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JEL Classification: J12, I38, H53

Keywords: Domestic violence, lockdown, social safety net, Public health, COVID-19

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Dynamic Impacts of Lockdown on Domestic Violence: Evidence from Multiple Policy Shifts in Chile*

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January 26, 2022

Abstract

We leverage staggered implementation of lockdown across Chile's 346 municipalities, identifying dynamic impacts on domestic violence (DV). Using administrative data, we find lockdown imposition increases indicators of DV-related distress, while decreasing DV reports to the police. We identify male job loss as a mechanism driving distress, and female job loss as driving decreased reporting. Stimulus payments to poor households act on both margins, their impacts partially differentiated by lockdown status. Once lockdown is lifted, police reports surge but we see a ratchet effect in distress. Our findings accentuate the controversy around welfare impacts of lockdown mandates.

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1 Introduction

Since the start of the COVID-19 pandemic, reports of a substantial surge in domestic violence have emerged from several countries, a phenomenon referred to as the shadow pandemic (UN Women., 2020). The fact of an almost universal increase suggests common mechanisms at play. In this paper we investigate the role of lockdown mandates. Analysis of optimal lockdown policy has focused on the trade off between fatalities and economic growth (Alvarez, Argente and Lippi, 2021). We extend the scope of debate over lockdown mandates by investigating their impact on domestic violence. We also provide estimates of the extent to which income support schemes have mitigated impacts on DV, allowing differences in impacts by lockdown status.

We investigate two mechanisms by which lockdown can lead to domestic violence (DV), which are job loss and mobility restrictions. Lockdown is associated with a decline in economic activity, manifest in employment and earnings losses. Recent evidence suggests that individual job loss triggers DV by generating both a negative income shock (that generates stress) and a positive time shock (that increases exposure or opportunities for crime) (Bhalotra et al., 2021). The mobility restrictions imposed by lockdown reinforce exposure. Additionally, by forcing isolation from social networks, they may impact the mental health of men and women, and limit the freedom of the victim to seek social or state support.[1]

Numerous studies have analysed the phenomenal increase in DV since the pandemic.[2] Our contribution lies in providing the first unbiased estimates of dynamic impacts of both *entry* to lockdown and *exit* from lockdown on multiple indicators of domestic violence, and in investigating the relevant mechanisms.

The study is set in Chile, which has implemented rolling lockdowns at municipality level. We analyse the first-wave of COVID-19 when, between March and September 2020, lockdown was imposed in 116 of Chile's 346 municipalities, generating 116 natural experiments, which we stack in an event study design. Events of lifting lockdown provide a further series of experiments. We investigate both imposition and lifting of lockdown, estimating dynamic impacts while allowing for treatment effect heterogeneity using the de Chaisemartin and D'Haultfœuille (2020) estimator. The identifying assumption is that the timing of lockdown mandates is conditionally random. We scrutinize this by displaying placebo or anticipation effects, with and without

[1] A number of studies indicate a deterioration of mental health during the pandemic, for instance, Giuntella et al. (2021), Etheridge and Spantig (2020). The latter show that women suffer more, and that isolation from social networks plays a role in this.

[2] Without attempting to be comprehensive, we refer to Leslie and Wilson (2020), Sanga and McCrary (2020), Hsu and Henke (2021), Bullinger, Carr and Packham (2020), Miller, Segal and Spencer (2020), Agüero (2021), Perez-Vincent et al. (2020), Anderberg, Rainer and Siuda (2020), Berniell and Facchini (2021)), Piquero et al. (2020), Ravindran and Shah (2020), Silverio-Murillo, Balmori de la Miyar and Hoehn-Velasco (2020), Asik and Nas Ozen (2021), Arenas-Arroyo, Fernandez-Kranz and Nollenberger (2021) and Beland et al. (2020), Gibbons, Murphy and Rossi (2020), Chalfin, Danagoulian and Deza (2021), Ivandić, Kirchmaier and Linton (2020), Erten, Keskin and Prina (2021).

conditioning upon COVID-19 infection and test rates. To allow for the possibility that we are underpowered to detect differences in pre-trends, we additionally study the sensitivity of our estimates to violations of the assumption of counterfactual parallel trends, following Rambachan and Roth (2021).

We use high-frequency administrative data on three alternative measures of DV that, together, capture incidence, tolerance and reporting, allowing that lockdown mandates may have acted differently on these margins.[3] We gather administrative data on the exact dates at which municipalities enter and exit lockdown, tri-weekly indicators of COVID-19 infection and testing rates, daily data on mobility from cell phone towers, monthly data on formal sector employment rates, and monthly data on stimulus payments.

We find that imposition of lockdown in a municipality is associated with an increase in calls to a police-managed DV helpline (#149 - *Fono Familia*), and increased occupancy of public shelters for abused women, alongside a decrease in formal crime reports to the police. This suggests an increase in distress that coincides with more limited redress. The placebo effects are consistent with the timing of lockdown mandates being idiosyncratic. In general, the dynamic effects of lockdown intensify with lockdown duration, and lockdown mandates act to *reinforce* impacts of COVID-19 on helpline calls (distress) and crime reports (redress seeking).[4]

Lifting lockdown generates a reversal in these patterns, but to varying degrees. We identify a ratchet effect in calls to the police, with calls remaining significantly higher than they were before lockdown was initiated, consistent with in-built persistence in DV within couples. There is no similar persistence in shelter use or in DV crime reports. The decline in crime reports is completely reversed, consistent with pent-up demand and reported cases after exit from lockdown are higher than they were before initiation of lockdown, mirroring the behaviour of distress calls.[5]

Impacts of both lockdown entry and exit on mobility and unemployment line up with the estimates for DV outcomes, consistent with these being relevant mechanisms. Lockdown imposition results in sharp declines in mobility and employment. Both exhibit some persistence after lockdown is lifted, potentially explaining the ratchet effect in helpline calls. In contrast to emerging results for other OECD countries (Cajner et al., 2020; Adams-Prassl et al., 2020;

[3]We restrict attention to cases where men are perpetrators and women are victims.

[4]Shelter occupancy is an exception to this pattern insofar as infection rates lead to lower rates of shelter use, which is consistent with the risk of infection acting as a deterrent. Conditional upon infection rates, lockdown increases shelter use just as it increases helpline calls, marking an increase in DV incidence or distress.

[5]Effect sizes computed as weighted averages of the dynamic coefficients indicate that lockdown entry leads to an escalation of calls by 106%, and lockdown exit only partially reverses this, such that calls remain 50% higher than they were before lockdown. Lockdown entry increases shelter use by 10%, and lockdown exit more than reverses this, with shelter use falling to about 7% below its baseline level. Crime reports decline by 4.5% after lockdown is imposed, and then they shoot up by 10.1%, thus remaining about 5.6% above their baseline level.

Farré et al., 2020), we find that lockdown had a larger impact on male than on female job loss in Chile.[6] Using a shift share approach, we show that male job loss contributes to explaining impacts of lockdown on incidence, and that female job loss contributes to explaining decreased reporting.

Further insight into the mechanisms leading from lockdown to domestic violence is gained by analysing impacts of federal stimulus payments targeted at low income households. After establishing that we use idiosyncratic municipality-month variation in payouts under this scheme, we find that it was associated with lower DV incidence and higher reporting in general, and that the moderating impact on incidence (measured by helpline calls) was larger in municipalities that were in lockdown.

Overall, the results are consistent with income shocks and exposure being mechanisms driving perpetration by men, and with reporting being sensitive to the woman's financial position. Many existing studies and recent media coverage discuss impacts of lockdown on exposure, but do not consider the role of job loss, or identify causal impacts of income support.

Recent research establishes a case for lockdown, showing that voluntary social distancing is below the socially optimal level (Eichenbaum, Rebelo and Trabandt, 2021; Farboodi, Jarosch and Shimer, 2021; and Toxvaerd, 2020). It is estimated that the optimal policy involves losing 6% of one year's GDP (or, equivalently, a permanent reduction of 0.3 percent) and that the total welfare costs are more than four times bigger due to the cost of deaths (Alvarez, Argente and Lippi, 2021). Our estimates suggest that current models under-estimate the welfare costs of lockdown.

Section 2 details the estimation strategy. The DV outcomes are analysed in Section 3, and the mechanisms in Section 4. Policy remediation is analysed in Section 5 and Section 6 concludes.

2 Empirical Design

2.1 Rolling lockdown entry and exit

We analyse the first COVID-19 wave in Chile, March 14th to 30 September 2020, during which 116 of the 346 municipalities entered lockdown, with entry and exit graduated across municipalities over time. On 30 September, 73 municipalities had exited lockdown. Essential workers including hospital and supermarket workers were exempt but otherwise the mandate was strict, with citizens allowed to go out just twice a week for 3 hours at a time, using a permit. Violations of lockdown conditions could be penalized with fines of up to 10 million

[6]Lockdown imposition reduces mobility by 35%. After lockdown is removed mobility only partially recovers, remaining 13% below baseline. Lockdown imposition reduces male employment by 3.4%. Lifting lockdown again generates only partial recovery, with employment remaining 1.5% below its baseline level.

Chilean pesos (12,000 US$), or short prison terms. Police personnel conducted spot checks, and thousands of individuals were penalized.

Lockdown was put in place at the discretion of the Ministry of Health based upon their assessment of the spread of the virus and the risk of contagion, but there was no declared metric, as a result of which announcement of the mandate at the municipality level was unexpected. Once announced, lockdown took effect within 1-3 days and lasted between 6-172 days, with an average length of 32.5 days. When lockdown was lifted it was initially lifted for weekdays, and only subsequently for weekends as well.

We compiled data on COVID-19 infection and testing rates from open repositories updated several times a week by the Chilean Ministry of Science. We manually gathered data on the exact dates of entry to and exit from lockdown for each municipality, available for other researchers here. Figure 1 provides a snapshot of the dynamics of entry and exit for the country. We created a video describing the dynamic nature of lockdown entry and exit, available here: https://bit.ly/3pUeULZ.

2.2 Empirical specification

We look to identify impacts of lockdown imposition *and* lockdown removal on three indicators of domestic violence, mobility, and male and female employment. Identification leverages temporal variation in exposure to lockdown across municipalities. Denote domestic violence $DV_{s,t}$, where s indexes municipalities and t indexes time. Motivated by the descriptive trends presented in Figures A1 and A2, we use the de Chaisemartin and D'Haultfœuille (2020) estimator (DID_M) to obtain unbiased estimates of dynamic and placebo effects. Denote lockdown status $Q_{s,t}$, which takes the value of 1 if lockdown is in place in municipality s at time t, and 0 if not. Then define

$$DID_{+,t}^{Lockdown} = \sum_{s:Q_{s,t}=1,Q_{s,t-1}=0} \frac{N_{s,t}}{N_{(1,0),t}}(DV_{s,t}-DV_{s,t-1}) \quad - \sum_{s:Q_{s,t}=Q_{s,t-1}=0} \frac{N_{s,t}}{N_{(0,0),t}}(DV_{s,t}-DV_{s,t-1}),$$

which for a particular t is the change in mean outcomes between $t-1$ and t among municipalities which adopted lockdown (switchers), relative to those that did not (non-switchers). The estimates are consistently weighted by municipality population, $N_{s,t}$ though we confirm that the broad results are not sensitive to weighting. We create an estimate of the average impact of lockdown imposition by taking the weighted average over all time-periods in which any switch occurs, the weight being the share of individuals switching in the equation at each t:

$$DID_{M}^{Lockdown} = \sum_{t=2}^{T} \frac{N_{(1,0),t}}{N} DID_{+,t}^{Lockdown}. \tag{1}$$

In estimating dynamic effects, rather than compare levels at t with those at $t-1$, DID_M compares levels in subsequent periods $t+k \forall k \in \{1,\ldots,K\}$ to those at $t-1$. Similarly, placebo (pre-lockdown) coefficients are estimated by comparing periods entirely unaffected by the lockdown, specifically comparing average changes in time periods $t-2, t-3, ..., t-L$ with levels in period $t-1$. We conduct inference on each parameter using a block (cluster)-bootstrap based on municipalities and consistently include as many post-treatment lags as are available in the data.

In order to capture only impacts of lockdown imposition, and not any additional impacts once municipalities exit lockdown, the analysis sample includes municipalities up until the point that they graduate out of lockdown. Estimates of impacts of lockdown exit are obtained analogously to estimates of entry. In the lockdown exit plots, pre-event coefficients compare municipalities that are all in lockdown, treated municipalities being those that in the future exit lockdown and control municipalities being those that remain in lockdown. The coefficient at time zero compares municipalities which exited lockdown between the current and previous period to those that remained under lockdown. By definition, the DID_M estimator captures municipality and month (or, in the case of shelter use, day and region) fixed effects (FE). All schools closed nation-wide on March 16, and thus impacts of school closure are absorbed by time FE. We control for COVID-19 infection, testing and positivity rates and also show results without these controls. Other predictors of lockdown timing such as population density are absorbed by municipality FE.

The DID_M estimator resolves potential bias arising in two-way FE model estimates when treatment varies over time and there is heterogeneity in treatment effects across units and time. It is not sensitive to compositional changes that arise as different municipalities enter (or exit) treatment. The identifying assumption is that the exact timing of lockdown mandates is quasi-random conditional upon municipality and year FEs. The placebo (pre-event) coefficients provide a partial test of parallel trends, as they reveal whether switchers and non-switchers had similar outcome trends at least *prior* to the imposition of lockdown.[7]

Although we will see that the placebo effects support the identifying assumption, we study sensitivity of our estimates to violation of parallel trends, following Rambachan and Roth (2021) to estimate partially identified 'Honest DiD' bounds, derived under the assumption that pre-lockdown trends are projected forward. These tests are useful, as they let us consider not only strict projection of any pre-treatment trends, but also bound post-treatment estimates in cases where these trends may further diverge from linearity. As such for each lag we present bounds under a range of settings, projecting pre-trends and allowing up to *another* 0.1 per

[7]The de Chaisemartin and D'Haultfœuille (2020) pre-trend coefficients differ from the standard test of pre-trends in event studies (Autor, 2003), which are potentially invalid when treatment effects are heterogeneous (Sun and Abraham, 2021).

100,000 unit divergence between each period. As the bounds are applied to the standard DiD estimator, we obtain the diagnostics for bias in the standard estimator (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020) These show between zero and 2.1% negative weights (Table A1), suggesting small, if any, bias in the standard estimator. This is consistent with our sample containing a large share of never-treated municipalities.

3 Results

All variables used in the analysis are described in the Data Appendix (Appendix B) along with descriptive plots. Most outcomes are measured at the municipality-month level but shelter use is at the region-day level. The descriptive plots reveal that the outbreak of the pandemic was associated with sharp increases in calls to the DV helpline and in use of public shelters, and a decrease in reported DV crimes. In this section, we provide estimates of causal effects of lockdown entry and exit conditional on the pandemic outbreak, and the fact that lockdown was imposed and lifted at different dates across municipalities. The results for DV indicators are in Figure 2, and for mobility and male and female employment rates in Figure 3.

Our main results are as follows. Lockdown imposition leads to an increase in DV helpline calls and public shelter use, but a decrease in DV crime reports. Investigating lifting of lockdown, we identify ratchet effects in distress calls (and in unemployment, a mechanism), alongside displacement effects in formal police reports. We demonstrate that job loss is a mechanism, with male and female job loss triggering changes in incidence and reporting respectively, and we show that income support mitigates impacts of lockdown.

3.1 Distress calls to the DV hotline

We obtained records of all calls to the DV hotline of the Chilean Police at the month×municipality level. Calls capture fairly serious concerns. The number is formally linked to the police and calls are geographically tracked. In cases where the call relates to an emergency, a patrol car is sent to the victim's address, and this results in a formal crime report. However, not all calls result in criminal complaints and, conversely, criminal complaints can be initiated without first calling this hotline. Panel (a) of Figure 2 indicates an increase in DV helpline calls following lockdown imposition, that increases sharply three months in. It shows parallel pre-trends for lead months -18 up until -2. There is a small but noteworthy increase in the month preceding lockdown consistent with our observation that coronavirus infections show a rise, on average, 5 weeks before lockdown, leading to voluntary distancing and stress. Averaging the dynamic effects over the first three (six) months following lockdown gives a 88% (106%) increase.[8]

[8]The spike after three months is based on a smaller number of municipalities, see Table A2.

Panel (b) shows that DV calls fall with lockdown removal, the decline increasing over time. The averaged coefficients show that only 50% of the increase in calls following lockdown imposition is reversed, indicating a ratchet effect. This is consistent with wider evidence of path dependence in DV. Helpline calls are tagged as being related to physical, psychological or economic violence. Analysing them separately, we find that lockdown drives roughly similar proportional increases in all three. However, as economic violence is an order of magnitude less frequent than other types, the coefficients for it border on significance (Appendix Table A3).

3.2 Occupancy of public shelters for abused women

We have day×region data on occupancy rates the night before day t. Panels (c)-(d) of Figure 2 show that the placebo coefficients closely track the zero line until the event of lockdown imposition or removal. After imposition, there is a sharp and increasing rise in public shelter use that persists through the 80-day window, albeit the coefficients become imprecise after about the 15-day mark, reflecting that the data grow more scarce as we move forward from the event date. The average indicates a 10% increase. This is reversed once lockdown is lifted.[9]

Shelter occupancy will under-estimate the demand for shelter during the pandemic if women perceive shelter use as elevating the risk of infection. Although Chilean shelters had infection limiting protocols, we see evidence consistent with this in Table A4, which shows that a higher COVID-19 infection rate (which is included as a control in the analysis) is associated with lower shelter use, even though it is associated with more helpline calls. We retain shelter use as it is a "harder" indicator of DV than distress calls, possibly capturing more extreme cases. It is still useful to study helpline calls as these are not directly sensitive to infection concerns, and will capture cases of varying intensity.

Given the sharp surge in DV following outbreak of the pandemic, we investigated whether the occupancy rate might under-estimate shelter demand for a different reason, which is that shelters were filled to capacity. This appears not to be the case. First, before the pandemic struck, there were spare spaces in shelters, the average occupancy rate was 62%, with a standard deviation of 42%. Second, using the DID_M estimator, we estimated impacts of lockdown on shelter capacity and found an (imprecise) increase of 1.3% in shelter spaces (Figure A3).

3.3 Police reports of DV

We obtained month×municipality level data on DV crimes filed with the police. Panels (e)-(f) of Figure 2 show that lockdown results in a significant decline of 4.5% in reporting DV. As this is despite the increase in distress calls and shelter use that we observe, it indicates impediments to reporting. Lockdown may create one or more of these impediments: female job loss, which

[9]The average effect is a 17% decline and we cannot reject that this is equal to the effect of lockdown entry.

leaves women economically vulnerable and more likely to tolerate DV; isolation from social networks which may make it harder to report for women who need support taking the decision to report; mobility restrictions make it harder to go into police or prosecutor offices to report; in the first wave, police capacity may have been compromised by social distancing rules and officer absences; or proximity to the perpetrator may make it harder to report and/or intensify the fear of backlash. We cannot discriminate between each of these, but we demonstrate the force of mobility restrictions and the role of female job loss.

Lifting lockdown leads to a complete reversal and, indeed, crime reports rise 10%, exceeding baseline levels by 5.6%, consistent with new demand (reflected in distress calls persisting at levels above baseline) added to pent-up demand.

4 Mechanisms: Mobility and Employment

We estimate dynamic impacts of lockdown entry and exit on mobility and employment. Then, using a shift-share instrument, we estimate the contribution of job loss to DV.[10]

4.1 Mobility

Using day×municipality data from cellphone records and the DID_M estimator we obtain Figure 3, panels (a),(b). Volatility in the series reflects that these are daily data. There is no evidence that municipalities that went into lockdown exhibited larger voluntary declines in mobility before lockdown than municipalities that did not go into lockdown in the sample period. This is interesting in its own right, and also supports the identifying assumption. The dynamic effects show that imposition of lockdown leads to a sharp drop in mobility of about 35%, which persists but attenuates over the three months after, averaging at 22%. This measures not the absolute mobility decline but the difference between areas that were and were not under lockdown.

Lifting lockdown resulted in an uptick in mobility which was statistically significant by about day-10, and increased to day-50 after which it starts to drop off, though it remains 20% higher than at baseline. That recovery was only partial, and it is consistent both with weekend restrictions remaining in place (evident in the spikes in the plot) and with infection rates only starting to fall, on average, 5 weeks after lockdown withdrawal. This ratchet effect in mobility lines up with the ratchet effect in distress calls, consistent with mobility being a mechanism by which lockdown impacted DV.

[10] We have also analyzed heterogeneous effects of lockdown entry and exit by measures of vulnerability of the municipality to COVID-19 related changes in mobility and employment. The results show clear differences in the impact of lockdown entry by vulnerability, with highly vulnerable municipalities displaying the largest increase in distress calls and the largest reduction in crime reporting. Regarding lockdown exit, we do not find clear differences by vulnerability.

4.2 Labour market outcomes

Using month×municipality data on private formal sector employment from administrative records, we obtain the DID_M estimates in Figure 3, panels (c)-(f). Lockdown imposition leads to a sharp and increasing descent in male employment that averages at about 1.15 percentage points or 3.4%. Lifting lockdown leads to partial recovery but male employment remains 1.4% below its baseline level. This ratchet effect matches the pattern for helpline calls, suggesting male employment as a mechanism, which we formalise in the next section. Impacts of lockdown on female employment are an order of magnitude smaller and exiting lockdown appears to reverse any impact.

We also see a sharp increase in worker contract suspensions under the state furlough scheme (Figure A4). The displayed estimates average over men and women but are dominated by movements for men. Although furlough protects income relative to job loss, the total impact of lockdown on earnings uncertainty includes its impacts on job loss and contract suspension.

4.3 Identifying the contribution of employment decline to the increase in DV

We use a shift-share strategy to identify impacts of employment loss on DV. We then combine these with the identified estimates of impacts of lockdown on employment to estimate employment-mediated impacts of lockdown on DV. To complete the mechanism chain, we require an estimate of β from:

$$DV_{st} = \alpha + \beta Employment_{st} + \mu_s + \phi_t + \varepsilon_{st}. \tag{2}$$

We identify this using using a Bartik instrument for $Employment_{st}$ (in levels rather than growth rates). Following Card (2009) (discussed in Goldsmith-Pinkham, Sorkin and Swift (2020), example 2) we define

$$B_{st} = \sum_{k=1}^{K} z_{s0k} \times g_{kt}$$

Where K indexes sector (Figure A5, shows sectoral differences in employment decline during COVID-19). The instrument interacts municipality s level baseline sectoral shares (z_{s0k}), with aggregate sector-specific employment rates (g_{kt}). Specifically, $z_{s0k} = (N_{s0k}/N_{0k}) \times (1/P_{s,2020})$, where N is number of workers by sector, P is municipal population, g_{kt} is total number of jobs lost between 2019 and 2020 in the country in sector k. The identifying assumption that baseline sector shares are uncorrelated with the COVID shock once we condition upon municipal and month FE seems reasonable.

Panel A of Table 1 shows shift share estimates of equation 2.[11] We estimate that a 1 percentage point decrease in male employment increases distress calls by 25% (by 1.3 relative

[11] We do not provide results for shelters because shelter data are at region and not municipality level.

to a mean of 4.8 per 100,000 individuals). Breaking this down, we see that male job loss triggers physical and psychological violence, with no significant impact on economic violence- for instance, a 1 pp decrease in male employment increases calls for physical violence by 37%.

Female job loss has no significant impact on helpline calls but it reduces crime reporting (which is not sensitive to male job loss). This is consistent with male job loss resulting in a larger income shock and hence more stress, and with female job loss acting through the woman's participation constraint, making her less likely to report DV.

The direction of impacts is consistent with our main finding that lockdown (and associated job loss) led to increased distress calls and lower crime reporting. Panel B provides the summary estimates from Figure 2. Panel C implements the accounting exercise to determine the proportion of the full impact in Panel B that can be attributed to employment. We conclude that male employment loss accounts for 32.6% of the increase in helpline calls. Female employment loss explains 6.5% of the decrease in crime reporting. This share is small because lockdown has smaller impacts on female than on male employment.

4.4 Discussion

Pre-pandemic research on DV has been challenged by the fact that it is often difficult to disentangle incidence from reporting, and we have seen limited discussion of the problem in pandemic-based research even though the pandemic (and lockdown) may directly affect reporting. Our finding that lockdown moves incidence and reporting in opposite directions highlights the relevance of this distinction.

Another consideration, neglected in the literature, is that lockdown may impact not only incidence but also tolerance levels. The mechanisms that we posit as driving impacts of lockdown can result in distress– evidence that lockdown has adversely influenced mental health (and more so among women) is provided in many recent studies, for example, Adams-Prassl et al. (forthcoming), Giuntella et al. (2021), Etheridge and Spantig (2020).[12]

4.5 Robustness checks

We now discuss sensitivity checks on the estimates in Figures 2-3. We display DID_M estimates removing the COVID-19 controls in Figures A6-A7. These estimates incorporate impacts that operate through lockdown changing COVID infection and testing rates. The placebo coefficients continue to be indistinguishable from zero, and the dynamic effects are larger, for example, for

[12] An increasing number of women seeking refuge in public shelters is a hard outcome that very likely signals domestic violence. At the same time it is a stylized fact that many women put up with DV for a long time and often it takes a shock – such as lockdown – to act as the last straw. Any or all of unemployment, increased time with the partner at home, social isolation and stress might trigger women to leave home or to seek helpline support.

distress calls, they are 10% larger. This is consistent with COVID indicators and lockdown tending to move helpline calls (and crime reports) in the same direction.

Direct impacts of COVID-19 infection rates on DV are in Table A4. A 1 SD increase in COVID infection rates (an increase of 0.21) increases helpline calls by 1.1% and decreases reporting by 0.08% conditional on lockdown. The units of change are not comparable as lockdown is a binary event, but the direct impacts of infection rates are small relative to the impacts of lockdown conditional on infection rates. COVID positivity rates behave similarly to COVID infection rates conditional on test rates, and the direct impact of test rates is smaller and often not significant.

Event studies using the conventional DID estimator are shown in Figures A8 and A9. The corresponding single index coefficient estimates are in Table A4. Table A1 and Figure A10 present diagnostics to assess bias in the conventional estimator Goodman-Bacon (2021); de Chaisemartin and D'Haultfœuille (2020). We find consistency across estimates that rely on comparison of treated municipalities with those treated earlier vs later vs never (Figure A10), and that negative weights sum to < 0.10, often closer to zero. Given this, the broad patterns described by the conventional estimator agree with those documented using DID_M.

Although the placebo effects shown in Figures 2 and 3 assuage the concern that lockdown mandates are correlated with underlying differences in trends in the outcomes prior to treatment, we present Rambachan and Roth (2021) bounds on the dynamic coefficients from the corresponding DiD event studies in Figures A11-A12, accounting for (relatively small) pre-event deviations from parallel trends, as well as additional uncertainty in these deviations in the post-treatment period. The estimated bounds confirm the main findings, though the bounds widen with time from adoption given the accumulation of uncertainty.

5 Policy Remediation

The national government introduced an emergency family income programme (*Ingreso Familiar de Emergencia*, IFE) in May 2020, providing cash transfers to low income households most affected by the pandemic, with eligibility based on income, assets and needs. Benefits comprised six payments between June and November 2020 of US$80-130 per person for families without any formal income, while households with some formal income received a partial payment. We detail payment amounts and the number of beneficiaries for the payments made during the study period in Table A5. By end September the state had spent over $2,223 million in emergency payments, 0.79% of 2019 GDP.[13] The trend in roll-out is in Figure A13a, showing that by September 2020 stimulus payments had reached nearly 8 million individuals, 42% of the

[13]For comparison,the first stimulus payment under the CARES act in the US amounted to 1.36% of 2019 US GDP, a total of 162 million payments that cost $292 billion.

population. Figure A13b shows the distribution of payments, confirming widespread exposure to IFE.

We investigate whether IFE mitigated impacts of lockdown mandates on DV. If it did, this would constitute evidence that economic stress is a mechanism by which lockdown mandates impact DV, at least among low income households who were the beneficiaries of the programme.[14]

We define the variable IFE_{ct} as the proportion of the municipal population who received an IFE payment, with baseline variation in the proportion eligible being absorbed by municipality FE. This proportion is initially fixed at zero, and it jumps discontinuously with the first payment. As we are interested in modelling an interaction term, we use the single coefficient model, having shown diagnostics that suggest any potential bias is small. We estimate:

$$DV_{ct} = \alpha + \beta Lockdown_{ct} + \gamma IFE_{ct} + \delta(Lockdown \times IFE_{ct}) + X_{ct}\Gamma + \mu_c + \phi_t + \varepsilon_{ct}.$$

The parameter γ measures the baseline impact of the policy, corresponding to the full impact in municipality-months not under lockdown. The impact of the policy in municipality-months under lockdown is given by γ plus δ. Municipality FE absorb the impacts of all fixed or slowly evolving factors like poverty, and time FE capture generic impacts of the pandemic across municipalities. As in the main analysis, we consistently control for the three COVID-19 indicators, and examine estimates that do not include these controls.

A potential concern with our specification is that, conditional upon all controls, exposure to IFE is not quasi-random. In particular, if municipalities with higher shares of IFE beneficiaries already had DV incidence declining more rapidly than municipalities with lower shares, then we might spuriously attribute changes in DV to IFE. To assess this concern, we regress lagged DV on IFE shares, using a series of lags for pre-COVID months (or, in the case of shelters, days). We do this for each of the three measures of DV, conditional upon the baseline controls. Figure A14 reports contemporaneous estimates (top row) and placebo coefficients. The placebos are, in general, small and insignificant. There is thus no evidence that municipalities with higher IFE shares had larger (or smaller) changes in DV pre-COVID.[15]

Table 2 presents the estimates, with all variables standardised as Z-scores for ease of comparison. Unstandardised estimates are in panel A, Table A6. We see that stimulus payments mitigate impacts of lockdown on all three measures of DV. They reduce impacts of lockdown on helpline calls by a bit more than 50%, reduce shelter use by more than lockdown increases it and,

[14]Chile also introduced contract suspension or furlough, for which only formal sector workers paying into an unemployment insurance scheme were eligible. Data on this scheme are released annually and the available data run to 30 June 2020. During March-June 2020, 800,000 workers were on furlough. It thus had much lower coverage than IFE. We investigated if furlough protection had a mitigating effect, but the estimates are imprecise.

[15]The placebo effects are similar to pre-event coefficients in an event study. The current model is not amenable to this because IFE is continuous and interacted with lockdown.

they increase crime reports by more than lockdown decreases them. IFE lowers DV irrespective of lockdown status, having larger impacts under lockdown only for helpline calls. These results are just slightly larger if we do not condition on the COVID variables (panel B, Table A6). In the only other paper attempting to analyse pandemic-specific policies on DV outcomes, Erten, Keskin and Prina (2021) also find evidence consistent with mitigation. Their effect sizes are not comparable because they use a dummy for the national timing of the introduction of stimulus payments, while we use variation in programme intensity by sub-region.

6 Conclusions

There is a long history of quarantines being imposed to prevent the spread of disease, dating back to the plagues in Europe and Asia in the Middle Ages (Adda, 2016). This paper investigates impacts of lockdown (mass quarantine) on rates of domestic violence exposure and reporting in Chile using administrative data. We leverage the unusual policy environment in Chile where lockdown entry and exit were staggered across hundreds of municipalities, creating considerable variation in exposure within the same country, region and even city. Using state-of-the-art observational techniques, we estimate dynamic effects of lockdown. We estimate impacts of both lockdown entry and exit, and we identify mechanisms.

We find that lockdown exacerbates DV, reinforcing the direct impacts of COVID-19, and that its impacts persist after lockdown is lifted. Our analysis of mechanisms indicates that job loss plays a role, with male and female job loss triggering changes in incidence and reporting respectively. Consistent with job loss constituting an income shock, income support programmes mitigate the effect. The analysis reveals mechanisms – job loss and exposure – that are of broader relevance to understanding DV, even outside pandemic conditions.

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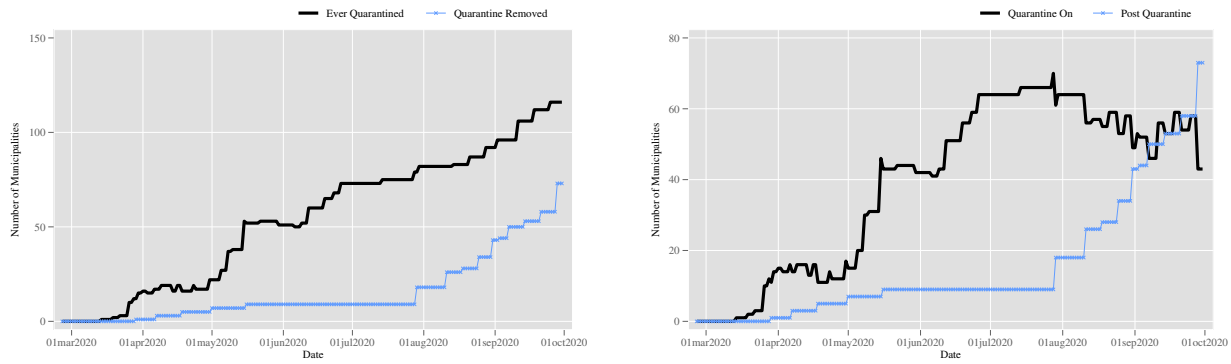
Figures and Tables

Figure 1: Temporal Dynamics of Lockdown Imposition and Removal

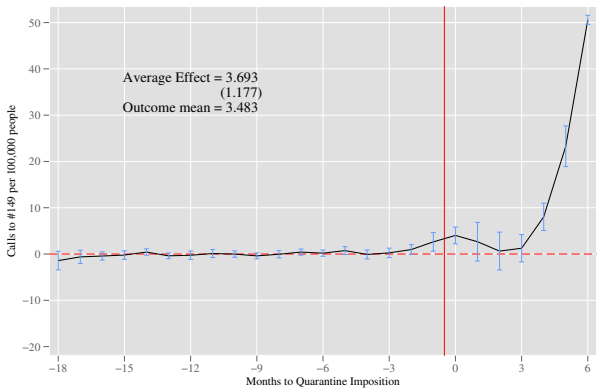


(a) Ever Locked-down

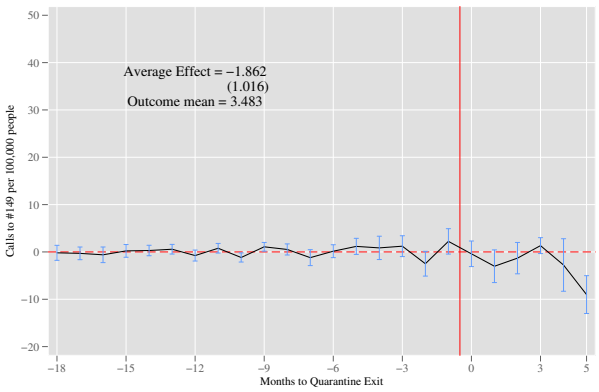
(b) Current Lockdowns

Panel (a) documents the accumulated number of municipalities ever locked-down, and for which the lockdown has been subsequently removed. The total number of municipalities in Chile is 346, 116 of which entered into lockdown between March 14 and September 30, 2020. Panel (b) documents the total number of municipalities currently in or out of lockdown at a given moment of time between March and September 2020. A supplementary video file documenting the dynamic nature of lockdown imposition as well as the total population under lockdown in the Metropolitan Region of Santiago is available online at: https://bit.ly/3pUeULZ.

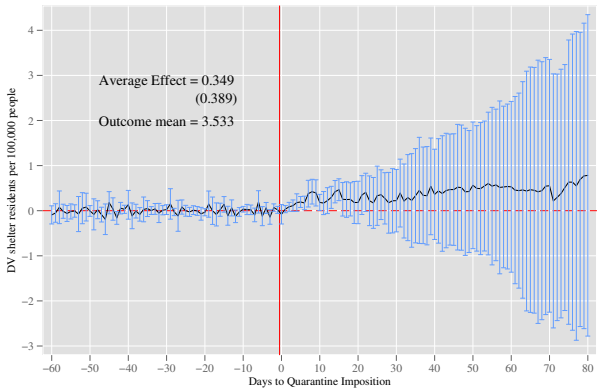
Figure 2: Impacts of lockdown on incidence of Intra-family violence



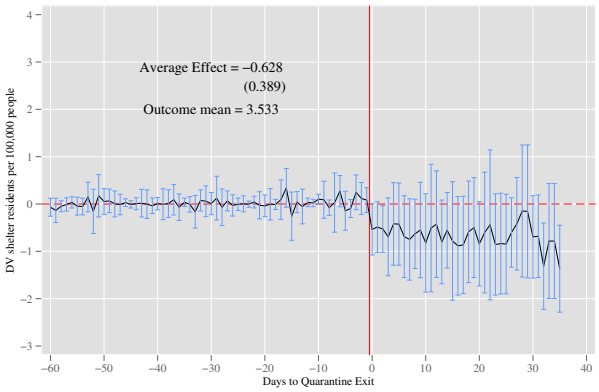
(a) Distress Calls (entry)



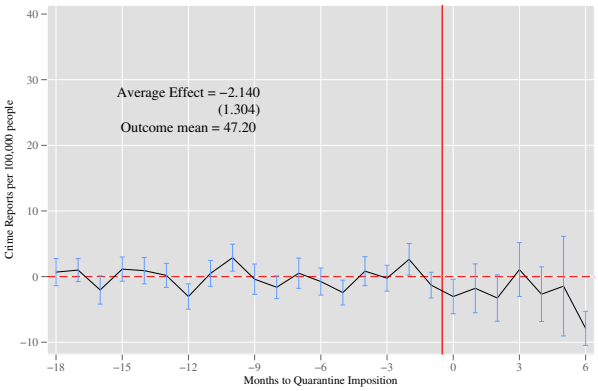
(b) Distress Calls (exit)



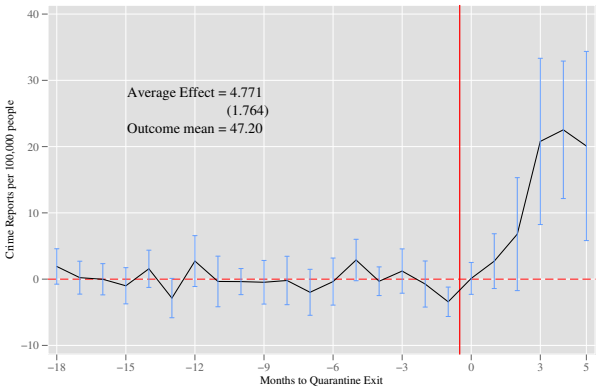
(c) Shelter Usage (entry)



(d) Shelter Usage (exit)



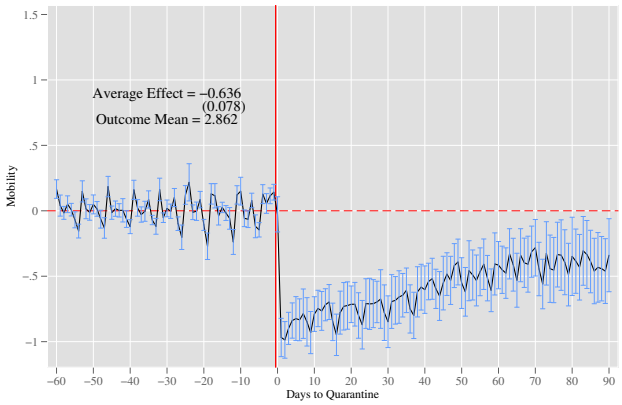
(e) Crime Reporting (entry)



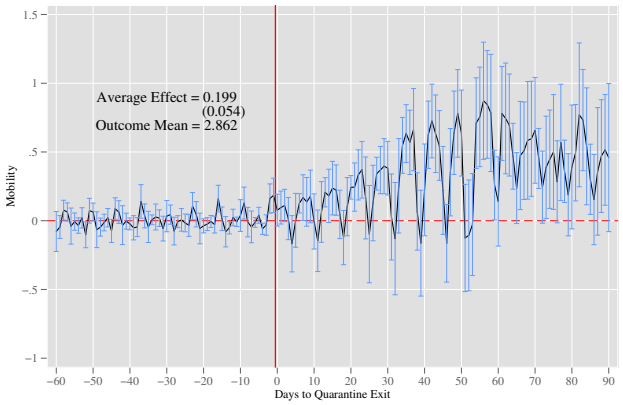
(f) Crime Reporting (exit)

Notes: Point estimates and confidence intervals are displayed from the DID_M estimator documenting placebo (pre-event) and dynamic (post-event) impacts of lockdown imposition (left-hand panels), or removal (right-hand panels) on rates of calls to the Chilean police family support hotline (panels (a) and (b)), the population of individuals residing in government run domestic violence shelters (panels (c) and (d)), or formal criminal complaints (panels (e) and (f)). The left-hand panel consists of all municipalities, where the event of interest refers to the imposition of lockdown (if the municipality has ever adopted). The right-hand panel consists of all municipalities which have ever entered lockdown (and hence could theoretically exit lockdown), where the event of interest refers to the removal of lockdown. In each case, controls for rates of COVID infection and testing are included. Specifications without controls are provided in Supplementary Materials. Confidence intervals are estimated using a block-bootstrap by municipality (panels (a), (b), (e) and (f)) or region (panels (c)-(d)).

Figure 3: Impacts of lockdown on mechanism variables

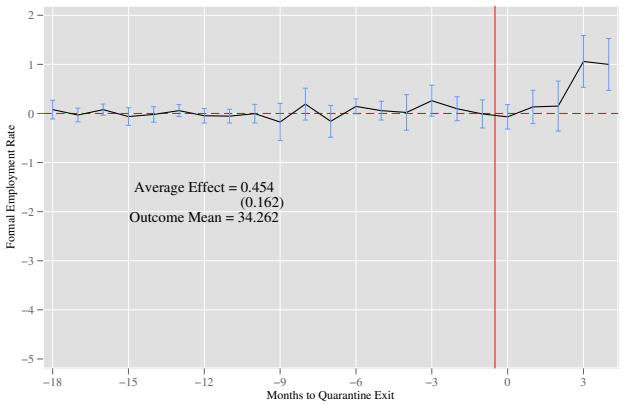


(a) Cell phone mobility patterns (entry)

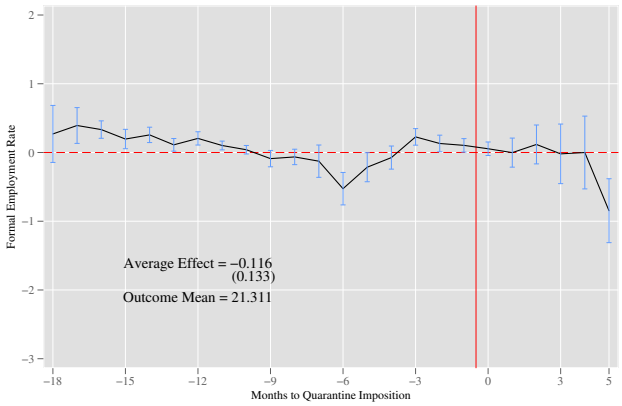


(b) Cell phone mobility patterns (exit)

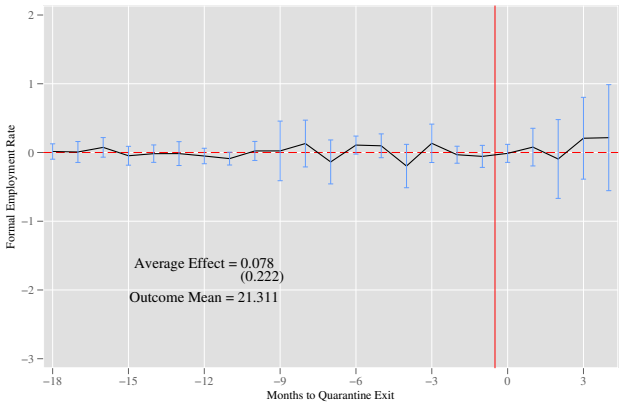
(c) Male formal employment rate (entry)



(d) Male formal employment rate (exit)



(e) Female formal employment rate (entry)



(f) Female formal employment rate (exit)

Notes: Refer to notes to Figure 2. Identical specifications are estimated however examining mobility patterns based on within-municipality daily movement from cell phone data (panels (a) and (b)), and municipal level employment rates in the formal private labour market from administrative records (panels (c) to (f)). All other estimation details follow those indicated in notes to Figure 2.

Table 1: Decomposing the contribution of gender-specific employment shocks to changes in domestic violence

	Calls				Crime
	All Calls	Economic	Physical	Psychological	Reporting
Panel A: Shift Share IV					
Formal Employment (Women)	0.442	-0.0142	0.271	0.185	1.182
	(0.587)	(0.0166)	(0.305)	(0.330)	(0.734)
Formal Employment (Men)	-1.227**	0.00170	-0.691**	-0.537*	-0.0518
	(0.576)	(0.0197)	(0.334)	(0.318)	(0.783)
Observations	4,475	4,475	4,475	4,475	4,468
R-squared	0.275	0.013	0.267	0.152	0.039
Mean Dep. Var.	4.865	0.0299	1.849	2.986	45.52
First Stage F-Statistic (C.-D.)	249	249	249	249	248.5
Panel B: Lockdown and Domestic Violence					
Lockdown	3.393***	0.085***	1.911***	1.697***	-2.140**
	(1.177)	(0.036)	(0.683)	(1.304)	(0.756)
Panel C: Scaled Estimates					
Mediator: Women's Job Loss	-1.2%	1.9%	-1.6%	-1.3%	6.5%
Mediator: Men's Job Loss	32.6%	-4.7%	42.6%	37.2%	-2.9%

Notes: Decompositions of the contributions of job loss to observed impacts of lockdown on domestic violence distress calls (columns 1 to 4) and crime reporting (column 5) are presented. These scaled estimates (panel C) provide estimates of the proportion of the total impact of lockdown on domestic violence (panel B) which can be explained by the estimated direct impact of formal employment changes on rates of domestic violence (panel A), interacted with the actual rates of job loss observed due to lockdown imposition. These rates of job loss are estimated in Figure 3c and 3e for men and women respectively.

Table 2: Stimulus Payments, Lockdown and Domestic Violence

	Calls to 149		Crime Reporting		Shelter Residence	
	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	0.114***	0.147***	-0.00802**	-0.00486	0.0315	0.0376
	(0.0181)	(0.0247)	(0.00323)	(0.00461)	(0.0401)	(0.0418)
IFE	-0.0359	-0.0262	0.0412***	0.0428***	-0.256*	-0.255*
	(0.0447)	(0.0435)	(0.0118)	(0.0111)	(0.140)	(0.142)
Lockdown×IFE		-0.0469**		-0.00443		-0.00967
		(0.0227)		(0.00481)		(0.0331)
Joint Estimate						
IFE +						
Lockdown×IFE		-0.073		0.038***		-0.264*
		(0.058)		(0.013)		(0.140)
Observations	7,262	7,262	26,915	26,915	4,128	4,128
R-squared	0.784	0.785	0.560	0.560	0.856	0.856

Each column regresses measures of DV incidence or reporting on time-varying receipt of IFE stimulus payments, which began in May, 2020, and further rolled out to broader populations there-after. IFE refers to the proportion of the municipal (columns 1-4) or regional (columns 5-6) population receiving transfers. Lockdown×IFE interacts each municipality's lockdown status with the proportion of IFE receipt. All regressions include geographic and time fixed effects and cluster standard errors by area. Outcome variables and independent variables are standardized as a z-score for ease of comparison of coefficients. "Joint Estimate" refers to the linear combination of the parameters on IFE and Lockdown×IFE along with the standard error of this combination, reported in columns where interactions are considered. *** p<0.01, ** p<0.05, * p<0.1.

Supplementary Materials

Dynamic Impacts of Lockdown on Domestic Violence: Evidence from Multiple Policy Shifts in Chile

Sonia Bhalotra, Emilia Brito, Damian Clarke, Pilar Larroulet, Francisco Pino

A Appendix Figures and Tables

Table A1: Negative Weights in Two-way Fixed Effect Models

	Number g,t	Number Negative g,t	Total Sum of Negative Weights
Lockdown Entry			
Distress Calls	334	7	-0.0046
Police Reporting	334	1	-0.0007
Shelters	1580	264	-0.0971
Lockdown Exit			
Distress Calls	130	0	—
Police Reporting	130	0	—
Shelters	132	0	—

Notes: The number of group×time specific estimates are displayed, as well as the number of units receiving negative weights following de Chaisemartin and D'Haultfœuille (2020). Each g,t group refers to treatment effects in municipalities which adopted at a specific time, in a specific post treatment year t. A full decomposition of the two-way fixed effect estimator for lockdown entry in models based on municipal data is provided in Figure A10.

Table A2: Proportion of Municipalities and Population Driving Estimates

	Lockdown Imposition		Lockdown Exit	
Time Period	Municipalities	Population	Municipalities	Population
0	128	16079843	43	5412691
1	91	13598284	18	1864586
2	59	10478789	9	692228
3	41	7274131	9	692228
4	27	4962373	7	600991
5	7	1680245	–	–
6	1	89493	–	–

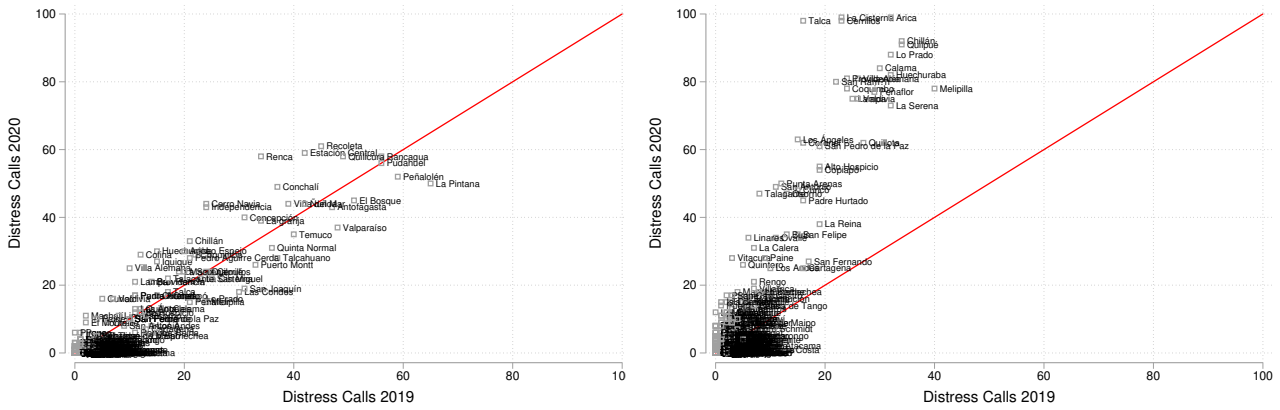
Notes: DID_M dynamic (post-lockdown) effects are based on municipalities which have entered lockdowns, and been in lockdown for at least x months (or exited lockdowns, and been out of lockdowns for x months in the case of lockdown exit), where x refers to the time period indicated on the horizontal axis of the DID_M result graph. As lockdown length varies by municipality, estimates of varying length are driven by different sub-groups of municipalities. The sub-groups having had at least 0-6 months of lockdown are indicated in the left-hand panel, and the subgroups having had at least 0-4 months out of lockdown are indicated on the right-hand panel.

Table A3: Aggregate DID_M estimates of lockdown imposition and removal on distress calls by type of violence

	All Calls		Physical Violence		Psychological Violence		Economic Violence	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lockdown Imposed	4.299***	3.693***	2.893***	2.205***	1.397**	1.814**	0.042	0.077**
	(1.107)	(1.177)	(0.683)	(0.727)	(0.672)	(0.749)	(0.029)	(0.031)
Lockdown Removed	-1.996*	-1.862*	-1.622***	-0.379	-1.659**	-0.467	-0.006	0.000
	(1.246)	(1.016)	(0.479)	(0.622)	(0.723)	(0.828)	(0.034)	(0.042)
Observations	7,266	7,266	7,266	7,266	7,266	7,266	7,266	7,266
Baseline Mean	3.483	3.483	1.283	1.283	2.185	2.185	0.015	0.015
COVID-19 Controls		Y		Y		Y		Y

Notes: Each column displays aggregate DID_M estimates of impacts of lockdown imposition and removal on DV distress calls by type of violence as classified by police telephone operators. Columns (1)-(2) replicate results using all calls (as in Figure 2), while columns 3-8 break this down by each violence type. Aggregate DID_M estimates are presented weighting by the number of affected individuals at each lag. Standard errors are estimated using a blocked bootstrap clustered by municipality. ***, ** and * indicate statistical significance at the 1%, 5% and 10%, respectively.

Figure A1: Calls to DV hotline – 2019 vs 2020

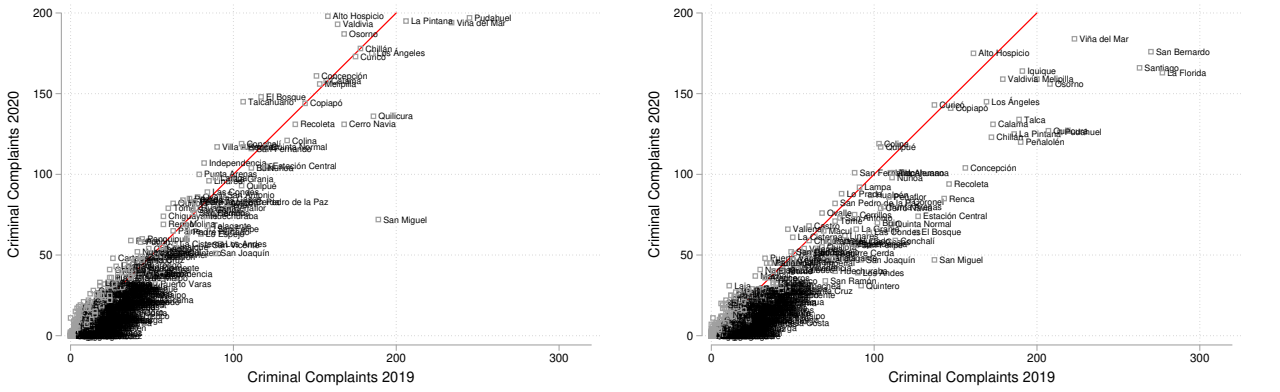


(a) January and February (pre): < 100 Calls

(b) April–June (post) < 100 Calls

Notes: Panel (a) presents a plot of municipalities by the number of calls to the police DV hotline in January and February 2019 (x-axis) and 2020 (y-axis). Panel (b) presents a plot of municipalities by the number of calls to the DV hotline in April-June 2019 (x-axis) and 2020 (y-axis). In both panels we have excluded municipalities with more than 100 calls per month for ease of visualization.

Figure A2: Criminal Complaints for Intra-Family Violence – 2019 vs 2020

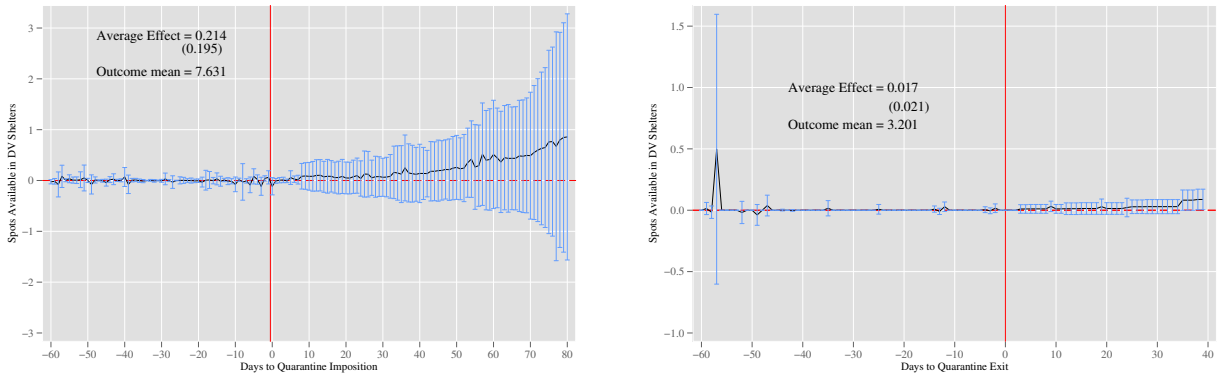


(a) January–February (pre): < 200 Complaints

(b) April-June (post) < 200 Complaints

Notes: Panel (a) presents a plot of municipalities by the number of criminal complaints for intra-family violence lodged in January and February 2019 (x-axis) and 2020 (y-axis). Panel (b) presents a plot of municipalities by the number of criminal complaints for intra-family violence lodged in April-June 2019 (x-axis) and 2020 (y-axis). In both panels we have excluded municipalities with more than 200 complaints per month for ease of visualization.

Figure A3: Lockdown Imposition and Removal and Supported Spots at DV Shelters

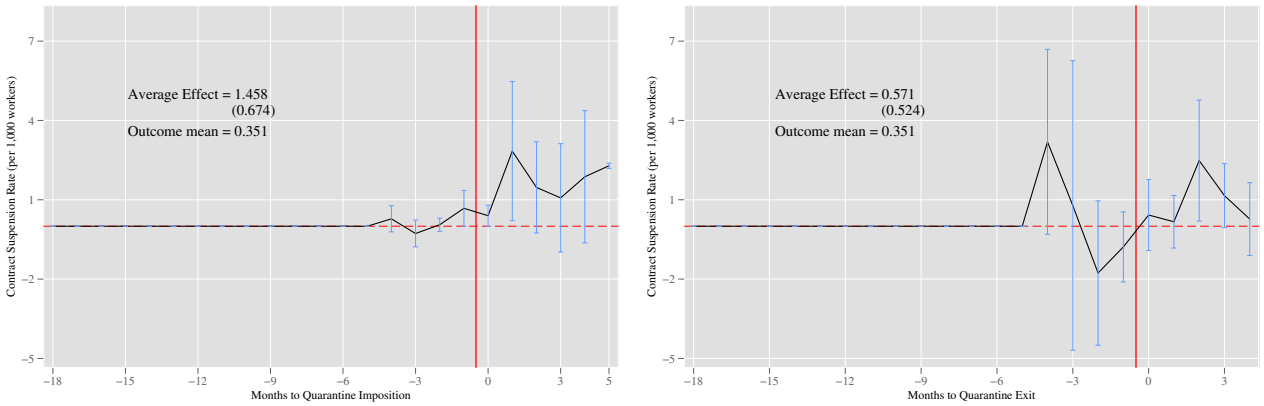


(a) Lockdown Entry

(b) Lockdown Exit

Notes: Refer to notes to Figure 2. Identical specifications are estimated however examining available spots at DV shelters. All other estimation details follow those indicated in notes to Figure 2.

Figure A4: Lockdown Imposition and Removal and Job Suspensions

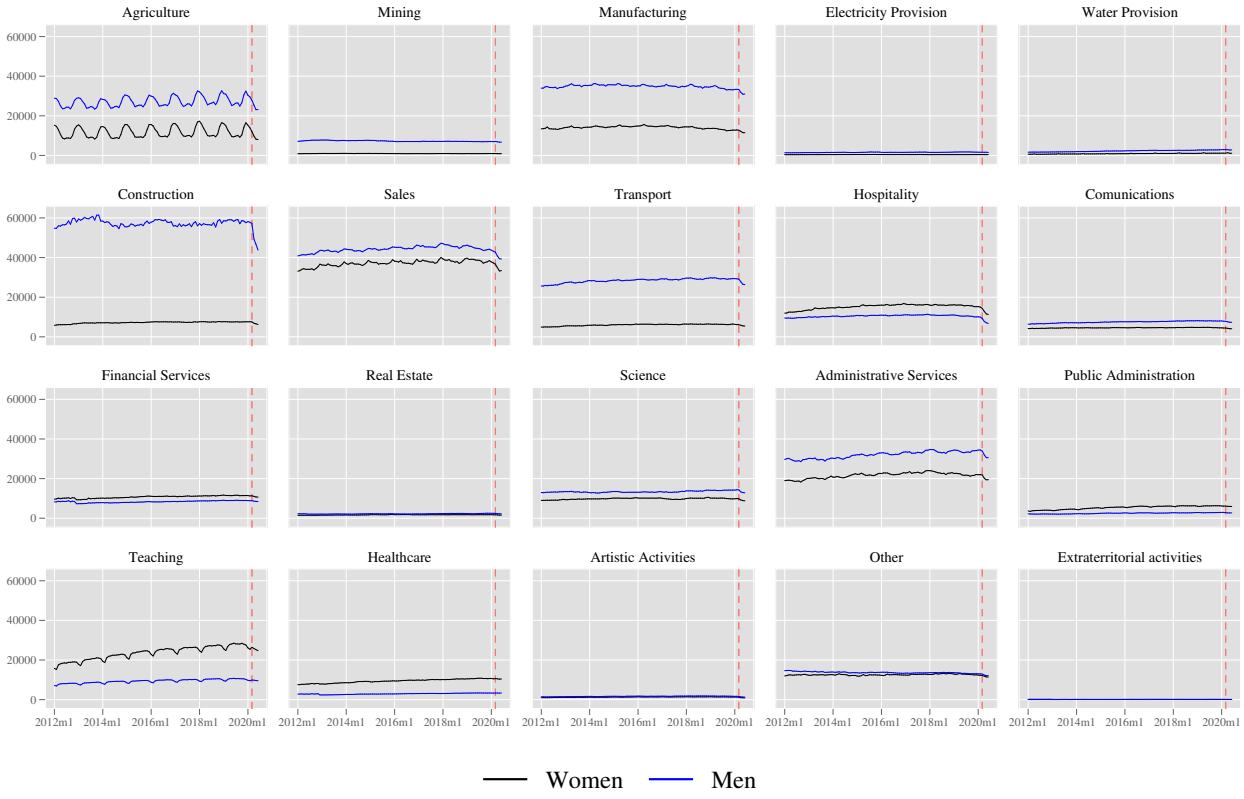


(a) Lockdown Entry

(b) Lockdown Exit

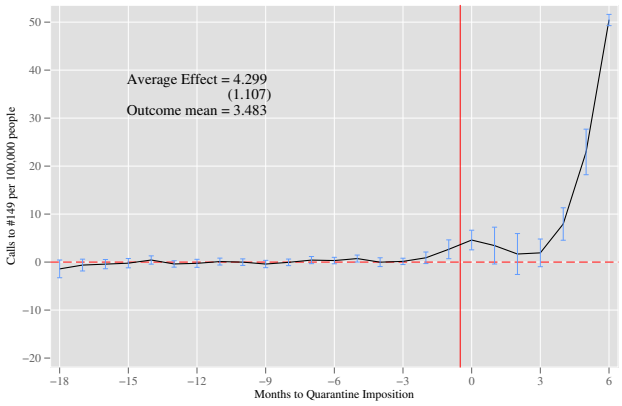
Notes: Refer to notes to Figure 2. Identical specifications are estimated however examining contract suspensions. All other estimation details follow those indicated in notes to Figure 2.

Figure A5: Sectoral Trends in Employment by Gender (Total Employment)

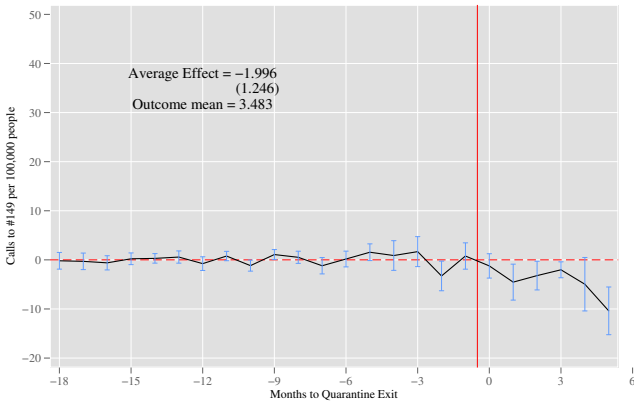


Notes: Data from a 12% sample of the universe of formal private workers is displayed as reported in the country's unemployment insurance database. The total number of workers in each employment class is displayed.

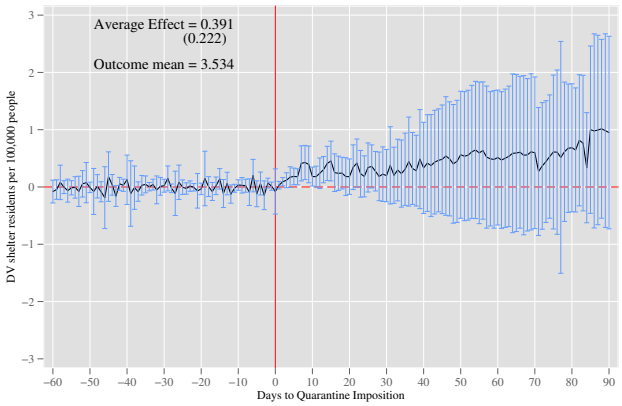
Figure A6: Impacts of lockdown on incidence of Intra-family violence (no COVID controls)



(a) Distress Calls (entry)

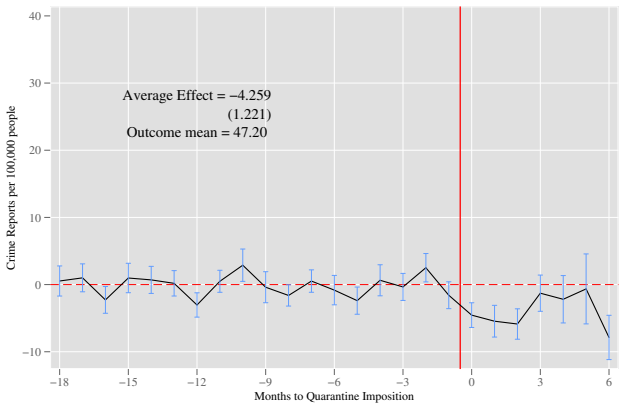


(b) Distress Calls (exit)

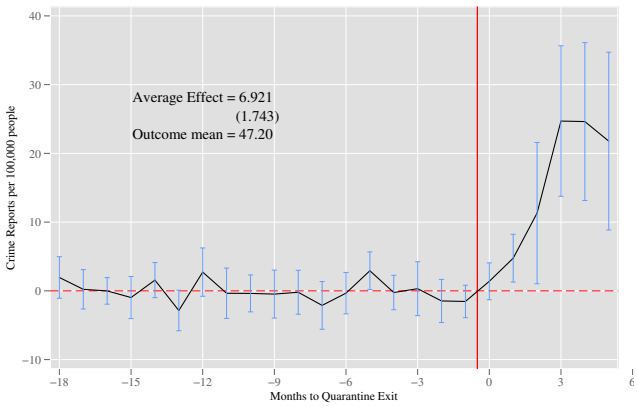


(c) Shelter Usage (entry)

(d) Shelter Usage (exit)



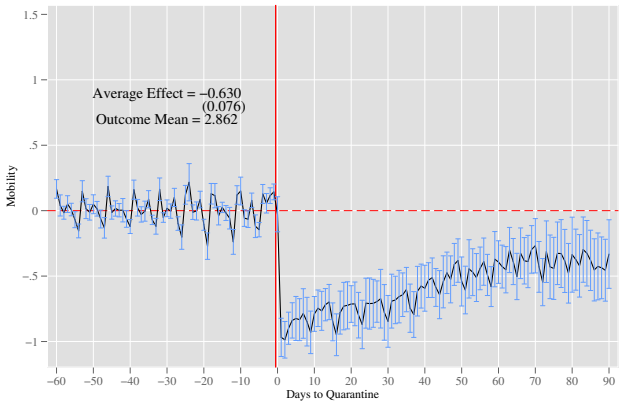
(e) Crime Reporting (entry)



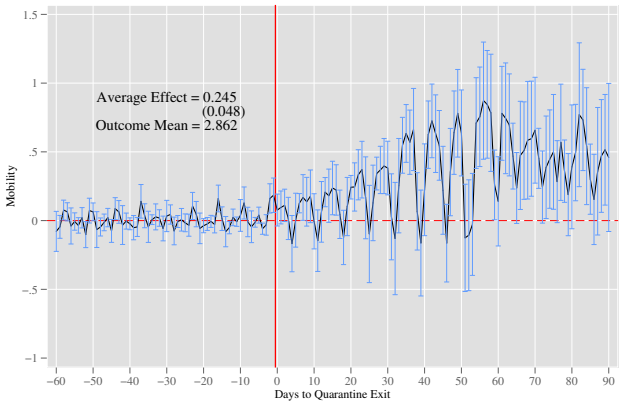
(f) Crime Reporting (exit)

Notes: Refer to notes to Figure 2. Identical specifications are estimated, here without controls for COVID infection and testing rates.

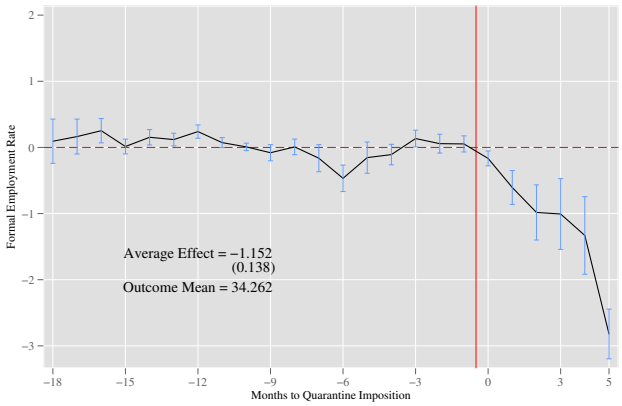
Figure A7: Impacts of lockdown on mechanism variables (no COVID controls)



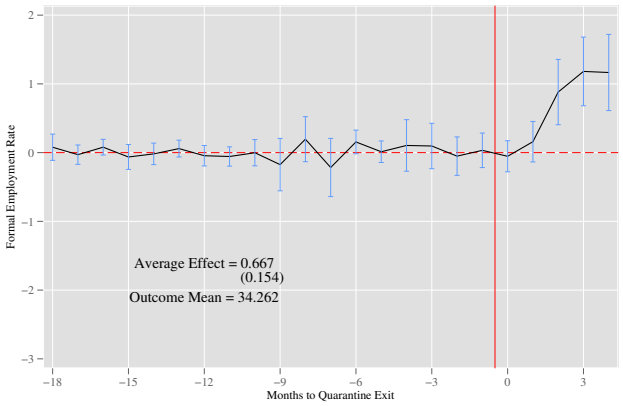
(a) Cell phone mobility patterns (entry)



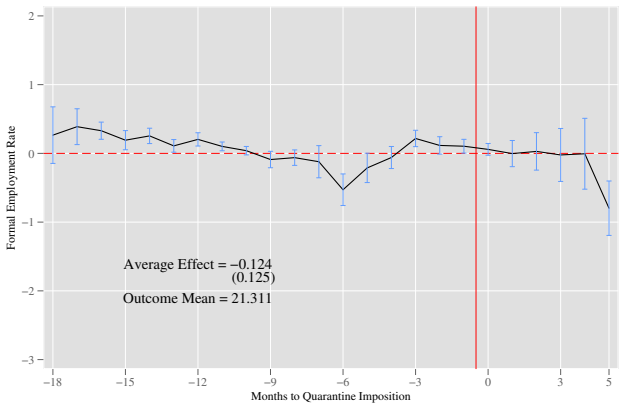
(b) Cell phone mobility patterns (exit)



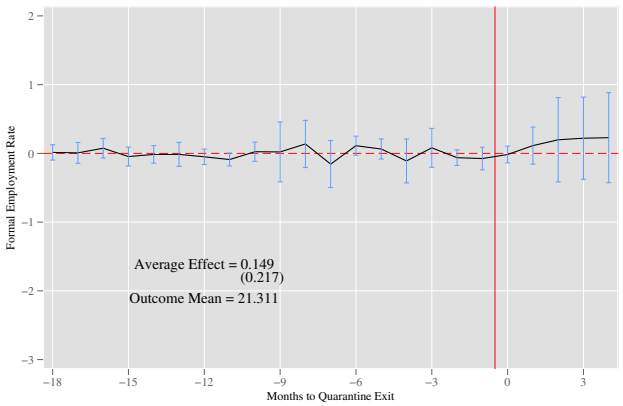
(c) Male formal employment rate (entry)



(d) Male formal employment rate (exit)



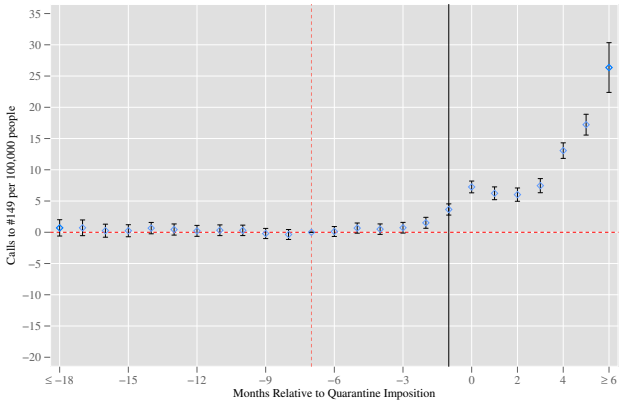
(e) Female formal employment rate (entry)



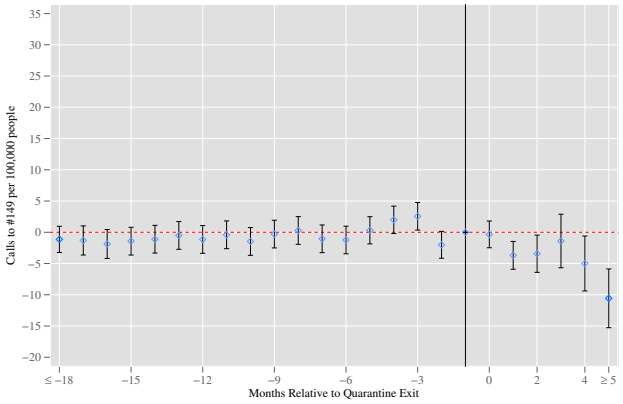
(f) Female formal employment rate (exit)

Notes: Refer to notes to Figure 3. Identical specifications are estimated, here without controls for COVID infection and testing rates.

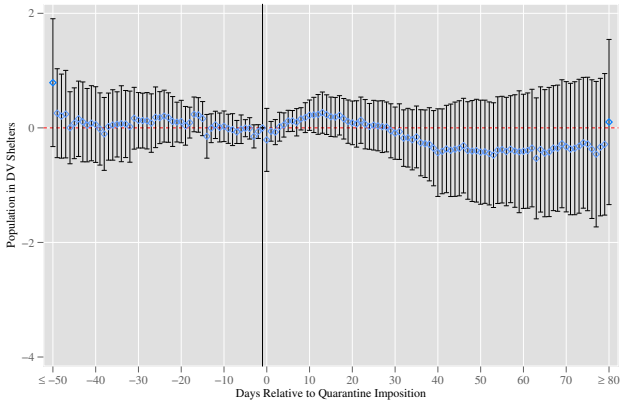
Figure A8: Event study estimates of impacts of lockdown on incidence of intra-family violence



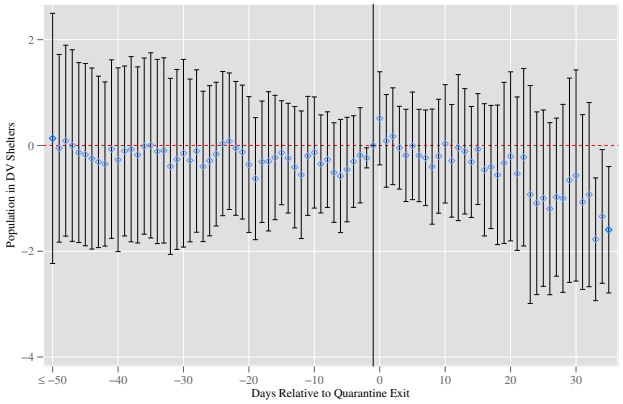
(a) Distress Calls (entry)



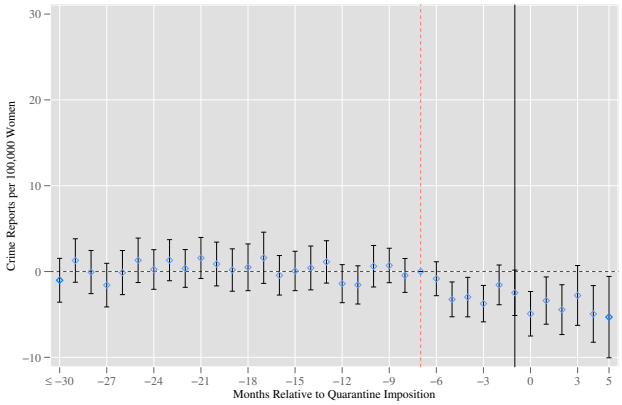
(b) Distress Calls (exit)



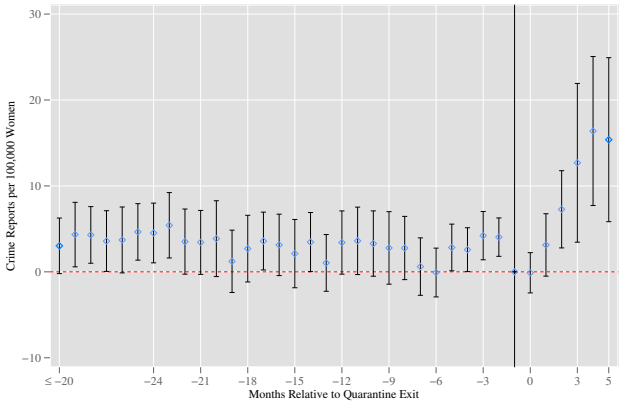
(c) Shelter Usage (entry)



(d) Shelter Usage (exit)



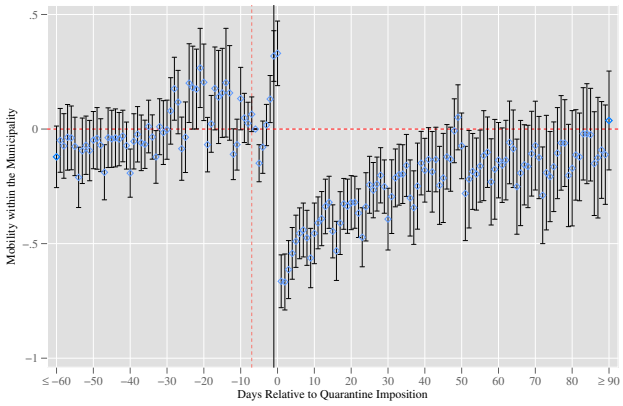
(e) Crime Reporting (entry)



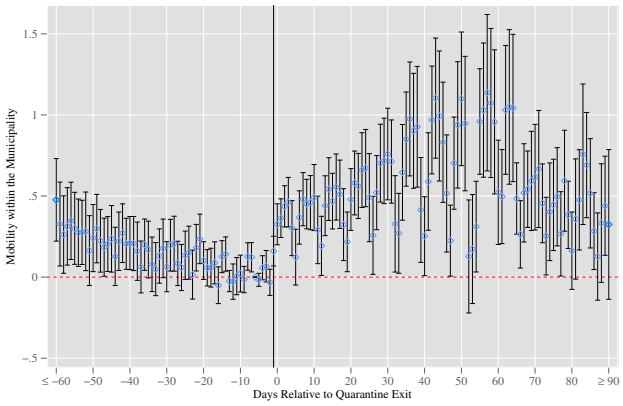
(f) Crime Reporting (exit)

Notes: Panel event study coefficients and 95% confidence intervals are displayed. The left-hand column consists of all municipalities, where the event of interest refers to the adoption of lockdown (if the municipality has ever adopted). The right-hand panel consists of all municipalities which have ever entered lockdown (and hence could theoretically exit lockdown), where the event of interest refers to the removal of lockdown. Cluster-robust standard errors are estimated by area. All other details follow those described in notes to Figure 2.

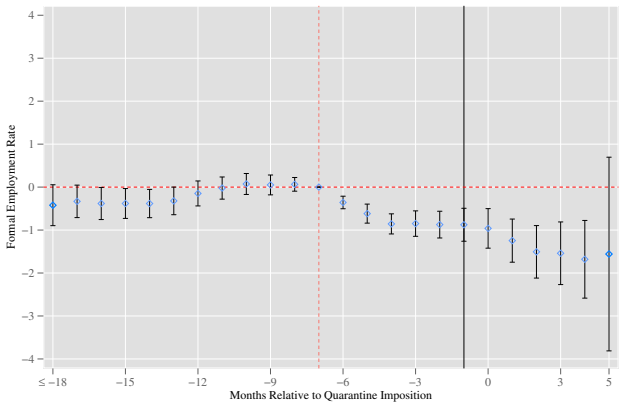
Figure A9: Event study estimates of impacts of lockdown on mechanism variables



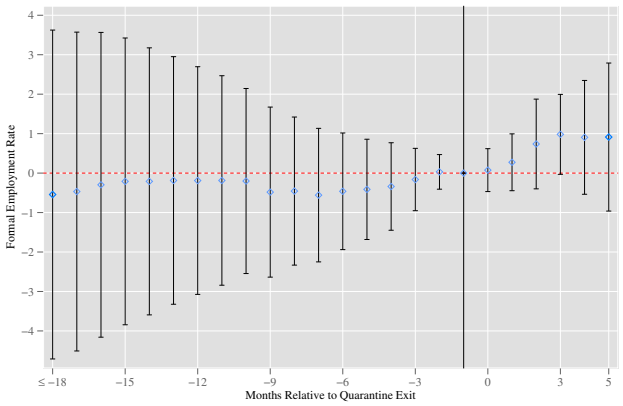
(a) Cell phone mobility patterns (entry)



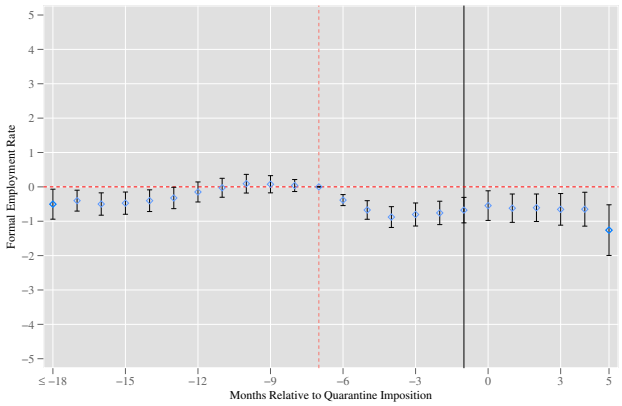
(b) Cell phone mobility patterns (exit)



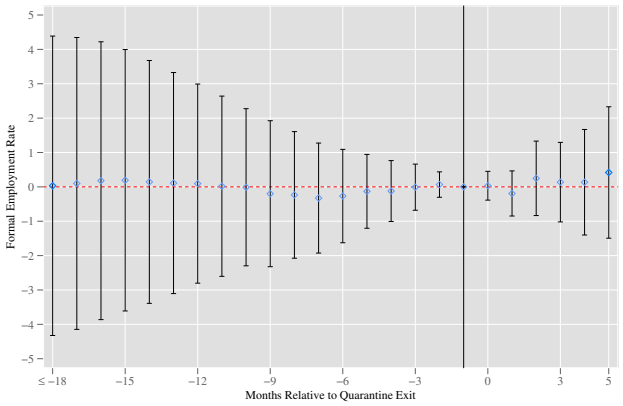
(c) Male formal employment rate (entry)



(d) Male formal employment rate (exit)



(e) Female formal employment rate (entry)



(f) Female formal employment rate (exit)

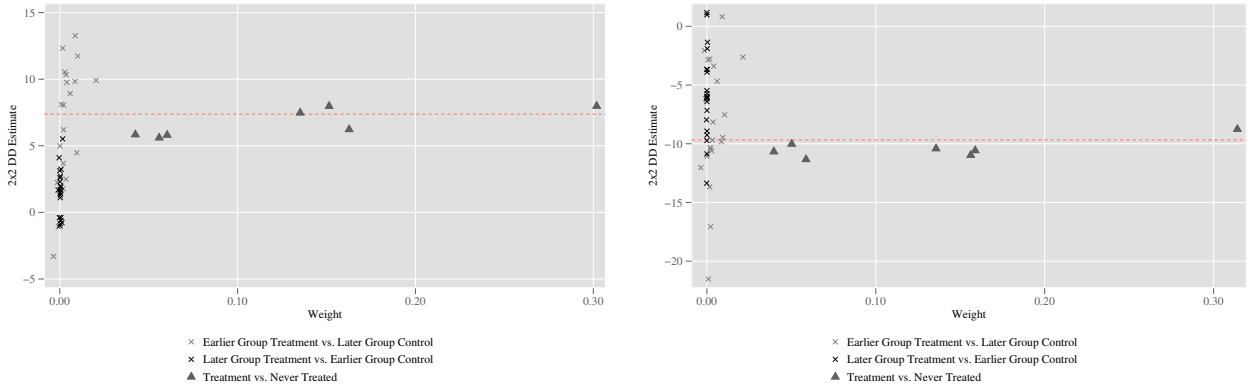
Notes: Refer to notes to Figure A8. Identical specifications are estimated however examining mobility patterns based on within-municipality daily movement from cell phone data (panels (a) and (b)), and municipal level employment rates in the formal private labour market from administrative records (panels (c) to (f)). All other estimation details follow those indicated in notes to Figure A8.

Table A4: Two-Way FE Models: DV and Mechanism Measures

	DV Measures			Mechanisms		
	Calls	Crime	Shelters	Mobility	Male Emp	Female Emp
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No COVID Controls						
Lockdown Imposed	7.792***	-6.596***	0.053*	-0.269***	-0.735***	-0.103
	(1.062)	(0.960)	(0.029)	(0.060)	(0.141)	(0.092)
Lockdown Removed	1.746	0.231	-0.025	0.442***	-0.019	-0.074
	(1.202)	(1.402)	(0.115)	(0.081)	(0.128)	(0.119)
Observations	7,266	26,919	4,576	74,992	7,266	7,266
Panel B: COVID Controls						
Lockdown Imposed	5.409***	-2.872***	0.155***	-0.256***	-0.589***	0.002
	(0.832)	(0.923)	(0.034)	(0.059)	(0.148)	(0.107)
Lockdown Removed	1.501	-0.216	0.035	0.429***	-0.028	-0.097
	(0.991)	(1.308)	(0.124)	(0.080)	(0.140)	(0.129)
Population	0.001**	-0.000***			-0.000	-0.000
	(0.000)	(0.000)			(0.000)	(0.000)
Diagnosed COVID cases per 1,000 people	0.268*	-0.175	-0.566***	0.024	-0.070***	0.011
	(0.149)	(0.140)	(0.164)	(0.040)	(0.019)	(0.015)
PCR tests per 1,000 people	-0.064**	-0.025	-0.166***	-0.022**	0.025***	0.004
	(0.029)	(0.031)	(0.042)	(0.009)	(0.004)	(0.003)
Rate of positive PCR tests	0.077	-0.161***	0.002	-0.001**	0.000	-0.011**
	(0.051)	(0.049)	(0.002)	(0.000)	(0.008)	(0.006)
Observations	7,266	26,919	4,528	74,992	7,266	7,266
Mean of Dep. Var. (baseline)	3.482	47.20	3.533	2.862	34.26	21.31

Notes: Each column displays a two-way fixed effect regression of the impact of lockdown on domestic violence measures (columns 1-3) or mechanism variables (columns 4-6). In columns 1-3, all measures are cast per 100,000 population. Column 4 refers to average trips within municipality per day, columns 5-6 are cast per 100,000 working age population. Lockdown Imposed is a binary variable taking the value of 1 only when municipalities are under lock-down, and 0 pre or post-lockdown. Lockdown removed switches to 1 post-lockdown in areas where lockdown has been imposed and then removed. Population is not included in columns 3-4 given that these are day by municipality measures for 2020 only. Fixed effects for area and time are consistently included, and standard areas are clustered by geographic unit. ***, ** and * indicate statistical significance at the 1%, 5% and 10%, respectively.

Figure A10: Decomposing the Two-way Fixed Effect Estimate: Municipal-level Lockdown Entry



(a) Distress Calls

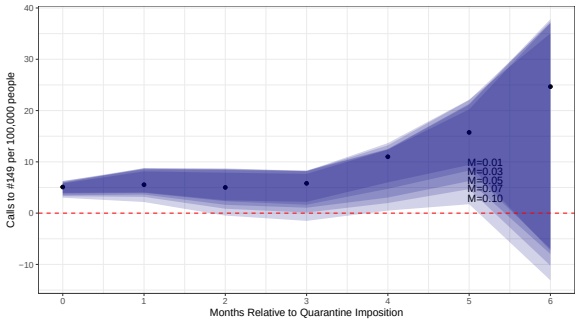
(b) Crime Reporting

Notes: Decomoposition of the two-way fixed effect estimator follows Goodman-Bacon (2021), plotting each group×time estimate as well as its weight in two-way fixed effect models. Results are presented for municipal by month records, in which each of the three Goodman-Bacon (2021) groups exist (treated vs never treated, early versus late adoption, late versus early adoption). The group-specific estimates are presented as points on the plot, while the aggregate two-way FE estimate is presented as the dashed horizontal line.

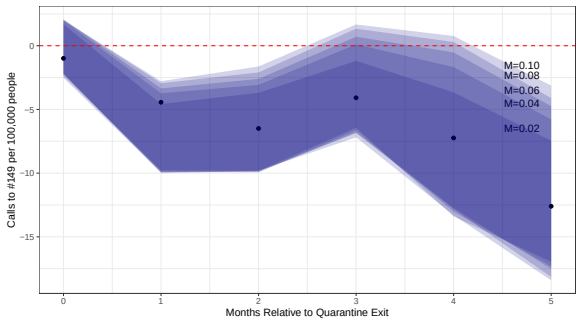
Table A5: Stimulus Payment Amounts and Dates

Payment	Date first deposit	Average amount
Payment 1	May 25, 2020	154,378 CLP
Payment 2	June 25, 2020	197,455 CLP
Payment 3	July 28, 2020	194,017 CLP
Payment 4	August 27, 2020	193,201 CLP

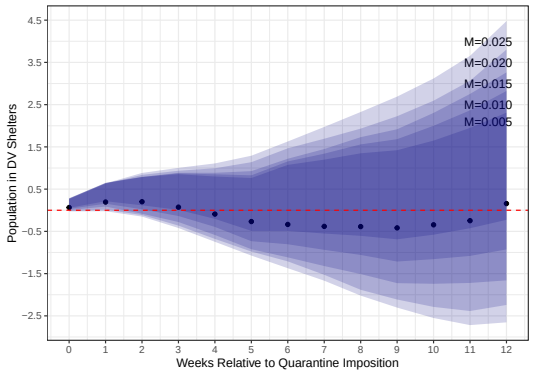
Figure A11: Honest DID bounds estimates of impacts of lockdown on incidence of intra-family violence



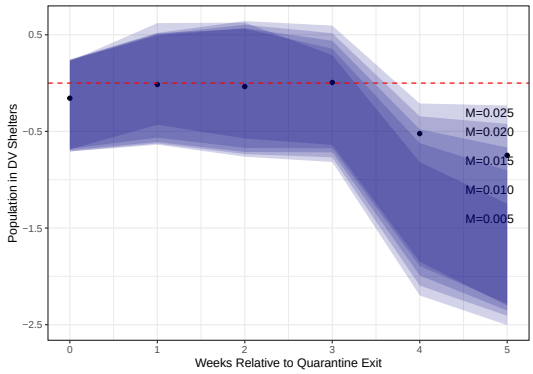
(a) Distress Calls (entry)



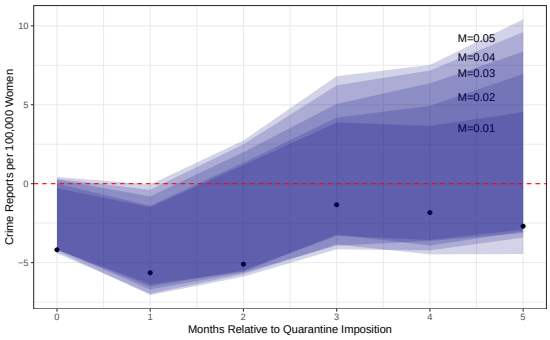
(b) Distress Calls (exit)



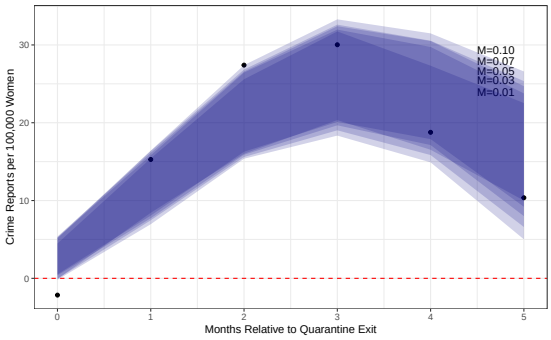
(c) Shelter Usage (entry)



(d) Shelter Usage (exit)



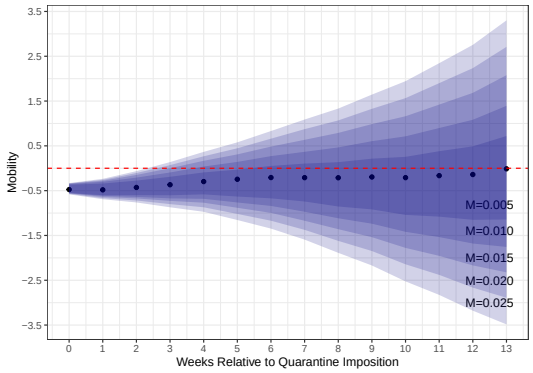
(e) Crime Reporting (entry)



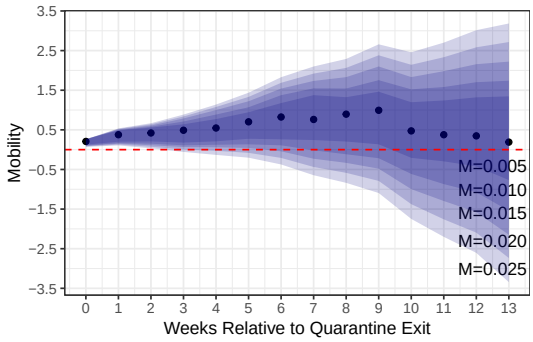
(f) Crime Reporting (exit)

Notes: Figures replicate post-event lags from panel event study models, however now rather than assuming parallel counterfactual trends between lockdown and non-lockdown municipalities, project any prevailing trends forward, resulting in partially identified 'Honest DiD' bounds. Additionally, these trends are allowed to vary by as much as M between each period, where varying values of M are plotted as alternative 95% CIs. In the case of shelter usage only, weekly, rather than daily estimates are plotted, given computational demands on bounds when many lags are included. Point estimates from event studies are included as solid circles for reference.

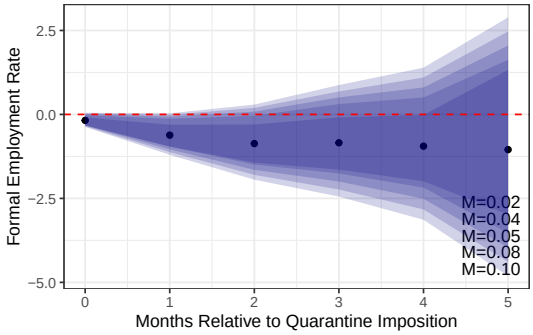
Figure A12: Honest DID bounds estimates estimates of impacts of lockdown on mechanism variables



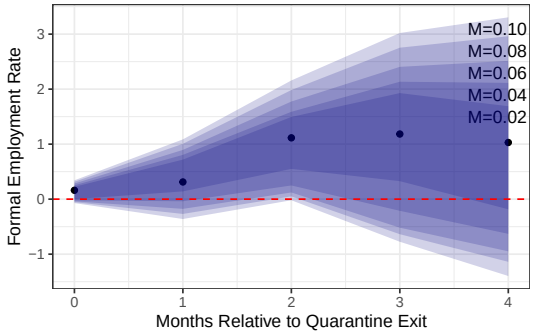
(a) Cell phone mobility patterns (entry)



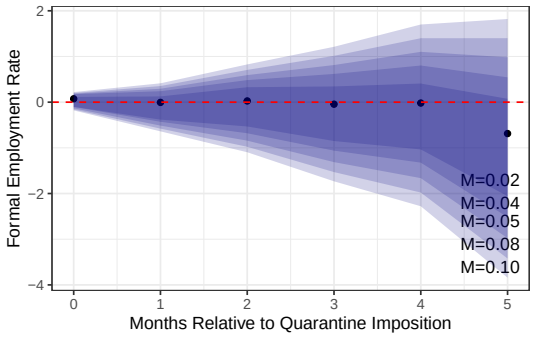
(b) Cell phone mobility patterns (exit)



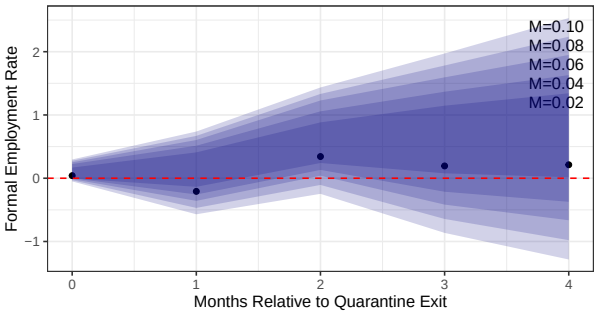
(c) Male formal employment rate (entry)



(d) Male formal employment rate (exit)



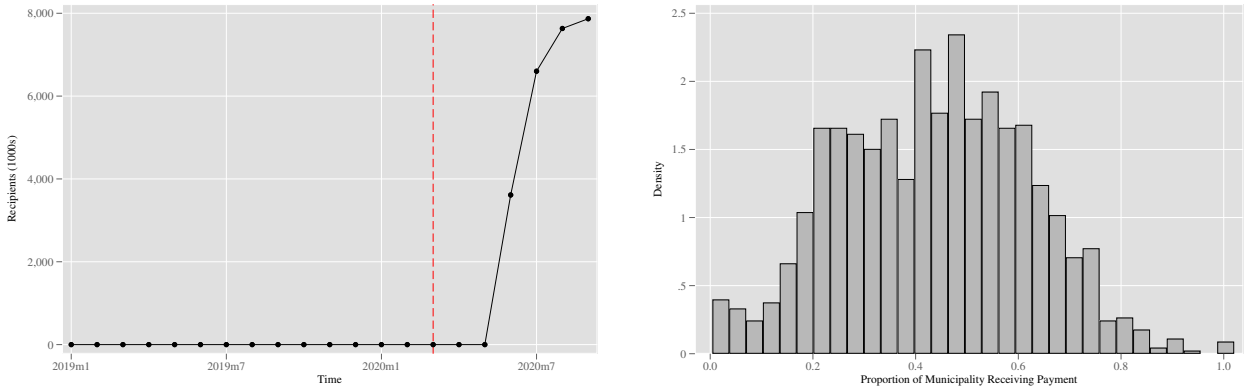
(e) Female formal employment rate (entry)



(f) Female formal employment rate (exit)

Notes: Refer to notes to Figure A11. Identical specifications are estimated however examining mobility patterns based on within-municipality movement from cell phone data (panels (a) and (b)), and municipal level employment rates in the formal private labour market from administrative records (panels (c) to (f)). In the case of mobility measures only, weekly, rather than daily estimates are plotted, given computational demands on bounds when many lags are included. All other estimation details follow those indicated in notes to Figure A11.

Figure A13: IFE Stimulus Payments

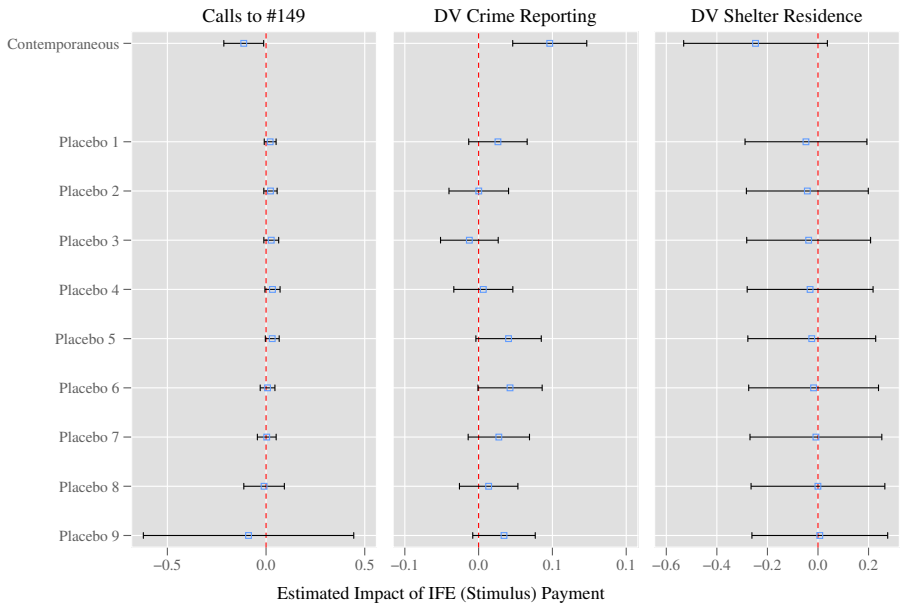


(a) Payments over Time

(b) Proportion of Recipients per Municipality

Notes: Panel (a) plots the temporal expansion of the number of IFE recipients nation-wide, based on administrative records provided by the Ministry of Social Development of Chile (Undersecretary for Social Evaluation). Panel (b) plots the average proportion of each municipality's residents receiving an IFE payment, calculated in the period following the introduction of the payment.

Figure A14: Placebo Tests – Stimulus Payment Impacts on DV Measures



Placebo tests consist of estimating two-way FE models with rates of IFE payments as the independent variable of interest on rates of domestic violence. In the case of 'Contemporaneous' models, this consists simply of a regression of rates of DV in time t on IFE (family emergency income payments) at time t, whereas placebos regress lagged rates of DV at time $t-k$ on IFE at time t. In the case of Calls and Crime, alternative placebos use lags $k \in \{10, 11, \ldots, 18\}$, such that in all cases DV outcomes are considered in months of 2019 or prior. In the case of shelters where daily data is used (starting from January 2020), lags $k \in \{60, 61, \ldots, 68\}$ are considered.

Table A6: Stimulus Payments, Lockdown and Domestic Violence (Alternative Specifications)

	Calls to 149		Crime Reporting		Shelter Residence	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Unstandardised						
Lockdown	5.239***	6.786***	-2.198**	-1.332	0.157	0.188
	(0.833)	(1.139)	(0.885)	(1.263)	(0.200)	(0.208)
IFE	-1.944	-1.421	12.65***	13.15***	-3.033*	-3.023*
	(2.424)	(2.357)	(3.625)	(3.413)	(1.664)	(1.680)
Lockdown×IFE		-6.689**		-3.777		-0.117
		(3.241)		(4.100)		(0.402)
IFE +						
Lockdown×IFE		-8.110*		9.375		-3.140*
		(4.824)		(5.860)		(1.670)
Observations	7,245	7,245	26,841	26,841	4,128	4,128
R-squared	0.784	0.786	0.560	0.560	0.856	0.856
Panel B: No COVID-19 Controls						
Lockdown	0.160***	0.206***	-0.0218***	-0.0231***	0.0144	0.0227
	(0.0202)	(0.0353)	(0.00342)	(0.00507)	(0.0330)	(0.0391)
IFE	-0.108	-0.0914	0.0456***	0.0448***	-0.260*	-0.259*
	(0.0777)	(0.0710)	(0.0124)	(0.0117)	(0.145)	(0.147)
Lockdown×IFE		-0.0728**		0.00199		-0.0132
		(0.0344)		(0.00526)		(0.0371)
IFE +						
Lockdown×IFE		-0.164*		0.046***		-0.272*
		(0.099)		(0.014)		(0.146)
Observations	7,262	7,262	26,915	26,915	4,176	4,176
R-squared	0.770	0.773	0.558	0.558	0.853	0.853

Refer to notes to Table 2. Identical models are estimated, however here using all variables in levels rather than standardized units (panel A), and not including controls for time-varying measures of COVID-19 intensity (panel B). All other details follow those described in Table 2. *** p<0.01, ** p<0.05, * p<0.1.

B Data Appendix

Table B1: Data Definitions and Sources

Variable	Description	Frequency	Unit of analysis	Period covered	Source
Distress calls to the Police DV hotline	Number of calls received by the domestic violence police line #149 per 100,000 inhabitants. The calls are classified as owing to complaints related to physical violence, psychological violence, and economic violence.	Monthly	Municipality	Jan 2019 - Sept 2020	Carabineros de Chile
Crimes reported for DV	Domestic violence crimes known to the police. They include formal complaints made to the police, as well as in flagrante offences	Monthly	Municipality	Jan 2015 - Sept 2020	Ministry of Interior, Undersecretary of Crime Prevention
Residents in DV Shelters	Number of residents in government-run domestic violence shelters measured as the number of women who slept in a shelter the night before per 100,000 inhabitants	Daily	Region	Jan 1, 2020 - Nov 6, 2020	Ministry of Women and Gender Equality
Spots in DV Shelters	Number of official spots available in government-run domestic violence shelters	Daily	Region	Jan 1, 2020 - Sept 30, 2020	Ministry of Women and Gender Equality
Lockdown entry	Dummy indicating a municipality is under lockdown	Daily	Municipality	Mar 14, 2020 - Sept 30, 2020	Ministry of Health, hand compiled by project RA.
Lockdown exit	Dummy indicating a municipality has exited lockdown	Daily	Municipality	Mar 14, 2020 - Sept 30, 2020	Ministry of Health, hand compiled by project RA.
COVID-19 testing rate	Number of COVID-19 PCRs over 1,000 inhabitants	Daily	Municipality	Mar 8, 2020 - Sept 30, 2020	Ministry of Science
COVID-19 infection rate	Number of confirmed COVID-19 cases over 1,000 inhabitants (7-day average)	Daily	Municipality	Mar 8, 2020 - Sept 30, 2020	Ministry of Science
COVID-19 positivity rate	Number of confirmed COVID-19 cases over PCRs (7-day average)	Daily	Municipality	Mar 8, 2020 - Sept 30, 2020	Ministry of Science
Mobility	Number of trips within and between municipalities measured as changes in cell phone connection towers	Daily	Municipality	Feb 26, 2020 - Sept 30, 2020	Cell phone metadata (Bravo and Ferres, 2020).
Employment	Number of employed individuals in the formal private sector over working age population	Monthly	Municipality	Jan 2019 - Sept 2020	Unemployment Insurance data managed by the Pensions Superintendence
Mean wages	Mean wage among employed individuals in the formal private sector	Monthly	Municipality	Jan 2019 - Sept 2020	Unemployment Insurance data managed by the Pensions Superintendence
Median wages	Median wage among employed individuals in the formal private sector	Monthly	Municipality	Jan 2019 - Sept 2020	Unemployment Insurance data managed by the Pensions Superintendence
Jobs furloughed	Number of jobs furloughed under the employment protection law over 100,000 pre-COVID jobs	Monthly	Municipality	April 2020 - Sept 2020	Pensions Superintendence
Jobs sectoral shares	Share of private sector workers under contract working in different economic sectors	Monthly	Municipality		12% random sample of affiliated workers to the Unemployment Insurance, data managed by the Pensions Superintendence
Stimulus payment	Number of people receiving the IFE benefit over population		Municipality	May 2020 - Sept 2020	Ministry of Social Development and Family

We use three measures of domestic violence which capture incidence and reporting: calls received by the police domestic violence hotline, criminal cases of domestic violence, and use of shelters for victims of domestic violence.

Figure B1a plots the national trend for calls received by the police to the #149 domestic violence hotline. The figure shows a sharp increase of around 300% following the first outbreak of COVID-19, with the first lockdown measures soon after. Prior to March 2020 around 1,000-1,500 calls per month were received, with this quantity increasing to anywhere between around 2,000-5,000 calls per month after March 2020.

Figure B1b shows the national trend for formal criminal cases of domestic violence filed with the police. In this case, we observe daily data from January 1 2018 to 31 May 2020. We see that by mid-March 2020, the rate of DV criminal complaints differs from that of previous years, in particular, being lower than the rate observed in 2018 and 2019.

In the case of shelters, we observe data for each one of the publicly run women's shelters in the country, recording their number of residents, and available spots on each day between January 1, 2020 and November 6, 2020.[16] Not all municipalities have a shelter. In emergency situations, individuals are placed in a shelter in their region (which contains their municipality). The daily averages for rate of residence in DV shelters and total capacity for the period under study are summarised in Table B2, and national trends are plotted in Figures B1c and B1d, respectively. Figure B3 shows correlations between the three main outcome variables.

We additionally have information from late February 2020 (before cases of COVID-19 were detected in Chile) recording movement within and between municipalities based on cellphone records. Baseline mobility within municipalities is approximately 3 trips per day (see Table B2), with trips measured as the average number of changes between cell phone connection towers from cell phone metadata.[17] Figure B2a displays mobility rates, showing a significant decrease in mobility since the start of the pandemic, that is more pronounced in municipalities subject to lockdown. Google's mobility index is plotted in Figure B4, showing a striking shift of activity away from workplaces and grocery stores towards residences. We do not use these data in the analysis as they provide regional aggregates, while the cell phone data provide the more fine-grained municipal measures.

We have labor market data containing information on individual monthly work histories, along with sector of work, and whether workers suffered job loss. Figure A5 (discussed in the main text, and hence presented in Appendix A), shows sectoral trends in formal employment for men and women, with the red line marking the first outbreak of the pandemic. We observe particularly sharp declines in construction, hospitality and artistic activities after March 2020. The construction sector employs a large share of the labour force, and mostly men. We supplement this information with data from a rolling labour market survey. Recognising that the survey is not designed to be representative at the municipality level, we do not rely upon these estimates but provide them for descriptive purposes as they cover the entire population of formal and informal sector workers. Figure B1 shows increases in unemployment and declines in labour force participation rates for both men and women following the COVID-19 outbreak in March 2020. They reveal that, starting from a lower baseline level, unemployment rates of men increased more than rates for women. Starting from a lower base too, labour force

[16] For this variable we extended the period beyond September 30 in order to use all the administrative information available. This allows us to pick up more lockdown exits in our data and to have more variation for a variable that is defined at the regional level.

[17] See (Pappalardo et al., 2020) who also provide a description of the data.

participation rates of women fell more than rates for men.
Finally, we obtained information on the total beneficiaries of the stimulus payments distributed since May 2020. This information comes from the *Registro Social de Hogares*.[18] These payments were targeted at those families most severely affected by the socioeconomic crisis brought on by the pandemic. Figure A13 shows the scope of stimulus payments up to September 2020. During this time, four payments were distributed. Table A5 shows the timing and average amount of each one of these (again, as these figures are discussed in the main text, they are provided in Appendix A).

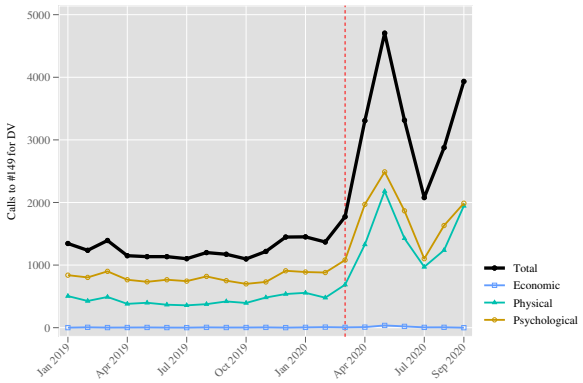
Table B2: Summary Statistics of Principal Measures

	Obs	Mean	Std. Dev.	Min.	Max.
Panel A: Distress Calls					
All Calls to #149 per 100,000 Inhabitants	7266	5.04	10.24	0.0	454.5
Calls to #149 for Economic Violence per 100,000	7266	0.02	0.37	0.0	25.9
Calls to #149 for Physical Violence per 100,000	7266	2.05	7.35	0.0	454.5
Calls to #149 for Psychological Violence per 100,000	7266	2.96	5.37	0.0	112.5
Panel B: Criminal Complaints					
Total Complaints to Police for DV	5190	21.68	34.60	0.0	364.0
Complaints to Police for DV per 100,000 Inhabitants	5190	42.21	30.00	0.0	970.9
Panel C: Women's Shelters					
Residents in DV Shelters per 100,000 Inhabitants	2336	3.67	2.39	0.0	11.3
Total Capacity of DV Shelters per 100,000 Inhabitants	2336	7.03	5.11	0.0	23.8
Panel D: Lockdown and Mobility Measures					
Quarantine Imposition	75428	0.11	0.32	0.0	1.0
Quarantine Exit	75428	0.04	0.21	0.0	1.0
Mobility within the Municipality per day	74992	2.33	1.82	0.0	16.1
Mobility outside the Municipality per day	74992	3.43	3.05	0.0	41.1
Total Mobility of the Municipality per day	74992	5.76	3.47	0.0	44.3
Panel E: Covid Measures					
COVID-19 testing rate	71622	0.73	0.86	0.0	28.9
COVID-19 infection rate	71622	0.09	0.21	0.0	12.5
COVID-19 positivity rate	71622	11.3	16.8	0.0	100.0
Panel F: Economic Measures					
Unemployment rate (women)	4984	0.08	0.12	0.0	1.0
Unemployment rate (men)	4987	0.08	0.10	0.0	1.0
Estimated Monthly Employment Rate (Women)	4984	0.44	0.15	0.0	1.0
Estimated Monthly Employment Rate (Men)	4984	0.68	0.14	0.0	1.0

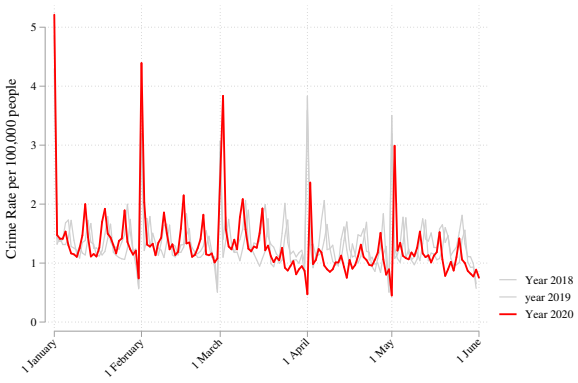
Notes: Summary statistics cover measures used in the paper at the same level used in analysis (the most disaggregated level possible). For panels A, B and F this is by municipality and month. For panel C this is by region (which includes multiple municipalities) and day. For panels D and E, this is municipality by day.

[18]This household register, (RSH for its initials in Spanish), is an information system used by the Ministry of Social Development to assign a wide set of subsidies and social programs. It combines verified self-reported information with administrative records.

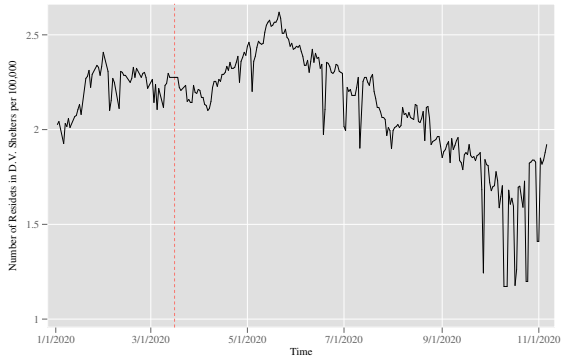
Figure B1: Descriptive Trends – Main Outcomes



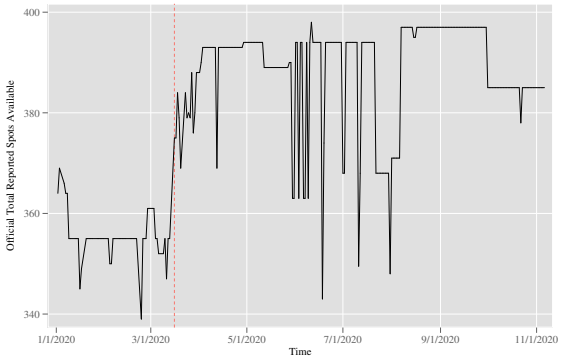
(a) Calls to #149



(b) Criminal Complaints for VIF



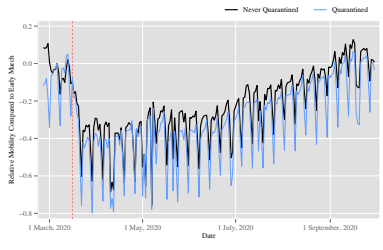
(c) Residents in Domestic Violence Shelters



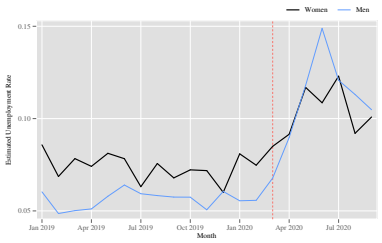
(d) Residents in Domestic Violence Shelters

Notes: Panel (a) shows total aggregate number of calls in the country for each month between Jan 2019 - Sept 2020. The thick black line shows the total number of all calls related to DV received by the police. These are then sub-classified as related to psychological, physical and economic violence. Vertical red line indicates March 2020, the first month in which a lockdown was applied. Panel (b) shows rates of crime reporting for DV. These are plotted based on the number of reports received nation-wide each day. Grey lines depict rates for the first 5 months of years 2018 and 2019, while the red line depicts similar rates for 2020. In all analyses in the paper, month by municipality aggregates (over a longer period of time) are used. Panel (c) shows the average rate of residence in government run DV shelters, calculated as the total proportion of residents who slept in a shelter the previous night. This figure covers state-run women's shelters only. Panel (d) documents the total number of available spots in these state-run DV shelters according to administrative records.

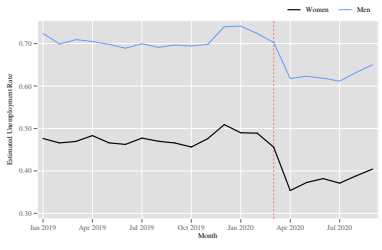
Figure B2: Descriptive Trends – Mechanism Variables



(a) Average Changes in Mobility in Lockdown and Non-lockdown Areas



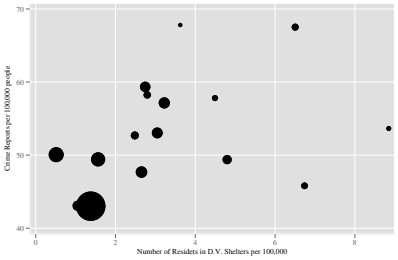
(b) Unemployment Rates



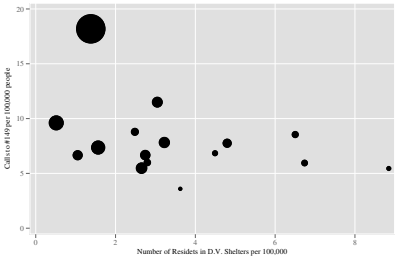
(c) Labour Force Participation Rates

Notes: Panel (a) presents daily changes in mobility (relative to early March) for municipalities that were locked-down compared to those that were never locked-down. Panels (b) and (c) present respectively monthly changes in unemployment rates and labour force participation rates for men and women. The data comes from the National Employment Survey (ENE).

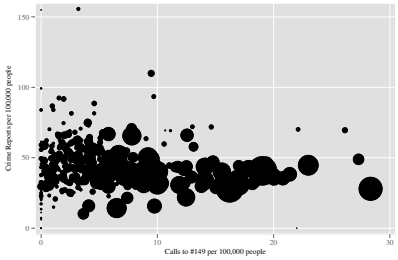
Figure B3: Raw Correlations between Measures of DV



(a) Crime Reporting and Shelter Residence



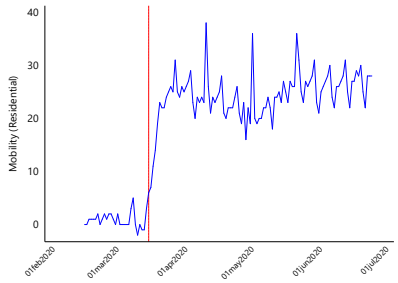
(b) Shelter Residence and Distress Calls



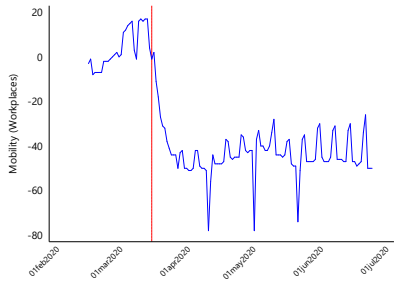
(c) Distress Calls and Crime Reporting

Notes: Plots document area-specific averages in rates of key DV measures between Jan-Sept 2020. In each case, averages are provided over the lowest level of aggregation possible (municipality in panel (c)), region in panels (a) and (b). Point sizes are scaled by area populations.

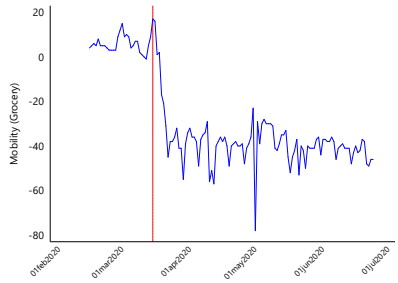
Figure B4: COVID-19 and Changes in Movement Patterns



(a) Residential



(b) Workplaces



(c) Grocery

Notes: The figure presents daily changes in mobility (relative to early March). Panel (a) shows mobility patterns in residential places, panel (b) shows workplaces, and panel (c) shows grocery stores.