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COVID-19 and The Rise of Intimate Partner Violence

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Abstract

Stay-at-home policies have been implemented worldwide to reduce the spread of the SARS-CoV-2 virus. However, there is a growing concern that such policies could increase violence against women. We find evidence in support of this critical concern. We focus on Peru, a country that imposed a strong lockdown starting on mid-March and where nearly two-thirds of women already experienced violence before COVID-19. Using administrative data on phone calls to the national helpline for domestic violence (*Línea 100*) and a difference-in-difference approach, we find that the incidence rate of the calls during the lockdown is nine percent larger than in previous periods and that the rise in phone calls has accelerated as the lockdown continues. We also uncover an important heterogenous pattern. We construct a stay-at-home index using Google's mobility measures and show that the increase is driven by states where the lockdown has been more pronounced, which more than doubles the incidence rate of calls to the *Línea 100*. These findings reinforce the need to identify policy options to combat the SARS-CoV-2 virus without affecting women's safety.

Keywords: Intimate partner violence, domestic violence, lockdowns, Peru, COVID-19.

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1. Introduction

Eliminating violence against women is not only a major public health issue (Krug et al., 2002; Bott et al., 2012) but also a key objective of the Sustainable Development Goals (United Nations, 2015). However, progress in this area could be stopped and even reversed by the onset of the SARS-CoV-2 virus. This research note provides the first systematic analysis documenting the unintended consequences of nonpharmaceutical policies to decrease the spread of the virus on intimate partner violence.

Stay-at-home policies are being widely used to reduce the impact of the virus. It is estimated that at least three billion people around the world are sheltering in place (Hall and Tucker, 2020) and 142 countries have imposed some form of stay-at-home requirements as of May 15 (Hale et al, 2020). These policies have raised multiple concerns, especially for their impacts on developing countries and on gender equality.[1] Scholars and International Organizations have argued that stay-at-home policies would increase violence against women (e.g., van Gelder et al, 2020; Peterman et al, 2020; Bradbury-Jones and Isham, 2020; UNFPA, 2020). This argument is often based on recent scholarship suggesting that intimate partner violence increased during past epidemics (Roesch et al, 2020; Durevall, and Lindskog, 2015) but also with economic downturns (e.g., see Buller et al, 2018; Cools and Kotsadam, 2017 for low- and middle-income countries and Van der Berg and Tertilt, 2012 for advanced economies). This could be further exacerbated in developing countries where most homes lack sufficient space and force people to be in much closer proximity (Brown, Ravallion, and Van De Walle, 2020).

[1] For a discussion on how COVID-19 could affect gender equality beyond intimate partner violence see Alon et al (2020). See also Chakraborty et al (2018); Węziak-Białowolska et al (2020) for studies about the link between violence against women and the workplace. Negative effects on gender equality could have intergenerational effects. See for example Imai et al (2014) and Kavanaugh et al (2018).

However, most of the current reporting about the increase on intimate partner violence (IPV) during the ongoing pandemic is anecdotal. In most cases, it relies on increases in reporting compared to the same month the year before.[2] Such analysis could be misleading. Consider the case of Peru, the country where we focus on this research note. Calls to the national helpline for violence against women (*Línea 100*) increased by 56 percent in April 2020 with respect to April 2019. But so, did the volume of calls in January (32 percent), a time before Peru implemented its lockdown policies to combat COVID-19. Also, previous work in Peru has documented seasonal increases in IPV during March and November in years before the onset of the virus (Agüero, 2019).

We consider a difference-in-difference model that accounts for all these features. This helps us contribute to the understanding of the unintended consequences of the nonpharmaceutical policies to combat COVID-19. We use monthly data on the number of calls to the *Linea 100* by state from January 2007 to April 2020.[3] Our model incorporates month fixed effects to account for the seasonal patterns documented earlier. We also add year and state fixed effects together with additional controls for state-specific trends. We find that calls to *Línea 100* increased its incidence rate by 1.09 times since Peru started its lockdown in Mid-March. We document a larger effect in April than in March. A key finding comes from the heterogenous increase based on measures of the severity of the stay-at-home behavior. We document a larger impact in states where the lockdown was stricter, raising the incidence rate of calls to the *Línea 100* by 2.1 times.

Focusing on calls to a helpline has many advantages with respect to other data sources during the ongoing pandemic. First, it is very well documented that police records are not

[2] See examples from The Guardian and The New York Times, both accessed on May 30, 2020.
[3] Peru is administratively divided into *regiones* (equivalent states in the United States), *provincias* (equivalente to counties) and *distritos* (municipalities). To ease its understanding, we use the term states instead of *regiones*.

reliable measures of violence against women (e.g., Palermo et al, 2014 and United States Bureau of Justice Statistics, 2017). Second, lockdown measures have severely limited the use of face-to-face interviews such as the widely use Demographic and Health Surveys. These surveys represent the main data source for intimate partner violence in many developing countries. However, in Peru and as in many other countries, these surveys are currently not been implemented. Third, for the handful of countries with a well-documented network of shelters for women, including Peru (e.g., Kavanaugh et. al., 2018), workers in these centers have not been declared as essential, so these centers are not operating during the lockdown. Thus, calls to *Línea 100* helpline provide the best available data to measure violence against women during the pandemic.

2. Peru's stay-at-home policies and intimate partner violence before COVID-19

On March 15, 2020, Peru's government announced that a nationwide lockdown would be implemented, effectively, the next day. The first positive test of COVID-19 was detected on March 6 and the first death was confirmed on March 19 after the lockdown had started. Peru's was one of the earliest coronavirus lockdowns in the region. This is shown in Figure 1, using Google's mobility data, where Peru is marked by the red solid line. We discuss the details of this dataset in the next section. Panel A shows a large decline in visits to retail stores and recreational centers the day the lockdown started (dashed vertical line). The decline takes place earlier --and is more abrupt-- than other South American countries, including Colombia (yellow line), Brazil (green) and Chile (black) and matches the levels observed in Italy (blue) who started its major lockdown earlier. In Appendix Figure A1, we show that these patterns are also observed for visits to groceries and pharmacies, parks, transit stations and workplaces. Back to Figure 1, Panel B shows that people avoided these places and stayed at home.

Peru is also a country with high levels of intimate partner violence. The 2019 Peruvian DHS, the latest available, shows that 58 percent of women aged 15 to 49 had experienced violence by their current or last partner. This figure has shown an important decline over the past ten years. In 2009, the rate was 77 percent. Understanding whether policies that seek to control a major pandemic lead to unintended negative consequences for women's safety is an important policy question. This is even more salient for developing countries, such as Peru, where the slow but consistent reductions in violence over the past ten years could be quickly reversed by the responses to COVID-19. The data and model to estimate the change in violence against women during the pandemic is described in next section.

3. Data and methods

The main variable for our analysis is the number of calls to the helpline *Línea 100* adjusted by population size. This helpline was created in 2006. Dialing 100 from any phone (landline or mobile) is free and connects the caller to a trained operator who records the call and if needed, refers the caller to the women shelters (*Centros de Emergencia Mujer*) located near the caller's location. For our analysis we use data at the month and state level on the volumes of calls per 100,000 people. This information is publicly available on the website of the Ministry of Women and Vulnerable Populations (*Ministerio de la Mujer y Poblaciones Vulnerables*), the government entity in charge of delineating the policy to reduce violence against women. This dataset is updated monthly and the most recent release, including calls during the month of April 2020, was made available at the end of May. At this frequency and aggregation level (by state), the data are available since January of 2007.[4] Microlevel data for the calls during 2020 will not be available until the second quarter of 2021. Thus, given the urgency of identifying a rise in calls during the pandemic, we opted to use the aggregated data. A possible drawback is that the aggregation would reduce the variance in the sample and would prevent us from finding statistically significant effects. As shown in the next section, that is not the case suggesting that delaying the analysis until the publication of the microdata would have prevented us to document the increase while it was happening.[5]

To test for the increase in calls to the helpline during the pandemic, we use a Poisson count model as follow:

$$\text{Calls}_{imt} = \exp(\beta \text{March}_m * \text{Y2020}_t + \theta \text{April}_m * \text{Y2020}_t + \alpha_i + \alpha_m + \alpha_t + \alpha_{it}) \qquad (1)$$

where the variable $Calls_{imt}$ represents the expected number of calls to the *Línea 100* in state i, in month m and year t. *March*Y2020* and *April*Y2020* are the interactions of interest in our difference-in-difference approach. *March* and *April* are binary variables to identify the calls that took place during each of these months, respectively and Y2020 is a binary indicator for the year 2020. These are the variables of interest and values bigger than one (for the exponentiated coefficients) indicate an increase in the rate of incidence of the calls during these months. As explained by Cameron and Trivedi (2013), an advantage of a Poisson specification is that fixed effects can be included without creating an incidental parameters problem. This is particularly important as some states, earlier in the sample, have relatively low counts by month. A second

[4] Website: https://www.mimp.gob.pe/contigo/contenidos/pncontigo-articulos.php?codigo=31.
[5] Microdata are only available for three years: 2017, 2018 and 2019. Using microdata for 2020 would allow us to identify calls by the gender of the victim, which not possible in the state-level report. While created as part of the plan to reduce violence against women, the *Línea 100* receives calls from or about men as victims too. Yet, these calls represent less than 15 percent of all recorded calls. The same can be said by age of the victim, where such classification is not available in the state-level data used in our main analysis. To explore the possible impact by gender and age, in Appendix Table A3, we conduct a time series analysis using coarser data (at the national level and without state-level variation) and for fewer years where these data are available (2014-2020). We continue to find that the increase is larger in April 2020 and seems to be concentrated on women (as expected) and for adults (aged 18+).

advantage is the consistency of the maximum likelihood estimates of the parameters, which does not require that the arrival process for calls to the *Línea 100* is actually Poisson (Cameron and Trivedi, 1986).

To estimate the differential effect net of seasonal effects documented by Agüero (2019) we include month fixed effects (α_m). Also, as shown in Appendix Figure A2 and Table A1, the number of calls has grown over time. In 2007, the first full year of operation of the *Línea 100*, an average of 0.93 calls per 100,000 people were registered. In 2019, the number jumped to 24.8 and in the first four months of 2020, the average is 31.4. To incorporate this secular increase, the model includes year fixed effects (α_t). The model further accounts for time-invariant as well as time-variant both observed and unobserved factors at the state level (e.g., cultural differences, gender norms, socioeconomic status, altitude and climate) as we added state fixed effects (α_i) and state-specific trends (α_{it}). As discussed in the next section, our results are robust to the inclusion of month-specific trends as well.

We compute robust standard errors clustered at the state-year level (350 clusters) and our findings are robust if using alternative clusters and constructions of the standard errors. For instance, we consider clustering by state-month without altering our findings. Using the Newey-West HAC correction yields smaller standard errors, which would imply larger t-statistics, hence, we opted for a more conservative approach. All these additional results are available upon request.

A second data source is Google COVID-19 Community Mobility Report and available at https://www.google.com/covid19/mobility/. For our analysis we used data released on May 27th, 2020. The dataset captures how visits and length of stay at different places change compared to the weeks of January 3rd and February 6th, 2020, which Google set as the baseline. Google calculates “these changes using the same kind of aggregated and anonymized data used to show popular times for places in Google Maps.” The data provide six categories: grocery and pharmacy (it relates to grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies); parks (including local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens); transit stations (i.e., public transport hubs such as subway, bus, and train stations); retail and recreation (i.e., restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters); residential (i.e., places of residence) and workplaces. For additional explanations of the data and privacy issues please visit the documentation available in the link above.

To match these data with the information on calls to the *Línea 100*, we aggregated the daily Google data into months and merge by state, month and year. This allows us to identify the states that experience a larger (smaller) intensity of the lockdown during March and April. We combined all six measures of mobility into one stay-at-home index as in Kling et al (2007). Specifically, we define each of the six mobility measures so that higher values correspond with higher stay-at-home outcomes (i.e., multiply all measures, except residential, by minus one), then we created a z-score for each and average them to construct the index. We expanded equation (1) by adding interactions of our stay-at-home index to the variables of interest (*March*Y2020* and *April*Y2020*) such that the new interaction varies also by state now. The results of applying these methods are discussed in the next section.

4. Results

Table 1 reports the estimation of equation (1) with the exponentiated coefficients. In Column (1) we show that calls to the helpline increased in April 2020. The incident rate increases by 9 percent compared to all other months ($p<0.05$). This is much smaller than the April-to-April growth of 56 percent suggesting that naïve comparisons overstate the true effects. Similarly, while the number of calls grew in March compared to the same month in 2019 (by 28 percent), the estimated coefficient for that month in Table 1 refutes that finding: the growth in calls cannot be distinguished from zero once we include month, year and state fixed effects (and state-level trends) incorporated in our model. We further reject the null hypothesis that the effects for March and April are equal ($\chi^2(1)=9.83$, $p=0.0017$). The larger growth in April implies that the increase in intimate partner violence measured by the calls to the *Línea 100* accelerates as the lockdown continued.

In Column (2) we expand equation (1) to include interactions with the mobility index by state and separately for March and April, in the form of a triple-difference strategy. We find that one standard deviation increase in the stay-at-home index is associated with doubling the incidence rate of calls during the pandemic ($p<0.01$). Thus, the largest increase in calls comes from areas where the lockdown was strongly followed.

We conducted several robustness checks. First, as described in the previous section, our results are not altered when considering alternatives ways to cluster the standard errors. Second, in Appendix Table A2 we change the dependent variable to the number of calls without adjusting for the state population. This exercise shows that our main results are conservative. A higher increase in calls is documented in that appendix table. Finally, using again calls per 100,000 people, column (3) of Table 1, indicates that our results are robust to the inclusion of month-specific trends. These checks strengthen the validity of our findings.

5. Discussion and conclusion

We provide the first systematic analysis of the unintended effects of the efforts to control the pandemic caused by the SARS-CoV-2 virus. We document an increase in calls to the helpline for violence against women in Peru after stay-at-home policies started in mid-March. Our estimates document a nine percent increased in April 2020 in a country where already 58 percent of women experienced violence before the virus arrived. This result hides an important heterogenous effect by the intensity of the lockdown within the country. We find that a one standard deviation increase in the stay-at-home index is associated with doubling the calls to the helpline during the pandemic.

Data limitations prevent us from isolating the exact mechanisms driving this heterogenous findings. On the one hand, the increase in violence could be due to the closer contact between a woman and her partner. On the other hand, the response to COVID-19 has led to large decline in economic activity. As discussed in the introduction, both factors are created by the nonpharmaceutical response to the disease and in this research note, we cannot isolate them with the available data used in this research note.

Given our findings, there is an urgent need to identify policies that could help combat COVID-19 without reducing women's safety. Examples of such policies for the context of developing countries are discussed in Peterman et al (2020) and de Paz et al (2020).

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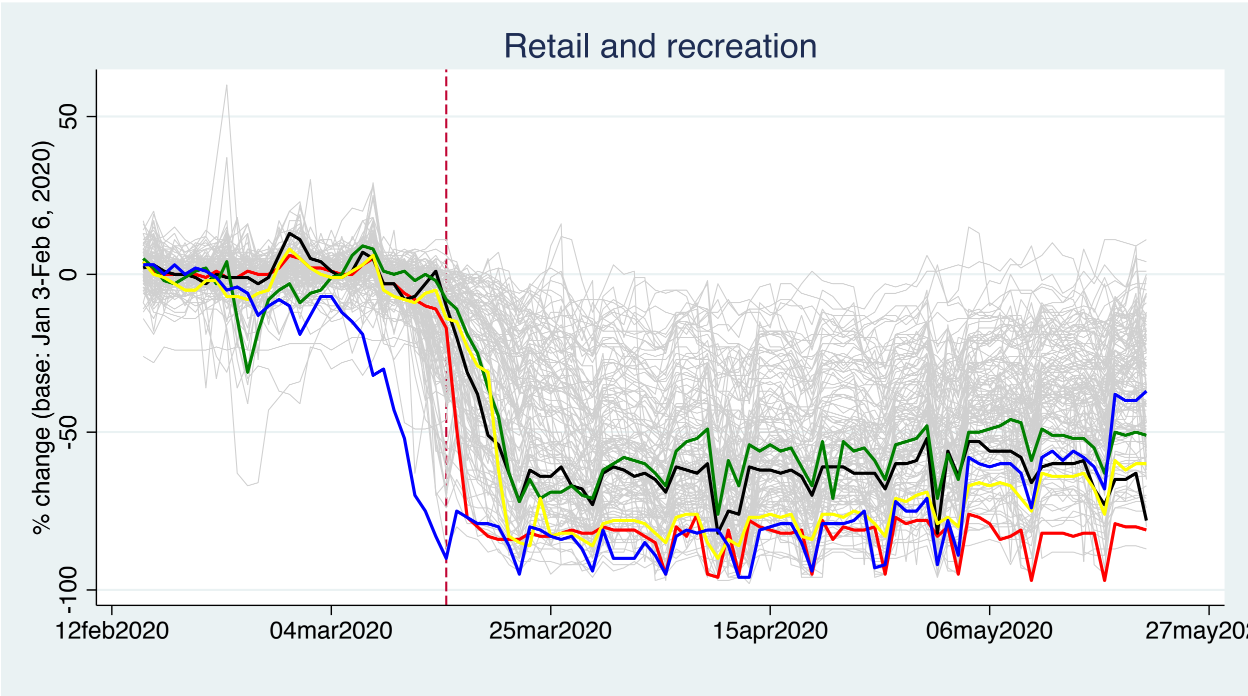
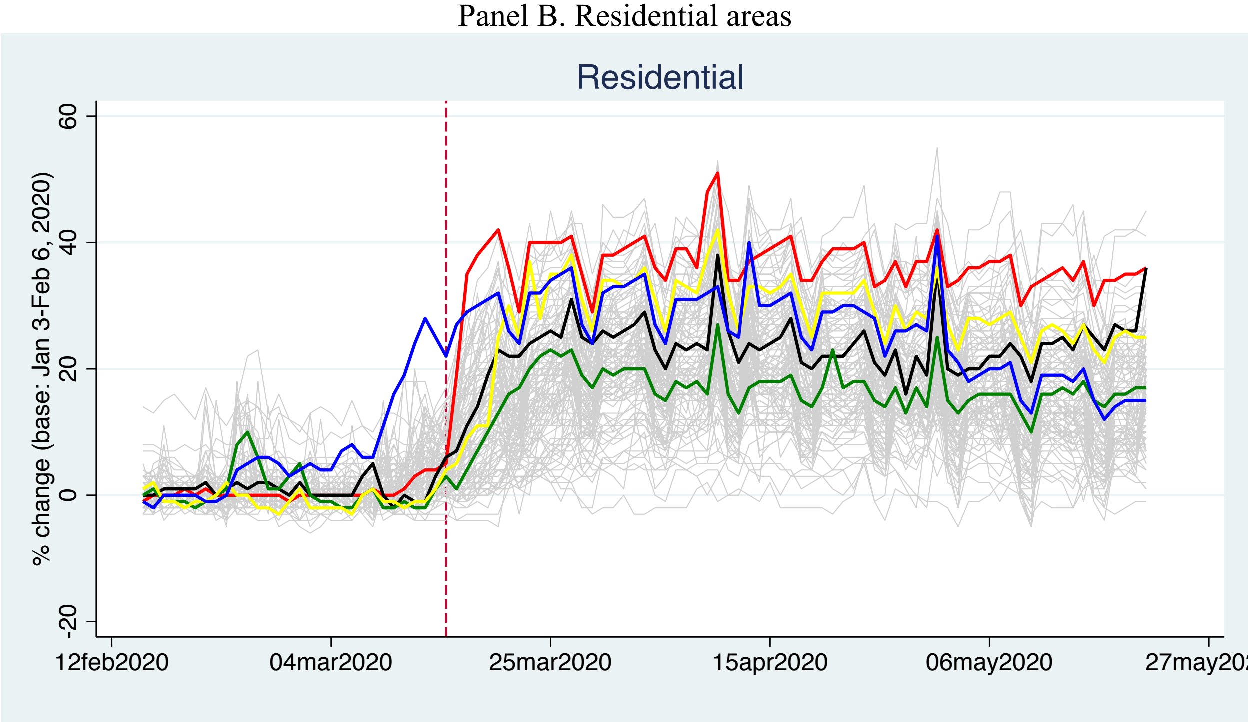
Figure 1. Measures of mobility in Peru and selected other countries

Panel A. Retail and recreation



Panel B. Residential areas



Note: Author's calculation based on Google mobility data available on https://www.google.com/covid19/mobility/. Peru is marked by a red solid line. Other countries are marked in grey, except for Brazil (green), Chile (black), Colombia (yellow) and Italy (blue). The dashed vertical line refers to March 15, the day before Peru implemented its lockdown.

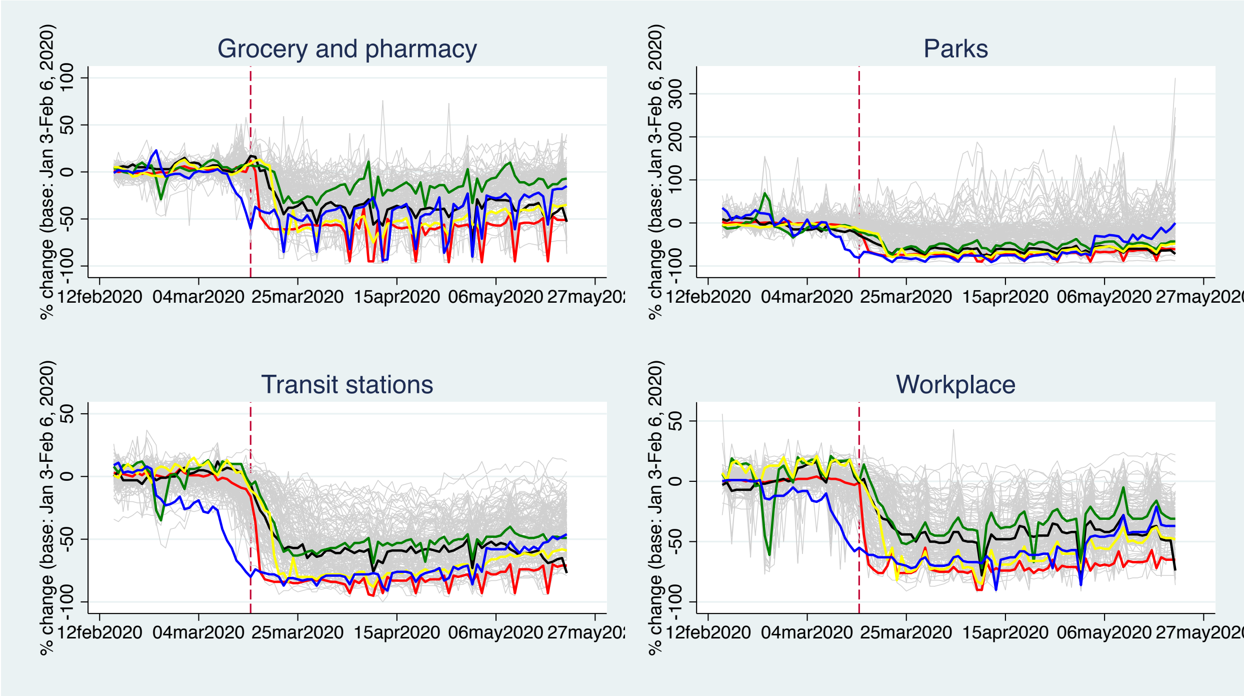
Table 1. Estimates of the calls to helpline during the pandemic (Poisson)

Dependent variable:	Number of calls to *Línea 100* per 100,00 people		
	(1)	(2)	(3)
March*Y2020	0.96	1.12	1.13
	(0.03)	(0.09)	(0.09)
April*Y2020	1.09**	0.52***	0.49***
	(0.05)	(0.12)	(0.11)
March*Y2020*Mobility index		1.71*	1.71*
		(0.49)	(0.49)
April*Y2020*Mobility index		2.11***	2.11***
		(0.44)	(0.44)
Month fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
State fixed effects	Y	Y	Y
State-specific trends	Y	Y	Y
Month-specific trends	N	N	Y
Pseudo R^2	0.604	0.604	0.606
Log-likelihood	-8702	-8693	-8666
N	4000	4000	4000

Note: Exponentiated coefficients. Robust standard errors, clustered at the state-year level in parentheses. See text for variables definitions and sources. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

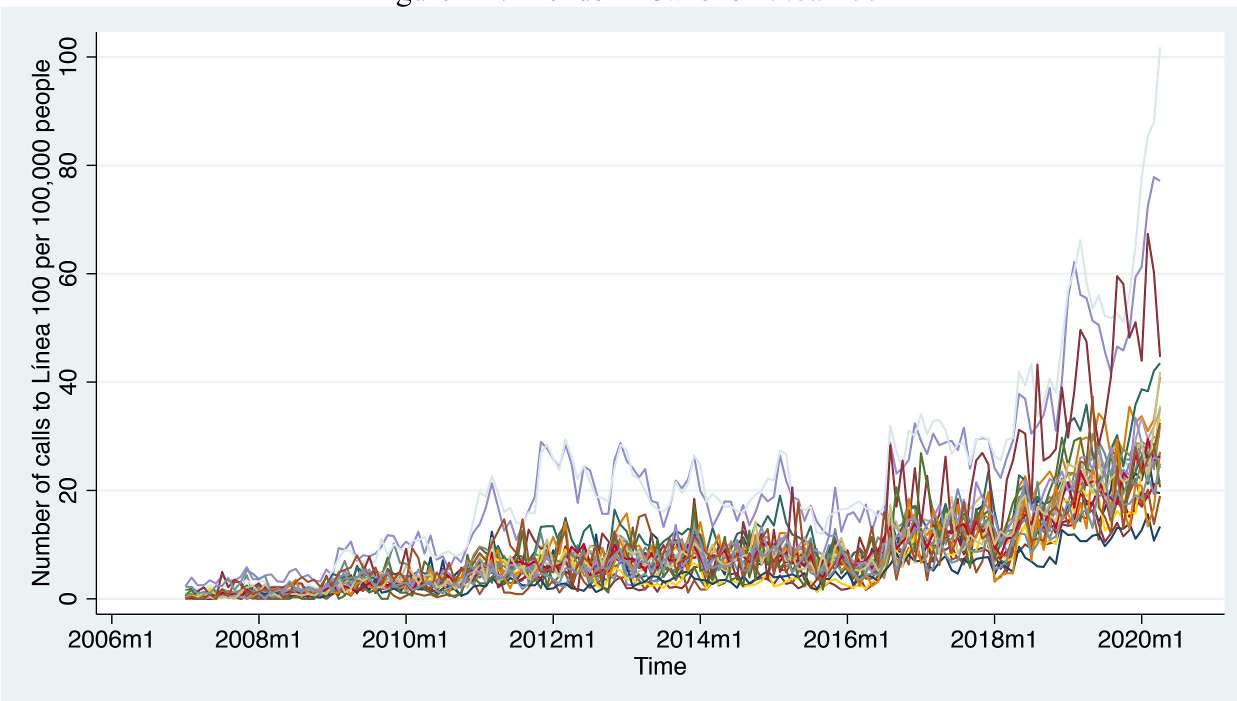
Online Appendix: Not for publication

Figure A1. Additional Measures of mobility in Peru and selected other countries



Note: Author's calculation based on Google mobility data available on https://www.google.com/covid19/mobility/. Peru is marked by a red solid line. Other countries are marked in grey, except for Brazil (green), Chile (black), Colombia (yellow) and Italy (blue). The dashed vertical line refers to March 15, the day before Peru implemented its lockdown.

Figure A2. Trends in Calls to *Línea 100*



Note: Author's calculation based on the data described in text. Each line represents a state.

Table A1. Calls to the *Línea 100* (2007-2020)

Year	Average number of calls per 100,00 people
2007	0.93
2008	1.36
2009	3.54
2010	3.83
2011	6.82
2012	8.00
2013	8.21
2014	8.17
2015	7.97
2016	9.64
2017	13.69
2018	15.67
2019	24.81
2020(*)	31.36

(*) Includes only January to April. Note: Author's calculation based on MIMP data. See text for details.

Table A2. Additional estimates of the calls to helpline during the pandemic (Poisson)

	Dependent variable: number of calls to *Línea 100*(*)	
	(1)	(2)
March*Y2020	0.98	1.26***
	(0.02)	(0.06)
April*Y2020	1.20***	0.31***
	(0.04)	(0.08)
March*Y2020*Mobility index		3.46***
		(0.93)
April*Y2020*Mobility index		3.52***
		(0.80)
Month fixed effects	Y	Y
Year fixed effects	Y	Y
State fixed effects	Y	Y
State-specific trends	Y	Y
Pseudo R^2	0.974	0.974
Log-likelihood	-24838	-24646
N	4000	4000

(*) The dependent variable is not adjusted by the state population. Note: Exponentiated coefficients. Robust standard errors, clustered at the state-year level in parentheses. See text for variable definitions and sources. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3. Calls to *Línea 100* during the pandemic (Poisson)

	Dep. var: Number of calls to *Línea 100*(*) by characteristics of the victim						
			Age group:				
	All	Women	0-5	6-11	12-17	18-59	60+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
March*Y2020	0.99	1.00	0.97	0.81**	0.78**	1.07	1.28***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.11)	(0.10)
April*Y2020	1.20**	1.22**	0.92	0.81***	0.75***	1.43***	1.61***
	(0.09)	(0.10)	(0.05)	(0.06)	(0.06)	(0.13)	(0.14)
Pseudo R^2	0.924	0.918	0.818	0.850	0.877	0.914	0.918
Log-likelihood	-4400	-3695	-738	-885	-958	-3126	-490
N	76	76	76	76	76	76	76

(*) Not adjusted by population. Note: Exponentiated coefficients. Robust standard errors, clustered at the month-year level in parentheses. All regressions include month and year fixed effects. See text for variable definitions and sources. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.