All Things Equal?
Heterogeneity in Policy Effectiveness against COVID-19 Spread in Chile

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Abstract

A number of variables affect the evolution and geographic spread of COVID-19. Some of these variables pertain to policy measures such as social distancing, quarantines for specific areas, and testing availability. In this paper, I analyze the effect that lockdown and testing policies had on new contagions in Chile, specially focusing on potential heterogeneity given by population characteristics. Using an Augmented Synthetic Control Method, I find substantial differences in the impact that quarantine policies had for different populations: While lockdowns were highly effective in containing and reducing new cases of COVID-19 in higher-income municipalities, I find no significant effect of this measure for lower-income areas. These differences could be partially attributed to heterogeneity in quarantine compliance, as well as differential testing availability for higher and lower income areas.

Keywords: Augmented Synthetic Control; Causal Inference; COVID-19; Observational Study

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1. Introduction

Like in most countries, the COVID-19 pandemic in Chile has deeply disrupted all aspects of daily life, starting from the way we approach the health care system, to job security, education, and even how we mobilize, among many others. Mitigating measures have become essential for preventing massive outbreaks and reducing systemic stress in hospitals and clinics. However, some of these measures may have had differential effects depending on the population characteristics.

In this paper, I provide evidence of heterogeneity in the effectiveness of quarantines or lockdowns at the municipality level in Chile during the first two months of the pandemic. I also shed light on some of the reasons that could explain these differential effects, such as the probability of compliance with lockdown measures by area, as well as differences in testing availability. The Chilean context provides a particularly rich setting to analyze the effectiveness of lockdown measures, as quarantines were implemented during the first two months of the pandemic at the municipality level. Municipalities are some of the smallest areas that have experienced quarantine in comparison to other countries, and allows me to analyze differential effects even within a city. Leveraging data for small lockdown areas and an Augmented Synthetic Control Method approach, I build a counterfactual for higher and lower-income municipalities that entered quarantine from a pool of untreated areas that resemble the evolution pattern of the treated units before the policy was implemented, finding substantial differences in the effectiveness of quarantine measures by income.

Understanding the effectiveness of containment measures is of critical importance during a pandemic, but not only its impact *on average*, but also for specific populations of interest. In terms of policy evaluations, average treatment effects are often of limited value as they hide potential negative or null effects for groups of interest (Imai & Ratkovic, 2013). In the case of quarantine policies, if certain populations are less likely to comply with lockdown measures due to differences in opportunity costs of staying at home, or asymmetry in information in terms of infections, then it is important to put in place complementary measures that will improve compliance.

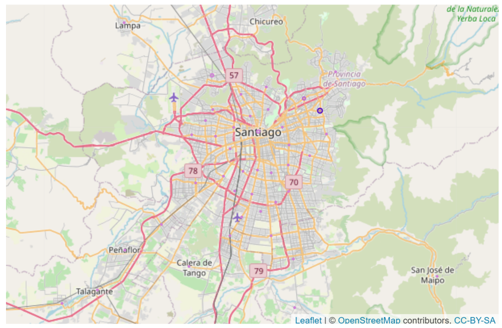
Evidence related to the effectiveness of lockdown or shelter-in-place measures has been mixed: While some research has found overall positive effects of quarantine policies (Dave et al., 2020; Fowler et al., 2020; Ullah & Ajala, 2020; Coven & Gupta, 2020), others find little evidence supporting these claims (Born et al., 2020; Gupta et al., 2020). In Chile, Cuadrado et al. (2020) find a positive effect related to quarantine measures, but like previous studies, it analyzes changes for a general population in a specific region, which does not necessarily identify the heterogeneity of the effect within smaller areas that differ in socioeconomic conditions. Given that measures that are effective for certain groups might not have the same effect on others, estimating the impact of some of these measures by income level can provide relevant feedback for policymakers to understand how to better target and complement current policies.

This paper is structured as following. Section 2 provides context of the Chilean case and the measures implemented to fight the spread of COVID-19. Section 3 outlines the augmented synthetic control method used for estimating the effects of lockdown policies by income at the municipality level and its results. In section 4, I discuss potential mechanisms that could explain part of the differential effectiveness of quarantines. Finally, section 5 concludes with some final remarks and further discussion.

2. COVID-19 and the Chilean Context

The spread of COVID-19 in Chile started slowly, with its first confirmed COVID-19 case on March 3rd, 2020. During the first weeks of the pandemic, most of the spread of the virus was contained in the east side of Santiago, in the Metropolitan Region, which is the most affluent area of the city. However, by mid-April, the virus had already spread throughout the city, as it can be seen in Figure 1.

To try to mitigate the spread of the virus, the Chilean government declared



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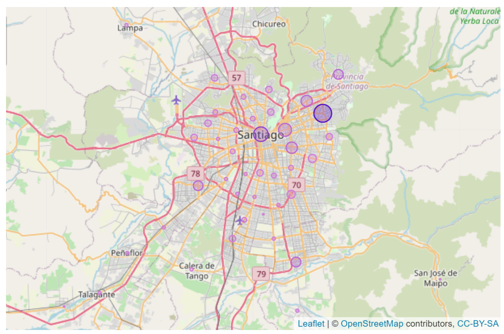

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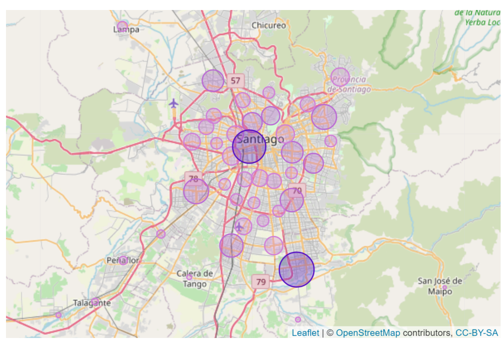


(c) Week 04/12/20 to 04/18/20

Figure 1: Number of total confirmed cases for different weeks during the COVID-19 pandemic in Santiago, Chile

the first lockdowns during the final week of March[2] in 7 municipalities of the

[2] Only two other municipalities had been in quarantine before March 25th: Caleta Tortel and Rapa Nui. Caleta Tortel is a remote and small southern municipality which declared an

Metropolitan Region, and a few other cities across the country. The second wave of quarantines were around mid-April, which included three municipalities. Finally, by the end of April, three additional municipalities in Santiago entered lockdown. Figure 2 shows the location of the different quarantines in the Metropolitan Region by timing, and Table 4 in the Appendix shows the exact dates municipalities went into and out of lockdown. To provide some context on the units of analysis, Chile has 346 municipalities in total, which drastically vary in size: from a couple of hundred residents to over 500,000 in 2017 (Biblioteca del Congreso Nacional de Chile, 2017). The capital city, Santiago, is composed of 40 municipalities and concentrates the majority of the country's population.

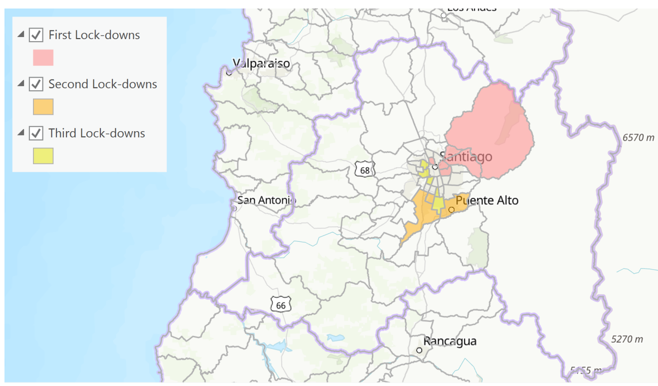


Figure 2: Municipalities that were in lockdown at different times during March and April in the Metropolitan Region (First lockdowns: started March 26th; Second lockdowns: started April 9th-16th; Third lockdowns: started April 23rd-30th)

In terms of the restrictions that lockdown measures posed on residents, if a municipality (or part of a municipality) was declared on quarantine, people that lived in that area could not leave their residence without a legal authorization. Additionally, non-residents were not allowed to transit in quarantined areas either. Essential services were still open during this time.

early quarantine due to cruise ship arriving with a confirmed case. Rapa Nui, or Easter Island, is an island far from the coast of Chile, and took early precautions after its firsts confirmed cases.

3. Effect of Quarantines

3.1. An Augmented Synthetic Control Method Approach

To assess the effect that quarantines had on the evolution of new cases at the municipality level, a natural approach would be to compare treated areas with those that are similar, but were not affected by lockdowns, assuming that conditional on some observable features, the assignment of quarantines was random. In this context, Synthetic Control Method lends itself nicely to estimate a causal effect of these policies (Athey & Imbens, 2017).

Synthetic Control Method (SCM) is a popular approach in causal inference settings that, under certain assumptions, provides a valid counterfactual for a unit which was treated at a specific point in time (Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015). SCM uses a weighted combination of untreated units from a donor pool to build a "synthetic" version of the treated one that resembles its behavior prior to the intervention. Some of the main advantages of the SCM are that it does not rely on extrapolation (weights are non-negative and sum to one), and that it is a transparent method in the sense that makes differences between treatment and its counterfactual explicit, as well as the contribution of each of the control units (Abadie, 2019).

Following the same line as traditional SCM, but also leveraging the fact that I have a staggered desing, where multiple municipalities entered lockdown at different points in time, I use the Augmented Synthetic Control Method (ASCM) proposed by Ben-Michael et al. (2020). The main advantage of ASCM over traditional synthetic control methods is that it provides "bias correction" when pre-treatment fit is imperfect. This bias correction means that even when the synthetic control does not closely follow the path of the treatment group in the pre-intervention period, ASCM provides a method to de-bias the original SCM estimate using, for example, a ridge-regularized linear regression as an outcome model. The trade-off in this case is that ASCM allows non-negative weights to improve pre-treatment fit, but the method focuses on minimizing extrapolation outside the convex hull.

In SCM and ASCM settings, three assumptions need to hold to estimate a valid average treatment effect on the treated: i) assignment of the treatment is random conditional on the donor pool, observable covariates, and pre-intervention path of the outcome, ii) Stable Unit Treatment Value Assumption (SUTVA), and iii) the intervention had no effect prior to its start date.

The first assumption relates to the idea that synthetic control methods use a weighted average of units from the donor pool to build an estimate of the missing potential outcome, and those units are chosen based on pre-intervention fit. Overall, the decision of declaring quarantine in a municipality depended on diverse factors, but the most important one was the progression of the spread: Areas with higher number of total cases and increasing number of new cases were likely candidates for this policy. However, decisions had a political component as well, which provides a level of exogeneity to the decision that makes the conditional ignorability assumption likely to hold in this setting. For example, when the first lockdowns were declared in March 25th, there were three other municipalities not affected that had the same or even a higher number of total cases than most of the areas that entered quarantine, and actually the municipality of Independencia, which entered early lockdown, was just top 30 in number of cummulative cases. The story is similar when we look at daily new cases: 3 out of the top 10 municipalities with the highest number of daily cases on March 25th did not experience quarantine. These three municipalities were also located high in the ranking of total cases, and are high-density population areas.

The second assumption, SUTVA, implies that the intervention only affects the treated units and does not affect non-treated municipalities. The geographic nature of lockdowns, however, might make this assumption less likely to hold: If residents from a municipality on lockdown were more likely to leave and mobilize to nearby areas that were not subjected to quarantines, these spillovers would break SUTVA. To avoid potential effects on neighboring municipalities, I build a buffer zone around treated units using the areas that would be more likely to experience spillovers due to quarantines, and exclude these zones from the donor pool. I also exclude two coastal municipalities (Vina del Mar and Concon), given that they are a common second-home destination for residents of Santiago.

Regarding the final assumption, anticipation effects could potentially play a role in the estimation of the effect of lockdowns if there is an important lag between the announcement of the measure and the start of quarantines. Given that people usually need to prepare for a quarantine, it is not uncommon to see surges in mobility in the period between the announcement and the beginning of lockdowns. In the case of Chile, the first and second waves of quarantines were announced one and two days before their implementation, respectively.[3] Even though the period between announcement and enforcement is short, I use the day of announcement as the starting period of treatment, to avoid potential confounding.

3.2. Main Results

To estimate effects of lock-downs on new cases over time, I use publicly available data from the Ministry of Health (Departamento de Epidemiologia, 2020) on number of new cases by municipality over time. Because these reports are only delivered every 2 to 3 days, I rely on interpolation to build daily data based on daily regional contagion rates, closely approximating the number of daily cases at the municipality level.[4]

For analyzing heterogeneous effects by income at the municipality level, I take three sets of municipalities for the period between March 15th and May 8th: 1) high-income areas that had quarantines prior to April 30th, 2020 in the capital city, 2) lower-income areas that had quarantines prior to the same date in the same region, and 3) other large municipalities that did not have lockdown measures before April 30th.[5] The latter group serves as the "donor" pool or

[3] For Puente Alto, the measure was announced on April 7th and enforced on April 9th.

[4] The idea of interpolation and its implementation was first suggested by Jorge Perez, who also made his data publicly available.

[5] Municipalities in the high-income group include: Las Condes, Lo Barnechea, Nunoa, Providencia, and Vitacura, while the areas in the lower-income group include: El Bosque,

counterfactual pool for the first two. Average characteristics for these different groups are shown in Table 1.

Table 1: Characteristics for municipalities groups

	Quarantined		Donor Pool	
	High-income	Low-income	Met. Region	Not in Met. Region
Population	191,910	296,713	164,470	181,845
Income per capita	$1,161,548	$331,131	$354,091	$310,308
Poverty rate	0.009	0.077	0.053	0.085
Public health care rate	0.321	0.774	0.775	0.808

Source: Observatorio Social (2017)

Table 2 and Figure 3 show the overall effect of quarantines on number of new cases over time for all municipalities that had quarantines in the Metropolitan Region. I use a 12-day mark to assess the effectiveness of the quarantine, because that is the number of days needed for most people to develop symptoms (Lauer et al., 2020). Figure 3 shows that after the 12 days since the start of the lockdown period, treated municipalities experience lower number of new cases over time, though the difference is not statistically significance at conventional levels and the magnitude of the effect is also modest.

This seemingly positive result, however, hides an important degree of heterogeneity in terms of effectiveness of quarantines. When I analyze higher-income municipalities in Santiago compared to other municipalities, we can see that the results differ by socioeconomic level (Figure 4).

Figure 4a shows the effect in difference of new cases over time for high-income municipalities. After the 12-day mark, there is a significant drop in

Independencia, Puente Alto, San Bernardo, and Santiago. The donor pool consists of municipalities that did not have quarantine at any point before April 30th, and that have a population of 70,000 residents or more. Municipalities that entered lockdown between April 30th and May 8th were also excluded, as they do not provide enough post-quarantine time for analysis.

Table 2: Estimated Average Treatment Effect on the Treated using ASCM for days 12 to 18 after start of lockdown

Days since Lock-Down Started	All	High-income	Lower-income
12	0.523	-3.769	5.996
	(2.687)	(1.601)	(5.03)
13	-0.889	-4.656	4.216
	(2.936)	(2.912)	(2.954)
14	1.003	-4.996	4.435
	(3.24)	(5.545)	(3.173)
15	0.489	-4.408	5.389
	(5.289)	(7.622)	(6.157)
16	-1.959	-9.9	4.898
	(4.147)	(4.712)	(5.203)
17	-2.503	-6.718	2.038
	(3.286)	(2.67)	(4.374)
18	-1.299	-8.179	3.057
	(5.684)	(3.634)	(4.332)
19	-0.955	-5.559	1.225
	(3.219)	(4.524)	(2.801)
20	-1.666	-5.666	0.69
	(4.086)	(3.964)	(4.807)
21	-1.716	-6.788	3.981
	(6.24)	(6.92)	(6.354)
Scaled Imbalance	0.16	0.312	0.13
Num. leads	23	45	23
Num. lags	32	10	32

Note: Standard errors in parentheses.

the number of new cases in comparison to the synthetic version of high-income municipalities. By the end of the series, confidence intervals are too wide and I

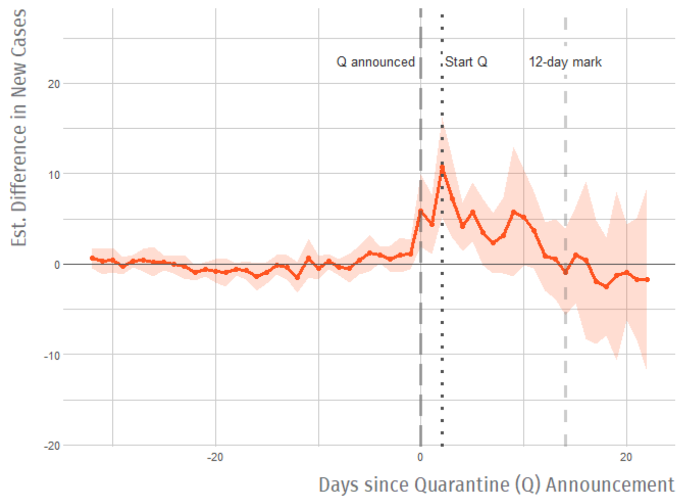


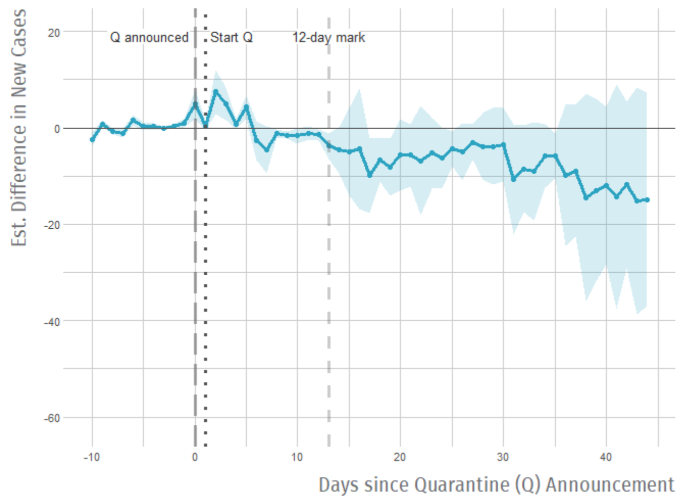
Figure 3: Estimated difference in number of new cases pre- and post-quarantine for municipalities in Chile using Augmented Synthetic Control Method (90% CI in shaded region)

do not have enough statistical power to reject a null effect, but the pattern shows a decreasing effect over time which is encouraging in terms of the effectiveness of lockdown measures.

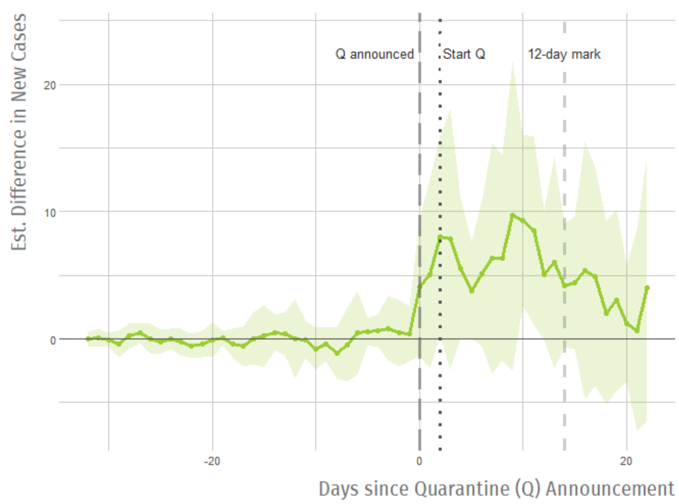
However, Figure 4b shows another side of the story. In this case, even though the effect is not statistically significant at 10% level, the estimate is opposite to what we would expect: there is an increase in number of new cases over time even after the 12-day mark. In this case, given that some lower-income municipalities entered lockdown later in time, the post-quarantine period of analysis is shorter compared to higher-income municipalities. However, the same results stand when using only early-adopters of quarantines for the lower-income group.

3.3. Robustness Checks

One potential concern for the identification of causal effects in this case would be that people change their mobility patterns from one municipality in lockdown to a neighboring area which is not in quarantine, breaking SUTVA.



(a) Estimated difference in number of new cases pre- and post-quarantine for high-income municipalities in the Metropolitan Region



(b) Estimated difference in number of new cases pre- and post-quarantine for lower-income municipalities in the Metropolitan Region

Figure 4: Estimated difference in number of new cases pre- and post-quarantine by income using Augmented Synthetic Control (90% CI in shaded region)

To avoid confounding the effect with potential spillovers, I run a robustness check of the ASCM by including a buffer zone around treated municipalities, which are excluded from the control pool (see Appendix for a map of the buffer zones). Results are shown in Table 3, and they are very similar to the original estimated average treatment effects on the treated for both groups.

Finally, as it was previously mentioned, another concern in terms of comparison of the effects between high- and lower-income municipalities is the timing of the lockdowns. If lower-income areas were systematically treated later in the pandemic, it could be the case that the timing factor is confounding my results. To avoid this potential issue, I only compare high- and lower-income municipalities that were treated roughly at the same time, using the same set of high-income areas, but only Santiago and Independencia as lower-income municipalities. Conclusions remain unchanged, as overall effects of lockdown measures were not effective in Santiago or Independencia, lower-income areas that were subject to quarantine at the same time that high-income municipalities (Figure 5).

Table 3: Estimated Average Treatment Effect on the Treated using ASCM for days 12 to 18 after start of lockdown excluding buffer municipalities

Days since Lock-Down Started	High-income	Lower-income
12	-3.661	7.864
	(2.063)	(7.019)
13	-5.638	7.863
	(3.536)	(6.031)
14	-5.171	9.723
	(9.727)	(8.492)
15	-4.815	13.545
	(12.777)	(10.626)
16	-6.496	11.424
	(5.905)	(9.367)
17	-5.005	7.749
	(3.551)	(7.358)
18	-5.82	6.265
	(4.619)	(5.395)
19	-7.52	2.12
	(6.853)	(5.602)
20	-6.897	1.829
	(6.423)	(5.503)
21	-4.661	7.427
	(10.941)	(6.511)
Scaled Imbalance	0.317	0.182
Num. leads	45	23
Num. lags	10	32

Note: Standard errors in parentheses.

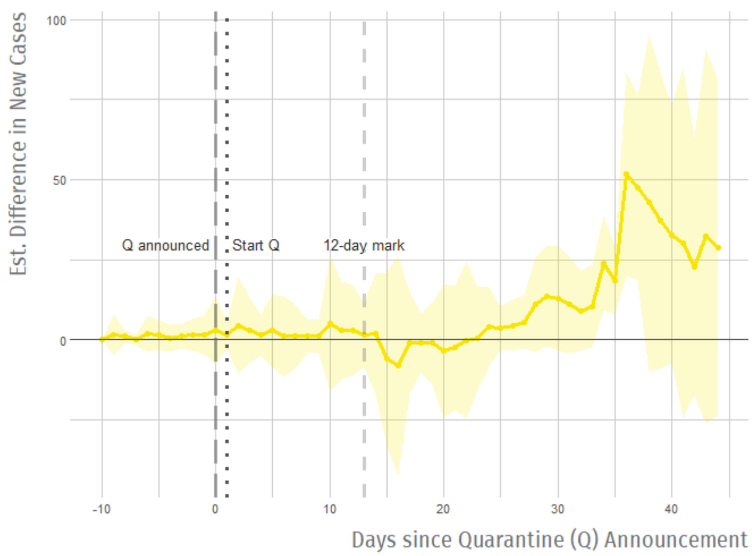


Figure 5: Estimated difference in number of new cases pre- and post-quarantine for early-entrance, lower-income municipalities using Augmented Synthetic Control Method (90% CI in shaded region)

4. Mediating Factors for Differential Effects

In this section, I study two different, but potentially complementary, hypotheses that could explain the heterogeneity in the effect of lockdowns on the number of new infections. The first one relates to the differential ability of households to stay at home during a lockdown, and the second one to the availability and timing of testing in different municipalities.

4.1. Mobility during lockdowns

Mobility has been highly reduced during the pandemic, both because of individual changes in behavior, but most importantly due to government policies aimed at avoiding contagion. Figure 6 shows data from Google Mobility Reports for the Metropolitan Region, which compares number of visitors to transit stations over time between mid-February and early May to a baseline prior to the pandemic.[6] I focus on transit data, as it is a measure that most likely approximates mobility to and from work during labor days. As Figure 6 shows, the biggest drop in mobility was given by closure of schools, with a 56% decrease. After that, there are no clear changes in mobility rates considering the active quarantines in Santiago. Excluding the day right before and after quarantines, there is no distinctive change in mobility for labor days when only the first wave of lockdowns was in place (i.e. high-income municipalities plus Santiago and Independencia), and when the second one started during that same period (i.e. half of the municipality of Puente Alto).

Given that quarantines were targeted to specific areas in the Metropolitan Region and were not widespread, it is possible that the aggregated mobility map is hiding movement reductions for those areas. To test potential differences, I use data from the Mobility Index Report created by the Data Science Institute from UDD and Telefonica (Universidad del Desarrollo, 2020) to analyze changes in mobility before and after quarantine, using the same Augmented Synthetic Control Method described in the previous section. The mobility index presented

[6]Baseline consists of the period between January 3rd, 2020 and February 6th, 2020.

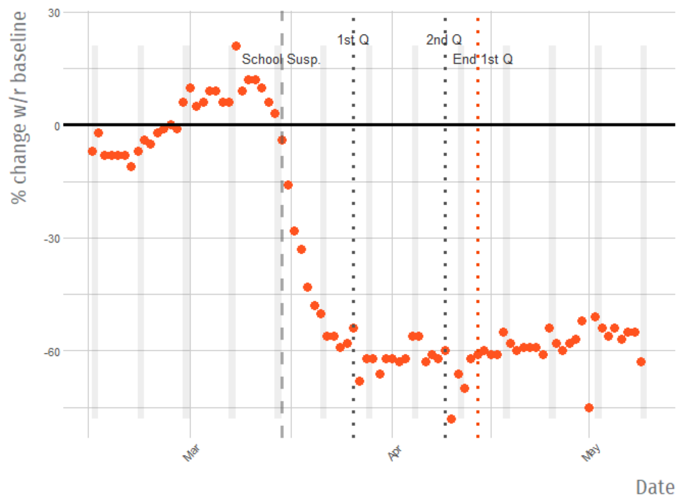


Figure 6: Percent change in transit station mobility measure with respect to baseline for the Metropolitan Region (Google, 2020), with weekends highlighted in shaded regions.

here measures the number of trips for a given individual, approximating his or her location using cellphone tower connections. A trip is then considered the movement from one tower to a different one, and the mobility index normalizes the number of trips by the population of each municipality, to make numbers comparable. Given the date range of the data, between end of February and April 12th, I focus only on those municipalities in the Metropolitan Region that were subjected to quarantines during the first wave.[7]

Figure 7 shows the results in terms of differences in the mobility index for lower- and higher-income municipalities that were subjected to lockdowns compared to their synthetic control. There is an important drop in mobility after the closure of schools on March 15th for higher-income municipalities, and that decrease in mobility is exacerbated due to quarantine measures. For lower-income

[7]High-income municipalities are the same ones as considered before, but for the lower-income municipalities I do not consider Puente Alto for this analysis.

municipalities, on the other hand, schools closures did not differentially affect their mobility compared to their synthetic comparison, but it did reduce trips during the first week of the quarantine. The effect decreases substantially with time, though, dissipating almost completely by day 9.

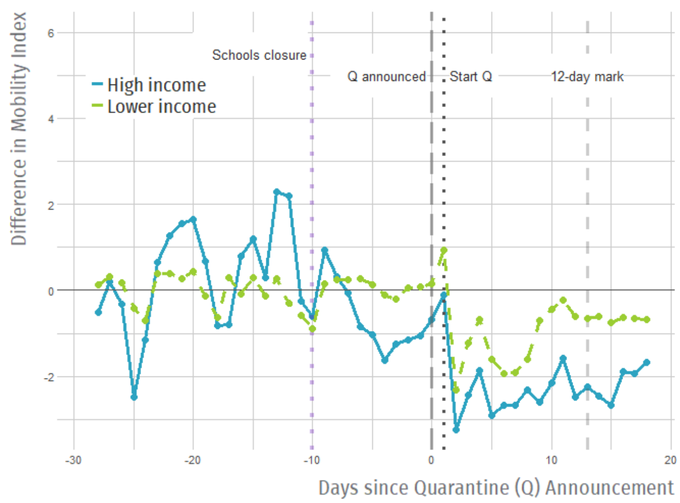


Figure 7: Difference in Mobility Index using ASCM for municipalities subjected to lockdowns by income level

Figure 7 clearly shows that income is an important mediating factor in mobility. It is not possible to recreate a synthetic control with a good pre-intervention fit for higher-income municipalities, because most of these areas entered quarantine at the same time, and in this case, income plays a key role in how people move. High-income municipalities appear to be more sensitive to overall policy measures, and reduced their overall mobility patterns even earlier than expected. Some of these differences could be due to higher ability for smoothing consumption (e.g. savings) or work-from-home opportunities that lower-income households do not have available, but more data would be required to study these hypotheses.

4.2. Testing Availability

One important factor that highly influences the containment of COVID-19 spread is testing and tracing policies. By properly identifying vectors that carry the disease, it makes it easier to isolate and mitigate contagion. However, testing is not equally available to all. During the first month of the pandemic in Chile, private and public hospitals had different protocols for testing potential cases of COVID-19: While private centers quickly adopted more flexible rules for testing, the public sector lagged behind, making it more difficult for patients to get tested[8].

Publicly available testing data supports these differences in testing availability. By analyzing the correlation between private center testing and estimated positivity rate using publicly available data (Ministerio de Salud de Chile, 2020),[9] I find a significant negative correlation of -0.61 for the month of April.[10] This means that when private centers increased their share of testing, number of new cases over total testing dropped (Figure 8), while the opposite was true for public-center testing. These patterns provide additional evidence that testing was more extensive in the private sector, where patients got tested with a lower probability of actually being infected. The difference between private and public center availability becomes particularly relevant when we consider that in high-income municipalities that had lockdown policies only 32% of residents were subscribed to the public health care system in 2017, while that number was 78% for lower-income areas that had quarantines before May 5th (Observatorio Social, 2017).

In addition to the availability of testing for different groups, proper timing

[8] The need for a physicians' referral, as well as the cost of the test are some of the barriers that differentially affected lower and higher income populations.

[9] Estimated positivity rate refers to the number of new daily cases over the number of informed tests for that day.

[10] Testing data is available continuously for type of testing center since 3/31/2020, and I use this data until 04/28/2020, given that the testing strategy changed to broader testing after that date.

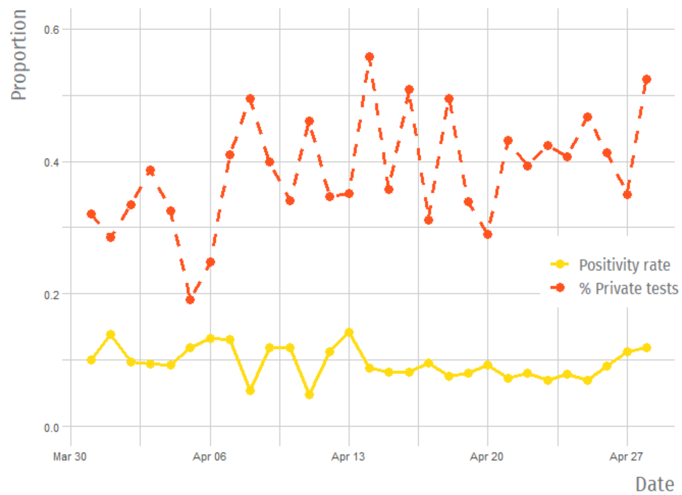


Figure 8: Estimated positivity rate and proportion of private testing by date

plays a key factor. Even though there is no official data related to the timing from testing to result confirmation, some reports show that test results could take between two to five days, depending on the lab (La Tercera, 2020). If we add these differences to the timing it takes for patients to actually get tested, the period between getting infected and having a confirmed diagnosis could likely be over a week.

Using publicly available data provided by the Ministry of Health (Departamento de Epidemiologia, 2020), I combine different reports that gather the week of first symptoms by municipality over time. With this data, I estimate the difference in new cases between reports, and the difference in number of patients that reported initial symptoms each week. Using the fact that reports are made available every two to four days, I estimate the maximum days between first symptoms and diagnosis for these new cases, and calculate the estimated proportion for days between first symptoms and confirmation, shown in Figure 9.

As it can be seen in Figure 9, for both high and lower-income municipalities, there is a lag of at least three days between showing first symptoms and getting a confirmed diagnosis. However, differences become significant after the 4-day mark: While nearly a quarter of new cases in high income municipalities have a confirmed diagnosis by day 5, only 15% of newly infected cases in lower-income municipalities have a confirmed test by that date. These differences remain fairly stable 7 days since first symptoms, and shed light on the fact that lower-income areas that experienced quarantine have almost consistently less timely diagnosis. One caveat of the data provided by the Ministry of Health is that is subject to changes between reports that could be due to reasons other than new cases (e.g. further investigation about initial symptoms); however, if we assume this measurement error is not systematically correlated with municipality's income, the difference between both curves is still informative.

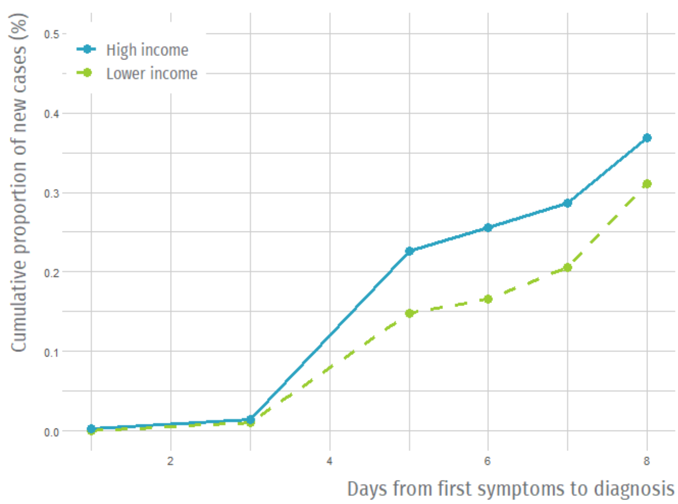


Figure 9: Cumulative proportion of new cases between reports by days since first symptoms to confirmed diagnosis, for high and lower income municipalities that were in quarantine in the Metropolitan Region.

5. Discussion

The effectiveness of mitigation measures plays a paramount role in contagion containment during a pandemic. For the same reason, understanding how interventions work for different populations is key to design and implement policies that will actually help reduce the spread of COVID-19. In this case, average treatment effects can hide potentially harmful evidence for populations that are more at risk.

In this paper I show evidence that small-area lockdown measures had a differential effect for high and lower-income populations. While quarantines proved effective in reducing new daily cases in more affluent areas, they did not have a significant effect on lower-income municipalities. Timely testing and difference in opportunity costs for staying at home might have played a role in explaining part of this difference. These results suggest that mobility-reduction measures are not equally effective, and current policies should potentially be accompanied by complementary measures that boost the effectiveness of lockdowns.

Given the speed with which governments need to act during a pandemic, *more* data, *better* data, and *timely* data are needed to assess some of these policies when they are implemented, and provide swift feedback that could help improve or complement current interventions.

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Appendix

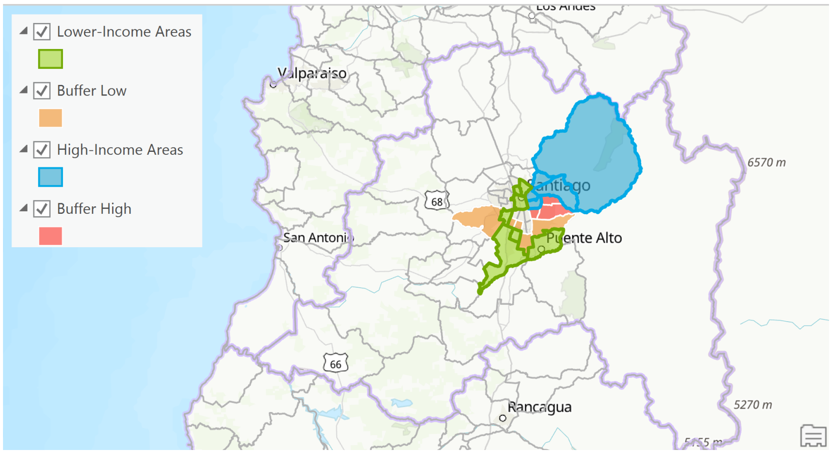

Figure 10: Map for high and lower-income municipalities that had lockdowns before May 5th, including buffer zones used for robustness test.

Table 4: Quarantines in Chile from early March to May 5th

Quarantines		March											April																														May			
		21	22	23	24	25	26	27	28	29	30	31	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	1	2	3	4
Santiago	Norte	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Sur	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nunoa	Norte	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Sur	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Independencia	Norte	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	Sur	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Las Condes		0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Lo Barnechea		0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Providencia		0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Vitacura		0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Puente Alto	Poniente	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
El Bosque		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
San Bernardo	Nororiente	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	Centro	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Otro	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Quinta Normal		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
Pedro Aguirre Cerda		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
La Pintana	Norte	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	Sur	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
San Ramon	Sur	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
	Norte	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Estacion Central		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
Caleta Tortel		1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rapa Nui		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Puerto Williams		0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Temuco		0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
Padre las Casas		0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chillan		0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Chillan Viejo		0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Osorno		0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
Punta Arenas		0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
San Pedro de la Paz		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hualpen		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nueva Imperial urbano		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arica urbano		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Angol urbano		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
Victoria urbano		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1

Note: High-income municipalities in blue, and lower-income municipalities in green.

Source: Data collected and publicly distributed by @soyDgo