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Is Remote Sensing Data Useful for Studying the Association between Pandemic-Related Changes in Economic Activity and Intimate Partner Violence?†

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The COVID-19 pandemic and the social restrictions put in place to address it have created a global concern about the resulting economic and social consequences. The increase in intimate partner violence (IPV) has been at the core of the discussion, and a growing body of literature seeks to establish a causal association between pandemic-driven employment and income losses, and IPV incidence.

To investigate economic downturns, researchers increasingly have access to high-frequency measures of economic activity collected across the globe from remote sensing technology. In a burgeoning literature, measures such as the density of night lights and air pollution have been validated as robust proxies of economic activity (Donaldson and Storeygard 2016; Henderson, Storeygard, and Weil 2012). The availability of these indicators create an opportunity for countries without regular or nationally representative income surveys to evaluate the impacts of COVID-19-induced recessions on outcomes such as IPV.

In this paper, we first investigate the usefulness of two of such measures in capturing changes in economic circumstances brought on by the COVID-19 pandemic in the country of Peru. Our analysis indicates that, when merged with labor force and consumption survey data, both measures successfully capture rich spatial and time variation in economic activity over the pandemic period.

Second, we study the extent to which the variation in income captured by remote sensing data exhibits the same association with behavioral outcomes—in this case, IPV—as income shocks measured with standard labor force and consumption data. Here we conclude that the income variation captured by remote sensing measures exhibits a weaker association with behavioral outcomes such as IPV, even compared with district-level labor market measures.

Specifically, we explore the use of remote sensing data alongside survey measures in explaining economic activity in Peru, where we have collected panel data on household income, labor force participation, and IPV from before and during the pandemic from a geographically disperse sample of households. In the analysis, we consider four proxies for economic activity. The first two are measures of the density of nitrogen dioxide (NO_2) and night lights, which have been used at the macro level and more recently to predict changes in economic activity due to the pandemic (Roberts 2021; Masaki, Nakamura, and Newhouse 2020). Our third measure is constructed from nationally representative surveys combined with population census data to measure district-level employment losses. The fourth proxy is individual-specific employment losses as predicted by the household's occupation.

All four measures predict income losses, with the latter two proxies having the highest elasticities. However, when considering their correlation with IPV, only the individual-specific indicator has predictive power. All of the other three measures fail to capture the changes in IPV between 2019 and the first semester of 2020.

We speculate that this is due to the aggregated nature of the remote sensing data. While these

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measures may be useful in detecting short-term changes in economic activity at subnational levels, they are too coarse to offer meaningful variation across households within the same location. As a result, they fail to explain more behavioral responses like IPV.

Below, we explain the data and methods used in our analysis and then discuss the policy implications of our findings.

I. Data

The main dataset is a socioeconomic phone survey we conducted between September and November 2020 by randomly dialing cell phone numbers in Peru, as explained in Agüero et al. (2022). The survey was retrospective for three time periods: all of 2019, April–May 2020, and July–August 2020. The sample consists of women between the ages of 18 and 49 who self-reported being in a domestic partnership in April 2020. We measure IPV by reproducing the set of six questions used in the Peruvian Demographic and Health Survey (ENDES). These questions ask about physical, sexual, and psychological violence. For each question, we recorded each event's frequency. Our surveys also asked for the employment sector of the top earner in 2019 as well as household income by adding up the income of each spouse for each reference period.

Night light data are from the Earth Observation Group (Elvidge et al. 2017), while the NO_2 data comes from OMI/Aura NO2 NASA project (Lamsal et al. 2020). We overlay these satellite measures on a shapefile with Peru's districts (the smallest administrative unit in Peru). We then take the area's average night light and NO_2 measures over the relevant periods for our phone survey: 2019, the second quarter of 2020, and the third quarter of 2020.[1]

For night lights, we calculate each district's average luminosity by averaging across all pixels within the district over the relevant time period. We label the variable Z_{it}^{NL} using individual i's district. Similarly, we calculate each district's average level of NO_2. We denote these values as $Z_{it}^{NO_2}$.[2]

We also use Peru's household survey (ENAHO) combined with the country's 2017 Population Census to construct a shift-share variable. The census has information on district level industrial composition, which we combine with employment information by economic sector from the ENAHO. We create a standard shift-share variable using the formula $Z_{it}^{shift\text{-}share} = \sum_n L_{d(i)n}^{2017}/L_{d(i)}^{2017} L_{nt}$, where $d(i)$ refers to i's district, $L_{d(i)n}^{2017}$ denotes total employment in industry n in district $d(i)$ in the 2017 census, and $L_{d(i)}^{2017}$ denotes total employment in district $d(i)$ in 2017. L_{nt} is national employment in industry n at time t, either 2019, the second quarter of 2020 or the third quarter of 2020, calculated using ENAHO.

Finally, we construct $Z_{it}^{sector} = L_{s(i)t}$, where $s(i)$ denotes the baseline economic sector for household's i's top earner, and $L_{s(i)t}$ is the total employment count in sector $s(i)$ at time t given by ENAHO. For this measure, $t = 0$ refers to the 2019 average employment count, while $t = 1$ refers to the second quarter of 2020.

II. Empirical Strategy

We first compute the percentage change in each of the four measurements between 2019 and 2020:II as $g_i^k = \frac{Z_{i,1}^k - Z_{i,0}^k}{Z_{i,0}^k} \times 100$ for $k \in (NO_2, \text{NL, shift-share, sector})$. We then use an empirical specification, which focuses on the measured change between 2019 and the second quarter of 2020, and compute a difference-in-differences specification

$$(1) \quad Y_{it} = \phi_t + \alpha_i + \sum_{j=1,2} \delta_j g_i^k \times 1[t = j] + u_{it},$$

where α_i and ϕ_t are individual and time fixed effects. The coefficients δ_j estimate the average effect of a percentage point increase in the underlying measure Z_{it}^k relative to 2019. We focus on this specification since our goal is to validate economic measures that capture

[1] Since the surveys used later on are representative for each quarter, we use the second and third quarter of 2020 for consistency and to approximate the periods collected in our survey, April–May and July–August.

[2] We remove 16 districts from the analysis where NO_2 levels are too low to detect correctly. These are districts with negative NO_2 values which the satellite-image processing algorithms allow for.

Table 1—Effects of Pandemic Shocks on Income and IPV

	(1)	(2)	(3)	(4)
Panel A. Effects on household income				
Mean (2019) = 1,493.5				
April–May (2020) g_d^{NO2}	1.839			
	(0.790)			
July–August (2020) $\times$ g_d^{NO2}	1.050			
	(0.816)			
April–May (2020) $\times$ g_d^{NL}		3.112		
		(1.329)		
July–August (2020) $\times$ g_d^{NL}		2.126		
		(1.092)		
April–May (2020) $\times$ $g_i^{shift\text{-}share}$			6.764	
			(1.360)	
July–August (2020) $\times$ $g_i^{shift\text{-}share}$			4.290	
			(1.222)	
April–May (2020) $\times$ g_i^{sector}				6.648
				(1.023)
July–August (2020) $\times$ g_i^{sector}				4.018
				(0.856)
g_d^k Mean	−20.87	16.04	−38.72	−48.73
g_d^k SD	36.31	24.12	19.49	25.78
Observations	3,150	3,150	3,150	3,150
Panel B. Effects on intimate partner violence				
Mean (2019) = 3.037				
April-May (2020) $\times$ $g_d^{NO_2}$	−0.00134			
	(0.00230)			
July-August (2020) $\times$ $g_d^{NO_2}$	0.000784			
	(0.00261)			
April-May (2020) $\times$ g_d^{NL}		−0.00403		
		(0.00331)		
July-August (2020) $\times$ g_d^{NL}		0.000293		
		(0.00484)		
April-May (2020) $\times$ $g_i^{shift\text{-}share}$			−0.00541	
			(0.00361)	
July-August (2020) $\times$ $g_i^{shift\text{-}share}$			−0.00850	
			(0.00530)	
April-May (2020) $\times$ g_i^{sector}				−0.00103
				(0.00239)
July-August (2020) $\times$ g_i^{sector}				−0.00795
				(0.00402)
g_d^k Mean	−17.11	19.06	−36.90	−47.26
g_d^k SD	34.57	26.16	20.48	27.86
Observations	1,059	1,059	1,059	1,059

Notes: Standard errors are clustered at the district level. Sample excludes all districts that ever had a negative NO_2 measurement in our final panel. Panel A reports OLS effects for income in nuevo soles and has 289 districts. Panel B reports Poisson effects on the count of any IPV and has 179 districts. The sample size is smaller in panel B due to separation during the Poisson estimation.

pandemic-related contractions. Finally, we cluster all standard errors by district. We have 289 districts in the sample.

III. Results

Results are presented in Table 1. Panel A reports effects on household income (in Peruvian nuevos soles).

All four measures of economic activity correctly predict the income changes observed in our household survey. For instance, for April–May 2020, a 10 p.p. decrease (increase) in ${g_d}^{NO_2}$ emissions results in a reduction (increase) in income equivalent to 18 nuevos soles (column 1). Similarly, a 10 p.p. drop in economic activity measured by night lights (column 2), local labor markets proxied by the shift-share shock (column 3), and employment in the household sector of operation (column 4) lead to income losses of 31, 68, and 66 nuevos soles, respectively. Interestingly, the implied elasticity is much higher for the shift-share and employment shocks, which suggests that variation in remote sensing data pick up dimensions of economic activity beyond labor markets and household income. We come back to this feature below.

In panel B, we focus on IPV using a Poisson model for the estimation given that the measure is based on the sum of violent acts. Both remote sensing measures and the shift-share variable fail to predict changes in IPV (see columns 1–3), while the employment change in the household's sector is a good predictor of IPV (column 4). A 10 p.p. drop in employment in the households' sector results in a statistically significant 8 percent increase in IPV during July–August of 2020. As explained in Agüero et al. (2022), one reason why employment shocks do not predict IPV in the early months of the pandemic might be that households used savings to buffer against negative employment shocks. Note that the shift-share variable has an equally large point estimate, but it is imprecisely estimated (column 3). In contrast, both night lights and NO_2 result in small and insignificant coefficients. Had we relied on columns 1–3, we may have concluded that IPV did not respond to reduced economic activity, which is contradicted by using more individualized data in column 4 and by prior work (Agüero 2021).

IV. Conclusion

Using our unique dataset from Peru, we evaluate the role of four measures of high-frequency proxies for economic activity in predicting changes in income and IPV created by the onset of the COVID-19 pandemic vis-à-vis individual-specific data.

All four measures correctly predict income losses. This expands prior work showing that widely available measures from satellites help identify changes not only at the macro level, but also at the household level and during the pandemic. The shift-share requires more data, however it can be computed from government surveys and census results.

Overall, we find that widely available data such as satellite measurements or shift-share variables are useful for studying income changes in our survey. However, these measures are not predictive for studying IPV. Only the micro-informed sectoral employment changes have predictive power for IPV. This study is a cautionary tale, showing that while remote sensing data may be useful for studying changes in income, they may be inadequate for studying more behavioral responses like IPV.

REFERENCES

Agüero, Jorge M. 2021. "COVID-19 and the Rise of Intimate Partner Violence." *World Development* 137: 105217.

Agüero, Jorge M., Erica Field, Ignacio Rodriguez Hurtado, and Javier Romero. 2022. "COVID-19, Job Loss, and Intimate Partner Violence in Peru." Unpublished.

Donaldson, Dave, and Adam Storeygard. 2016. "The View from Above: Applications of Satellite Data in Economics." *Journal of Economic Perspectives* 30 (4): 171–98.

Elvidge, Christopher D., Kimberly Baugh, Mikhail Zhizhin, Feng Chi Hsu, and Tilottama Ghosh. 2017. "VIIRS Night-Time Lights." *International Journal of Remote Sensing* 38 (21): 5860–79.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review* 102 (2): 994–1028.

Lamsal, Lok N., Nickolay A. Krotkov, Sergey V. Marchenko, Joanna Joiner, Luke Oman,

Alexander Vasilkov, Bradford Fisher, Wenhan Qin, Eun-Su Yang, Zachary Fasnacht, Sungyeon Choi, Peter Leonard, and David Haffner. 2020. "OMI/Aura NO2 Tropospheric, Stratospheric & Total Columns MINDS Daily L3 Global Gridded 0.25 degree x 0.25 degree." https://disc.gsfc.nasa.gov/datasets/OMI_MINDS_NO2d_1/summary (accessed on January 10, 2021).

Masaki, Takaaki, Shohei Nakamura, and David Newhouse. 2020. "How Is the COVID-19 Crisis Affecting Nitrogen Dioxide Emissions in Sub-Saharan Africa?" *Poverty and Equity Notes* 21. Washington, DC: World Bank Publications.

Roberts, Mark. 2021. "Tracking Economic Activity in Response to the COVID-19 Crisis Using Nighttime Lights: The Case of Morocco." The World Bank Policy Research Working Paper Series 9538.