COVID-19 Crisis Monitor: Assessing the Effectiveness of Exit Strategies in the State of São Paulo, Brazil

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WORKING PAPER SERIES Nº 2022-10

DEPARTMENT OF ECONOMICS, FEA-USP
WORKING PAPER Nº 2022-10

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Abstract:

As COVID-19-related health indicators improve after restrictive measures were set in place in different parts of the world, governments are expected to provide guidance on how to ease interventions while minimizing the risk of resurgent outbreaks. Whereas epidemiologists track the progress of the disease using daily indicators to better understand the pandemic, economic activity indicators are usually available at a lower frequency, and with considerable time lags. We propose and implement a timely trade-based regional economic activity indicator (EAI) that uses high-frequency traffic data to monitor daily sectoral economic activity in different sectors for the Brazilian State of São Paulo, a highly impacted region, overcoming the challenge of real-time assessment of the economy amid the COVID-19 outbreak. We then use this novel set of information combined with hospitalization rates to provide a first assessment of the São Paulo Plan, the COVID-19 exit strategy designed to gradually lifting interventions introduced to control the outbreak in the State. Available data show that, in its first 60 days, the phased strategy pursued in São Paulo has been effective in gradually reactivating economic activity while maintaining the adequate responsiveness of the healthcare system.

Keywords: COVID-19; Economic Impacts; Input-Output Analysis

JEL Codes: C55; C67; R11; R40

NEREUS

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TD Nereus 06-2020
São Paulo
2020

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Abstract. As COVID-19-related health indicators improve after restrictive measures were set in place in different parts of the world, governments are expected to provide guidance on how to ease interventions while minimizing the risk of resurgent outbreaks. Whereas epidemiologists track the progress of the disease using daily indicators to better understand the pandemic, economic activity indicators are usually available at a lower frequency, and with considerable time lags. We propose and implement a timely trade-based regional economic activity indicator (EAI) that uses high-frequency traffic data to monitor daily sectoral economic activity in different sectors for the Brazilian State of São Paulo, a highly impacted region, overcoming the challenge of real-time assessment of the economy amid the COVID-19 outbreak. We then use this novel set of information combined with hospitalization rates to provide a first assessment of the São Paulo Plan, the COVID-19 exit strategy designed to gradually lifting interventions introduced to control the outbreak in the State. Available data show that, in its first 60 days, the phased strategy pursued in São Paulo has been effective in gradually reactivating economic activity while maintaining the adequate responsiveness of the healthcare system.

1. Introduction

The COVID-19 pandemic has brought unforeseen and unpredictable effects in terms of both health and economics. With unprecedented research efforts that generated several articles tackling clinical presentation, preventive and treatment measures, and possible correlated and permanent effects of the disease, as well as various other articles exploring its economic effects (from micro to macroeconomic elements), researchers worldwide seek to contribute with actionable insight to tackle the challenges presented by the pandemic.

The State of São Paulo, a highly impacted, densely populated area that represents the economic core of Brazil, sought to follow in the footsteps of Asian, European and other countries in the use of evidence to design policy intervention (OECD, 2020; European Commission, 2020; World Health Organization, 2020; Oxford Martin School – Global Health Platform, 2020; Haddad and Bugarin, 2020). To better understand the evolution of the disease and its territorial economic impacts due to social distancing measures, the State government established a set of parameters to manage the crisis. This endeavour was tackled alongside a network of researchers and qualified public sector personnel, and ultimately led to the institutionalization of two consulting bodies – one composed of health professionals (Contingency Centre) and another of economists (Economic Council) – to advise on necessary policy to mitigate the sanitary and economic effects of the disease.

Once the data and indicators used to monitor the disease were defined and officially announced, a new challenge arouse: guaranteeing effective monitoring of economic indicators. The central argument is the need to pave the way for a clear cost-benefit analysis between more flexible economic operations and the spread of the disease. The effectiveness of sanitary safeguard measures is bounded by the economic stress on households due to reduced income as a side product of guaranteeing health service attendance. With the *São Paulo Plan*[1], economic activities started slowly taking up operations, after a period of closure and suspension. However, there may be an imminent threat of disease spread with an increase of economic activity.

This article presents an initial approach to further crisis monitoring strategies. A link between high-frequency transportation flows (cargo and passengers) and sanitary results, through economic indicators, may shed light on possible future disease outbreak and pave the way to a cost-benefit analysis. Section 2 lays out the mathematical model behind the empirical strategy for specifying and implementing a novel index of regional sectoral economic activity, and presents its results. The index combines input-output analysis and traffic data. As an example of potential applications of the proposed index, Section 3 then moves on to addressing the link between economic activity and the spread of COVID-19 in the context of the São Paulo Plan. The empirical results are presented highlighting the link between transportation flows within and between regions, economic activity disaggregated by tradable and non-tradable sectors, and the spread of the disease, providing the first systematic assessment of the Plan. The analysis reveals that the phased strategy pursued in São Paulo has been effective in reactivating economic activity while maintaining the adequate responsiveness of the healthcare system. Finally, we discuss the application of the results in guiding policy design, and possible implications for COVID-19 exit strategies pursued elsewhere.

2. Monitoring Regional Sectoral Economic Activity

There is a wide literature relating the demand for freight and passenger transport to economic activity (Boyce and Williams, 2015). A usual question in project appraisal is whether one can predict the evolution of domestic demand for freight [and passenger] transport to a reasonably high level of explanation with a few readily available variables (Bennathan et al., 1992). As transport is a derived demand, its level of activity in general relates to the levels of output in an economy. Therefore, one of the key elements in forecasting models of traffic demand is the information on economic trends. Studies often find a close link between GDP and traffic levels, which becomes more evident when the elements making up the GDP forecasts are identified (Cole, 2005; Ortúzar and Willumsen, 2011).

More recently, a related strand of research has benefitted from the availability of detailed traffic-flow data based on sensor readings to reverse the question and look at ways of using traffic intensity metrics[2] to construct coincident and leading indicators of regional economic activity (van Ruth, 2014; Hooijmaaijers, 2017; Nolan, 2019; Li et al., 2020). However, the use of weights based on traffic flows measured taking into account only direct links involving the study region neglects the intricate structure of interregional input-output flows that may potentially affect regional activity. Combining traffic intensity data in the whole network with measures of regional economic activity embedded in trade relations everywhere may enhance the accuracy of the indicator by accounting to the systemic nature of a region's output (Sonis et al., 1996).

There are alternatives to the use of high-frequency data on sensor readings to address this issue. The Transportation Services Index (TSI), for instance, created by the U.S. Department of Transportation (DOT), Bureau of Transportation Statistics (BTS), measures the monthly movement of freight and passengers, combining available data on freight traffic, as well as passenger travel (Lahiri et al., 2002). The monthly measurement of transportation services output at the national level has proved deemed important to follow business cycles in the USA (Lahiri and Yao, 2011). Nonetheless, its relative low frequency, time lag in its release, and aggregate geographical dimension impose limitations to its use as an indicator for timely monitoring of regional economic activity.

We add to this debate departing from a similar approach to van Ruth (2014), who has shown that it is possible to construct indicators of regional economic activity based on local traffic intensity data. In her monthly indicator of traffic intensity in the Eindhoven region, in the Netherlands, she was able to show convincingly the link between traffic intensity and economic activity at the regional level. However, the choice of the study region was based on its high specialization in manufacturing activities, justifying the procedure of computing daily averages over all sensors in the sample. Accordingly, such procedure defined for a wider range of areas presenting different degrees of economic specialization could lead to a less clear correlation.

Therefore, we propose a novel indicator of regional economic activity that tackles some of the aforementioned issues. A good index should be simple, policy relevant, reliable, and timely (National Research Council, 2002). We rely on close-to-real-time big data sources (i.e. radar sensors) together with structural economic statistics (i.e. input-output system), which represent useful economic concepts in order to create a set of indicators that allow early identification of large economic changes. In doing that, we provide insight into economic activity, at a level of timeliness and granularity not possible for official economic statistics, achieving the desirable goals pursued in modern economic activity monitoring projects (Nolan, 2019). We then show the usefulness of the proposed indicator for policy evaluation in the context of a regionally heterogeneous plan designed to mitigate the economic effects of the COVID-19 pandemic in São Paulo, Brazil.[3]

The purpose of this section is to show the general structure of the proposed index of regional economic activity that takes into account each region's insertion into an integrated multi-sectoral interregional system. We consider there are n domestic regions, r = 1, ..., n, and the rest of the world, *row*, which exhaust the space of the economy. Economic interactions take place inside and outside each region (intraregional, interregional and international trade). In our multi-sectoral economy, there are j sectors, s = 1, ..., j, provided by $n+1$ different sources.

We then assume we can measure, for each sector s in region r, the value added contents embedded in trade flows associated with each regional origin-destination pair, such that we can complete the information in Table 1.

Table 1. Regional Value Added in Trade Flows, by Sector

	Destination					
Origin	R$_1$	R$_2$	…	R$_{n-1}$	R$_n$	ROW
R$_1$	$va_{1,1}^{r,s}$	$va_{1,2}^{r,s}$	…	$va_{1,n-1}^{r,s}$	$va_{1,n}^{r,s}$	$va_{1,row}^{r,s}$
R$_2$	$va_{2,1}^{r,s}$	$va_{2,2}^{r,s}$	…	$va_{2,n-1}^{r,s}$	$va_{2,n}^{r,s}$	$va_{2,row}^{r,s}$
⋮	⋮	⋮		⋮	⋮	⋮
R$_{n-1}$	$va_{n-1,1}^{r,s}$	$va_{n-1,2}^{r,s}$	…	$va_{n-1,n-1}^{r,s}$	$va_{n-1,n}^{r,s}$	$va_{n-1,row}^{r,s}$
R$_n$	$va_{n,1}^{r,s}$	$va_{n,2}^{r,s}$	…	$va_{n,n-1}^{r,s}$	$va_{n,n}^{r,s}$	$va_{n,row}^{r,s}$
ROW	$va_{row,1}^{r,s}$	$va_{row,2}^{r,s}$	…	$va_{row,n-1}^{r,s}$	$va_{n,n}^{r,s}$	$va_{row,row}^{r,s}$

According to Table 1, a region's sectoral output is potentially associated with transactions involving economic agents located not only in the region, but also elsewhere. Define the sets of origins, *O*, and destinations, *D*, both comprising all domestic regions, *r*, add the rest of the world, *row*. Thus, we can compute total value added of sector *s* in region *r*, va^{rs}, as:

$$va^{rs} = \sum_{o \in O, d \in D} va_{o,d}^{r,s} \tag{1}$$

We also calculate region's *r* total value added, va^{r}, as:

$$va^{r} = \sum_{s} va^{rs} \tag{2}$$

In order to monitor sectoral regional economic activity, we would need to follow va^{rs} over time. This information, when available, is usually published with a delay and at a low frequency (annual). To circumvent such informational constraint, we could track changes in trade flows for each regional origin-destination pair, and combine them with the information in Table 1 to calculate a trade-weighted index of regional economic activity.

Thus, if we can observe, in each period *t*, changes in values of flows from each origin *o*, to each destination *d*, $\Delta F_{t,o,d}$, a regional index of economic activity could be calculated as

$$EAI_t^{r,s} = \sum_{o \in O, d \in D} w_{o,d}^{r,s} \, \Delta F_{t,o,d} \tag{3}$$

where $EAI_t^{r,s}$ is the economic activity index for sector *s*, in region *r*, in time *t*, and the weights $w_{o,d}^{r,s}$ are calculated as

$$w_{o,d}^{r,s} = \frac{va_{o,d}^{r,s}}{\sum_{o \in O, d \in D} va_{o,d}^{r,s}} \tag{4}$$

such that

$$\sum_{o \in O, d \in D} w_{o,d}^{r,s} = 1 \tag{5}$$

The implementation of the index depends on two pieces of information: first, we need to define an empirical strategy to estimate values in Table 1, so that we can define the weights, $w_{o,d}^{r,s}$; second, we have to collect timely information to estimate $\Delta F_{t,o,d}$. In what follows, we describe our approach to this problem.

2.1. Measurement of Domestic Value Added in Trade Flows[4]

This sub-section reports on the results of an application with an interregional input-output matrix for Brazil, which allows calculating the total value-added that is embodied in specific trade flows. This set of information generates estimates for Table 1. Thus, the concept of embedded value-added in this paper is defined within the input-output framework, which determines the value added content via coefficients of sectoral value-added per monetary unit of a given sector. The input-output system was developed as part of a technical cooperation initiative involving researchers from the Regional and Urban Economics Lab at the University of São Paulo (NEREUS), the Institute of Economic Research Foundation (FIPE), and the State of São Paulo Secretariat of Economic Development (FIPE-NEREUS, 2020). A fully specified interregional input-output database was estimated for 2015, considering 67 sectors in 17 regions (Regional Health Departments) in the State of São Paulo, and a residual endogenous domestic region, the rest of Brazil. Using this database together with information on regional value added by sectors, we develop the weights for our trade-based index of regional economic activity. We estimate, for each flow originated in one of the Brazilian regions, measures of value added in trade that are further used to calculate our index. The parsimonious approach proposed in Los et al. (2016), based on "hypothetical extraction", serves as the methodological anchor.

The input-output model can be expressed by

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \tag{6}$$

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{L}\mathbf{f} \tag{7}$$

where $\mathbf{x}$ and $\mathbf{f}$ are the vectors of gross output and final demand; $\mathbf{A}$ is a matrix with the input coefficients (a_{ij}); $\mathbf{I}$ is the identity matrix; and $\mathbf{L}$ is the Leontief inverse.

Considering a national interregional input-output model with *n* different regions and the ROW as a column vector in the final demand, (6) and (7) can be represented as[5]

$$\begin{bmatrix} \mathbf{x}^1 \\ \vdots \\ \mathbf{x}^n \end{bmatrix} = \begin{bmatrix} \mathbf{A}^{11} & \cdots & \mathbf{A}^{1n} \\ \vdots & \ddots & \vdots \\ \mathbf{A}^{n1} & \cdots & \mathbf{A}^{nn} \end{bmatrix} \begin{bmatrix} \mathbf{x}^1 \\ \vdots \\ \mathbf{x}^n \end{bmatrix} + \begin{bmatrix} \mathbf{f}^{11} & \cdots & \mathbf{f}^{1n} & \mathbf{f}^{1row} \\ \vdots & \ddots & \vdots & \vdots \\ \mathbf{f}^{n1} & \cdots & \mathbf{f}^{nn} & \mathbf{f}^{nrow} \end{bmatrix} \mathbf{i} \tag{8}$$

$$\begin{bmatrix}\mathbf{x}^1\\ \vdots\\ \mathbf{x}^{\mathrm{n}}\end{bmatrix}=\left\{\begin{bmatrix}\mathbf{I} & \cdots & \mathbf{0}\\ \vdots & \ddots & \vdots\\ \mathbf{0} & \cdots & \mathbf{I}\end{bmatrix}-\begin{bmatrix}\mathbf{A}^{11} & \cdots & \mathbf{A}^{1\mathrm{n}}\\ \vdots & \ddots & \vdots\\ \mathbf{A}^{\mathrm{n}1} & \cdots & \mathbf{A}^{\mathrm{nn}}\end{bmatrix}\right\}^{-1}\begin{bmatrix}\mathbf{f}^{11} & \cdots & \mathbf{f}^{1\mathrm{n}} & \mathbf{f}^{\mathbf{1row}}\\ \vdots & \ddots & \vdots & \vdots\\ \mathbf{f}^{\mathrm{n}1} & \cdots & \mathbf{f}^{\mathrm{nn}} & \mathbf{f}^{\mathbf{nrow}}\end{bmatrix}\mathbf{i}$$
$$=\begin{bmatrix}\mathbf{L}^{11} & \cdots & \mathbf{L}^{1\mathrm{n}}\\ \vdots & \ddots & \vdots\\ \mathbf{L}^{\mathrm{n}1} & \cdots & \mathbf{L}^{\mathrm{nn}}\end{bmatrix}\begin{bmatrix}\mathbf{f}^{11} & \cdots & \mathbf{f}^{1\mathrm{n}} & \mathbf{f}^{\mathbf{1row}}\\ \vdots & \ddots & \vdots & \vdots\\ \mathbf{f}^{\mathrm{n}1} & \cdots & \mathbf{f}^{\mathrm{nn}} & \mathbf{f}^{\mathbf{nrow}}\end{bmatrix}\mathbf{i} \tag{9}$$

where $\mathbf{i}$ is a column vector with all elements equal unity which sums all elements in each of the *n*+1 rows of the matrix $\mathbf{f}$.

Following Los et al. (2016), the value added in region *r* (va^r) can be expressed as

$$va^1 = \mathbf{v}_1(\mathbf{I}-\mathbf{A})^{-\mathbf{1}}\mathbf{fi} \tag{10}$$

where $\mathbf{v}_1$ is a row vector with ratios of value added to gross output in the *j* sectors in region *n* as elements ($\tilde{\mathbf{v}}_1$) and zeros elsewhere ($\mathbf{v}_1 = [\tilde{\mathbf{v}}_1 \quad \mathbf{0}]$); and $\mathbf{i}$ is a column vector which all elements are unity.

In order to attribute the amount of domestic value added in sales from region *1* to domestic region *n*, as proposed by Los et al. (2016), we consider a hypothetical world where region *1* does not sell anything to region *n*. In this case, the new value added or hypothetical value added can be represented by

$$va^*_{1,n} = \mathbf{v}_1(\mathbf{I}-\mathbf{A}^*_{1,n})^{-\mathbf{1}}\mathbf{f}^*_{1,n}\mathbf{i} \tag{11}$$

where $\mathbf{A}^*_{1,n}$ and $\mathbf{f}^*_{1,n}$ are the hypothetical matrix of input coefficients and final demand, respectively, expressed as

$$\mathbf{A}^*_{r,t} = \begin{bmatrix}\mathbf{A}^{11} & \cdots & \mathbf{0}\\ \vdots & \ddots & \vdots\\ \mathbf{A}^{\mathrm{n}1} & \cdots & \mathbf{A}^{\mathrm{nn}}\end{bmatrix} \tag{12}$$

$$\mathbf{f}^*_{1,n} = \begin{bmatrix}\mathbf{f}^{11} & \cdots & \mathbf{0} & \mathbf{f}^{\mathbf{1row}}\\ \vdots & \ddots & \vdots & \vdots\\ \mathbf{f}^{\mathrm{n}1} & \cdots & \mathbf{f}^{\mathrm{nn}} & \mathbf{f}^{\mathbf{nrow}}\end{bmatrix} \tag{13}$$

In addition, in order to attribute the amount of domestic value added in exports from region 1 to the *row*, we consider a hypothetical world where region 1 does not export to the *row*. In this case, the hypothetical value added can be represented as

$$va_{1,row}^{*} = \mathbf{v}_1(\mathbf{I} - \mathbf{A})^{-\mathbf{1}}\mathbf{f}_{1,row}^{*}\mathbf{i} \tag{14}$$

where $\mathbf{A}$ is the original matrix with the input coefficients as in (10); and $\mathbf{f}_{1,row}^{*}$ is the hypothetical matrix of final demand, expressed as

$$\mathbf{f}_{1,row}^{*} = \begin{bmatrix} \mathbf{f}^{11} & \cdots & \mathbf{f}^{1n} & \mathbf{0} \\ \vdots & \ddots & \vdots & \vdots \\ \mathbf{f}^{n1} & \cdots & \mathbf{f}^{nn} & \mathbf{f}^{\mathbf{nrow}} \end{bmatrix} \tag{15}$$

From (10) and (11), we can define the regional value added (across all sectors)[6] in sales from region 1 to region *n* as follows:

$$va_{1,n}^{1,\bullet} = va^{1} - va_{1,n}^{*} \tag{16}$$

and, from (10) and (14), we can define regional value added (across all sectors) from region 1 to the ROW as

$$va_{1,row}^{1,\bullet} = va^{1} - va_{1,row}^{*} \tag{17}$$

Similarly, we can attribute the amount of regional value added in transactions from region 1 to all regions (1, 2, …, *n*), and from each region to the *n*-regions (1, 2, …, *n*), including itself. We can also attribute the regional value added from each region to the ROW. In this sense, in an interregional system with *n* regions and the ROW exogenous, we can compute regional value added embedded in trade flows for the *n* domestic regions, as illustrated in Table 2.

Table 2. Domestic Value Added in Trade Flows in an Interregional System with Exogenous ROW, by Sector

Hypothetical no export	to					
From	R_1	R_2	…	R_{n-1}	R_n	ROW
R_1	$va_{1,1}^{r,s}$	$va_{1,2}^{r,s}$	…	$va_{1,n-1}^{r,s}$	$va_{1,n}^{r,s}$	$va_{1,row}^{r,s}$
R_2	$va_{2,1}^{r,s}$	$va_{2,2}^{r,s}$	…	$va_{2,n-1}^{r,s}$	$va_{2,n}^{r,s}$	$va_{2,row}^{r,s}$
⋮	⋮	⋮		⋮	⋮	⋮
R_{n-1}	$va_{n-1,1}^{r,s}$	$va_{n-1,2}^{r,s}$	…	$va_{n-1,n-1}^{r,s}$	$va_{n-1,n}^{r,s}$	$va_{n-1,row}^{r,s}$
R_n	$va_{n,1}^{r,s}$	$va_{n,2}^{r,s}$	…	$va_{n,n-1}^{r,s}$	$va_{n,n}^{r,s}$	$va_{n,row}^{r,s}$

2.2. Use of Traffic Intensity Indicators as a Measure of Change in Trade Volumes

In this sub-section, we describe how we calculate changes in traffic volumes during the pandemic using high-frequency traffic data from different sources in the state of São Paulo, including automated vehicle identification on toll stations and smart camera records. These datasets allow us to track specific vehicles and infer their origin and destination in each trip that they make. We then aggregate these trips in order to calculate total traffic flows of passenger and freight vehicles between all pairs of regions (Regional Health Departments) in each day of our analyses. The overall procedure consists of seven steps, which we detail next.

1. First, we extract data from automated vehicle identification from 341 toll stations located on intermunicipal highways in the state of São Paulo. In the year of 2018, 600 million registers were collected in these toll stations. Each register includes a vehicle identifier, a toll station identifier, and a timestamp. Therefore, we can identify, for each vehicle, the exact moment in time when they crossed each toll station and to calculate the trip duration between any two records. By connecting consecutive records from the same vehicle, we are able to define the trip route, considering four parameters to join the legs: time between toll passages, inversion direction angle, accumulated distance and rest time for truck drivers.

2. This dataset from toll stations is then combined with similar information from 4870 smart cameras that are located in urban areas of the state. These cameras recorded 3 billion vehicle registers during the year of 2018. By combining both datasets, we are able to expand the temporospatial coverage of our tracking and to be more precise about trip segments that were made within urban areas.

3. Based on the combined dataset of records from toll stations and smart cameras, we aggregate and anonymize the individual trips in order to guarantee the privacy of travellers. Next, a gravitational distribution model, considering the fleet of cars and trucks as an attraction factor per zone, is used to estimate origins and destinations of aggregated trips by day and by pair of origin and destination. Given the spatial coverage of tolls and smart cameras, we are able aggregate flows using 1,054 traffic zones in the state, which include one zone for each 645 municipalities, 24 frontier zones and 385 additional subdivisions to split larger cities and transportation hubs.

4. The origin and destination flows calculated in the previous step are then allocated to a highway simulation network and calibrated with expansion weights to match the average daily volume of vehicles from several other sources by the transport department of São Paulo.

5. The calibrated highway simulation network is a powerful tool to provide any transport engineering analysis, but it is static when considering the average flows of a year. Therefore, traffic variations from 451 monitoring stations (toll plazas, Service Level - LOS, fixed radar speed system) are used to update the highway simulation network and its matrices of passenger and freight vehicles.

6. The updated information is made available to decision makers through an online Business Intelligence Dashboard System. Among the information that can be extracted from these dashboards are the aggregated traffic flows by day and by pair of regions both by passenger and by freight vehicles. This level of aggregation is the same one used in our integrated framework of interregional trade flows as described in the previous section.

7. For tracking the traffic flow development during the pandemic, each dataset is updated within the monitoring system according to its technological limitations. For example, data from toll stations is updated every six hours, data from monitoring equipment of LOS was updated every three days.

2.3. Descriptive Results

Based on equation (3), the *EAI* was calculated for all dates from March 29 to August 1, 2020.[7] For each day, the index was also calculated for each of the 17 Regional Health Departments (DRS in Portuguese), and for two groupings of sectors (tradable and non-tradable)[8] and the State total. Changes in values of flows from each origin o, to each destination d, $\Delta F_{t,o,d}$, reflect rolling-seven-day averages to take into account weekly seasonality.

The choice of DRS to define the regional setting is particularly relevant for the COVID-19 crisis monitoring in the State of São Paulo. Each DRS is responsible, among other things, for investment planning, monitoring and advertising of health analyses and indicators, epidemiological and risk analysis, and control of the application of state and federal resources allocated to the health system. The use of a common regionalization also provides a cognitive alignment between health scientists and economists on the analysis of regional processes. Table 3 presents basic socioeconomic indicators for the 17 DRS in the state. It is noteworthy the relevance of the São Paulo Metropolitan Region, associated with DRS I, that hosts 47.4% of the state population, and is responsible for 53.8% of its GDP.

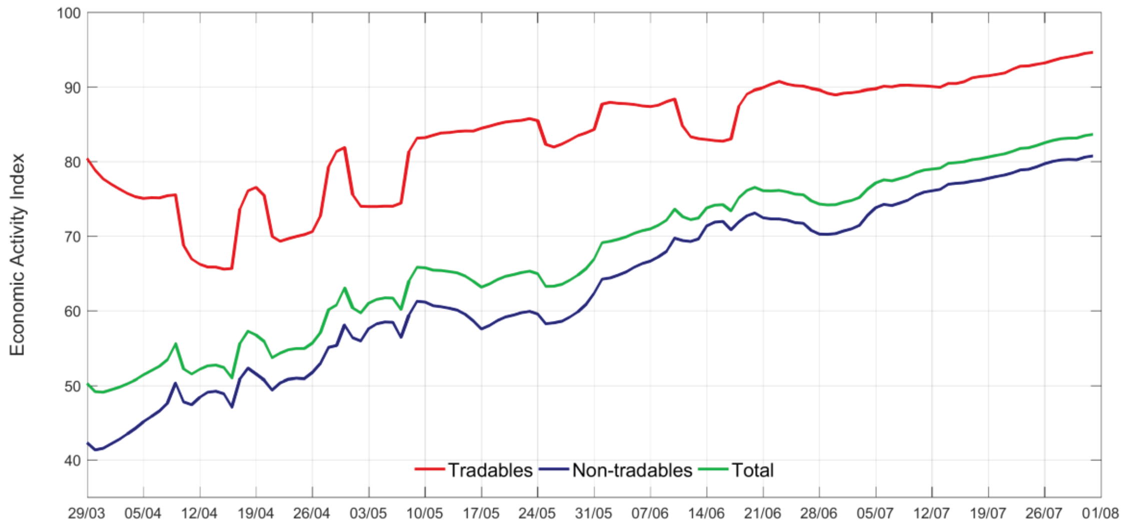
Table 3. Number of Municipalities, GDP, and Population: State of São Paulo, by DRS-region (2017)

Region	*Municipalities*	*GDP (Billion BRL)*	*Population (Million)*	*GDP Per Capita (1,000 BRL)*
DRS I - Grande São Paulo	39	1,140.6	21.4	53.3
DRS II - Araçatuba	40	23.3	0.8	29.9
DRS III - Araraquara	24	37.0	1.0	36.7
DRS IV - Baixada Santista	9	61.1	1.8	33.4
DRS V - Barretos	18	17.6	0.4	40.2
DRS VI - Bauru	68	56.1	1.8	31.7
DRS VII - Campinas	42	287.3	4.5	63.3
DRS VIII - Franca	22	22.6	0.7	32.0
DRS IX - Marília	62	34.0	1.1	29.9
DRS X - Piracicaba	26	68.4	1.6	44.0
DRS XI - Presidente Prudente	45	21.9	0.8	28.4
DRS XII - Registro	15	8.5	0.3	29.9
DRS XIII - Ribeirão Preto	26	60.1	1.5	40.5
DRS XIV - São João da Boa Vista	20	27.4	0.8	33.1
DRS XV - São José do Rio Preto	102	51.9	1.6	32.4
DRS XVI - Sorocaba	48	91.9	2.5	37.1
DRS XVII - Taubaté	39	110.3	2.5	44.2
State of São Paulo	645	2,119.9	45.1	47.0
% of Brazil	11.6	32.2	21.7	148.3

Source: Instituto Brasileiro de Geografia e Estatística (IBGE): "Produto Interno Bruto dos Municípios" - https://sidra.ibge.gov.br/tabela/5938, and "População residente estimada" - https://sidra.ibge.gov.br/tabela/6579.

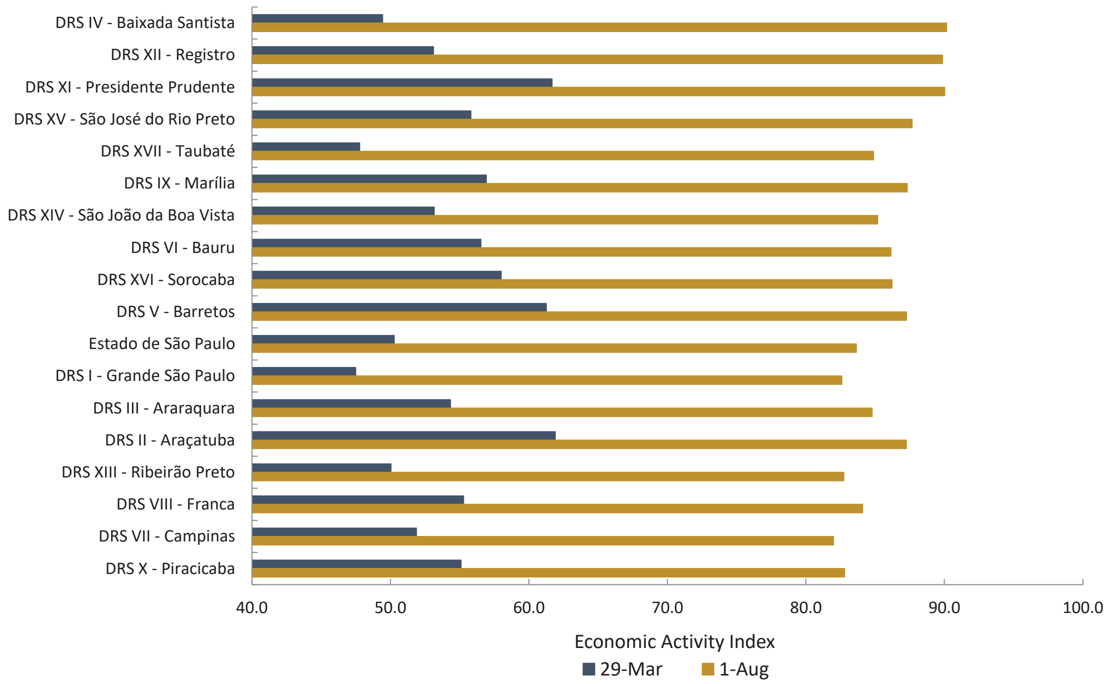
The average value for the total EAI was of 50.27% on March 29, indicating that on average, economic activity in São Paulo was 49.73 percentage points below the pre-crisis level.[9] At the end of the period (August 1), the State economy had already recovered 33.21 percentage points, presenting an EAI equal to 83.48%. Figure 1 plots the average EAI for the State by different sectors.[10] Economic activities faced different degrees of exposition to confinement measures after the initial shutting down of non-essential businesses in March. Non-tradable sectors (i.e. services) were the most affected, presenting an EAI equal to 42.33% (57.67 p.p. below the pre-crisis level) while tradable sectors seemed economically less vulnerable to the pandemic as the EAI reached 80.44% on March 29.

Figure 1. Economic Activity Index: State of São Paulo (March 29 - August 1, 2020)



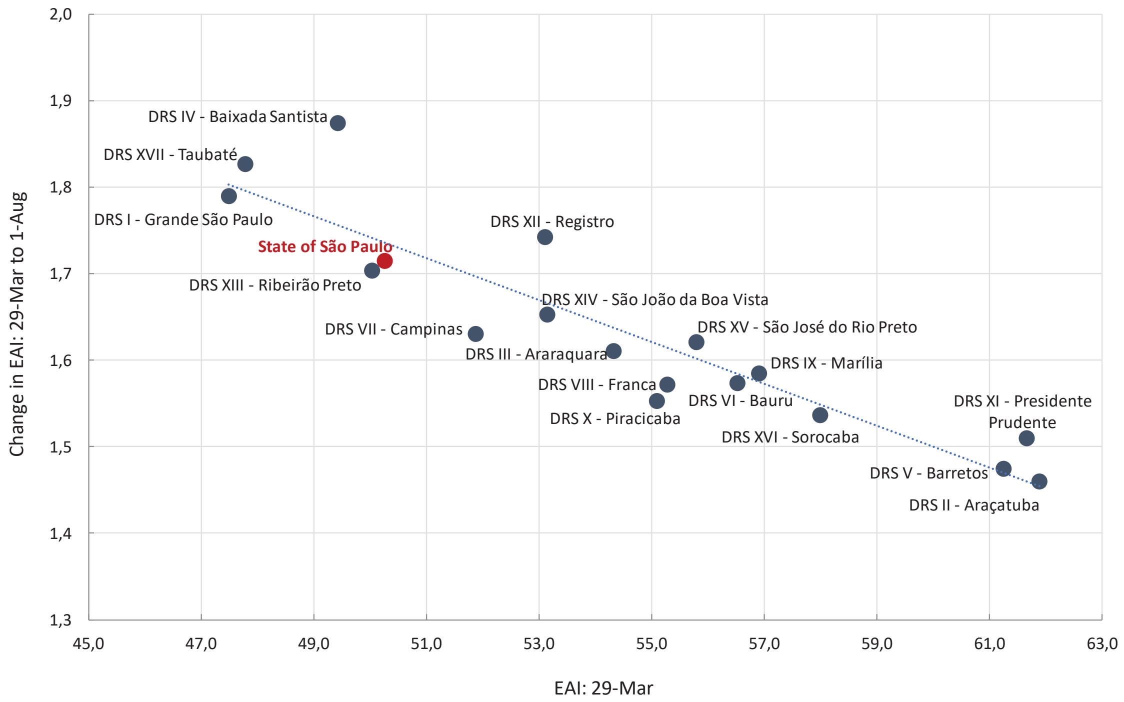
Not only sectors but also regions were affected in different ways, with the main urbanized areas facing stronger restrictions. Figure 2 shows the average EAI within each of the DRS, presenting different levels of economic vulnerability in the beginning of the pandemic. Initial economic losses were more heavily concentrated in the regions that most contribute to the state's GRP, which coincide with the most densely populated areas. As we will see in the next section, more densely populated regions are also the main vector for promoting contamination amid the initial outbreak of coronavirus in São Paulo. The recovery rate was neither homogenous across regions. In Figure 2, DRS are ranked from top to bottom according to the speed of recovery, measured as the ratio of change in the EAI in the period, and the initial distance from the pre-crisis level. Part of the difference is associated with the regionally differentiated flexibility measures contemplated in the São Paulo Plan, as we will make it clearer in the next section.

Figure 2. Economic Activity Index, by DRS (March 29 and August 1, 2020)



While the analysis of Figure 2 reveals different levels of regional resilience based on a conditional convergence framework, we can also look at the evolution of the EAI in each region comparing its initial level its growth rate in the period. Figure 3 presents an apparent process of absolute convergence in the regional EAI, i.e. regional economies that have been hardest hit by the COVID-19 pandemic outbreak are those that presented the fastest recovery.

Figure 3. Regional Convergence of the Economic Activity Index, by DRS (March 29 - August 1, 2020)



3. Economic Activity and the Spread of COVID-19

São Paulo is the state that has been hit the hardest in Brazil, with over 552,318 confirmed cases and 23,236 deaths through August 1, 2020 (Table 4).[11] On March 29, the state government issued an executive order closing all non-essential businesses in order to reduce the transmission of COVID-19. Sequentially, on May 29, a plan for gradually lifting restrictive measure on different economic sectors was crafted with representatives from the business community and public officials (health professionals, state-level secretaries and mayors). To ensure the reopening would proceed smoothly and safely, decisions were to be driven by public health data. The São Paulo Plan defined a set of key public health metrics[12], which would determine *if*, *when* and *where* it would be appropriate to proceed though reopening phases. Public health data trends indicating significant increases in viral transmission could even result in returning to prior phases or closing sectors of the economy. A dashboard monitored by the Contingency Centre allows permanent updates of public health indicators. Before and during reopening, these indicators must continue to show progress. As the regional economies reopen, the state administration provides guidance that each sector, industry and business must follow. Finally, the Plan also includes a testing and tracing strategy that took off only recently.

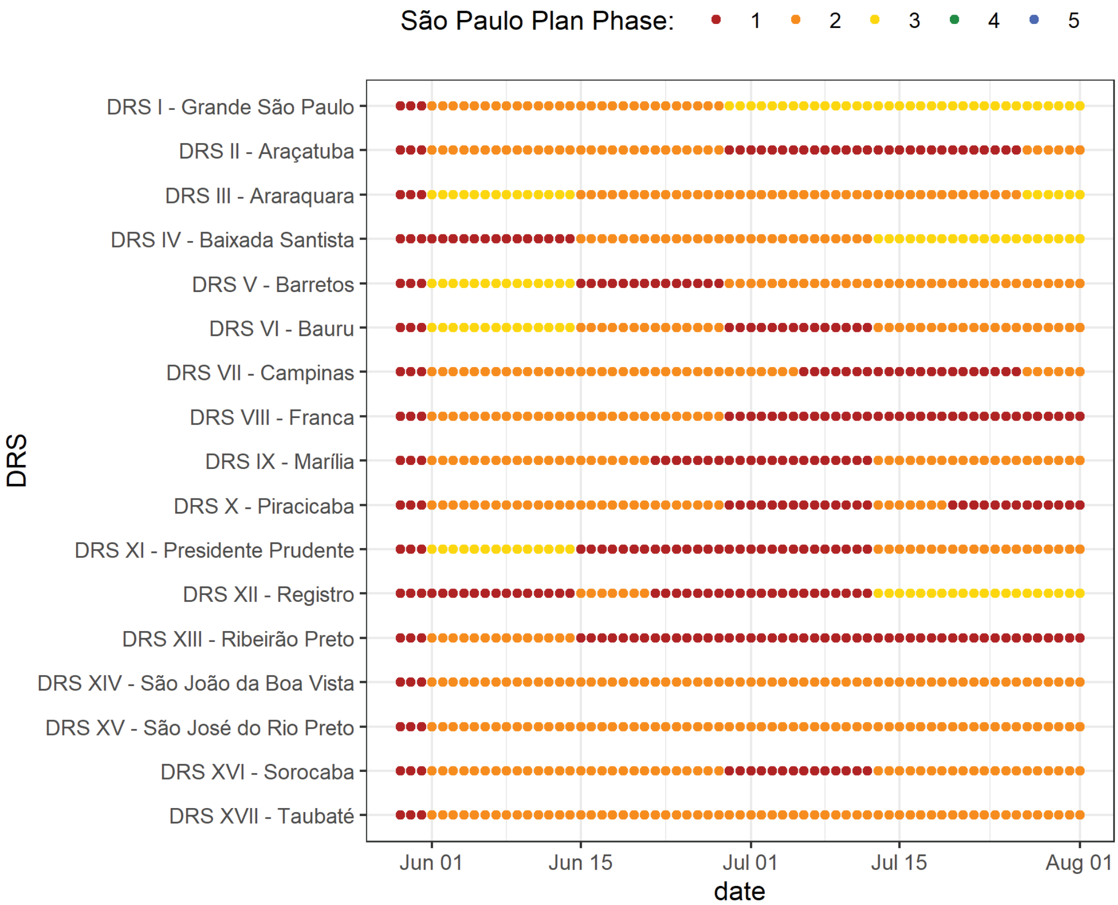
Table 4. Coronavirus Cases: State of São Paulo, by DRS (accumulated until August 1, 2020)

Region	*Confirmed cases*		*Deaths*	
	Value	*%*	*Value*	*%*
DRS I - Grande São Paulo	306,945	55.6	15,680	67.5
DRS II - Araçatuba	7,468	1.4	201	0.9
DRS III - Araraquara	5,904	1.1	97	0.4
DRS IV - Baixada Santista	36,420	6.6	1,376	5.9
DRS V - Barretos	4,311	0.8	140	0.6
DRS VI - Bauru	15,224	2.8	321	1.4
DRS VII - Campinas	54,204	9.8	1,884	8.1
DRS VIII - Franca	3,264	0.6	86	0.4
DRS IX - Marília	5,267	1.0	127	0.5
DRS X - Piracicaba	19,581	3.5	570	2.5
DRS XI - Presidente Prudente	4,186	0.8	133	0.6
DRS XII - Registro	3,496	0.6	72	0.3
DRS XIII - Ribeirão Preto	18,657	3.4	612	2.6
DRS XIV - São João da Boa Vista	5,266	1.0	143	0.6
DRS XV - São José do Rio Preto	22,923	4.2	615	2.6
DRS XVI - Sorocaba	21,660	3.9	644	2.8
DRS XVII - Taubaté	17,420	3.2	535	2.3
State of São Paulo	552,318	100.0	23,236	100.0
% of Brazil	20.4		24.8	

Source: "Boletins informativos e casos do coronavírus por município por dia". Available: https://brasil.io/dataset/covid19/caso_full/. Original source: State Health Departments

The São Paulo Plan divided the economic opening of each DRS according to a phase classification ranging from 1 (more restrictive) to 5 (less restrictive). Figure 4 shows the timeline of phase change in each DRS of the State. Initially, all DRS were classified on phase 1. On June 1st, the first phase changes were enacted, with 11 DRS being moved to phase 2 and 4 DRS to phase 3. Next, the phase of each DRS was changed up or down according to their health indicators. On August 1st, 3 DRS were classified on phase 1, 10 DRS on phase 2, and 4 DRS on phase 3.

Figure 4. Changes of Phases in Each DRS in the São Paulo Plan (May 29 - August 1, 2020)



Therefore, the daily monitoring of health indicators in each DRS is key for the sound implementation of the São Paulo Plan. However, the lack of timely, daily regional economic indicators precluded the broader monitoring of the Plan, as well as its proper evaluation. The use of the EAI provides a unique opportunity to close this gap. We can provide the first assessment of the Plan combining the analysis of traffic, economic, and health indicators.

3.1. Empirical Strategy

The objective of our empirical analyses is to provide an evaluation of the São Paulo Plan – in the first 2 months since its implementation – that considers both the effects of lifting interventions on the economic activity, and the possible impact of easing restrictions on the spread of COVID-19. Specifically, we want to answer whether the changes of phases from the São Paulo Plan affected the COVID-19 spread through an increase in the economic activity, measured by the proposed EAI.

To reach this goal, our empirical analysis will be separated into three steps:

1) Identify the effect of phase changes on the EAI.
2) Estimate the relationship between changes in the EAI and the spread of COVID-19 in the State.
3) Compute a counterfactual exercise comparing the EAI and COVID-19 spread that were observed in the period of our analysis against what would happen if all DRS remained with the most restrictive classification for the economic activity.

It is important to notice that the main challenge for estimating the effect of the São Paulo Plan on the epidemic is the endogeneity of variables. Changes in the phase classifications of DRS are not exogenous, instead, they are decided based on the evolution of the disease in each region and in the health capacity of regions to deal with it. Therefore, a simple estimation associating changes in classification and COVID-19 outcomes would likely lead to biased estimates of effects because regions with better health prospects are exactly the ones where economic restrictions are more likely to be removed. Given that, our empirical strategy tries to overcome this challenge by defining a structural path of causality. We first isolate the effect of phase changes on economic activity assuming that parallel trends hold for this relation. Next, we assume that there is no reverse causality between COVID-19 outcomes and the EAI of regions.

3.1.1. The effect of phase changes on the EAI

For the first question, that is, the effect of phase changes on the economic activity, we estimate a fixed effect model described by the following equation:

$$EAI_{t,i} = \alpha_i + \tau_d + \beta_2 F2_{t,i} + \beta_3 F3_{t,i} + \varepsilon_{t,i} \tag{18}$$

Where $EAI_{t,i}$ is the economic activity index of region i on date t. The fixed effects of the model are α_i, that captures the region specific means of the index, τ_d that controls for the evolution of the index regardless of phase changes. The inclusion of this later set of controls is critical: it accounts for the fact that the economic activity was increasing in the different regions even without the official ease of economic restrictions. Finally, $F2_{t,i}$ and $F3_{t,i}$ are dummy variables that indicate if region i is classified on either phase 2 or 3 on date t. Therefore, coefficients β_2 and β_3 represent the average marginal effect of regions being classified respectively on phases 2 and 3 of the São Paulo Plan.

Table 5 presents the results of this estimation. On columns 1-3, the dependent variable are the different versions of the EAI (Tradables, Non-tradables and Total). On columns 4 and 5, the equation is estimated using internal regional mobility[13] as the dependent variable instead of the EAI. The coefficients can be interpreted as the level effect of each phase compared to the level that would be expected if regions remained on phase 1. For example, the coefficient of 1.110 for phase 2 on Total EAI indicates that moving from phase 1 to phase 2 leads to an average increase of 1.110 percentage points on Total EAI. Results from all specifications are consistent, showing positive and significant effects of phase 2 and phase 3 in all indicators. While the effects for both phases are positive, they are larger for phase 3, which is an expected result since the economic flexibility is higher in phases with higher classification. Moreover, the effects of moving to less restricted phases are stronger to non-tradable activities.

Table 5. Regression Results: Effect of Phase Change on EAI and Mobility

	EAI			Mobility Index	
	Tradable	Non-tradable	Total	Freight	Passengers
	(1)	(2)	(3)	(4)	(5)
Phase 2	0.412 ***	1.476 ***	1.110 ***	0.622 ***	2.212 ***
	(0.052)	(0.115)	(0.095)	(0.187)	(0.186)
Phase 3	0.718 ***	2.442 ***	2.322 ***	1.591 ***	3.666 ***
	(0.076)	(0.168)	(0.140)	(0.275)	(0.274)
Fixed effects:					
DRS	yes	yes	yes	yes	yes
Date	yes	yes	yes	yes	yes
Obs.	1,751	1,751	1,751	1,751	1,751
R^2	0.992	0.978	0.981	0.941	0.953

Note: *p<0.1; **p<0.01; ***p<0.001.

3.1.2. The effect of EAI on COVID-19

In the second step of our empirical analysis, we estimate the average effect of changes in the EAI on COVID-19 outcomes. Specifically, we estimate the following two specifications:

$$y_{t,i} = \left(\sum_q \gamma_q \, S_{q,t-7,i} \right) + \phi EAI_{t-t',i} + \epsilon_{t,i} \tag{19}$$

$$y_{t,i} = \left(\sum_q \gamma_q \, S_{q,t-7,i} \right) + \left(\sum_q \phi_q \, S_{q,t-t',i} EAI_{t-t',i} \right) + \epsilon_{t,i} \tag{20}$$

Where $y_{t,i}$ is a health variable, measured in log per capita terms. In our preferred specification, we focus our analysis on COVID-19-associated hospitalizations as this variable is less subject to measurement error and less likely to be under-notified if compared to COVID-19 cases or even deaths.[14] Researchers are looking at the daily hospitalization rates attributed to COVID-19 to help guide planning and prioritization of health care system resources (Garg et al., 2020). The first summation term in the right-hand side of both equations controls for the stage of the disease spread in each region over time. The term $S_{q,t,i}$ is a vector of dummies representing bins[15] of the accumulated number of deaths in each DRS in the week before each observation. This vector flexibly controls for the non-linear pattern of the epidemiological evolution of the dependent variable. The main coefficient of interest is ϕ which estimates the marginal effect of lagged changes in the EAI on the dependent variable. The size of the lag term t' depends on the epidemiological characteristics of the dependent variable. Because we are focusing on COVID-19 hospitalizations, we use t' equal to 12, representing the virus average estimated infection-to-death period of 24 days (Flaxman et al. 2020) minus the average period between mechanical ventilation and death that is observed in the state of São Paulo individual level data of COVID-associated deaths. The difference between the two specifications are associated with coefficient ϕ. In Equation 19, only a single average effect of lagged EAI is estimated, meanwhile, Equation 20 allows the EAI effect to vary according to the epidemic stage during the lagged period.

Table 6 presents the result of these estimations. Column (1) indicates that a one percentage point increase on EAI is, on average, associated with a 0.5% increase in the number of hospitalizations per capita after 12 days. Meanwhile, results from column (2) suggest that EAI effects are higher in the earlier stages of the pandemic. When deaths per million are below 100, a one percentage point is associated with a 0.6% increase in hospitalizations 12 days later. That effect decreases to 0.4% when COVID-19-associated deaths per million are between 300-400, and it becomes statistically non-significant above that level.

Table 6. Regression Results: Effect of EAI Changes on COVID-19 Hospitalization Rates

	Log hospitalizations per million residents per day	
	(1)	(2)
EAI (-12 days)		
average effect	0,005***	
	(0,002)	
Deaths per million (-12 days)		
0-100		0,006***
		(0,002)
100-200		0,005***
		(0,002)
200-300		0,006**
		(0,002)
300-400		0,004**
		(0,002)
400-500		0,002
		(0,002)
500-600		0,020
		(0,002)
Fixed effects:		
Accumulated deaths per capita in -7 days	yes	yes
Obs.	1.105	1.105
R^2	0,406	0,410

Note: *p<0.1; **p<0.01; ***p<0.001.

3.1.3. Calculating the effect of the São Paulo Plan on COVID-19 hospitalizations

The final step of our empirical framework combines the results of the previous two estimations to calculate the effect of the São Paulo Plan on COVID-19-associated hospitalizations in the period of our analysis. The calculation is based on a counterfactual analysis that uses the results of the previous two subsections to estimate total hospitalizations under two different scenarios: (A) the observed scenario and phase changes that were adopted by the São Paulo Plan; (B) an alternative scenario where all DRS remained under the most extreme economic restrictions (phase 1) throughout the whole period. By comparing the estimated number of hospitalizations in both scenarios we have an estimate of the impacts of the plan.

We start this procedure by calculating a counterfactual EAI for each region in scenario B ($\widehat{IAE}_{t,i}$). This calculation can be described by equation 21:

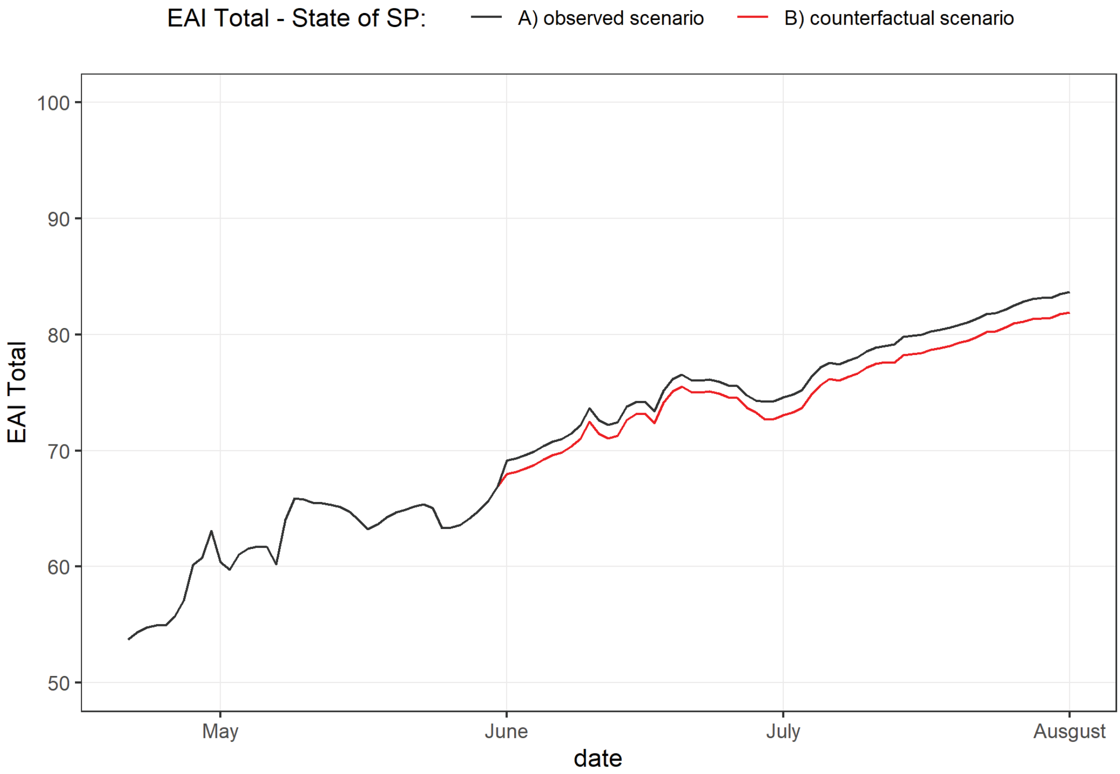
$$\widehat{EAI}_{t,i} = EAI_{t,i} - \hat{\beta}_2 F2_{t,i} - \hat{\beta}_3 F3_{t,i} \tag{21}$$

The terms $\hat{\beta}_2$ and $\hat{\beta}_3$ are the results from Model (3) presented in Table 5, and correspond to the estimated effect phase changes on Total EAI. Notice that if a region is already observed in phase 1 in scenario A, its EAI will be the same in both scenarios. Figure 5 shows the aggregated EAI for the State of São Paulo for both scenarios. Up until the beginning of June, the EAI is the same in both scenarios, as all DRS were under the most restrictive classifications. With the beginning of changes in classifications in June, the difference between scenarios starts to show up, with slightly lower Total EAI for the scenario where all regions are assumed to remain in phase 1. The difference between the scenarios increase over time as more regions are classified into more flexible phases. However, even in the last date of our comparison, the difference between the scenarios is of only 1.93 percentage points.

Next, we use these simulated and observed EAI to project the number of hospitalizations in each DRS in each date using the results from Table 6. Specifically, we calculate:

$$\begin{gathered}\hat{y}_{i,t} = \left(\sum_q \hat{\gamma}_{q,t-7,i}\, S_{q,t,i}\right) + \hat{\phi} EAI_{t-t',i} \\ \hat{\hat{y}}_{i,t} = \left(\sum_q \hat{\gamma}_{q,t-7,i}\, S_{q,t,i}\right) + \hat{\phi} \widehat{EAI}_{t-t',i}\end{gathered} \tag{22}$$

Figure 5. Observed and Counterfactual EAI for the State of São Paulo

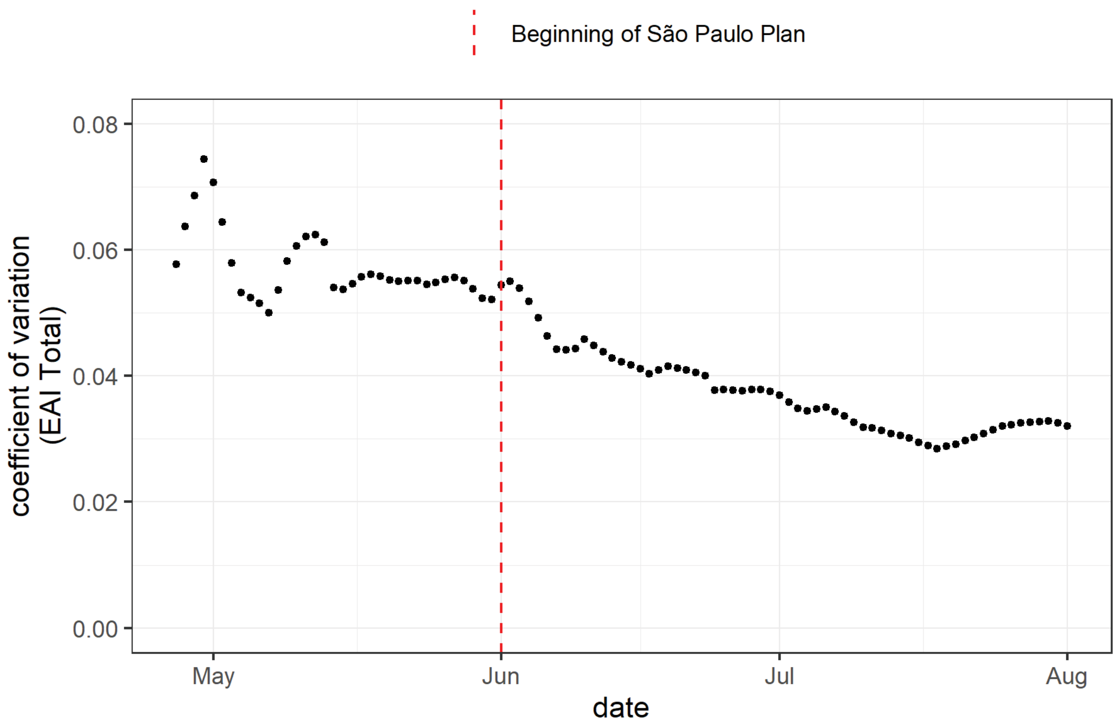


That is, $\hat{y}_{i,t}$ corresponds to the fitted log of hospitalizations per capita in scenario A, and $\hat{\hat{y}}_{i,t}$ is the corresponding value from scenario B. We can use $\hat{\hat{y}}_{i,t}$ to $\hat{y}_{i,t}$ to project the total number of hospitalizations in each scenario. We run this calculation twofold: first assuming a single average effect of lagged EAI on new hospitalizations as reported on Table 6, Column (1); next, we allow the effect of lagged EAI to vary according to the stage of the pandemic using the coefficients from Column (2). In the first case, we find that the number of hospitalizations in the counterfactual scenario would be 0.52% lower if compared to the projected number using observed EAI. This difference could range between 0.15%-0.95% given a 95% confidence interval and the standard errors of all estimates involved in the simulations. The observed number of COVID-19 hospitalizations in the State of São Paulo between May 29 up until August 1st was of 119,461, therefore, if we apply our main central effect to this total, we would have approximately 621 fewer new hospitalizations if no flexibility were adopted throughout the period. In the second case where we allow more flexibility to the effect of EAI on hospitalizations, results are consistent. The simulated total number of hospitalizations would be 0.21% lower if economic restrictions had not been released. This effect ranges from 0.04%-0.59% given a 95% confidence interval of all estimates. The central result corresponds to 250 fewer hospitalizations between May 29 and August 1st.

3.1.4. Calculating the effect of the São Paulo Plan on EAI volatility

One additional objective of the São Paulo plan was to anchor expectations.[16] It is a communication tool that allows economic agents to temporally allocate their efforts in production and consumption, reducing informational uncertainty due to the COVID-19 pandemic. To assess the effectiveness of the Sao Paulo Plan as a mechanism of anchoring expectations we have estimated the daily coefficient of variation of the rolling-7-day EAI (Figure 6 below). This descriptive analysis indicates that the São Paulo Plan may have smoothened the series and worked as an anchor for expectations guiding economic activity.

Figure 6. Coefficient of Variation of Total EAI – (April, 21 – August 1, 2020)



4. Final Discussion and Possible Extensions

COVID-19 crisis monitoring involves preparations to implement and roll back non-pharmaceutical interventions, including setting up expert committees to examine initial control measures and define gradual relaxing of social restrictions (Petersen et al., 2020). Nonetheless, up against enormous uncertainties, combining timely tracking of epidemiological and socioeconomic indicators is fundamental for informing officials during the implementation of exit strategies.

We proposed a timely trade-based regional economic activity indicator (EAI) combining high-frequency truck and passenger vehicle traffic data with economic input-output flows. The EAI monitors daily sectoral economic activity in the Brazilian State of São Paulo. The use of this novel set of information, combined with COVID-19-associated hospitalizations, provided a first assessment of the São Paulo Plan, the COVID-19 exit strategy designed to gradually lifting interventions introduced to control the outbreak in the State. We show that, in its first 60 days, the phased strategy pursued in São Paulo has been effective in gradually reactivating economic activity *pari passu* to a relatively small number of additional hospitalizations associated with the flexibilization in phases. The timing of the reopening of non-essential activities has shown to be relevant to the impact on hospitalization rates increases, with stronger effects during the ascending part of the pandemic curve. Thus, trends in the evolution of the pandemic should be part of the key public health metrics monitored to determine smooth and safe reopening. Moreover, taking into account regional heterogeneity has proved to be an important feature of the COVID-19 exit strategy. State coordination of preparedness efforts moving forward was an essential mechanism that took into account the interconnectedness of the regional economies, which may be important at different spatial scales (Ruktanonchai et al., 2020). In Brazil, for instance, lack of central coordination in a strongly integrated interregional system (Haddad and Hewings, 2005) may have contributed to complicating epidemiological assessments and public health efforts to curb the pandemic (Candido et al., 2020; Souza et al., 2020).

This study has important limitations. The State of São Paulo is strongly connected with its neighbouring states. According to the input-output data (FIPE-NEREUS, 2020), interstate trade reaches almost fourfold international trade values involving the state economy. As the spread of diseases does not respect administrative borders (Ruktanonchai et al., 2020), the lack of coordinated nation-wide measures to control the COVID-19 epidemic may have imposed limitations to the effectiveness of the São Paulo Plan.

Possible extensions of the EAI analysis include, but are not restricted to: (i) validation of the series' trend in comparison to invoice records to guarantee robustness in portraying economic activity; (ii) control of effect on disease spread by expansion of testing; (iii) EAI sensitivity to local characteristics (for instance, composition of regional economic structures, population socioeconomic characteristics); and (iv) EAI and labour market effects.

This study is the first of a series sought to facilitate crisis monitoring under an economic lens. Using literature on regional economic analysis and high-frequency traffic data, the model derives a connection between economic activity and health impacts. We shed light on the possibility of, given a clear means of anchoring expectations, inducing a responsible suspension of restrictive measure while keeping virus spread at bay.

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[1] For a detailed description of the *São Paulo Plan*, please refer to https://www.saopaulo.sp.gov.br/planosp/, information in Portuguese.

[2] As Garcia et al. (2008) observed, whereas it is fairly accepted that freight transport, measured in ton-km, is closely related to the level of economic activity of a region, there is hardly any study that investigates if this correlation still holds for transport indicators that are independent of the volumes transported.

[3] The Treasury Department in São Paulo tracks overall economic activity in the State monitoring daily value-added tax (VAT) collection and VAT-generating transactions. In spite of its usefulness, this indicator has a partial coverage of the state economy, as the VAT tax base is restricted to approximately one-third of GRP, including mainly manufacturing activities in the formal sector, with a poor coverage of services activities. Moreover, it does not provide a regional disaggregation.

[4] This section draws on Haddad et al. (2020).

[5] In this application, the rest of the world is an endogenous region, which precludes the possibility of including the effects of foreign sales on a domestic region's performance.

[6] Similar measures can be calculated for each sector s in region 1, $va_{1,n}^{1,s}$.

[7] Data were processed on July 3, 2020. There are weekly releases of the daily indicators throughout the pandemic period.

[8] Out of the 67 economic activities defined in the interregional input-output table, we aggregated all 38 agricultural and manufacturing activities into the tradable sector, and all 29 services activities into the non-tradable sector. We used the information on traffic flows of passengers between all pairs of regions together with the latter, while using freight vehicles with the former.

[9] The EAI measures economic activity in relation to the average of the first three weeks of March 2020, considered as the benchmark pre-crisis level.

[10] The appendix presents similar plots within each DRS.

[11] The data about COVID-19 related deaths are reported in two different ways. Table 4 presents statistics of count of deaths according to date of register, whereas an alternative public source of information publishes deaths count by date of fatality.

[12] Five health indicators were grouped into two categories concerned with (i) *health system capacity* (average occupancy rate of ICU COVID beds in the last 7 days (%), COVID ICU Beds / 100k habitants); and (ii) *evolution of the pandemic* (# of new cases in the last 7 days / # of new cases in the previous 7 days, # of new hospitalizations in the last 7 days / # of new hospitalizations in the previous 7 days, # of deaths by COVID in the last 7 days / # of deaths by COVID in the previous 7 days).

[13] We measure intraregional mobility as the changes in values of traffic of passengers within each DRS, i.e. $\Delta F_{t,o,d}$, for o=d.

[14] The number of deaths is usually a more consistent epidemiological statistic (Subaraman, 2020). However, our analysis evaluates a very recent period, and the number of deaths by date of occurrence tends to be underestimated in more recent dates because there is a substantial lag between death dates and their registration in official systems. Once COVID-associated death statistics are consolidated, an important robustness check will be to verify the consistency of our results using lagged COVID-19 deaths as the dependent variable of our model.

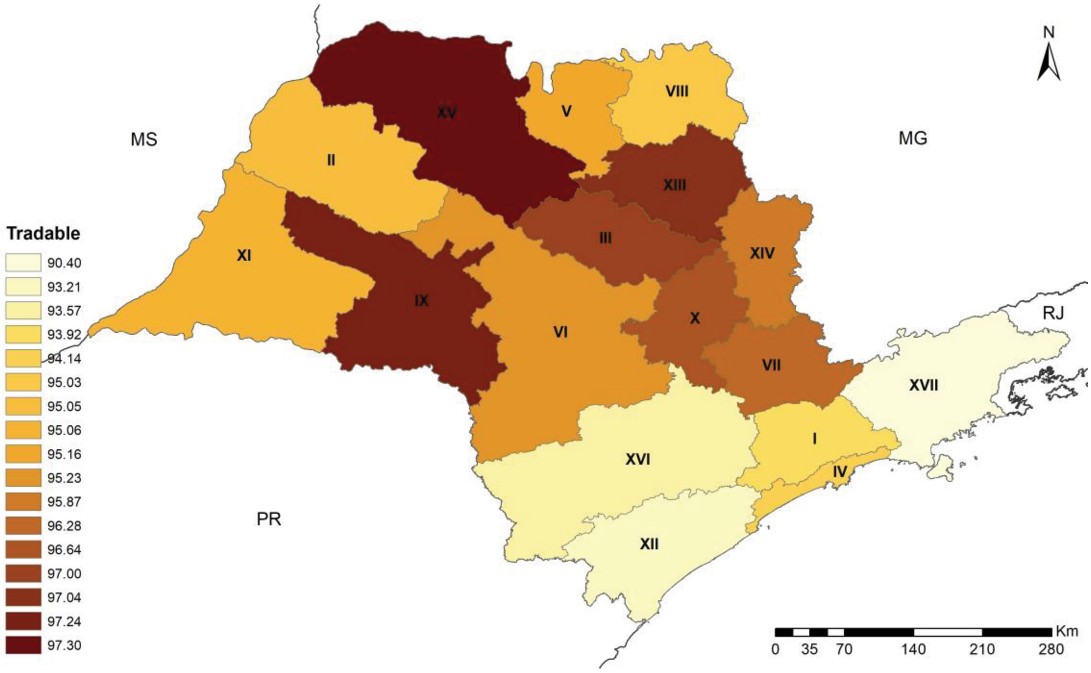
[15] In our preferred specification, bins are defined as 0-100, 100-200, …, 700-800 death per million residents.

[16] This follows the rational expectations argument frequently adopted in macroeconomic policy effectiveness discussions as explored by Lucas and Sargent (1981) and others.

Supplementary material

Figure A1. Economic Activity Index, August 01, 2020

Tradable



Non-tradable

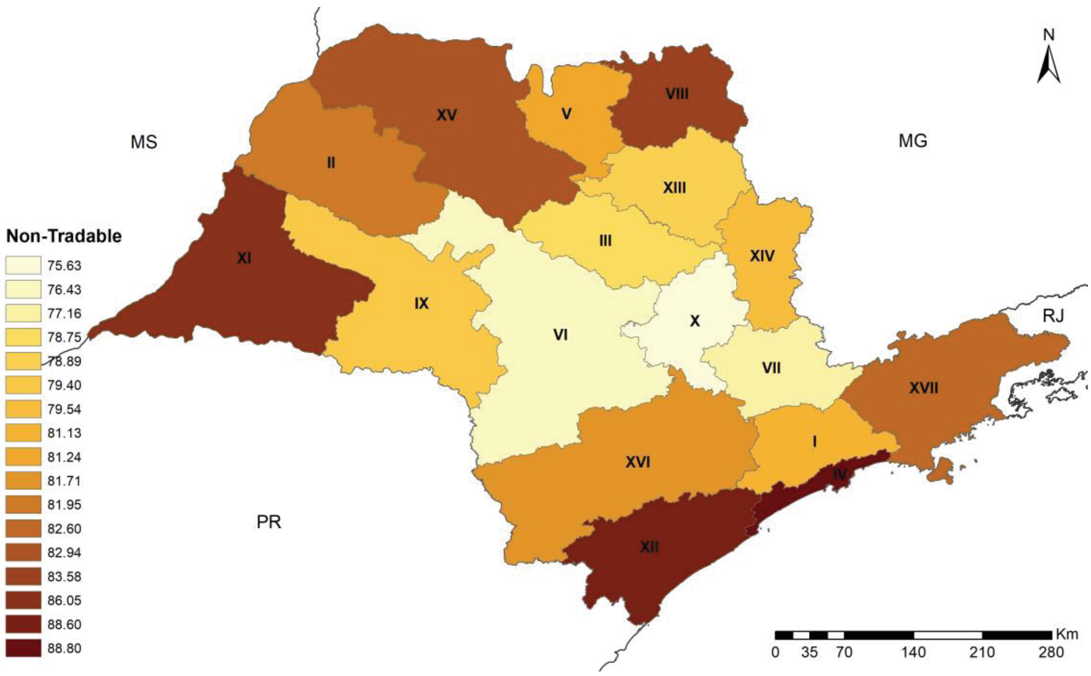


Figure A1. Economic Activity Index, August 01, 2020 (cont.)

Total

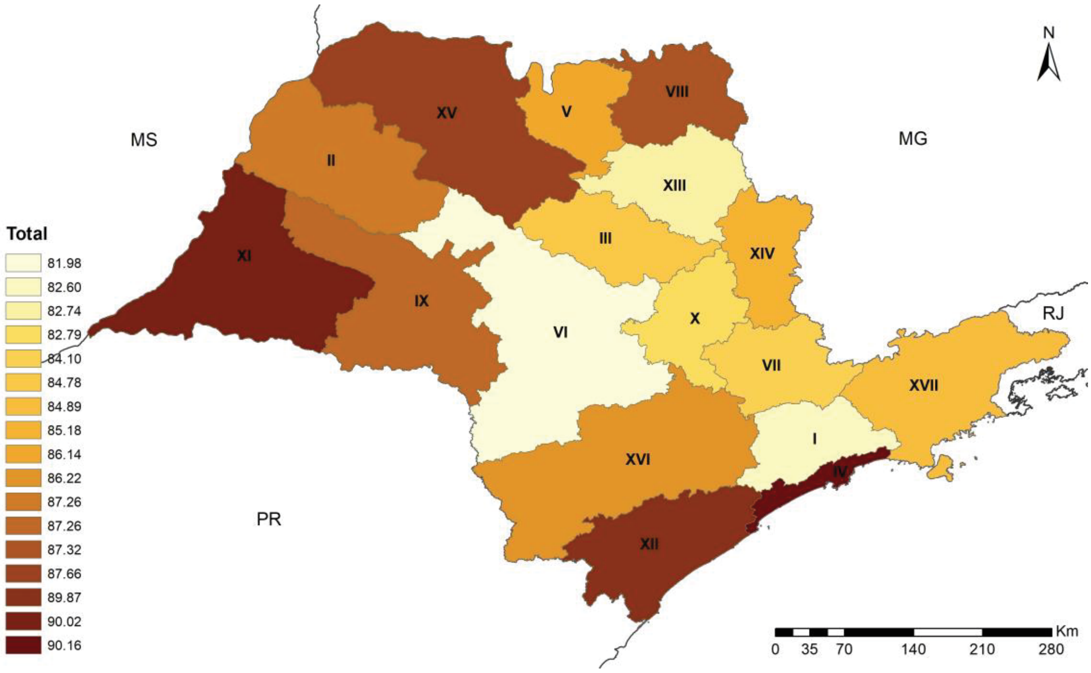


Figure A2. Regional Economic Activity Indicator

Figure A2. Regional Economic Activity Indicator (cont.)

Figure A3. Intra-regional traffic intensity (freight and passenger) by region of the Brazilian State of São Paulo

Figure A3. Intra-regional transportation flows by region of the Brazilian State of São Paulo (cont.)

Figure A4. Confirmed cases of coronavirus (rolling 7-day average) by region of the State of São Paulo – until August 1, 2020

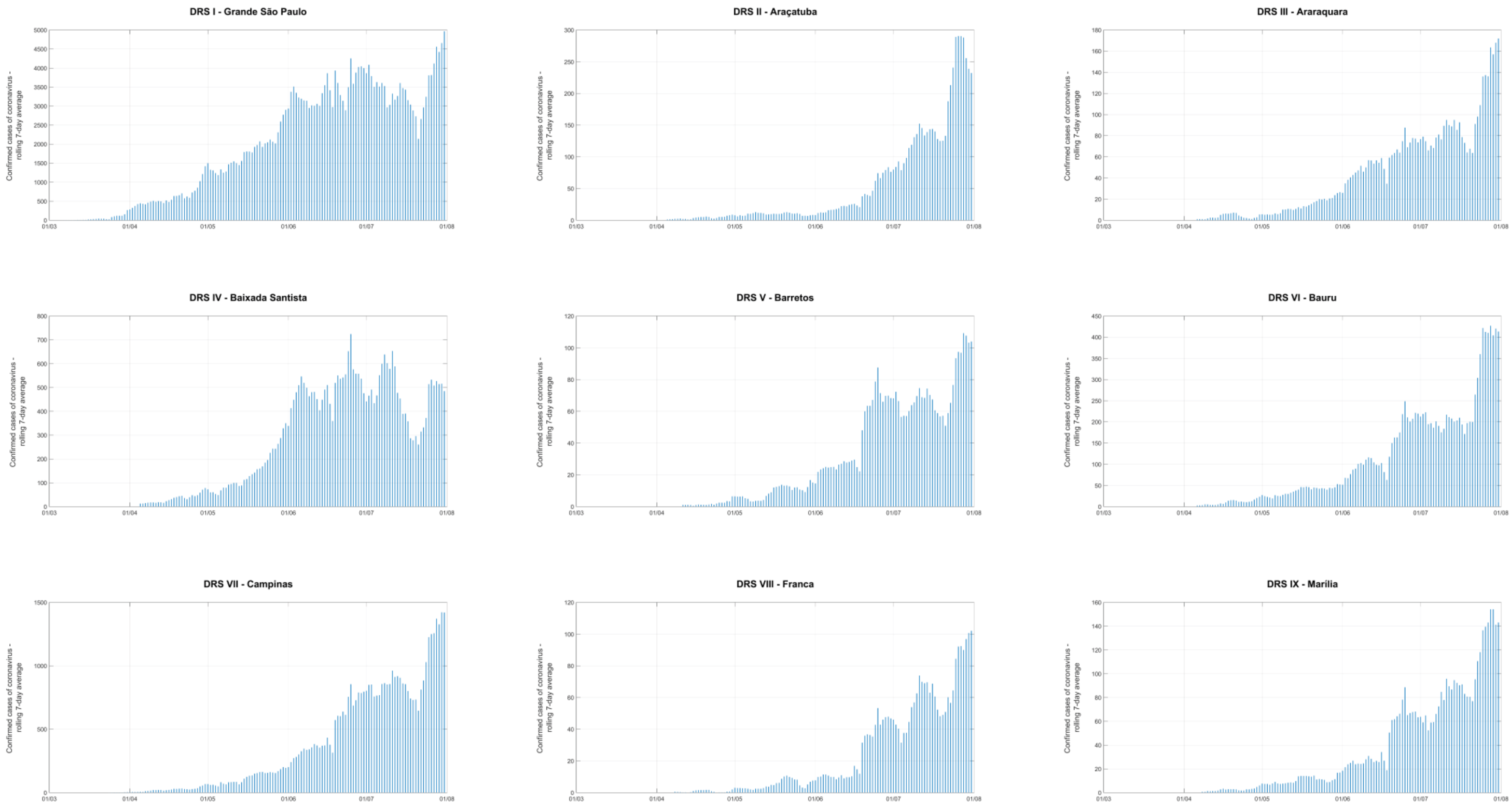


Figure A4. Confirmed cases of coronavirus (rolling 7-day average) by region of the State of São Paulo – until August 1, 2020 (cont.)

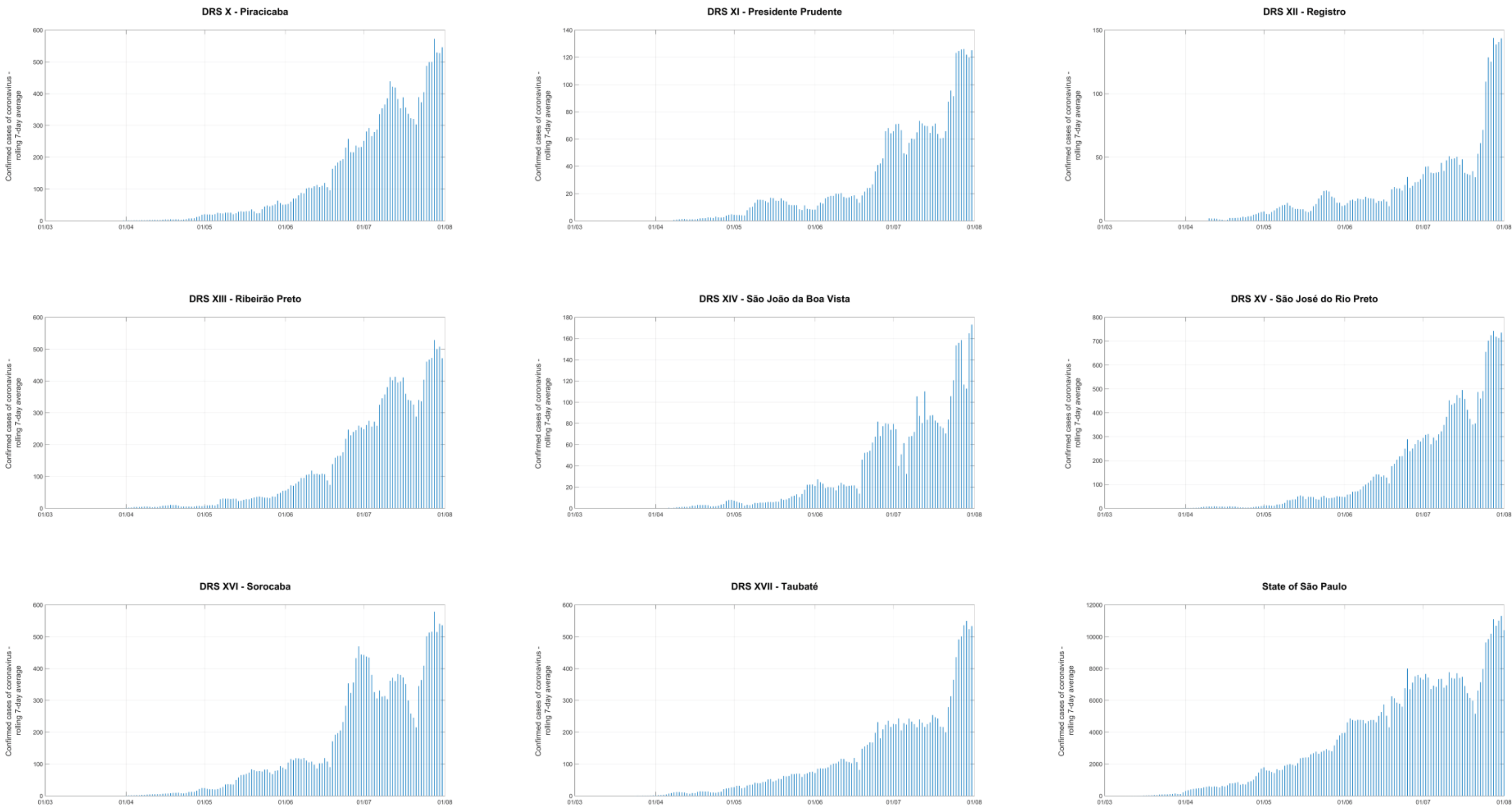


Figure A5. Deaths due to coronavirus (rolling 7-day average) by region of the Brazilian State of São Paulo – until August 1, 2020

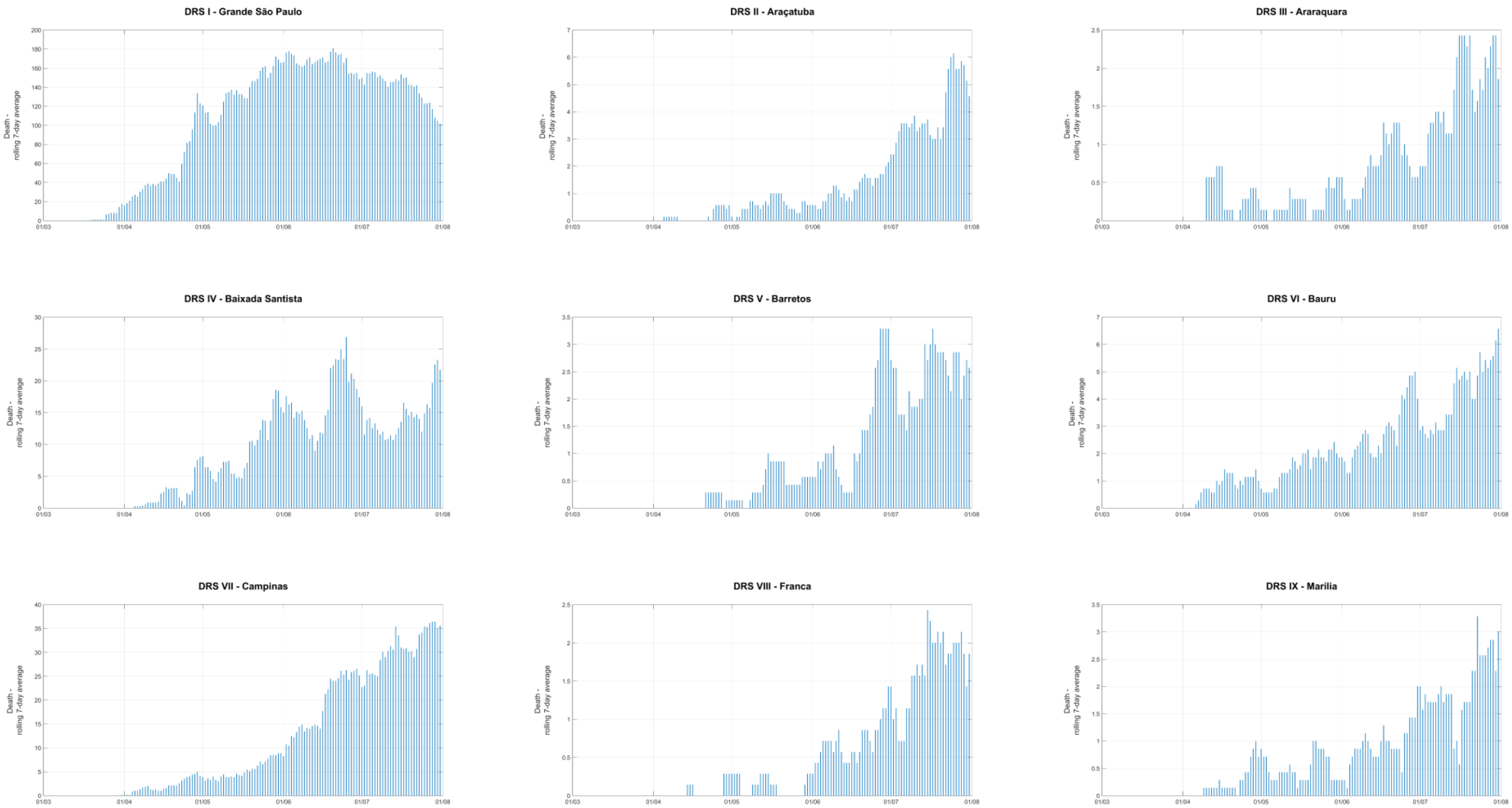


Figure A5. Deaths due to coronavirus (rolling 7-day average) by region of the Brazilian State of São Paulo – until August 1, 2020 (cont.)