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PIER Working Paper 20-016

Activity and the incidence of emergencies: Evidence from daily data at the onset of a pandemic

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Activity and the incidence of emergencies: Evidence from daily data at the onset of a pandemic[††]

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Abstract

This study examines the effect of social and economic activity on emergency room care utilization. In the wake of the COVID-19 pandemic emergency non-respiratory visits dramatically dropped in many countries around the globe. Using daily level data of all public healthcare facilities in Chile with novel mobility data we show that the crisis-induced changes in mobility patterns explain a large portion of the 50 percent drop in non-respiratory emergency room visits in the country. Our results reveal that an important reason for the dramatic drop in non-COVID-19 utilization of emergency care is the lower incidence of emergencies. We also provide evidence that the lower emergency department utilization did not cause higher mortality. These results suggest that measures restricting mobility during a public health crisis may have the unexpected benefit for public health of freeing up healthcare resources.

Keywords: Health Care, Emergencies, Mobility.

JEL classification: H12, I11, I12, I15

[††]An earlier version of this paper circulated under the title "Where are the missing emergencies? Lockdown and health risk during the pandemic". We owe special thanks to Amit Gandhi, Matias Busso, Frank Diebold, Hanming Fang, Aviv Nevo, José Víctor Ríos-Rull, Nicolas R. Ziebarth, and seminar participants in Universidad de Chile for their helpful comments and suggestions.

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1 Introduction

This study examines how demand for emergency room care responds to social and economic activity, leveraging novel datasets of daily ED utilization and daily indexes of mobility.[1] Then, it uses this relationship to provide an explanation for the striking drop in emergency care utilization observed around the globe during the COVID-19 pandemic (Garcia et al., 2020; Rodríguez-Leora et al., 2020).[2]

Our analysis provides novel empirical evidence on the factors that contribute to demand for ED visits, an area on which there is scant research despite the fast-growing use of ED care in recent years.[3] We show a strong link between ED visits and mobility—a proxy for social and economic activity—at the daily level. For instance, *before* the pandemic, days when the mobility indexes we use in this paper indicate a 1 standard deviation increase in people staying at their "residential" location, there are 0.2 standard deviation less ED visits overall.[4] The relationship between mobility and ED visits is strongest for visits related to trauma or poisoning, although it is statistically significant for all of the causes identified in our dataset. This result provides the novel finding that short-run changes in social and economic activity affects the demand for ED care.

After establishing the relationship between mobility and ED visits, we quantify the portion of the 50 percent drop in visits at the onset of the pandemic that can be explained by the change in mobility patterns that occurred concurrently.[5] A decomposition analysis reveals that changes in mobility can explain most of the drop ED visits during the pandemic.

[1] In its May 25, 2020 issue, "The Economist" uses the same mobility data to construct state-level daily "economic activity" indexes for the U.S., see `https://tinyurl.com/y887ocs9`

[2] For instance, according to NHS England figures, in March 2020 the number of people attending Accidents and Emergency departments in English hospitals was down 29 percent from the same month the previous year—about 1.5 million in March 2020, compared to nearly 2.2 million in March 2019. Emergency admissions were also down, falling by 23 percent on last March, to nearly 428,000 ("Coronavirus: A&E visits drop sharply as calls to 111 double," Philippa Roxby, BBC News, April 9, 2020). See also, Solomon et al. (2020).

[3] Lane et al. (2019) shows that the number of ED visits per 1000 people in the U.S. increased from 416.92 in 2010 to 448.19 in 2016.

[4] This relationship results from a simple OLS regression of total visits on the Google Mobility "residential" index that we define in more detail below. Adding region fixed-effects and day-of-the-week fixed effects changes the coefficient to -0.23. In both cases, it is statistically significant at all conventional levels.

[5] For instance, the "residential" index increased by almost 12 standard deviations after March 13.

In other words, using the model estimates—obtained with data *before* the pandemic—we predict almost the same drop in non-respiratory ED utilization observed in the data during the pandemic.

Our results contrast with the view that many patients, some with potentially serious conditions, have stopped going to the ED due to fear of contracting the novel SARS-CoV-2 virus at the hospital, which has been the leading hypothesis held by health care practitioners to explain this phenomenon.[6] Mobility data is a proxy, albeit imperfect, for social and economic activity. Therefore, it provides a lower bound for the share of the reduction in emergency care utilization that can be explained by lower social and economic activity as opposed to changes in willingness to visit the ED.[7] Overall, our results imply that most of decrease in ED utilization can be attributed to a lower need of emergency care during the pandemic. We provide additional support for this explanation from intra-week patterns in ED demand. Finally, we show that there are no discernible increases in mortality after the onset of the pandemic.

Understanding the reasons for the decrease in ED utilization allows to shed light on its implications for population health in the short and medium run and also for our understanding of the role played by the policies surrounding the pandemic. If most of the decrease was due to a lower willingness to visit the ED—for instance, due to fear of contracting the virus—the pandemic could have dire consequences on population health well beyond the direct health effects of the SARS-CoV-2 virus due to worsening conditions of the untreated patients. Alternatively, if most of the decrease in ED visits was due to a lower incidence of

[6]See, for example, reports in New York: "Amid the Coronavirus Crisis, Heart and Stroke Patients Go Missing, Gina Kolata, The New York Times, April 25, 2020; New Haven: "Hospital admissions for strokes appear to have plummeted, a doctor says, a possible sign people are afraid to seek critical help," Kevin Sheth, The Washington Post, April 9, 2020; Michigan: "ER visits drop amid COVID-19 outbreak; doctors fear patients avoiding hospitals during pandemic," Jim Kasuba, News-Herald, April 14, 2020; Vancouver: "ER doctors worry people with serious health concerns are avoiding the hospital," Randy Shore, Vancouver Sun, April 22, 2020; England: "Fears that seriously ill people are avoiding A&E as numbers drop," Sarah Marsh, The Guardian, March 27, 2020; Chile: "Qué pasa con las urgencias? Atenciones bajaron 51% desde la llegada del covid-19," Max Chávez, El Mercurio, April 20, 2020.

[7]If we included any other variable that captures social and economic activity and is positively correlated with ED visits, we could explain a higher share of the drop in ED visits.

accidents and health conditions that required an emergency visit—as we find in this paper—the negative consequences associated with lower utilization can be muted. Importantly, this reason indicates an overlooked benefit of lockdowns for public health, as they decrease the incidence of certain conditions and free up healthcare resources to confront the pandemic. Moreover, by assessing the relative importance of each explanation we can also uncover what specific factors contributed to a much lower use of emergency care after the onset of the pandemic relative to "normal times."

The Chilean context is well-suited for this analysis for three important reasons: First, detailed, high-quality ED data is available daily at the hospital level, which allows us to construct a high-frequency panel at the regional and type-of-emergency levels that we combine with the mobility data. Second, during the period of our analysis the spread of the COVID-19 virus was well contained in the country, so health care facilities operated below their capacity during the pandemic. Excess capacity of hospitals and ED rooms helps us rule out unmet demand due to supply-side factors as an explanation for the decrease in ED visits. Finally, the drop in ED visits in Chile is comparable in magnitude to the decrease reported elsewhere, which suggests that our results are informative to other countries as well.

Our paper is connected to previous studies linking changes in economic conditions to health outcomes. Starting with the work of Ruhm (2000), several papers have empirically studied the relationship between the unemployment rate and health outcomes, including mortality, cardiovascular diseases and occupational injuries, with mixed conclusions. Although most of the early work confirmed the "pro-cyclical" behavior of mortality uncovered by Ruhm for the U.S. between 1972 and 1991, several other studies reach a different conclusion when using other outcomes, other countries, or more recent time periods (see, e.g., Cutler et al., 2002; Ruhm, 2015, and Stevens et al., 2015). In their review article, Catalano et al. (2011) suggest that the variability in the empirical estimates likely reflect the myriad of mechanisms linking economic outcomes to health care outcomes. In fact, the economic theory (e.g., Grossman, 1972) as well as the medical literature provide hypotheses for either positive or negative effects of unfavorable economic conditions on health. For example, an economic crisis can affect family income and alter nutrition by reducing food consumption, but also the individual's decision to work and the time devoted for caregiving, fertility decisions, access to healthcare services, and public health spending.[8] Our paper provides novel high-frequency evidence that ED usage increases with social and economic activity in a one-month period (*before* the pandemic) sample when macro-economic conditions are stable and therefore most of the confounding mechanisms at play in longer periods of time are absent.

To our knowledge, this is the first paper studying short-run determinants of ED demand, even if ED visits represent almost half of the hospital-associated health-care contacts in the U.S. and are the portal of entry for roughly half of all hospital admissions (Marcozzi et al., 2018; Pitts et al., 2010).[9] Of particular controversy is the existence of nonurgent ED visits (Durand et al. 2011; Uscher-Pines et al. 2013). In fact, several studies have argued that many ED cases are actually nonurgent and thus could be handled in less expensive, regular physician visits without any deterioration in the patient's condition.[10] The large drop in ED visits at the onset of the pandemic could suggest that a large fraction of pre-COVID-19 emergency-room visits were only marginally beneficial to patients. In contrast, our findings suggest that the lower incidence of conditions due to lower exposure to risk played an important part in this decrease, bounding the role played by behavioral responses related to the decision to go to the ED.

[8] Catalano et al. (2011) write that a change in economic circumstances requires individuals to "[...] adapt somatically and behaviorally in ways that allow them to meet social and economic obligations. In the case of economic decline, some of these adaptations increase the risk of illness while others reduce it." (p. 444). Also, a strand of the literature studies the effect of retirement on health (Coe and Zamarro, 2011; Behncke, 2012; Eibich, 2015; Shai, 2018).

[9] Coster et al. (2017) provides a recent review of the literature analyzing the factors that make people with a (potentially urgent) condition to choose an ED over nonurgent care.

[10] The OECD reports that between 12 and 56 percent of ED visits in OECD countries are non-urgent (James et al., 2017) and these represented $38 billion per year (Delaune and Everett, 2008) in the U.S. One potential explanation is that patient preferences for seeking emergency care are high because of the access to a wide array of medical services is accessible 24 hours a day, 7 days a week (Durand et al., 2012). An important caveat is that there is a not a clear consensus of what an urgent visit is. See Durand et al. (2011) for a review of the classification methods used in the health literature and their implications. Also, UnitedHealthcare Group estimates that 18 out 27 million ED visits in the US are avoidable, representing US 32 Billion of potential savings (see `https://www.unitedhealthgroup.com/content/dam/UHG/PDF/2019/UHG-Avoidable-ED-Visits.pdf`).

Finally, our paper contributes to a growing body of empirical research analyzing the impacts of the lockdown measures implemented to confront the COVID-19 pandemic. This literature has been mostly focused on analyzing their impact on the spread of the disease (Fang et al., 2020; Juranek and Zoutman, 2020; Qiu et al., 2020).[11] Alexander and Karger (2020) study the effect of the lockdown on consumption. Our focus is on the demand for health care related to the regular health-care needs of the population during the pandemic. As pandemics and epidemics can generate public health crises that pose significant strains to health care systems, an important fraction of the available resources may need to be shifted away from the regular health care needs of the population. Our paper provides novel insights suggesting that lockdowns may generate positive public-health externalities by reducing the demand for emergency room services.[12]

The paper is organized as follows: Section 2 presents a brief summary of the unfolding of the pandemic in Chile. Section 3 introduces the data. Section 4 documents the decrease in ED visits in Chile. Section 5 presents our main empirical strategy and the results. Section 6 examines the trends in mortality. Section 6 concludes.

2 The COVID-19 crisis in Chile

In this section we provide a brief timeline of the unfolding of the COVID-19 pandemic in Chile. The goals of this section are two. First, we justify the use of March 13, 2020 as the date that marks the start of the crisis in Chile. Second, we show that within our period of analysis (up to April 28, 2020), the crisis was well contained in the country.

The confirmation of the first case of COVID-19 in Chile occurred on March 3, 2020. On March 15 the government announced the first set of measures restricting mobility. All these measures started on March 16, and mainly contemplated a nationwide closing of schools and

[11] Farboodi et al. (2020) show that individual's optimizing behavior generated social distance before shelter-in-place restrictions came into effect.

[12] Adda (2016) provides a comprehensive analysis of the economic costs of infections and a cost-benefit analysis of social distancing interventions.

educational establishments, restaurants, and movie theaters, as well as forbidding events with more than 50 people. Further measures adopted were a national night curfew between 10 PM and 5 AM starting on March 22, and localized lockdowns in specific municipalities starting on March 26.[13] On March 23, when there were were 93 total positive cases, the first death related to COVID-19 was identified.

Figure 1 shows the evolution of COVID-19 cases and deaths over time, between March 1 and April 28, 2020. By April 28 the total number of cases and deaths were 13,813 and 198, respectively. [14] We include a dashed vertical line on March, 13 which we use to mark the onset of the crisis in Chile.[15] On March 13 (two days before the nationwide lockdown measures) the national cumulative number of cases was only 33, and there were no COVID-19-related deaths reported. However, cases and deaths started to increase rapidly afterwards.

3 Data

Our main empirical analysis combines daily data from the Google Community Mobility Reports with daily administrative data on ED admissions. We describe each dataset in the following two subsections.

3.1 The Google Community Mobility Reports

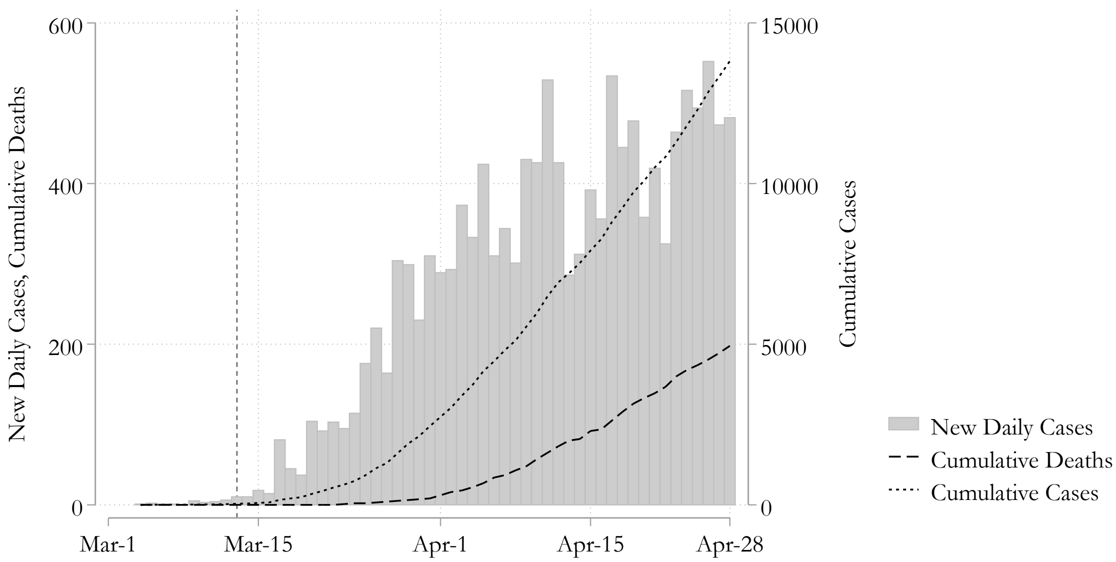
Our mobility data comes form the Google Community Mobility Reports. The data was released by Google in an effort to inform the debate around COVID-19. These mobility reports use mobile geo-locations to compute an index of the time spent by users in six

[13]Lockdowns were implemented selectively. Due to their initial higher contagion rate seven municipalities of the Santiago metropolitan area were under a total lockdown that lasted fifteen days. People under lockdown were required to obtain a special permit to move from one location to another. Later, thirteen additional municipalities across the country were under temporary lockdown at some point between March 30 and April 23.

[14]These figures are fairly low (both in absolute terms and in a per-capita basis) compared to the spread of the pandemic in other OECD countries.

[15]The main results of the paper are robust to the definition of the beginning of the post-COVID-19 period. See Appendix Figure A6.

Figure 1: Number of COVID-19 cases in Chile



Note: The graph shows the number of new daily cases, the number of cumulative cases, and the number of deaths of COVID-19 in Chile. Dashed vertical line is plotted on March, 13 and indicates the last weekday before the first of set of mobility restricting measured were adopted. Data from Our World in Data `https://ourworldindata.org/coronavirus`.

different categories of places: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces and residencies. The report for a particular day and location shows how visits and length of stay at different places differ with respect to a baseline. The baseline is the median value, for the corresponding day of the week, during the 5-week period between January 3 to February 6, 2020. The data is available at the daily-level for all 16 regions of Chile.[16] The mobility data was captured among users of Android Phones who had opted in to turn on their location services.[17] Although the Google Mobility data we use in this paper was released in the context of the COVID-19 pandemic, previous studies have shown that Google Location data has an accuracy level similar to a GPS (see an example of Ruktanonchai et al., 2018 for the UK). The mobility data has been used recently by Wellenius et al. (2020) and Dasgupta et al. (2020) to estimate the impact of state policies to foster social distancing on

[16]Regions are the main sub-national administrative units.

[17]According to the 2017 Socio-Economic Survey (CASEN), 92 percent of Chileans over 18 have a working cellphone. As of January 2020, Android had a market share of 85 percent (see `https://gs.statcounter.com/os-market-share/mobile/chile`)

mobility during the pandemic.

The mobility data is available from February 15, 2020. In this paper, we use data up to April 28, 2020. In Appendix A1 we show plots of the time series of each mobility index in the six categories of places. Beginning on March 13, there is a sharp decrease on time spent in all categories, except for the residential category which increases substantially. For comparison, we also show how the mobility indexes compared to those in the U.S. We find that the mobility in Chile decreased in most categories much more than in the U.S., especially in retail and recreation, and in grocery and pharmacy.[18]

3.2 Emergency Visits

The data for emergency visits comes from daily public reports by the Chilean Ministry of Health. The data shows the number of ED visits in each hospital in Chile, split by categories of related diagnoses.[19] In 2020 and before the COVID-19 crisis, the average day-region had 2,795 ED visits. In this paper we focus on non-respiratory visits, which accounted for 84 percent of the total visits in the period of analysis.[20] Within the non-respiratory visits, we show results for the main sub-categories: trauma or poisoning (that correspond to 16 percent of non-respiratory visits), circulatory system (3 percent), diarrhea (5 percent), and all other non-respiratory causes (76 percent). Although the first three constitute a relatively small share of cases, they are the main focus of our study because they are well-defined causes of ED. We expect that the trauma or poisoning category is strongly related to mobility patterns. Also, several recent media reports have highlighted the drop in the circulatory

[18]Even if the timing of some of the lockdown measures differed across regions, the mobility data shows a systematic break in mobility patterns across all regions after March 13, which justifies the use of a single date to define the 'pre-COVID-19' period across all regions. This evidence is consistent with Farboodi et al. (2020), who show that individuals in the U.S. reduced their activities during the COVID-19 pandemic before any legal restrictions on movement were implemented. In this paper, we do not take as stance regarding the causes behind the drop in mobility, which are likely a combination of the many policies implemented to increase social distancing discussed in Section 2, as well as a general fear of the population to leave their residencies.

[19]The cases are classified using the ICD classification method. Each category in the data corresponds to related ICD codes.

[20]We exclude all respiratory causes from our analysis. These are comprised of acute bronchitis (J20-J21), influenza (J09-J11), pneumonia (J12-J18), and other respiratory causes (J22; J30-J39, J47, J60-J98).

Table 1: Descriptive statistics by period of analysis

	Before March 13	Post March 13
Panel A: ER visits		
All Non-Respiratory	2,337.19	1,159.75
	(2984.70)	(1552.19)
Trauma or Poisoning	380.56	175.41
	(499.07)	(244.14)
Circulatory System	61.93	43.60
	(84.50)	(60.33)
Diarrhea	144.91	42.76
	(155.79)	(59.80)
All Other Causes	1,749.78	897.98
	(2264.47)	(1203.75)
Panel B: Mobility Index		
Residential	0.72	20.40
	(1.76)	(6.17)
Non-Residential	0.00	-4.61
	(1.00)	(1.43)
Workplaces	4.36	-36.55
	(10.45)	(16.68)
Retail and Recreation	1.13	-59.27
	(8.53)	(16.86)
Grocery and Pharmacy	3.67	-37.34
	(7.39)	(18.87)
Parks	-5.99	-61.04
	(19.93)	(13.60)
Transit Stations	0.74	-57.62
	(10.24)	(17.78)

Notes: Panel A shows average daily number of emergency daily visits by region in each category. Panel B shows average Google Community Mobility Report indexes by region in the different categories. Both panels show summary statistics before and after March 13. Standard deviations are reported in parenthesis.

system category and have reported of recent cases where individuals have not sought timely ED care. In addition, circulatory system causes are likely among the most severe well-defined cause that individuals go to the ED for. However, circulatory system visits only constitute a very small fraction of the ED visits in Chile.

Table 1 describes the change in ED visits (Panel A) and in the mobility indexes (Panel B) for the periods before and after the beginning of the pandemic. There is a large change in all the variables. For example, relative to the pre-COVID-19 period, the number of visits and length of stay at workplaces during the post-COVID-19 period decline by 4.16 standard deviations. In turn, the residential index increases by 11 standard deviations. Panel B also shows a "non-residential" index that we construct as the principal component of all out-of-residencies indexes, standardized using its pre-pandemic mean and average. As we discuss in section 5, we use a principal component analysis due to the high collinearity in the mobility indexes.

4 The Decrease in Emergency Visits

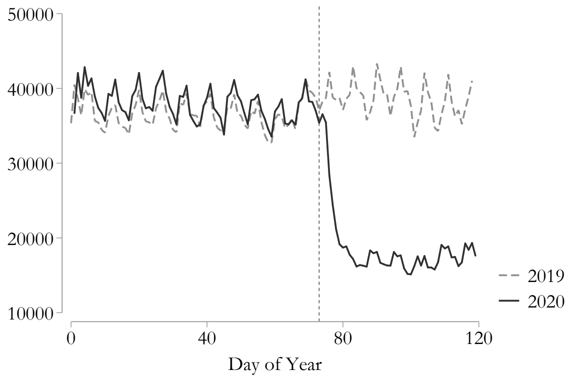
As in many other countries, there was a sharp drop in emergency visits in Chile after the beginning of the pandemic, in mid-March 2020. Figure 2 shows the total number of all non-respiratory ED visits in Chile for 2019 and 2020. These visits decreased on average from 37,592 before the pandemic to 19,109 after the beginning of the pandemic, which represents a drop of 49 percent.

To quantify the drop in ED visits we estimate a difference-in-differences model. For each diagnosis k we estimate the regression equation

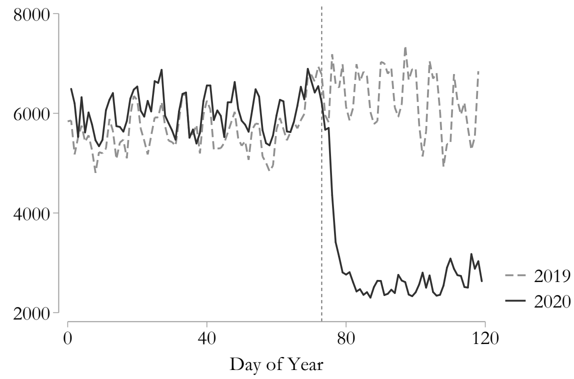
$$Y_{dykr} = \beta_k \text{COVID-19} + \gamma_k 1\{Post\} + \mu_{dow,k} + \nu_{mk} + \tau_{yk} + \alpha_{rk} + \epsilon_{dykr} \tag{1}$$

where Y_{dykr} is the number of visits of diagnosis k in the day d counted after January 1 of year y in region r, COVID-19 denotes the post-March 13, 2020 (pandemic) period; and $1\{Post\}$

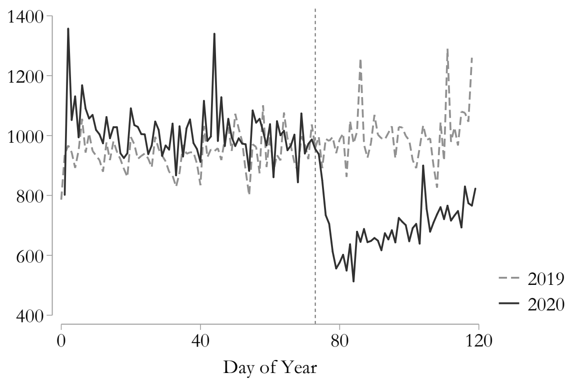
Figure 2: Emergency Room Visits in Chile in 2019 and 2020



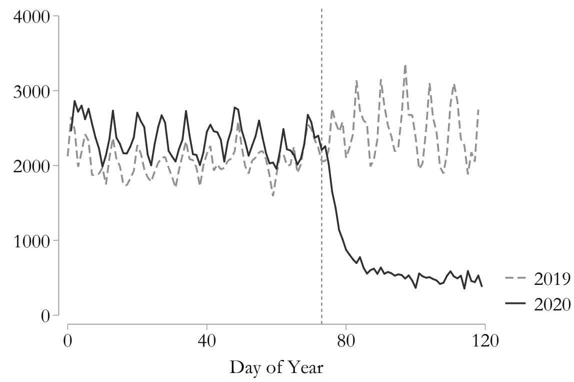
(a) All Non-Respiratory



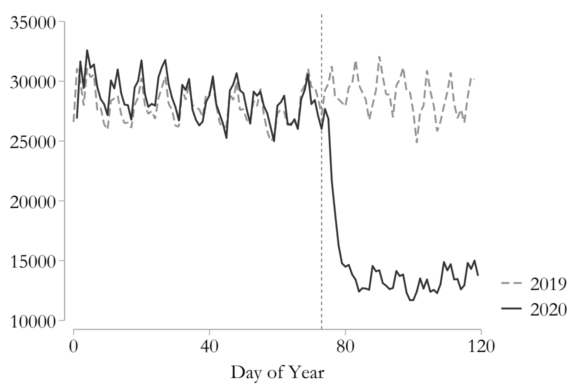
(b) Trauma and Poisoning



(c) Circulatory System



(d) Diarrhea



(e) All Other Causes

Note: The graph shows total emergency visits in Chile for the days after the first Wednesday of the year for the years 2019 and 2020 (January 2 and January 1, respectively) in different categories. The vertical line indicates March 13, 2020, which indicates the date when COVID-19 started spreading.

is an indicator for the period after March 13 in the two years in our sample. The terms $\mu_{dow,k}$, ν_{mk}, τ_{yk}, and α_{rk} are diagnosis-dependent fixed effects for day of the week (dow), month of the year (m), year, and region, respectively.

We present the results in Table 2. We find a statistically significant drop in all the categories. The beginning of the COVID-19 pandemic led to a decrease of 1,430 non-respiratory emergency visits, of which 262, 25, and 138 were due to trauma or poisoning, circulatory system, and diarrhea, respectively. These figures represent a 57 drop relative to the pre-pandemic average for non-respiratory visits combined, and a 66, 38, and 92 percent drop for each respective category.

Table 2: Effect of the pandemic on emergency visits by category

	(1) All Non-Respiratory	(2) Trauma or Poisoning	(3) Circulatory System	(4) Diarrhea	(5) All Other Causes
COVID-19 post	-1429.799**	-261.807**	-24.672**	-138.265***	-1005.054**
	(511.400)	(95.206)	(10.995)	(45.103)	(362.602)
N	3570	3570	3570	3570	3570
R-Squared	0.94	0.92	0.94	0.85	0.94
Mean Dep. Variable	2,506.33	396.99	65.16	150.75	1893.43

Note: The table shows the effect of the pandemic spread on total emergency room visits in Chile between January 1 and April 28, where we use 2019 as the control group for 2020. The estimation includes day of the week, month of the year, year, and regional fixed effects. The mean dependent variable includes only observations before March 13 in 2019 and 2020. Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

5 Empirical Analysis

The goal of the empirical analysis is to quantify the share of the decline in emergency room visits that can be explained by changes in risk exposure to non-COVID-19 diseases, as proxied by a set of observable variables. If most of the decline in visits is predicted by changes in these observables, the decrease in ED visits attributed to unobservable factors —like individuals' willingness to visit the ED— would be small. In this case, the decline would be mostly attributed to a lower incidence of conditions that warrant a visit to the ED.

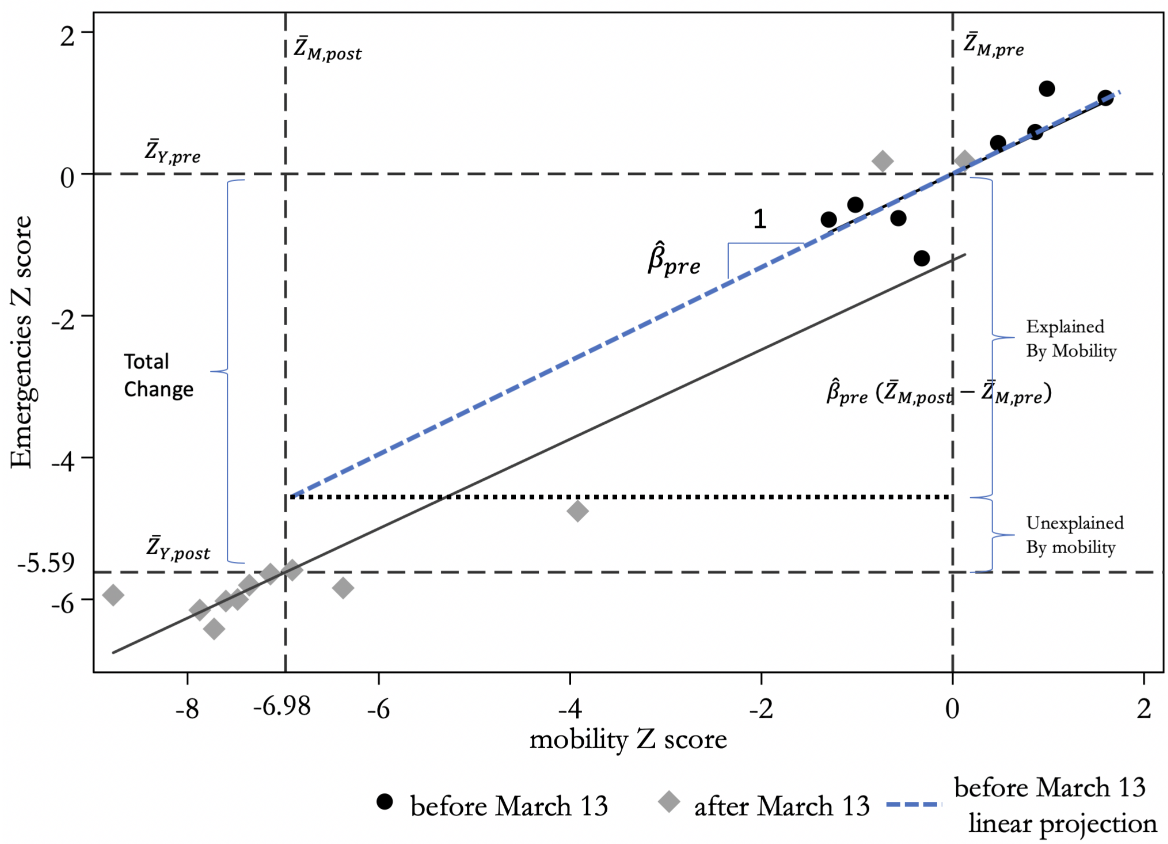
Alternatively, if the drop in ED visits cannot be explained by these observables, the drop in the ED would be explained by unobservable factors that include, among others, changes in attitudes towards visiting the ED because of the fear of contracting the SARS-CoV-2 virus at the hospital.

Our approach consists of using the pre-COVID-19 period to infer the relationship between mobility (as a proxy for social and economic activities and risk exposure) and the various types of ED visits. We then use the empirical relationship between those two variables in the pre-COVID period to predict the number of emergency room visits in the period after the onset of the COVID crisis. That is, we use the data before March 13 as our 'training' dataset, from which we estimate the parameters relating mobility with emergency visits. Then, we use those estimates to construct the emergency visits predicted by the model under the post-COVID-19 mobility patterns. These predictions allow us to quantify the share of the decrease in visits which can be attributed to changes in mobility.

Figure 3 provides a simple explanation of our approach. The figure plots the Z-score of the index for mobility to transit stations against the Z-score of the trauma or poisoning visits in the capital city (Santiago). Z-scores for the entire sample period are based on the means and standard deviations in the pre-COVID period. Therefore, the magnitude in both axes corresponds to the deviation of a particular measurement with respect to its pre-COVID mean as fraction of its pre-COVID standard deviation.

The linear fit for the data before March 13 indicates that, in days when the mobility index is one standard deviation lower than average, there are also (on average) 0.77 standard deviations less ED visits due to trauma or poisoning. In the case of a simple univariate model for ED visits, our empirical strategy would consist of (i) estimating the slope $\hat{\beta}_{pre}$ using the pre-COVID period, and (ii) using $\hat{\beta}_{pre}$ to project the linear relationship up to the mean mobility in the post-COVID period $\bar{Z}_{M,post}$. The share of total change in average visits $\bar{Z}_{Y,post} - \bar{Z}_{Y,pre}$ that is explained by the change in mobility corresponds to $\hat{\beta}_{pre}(\bar{Z}_{M,post} -$

Figure 3: Empirical Strategy



Note: The figure shows a binned scatter plot of the normalized (Z-score) transit stations mobility and normalized (Z-score) trauma and poisoning emergency visits in the Metropolitan region (Santiago and its surroundings). The normalizations use the corresponding pre-March 13 mean and variances in Santiago. The straight lines represent the linear fit for each period.

$\bar{Z}_{M,pre}$).[21] In the example presented in Figure 3, the transit stations mobility index alone would allow us to explain 96% of the decline in ED visits for Santiago.[22]

Our main empirical strategy uses the insight described in Figure 3, but allows for a flexible relationship between ED visits and the six different mobility indexes included in the Google Mobility Reports. As we discuss in more detail in Section 5.4, this decomposition is akin to the (three-fold) Blinder-Oaxaca decomposition of gender wage gaps used in the

[21] Our object of interest is to decompose the decline in ED visits. In principle we could also perform a decomposition of the pre/post-March 13 differences using the 2019 data. However, this analysis requires assumptions on mobility patterns and their impact on emergencies in 2019 (which we do not observe).

[22] The average transit stations mobility score in the pandemic is $\bar{Z}_{M,post} = -6.98$. The linear projection of the pre-March-13 relationship predicts a drop of $.64 \times 6.97 = 5.37$, which corresponds to 80% of the actual decline ($\bar{Z}_{Y,post} = 5.59$).

labor economics literature.

5.1 Model Specification

We posit a simple linear model relating ED visits in day d, for diagnosis k and region r to mobility:

$$Y_{dkr} = f_{kr}(\mathbf{M}_{dr}) + \mu_{dow(d),k} + \epsilon_{dkr} \tag{2}$$

where f_{kr} is a type- and region-specific function, $\mathbf{M}_{dr} \in R^6$ is a vector containing the daily measures of the Google Mobility Report in the six categories of places, and $\mu_{dow(d),k}$ are type-specific dummy for the day of week (Monday, Tuesday, etc.).

In our first specification we use a parsimonious linear model for f_{kr}. Also, given the high collinearity of the mobility indexes, we compute two additional indexes. The first one Z^{res}_{dr} is simply the residential mobility index, and the second one $Z^{non-res}_{dr}$ is the first principal component derived from the non-residential terms.[23] For ease of interpretation, we standarize both indexes at their pre-March 13 level. Thus, our first specification is $f^a_{kr} = \alpha_{kr} + \beta_k Z^{res}_{dr} + \gamma_k Z^{non-res}_{dr} + \mu_{dow(d),k} + \epsilon_{dkr}$. We estimate the coefficients of this first specification via OLS.

In our second specification we allow f_{kr} to contain all the mobility indexes and a full set of interaction terms between the region and the mobility indexes as well. The specification thus becomes: $f^b_{kr} = \alpha_{kr} + \sum_{j=1}^{6} \beta_{krj} M_{drj} + \mu_{dow(d),k} + \epsilon_{dkr}$. We estimate this model via lasso.[24]

As noted above, we estimate the model using the 2020 data for the *pre-COVID-19 period only*. Then, we compute the predicted values, $\widehat{Y}_{dkr}$, for the entire sample: the pre-COVID-

[23] The non-residential component explains 68 percent of the variance of the non-residential indexes. In robustness checks we examine how our results change by using two principal components derived from all six indexes.

[24] We estimate lasso using the implementation of Friedman et al.'s (2010) coordinate descent algorithm. We use Townsend (2018). Also, in reality we implement elastic net, which is a generalization of lasso, but the elastic-net penalty found by the algorithm is the same as lasso's.

19 period (in-sample prediction); and post-COVID-19 period (out-of-sample prediction). Finally, we compute the country-level predicted totals as the sum of the regional predictions $\widehat{Y}_{dk} \equiv \sum_r \widehat{Y}_{dkr}$.

5.2 Pre-COVID-19 relationship between ED and mobility

Table 3 shows the estimation results of Equation (2) by OLS in the pre-pandemic period. We find a significant relationship between the pre-COVID-19 emergencies and the pre-COVID-19 mobility indexes for types of conditions. Overall, we find that an increase of one standard deviation in the residential index decreases the average daily visits by 34 (or 1.5 percent of the sample average). On the other hand, an increase of non residential index by one standard deviation increases ED visits increase the average daily visits by 52 (or 2.2 percent of the sample average).

The F statistic (and its corresponding p-value) for the joint test that both coefficients of the mobility variables equal zero in the pre-COVID-19 (training) sample ($\beta_{k1} = \beta_{k2} = 0$) is $F = 11.37(0.00)$ for the group of all non-respiratory visits. However, we do find heterogeneity in the explanatory power of the mobility variables across the different types of diseases. As expected, the mobility variables have the highest predictive power (as measured by the F-statistic) for Trauma or poisoning visits ($F = 11.34(0.00)$). On the other hand, mobility indexes have the lowest predictive power for visits related to Diarrhea ($F = 2.40(0.09)$).

Table 3: OLS estimates

	(1) All Non-Respiratory	(2) Trauma or Poisoning	(3) Circulatory System	(4) Diarrhea	(5) All Other Causes
Residential	-33.98***	-12.95***	0.11	-1.21	-19.94**
	(10.87)	(3.37)	(0.58)	(1.24)	(9.21)
Non Residential	52.18***	9.26***	1.31**	2.71**	38.90***
	(11.23)	(2.38)	(0.60)	(1.35)	(9.92)
N	448	448	448	448	448
R^2	0.994	0.986	0.979	0.968	0.992
F-stat.	15.34	11.34	2.55	2.40	11.09
p-value	0.00	0.00	0.08	0.09	0.00
Mean dep. var.	2337	381	62	145	1750

Notes: The table shows the results of a OLS estimation of Equation (2) in the pre-pandemic period. Robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

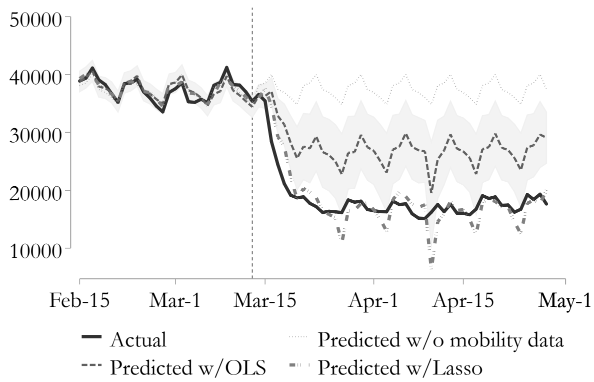
5.3 Post-COVID predictions

We present the predicted ED visits for our selected subgroups of ED cases in Figure 4. Each panel in the figure presents (*i*) the actual time series, (*ii*) the prediction from a model that only includes day-of-week and region fixed effects, and omits the mobility data; (*iii*) the OLS prediction, and (*iv*) the lasso prediction.

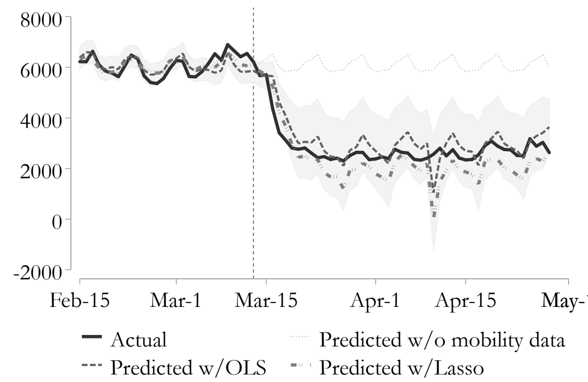
We find that the mobility patterns explain a large fraction of the decrease in the emergency visits for all non-respiratory visits, and trauma or poisoning emergencies and other causes among them, cases where the mobility is highly correlated with emergencies in the pre-COVID-19 period. For the case of AMI visits, the models do a worse job predicting the number of visits. We think this is natural because AMIs are less dependent than the other types of ED visits we study on the mobility indexes.[25] We provide numbers for the share of the explained drop in the next subsection.

[25] The lasso predictions are somewhat sensitive to the seed choice. In the Appendix we show lasso results with different initial seeds.

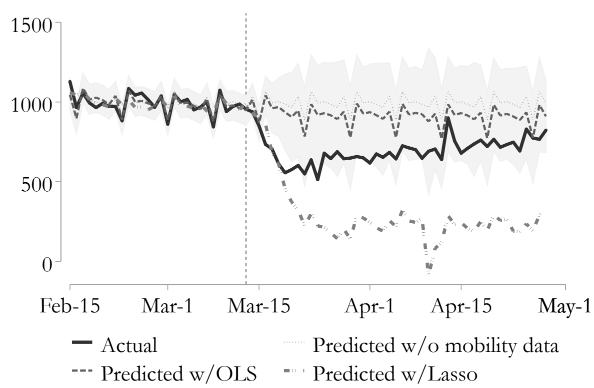
Figure 4: Actual and Predicted Emergencies by Type



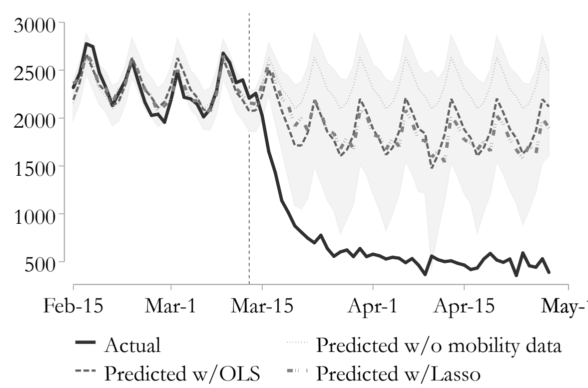
(a) All Non-Respiratory



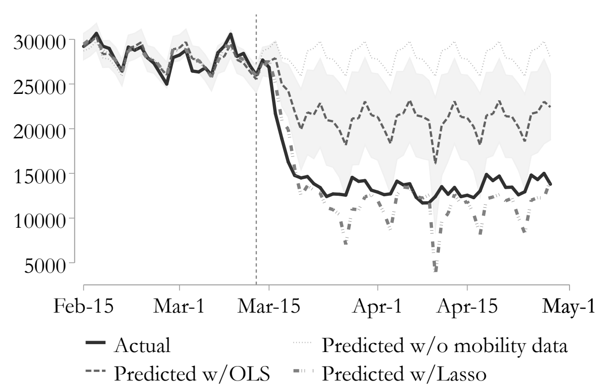
(b) Trauma or Poisoning



(c) Circulatory System



(d) Diarrhea



(e) All Other Causes

Note: The vertical line divides the period that was used for prediction and the actual evolution using Google's Community Mobility Reports and regional fixed effects. Lasso and Elastic Net predictions are equivalent for all non-respiratory and trauma or poisoning categories.

5.4 Decomposition

We formalize the graphical analysis with a decomposition of the differences in emergencies across periods using the Oaxaca-Blinder method. This method, derived by Blinder (1973) and Oaxaca (1973) is traditionally applied in labor economics to study the wage gap across groups (e.g., males vs. females) by decomposing the gap into the part that can be explained by observable characteristics (e.g., differences in "endowments," such as education in the gender wage gap literature) and the part of the gap that cannot be explained by observables. We apply the same logic to decompose differences in average visits across the two groups of observations defined by the calendar time: the group of post-March 13 days and the group of pre-March 13 days. The goal of the decomposition is to quantify the part of the difference in average visits across the two groups that can be explained by the model, particularly by the mobility variables.

To simplify the notation, we rewrite the general model for average visits in each period as:

$$\begin{aligned} E[Y_{pre}] &= \bar{X}'_{pre}\beta_{pre} \\ E[Y_{post}] &= \bar{X}'_{post}\beta_{post} \end{aligned}$$

A "three-fold" decomposition of the gap $E[Y_{pre}] - E[Y_{post}]$ can be written as:

$$E[Y_{post}] - E[Y_{pre}] = (\bar{X}_{post} - \bar{X}_{pre})'\beta_{pre} + \bar{X}'_{pre}(\beta_{post} - \beta_{pre}) + (\bar{X}_{post} - \bar{X}_{pre})'(\beta_{post} - \beta_{pre}) \quad (3)$$

The first part of this decomposition, $(\bar{X}_{post} - \bar{X}_{pre})'\beta_{pre}$, corresponds to the difference in average visits across periods that can be explained by observables. This component corresponds to the part of the gap that can be explained by extrapolating the pre-COVID-19 relationship (β_{pre}) onto the post-COVID-19 average mobility ($\bar{X}_{post}$) (see Figure 3). Consequently, the sum of the second term and the third term $\bar{X}'_{pre}(\beta_{post} - \beta_{pre}) + (\bar{X}_{post} - \bar{X}_{pre})'(\beta_{post} - \beta_{pre})$ corresponds to the part of the gap that cannot be explain by observables.

Diving each side of Equation (3) by $E[Y_{pre}]$ we can re-write the equation as

$$\underbrace{\frac{E[Y_{post}] - E[Y_{pre}]}{E[Y_{pre}]}}_{\text{Difference \%}} = \underbrace{\frac{(\bar{X}_{post} - \bar{X}_{pre})'\beta_{pre}}{E[Y_{pre}]}}_{\text{Explained by Observables \%}} + \underbrace{\frac{\bar{X}'_{pre}(\beta_{post} - \beta_{pre}) + (\bar{X}_{post} - \bar{X}_{pre})'(\beta_{post} - \beta_{pre})}{E[Y_{pre}]}}_{\text{Unexplained by Observables \%}}, \tag{4}$$

which results in the share of the explained and unexplained gap in percentage terms.

Table 4 shows the result of this decomposition, where each panel corresponds to a different type of ED visit. The last row of each panel presents the standard error of the OLS explained share in parenthesis.[26] Panel (A) shows that all non-respiratory visits dropped from 37,959 to 18,555 visits per day, a 50.4 percent decrease after the onset of the crisis. Our OLS model predicts a drop of 26.3 percent. Thus, a simple linear model of the Google mobility indexes predict 52.1 percent of the total drop in non-respiratory ED visits. Moreover, the lasso regression is able to explain 100.4 percent of the overall drop.

The other panels of Table 4 repeat the decomposition for other causes. Panel (B) shows that both the OLS regression and the lasso regression explain more than 90.7 percent of the decrease for trauma or poisoning visits. Panels (C) and (D) shows the results for circulatory system diseases and diarrhea. However, the standard errors of the OLS prediction are large, as was expected given the low F statistics of the regression of these visits on the mobility indexes. This indicates that the explained share estimates are not precise when calculated for these specific causes. Finally, Panel (E) presents the explained share for all other causes. The results are similar to those of Panel (A).

[26]The standard errors are computed using the formulas in Jann (2008).

Table 4: Decomposition of the Drop in Emergency Visits

	(1)	(2)	(3)
	Observed	Predicted	
		OLS	Lasso
Panel A:		All Non-Respiratory	
Before March 13 (A1)	37,395	37,395	37,395
After March 13 (A2)	18,555	27,571	18,482
Difference (%) ([A2 -A1]/A1)	-50.4%	-26.3%	-50.6%
Difference Explained by Model (%)		52.1%	100.4%
		(18.86)	
Panel B:		Trauma or Poisoning	
Before March 13 (A1)	6,090	6,090	6,089
After March 13 (A2)	2,806	3,110	2,324
Difference (%) ([A2 -A1]/A1)	-53.9%	-48.9%	-61.8%
Difference Explained by Model (%)		90.7%	114.7%
		(25.19)	
Panel C:		Circulatory System	
Before March 13 (A1)	991	991	991
After March 13 (A2)	698	915	293
Difference (%) ([A2 -A1]/A1)	-29.6%	-7.7%	-70.5%
Difference Explained by Model (%)		26.0%	238.0%
		(49.39)	
Panel D:		Diarrhea	
Before March 13 (A1)	2,318	2,318	2,319
After March 13 (A2)	684	1,910	1,885
Difference (%) ([A2 -A1]/A1)	-70.5%	-17.6%	-18.7%
Difference Explained by Model (%)		25.0%	26.5%
		(17.60)	
Panel E:		All Other Causes	
Before March 13 (A1)	27,997	27,997	27,996
After March 13 (A2)	14,368	21,637	12,850
Difference (%) ([A2 -A1]/A1)	-48.7%	-22.7%	-54.1%
Difference Explained by Model (%)		46.7%	111.1%
		(17.60)	

Note: The table shows the Oaxaca-Blinder decomposition for the observed drop in ED visits. We report the share of the drop that can be explained by OLS and Lasso models. Column (2) includes robust standard errors in percentage points of the share explained by the model.

5.5 Robustness

Model Specification In this section we examine the robustness of our main results to different model specifications. Each column of Table 5 presents a different specification. Columns (1)-(6) show OLS estimates and the standard errors of the explained share. Column (1) replicates the results of our main specification, where the mobility explanatory variables are residential and non-residential mobility. Column (2) replaces the residential and non-residential mobility indexes with the two principal components that explain the most variance of the six mobility indexes. Column (3) shows the results of using three principal components. Finally, Column (4) presents results of two principal components of a subset of the mobility indexes residential, workplaces, retail and recreation, and grocery and pharmacy.

Table 5: Robustness Checks: Explained Shares (%)

	(1)	(2)	(3)	(4)
All Non-Respiratory	52.15	59.86	58.20	52.19
	(18.85)	(21.66)	(22.48)	(22.42
Trauma or Poisoning	90.78	128.60	132.04	122.23
	(25.19)	(29.65)	(30.49)	(30.20)
Circulatory System	25.98	55.00	61.61	57.54
	(49.40)	(58.16)	(59.22)	(55.45)
Diarrhea	25.01	20.92	15.00	5.21
	(17.60)	(20.90)	(21.75)	(21.13)
All Other Causes	46.66	48.08	45.52	40.84
	(20.27)	(23.21)	(24.14)	(24.18)

Notes: The table shows the ED visits explained shares in percentage terms according to different specifications as explained in the text. Robust standard errors in parentheses.

Definition of the pre-COVID period In Appendix A3, we show the robustness of our results to changes in the definition of the pre-COVID period. We show that our findings remain stable after using any date between March 3 and March 12 as the start of the pandemic.

5.6 Additional evidence from changes in intra-week patterns

In this section we provide evidence from intra-week patterns suggesting that: (*i*) intra-week patterns before the pandemic are consistent with the idea that ED visits are related to social and economic activity, and (*ii*) the change in the intra-week patterns during the pandemic is consistent with the idea that the change in social and economic activity played a role in the drop in ED visits. This evidence also provides an explanation for why our model estimated using the mid-February to mid-March period fits the (out-of-sample) pandemic period well.[27]

Figure 5 plots the excess ED visits by visit category for each day of the week relative to Sundays (in percentage terms), and their corresponding 95 percent confidence interval. We split the 2020 sample into two groups: the pre-March 13 period and the post-March 26 period, after the post-COVID-19 visits stabilized (see Figure 2). For 2019 we use the equivalent dates (pre-March 15 and post-March 26).

For all non-respiratory visits combined, and particularly for the visits related to trauma and poisoning, the 2019 patterns change significantly between the equivalent "pre-COVID-19" period and "COVID-19" period (see Panels (a) and (b) of Figure 5). The pre-COVID-19 period contains mostly summer months, when schools are closed and many people are in vacation. This evidence from intra-week patterns before the pandemic strongly suggests that ED visits for these categories are linked to social and economic activity.

Figure 5 also shows that the pre-COVID-19 period in 2020 match the corresponding period in 2019 well. By contrast, the COVID-19 period in 2020 follows the "summer pattern" much more closely than the pattern of the corresponding period for the year 2019. This provides suggestive evidence that during the pandemic the relationship between economic activity and ED visits follows closely the relationship in the summer months, and not the relationship in the corresponding period of 2019. This, in turn, provides a reason for why estimating this relationship during the summer months allows us to fits the data well for the

[27] As noted in Table 1, the model is estimated within a range of mobility values that is very different from the one during the pandemic. The fact that we fit the data during the pandemic suggests that the linear model is a good specification in the entire range of observed mobility.

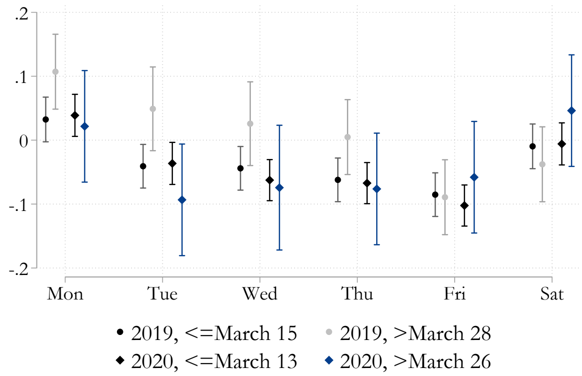
pandemic period.

For diseases related to the circulatory system and diarrhea the pre-COVID-19 period and COVID-19 period show similar intra-week patterns. This evidence reinforces our finding that the link between social and economic activity is weaker for these causes, as discussed in section 5.2.

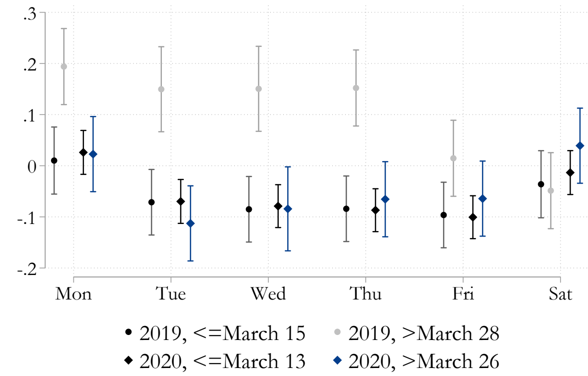
Overall, the evidence presented in Figure 5) provides auxiliary evidence on the relationship between social and economic activity and ED visits that is consistent with our analysis using mobility data, as well as a plausible explanation for the suitability of our model to explain the ED visits in the pandemic period using the available mobility data.[28]

[28] In terms of Equation (3) we can explain the decrease in ED visits because $\beta^{pre} \simeq \beta^{post}$.

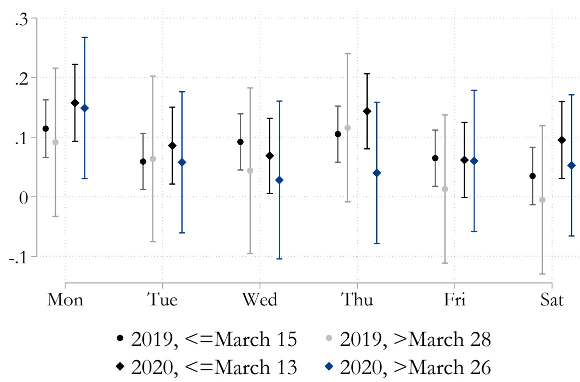
Figure 5: Excess Visits relative to Sundays



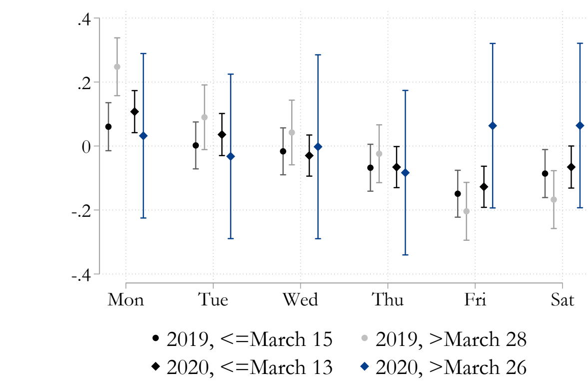
(a) All Non-Respiratory



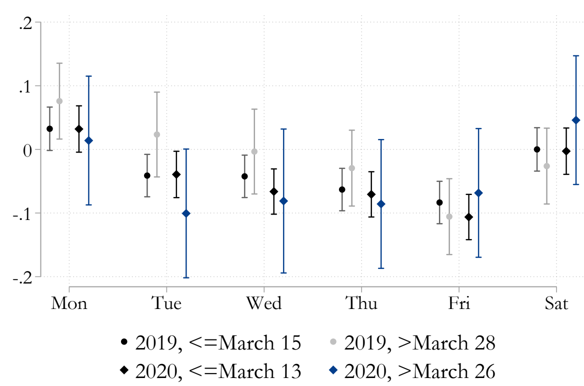
(b) Trauma or Poisoning



(c) Circulatory System



(d) Diarrhea



(e) All Other Causes

Note: This figure plots OLS estimates of the logged number of visits on indicators for the day of the week, using Sunday as the omitted category. For 2020, we split the sample into two groups: the pre-March 13 period and the post-March 26, after the post-COVID-19 visits reached their 'steady state' (see figure 2). For 2019 we use the equivalent dates (pre-March 15 and post-March 26).

6 Evidence from mortality data

In this section we provide complementary evidence from death records to show that the decrease in ED visits was not accompanied with a significant increase in mortality. We take the absence of a surge in mortality as suggestive evidence that individuals with life-threatening conditions did not stop from going to the ED due to the fear of contracting the virus.

We first use death records for all reported deaths at the region-week level from January 1, 2010 to May 19, 2020.[29] Figure 6 shows the number of deaths in 2020 relative as well as the average of previous years. On average, there were roughly 2,000 deaths per week in 2020. Although deaths in 2020 were higher than in previous years, we do not find discernible changes for the period after March 13, when emergencies decreased. It is important to note that although the data 6 includes COVID-related deaths, these deaths represents a small share of the total number: by the end of April 2020 there had been around 200 COVID-related deaths (see Figure 1).

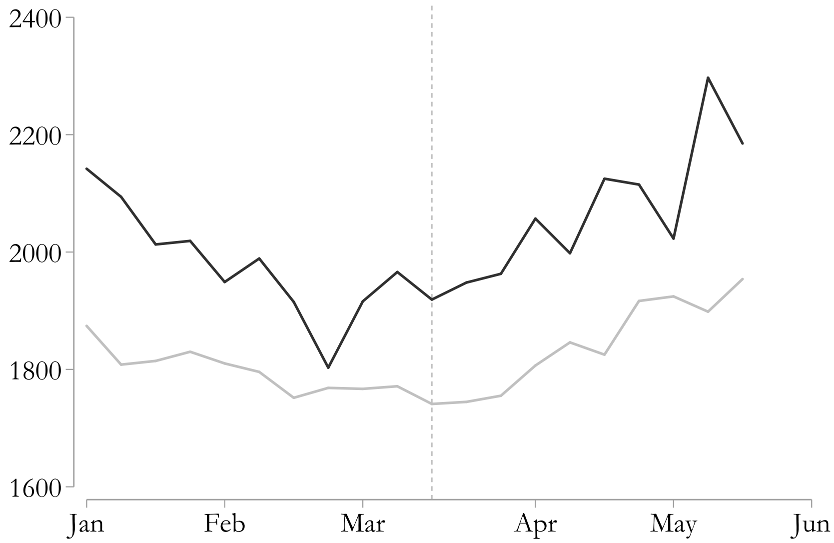
We formalize the graphical analysis by estimating a difference-in-differences model for the number of deaths with a similar specification as that of Equation (1):

$$Y_{rwy} = \gamma_1 Post_w + \gamma_2 Post_w \times 1\{2020\} + \psi_t + \phi_r + \epsilon_{rwy}. \tag{5}$$

The dependent variable in the equation is either the number or the log number of deaths reported in a given region-week-year, $Post_w$ refers to the period after week 11 (around March 13) for every year, and ψ_r and ϕ_r are region and year fixed effects, respectively. Our coefficient of interest is γ_2, which measures the extra number of deaths reported during the COVID-19 period relative to the deaths reported in the same period of time during the previous years, after controlling for the higher overall mortality 2020. We estimate the model for the first 18 weeks of each year to match the data of our main analysis.

[29]The data was released by the civil registry department (*Servicio de Registro Civil*), the governmental agency which manages official birth and death records, and is available at `https://www.registrocivil.cl/`.

Figure 6: Number of deaths per week: 2010-2020



Note: The plot shows the number of weekly deaths over time. The black line shows the data for 2020 and the gray line represents the 2010-2019 average for the same week of the year. The vertical line indicates the beginning of the COVID-19 period.

Table 6 presents the estimates of Equation (5). The results show a non-significant increase in deaths during the COVID-19 period, which means that the drop in emergencies did not directly correspond with a statistically significant change in deaths. This suggests that the drop in emergencies was unlikely to be driven by a decline in life-threatening ED visits. These findings provide evidence against the hypothesis that patients with severe conditions stopped going to the ED because of the fear of contracting the virus at the hospital.

If most of the drop in ED was due to a lower incidence of conditions, in principle we should observe a drop in deaths in the COVID-19 period. There are two possible explanations for why overall deaths remained stable despite the large drop in the number of ED visits. First, the stability in the overall number of deaths might mask a decrease in mortality due to lower mobility (e.g., due to a lower number of car accidents) that is coupled with an offsetting increase in the mortality rate of other conditions due to the fear of visiting the ED. We call this the “off-setting deaths” hypothesis.

Table 6: Change in deaths during post-COVID-19 period

	(1)	(2)	(3)
Dep. Variable	Log(deaths)	Log(deaths)	# Deaths
Post $\times$ 1{2020}	0.013	0.013	1.136
	(0.017)	(0.017)	(1.404)
N	3005	3005	3005
R-Squared	0.97	0.98	0.99
Year FE	Yes	No	No
Region FE	Yes	No	No
Region $\times$ Year FE	No	Yes	Yes

Note: Coefficients represent the change in dependent variable after week 11 (March, 13 in 2020) in year 2020, relative to the same period of the year during 2010-2019. Sample include all 16 Chilean regions and deaths between 2010-2020. Clustered standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

An alternative explanation is that the lower incidence of emergencies was mostly concentrated among cases with low mortality. Under this "selection" hypothesis we would expect lower ED visits without a corresponding decrease in mortality. Although we cannot fully rule the "off-setting deaths" hypothesis without detailed data on cause-specific mortality for 2020, we provide suggestive evidence in favor of the "selection" hypothesis using data for earlier years. As explained below, we find that ED visits decreased the most for causes that are less fatal on average, suggesting that the "missing emergencies" correspond mostly to low-severity cases.

Column (1) of Table 7 presents differences-in-differences estimates for the change in non-respiratory visits for each cause using the same specification as in Equation (1). Column (2) shows the ratio between deaths and total non-respiratory ED visits, using death records for each type for period 2010-2017.[30]

The two set of results indicate that the category that decreased its share the most during the pandemic (Trauma or Poisoning) is also the least fatal category with a 0.0047 death-to-visits ratio. On the other hand, the category that gained the most share (diseases of the

[30]The type-specific mortality data was provided by the Chilean Ministry of Health and is available only until 2017.

circulatory system) is also the most fatal one with a death-to-visits ratio of 0.079. These numbers suggest that the drop in visits was *selective*, in the sense that the drop in ED visit was concentrated among the least fatal categories. Given that we see selection across categories, it is plausible that there was selection within categories as well, so that the visit drop was concentrated in the less fatal cases even within categories. Sufficient selection could explain a large drop in ED visits happening concurrently with no significant drop in mortality.

Table 7: Change in Share of Visits and Mortality

Type	ED Visit Share Change (%) (1)	Deaths-to-ED Visits Ratio (2)
Trauma or Poisoning	-1.87***	0.47%
	(0.41)	
Circulatory System	1.23***	8.48%
	(0.12)	
Diarrhea and Other Causes	0.64	0.63%
	(0.38)	

Note: Column (1) presents differences-in-differences estimates for the change in the share of non-respiratory visits for the main ED visits causes between January 1 and April 28, where we use 2019 as the control group for 2020. The estimation includes day of the week, month of the year, year, and regional fixed effects. Clustered standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$ Column (2) shows the average weekly ratio between deaths and total non-respiratory ED visits for the period 2010-2017.

7 Summary and Conclusion

The overall utilization of emergency care has decreased dramatically during the COVID-19 pandemic worldwide. In this paper, we leverage high-frequency data from Chile to show that observed changes in population's mobility can explain most of that decrease.

The portion of the decrease that is left unexplained by our model includes all other determinants of the observed drop in ED visits not captured by the mobility measures, such as a decrease in the willingness to visit the ED due to fear of contracting the virus at the hospital. Therefore, our findings provide an upper bound to the role that individuals' behavioral responses in the decision of whether to go to the ED has played in decreased ED utilization, which are potentially welfare-decreasing. Moreover, our results suggest that lockdown measures may have had an unexpected positive effect by freeing up healthcare resources to confront the pandemic.

Although our results suggest that most of the decrease in emergency room visits is simply due to a lower need of emergency care, we cannot reject that some portion of the decrease is due to fear of contracting the virus while visiting the hospital, particularly for diseases related to the circulatory system, where the mobility data used in this paper has a relatively weak fit to the incidence of emergencies. Even a small share of fear-induced drop in emergency-care utilization for serious conditions may signify large welfare losses overall. While not conclusive, our evidence from mortality data provides some reassurance on this regard, as the sharp drop in ED visits was not followed with a increase in mortality.

An important caveat of our results is that they are focused on the context emergency care, and during a period where the pandemic was well contained. Our results cannot be directly extrapolated to either inpatient or outpatient visits, or to health care systems hard-hit by the crisis. We expect that drop in the willingness to visit the hospital to have a much stronger effect among elective or routine visits, or when hospitals are overwhelmed with COVID-19 cases; which could in turn have negative consequences for health in the medium or long run.[31]

[31] In fact, De Rosa et al. (2020) find that heart attacks fatality rates increased in northern Italy during the lockdown period.

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Appendix

A1 Google Mobility Report

The Google Mobility Report shows how visits and length of stay at different places change compared to a baseline. The baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The data was publicly available as of April 2020 in `https://www.google.com/covid19/mobility/`.

These changes are calculated using the same kind of aggregated and anonymized data used to show popular times for places in Google Maps. Mobility trends are split in the following categories:

1. Retail and recreation: Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.

2. Grocery and pharmacy: Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.

3. Parks: Mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens.

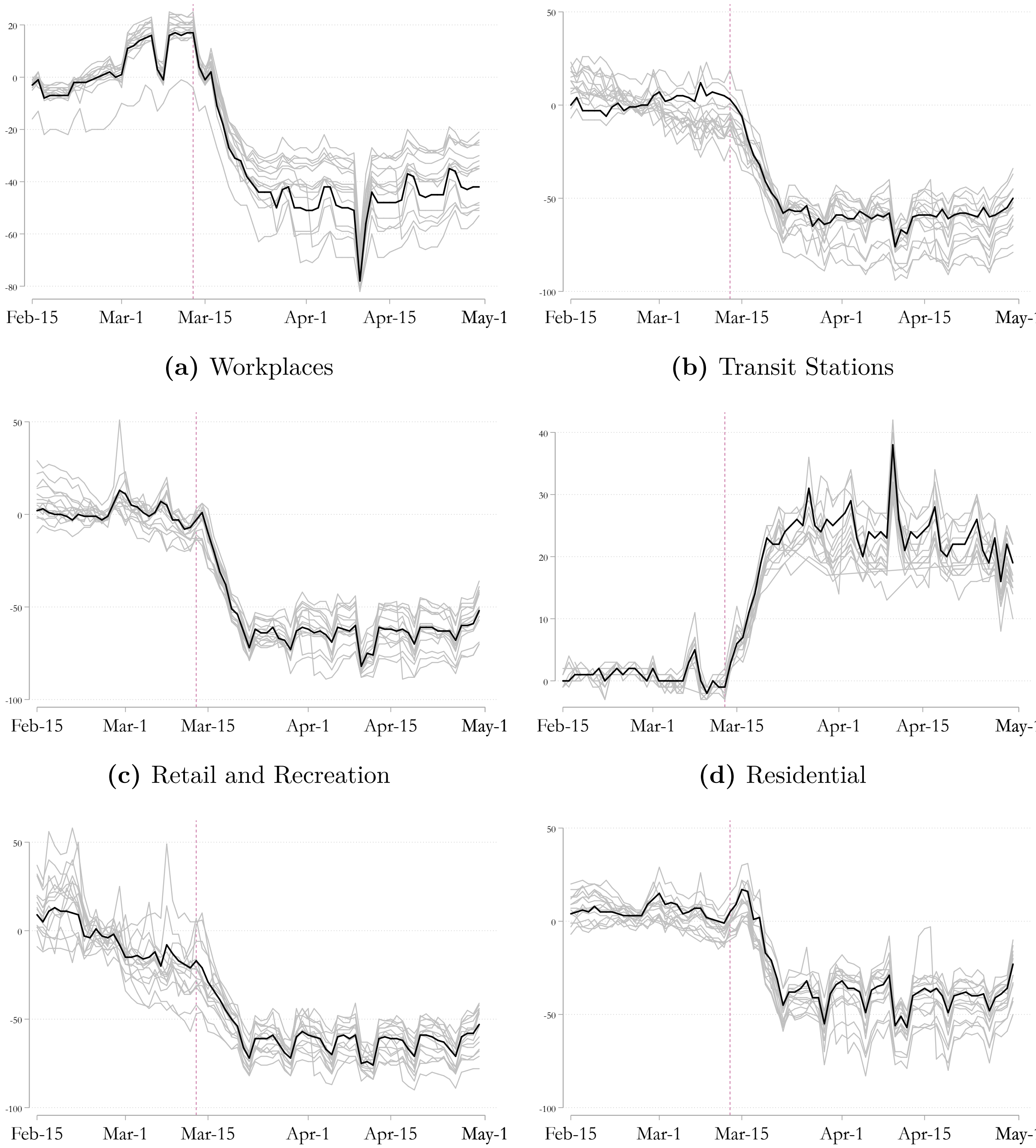
4. Transit Stations: Mobility trends for places like public transport hubs such as subway, bus, and train stations.

5. Work: Mobility trends for places of work.

6. Residential: Mobility trends for places of residence.

Figure A1 presents the mobility indexes in Chile at the regional and national levels in grey and black lines, respectively. Figure A2 shows the mobility indexes for Chile and the U.S. More details on how mobility index are calculated can be found in `https://www.google.com/covid19/mobility/data_documentation.html?hl=en#about-this-data`.

Figure A1: Mobility evolution across Chilean regions



(a) Workplaces

(b) Transit Stations

(c) Retail and Recreation

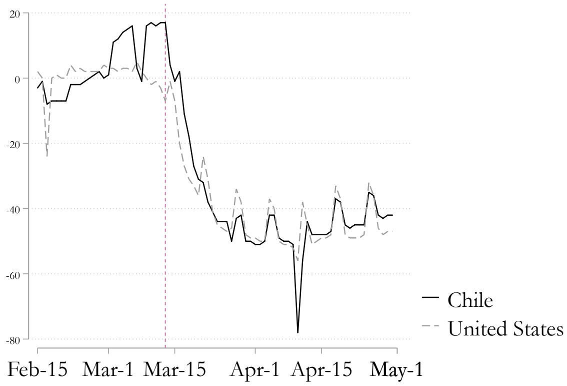
(d) Residential

(e) Parks

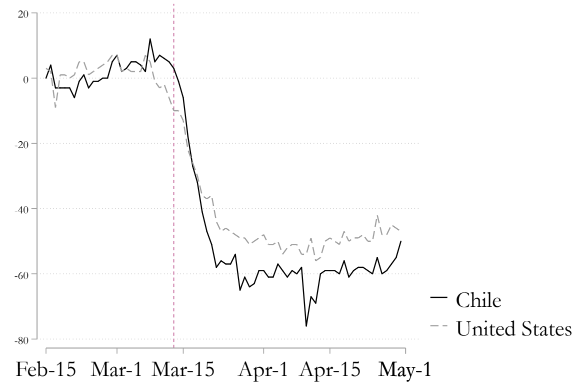
(f) Grocery and Pharmacy

Note: The figure presents the different mobility indexes for the Chilean regions. Each panel shows how visits and length of stay at different places changed compared to a baseline period. This baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The gray lines indicate different regions, and the black line show the national average. The vertical line indicates March 13, which denote the beginning of the COVID-19 pandemic in Chile.

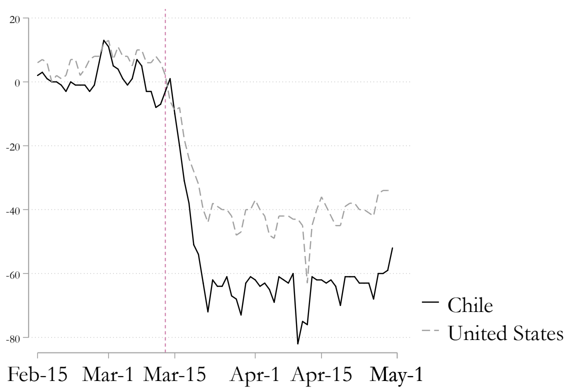
Figure A2: Mobility evolution in Chile and the United States



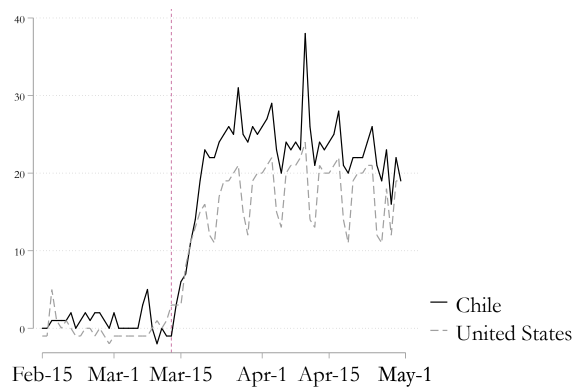
(a) Workplaces



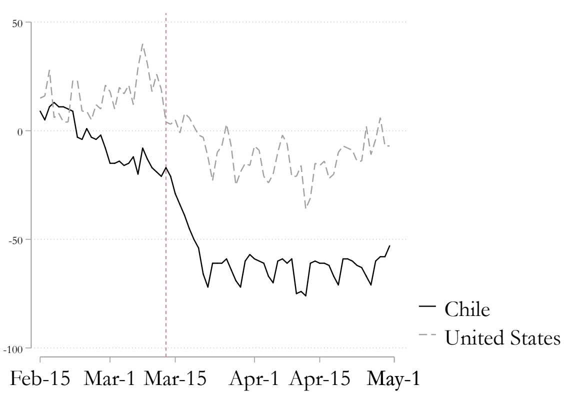
(b) Transit Stations



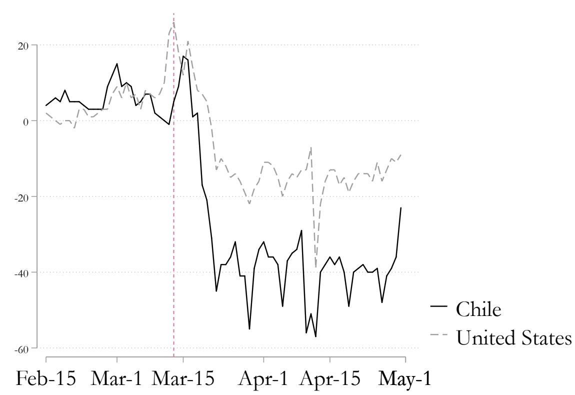
(c) Retail and Recreation



(d) Residential



(e) Parks



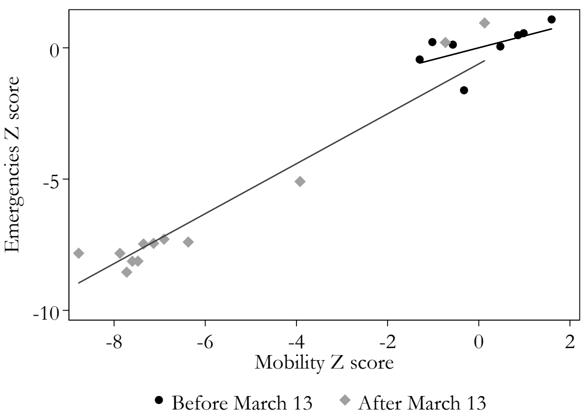
(f) Grocery and Pharmacy

Note: The figure presents national mobility indexes for Chile and the United States. Each panel shows how visits and length of stay at different places changed compared to a baseline period. This baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. The gray lines indicate different regions, and the black line show the national average. The vertical line indicates March 13, which denote the beginning of the COVID-19 pandemic in Chile.

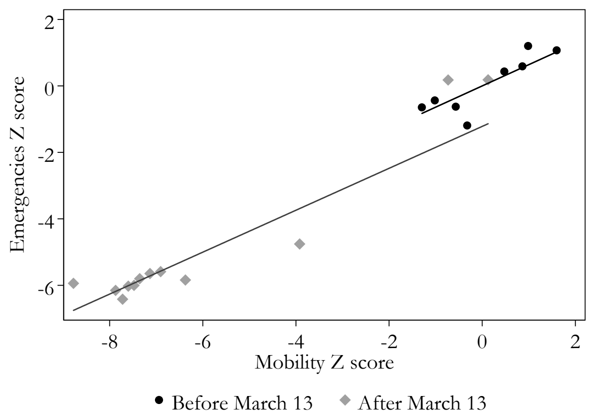
A2 Normalized Mobility and Emergency Visits

We present in Figure A3 more examples of binned scatter plots relating (normalized) emergency visits with (normalized) mobility measures. We show these plots for all non-respiratory conditions and for trauma and poisoning in the Metropolitana and the Biobío region, which gather 50 percent of the country's inhabitants.

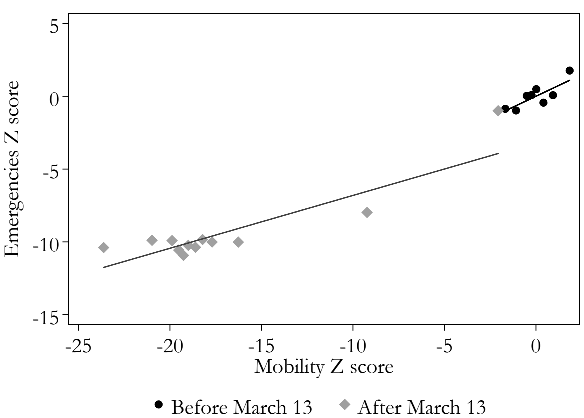
Figure A3: Normalized Mobility and ED visits



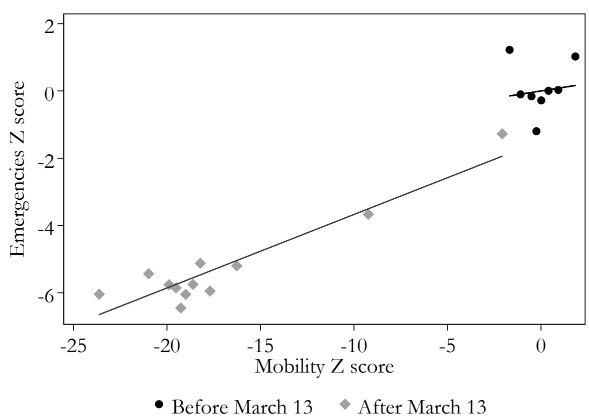
(a) Non-Respiratory - Metropolitana



(b) Trauma or Poisoning - Metropolitana



(c) Non-Respiratory - Biobío



(d) Trauma or Poisoning - Biobío

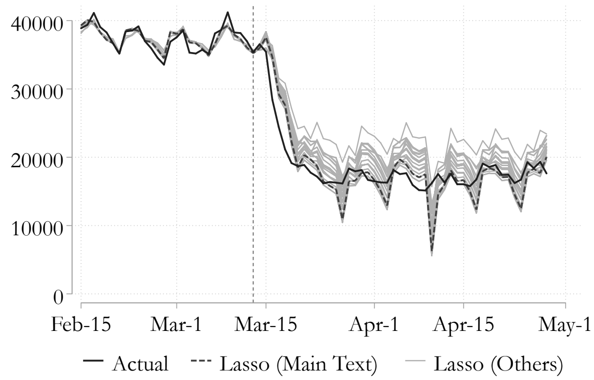
Note: The Figure presents binned scatter plots of transit station mobility and emergency visits in the Metropolitana and Biobío regions of Chile. The dotted lines show a linear fit for observations before and after March 13, the date of the beginning of the COVID-19 pandemic.

A3 Further Robustness Checks

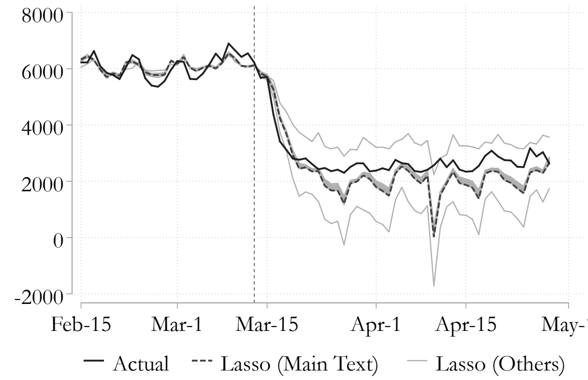
A3.1 Lasso Regressions

Figure A4 shows plots for different seeds of the same lasso specification and the sample sample as in the main text. These plots are meant to show only the instability in variable selection in the pre-COVID period for each emergency type and not the standard errors of lasso.

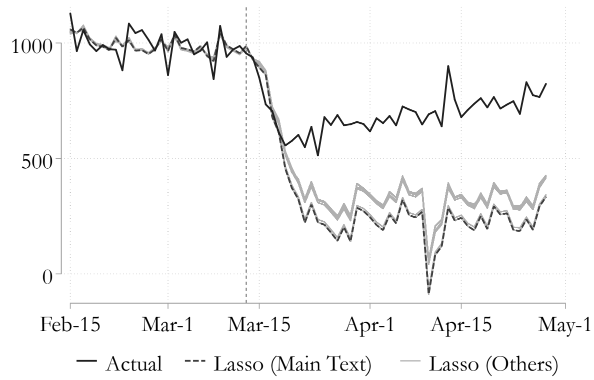
Figure A4: Lasso predictions—Actual and Predicted Emergencies by Type



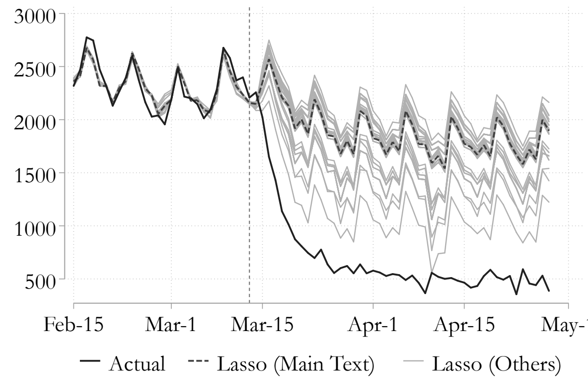
(a) All Non-Respiratory



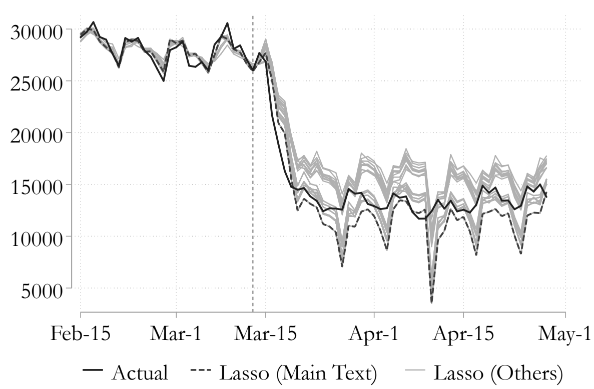
(b) Trauma or Poisoning



(c) Circulatory System



(d) Diarrhea



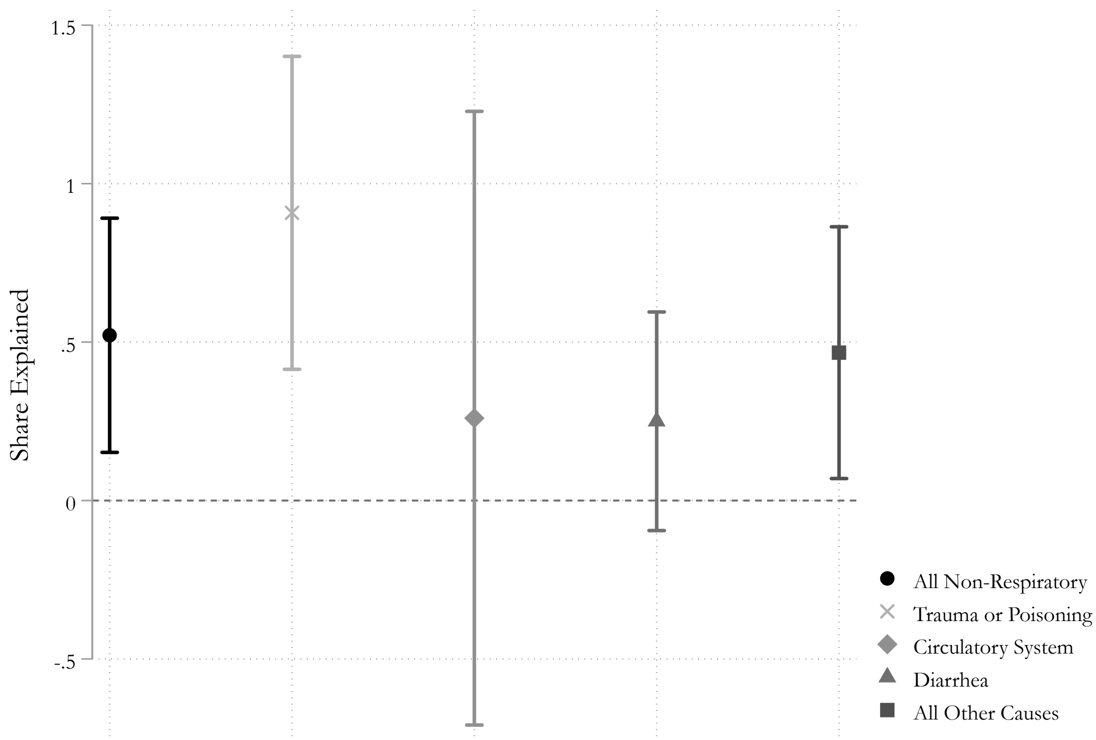
(e) All Other Causes

Notes: The vertical line represents the period that was used for prediction and the actual prediction using Google's Community Mobility Reports and regional fixed effects. Lasso and Elastic Net predictions are equivalent for all non-respiratory and trauma or poisoning categories.

A3.2 Estimation period

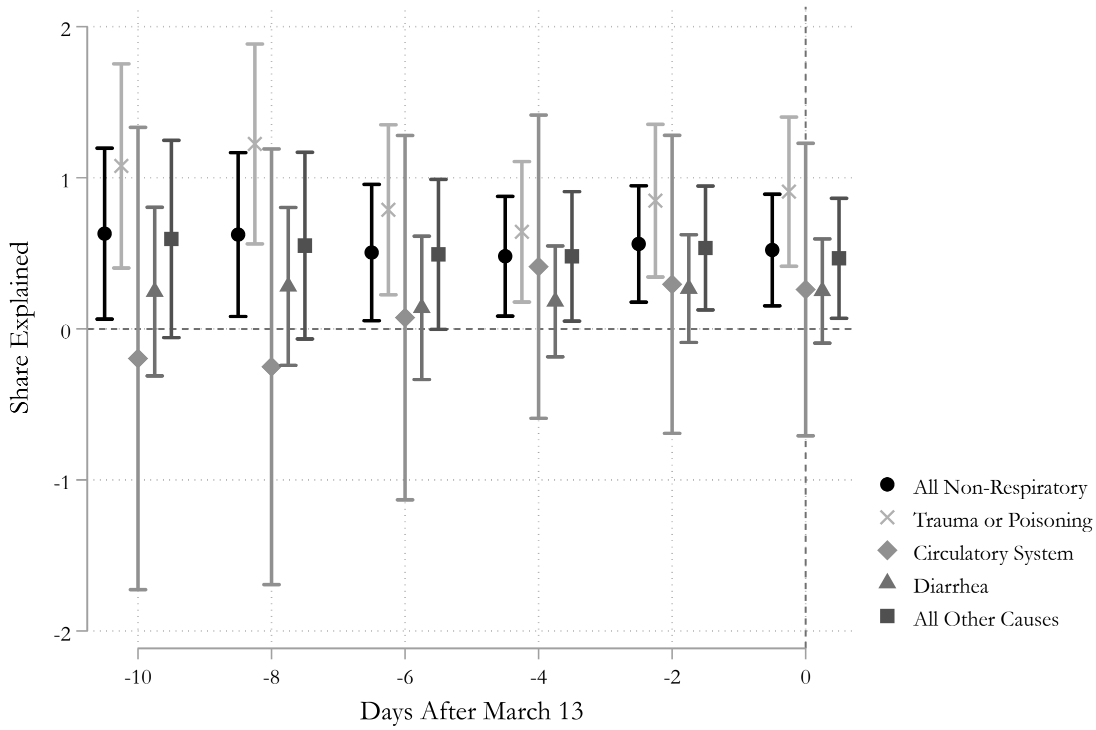
Figure A6 shows the share of the variation explained by our OLS model by modifying the end and the beginning of the pre- and post-Covid-19 periods.

Figure A5: Share Explained by the Model



Note: Figure shows the share of the variation explained. Each estimate includes 95% confidence intervals based on the standard errors of the prediction. Relative to March 13, each point estimate represent the share of the variation during the post-Covid-19 period that can be explained with pre-Covid-19 data. Shares are calculated following the methodology described in Equation (3) and Table 4, but adapting the definition of the post-period to the date indicated in the horizontal axis.

Figure A6: Robustness of the OLS Estimates to the Pre-Covid-19 period definition



Note: Figure shows the share of the variation explained by the model by modifying the end and the beginning of the pre- and post-Covid-19 periods. Each estimate includes 95% confidence intervals based on the standard errors of the prediction. Relative to March 13, each point estimate represent the share of the variation during the post-Covid-19 period that can be explained with pre-Covid-19 data. The end and the beginning of each period is indicated in the horizontal axis. Shares are calculated following the methodology described in Equation (3) and Table 4