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Impact of COVID-19 Restrictions in Costa Rica: a Local Approach*

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Central Bank of Costa Rica

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Abstract

During the COVID-19 pandemic, governments have implemented restrictive measures to impede mobility, aiming to reduce the number of infections and deaths caused by the disease. However, these measures harm economic activity. This study uses municipality variation in the restrictions that the government has implemented in Costa Rica to measure the effects of these restrictions on economic activity and health outcomes. We collect data on the sanitary alerts and restrictions announced by the government from March 15th, 2020 to July 31st, 2021, and use electricity consumption to approximate economic activity. We estimate that imposing a more restrictive sanitary alert reduces the weekly growth rate number of cases by 7% and of deaths by 10%, but it reduces commercial electricity consumption by 1.5%, which we associate with a decrease in economic activity of about 1.88%.

JEL Codes: E23, I12, I15, I18.

Keywords: COVID-19, Coronavirus, Sanitary Restrictions, Economic Impact.

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1 Introduction

Most governments have imposed social distancing measures to try to limit the spread of COVID-19. These measures have restricted economic activity by reducing business opening hours, restraining consumers' mobility, and in the most extreme cases by forbidding the operation of some activities. Such measures generate a trade-off between health and economic outcomes: By tightening those restrictions the governments aim to reduce the transmission of the virus, but the same restrictions might harm economic activity and increase unemployment.

In the case of Costa Rica, the government has, as well, implemented some measures to limit social interactions. However, the severity of the restrictions has varied geographically by municipality, the smallest political unit in the country. The objective of this article is to exploit this difference in the restrictions to understand how effective those measures were in improving health outcomes and the impact they had on economic activity.

To fulfill this objective, we have created a new data set containing information gathered from different public institutions: We were able to obtain daily information about the sanitary alerts and restrictions that the government has imposed and daily information on the number of new cases and new deaths associated to COVID-19, which we use as health outcomes. Further, we have monthly electricity consumption, which is disaggregated by sector: household consumption, commercial and industrial use. Electricity consumption is our main proxy for economic activity, following previous studies that have found a positive relationship between these two variables (e.g., Chen et al. 2020; Beyer et al. 2021). Finally, we use point of sale transaction data from one of the main acquires in Costa Rica to check how robust our results are in terms of the effect of the restrictions on economic activity.

Before presenting our main results, it is important to give a background about the evolution of the COVID-19 pandemic in Costa Rica. The first case was confirmed on March 7th, 2020. The patient was a 54-year-old male Costa Rican citizen who presumably was infected during a visit to Panama City. The first death associated with COVID-19 was confirmed on March 18th, an 87-year old male.

The government tried from the early days to contain the spread of the virus. In early March the National Emergency Committee (CNE) decreed a yellow-level sanitary alert. On March 16th, the government decreed a state of national emergency. Along with this decree, the government announced that classes were suspended in all public and private schools and that only citizens and legal residents could enter the country and those entering had to remain in quarantine for at least 14 days.

In late March, numerous new prevention measures were announced: the government in-person workforce was reduced by 80%, beaches, temples, and religious services were completely closed. Additionally, a night vehicle restriction was imposed to reduce mobility, and businesses were forced to close at night. In the beginning, these measures were imposed on the whole country, but later the government decided to tailor them by municipality. The government decided to announce different sanitary alert levels by municipality, and decree restrictions drawn from the sanitary alert. We use this geographical variation along with the changes in the severity of the restrictions to study the effect of those measures on the spread and fatality of the virus in the country and the inconvenient collateral effects on economic activity.

To exploit this information, we use the variation in the alert levels among municipalities to identify how different was the health outcomes and the evolution of economic indicators for distinct alert levels. Importantly for our empirical strategy, our analysis shows that pre-pandemic characteristics, such as population density, percentage of male population, or poverty rates, cannot explain the number of alerts or their duration for each municipality. Our main results show that the government restrictions had a positive effect on health outcomes but had a negative significant effect on economic activity.

Our estimation implies that a change from a yellow alert to an orange alert (more restrictive) reduces the growth rate of new COVID cases by 7% and deaths associated with COVID by 10%. However, the same change in alerts implies a reduction of 1.5% in commercial use electricity consumption. Given the elasticity we calculate between electricity consumption and economic activity, this reduction translates to a decrease of about 1.88% in economic activity, which we relate to the economic costs of the sanitary restrictions. However, we do not find any significant effect on industrial, residential, or total electricity consumption. To understand this difference, we showed that the restrictions in mobility were the restrictions that affected directly economic activity, and these restrictions are mostly linked to the commercial sector.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 includes details of the data used in our analysis. We describe our estimation framework in Section 4. Section 5 presents the results corresponding to the benefits of the sanitary restriction. Then, Section 6 discusses the costs of the sanitary restrictions. Finally, Section 7 concludes.

2 Literature Review

There has been a large interest in understanding how effective have been the mobility restrictions imposed by the governments to reduce the COVID-19's transmission and the economic implications of these measures. We discuss some of this work.

Most of the studies that have focused on how effective the mobility restrictions are have concluded that these measures are useful to contain the virus' transmission. From an empirical point of view, the main challenge in these analyses is how to disentangle the effect of the mobility restrictions from other confounding forces such as the natural evolution of the number of cases or the reduction in mobility that is self-imposed by the citizens due to fear, altruism or any other motivation.

This problem has been solved in different ways. Fang et al. (2020) exploit the exogenous variations in human mobility created by lock-downs of Chinese cities to estimate the effectiveness of these lock-downs in controlling the spread of the COVID-19 pandemic. They used a difference-in-difference (DID) strategy that allows them to utilize this exogenous variation to disentangle the mobility restrictions from other confounding effects. Kraemer et al. (2020) use mobility data from Wuhan before and after the restrictions imposed by the government. They show that before the restrictions, mobility and the number of cases were positively related, but after those restrictions were implemented, this correlation became negative. Both studies conclude that the restriction in Wuhan helped to contain the virus transmission.

Other studies have focused on the evolution of the pandemic in the United States. Ghirelli et al. (2022) analyzed the relation between weather and the effective reproduction coefficient (R_t). They used County-level information. Their main result is that the coefficient R_t is inversely proportional to the county's temperature, a result pointing that the pandemic could aggravate during the winter months in the countries that experience four seasons. Sen et al. (2020) showed that the statewide stay-at-home orders that were issued by some states (Colorado, Minnesota, Ohio, and Virginia) reduce significantly the number of hospitalizations: actual hospitalizations were significantly below the forecast of the number of hospitalizations obtained from an exponential model that exhibits a good in-sample forecast.

Yilmazkuday (2021) used a DID approach in a cross-section study to evaluate whether less human mobility is related to a lower number of cases and deaths associated with COVID-19. He used Daily Google mobility data of 130 countries at the beginning of the pandemic. He showed that staying at home and reducing the number of visits to retail and recreation places significantly reduced the number of cases and deaths associated with COVID-19.

In terms of the economic impact of COVID-19 and of the mobility restrictions imposed by some governments, there is a variety of topics that have been studied in the literature. Among those topics, there are studies that analyze the effect of restrictions on GDP (Maliszewska et al. 2020; Fernandes 2020), the observed disruption of global supply chains (Guan, Wang, Hallegatte, Davis, Huo, Li, Bai, Lei, Xue, Coffman, Cheng, Chen, Liang, Xu, Lu, Wang, Hubacek & Gong 2020; Javorcik 2020), the changes on commodities prices (Gil-Alana & Monge 2020, Umar et al. 2021), and analysis of policies that were implemented by the governments to prevent further economic decline (Albulescu 2020; Elgin et al. 2020; Loayza & Pennings 2020).

The work, that we are aware of, closest to ours is the one by Vespe et al. (2021). They used Mobile Network data to analyze how a three-tier alert system level affected mobility and economic activity in Italy. As we do, they use electricity consumption as a proxy for GDP. However, they use a different approach to estimate the impact of the restrictions on GDP. They calculate the link between alert level and mobility, and the relation between mobility and electricity consumption. Then, using these two, they estimate, in an indirect way, the effect of changing alert levels on electricity consumption and relate this to GDP variation.

There are a few other papers that have studied the economic impact of the COVID-19 pandemic in Latin America. Leyva & Urrutia (2022) focus on the effects of the restrictions on labor markets with special emphasis on informal unemployment. They showed that, opposite to previous economic crises, during the crisis caused by COVID-19, the informality rate fell in the five Latin-American countries that they focused on. They argued that it is necessary to consider the existence of both negative labor supply shocks and negative informal economy productivity shocks to reproduce this fact. Haddad et al. (2020) and Bonet-Morón et al. (2020) use input-output models to study the regional and sectoral impact that the mobility restrictions measures imposed by the government could have generated. They consider different scenarios in which different groups of workers are forced to stop working and estimate the effect of such measures on GDP.

3 Data

Our data, and therefore our analysis, is divided by municipalities. Costa Rica has an administrative division of seven provinces, and by 2020, they were subdivided into 82 municipalities.[1] Each municipality possesses a form of local government run by a mayor.

We take advantage, as well, of the Costa Rican Social Security System (CCSS, by its initials in Spanish) structure. This social security system is universal and of free access to all the residents in the country. Moreover, one important part of the system is a network of 1,014 Basic Teams for Comprehensive Health Care (EBAIS, by its initials in Spanish) and 859 Periodic Visiting Stations distributed throughout the national territory. This network objective is to provide preventive medicine and basic medical consults, which allows a close relationship between the CCSS and the population and results in less pressure on the hospital system. They have been a key part of the strategy to face COVID-19, since they conduct and register COVID-19 tests, monitor the progress of each patient, and decide if they should be moved to a major Hospital. This structure allowed the government to have information about new COVID cases and deaths associated with this virus at the municipality level. We use this database that is organized and provided by the Ministry of Health.

[1] A new municipality was created by law in September 2021. Our data is before that date.

This same data is used by the government as an input to decide periodically the alert level that is set for each municipality and the restrictions associated with that alert. Each alert is characterized by a color: green, yellow, orange, and red in order of severity. Manually, we created a daily database at the municipality level from all the decrees published by the National Emergency Commission (CNE, by its initials in Spanish) in which we collect each municipality alert level, the percentage of license plates that can circulate each day, the hours of the day that vehicles cannot circulate, the business closure times, and the business capacity limitations set by the government. This data ranges from March 15th, 2020 to July 31st, 2021. For the estimation, it is important that during this period, and for all municipalities, alert levels were either yellow or orange. Therefore, we can analyze only the change from one alert level to the other.

To assess the economic cost of the restrictions, we use electricity consumption as a proxy for economic activity. The choice of this variable is based on a stream of literature that has found a positive relationship between economic activity and electricity consumption. More in line with this paper, previous studies have also employed electricity consumption to measure the impact of the COVID-19 pandemic (e.g., Beyer et al. 2021; Vespe et al. 2021).

Electricity consumption data was provided by the National Center for Energy Control (CENCE, by its initials in Spanish) at the municipality level and with monthly frequency. This database allows us to differentiate between electrical consumption uses by: residential, commercial, and industrial, and it ranges from January 2017 to June 2021. Using this data and Value Added Tax data (VAT), we tested if the positive relationship between electricity consumption and economic activity also holds for Costa Rica. Appendix A shows that an increase of 1% in electricity consumption is associated with a 1.36% increase in economic activity.

We also use point of sale (POS) transactions data as an alternative way to estimate the economic cost of the restrictions. This data contains the weekly aggregate value of all credit or debit card payments processed in the territory by one of the largest acquirers in the country, disaggregated at the municipality level. The card transaction also moves together closely with economic activity. Appendix B reports the results of regressing VAT on point of sale (POS) transactions, suggesting that a 1% increase in card payment value is associated with a 0.79% increase in economic activity.

We also use the Municipality Risk Index (IRC, by its initials in Spanish) developed by the Costa Rican local authorities with data from COVID-19 tests positive rates, the number of hospitalizations associated with COVID-19, and the number of active cases. Authorities combine these variables to create an index that ranges from 0 to 3. They use this index to define the level of alert at which each municipality should be at each moment in time. If the index is equal to 0 the risk is low (green color), if it is between 0.01 and 1.99 risk is intermediate (yellow), if it is between 2.00 and 2.99 risk is high (orange), and if it is equal to 3 risk is very high (red). The alert level is set to be yellow if the risk is either low or intermediate and orange if the risk is high or very high (Comisión Nacional de Emergencias 2021).

Using the index value for the period from July 2020 to June 2021, we present in Figure 1 a heat map that follows the color of risk assigned to each municipality every week. The figure confirms that, for a given week, there is significant risk variation across municipalities and that there is significant variability across time. This variation is the one we exploit in our estimation.

4 Empirical Strategy

4.1 Benefits Related to the Restrictions

As outcome variables, we follow Chernozhukov et al. (2021), and consider the weekly growth rate of confirmed cases and deaths in each municipality. We approximate the weekly growth rate of confirmed cases from t to $t-7$ by:

$$\Delta log(\Delta C_{it}) \equiv log(\Delta C_{it}) - log(\Delta C_{i,t-7}) \tag{1}$$

where C_{it} is the cumulative number of confirmed cases in municipality i on day t, and Δ denotes the differencing operator over 7 days from t to $t-7$. Therefore $\Delta C_{it} \equiv C_{it} - C_{i,t-7}$ corresponds to the number of new confirmed cases during the last seven days.

Similarly, we approximate the weekly growth rate of deaths from t to $t-7$ by:

$$\Delta log(\Delta D_{it}) \equiv log(\Delta D_{it}) - log(\Delta D_{i,t-7}) \tag{2}$$

where D_{it} is the cumulative number of deaths cases in municipality i on day t.

At the onset of the pandemic, some municipalities did not report any new confirmed cases or deaths for several weeks. To deal with these frequent zeros in our dataset, we use the inverse hyperbolic sine transformation ($\ln(y + (y^2 + 1)^{\frac{1}{2}})$). This transformation does not drive our results, though: Section 5.3 shows that our conclusions are robust to alternative ways to deal with the zeros in the data.

Although our full dataset comprises information between March 15th, 2020, to July 31st, 2021, before June 3rd, 2020, and after May 18th, 2021, all the country was under the same sanitary alert. Figure 2 shows the portion of municipalities in an orange alert each day. Therefore, to take advantage of variation in alerts across municipalities, we restrict attention in our main analysis to the period between June 3rd, 2020, and May 18th, 2021. Later on, in Section 5.3, we show that our results are similar when using the entire dataset.

Figure 1: Evolution of the Risk Assigned to Each Municipality to Set Sanitary Alerts, July 2020-June 2021

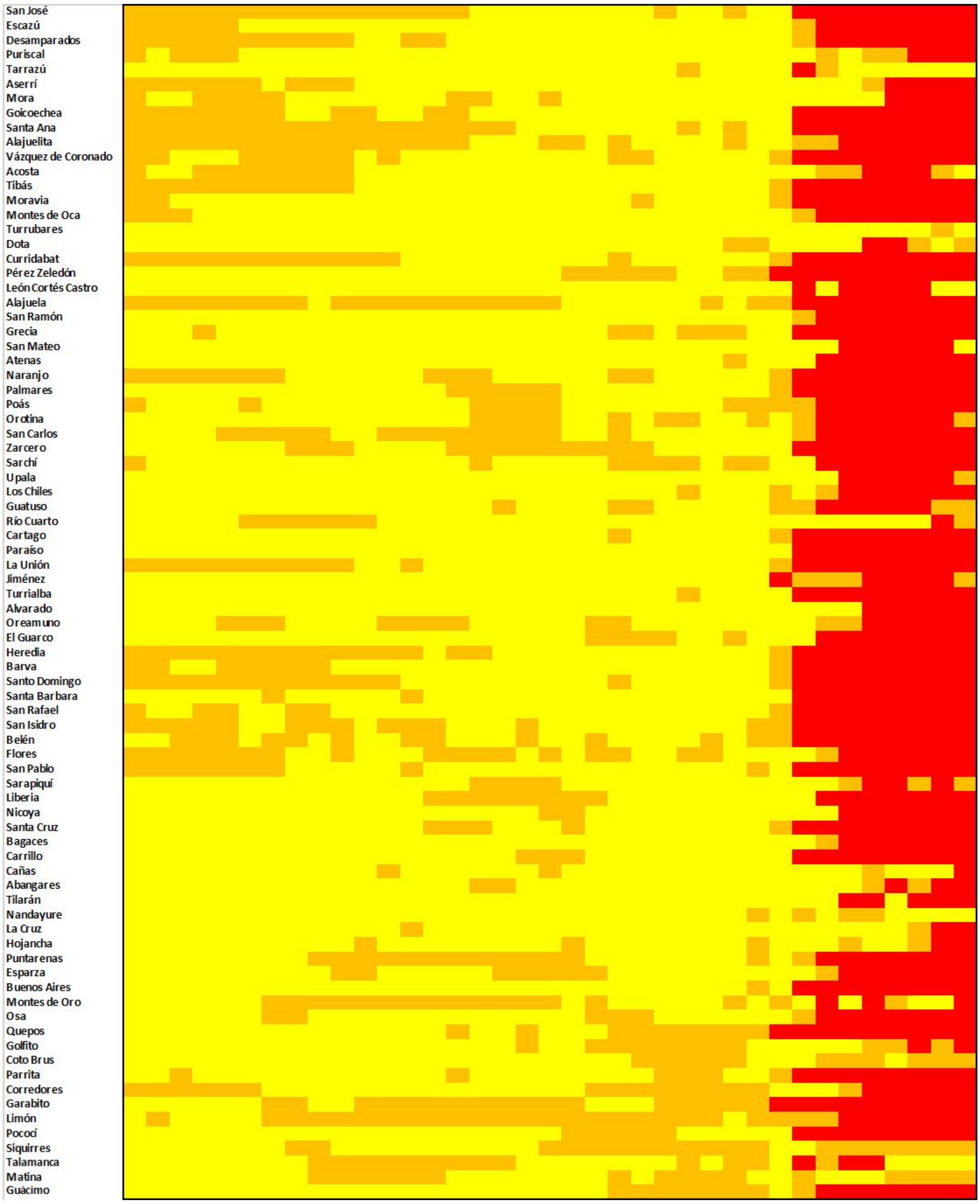
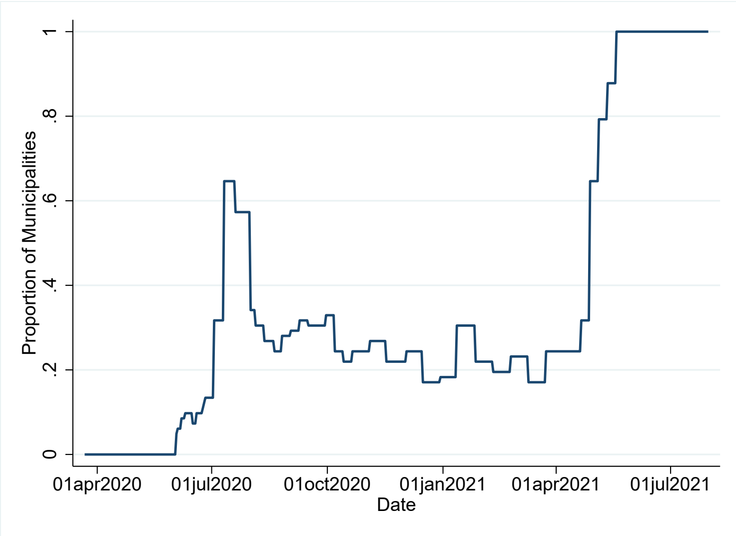


Figure 2: Portion of Municipalities in an Orange Alert



The left panel of Figure 3 shows the distribution of the number of sanitary alert switching across municipalities. Municipalities switched, on average, 5.14 times between alerts (median: five times). The switching does not seem to correlate with pre-pandemic differences across municipalities. To evaluate this, we use data from the 2019 National Household Survey, population dynamics calculated by the National Institute of Statistics and Censuses (INEC, by its initials in Spanish), and local government finance statistics from the Comptroller General of the Republic of Costa Rica (CGR, by its initials in Spanish). Table 1 shows that variables such as population density, percentage of male population, health insurance coverage, income per capita, or municipal revenues do not explain the number of times a municipality switches between alerts. Appendix C shows the result holds regardless of whether we use a Poisson regression model or a negative binomial regression model.

Moreover, the right panel of Figure 3 depicts the distribution of the average length of each alert level in days. Each sanitary alert lasts, on average, 57.24 days (median 29). Similar to the case of the number of switches, Table 2 shows that characteristics for each municipality in 2019 cannot explain the length of each alert at conventional levels.

Our estimation of the effect of an orange alert on the growth rate of confirmed COVID-19 cases uses the following specification:

$$\Delta log(\Delta C_{it}) = \alpha + \gamma Orange_{i,t-7} + \mathbf{X}_{i,t-7}\beta + \beta_d + \beta_m + \beta_i + \beta_m\beta_i + \varepsilon_{it} \qquad (3)$$

where $\Delta log(\Delta C_{it})$ is the weekly growth rates of confirmed COVID-19 cases for municipality i at day t. $Orange_{i,t-7}$ is an indicator variable equal to 1 if municipality i was under an orange alert 7 days before, and equal to zero otherwise. We choose a lag of 7 days to account for the incubation period, i.e., the time from infection to symptom onset. Most of the studies suggest a median incubation period of COVID-19 of 4 to 5

Table 1: Number of Switches Between Sanitary Alerts and Pre-pandemic Differences Across Municipalities.
(N= 81 and 81 Clusters)

	Number of alert switches
	(1)
Population density	0.000
	(0.000)
% Male population	-36.865
	(41.519)
% Population age 65 or above	-34.619
	(22.331)
% Population with health insurance	-16.393
	(149.159)
% Urban population	5.249
	(3.666)
% Population in poverty	9.862
	(17.977)
Income per capita (thousand CRC)	-0.136
	(0.000)
Municipality in Greater Metropolitan Area (=1)	-2.091
	(3.904)
Municipal revenues (million CRC)	0.000
	(0.000)
Municipal expenditures (million CRC)	0.000
	(0.000)
Constant	31.145
	(26.960)
Adjusted R^2	-0.035

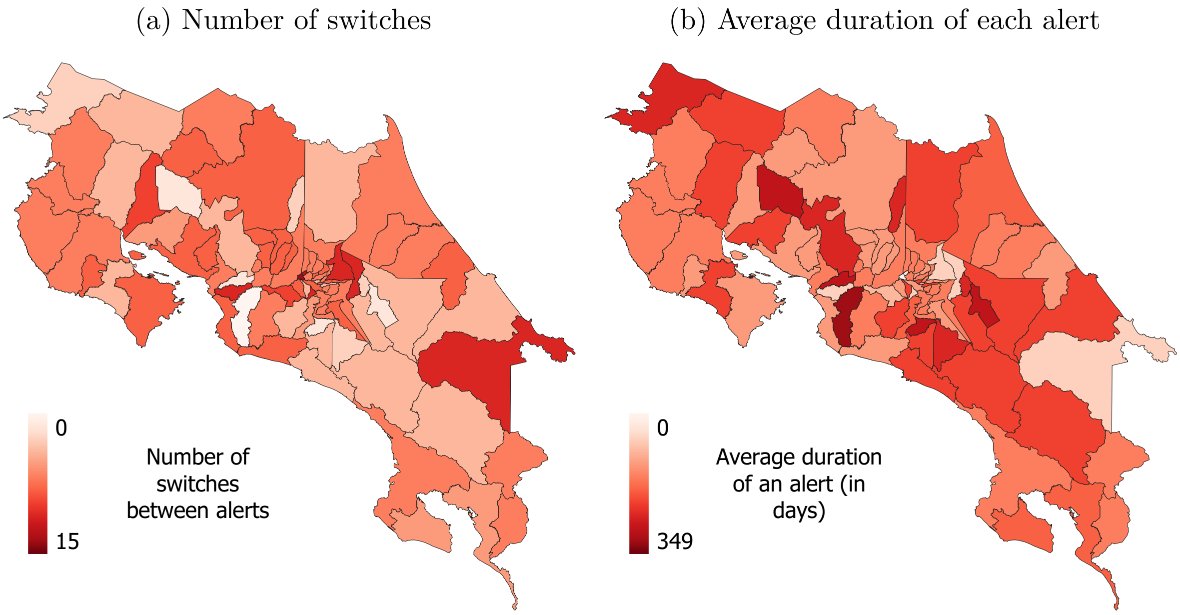
Notes: Robust standard errors, adjusted for clustering by municipality, are in parentheses. We consider only 81 municipalities to evaluate the pre-pandemic characteristics because Río Cuarto was established in 2017, and local government finance statistics are unavailable for 2019. CRC = Costa Rican colón.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Length of a Sanitary Alert by Pre-pandemic Characteristics (N= 497 and 81 Clusters)

	Confirmed cases (1)
Population density	-0.002
	(0.002)
% Male population	403.387
	(480.020)
% Population age 65 or above	341.279
	(243.961)
% Population with health insurance	169.948
	(149.159)
% Urban population	-42.813
	(32.634)
% Population in poverty	-113.339
	(171.123)
Income per capita (thousand CRC)	-0.136
	(0.321)
Municipality in Greater Metropolitan Area (=1)	17.267
	(32.634)
Municipal revenues (million CRC)	0.000
	(0.001)
Municipal expenditures (million CRC)	0.000
	(0.001)
Constant	-222.641
	(300.201)
Adjusted R^2	-0.008

Notes: Robust standard errors, adjusted for clustering by municipality, are in parentheses. We consider only 81 municipalities to evaluate the pre-pandemic characteristics because Río Cuarto was established in 2017, and local government finance statistics are unavailable for 2019. CRC = Costa Rican colón.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3: Sanitary Alert Switching and Average Alert Duration Across Municipalities.



days. (e.g., Lauer et al. 2020; Guan, Ni, Hu, Liang, Ou, He, Liu, Shan, Lei, Hui, Du, Li, Zeng, Yuen, Chen, Tang, Wang, Chen, Xiang, Li, Wang, Liang, Peng, Wei, Liu, Hu, Peng, Wang, Liu, Chen, Li, Zheng, Qiu, Luo, Ye, Zhu & Zhong (2020); McAloon et al. 2020). Moreover, there is a period of approximately two days to obtain the test result from the laboratory (Rosero Bixby 2021). Therefore, seven days can be a benchmark for when we can plausible identify any possible effects of an orange alert. Moreover, Section 5.2 shows that our results also hold under alternative timing assumptions that replicate the incubation period of COVID-19.

We also consider a vector of municipality characteristics, $\mathbf{X}_{i,t-7}$. Motivated by the Susceptible-Infected-Recovered-Dead (SIRD) model, we include as controls the logarithm of new confirmed cases and its growth rate seven days before, both at the national and municipal level. These variables allow us to account for the natural dynamics of the outbreak and to reduce the endogeneity in the alert assignment.

The vector $\mathbf{X}_{i,t-7}$ also includes as a control a population-weighted average of municipality's i immediate neighbors in an orange alert. We add this control to incorporate any possible externalities across municipalities due to the fact that, being Costa Rica a relatively small country, citizens move frequently across municipalities. Finally, β_d, β_m, and β_i corresponds to day of the week, month, and municipality fixed effects, respectively.

On the other hand, our estimation of the effect of an orange alert on the growth rate of deaths related to COVID-19 is based on the following specification:

$$\Delta log(\Delta D_{it}) = \alpha + \gamma Orange_{i,t-25} + \mathbf{X}_{i,t-25}\beta + \beta_d + \beta_m + \beta_i + \beta_m\beta_i + \varepsilon_{it} \tag{4}$$

where $\Delta log(\Delta D_{it})$ is the weekly growth rates of COVID-19-related deaths for municipality i at day t. The rest of the specification follows closely specification (3); however, now we consider alerts imposed 25 days before to match the clinical progression of COVID-19. According to many studies, the median time from exposure to symptom onset is four days; the median time from onset of illness to hospitalization is five days; the median time in a hospital ward is four days; and the median length in ICU is twelve days. The Ministry of Health also incorporates the same assumption on the clinical progression to model the COVID-19 propagation in the country (Sánchez et al. 2020). Although not necessarily after those 25 days the patient dies, we consider the period indicative of when to expect changes in deaths after a modification in a sanitary alert. Moreover, Section 5.2 shows that our results also hold under alternative timing assumptions, timing that is in line with findings in studies that estimate the time from symptom onset to decease. Despite these studies being less common, the available evidence suggests roughly three weeks from exposure to death (e.g., Linton et al. 2020; Zhou et al. 2020).

In line with the previous discussion, the vector $\mathbf{X}_{i,t-25}$ in equation (4) includes as controls the logarithm of COVID-19 related deaths and its growth rate 25 days before, both at the national and municipal level.

4.2 Costs Related to the Restrictions

To analyze the costs related to the sanitary restrictions, we estimate the specification:

$$\Delta log(y_{im}) = \alpha + \gamma Orange_{i,m} + \mathbf{X}_{i,m}\beta + \beta_i + \beta_m + \beta_i\beta_m + \varepsilon_{im} \tag{5}$$

where $\Delta log(y_{im})$ is the monthly growth rates of electricity consumption for municipality i during month m. We consider four types of electricity consumption: total, residential, commercial, and industrial. $Orange_{i,m}$ represents the fraction of the month that a municipality was under an orange alert; therefore, it ranges from 0 to 1. $\mathbf{X}_{i,m}$ is a vector containing municipality i's characteristics during month m, in particular, it contains the logarithm of monthly new confirmed cases and its growth rate, both at the national and municipal level. Finally, β_m and β_i correspond to month and municipality fixed effects, respectively.

5 Results - Benefits Related to the Restrictions

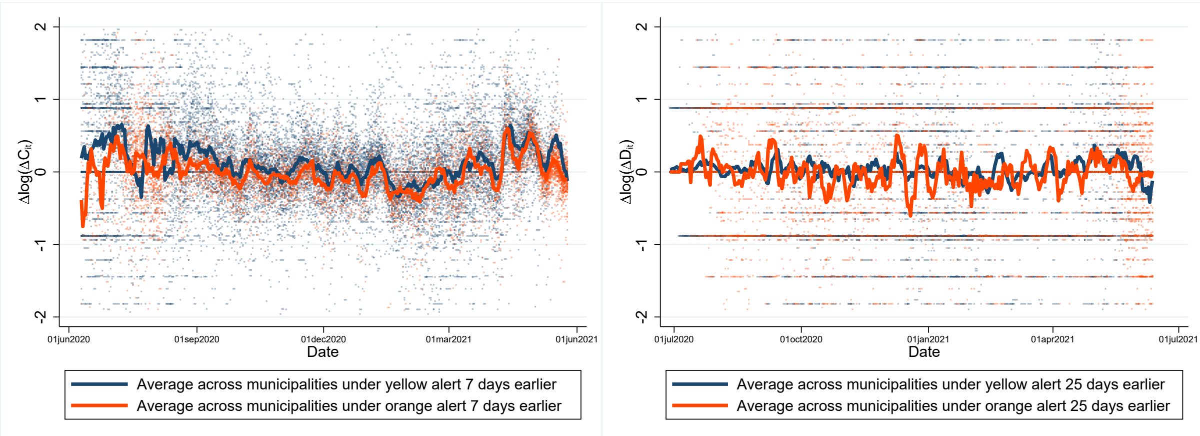
5.1 Estimates

We begin our analysis with some simple evidence of the effect of an orange alert on the number of cases and deaths growth. Figure 4 shows the weekly average number of cases and deaths conditional on whether municipalities are under an orange or yellow alert.

Following our discussion from Section 4, we take 7 and 25-day lags of alert for cases and death growth, respectively. The left panel of the figure shows that municipalities with an orange alert have on average 13 percentage points lower number of cases growth than municipalities without an orange alert. The right panel also illustrates that municipalities with an orange alert tend to have on average 4 percentage points lower number of deaths growth. Although the differences in means are statistically significant at the 1% level, these figures are merely suggestive because the patterns observed in them may be driven by confounders. Therefore, we proceed with a more formal estimate of the effect of an orange alert.

Figure 4: Weekly Growth of Confirmed Cases and Deaths Given a Sanitary Alert

(a) Confirmed cases (b) Deaths



Notes: Number of cases and deaths growth conditional on a sanitary alert. In these figures, blue points are the number of cases or deaths growth rate in municipalities in a yellow alert 7 (25 for deaths) days prior. Orange points are municipalities with an orange alert 7 (25 for deaths) days prior. The blue line is the average across municipalities in a yellow alert 7 (25 for deaths) days earlier. The orange line is the average across municipalities on an orange alert 7 (25 for deaths) days earlier.

Table 3 reports our main results for the benefits related to the restrictions after estimating equations (3) and (4). Column (1) suggests that an orange alert reduces the weekly growth rate of confirmed cases by 6.9 percent, while Column (2) indicates that an orange alert reduces the weekly growth rate of deaths by 9.5 percent. Both estimates are statistically significant at the 1% level. This confirms that the sanitary restrictions helped to contain COVID-19's spread and to reduce the number of fatalities associated with this virus.

Table 3: The Effect of an Orange Alert on Weekly Growth Rates of Confirmed COVID-19 Cases and Deaths
(N= 28,700 and 82 Clusters)

	Weekly growth rate of	
	Confirmed cases	Deaths
	(1)	(2)
lag(Orange alert, 7)	**-0.069**	
	(0.025)***	
lag(Orange alert, 25)		**-0.095**
		(0.031)***
Adjusted R^2	0.514	0.028

Notes: Fixed effects specification. Robust standard errors, adjusted for clustering by municipality, are in parentheses. All regressions include municipality-by-month fixed effects, day fixed effects, percentage of neighbor municipalities in orange alert, and the logarithm of new cases and deaths, and their growth rate, both at the national and municipal level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Robustness: Alternative Timing

As a check for the validity of our findings in Table 3, we analyze the shape of the alert's effect. To do so, we reestimate equations (3) and (4) to trace the policy's effect on individual days after it took place. Due to the virus' incubation period and its clinical progression, significant changes in the number of cases or fatalities immediately after imposing an alert are unlikely to be caused by the treatment and would cast doubt on the research design.

Figure 5 summarizes the results for the weekly growth rate of confirmed cases. At a 5% significance level, our findings suggest a delay of roughly 6 to 11 days between an alert change and a change in the number of cases. The delay is in line with the incubation period of COVID-19. According to most studies, symptoms typically appear within four or five days after infection (e.g., Lauer et al. 2020; Guan, Ni, Hu, Liang, Ou, He, Liu, Shan, Lei, Hui, Du, Li, Zeng, Yuen, Chen, Tang, Wang, Chen, Xiang, Li, Wang, Liang, Peng, Wei, Liu, Hu, Peng, Wang, Liu, Chen, Li, Zheng, Qiu, Luo, Ye, Zhu & Zhong 2020; McAloon et al. 2020).

On the other hand, Figure 6 depicts the results for the weekly growth rate of deaths. At a 5% significance level, our findings suggest a delay of roughly 19 to 33 days between setting an orange alert and a reduction in the number of deaths. Again, the pattern is consistent with the time from exposure to death found in previous studies (e.g., Linton et al. 2020; Zhou et al. 2020).

Figure 5: Alternative Timing for the Effectiveness of an Orange Alert on the Weekly Growth Rate of Confirmed Cases

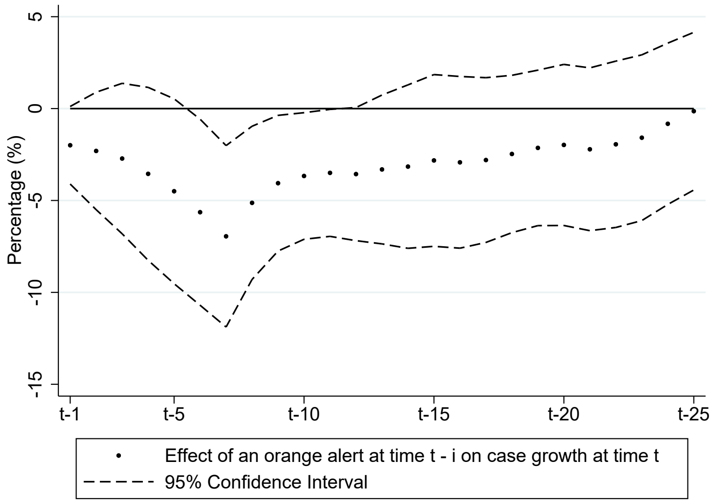
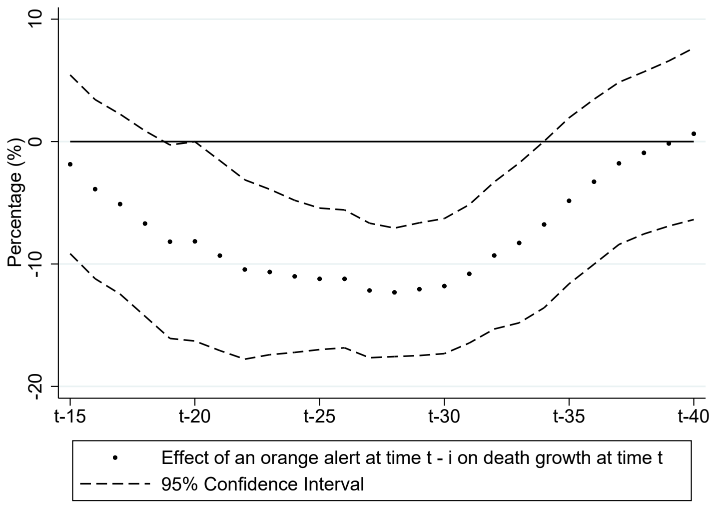


Figure 6: Alternative Timing for the Effectiveness of an Orange Alert on the Weekly Growth Rate of Deaths



5.3 Robustness: Alternative Specifications

Our main analysis of the benefits related to the restrictions yields a clear message: sanitary alerts have a significant effect on reducing the weekly growth rate of confirmed COVID-19 cases and deaths. Moreover, the shape of the effect is consistent with the dynamics of the virus. In this section, we further investigate the sensitivity of our message. Figure 7 shows the point estimate and the 95% confidence intervals for the following specifications:

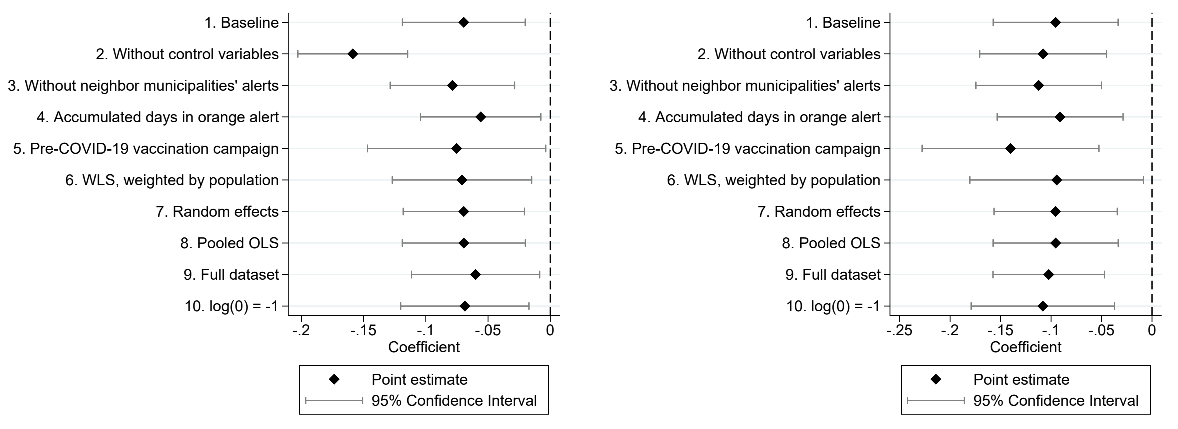
1. Baseline specification in Table 3.
2. Estimate equations (3) and (4) without any control variables.
3. Exclude the sanitary alert of neighbor municipalities.
4. Include as control the percentage of days a canton has been under orange alert during the pandemic.
5. Restrict the sample to the period before the COVID-19 vaccination campaign began. The progress of the vaccination campaign can have an impact on reducing the number of cases and deaths. However, we do not have detailed information at the municipality level to include vaccination as a control. To investigate how our results change due to the presence of the vaccination campaign, we restrict attention to the period before the campaign began, i.e., before December 24th, 2020 (Ministerio de Salud 2020).
6. Use weighted least squares estimates (WLS), weighting by municipality population.
7. Use a random effects model instead of a fixed effects model. Although the results are similar, a Hausman test rejects the appropriateness of the random effects model.
8. Use pooled ordinary least squares. We include in this specification municipality-level characteristics (population density, poverty rate, the percentage of people with health insurance, and the percentage of people living in urban areas).
9. Consider the full dataset, i.e., from March 15th, 2020, to July 31st, 2021.
10. Assume that $log(0) = -1$, instead of the inverse hyperbolic sine transformation, to deal with the presence of zeros in our data.

Figure 7 illustrates that our main message is robust to alternative specifications: the estimated coefficients of the orange alert are negative and significant at the 5% level for both the number of cases and the number of deaths. This confirms the relevance of the restrictions on reducing the incidence of COVID-19 and its negative effects.

Note that the point estimate associated with Specification 2., where we omit the control variables, indicates a stronger effect of the sanitary restrictions, especially for the growth rate of the number of confirmed cases. This result highlights the need of including the control variables to reduce endogeneity concerns and to avoid overestimating the impact of the sanitary alerts.

Figure 7: Alternative Specifications for Benefits Related to the Restrictions

(a) Confirmed cases (b) Deaths



5.4 Mechanism

We now investigate which restrictions have the most impact on explaining the reduction in the growth rate of cases and deaths. For this, we use the data we hand-collected from official reports on the implemented policies and estimate the specification:

$$\Delta log(\Delta C_{it}) = \alpha + \mathbf{\Phi}_{i,t-7}\gamma + \mathbf{X}_{i,t-7}\beta + \beta_d + \beta_m + \beta_i + \beta_m\beta_i + \varepsilon_{it} \tag{6}$$

for the weekly growth rate of confirmed cases, and

$$\Delta log(\Delta D_{it}) = \alpha + \mathbf{\Phi}_{i,t-25}\gamma + \mathbf{X}_{i,t-25}\beta + \beta_d + \beta_m + \beta_i + \beta_m\beta_i + \varepsilon_{it} \tag{7}$$

for the weekly growth rate of deaths. The main difference with respect to specifications (3) and (4) is that we include, instead of our orange alert variable, a vector of sanitary measures $\mathbf{\Phi}_{i,t-j}$, where $j = 7$ for confirmed cases and $j = 25$ for deaths.

Table 4 reports the results. Compared to the scenario where 100% of license plates can circulate, restricting two last digits per day reduces roughly 9 percent the growth rate of confirmed cases and 8 percent the growth rate of deaths. A restriction of half of the last digits does not seem to have a significant impact. Nevertheless, in Costa Rica, this restriction has been implemented mainly on weekends, so its effects might be captured by the day of the week fixed effects. Finally, the most restricting measure of allowing only two last digits to circulate reduces 13 percent the growth rate of confirmed cases but does not significantly affect the growth rate of deaths.[2]

[2] In our baseline period, the government has only implemented this measure for ten days in 34% of the municipalities.

Besides the percentage of plates that can circulate, the fraction of the day that vehicles cannot circulate seems to have a significant effect. The stronger restriction in this regard has been a limit of twelve driving hours per day. This measure implies a reduction in the growth rates of cases and deaths of 35 and 30 percent, respectively. It is important to note that most of the time the driving restriction coincides with the hours that business can operate; therefore, this result captures the joint effect of both restrictions.

Table 4: The Effect of Policies on Weekly Growth Rates of Confirmed COVID-19 Cases and Deaths
(N= 28,700 and 82 Clusters)

	Weekly growth rates of	
	Confirmed cases	Deaths
	(1)	(2)
100% of license plates can circulate	vs.	vs.
80% of license plates	**-0.090**	**-0.082**
	(0.018)***	(0.025)***
50% of license plates	**-0.001**	**-0.034**
	(0.014)	(0.018)*
20% of license plates	**-0.131**	**0.038**
	(0.044)***	(0.096)
Fraction of day that vehicles cannot circulate	**-0.690**	**-0.592**
	(0.158)***	(0.181)***
Adjusted R^2	0.521	0.032

Notes: Fixed effects specification. Robust standard errors, adjusted for clustering by municipality, are in parentheses. All regressions include municipality-by-month fixed effects, day fixed effects, percentage of neighbor municipalities in orange alert, and the logarithm of new cases and deaths, and their growth rate, both at the national and municipal level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Results - Costs Related to the Restrictions

6.1 Estimates

Table 5 reports our main results for the costs related to the restrictions. We consider four different categories for electricity consumption growth: total, residential, commercial, and industrial. While the magnitude of the point estimate of sanitary restrictions on total and residential consumption growth does not appear relevant, its effect on commercial and industrial use is more important. However, the effect on industrial consumption is not statistically distinct from zero at conventional levels across all the robustness checks. All in all, our analysis suggests that sanitary restrictions appear to have mainly a significant impact on commercial electricity. Our estimation shows that imposing an orange alert rather than a yellow one reduces monthly commercial electricity use growth by 1.5 percent. Given the elasticity between economic activity and commercial electricity use in Appendix A, this reduction corresponds to approximately a fall of 1.88% in economic activity.

Table 5: The Effect of an Orange Alert on Monthly Electricity Consumption Growth (N= 822 and 82 Clusters)

	Monthly growth rate of electricity consumption			
	Total	Residential	Commercial	Industrial
	(1)	(2)	(3)	(4)
Orange alert	**-0.005**	**-0.007**	**-0.015**	**-0.060**
	(0.009)	(0.006)	(0.008)*	(0.033)*
Adjusted R^2	0.473	0.714	0.543	0.314

Notes: Fixed effects specification. Robust standard errors, adjusted for clustering by municipality, are in parentheses. All regressions include municipality-by-month fixed effects, percentage of neighbor municipalities in orange alert during the month, and the logarithm of new cases and deaths, and their growth rate, both at the national and municipal level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

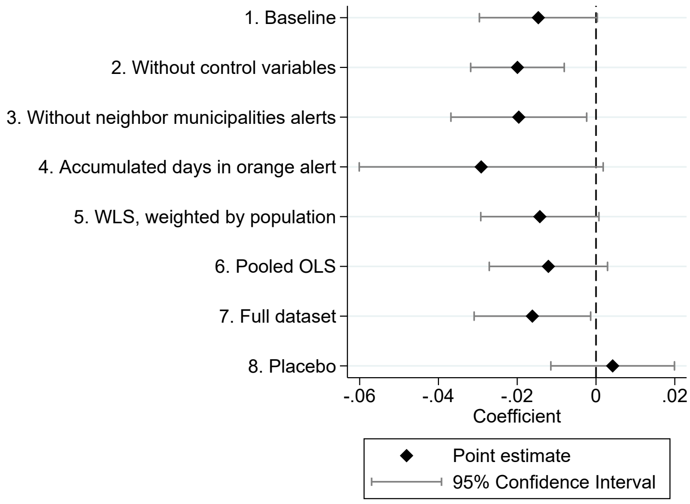
6.2 Robustness: Alternative Specifications

The analysis of the costs related to the restrictions suggests that sanitary alerts have a significant effect on reducing the monthly growth rate of commercial electricity consumption. In this section, we investigate the robustness of our conclusions. We focus on the impact of the restrictions on commercial electricity consumption, and present the corresponding estimates for the other types of electricity consumption in Appendix D. Figure 8 shows the point estimate and the 95% confidence intervals for the following specifications:

1. Baseline specification in Table 5.
2. Estimate equation (5) without any control variables.
3. Exclude the sanitary alert of neighbor municipalities.
4. Include as control the percentage of days a canton has been under orange alert during the pandemic.
5. Use weighted least squares estimates (WLS), weighting by municipality population.
6. Use pooled ordinary least squares. We include in this specification municipality-level characteristics (population density, poverty rate, the percentage of people with health insurance, and the percentage of people living in urban areas).
7. Consider the full dataset, i.e., from March 15th, 2020, to July 31st, 2021.
8. Estimate a placebo test where we explore the capacity of an orange alert in month t to explain electricity consumption in month $t-1$.

Figure 8 illustrates that, except for the placebo test, the estimated coefficient for the cost related to the restrictions is negative and significant at the 10% level in most specifications. For the placebo, the estimate suggests that an orange alert at time t cannot explain commercial electricity consumption at time $t-1$, confirming that we are effectively measuring the effect of the restrictions.

Figure 8: Alternative Specifications for Costs Related to the Restrictions - Commercial Electricity Consumption



6.3 Robustness: Point of Sale Transaction Data

As an alternative to using electricity consumption data for approximating the costs of the sanitary restrictions, we reestimate equation (5) using as the dependent variable the monthly growth rate of point of sale transactions.

Table 6 presents the results, that are in line with the previous findings. A municipality in orange alert during the whole month experiences a reduction of 3.52% in the growth rate of point of sale transactions. This reduction is significant at the 1% level. Given the elasticity between economic activity and point of sale transactions obtained in Appendix B, a decrease of 3.52% in card transactions corresponds to a reduction in terms of economic activity of about 2.77%.

Table 6: The Effect of an Orange Alert on Point of Sale Transactions Growth (N= 894 and 81 Clusters)

	(1)
Orange alert	**-0.035**
	(0.013)***
Adjusted R^2	0.843

Notes: Fixed effects specification. Robust standard errors, adjusted for clustering by municipality, are in parentheses. All regressions include municipality-by-month fixed effects, percentage of neighbor municipalities in orange alert during the month, and the logarithm of new cases and deaths, and their growth rate, both at the national and municipal level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.4 Mechanism

Similar to the benefits, we study which restrictions have the most impact on explaining the reduction in the growth rate of electricity consumption. In particular, for each type of electricity consumption we estimate:

$$\Delta log(y_{im}) = \alpha + \mathbf{\Phi}_{i,m}\gamma + \mathbf{X}_{i,m}\beta + \beta_i + \beta_m + \beta_i\beta_m + \varepsilon_{im} \tag{8}$$

where $\mathbf{\Phi}_{i,m}$ is a vector of sanitary measures in municipality i during month m.

Table 7 display the results. Column (1) displays total electricity consumption growth, whose coefficients do not show any consistent pattern or statistical significance. Column (2) corresponds to residential electricity consumption. Although the coefficients are not always significant, their positive magnitude suggests that the sanitary policies led to spending more electricity at home, which is consistent with people staying more at home. Column (3) refers to commercial electricity consumption. The percentage of plates allowed to circulate seems to have a negative and statistically significant effect on commercial activity. This is consistent with people staying at home and reducing the number of shopping visits to retail and commercial shops. Lastly, Column (4) suggests no significant effect of the sanitary restrictions on industrial electricity consumption.

Table 7: The Effect of Policies on Monthly Electricity Consumption Growth
(N = 822 and 82 Clusters)

	Monthly growth rate of electricity consumption			
	Total	Residential	Commercial	Industrial
	(1)	(2)	(3)	(4)
100% of license plates can circulate	vs.	vs.	vs.	vs.
80% of license plates	**-0.074**	**0.089**	**-0.518**	**0.016**
	(0.064)	(0.035)***	(0.052)***	(0.147)
50% of license plates	**0.195**	**0.081**	**-0.359**	**0.163**
	(0.231)	(0.070)	(0.111)***	(0.385)
20% of license plates	**-0.274**	**0.058**	**-0.667**	**0.075**
	(0.120)**	(0.080)	(0.123)***	(0.372)
Fraction of day that vehicles cannot circulate	**0.259**	**0.026**	**0.163**	**0.395**
	(0.150)	(0.103)	(0.184)	(0.409)
Adjusted R^2	0.475	0.713	0.542	0.310

Notes: Fixed effects specification. Robust standard errors, adjusted for clustering by municipality, are in parentheses. All regressions include municipality-by-month fixed effects, percentage of neighbor municipalities in orange alert during the month, and the logarithm of new cases and deaths, and their growth rate, both at the national and municipal level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Concluding Remarks

Around the world, the COVID-19 pandemic has pushed governments to adopt various policies to slow down the spread of the disease. However, the possible health benefits come at a cost in terms of a reduction in economic activity. This paper uses variation in the sanitary restriction across municipalities in Costa Rica to assess its impact on economic activity, confirmed cases, and deaths.

Our analysis offers evidence that sanitary measures reduced the weekly growth rate of confirmed cases by 7% and of deaths associated with COVID-19 by 10%. In addition, the results suggest there is a delay of 6 to 11 days between a change in the sanitary alert level and a reduction in the number of confirmed cases, and of 19 to 33 days between a change in the sanitary alert level and a reduction in the number of deaths. This pattern is in line with the natural dynamics of the disease, given its incubation period and clinical progression.

Then, we use electricity consumption to approximate the effect of the restrictions on economic activity. Our findings suggest that the preventive measures reduce monthly commercial electricity growth by roughly 1.5% and of the value of card transactions by 3.52%. These reductions suggest a negative effect in economic activity between 1.88% and 2.77%.

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A Appendix. Electricity Consumption and Economic Activity

Table 8: Relationship Between Economic Activity and Electricity Consumption Between July 2019 and April 2021 (N= 1,782 and 81 Clusters)

	log(VAT)			
	(1)	(2)	(3)	(4)
log(Total electricity consumption)	**1.364**			
	(0.083)***			
log(Residential electricity consumption)		**1.525**		
		(0.114)***		
log(Commercial electricity consumption)			**1.255**	
			(0.083)***	
log(Industrial electricity consumption)				**0.785**
				(0.080)***
Adjusted R^2	0.769	0.683	0.751	0.463

Notes: Robust standard errors, adjusted for clustering by municipality, are in parentheses. All regressions include month fixed effects. VAT = Valued Added Tax.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Appendix. Point of Sale Transactions and Economic Activity

Table 9: Relationship between Point of Sale Transactions and Economic Activity between July 2019 and April 2021 (N= 1,782 and 81 Clusters)

	log(VAT)
	(1)
log(POS transactions)	**0.787**
	(0.052)***
Adjusted R^2	0.746

Notes: Robust standard errors, adjusted for clustering by municipality, are in parentheses. All regressions include month fixed effects. POS = Point of Sale. VAT = Valued Added Tax.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Appendix. Number of Switches and Pre-pandemic Differences Between Municipalities

Table 10: Number of Switches Between Alerts and Pre-pandemic Differences Across Municipalities.
(N= 81 and 81 Clusters)

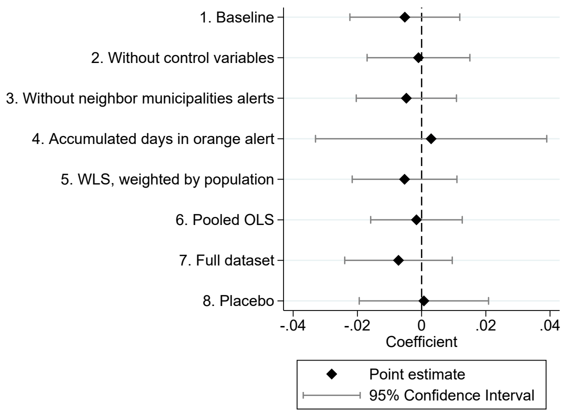
	Number of alert switches	
	(1)	(2)
Population density	0.000	0.000
	(0.000)	(0.000)
% Male population	-8.003	-8.030
	(7.813)	(7.912)
% Population age 65 or above	-7.090	-7.079
	(4.236)*	(4.272)*
% Population with health insurance	-3.561	-3.536
	(2.926)	(2.930)
% Urban population	1.037	1.034
	(0.656)	(0.658)
% Population in poverty	2.036	2.003
	(3.167)	(3.188)
Income per capita (thousand CRC)	0.003	0.002
	(0.006)	(0.006)
Municipality in Greater Metropolitan Area (=1)	-0.386	-0.383
	(0.650)	(0.654)
Municipal revenues (million CRC)	0.000	0.000
	(0.000)	(0.000)
Municipal expenditures (million CRC)	0.000	0.000
	(0.000)	(0.000)
Constant	7.379	7.395
	(5.049)	(5.108)

Notes: Robust standard errors, adjusted for clustering by municipality, are in parentheses. We consider only 81 municipalities to evaluate the pre-pandemic characteristics because Río Cuarto was established in 2017, and local government finance statistics are unavailable for 2019. Column (1) uses a Poisson regression model, while Column (2) uses a negative binomial regression model. CRC = Costa Rican colón.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

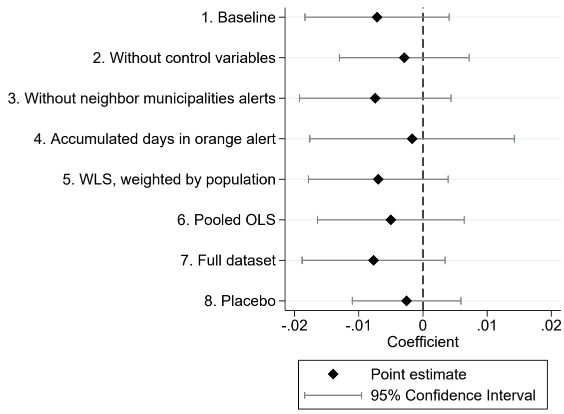
D Appendix. Costs Related to the Restrictions - Robustness: Alternative Specifications

Figure 9: Alternative Specifications for Costs Related to the Restrictions

(a) Total Electricity Consumption



(b) Residential Electricity Consumption



(c) Industrial Electricity Consumption