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Where are the missing emergencies?
Lockdown and health risk during the pandemic

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Where are the missing emergencies? Lockdown and health risk during the pandemic

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Abstract

Abstract: Health care practitioners around the globe have observed that the COVID-19 crisis has been associated with an unprecedented decrease in non-COVID-19 visits to emergency departments. We corroborate this observation using administrative daily data from Chile and study the potential causes for this decrease. To that end, we merge regional emergency visits with Google mobility data and show that the crisis-induced changes in mobility patterns explain a significant portion of the overall drop in non-respiratory emergency room visits, especially for visits related to trauma and poisoning. 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. This result suggests that lockdown measures may have the unexpected benefit for public health of freeing up healthcare resources to confront the pandemic.

Keywords: Emergency, COVID-19, hospitals.

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1 Introduction

Emergency care utilization around the globe has plummeted after the onset of the COVID-19 pandemic (Garcia et al., 2020; Rodríguez-Leora et al., 2020). The leading explanation offered by health care practitioners for this phenomenon is that many patients, some with potentially serious conditions, have stopped going to the emergency department (ED) due to fear of contracting the novel SARS-CoV-2 virus at the hospital. However, another cause of the drop in emergencies is that individuals were confined to their homes and stopped working, commuting, or exercising outdoors. The large decline in these activities brought about by the pandemic could have lead to a decrease in accidents and other health emergencies related to these activities. Therefore, part of the drop in emergency care utilization could have been due to the decrease in risky behavior and the subsequent decrease in the need of emergency care.

Disentangling these two explanations is important because they each contain different 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. On the one hand, 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. On the other hand, if most of the decrease in ED visits was due

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1 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)

to a lower incidence of accidents and health conditions that required an emergency visit, the negative consequences associated with lower utilization would be muted. Importantly, this cause would indicate an overlooked benefit of lockdowns for public health, as they 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.”

In this paper, we shed light on the causes of the drop in emergency care visits by quantifying the fraction of the drop that can be explained using data on high-frequency (daily) mobility in Chile. Mobility data is an observable proxy for social and economic activity that is, in principle, related to the incidence of some types of emergencies. Therefore, the extent to which the decrease in mobility can explain the decrease in emergency care 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.

We start by documenting large declines in ED visits in Chile that occurred following the adoption of initial measures aimed to increase social distance. Similar to what has been reported elsewhere, we observe substantial decreases across several subgroups of ED cases. During the period of analysis, total non-respiratory ED visits declined by 49 percent. This decline includes a 25 percent reduction in visits related to heart attacks and a 54 percent decline in visits related to trauma and poisoning.

To examine the relationship between ED visits and mobility, we combine daily data on emergency room utilization with daily mobility patterns recently released by Google. Based on the daily variation in mobility before the adoption of social distance measures (the “pre-COVID-19 period”), we estimate a simple and parsimonious model that relates daily mobility patterns with ED visits in the pre-COVID-19 period. Then, we compare the actual visits to those predicted by the model under the mobility patterns observed during the pandemic. In other words, we “train” our data during the pre-COVID-19 period to investigate the extent to which the decline in ED visits during the pandemic can be predicted with the observed
changes in mobility.

We find that a simple linear model relating emergency visits to the six mobility measures provided by Google allows us to predict 42 percent of the decline in non-respiratory visits after the onset of the pandemic. We further investigate the ability of the model to predict the decline in two selected subgroups of ED non-respiratory cases, trauma and poisoning, and heart attacks, for which we can predict 95 percent and 90 percent of the respective drop using our OLS specification. However, the mobility variables only poorly explain the levels of heart attack visits, and the ability of our model to predict their drop is highly dependent on the specification. Using a flexible lasso, higher polynomials, and interactions of the mobility variables with regional effects, we are able to predict 60 percent of the overall drop in non-respiratory cases and all of the drop in trauma and poisoning, but none of the drop in heart attacks.

The Chilean context is well-suited for this analysis for three important reasons: First, detailed 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 virus was well contained in the country so hospitals operated well below their capacity during the pandemic. Excess capacity of hospitals and ED rooms helps us rule out unmet demand due to supply-side factors. 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 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 its impact on the spread of the disease (Fang et al., 2020; Juranek and Zoutman, 2020; Qiu et al., 2020). Alexander and Karger (2020) study the effect of the lockdown on consumption. Our paper provides novel insights by showing

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3Farboodi et al. (2020) show that individual’s optimizing behavior generated social distance before shelter-in-place restrictions came into effect.
that lockdowns generate positive public-health externalities by reducing the demand for emergency room services.\footnote{Adda (2016) provides a comprehensive analysis of the economic costs of infections and a cost-benefit analysis of social distancing interventions.}

In addition to providing insights specific to pandemics like the COVID-19 crisis, our paper also connects to broader questions in health economics and health care policy. First, our paper contributes to the debate regarding the productivity of health care spending. The large drop in ED visits brought about by the pandemic and the lockdown measures could suggest that a large fraction of pre-COVID-19 emergency-room visits were only marginally beneficial to patients. In fact, several studies have argued that many ED cases are actually non-urgent and thus could be handled in less expensive, regular physician visits without any deterioration in the patient’s condition.\footnote{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.} Our findings suggest that the lower incidence of conditions due to lower exposure to risk played an important role in this decrease bounding the role played by behavioral responses related to the decision to go to the ED.

Second, this paper is also related to the literature on countercyclical health, which suggests that the economic downturns can improve health by decreasing working hours and changing individual’s allocation of time and health behavior (see, e.g., Ruhm, 2000, 2005a,b, 2007; Evans and Moore, 2012), by their effect on traffic (He, 2016; Rodríguez-López et al., 2016), or due to countercyclical quality of health care (Stevens et al., 2015). Our results show that lower social and economic activities, as measured by mobility patterns, decrease the incidence of health conditions that lead to emergency room visits.

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 concludes.
2 The COVID-19 crisis in Chile

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 educational establishments, restaurants, and movie theatres, 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. 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. By April 14 the total number of cases and deaths were 7,525 and 82, respectively. We include a dashed vertical line on March, 13 which we use to mark the onset of the crisis in Chile. 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.

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6Lockdowns 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.

7These 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.
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 Department of Epidemiology, Ministry of Health, Government of Chile; via https://github.com/maibennett and Our World in Data https://ourworldindata.org/coronavirus.

3 Data

Our main empirical analysis combines daily administrative data on ED admissions with daily data from the Google Community Mobility Reports. Table 1 summarizes the data we use in this paper.

3.1 The Google Community Mobility Reports

The Google Community Mobility Reports use mobile geo-locations to compute an index of the time spent by users in six different categories of places: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces and residential. The report 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 mobility data is available from February 15, 2020. In this paper, we use data up to April 11, 2020. The data were released by Google in an effort to inform the debate around COVID-19. The data is available at the daily-level for all 16 Chilean regions.\(^8\) In the Appendix we show plots of the time series of each mobility index in the six categories of places for our period of analysis. Beginning on March 13, there is a sharp decrease on time spent in most categories, except for residential. These plots reflect nationwide compliance with government measures that aimed to increase social distance among the population. 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.

### 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.\(^9\) 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.\(^10\) Within the non-respiratory visits, we show results for two sub-categories of interest: trauma and poisoning, that correspond to 16 percent of cases, and heart attacks (or acute myocardial infarction, AMI) which account for 0.1 percent of cases. Trauma and poisoning cases are interesting because they constitute in our dataset the largest well-defined cause of ED visits and because we expect this category to be strongly related to mobility patterns. We also focus on AMI due to the several recent media reports highlighting the drop in this category, and the report of recent cases where

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\(^8\)Regions are the main sub-national administrative units.  
\(^9\)The cases are classified using the ICD classification method. Each category in the data corresponds to related ICD codes.  
\(^10\)We exclude all respiratory causes from our analysis that contain acute bronchitis (J20-J21), influenza (J09-J11), pneumonia (J12-J18), and other respiratory causes (J22; J30-J39, J47, J60-J98).
<table>
<thead>
<tr>
<th></th>
<th>Before March 13</th>
<th>Post March 13</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: ED visits</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Non-respiratory:</td>
<td>2,328.82</td>
<td>1,183.35</td>
</tr>
<tr>
<td>(177.67)</td>
<td>(342.48)</td>
<td></td>
</tr>
<tr>
<td>Heart Attacks</td>
<td>2.77</td>
<td>2.08</td>
</tr>
<tr>
<td>(1.57)</td>
<td>(1.61)</td>
<td></td>
</tr>
<tr>
<td>Trauma or Poisoning</td>
<td>378.22</td>
<td>175.86</td>
</tr>
<tr>
<td>(45.93)</td>
<td>(57.68)</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Mobility Index</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residential</td>
<td>0.68</td>
<td>19.57</td>
</tr>
<tr>
<td>(1.70)</td>
<td>(6.68)</td>
<td></td>
</tr>
<tr>
<td>Workplaces</td>
<td>4.36</td>
<td>-34.63</td>
</tr>
<tr>
<td>(9.36)</td>
<td>(17.31)</td>
<td></td>
</tr>
<tr>
<td>Retail and Recreation</td>
<td>1.13</td>
<td>-56.57</td>
</tr>
<tr>
<td>(7.48)</td>
<td>(18.34)</td>
<td></td>
</tr>
<tr>
<td>Grocery and Pharmacy</td>
<td>3.67</td>
<td>-32.98</td>
</tr>
<tr>
<td>(6.57)</td>
<td>(19.20)</td>
<td></td>
</tr>
<tr>
<td>Parks</td>
<td>-5.99</td>
<td>-58.60</td>
</tr>
<tr>
<td>(17.81)</td>
<td>(12.90)</td>
<td></td>
</tr>
<tr>
<td>Transit Stations</td>
<td>0.74</td>
<td>-54.12</td>
</tr>
<tr>
<td>(8.52)</td>
<td>(17.46)</td>
<td></td>
</tr>
</tbody>
</table>

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.
individuals have suffered an AMI and have not sought timely ED care. In addition, AMIs are likely among the most severe well-defined cause that individuals go to the ED for. However, AMIs constitute only a very small fraction of the ED visits in Chile.

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

$$ Y_{dkr} = \beta_{COVID-19k} + \mu_{dow,k} + \nu_{mk} + \tau_{yk} + \alpha_{rk} + \epsilon_{dkr} $$

where $d$ is the day counted after January 1, $y$ is year, $m$ is month of the year and $r$ is region.

We present the results in Table 2. We find a statistically significant drop in the three categories. The beginning of the COVID-19 pandemic led to a decrease of 1,290 non-respiratory emergency visits, of which 240 and 0.76 were due to trauma and poisoning and AMI, respectively. These figures represent 52, 61, and 25 percent of the average number of regional daily visits in the pre-pandemic period for three categories, respectively.\footnote{For AMI, in which the mean is close to zero, a Poisson model with a similar specification results in an estimate of -0.285 and standard error of 0.065.}

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 accidents or non-COVID-19
Figure 2: Emergency Room Visits in Chile in 2019 and 2020

(a) All Non-Respiratory

(b) Trauma and Poisoning

(c) Acute Myocardial Infarction

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.

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

<table>
<thead>
<tr>
<th>COVID-19 Spread</th>
<th>(1) All Non-Respiratory</th>
<th>(2) Trauma and Poisoning</th>
<th>(3) Acute Myocardial Infarction</th>
</tr>
</thead>
<tbody>
<tr>
<td>COVID-19 Spread</td>
<td>-1290.15** (456.65)</td>
<td>-240.01** (85.85)</td>
<td>-0.76** (0.27)</td>
</tr>
<tr>
<td>N</td>
<td>3150</td>
<td>3150</td>
<td>3150</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.19</td>
<td>0.20</td>
<td>0.19</td>
</tr>
<tr>
<td>Mean Dep. Variable</td>
<td>2,506.19</td>
<td>396.61</td>
<td>3.02</td>
</tr>
</tbody>
</table>

Note: The table shows the effect of the pandemic spread on total emergency room visits in Chile between January 1 and April 14, 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
diseases, as proxied by an observable set of indicators. If most of the decline in visits is predicted by changes in these observables, the decrease in ED visits attributed to a decline in 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, and use those estimates to construct the emergency visits predicted by the model under the post-COVID-19 mobility patterns.

Figure 3 provides a simple explanation of our approach. The figure plots the Z-score of the mobility to transit stations measure against the Z-score of the trauma and 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 axis corresponds to the deviation of a particular measurement with respect to the pre-COVID mean as fraction of the pre-COVID standard deviation.
In the case of a simple univariate model for ED visits, our empirical strategy would consist of (i) estimating the slope $\hat{\beta}_{\text{pre}}$ using the pre-COVID period, and (ii) using $\hat{\beta}_{\text{pre}}$ to project the linear relationship up to the mean mobility in the post-COVID period $\bar{Z}_{M,\text{post}}$. The share of total change in average visits $\bar{Z}_{Y,\text{post}} - \bar{Z}_{Y,\text{pre}}$ that is explained by the change in mobility corresponds to $\hat{\beta}_{\text{pre}}(\bar{Z}_{M,\text{post}} - \bar{Z}_{M,\text{pre}})$. 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 labor economics literature.\footnote{In principle we could also perform a decomposition of the pre/post-March 13 differences using the 2019 data. However, the analysis would require assumptions on mobility patterns and their impact on emergencies in 2019 (which we do not observe).}

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 indices included in the Google Mobility Reports.

5.1 Model Specification

We posit a simple linear model for non-respiratory and trauma and poisoning visits in day $d$, for diagnosis $k$ and region $r$:

$$Y_{dkr} = f_{kr}(M_{dr}) + \mu_{dow(d),k} + \epsilon_{dkr}$$

(2)

where $f_{kr}$ is a type- and region-specific function, $M_{dr} \in \mathbb{R}^6$ 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 $f_{kr}$: $f_{kr}^a = \alpha_{kr} + \sum_{j=1}^{6} \beta_{kj}M_{drj} + \mu_{dow(d),k} + \epsilon_{dkr}$. We estimate the coefficients of this first specification via OLS. In our second specification we allow $f_{kr}$ to contain the squared terms of the mobility indexes and a full set of interaction terms between the region and the mobility indices as well. The specification thus becomes: $f_{kr}^b = \alpha_{kr} + \sum_{j=1}^{6} \beta_{krj}M_{drj} + \sum_{j=1}^{6} \beta_{kj}M_{drj}^2 + \mu_{dow(d),k} + \epsilon_{dkr}$. We estimate this model via lasso. In addition, to account for the low incidence of heart attacks we estimate Poisson (count) models with similar specifications for AMI visits that we either estimate via maximum likelihood or by lasso.\footnote{We estimate lasso using the implementation of Friedman et al.'s (2010) coordinate descent algorithm. We use Townsend (2018) for the linear models and the R glmnet package for the Poisson models. 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 for the linear models.}

As noted above, we estimate the model using the 2020 data for the pre-COVID-19 period only. Then, we compute the predicted values, $\hat{Y}_{dkr}$, for the entire sample: the pre-COVID-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 $\hat{Y}_{dk} \equiv \sum_r \hat{Y}_{dkr}$.\footnote{We estimate lasso using the implementation of Friedman et al.'s (2010) coordinate descent algorithm. We use Townsend (2018) for the linear models and the R glmnet package for the Poisson models. 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 for the linear models.}
5.2 Pre-COVID-19 relationship between ED and mobility

We estimate Equation (2) in the pre-pandemic period. We find that the mobility data is strongly correlated in the pre-COVID-19 period with non-respiratory and trauma and poisoning emergencies, but not with AMI visits. The $F$ statistic (and its corresponding $p$-value) for the joint test that the six coefficients of the mobility variables equal zero in the pre-COVID-19 (training) sample ($\beta_{k1} = \beta_{k2} = \ldots = \beta_{k6} = 0$) are $F = 11.37(0.00)$, $F = 7.67(0.00)$, $F = 2.50(0.02)$ for the non-respiratory, the trauma and poisoning, and the heart attacks visits, respectively. We show the estimation results in the Appendix.

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 (or Poisson) 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 and poisoning emergencies 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.\textsuperscript{14} We provide numbers for the share of the explained drop in the next subsection.

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)\textsuperscript{14}

\textsuperscript{14}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) Acute Myocardial Infraction

Note: The vertical line represents divides 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.

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:

\[
E[Y_{pre}] = \bar{X}_{pre}' \beta_{pre}
\]

\[
E[Y_{post}] = \bar{X}_{post}' \beta_{post}
\]

A “three-fold” decomposition of the gap \(E[Y_{pre}] - E[Y_{post}]\) can be written as:

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

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 \(\beta_{pre}\) from the pre-COVID-19 average mobility \(\bar{X}_{pre}\) 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 we cannot explain by observables.

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

\[
\frac{E[Y_{post}] - E[Y_{pre}]}{E[Y_{pre}]} = \left(\frac{(\bar{X}_{post} - \bar{X}_{pre})'}{E[Y_{pre}]} \beta_{pre}\right) + \left(\frac{\bar{X}_{pre}' (\beta_{post} - \beta_{pre}) + (\bar{X}_{post} - \bar{X}_{pre})'(\beta_{post} - \beta_{pre})}{E[Y_{pre}]}\right). \tag{4}
\]

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

Table 3 shows the result of this decomposition, where each panel corresponds to a different type of ED visit. Panel (a) shows that total non-respiratory visits dropped by 18,327 visits
per day, a 49.2 percent decrease after the onset of the crisis. Our OLS model predicts a drop of 7,682. Thus, a simple linear model of the Google mobility indexes predict 41.9 percent of the drop in the non-respiratory ED visits. Moreover, the lasso regression is able to explain 60 percent of the overall drop. Panel (b) repeats the decomposition for trauma and poisoning. We find that both the OLS regression and the lasso regression can explain more than 95 percent of the decrease. Finally, Panel (c) shows that the simple Poisson regression can explain 90 percent of the decrease in AMI. However, we think the AMI result is not very plausible due both to the contradicting lasso prediction of an increase in 148 percent in AMI visits and the low OLS \( F \) statistic.

### Table 3: Decomposition of the Drop in Emergency Visits

<table>
<thead>
<tr>
<th>Panel (a)</th>
<th>Total Non-respiratory</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td>Predicted</td>
<td>OLS</td>
<td>Lasso</td>
</tr>
<tr>
<td>Before March 13 (A1)</td>
<td>37,051</td>
<td>37,051</td>
<td>37,051</td>
</tr>
<tr>
<td>After March 13 (A2)</td>
<td>18,580</td>
<td>29,370</td>
<td>24,288</td>
</tr>
<tr>
<td>Difference, in levels (A1-A2)</td>
<td>-18,471</td>
<td>-7,682</td>
<td>-12,764</td>
</tr>
<tr>
<td>Difference (%) (A1-A2)</td>
<td>-49.9%</td>
<td>-20.7%</td>
<td>-34.4%</td>
</tr>
<tr>
<td>Difference Explained by Model (%)</td>
<td>-</td>
<td>41.6%</td>
<td>69.1%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel (b)</th>
<th>Trauma and poisoning</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td>Predicted</td>
<td>OLS</td>
<td>Lasso</td>
</tr>
<tr>
<td>Before March 13 (A1)</td>
<td>6,010</td>
<td>6,010</td>
<td>6,010</td>
</tr>
<tr>
<td>After March 13 (A2)</td>
<td>2,754</td>
<td>2,932</td>
<td>2,920</td>
</tr>
<tr>
<td>Difference, in levels (A1-A2)</td>
<td>-3,256</td>
<td>-3,079</td>
<td>-3,090</td>
</tr>
<tr>
<td>Difference (%) (A1-A2)</td>
<td>-54.2%</td>
<td>-51.2%</td>
<td>-51.4%</td>
</tr>
<tr>
<td>Difference Explained by Model (%)</td>
<td>-</td>
<td>94.5%</td>
<td>100.4%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel (c)</th>
<th>Acute myocardial infarction</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td>Predicted</td>
<td>OLS</td>
<td>Lasso</td>
</tr>
<tr>
<td>Before March 13 (A1)</td>
<td>44</td>
<td>44</td>
<td>44</td>
</tr>
<tr>
<td>After March 13 (A2)</td>
<td>32</td>
<td>34</td>
<td>58</td>
</tr>
<tr>
<td>Difference, in levels (A1-A2)</td>
<td>-11</td>
<td>-10</td>
<td>15</td>
</tr>
<tr>
<td>Difference (%) (A1-A2)</td>
<td>-26%</td>
<td>-23%</td>
<td>33%</td>
</tr>
<tr>
<td>Difference Explained by Model (%)</td>
<td>-</td>
<td>86%</td>
<td>-148%</td>
</tr>
</tbody>
</table>

Note: The table shows the result of a Oaxaca-Blinder decomposition of the drop in visits into a part that is explained by the mobility indexes and a part that is not.
6 Summary and Conclusion

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

Our results call into question the idea that most of the decrease in ED visits can be attributed to a widespread fear of attending the ED. By using a simple model we quantify the portion of the decrease in ED visits that is due to a change in mobility. 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 at least 40 to 60 percent 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. Even a small share of fear-induced drop in emergency-care utilization for serious conditions may signify large welfare losses overall. In particular, the mobility data used in this paper does not fit well the incidence of heart attacks, and therefore we cannot rule out that an important fraction of the reduction in emergencies for heart attacks is due to patients with heart attacks having a lower willingness to visit the hospital. Moreover, a complete assessment of the lower ED utilization brought about by the pandemic would require data on health outcomes.
References


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James, Chris, Caroline Berchet, and Tim Muir (2017) “Addressing operational waste by better targeting the use of hospital care,” *OECD*.


Rodríguez-Leora, O, B Cid-Álvarezd, S Ojedae et al. (2020) “Impacto de la pandemia de COVID-19 sobre la actividad asistencial en cardiología intervencionista en España,” *REC Interv Cardiol*.


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.


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

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

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 more examples of binned scatterplots relating (normalized) emergency visits with (normalized) mobility measures. We show the case of all non-respiratory conditions and trauma and poisoning for 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 scatterplots 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 OLS estimates

Table A1 shows the results of estimating Equation 2 by OLS.

<table>
<thead>
<tr>
<th></th>
<th>All non-respiratory</th>
<th>Trauma and Poisoning</th>
<th>Acute Myocardial Infraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>115.60 (104.77)</td>
<td>15.57 (16.87)</td>
<td>-0.02 (0.09)</td>
</tr>
<tr>
<td></td>
<td>-0.85 (14.73)</td>
<td>2.56 (2.75)</td>
<td>-0.10 (0.07)</td>
</tr>
<tr>
<td>Workplaces</td>
<td>11.80 (29.88)</td>
<td>2.52 (4.99)</td>
<td>-0.02 (0.09)</td>
</tr>
<tr>
<td></td>
<td>5.91 (4.68)</td>
<td>3.45*** (0.86)</td>
<td>-0.04* (0.07)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(10.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Retail &amp; Recreation</td>
<td>-184.72*** (32.57)</td>
<td>-31.08*** (5.60)</td>
<td>-0.16*** (0.02)</td>
</tr>
<tr>
<td></td>
<td>-3.83 (2.51)</td>
<td>-1.49** (0.58)</td>
<td>-0.01 (0.02)</td>
</tr>
<tr>
<td>Grocery &amp; Pharmacy</td>
<td>186.91*** (45.94)</td>
<td>34.58*** (7.87)</td>
<td>0.14*** (0.04)</td>
</tr>
<tr>
<td></td>
<td>2.50 (4.29)</td>
<td>1.10 (0.86)</td>
<td>0.01 (0.02)</td>
</tr>
<tr>
<td>Parks</td>
<td>3.39 (16.44)</td>
<td>1.81 (2.75)</td>
<td>-0.04*** (0.01)</td>
</tr>
<tr>
<td></td>
<td>5.49** (2.33)</td>
<td>1.02*** (0.39)</td>
<td>-0.02*** (0.01)</td>
</tr>
<tr>
<td>Transit Stations</td>
<td>56.35*** (13.81)</td>
<td>4.89** (2.31)</td>
<td>0.11*** (0.02)</td>
</tr>
<tr>
<td></td>
<td>1.32 (2.20)</td>
<td>2.05*** (0.63)</td>
<td>0.03* (0.02)</td>
</tr>
</tbody>
</table>

Region F.E. N Y N Y N Y
Day-of-week FE N Y N Y N Y
F-stat. 12.13 11.37 8.48 7.67 12.56 2.50
p-value 0.00 0.00 0.00 0.00 0.00 0.02
$R^2$ 0.12 0.99 0.12 0.99 0.13 0.68
$R^2$adj 0.11 0.99 0.11 0.99 0.12 0.66

Notes: The table shows the results of an OLS estimation of Equation (2) in the pre-pandemic period. For comparison purposes, the table shows the results of running an OLS model for AMI visits even if in the main analysis we estimate a Poisson model for this category. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

A4 Robustness of the Lasso Regressions

Figure A4 shows plots for different seeds of the same lasso specification and the 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) Acute myocardial infarction

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.