 MSO. The custom code is available from the authors.

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Author contributions

F.M., V.F., F.J. and P.M. designed the analysis methods, performed the analyses and wrote and revised the paper. P.M. processed the data. All authors conceived the paper, designed the research, offered revision suggestions and contributed to the interpretation of the findings.

Competing Interests

The authors declare no competing interests.