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Unintended Consequences of Lockdowns, COVID-19 and the Shadow Pandemic in India. A Reproduction Study of Ravindran and Shah.

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Shah.**

Ryan McWay

May 2025

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Unintended Consequences of Lockdowns, COVID-19 and the Shadow Pandemic in India. A Reproduction Study of Ravindran and Shah. (Nature Human Behavior, 2023)*

Ryan McWay[†]

April 7, 2025

Abstract

Ravindran and Shah (2023) assesses the effect of COVID-19 lockdowns on violence against women (VAM) in India. Using a dynamic fixed effects methodology exploiting spatio-temporal variation in the timing and intensity of ‘stay-at-home’ mandates in Indian districts, the authors find that government-mandated lockdowns increased complaints of domestic violence in districts with the strictest lockdown rules. I successfully computationally reproduce their results. Further, I test the replicability of the results by re-analyzing the results using a Poisson estimator as opposed to the ordinary least squares (OLS) estimator used by the original authors. I find that lower bound censoring of the outcome measure resulted in attenuation of the marginal effect of government-mandated lockdowns. The effect of mobility restrictions on VAW are understated in the original study. This provides support for the internal validity of Ravindran and Shah (2023)’s results by suggesting that may present lower bound estimates of an under-reported consequence of mobility restrictions during the COVID-19 pandemic.

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1 Introduction

A reproducibility crisis has become apparent in the social sciences over the past several decades (Sterling, 1959; Dreber and Johannesson, 2019). Subsequently, the irreproducibility of findings has resulted in a loss of faith in scientific evidence from the general public and more importantly from policy-makers and stakeholders who might implement this knowledge (Change and Li, 2015). Reproductions and replications are considered an essential diagnostic tool for determining which bodies of evidence are considered reliable for use outside of academia and add to the foundations of existing literature within academia (King, 1995; Maniatis et al., 2017; Moonesinghe et al., 2007; Peterson and Panofsky, 2021).

To improve our body of evidence for violence against women (VAW), I replicate Ravindran and Shah (2023). This 2023 article from *Nature Human Behavior* examines the effect of COVID-19 mobility restrictions in India on VAW complaints. The authors exploit variation in the timing and intensity of lockdowns using district level zone classification for green, orange, and red zones for lockdown restrictions. Using a dynamic fixed effects model, the authors find that harsher mobility restrictions led to increased complaints of domestic violence and cybercrimes.¹ But they find a reduction in rape and sexual assault complaints.² This suggests VAW at home and online increased while public VAW decreased following mobility restrictions. This provides evidence of the ‘shadow pandemic’ against women in India.

I successfully recreate a computational reproduction of the results using the public replication packet provided by the authors. Despite this, there are some minor coding errors which should be addressed for an updated replication packet. Testing the robustness/reproducibility of these results, I note that the count of VAW complaints follows a Poisson distribution. Nearly half of monthly district observations for VAW report no complaints. As a socially contentious subject, VAW is likely under-reported/suffering from lower-bound censoring of the distribution as evidence in the data. To remedy this, I re-estimate the results using a Poisson fixed effects estimator. The replicated results magnify the effects and highlight an attenuation of treatment effects particularly in orange zones (viz., medium mobility restrictions). This validates the internal validity of the study. And uncovers that the ‘shadow pandemic’ had far larger effects than originally reported.

¹“Using a difference-in-differences empirical strategy, we find evidence of a 0.48 standard deviation (s.d.) ($P < 0.001$, 95% confidence interval (CI) 0.232 to 0.733) or 135% increase in domestic violence complaints in May 2020 in districts that saw the strictest lockdown measures (red zone districts) relative to districts that saw the least strict measures (green zone districts). Red zone districts also experienced a 0.71 s.d. ($P < 0.001$, 95% CI 0.417 to 0.999) or 186% increase in cybercrime complaints relative to green zone districts in May 2020.” (Ravindran and Shah, 2023)

²“Rape and sexual assault complaints fell significantly by 0.39 s.d. ($P = 0.003$, 95% CI -0.642 to -0.137) in red zones in May 2020 relative to green zone districts, probably due to decreased mobility in public spaces, public transport and workplaces.” (Ravindran and Shah, 2023)

This reproduction confirms the results of Ravindran and Shah (2023) and solidifies a contribution to the development economic literature on gender disparities. Additionally, this replication build on the Mertonian norms (Merten, 1942) for the practical application of the open science movement in contemporary scientific research as a validation tool for stakeholders and a correction tool for researchers. This study builds on a growing literature reporting replication studies to verify internal validity and assessing the external validity of influential findings in economics (McWay et al., 2024; McWay, 2024; McWay and Braaksma, 2025; Cong et al., 2024; Kurtz and McWay, 2025)

2 Computational Reproduction

I computationally reproduce³ the results of Ravindran and Shah (2023). This is a reproduction of the 2023 publication in *Nature Human Behavior*⁴. The data and code used in this reproduction come from the publicly published replication packet⁵ of the original study through OpenICPSR. The replication packet was downloaded on March 21st, 2025. The reproduction, along with the replication, was conducted in Stata 16 – compatible with the original coding software in the replication packet Stata MP. I reproduced all tables and figures presented in the manuscript as well as the online appendix. I confirm I can reproduce the exact reported exhibits and parameter values as those produced in the original publication.

Although, minor coding errors were identified. Beyond the requirement to download the package `reghdfe` provided by the authors in the replication packet, the online appendix replication requires downloading the `binscatter` package to reconstruct some figures. Further, the `master.do` file (e.g., the main replication script) is designed to create an absolute directory path for relative references called throughout the subsequent scripts in the replication packet. Yet each script re-asserts a separate, different absolute path. For replication purposes, I recommend the authors update the replication packet to establish the directory path *only* in the master dofile rather than in each script separately. Further there is a minor concern with the estimation. The manuscript describes 639 Indian districts in the sample. But the final data set used for estimation uses a district ID with only 585 unique labels. These are the spatial fixed effects underpinning the difference in differences design. This is different from the 622 unique district names in the final data set and the 639 districts reported in the manuscript. Re-estimating the results using the district names rather than the district ID does not qualitatively change the results, but it does shift the point estimates. This minor error raises concern that other small mistakes

³Dreber and Johannesson (2023) defines computational reproducibility as “The extent to which results in original studies can be reproduced using both the data and code from those studies.”

⁴The original paper can be found at: <https://doi.org/10.1038/s41562-022-01513-5>

⁵The replication packet for the original study can be found here: <https://www.openicpsr.org/openicpsr/project/165302/version/V1/view>

may exist in the data which *do* have implications on the results. A potential remedy for the authors to resolve this concern when re-uploading an updated replication packet is to assert known constants (i.e., such as the number of districts, month-year pairs, or final number of observations) in the cleaning process of building the final data set as suggested by McWay et al. (2021).

Nonetheless, this study is computationally reproducible from raw data (CRR) as described by the Guide for Advancing Computational Reproducibility in the Social Sciences (ACRe) established by the Berkeley Initiative for Transparency in the Social Sciences (BITSS) (Bogdanoski et al., 2020). Therefore, I assign the computational reproducibility of Ravindran and Shah (2023) as a Level 10⁶ within the BITSS 10 point scale. Table 1 provides an overview of the computational reproducibility of the manuscript as suggested by Rose et al. (2025). Since the study is CRR under the BITSS definition of computationally reproducible, the results of this study can be analyzed through a robustness reproduction.

3 Robustness Reproduction: Poisson Estimator

Noting the successful reproduction of the study’s findings, I examine the robustness reproducibility of the study. I test the sensitivity of the results by re-analyzing the the three outcomes of interest – domestic violence cases, cybercrime complaints, and rape or sexual assault cases – by modifying the estimator. Rather than using an ordinary least squares (OLS) estimator, I re-estimate the results using a Poisson estimator. This is motivated by the potential of lower-bound censoring of the dependent variable. The decision to conduct this robustness check was taken after reading the paper but prior to observing the replication packet. These sensitivity analyses were not pre-registered and are vulnerable to ad-hoc decision-making in the replication process.

The original authors estimate a variant of the difference in differences identification strategy. Their preferred specification in Equation 1 estimates the quasi-random government classifications of district lockdown zones over time using a dynamic fixed effects model with an OLS estimator.

$$Y_{dmy} = \alpha + \gamma_d + \lambda_{my} + \sum_{i=1}^8 \beta_{ir} \theta_i \times \text{RedZone}_d + \sum_{i=1}^8 \beta_{io} \theta_i \times \text{OrangeZone}_d + X_{dy} \delta + \varepsilon_{dmy} \quad (1)$$

Y represents the three VAW outcome measures: domestic violence, cybercrimes, and rape or sexual assault complaints aggregated to the district level for each month-year.

⁶“Level 10 (L10): All necessary materials are available and produce consistent results with those presented in the paper. The reproduction involves minimal effort and can be conducted starting from the analytic data (CRA) and the raw data (CRR).” (Bogdanoski et al., 2020)

The coefficients of interest are β for months i in districts classified as red zones or orange zones relative to outcomes in green zone districts. γ is a district d spatial fixed effect and λ is month by year my temporal fixed effect. X is a control for district-year population levels. ε are heteroskedastic-robust standard errors clustered at the district level.

The three outcome measures are count variables, e.g., they are the count of the number of complaints in each district for a given month. Examining the three outcome measures, I note that 47.41 percent of the monthly district observations report zero complaints. This is 3,285 green zone observations (62.12 percent of observations with green zone classifications), 3,152 orange zone observations (45.64 percent for orange zone classifications), and 942 red zone observations (27.96 percent of red zone classifications). This suggests that the count variable distribution likely suffers from lower bound censoring at zero. This is consistent with the authors' claim that their results likely suffer from an under-reporting of VAW in India.⁷ The proportion of censoring at zero is identical for all three outcome measures. While strange, exploring the data did not reveal any obvious errors in the data or cleaning process. Censoring is not correlated with a specific year, month, district, or zone classification over time nor their combination. Rather, I believe the source of the censoring derives from the district-level reporting of complaints. This extensive margin change may be moderated by self-censoring by the women willing to report complaints or censored by government officials reporting complaints for official record.

Censoring is a statistical concern as it will attenuate results. I account for this by re-estimating the results using a Poisson estimator. This estimator uses a Poisson distribution rather than a normal distribution to describe the population distribution of the outcome measure. The Poisson distribution appropriately approximates the distribution of a count variable such as number of reported complaints. I estimate Equation 1 as a Poisson fixed effects estimation using the Stata command `xtpoisson` using Equation 7.

To estimate a treatment effect using a Poisson distribution, I use a non-linear maximum likelihood estimator (MLE) opposed to the linear OLS. I parameterize the input vector x with parameters β to recover the mean of the distribution.

$$\lambda := \mathbb{E}[Y|x] = e^{\beta'x} \quad (2)$$

With a probability mass function of $p(y|x; \beta)$.

$$p(y|x; \beta) = \frac{\lambda^y}{y!} e^{-\lambda} = \frac{e^{y\beta'x} e^{-e^{\beta'x}}}{y!} \quad (3)$$

I can generalize this for m vectors of x (e.g., the month by zone treatment arms) along

⁷“Underreporting of VAW is almost always a potential concern (see, for example, ref. 30). We acknowledge that there may have been potential changes in reporting during the lockdowns. In fact, Poblete-Cazenave, R. (unpublished manuscript) finds evidence of a 60% reduction in reported crimes to the police as a result of the lockdowns in Bihar, India.” (Ravindran and Shah, 2023)

a set of m values for the outcome measures of VAW (Y). This posits a linear relationship between treatment status and VAW (e.g., $Y_i|X_i \sim \text{Poisson}(\exp(X_i'\beta))$).

$$p(y_1, \dots, y_m | x_1, \dots, x_m; \beta) = \prod_{i=1}^m \frac{e^{y_i \beta' x_i} e^{-e^{\beta' x_i}}}{y_i!} \quad (4)$$

The maximum likelihood to determine the set of β parameters with the largest possible probability can be written as the following likelihood function.

$$L(\beta | X, Y) = \prod_{i=1}^m \frac{e^{y_i \beta' x_i} e^{-e^{\beta' x_i}}}{y_i!} \quad (5)$$

This can be linearized through the following log-likelihood function noting that $y!$ can be dropped as a constant in the distribution.

$$l(\beta | X, Y) = \log(L(\beta | X, Y)) = \sum_{i=1}^m \left(y_i \beta' x_i - e^{\beta' x_i} \right) \quad (6)$$

I translate Equation 1 from the OLS fixed effects estimator into a MLE Poisson fixed effects estimator as the following estimation equation. Equation 7 can be estimated using the quasi-conditional maximum likelihood estimator (QCMLE) proposed by Woolridge (1999).

$$l(\beta | X, Y_{dmy}) = \sum_{j=1}^m \left(Y_{j dmy} \sum_{i=1}^8 \beta_{jir} \theta_i \times \text{RedZone}_d + Y_{j dmy} \sum_{i=1}^8 \beta_{jio} \theta_i \times \text{OrangeZone}_d - e^{\sum_{i=1}^8 \beta_{jir} \theta_i \times \text{RedZone}_d} - e^{\sum_{i=1}^8 \beta_{jio} \theta_i \times \text{OrangeZone}_d} - e^{X_{jdy} \delta \times \gamma_d \times \lambda_{my} \times \varepsilon_{dmy}} \right) \quad (7)$$

I estimate Equation 7 to replicate the main reported findings from Table 1 and Figure 3 of Ravindran and Shah (2023). The first three columns of Table 2 presented the reproduced results using the OLS estimation and the final three columns report replication results using the Poisson estimator. Using the main specification in Panel A, the Poisson estimators for domestic violence in Column 4 are comparable to the effect sizes in Column 1 for red zone effects. But the orange zone effects are considerably larger. Exemplary of this change, orange zone effects in May 2020 increases from 0.0941 to 0.402. The increase in the magnitude size is consistent for both cybercrimes and rape or sexual assault complaints presented in Columns 5 and 6 compared to Columns 2 and 3, respectively. This suggests that censoring does have attenuation bias particularly for districts in orange zones (e.g., the medium level of lockdown status). This highlights that the ‘shadow pandemic’ of VAW was more pronounced following lockdown measures than originally reported by Ravindran and Shah (2023). This finding is robust to the flexible form specification in Panel B. Because the magnitude of the effects for districts with orange

zone status increased more than those with red zone status, the statistical significance difference between the two estimates in April and May vanish with the Poisson estimator. Instead, it appears that the negative effect of mobility restricts had similar effects in all Indian districts that imposed some degree of lockdown measures.

In Figure 1, I reproduce the three sub-plots of Figure 3 of Ravindran and Shah (2023) on the left-hand panel using the OLS estimation method and replicate these results using the Poisson estimator for the three sub-plots on the right-hand panel. The Poisson event studies mirror the original results for the pre-lockdown pre-trend periods adding confidence that parallel trends holds with the new estimator. While the measured effects in the lockdown period of the plots highlight both the large magnitude shift in the effect size, as well as that red and orange zones have indistinguishable effects on VAW.

4 Conclusion

In this replication, I computationally reproduce and replicate the results of Ravindran and Shah (2023). I test the robustness reproducibility of COVID-19 lockdown restrictions in India on violence against women (VAW) by estimating a Poisson fixed effects model. My results show that VAW are more pronounced than originally reported due to censoring of the reporting VAW complaints in the data. This validates the internal validity of the study while underscoring the magnitude of the ‘shadow pandemic’ that occurred towards women in India. This replication contributes to the Mertonian Norms (Merten, 1942) for the application of the open science movement in the development economics literature to validate findings for use by policy-makers to remedy this unintended consequence. My replication also builds towards the larger body of evidence replicating economic science (Brodeur et al., 2024, 2025; Mikola et al., 2025; Rose et al., 2025).

References

- Bogdanoski, A., C. Christiano, J. Ferguson, F. H. Guardia, K. Hoeberling, E. Miguel, E. Ng, and L. Vilhuber (2020). Guide for Advancing Computational Reproducibility in the Social Sciences. Berkeley Initiative for Transparency in the Social Sciences.
- Brodeur, A., D. Mikola, N. Cook, R. McWay, and et al. (2024). Mass Reproducibility and Replicability: A New Hope. *IZA Discussion Paper* (16912).
- Brodeur, A., D. Valenta, A. Marocci, R. McWay, and et al. (2025). Comparing Human-Only, AI-Assisted, and AI-Led Teams on Assessing Research Reproducibility in Quantitative Social Science. *IZA Discussion Paper* (17645).
- Change, A. C. and P. Li (2015). Is Economics Research Replicable? Sixty Published Papers from Thirteen Journals Say “Usually Not”. *Board of Governors of the Federal Reserve System (US)* (2015-83).
- Cong, X., N. A. Kouchekinia, and R. McWay (2024). Spatial Polarisation. A Replication Study of Cerina et al. (The Economic Journal, 2023). *I4R Discussion Paper Series*.
- Dreber, A. and M. Johannesson (2019). Statistical Significance and the Replication Crisis in the Social Sciences. *Oxford Research Encyclopedia of Economics and Finance*.
- Dreber, A. and M. Johannesson (2023). A Framework for Evaluating Reproducibility and Replicability in Economics. *SSRN* (4458153).
- King, G. (1995). Replication, Replication. *PS: Political Science Politics* 28(3), 444–452.
- Kurtz, E. and R. McWay (2025). The Null Result Penalty. A Replication Study of Chopra et al. (The Economic Journal, 2023). *Working Paper*.
- Maniadis, Z., F. Tufano, and J. A. List (2017). To Repliate or not to Replicate? Exploring Reproducibility in Economics Through the Lens of a Model and a Pilot Study. *The Economic Journal* 127(605).
- McWay, R. (2024). Outsourcing Education: Experimental Evidence from Liberia. A Replication Study of Romero, Sandefur, and Sandholtz (American Economic Review, 2020). *I4R Discussion Paper Series*.
- McWay, R., J. Allen, and H. Yu (2021). Setting up a Dofile for Team Research. *SSRN* (3965114).
- McWay, R. and M. Braaksma (2025). The Political Consequences of Resource Scarcity: Targeted Spending in a Water-stressed Democracy. A Replication Study of Mahadevan and Shenoy (Journal of Public Economics, 2023). *Working Paper*.
- McWay, R., K. Nchare, and P. Sun (2024). Market Access and Quality Upgrading: Evidence from Four Field Experiments. A Replication Study of Bold et al. (American Economic Review, 2022). *Journal of Comments and Replications in Economics* 3(2024-2).
- Merten, R. K. (1942). *The Normative Structure of Science*. University of Chicago Press.
- Mikola, D., A. Brodeur, J. P. Aparicio, R. McWay, and et al. (2025). Predicting Repro-

- ducibility and Robustness. *IZA Discussion Paper*.
- Moonesinghe, R., M. J. Khoury, and A. C. J. W. Janseens (2007). Most Published Research Findings are False – But a Little Replication Goes a Long Way. *PLoS Medicine* 4(2).
- Peterson, D. and A. Panofsky (2021). Self-Correction in Science: The Diagnostic and Integrative Motives for Replication. *Social Studies of Science* 51(4), 583–605.
- Ravindran, S. and M. Shah (2023). Unintended Consequences of Lockdowns, COVID-19 and the Shadow Pandemic in India. *Nature Human Behavior* 7, 323–331.
- Rose, J., F. Neubauer, J. Ankel-Peters, A. Dreber, M. Johannesson, A. Toner-Rodgers, C. Cornejo-Roman, C. H. de la Cruz, C. Fabri, C. S. Hauser, C. Kronenberg, J. Goldberg, J. Pinillos, M. Brun, M. Beeder, R. Scarfe, R. McWay, and V. Rayamajhee (2025). Robustness Reproducibility in Economics (R2E). *Ruhr Economic Papers*.
- Sterling, T. D. (1959). Publication Decision and the Possible Effects on Inferences Drawn from Tests of Significance or Vice Versa. *Journal of The American Statistical Association* 54, 30–34.
- Woolridge, J. M. (1999). Distribution-free Estimation of Some Nonlinear Panel Data Models. *Journal of Econometrics* 90(1), 77–97.

5 Exhibits

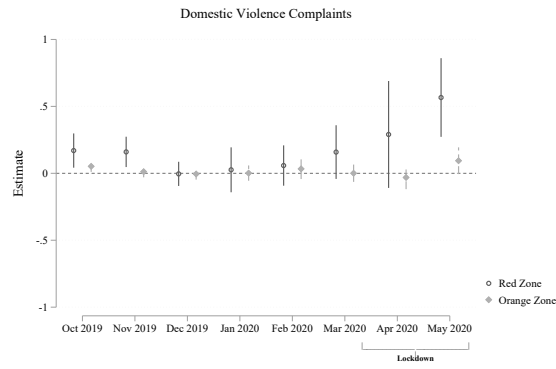
Table 1: Computational Reproducibility

	Fully	Partially	No
Raw data provided	x		
Cleaning code provided	x		
Analysis data provided	x		
Analysis code provided	x		
Reproducible from raw data	x		
Reproducible from analysis data	x		

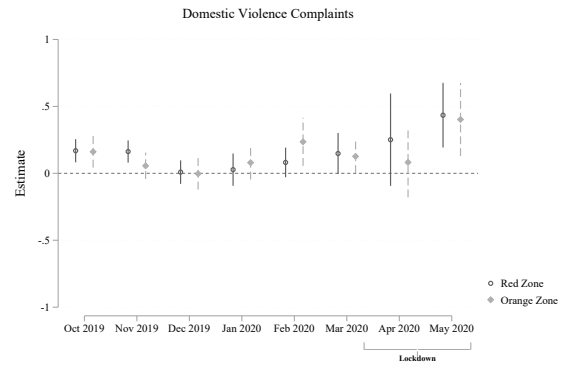
Table 2: Reproduction of Table 1 with OLS and Poisson Estimators

Panel A: Main Specification						
	Original OLS Estimator			Original Poisson Estimator		
	(1) Domestic Violence	(2) Cybercrime	(3) Rape and sexual assault	(4) Domestic Violence	(5) Cybercrime	(6) Rape and sexual assault
Red zone × May 2020	0.566*** (0.150) [0.0002]	0.130*** (0.0273) [0.0000]	-0.304*** (0.100) [0.0025]	0.434*** (0.123) [0.0004]	0.577*** (0.118) [0.0000]	-0.847*** (0.122) [0.0000]
Red zone × Apr 2020	0.290 (0.203) [0.1540]	0.0648* (0.0347) [0.0624]	-0.455*** (0.114) [0.0001]	0.251 (0.176) [0.1540]	0.332* (0.171) [0.0522]	-2.044*** (0.174) [0.0000]
Orange zone × May 2020	0.0941* (0.0508) [0.0644]	0.0231** (0.00905) [0.0108]	-0.0647** (0.0287) [0.0245]	0.402*** (0.139) [0.0039]	0.547*** (0.124) [0.0000]	-0.908*** (0.0960) [0.0000]
Orange zone × Apr 2020	-0.0309 (0.0445) [0.4880]	-0.00200 (0.00727) [0.7830]	-0.0977*** (0.0336) [0.0038]	0.0822 (0.133) [0.5370]	0.165 (0.121) [0.1710]	-2.242*** (0.106) [0.0000]
Adjusted R^2	0.769	0.793	0.728			
Red zone – orange zone (May 2020)	0.472	0.107	-0.239	0.0321	0.0301	0.0614
P value	0.00138	0.0000964	0.0253	0.867	0.865	0.699
Red zone – orange zone (April 2020)	0.321	0.0668	-0.358	0.169	0.167	0.198
P value	0.114	0.0575	0.00329	0.441	0.429	0.351
District FEs	✓	✓	✓	✓	✓	✓
Month-Year FEs	✓	✓	✓	✓	✓	✓
Dependent Variable Mean	.42	.07	.26	.42	.07	.26
Observations	15563	15563	15563	15518	15518	15518
Panel B: Flexible Form Specification						
Red zone × May 2020	0.615*** (0.166) [0.0002]	0.130*** (0.0305) [0.0000]	-0.460*** (0.161) [0.0045]	0.603*** (0.153) [0.0001]	0.611*** (0.156) [0.0001]	-1.268*** (0.155) [0.0000]
Red zone × Apr 2020	0.339 (0.212) [0.1110]	0.0649* (0.0376) [0.0849]	-0.611*** (0.174) [0.0005]	0.420** (0.199) [0.0352]	0.366* (0.201) [0.0686]	-2.464*** (0.203) [0.0000]
Orange zone × May 2020	0.108* (0.0576) [0.0621]	0.0235** (0.0103) [0.0233]	-0.0931** (0.0472) [0.0490]	0.531*** (0.124) [0.0000]	0.540*** (0.126) [0.0000]	-1.353*** (0.124) [0.0000]
Orange zone × Apr 2020	-0.0174 (0.0473) [0.7130]	-0.00168 (0.00817) [0.8380]	-0.126** (0.0514) [0.0145]	0.211* (0.126) [0.0935]	0.158 (0.128) [0.2170]	-2.687*** (0.126) [0.0000]
Adjusted R^2	0.774	0.797	0.738			
Red zone – orange zone (May 2020)	0.508	0.107	-0.367	0.0714	0.0711	0.0856
P value	0.00183	0.000468	0.0304	0.730	0.729	0.659
Red zone – orange zone (April 2020)	0.357	0.0666	-0.485	0.208	0.208	0.222
P value	0.0939	0.0812	0.00806	0.386	0.385	0.346
District FEs	✓	✓	✓	✓	✓	✓
Month-Year FEs	✓	✓	✓	✓	✓	✓
Dependent Variable Mean	.42	.07	.26	.42	.07	.26
Observations	15563	15563	15563	15518	15518	15518

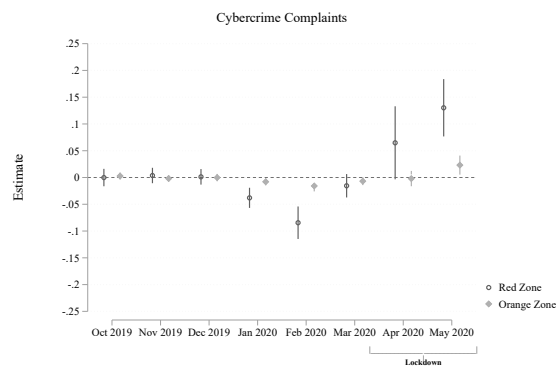
Notes: This table reproduces Table 1 from Ravindran and Shah (2023). The first three columns reproduce the OLS results. While the final three columns reanalyze the results using a Poisson estimator. Standard errors are heteroskedastic robust HC1 clustered at the district level reported in parentheses. p-values are reported in brackets and statistical significance is displayed as * < 0.1, ** < 0.05, *** < 0.01.



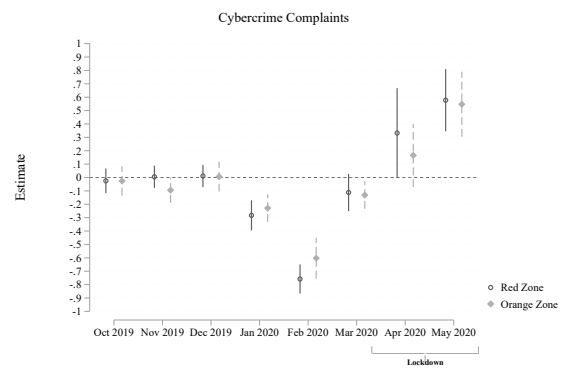
(a) Domestic violence complaints
OLS



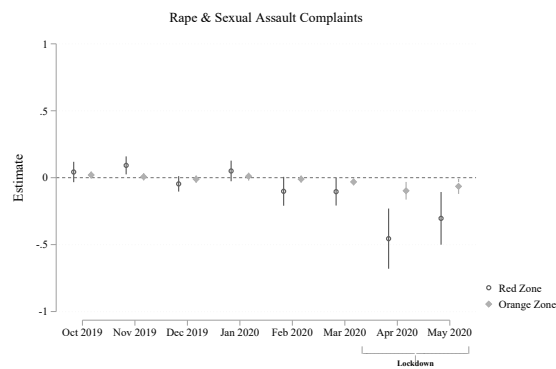
(b) Domestic violence complaints
Poisson



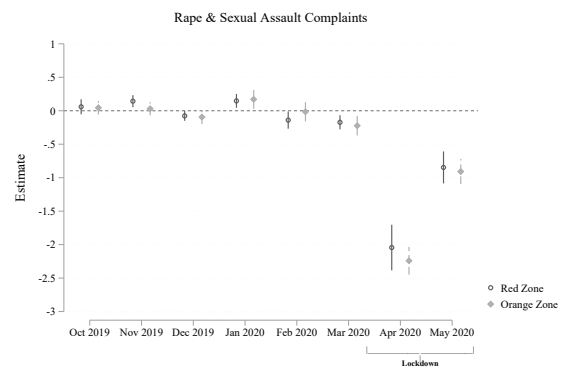
(c) Cybercrime complaints
OLS



(d) Cybercrime complaints
Poisson



(e) Rape and sexual assault complaints
OLS



(f) Rape and sexual assault complaints
Poisson

Figure 1: Reproduction of Figure 3 with OLS and Poisson Estimators

Notes: This is a recreation of Figure 3 from Ravindran and Shah (2023). The left three panels are reproductions of the OLS estimates from the original authors. The right three panels are re-analyses using a Poisson estimator. The diamonds represent orange zone district effects for each month, and circles represent red zone district effects for each month. The tails display 95% confidence intervals