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COVID-19, Job Loss, and Intimate Partner Violence in Peru*

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Abstract

We collect retrospective panel survey data on household socioeconomic status and domestic conflict from a large nationwide sample in Peru and find a sizable and sustained increase in intimate partner violence (IPV) during the COVID-19 pandemic. The incidence of physical IPV increased by an estimated 56% from 2019 to April/May 2020, and the increase was sustained until July/August 2020, the latest data point collected in our survey. Households most likely to lose a job experienced the largest increases in IPV over the period, measured by variation in the level of job loss across occupations. These patterns suggest that part of the increase in IPV was a causal effect of income shocks created by the COVID-19 pandemic.

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1 Introduction

Worldwide, the COVID-19 pandemic has generated great concern over its economic and social effects. An increase in intimate partner violence (IPV) is one of the most critical worries. Early in the pandemic, global stakeholders raised alarm bells by predicting an additional 31 million cases of gender-based violence worldwide (Fund, 2020). A growing number of papers has documented increases in IPV in both developed and developing countries over the past year (Bourgault et al., 2021).

However, two important issues remain in firmly establishing a causal association between the pandemic and the incidence of IPV. First, the bulk of recent empirical work has studied trends in the frequency of helpline calls or police reports to evaluate pandemic-driven changes in IPV (e.g., Leslie and Wilson, 2020; Bullinger et al., 2020; Perez-Vincent et al., 2020; Agüero, 2021). Yet, as the lockdown restricts access to in-person services, including social support networks, it is unclear the extent to which increases in IPV-related emergency calls reflect a substitution away from traditional sources of victim support.

Second, to the extent that the larger volume of calls is indeed reflective of new incidents of violence, little is still understood about the particular *mechanisms* through which the pandemic has exacerbated domestic violence, and, specifically, what role have pandemic-related economic shocks played in increasing IPV versus more generalized social unrest or disease-related anxiety. This distinction is important because it influences both policy prescriptions and projections of future trends in IPV as the pandemic continues to evolve in much of the world. Given that the social and epidemiological dynamics frequently depart from the specific patterns of economic reverberations of a global disease shock, predicting who will be most at risk of IPV going forward and extrapolating to other settings requires disentangling the specific mechanisms at play.

The goal of this paper is to address these two issues. We focus on the case of Peru, a country that has been hit particularly hard by COVID-19 in the worst-hit region of the world, despite a rapid and strict policy response by the government. In mid-March 2020, the Peruvian government imposed a broad and early lockdown throughout the country to stop the spread of the virus, and in April they issued an extension of the confinement. Despite these efforts, by 2021 Peru was only behind Brazil in the number of cases and deaths from coronavirus in Latin America. As of September 2021, Peru confirmed 2.17 million cases and nearly 200,000 deaths related to coronavirus. In addition, the economy experienced an 11% decline in GDP and unemployment more than doubled in 2020 compared to 2019. Moreover, both the incidence of new cases and deaths from Covid-19 continue to rise.

The potential consequences of these economic and disease shocks on IPV are particularly concerning in Peru, a country that was already suffering from high and growing rates of gender-based violence pre-pandemic. *Demographic and Health Survey* (DHS) data from 2017 indicate that more than one-third of Peruvian women have experienced physical or sexual violence from an intimate partner during their lifetime.[1] Between 2018 and 2019, the rate of feminicides in Peru increased by 10 percent. While the reason for the increase is still debated, the upward trends suggest that gender-based violence tolerance might have been unresponsive to substantial policy effort to tackle the issue and social protests and media coverage to draw attention to the crisis (Organization, 2019). Indeed, data from the national victims helpline *Línea 100*, reveal that calls have nearly doubled since March 2020, indicating that the pandemic has been yet another factor exacerbating violence against women in Peru (Agüero, 2021). However, given that the country closed all in-person domestic violence services the moment the lockdown started, including hundreds of government shelters for abused women, it is unclear how much of the increase reflects a surge in pandemic-related cases versus substitution across reporting platforms.

To address these questions, we partnered with the Peruvian Ministry of Women and Vulnerable Populations (MIMP) to conduct a phone-based survey of a large sample of 1077 urban women located in cities across the country. Along with demographic data on the household, the survey collected data on the incidence of physical and psychological IPV, as well as changes in economic circumstances, including income and employment, at three points in time pre- and during the pandemic.

We first study time trends in survey reports of IPV over the pandemic period to assess whether they align with the patterns in administrative reports from hotline calls. Second, in order to firmly attribute time trends to a causal impact of the pandemic on domestic violence, our analysis makes use of industry variation in the degree of economic contraction experienced as a result of the pandemic.

We find a large increase in the rate of IPV during the pandemic, on the order of 53% relative to 2019. Moreover, households most at risk of employment shocks experience significantly larger increases in IPV compared to pre-pandemic levels. A 10 percentage point increase in job loss in the household head's primary economic sector, which corresponds to a 4.5% decrease in income and 0.165 fewer days outside home per week, is associated with a

[1] Proportion of ever-partnered women aged 15-49 years experiencing intimate partner physical or sexual violence at least once in their lifetime. Encuesta Demográfica y de Salud (ENDES), 2017, Instituto Nacional de Estadística e Informática.

14.2% increase in physical and sexual IPV and a 4.9% increase in psychological IPV in July-August of 2020. These effects are sizeable considering that the job loss rate in the primary economic sector for the median household was 58%. However, we find no link between IPV and local cases of COVID-19 or with local economic conditions. All together, these patterns imply that economic stress rather than disease anxiety explains the recent surge in domestic violence in our setting, and that the effect of economic stress as a result of job losses goes beyond local economic unrest, despite the fact that both local economic unrest and disease anxiety had been felt throughout the country over this period.

Our results are related to prior work exploring the role of income on IPV, specially to work on cash transfers in developing countries prior to the pandemic (e.g., Hidrobo and Fernald, 2013; Hidrobo et al., 2016; Haushofer and Shapiro, 2016; Heath et al., 2020). Consistent with these studies, we show that a critical mechanism for the increase in violence during the pandemic is through the income shocks affecting households. In that regard, our paper is also related to work trying to identify the role of the U.S. CARES Act and similar policies applied in other countries (Leslie and Wilson, 2020; Chetty et al., 2020; Erten et al., 2021). Our findings suggest that such transfers, by reducing the economic hardship of families, have the potential to minimize the impact of economic contraction on violence against women.

2 Peru's lockdown measures

Peru adopted one of the earliest and most severe lockdowns in Latin America. The first case of COVID-19 was confirmed on March 6th of 2020. Ten days later, on March 16th, the government enacted a nation-wide lockdown through a National State of Emergency (Decreto Supremo 044-2020-PCM). The first COVID-19 death was confirmed on March 19th, after the lockdown had been enacted. The National State of Emergency suspended several constitutional rights, including freedom of movement and transit, as well as the right to gather.

The severe lockdown lasted for over three months, with a localized lockdown approach starting on June 26th of 2020. As in most countries, the State of Emergency was enacted at first for 15 days, but the Peruvian government extended it many times to lower the risk of infection of the disease. The economic reactivation plan, which allowed people working in specific sectors to commute and work outside their homes, was organized in four phases and started in May of 2020. For instance, restaurants were only allowed to start offering food delivery services in May of 2020. The fourth and final phase started in October of 2020.

Overall lockdown policies were most severe during March, and were progressively loosened until October 2020. This helps contextualize our results. We asked our respondents about their experiences during April-May 2020, and July-August-2020, in order to understand the dynamic effects of the COVID-19 pandemic as restrictions were gradually lifted.

3 Data

We combine three datasets for the analysis. The main dataset is a socioeconomic phone survey we conducted between September and November 2020 by randomly dialling cellphone numbers in Peru. Women reached by phone were included in the sample if they were between the ages of 18 and 49 and self-reported to be in a domestic partnership in April 2020. We complemented these random dialling respondents with another sample of urban women that were surveyed in 2019 as part of a baseline for an impact evaluation of an intervention of the Peruvian Ministry of Women that was put on hold due to the pandemic. The final sample size is 1077 respondents, 794 from the random dialling and 283 from the panel sample.[2] Panel data from these latter respondents allow us to assess the quality of retrospective data on IPV, income and employment collected from the cross-section sample.

The survey was retrospective and focused on three recall time periods for information on IPV. First, we asked about prevalence of violence in 2019, prior to the pandemic. We then asked about IPV at two distinct points during the pandemic: April-May 2020 and July-August 2020. April and May were the months at the very start of the pandemic, in which the strictest lockdown measures were enacted throughout the country, while by July and August the lockdown was much less strict and varied greatly across municipalities.[3]

To inquire about domestic violence, we reproduced the set of questions on IPV used in the Peruvian Demographic and Health Survey (ENDES), which asks respondents to report on multiple dimensions of domestic violence. We focus on 6 questions in particular, in order

[2]The latter sample was not restricted to be younger than 49 years old. However, only 70 respondents were older than 49 and we included them in the analysis.

[3]The *Decreto Supremo N° 116-2020-PCM* established a targeted lockdown starting on July 1st, 2020.

to create measures of physical and psychological IPV.[4] For each of the 6 question we record the frequency of occurrence (never, once, two or more) within each of the three time periods. We split the 6 questions into two categories, physical and psychological IPV.[5] Finally, we take the sum across the questions in each category to end up with a count of psychological and physical incidence.

Our survey also asks about income and employment in each time period. Specifically, respondents are asked to report both employment status and average monthly income of the respondent and her spouse, excluding government transfers. We combine these two income sources to obtain a proxy for the household's earned income. Additionally, we ask about the primary earner's economic sector before the pandemic. We use this income and employment information to characterize patterns of income shocks across sectors and districts that coincide with the pandemic.

Because of the severity of the lock-down imposed by the government and the potential for mobility restrictions alone to influence domestic conflict, another variable of interest from our survey is the number of days individuals left the house. For each time period, we asked households how many days per week on average they left their home to socialize or to make purchases (e.g., buy groceries).Responses to these two questions were also added together to create a "total days out" outcome.

For our analysis we employ two additional datasets, the National Household Survey (ENAHO) and the Peruvian Demographic and Health Survey (ENDES). The former is released on a quarterly basis and provides information on occupation, earnings, and employment status from a nationally-representative sample of respondents. We use the 2019 ENAHO survey to measure employment outcomes prior to the pandemic, while data from the second quarter of 2020 enable us to measure employment changes during the pandemic.

[4] These 6 questions are:

1. With what frequency has your partner said or done things to humiliate you in front of others?
2. With what frequency has your partner insulted, yelled, broken your belongings, threatened to hit you or throw something to you?
3. With what frequency has your partner pushed, shook you or thrown something at you?
4. With what frequency has your partner slapped you or twisted your arm?
5. With what frequency has your partner hit you with their fist or something that could have hurt you?
6. With what frequency has your partner used physical strength to force you to have sexual relations, even if you didn't want to?

[5] Questions 1-2 are used to construct our psychological IPV measure, while questions 3-6 are used for the physical IPV measure.

The ENDES is a nationally representative survey that provides measures of IPV prevalence, conducted annually. We use the ENDES samples of 2011 to 2019, prior to the COVID-19 pandemic, to construct a placebo test to validate our main empirical specification.

Table 1 compares demographic data from our 2020 phone survey with the ENAHO and ENDES datasets. Our phone survey mainly captured urban areas: 92.9% of our respondents live in an urban district.[6] As a result, we only compare our survey with the urban subsamples from the ENAHO and ENDES datasets. On average, our sample is more educated and wealthier at baseline than the national average obtained from these samples, which likely reflects differential response patterns in phone surveys compared with in-person surveys. Moreover, women in our phone survey sample report a significantly higher prevalence of IPV relative to the urban average observed in the 2019 ENDES.

Several reasons could explain the differences between our survey and the ENDES. It is possible that sample difference in IPV rates are similarly driven by differences in unobservable risk factors correlated with phone ownership or phone pick-up rates. Differential reporting biases in phone interviews relative to in-person surveys might also explain some of this pattern, for instance if greater anonymity provided by phone interviews increases respondents' willingness to report on potentially stigmatizing events (Aguero and Frisancho (2021), Bulte and Lensink (2019); Cullen (2020), Joseph et al. (2017), Peterman et al. (2018)). The pandemic itself may explain the differences as well. Pandemic related stress and its associated increase in IPV may have helped normalize IPV, leading to respondents being more open about their own experiences with a survey. Recall bias is also a concern, as respondents may have over-reported what happened in the past. However, in Appendix Section A.2, we use data from our panel sample to rule out that this difference is due to a bias in *retrospective* reporting on IPV incidence.

While the differences in levels of 2019 IPV reported in our sample relative to the urban samples are evident, it is important to note that we are estimating within-sample trends in IPV over the pandemic period using self-reported incidence of violence at various points in time among the same sample of women. Hence, in terms of external validity, it is worth keeping in mind that our results pertain to Peruvian women in the upper median of reported IPV risk.

[6] An urban district is a district with at least 50% of its inhabitants living in an urban town, based on the 2017 Census.

Table 1: Descriptive Statistics

Variable	Nationally Representative Survey	Phone Survey (2020)	Diff.	S.E.
A: Demographics				
% of women w/complete secondary	0.66	0.74	0.08	0.01***
Age (women)	35.81	35.59	-0.22	0.28
Age (male partner)	40.10	37.92	-2.71	0.30***
Household size	4.41	5.03	0.62	0.06***
Number of children	2.19	1.73	-0.47	0.04***
Household income	1145.4	1,481.5	336.0	39.6***
Household income (avg. 2020Q1)	1,087.1	778.3	-308.7	39.3***
Household income (avg. 2020Q2)	774.4	962.5	188.1	40.7***
B: Domestic Violence				
Psychological IPV	0.10	0.26	0.17	0.01***
Physical and sexual IPV	0.10	0.16	0.06	0.01***

Notes. Descriptive statistics comparing our 2020 phone survey to the urban sub-samples from two nationally representative surveys conducted in 2019 and 2020 (ENAHO and ENDES). In practice, our 2020 phone survey skews urban, hence we only compare our survey to urban sub-samples. % of women w/ complete secondary refers to fraction of women that completed secondary education. Age refers to year of age. Household size refers number of people living in the household. Household income refers to the total income earned by all members in the household. Unless otherwise noted, all questions for the Nationally Representative Survey refer to 2019 values. Panel A compares our 2020 survey to ENAHO. Panel B compares the ENDES survey to our measures of IPV. These refer to the fraction of women that have had an IPV event during 2019, as reported by the ENDES and our survey.

4 Empirical Strategy

Our analysis leverages substantial heterogeneity in the unanticipated employment shocks experienced across economic sectors in Peru to investigate the extent to which those most impacted by the pandemic in economic terms experienced disproportionate increases in violence. Fundamentally, we argue that the differential decreases in employment across sectors are exogenous to other IPV trends over this period. The fact that we are focusing on trends over a relatively short period of time and make use of variation in economic impacts across economic sectors makes this assumption more plausible. As a robustness check, in the appendix Table A6 we make use of further variation across space in employment shocks using variation in the sector composition of local labor markets across districts in our sample. We interpret these as results as effects of local labor market conditions on IPV and find similar predictions.

Our main empirical strategy uses variation in employment impacts over the year based on the household head's primary economic sector. Using panel data on self-reported violence, our main estimates employ a standard difference-in-difference strategy to evaluate the effect of economic shocks on IPV. The main estimating equation is of the form:

$$Y_{it} = \sum_{j=1,2} \gamma_j g_i^{\text{sector}} \times 1[t=j] + \alpha_i + \tau_t + u_{it} \tag{1}$$

where Y_{it} is an outcome for person i measured in period t, and α_i and τ_t capture individual and time fixed effects respectively. g_i^{sector} is our measure of an individual exposure to pandemic-related employment shocks, based on the main breadwinner's pre-pandemic occupation. As explained in more detail below, shocks are measured as a percentage change between the second quarter of 2020 (the months April to June) relative to the second quarter of 2019. Therefore, the coefficients γ_1 and γ_2 can be interpreted as the effect of a one percentage point increase in pandemic-related job loss. For ease of notation, we use $t=0$ to denote the calendar year 2019, $t=1$ for the months of April and May of 2020, and $t=2$ for the months of July and August of 2020.

Sector-level variation in employment loss

We classify economic sectors according to employment losses at the pandemic's onset. Using the nationally-representative ENAHO dataset, we calculate the number of people employed in each of the 22 two-digit sector codes in the second quarter of 2020. We then obtain percentage changes in employment in each sector relative to the 2019 average, which capture the variation in employment losses that occurred soon after the pandemic started.[7]

With this strategy, we measure the shock g^{sector} as

$$g_i^{\text{sector}} = \frac{L_{s(i)1} - L_{s(i)0}}{L_{s(i)0}} \times 100 \tag{2}$$

Where $s(i)$ denotes the baseline economic sector for the main breadwinner of household i, and $L_{s(i)t}$ is the total employment count in sector $s(i)$ at time t. For this measure, $t=0$ refers to the 2019 average employment count given by ENAHO, while $t=1$ refers to the second quarter of 2020.[8] We link the sector-level measure of exposure to households in our phone survey sample using information on the the economic sector in which the main breadwinner of the household worked before the pandemic. Standard errors are clustered at the economic-sector level.

[7]The specific employment changes in each sector can be found in the appendix Table A1.

[8]Note that our phone survey asks about IPV during April-May 2020, while we use ENAHO data from the second quarter which is April-June because the ENAHO survey is collected on a quarterly basis. With a slight abuse of notation, we are letting $t=1$ denote April and May for our outcome variable Y_{it}, while $t=1$ denotes April-June for the shock variable $g_i^{\text{sector}} = \frac{L_{s(i)1} - L_{s(i)0}}{L_{s(i)0}} \times 100$.

Figure A1 shows no evidence of differences in pre-existing IPV trends predicted by our measure of exposure. Using repeated cross sectional data from the ENDES surveys from 2011 to 2019 and our own survey, we run a linear probability model similar to Equation (1), where instead of household fixed effects we include district fixed effects, as shown below:

$$1[\text{IPV} > 0]_{it} = \sum_{j=2012}^{2019} \gamma_j g_i^{\text{sector}} \times 1[t = j] + \phi_d + \tau_t + u_{it} \tag{3}$$

where ϕ_d are district fixed-effects, and this regression excludes 2011 as the reference year.[9] The estimated deviations from 2011 for physical and psychological IPV during the pandemic are much larger than anything we detect before the pandemic, helping rule out differences in pre-trends.

Poisson and OLS Specifications

When analyzing domestic violence outcomes, we employ a Poisson regression. The reasons are twofold. First, we are measuring domestic violence incidence as a count, hence a count data model is appropriate. Second, we ask about violent episodes for differing lengths of time in 2019 and 2020. Specifically, our survey instrument first asks about the number of IPV incidents a respondent experienced during all of 2019, and then asks separately about the number of incidents during April-May 2020 and July-August 2020.[10] These differences in exposure windows complicate the analysis and preclude more standard OLS methods since it is necessary to control for the fact that a violent episode is more likely to occur over the course of one year than during two months. The Poisson model accounts for this difference by controlling for the exposure E_t for each time period t.

Poisson models have a complication that they cause the samples to decrease due to separation (Correia et al., 2021). Essentially, the Poisson estimator requires households that had some change in IPV incidence, excluding households with no variation. As a result our Poisson models have smaller samples than the OLS models. The main benefit of the Poisson model is that it meaningfully captures differences in the incidence of IPV instead

[9] Note that we cannot include household fixed effects because the ENDES is not an individual level panel, but rather repeated cross sections. Further, there are no count of incidents in the ENDES, only a dummy variable for any IPV event during 2019. Hence we run a simple linear probability OLS instead of the poisson regression of the main estimates.

[10] Our motivation for asking about IPV incidence over the year in 2019 was to generate statistics on baseline IPV that could be readily compared with nationally representative survey data from the same period, which did not exist for the variable *days out*.

of differences in timing, which allows us to estimate the change in IPV incidence relative to 2019. However, for the IPV outcomes, we also ran conventional linear probability models which can be seen in Appendix Tables A3. The results agree with the Poisson model results, and we show the latter because of their ability to estimate time trends.

For income and days spent outside, we employ a standard OLS since our survey questions on income and days out use a consistent window across time periods. For example, when we ask about income we ask for average monthly income for 2019, or average monthly income between April-May. For days out, we ask the average numbers of days out shopping or socializing within the last week.

5 Results

5.1 Trends in IPV during the pandemic

We start by examining time trends from our survey data in order to confirm that IPV these reports follow the same pattern that has been documented using hotline data (Agüero, 2021).

Table 2 shows estimates from a Poisson model of the count of IPV cases on time dummies for April-May and July-August of 2020, relative to 2019. Columns 1 and 2 report estimates for psychological violence, physical violence (which includes sexual violence), respectively; column 3 reports estimates for any violence.

Overall, the estimates indicate a substantial increase in self-reported cases of IPV during the pandemic, including large and statistically significant increases in both time periods and for most types of violence. Both, physical and psychological violence, increased during at the onset of the pandemic (April-May 2020), while the most strict mobility restrictions were in place. In April/May, physical violence (column 2) increased relative to 2019 levels by 48.9%, while psychological violence increased by 56.3% (column 1). The incidence rate for *any* type of violence increased by 53.45% during April-May 2020 (column 3).

We also find evidence of that higher rates of IPV persist even as mobility restrictions became less severe during July-August 2020, although the rates fall from those of April-May 2020. Psychological violence increased by 27.2% and physical by 39.4% (columns 1 and 2, respectively). In July-August 2020, the rate of any violence was 32.4% higher than 2019 levels, which is significantly lower than the estimated increase immediately after the pandemic.

In Table 3 we examine whether the timing of increases in violence coincided with changes

Table 2: IPV Time Trends 2019-2020

	(1) Psychological	(2) Physical	(3) Any Violence
April-May (2020)	0.563***	0.489***	0.534***
	(0.0883)	(0.113)	(0.0767)
July-August (2020)	0.272***	0.394**	0.324***
	(0.0896)	(0.160)	(0.104)
Outcome Mean (2019)	1.985	2.223	3.042
Observations	981	606	1083

Notes. Results of a Poisson regression, where we control for different lengths of exposure between our 3 time periods (2019, April-May (2020) and July-August (2020)). Each column refers to a different measure of intimate partner violence from our survey. "Psychological" refers to psychological violence. "Physical" refers to acts of physical or sexual violence. "Any" refers to any type of violence, which is the sum of "Physical" and "Psychological".
April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.
Standard errors are clustered by the main breadwinner's economic sector.

Table 3: Income Time Trends 2019-2020

	(1) Household's Income	(2) Wife's Income	(3) Husband's Income	(4) Wife's Days Out
April-May (2020)	-704.4***	-333.7***	-408.6***	-3.510***
	(65.16)	(41.60)	(50.33)	(0.225)
July-August (2020)	-516.0***	-255.5***	-274.8***	-2.813***
	(45.83)	(28.61)	(31.81)	(0.173)
Outcome Mean (2019)	1488.1	632.8	939.3	5.252
Observations	3231	3167	2922	3231

Notes. Results of an OLS regression. For each partner, we ask what average monthly earnings were during 2019, April-May 2020 and July-August 2020. We then add the earnings of each partner together to calculate household income in Peruvian Soles. Wife's Days Out is the average number of days in a week the wife left to socialize or shop for groceries.
April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.
Standard errors are clustered by the main breadwinner's economic sector.

in household income and physical mobility, for different measures of household income.[11] Column 1 shows that, in April-May 2020, households experienced average income loss of 704.4 Nuevos Soles (S/). Given that average income is S/.1,081.3, this is an extremely large income shock, amounting to a 65% loss in earned income for the average household in our sample.[12] Columns 2 and 3, respectively, show the changes in income for each spouse. Husbands loss more money (S/409) relative to wives (S/.334). In July/August the decline in income for both persist but a lower magnitude.

In column 4, we examine the time trends in physical mobility, which we proxy with the reported number of days per week respondents left their home during a typical week in each period. On average, households left home 3.5 fewer days per week in April-May 2020 relative to April-May 2019. As with income and IPV, by July-August 2020, mobility restrictions have become less severe.

5.2 IPV Trends by Economic Sector

The previous estimates document nothing short of economic disaster experienced by the average household in Peru over the first half of 2020. As abrupt economic stress is a risk-factor associated with IPV (e.g., Arenas-Arroyo et al. (2021), Schneider et al. (2016)), we should expect to see corresponding patterns of change in the incidence of violence due to dramatic increases in financial insecurity. Hence, to establish a causal relationship between pandemic-related economic contraction and IPV, we exploit sector-level and spatial variation in employment impacts. Table A1 shows that, while most sectors witnessed important employment losses, not all sectors were equally affected by the crisis. For instance, while employment in hotel and food services dropped by 80%, employment in agriculture *increased* by 13%.

Table 4 shows the estimates for Equation (1) using sector-level variation. As mentioned before, g_i^{sector} is the percentage change in employment that took place to the sector where household i worked before the pandemic. A negative (positive) coefficient implies that a one percentage point *increase* in g_i^{sector} decreases (increases) violence. Hence the estimated

[11] As described in the previous section, because count data are no longer a concern, the income and mobility estimates are derived from an OLS model regressing the outcomes of interest on time dummies for April-May and July-August of 2020, relative to 2019.

[12] This relationship is not driven by extreme values. In results available upon request, we show the estimated effect on log income, which implies a 52.1% decline. Also, the probability of having non-zero income decreases by 30.2 percentage points. As an additional check, we use the inverse hyperbolic sine transformation to smooth out extreme values without dropping observations with zero. The results are consistent with our previous estimates, yielding an estimated loss in earned income of 42.2%.

coefficients refer to occupations that gained jobs, or lost relatively fewer jobs during the pandemic.

Results from these estimates indicate that increases in IPV correspond to the pattern of employment losses brought about by the pandemic, and especially patterns of physical violence. In particular, we find statistically significant increases in physical violence during July-August 2020 that vary strongly with employment losses over the period. For a drop in employment in the median sector (58.2%), psychological violence increased by 82.6% ($-58.2 \times -0.0142 = 0.826$), while the rate of physical violence increased by around 28.6%. The rate of any violence increased by 50.2%

Interestingly, there is no statistical correspondence between changes in IPV and changes in employment in the early period of the pandemic when IPV impacts are the largest. A plausible explanation is that violence increased initially due to the stress effects of economic uncertainty. Because the COVID-19 pandemic was an unprecedented shock, there was likely a high degree of uncertainty as to which sectors and households would be most impacted by the crisis. By July 2020, patterns of economic impact had been revealed, and hence it is likely that stress responses converged to follow more closely patterns of economic impact. That is, those most heavily hit by income losses continued to experience stress and household conflict, while those who were spared significant economic loss improved in terms of anxiety-induced conflict.

Another possible factor giving rise to this pattern is the use of savings. Households may have relied on their savings at the beginning of the pandemic to insulate them from negative employment shocks. As savings were used, they became more exposed to the employment shocks. Unfortunately we don't have panel data on savings in our survey. However, we do ask about savings use during April and May 2020. As suggestive evidence, we correlate savings use during April and May 2020 with the employment shocks in Appendix Table A4. We find that positive employment shocks correlate with lower savings use in April and May. This is suggestive evidence that more protected households did indeed use less of their savings and this could account for the lack of impacts by sector in the early stages of the pandemic.

Table 5 investigates the correspondence between patterns of household income and physical mobility as they relate to sector-level employment losses. The estimates indicate that aggregate job losses indeed correspond to reported household income. Interestingly, employment shocks also track closely with restrictions on physical mobility even in July-August 2020. This is likely explained by the fact that physical mobility restrictions are followed more closely when household members are unemployed and have lower household income,

Table 4: IPV by Employment Shocks

	(1) Psychological	(2) Physical	(3) Any Violence
April-May (2020)	0.465***	0.434***	0.453***
	(0.0751)	(0.118)	(0.0870)
July-August (2020)	0.0360	-0.339	-0.103
	(0.0525)	(0.249)	(0.107)
April-May (2020)$\times g_i^{\text{sector}}$	-0.00210	-0.00117	-0.00172
	(0.00159)	(0.00225)	(0.00169)
July-August (2020)$\times g_i^{\text{sector}}$	-0.00492***	-0.0142***	-0.00864***
	(0.00187)	(0.00413)	(0.00211)
Outcome Mean (2019)	1.985	2.223	3.042
Observations	981	606	1083

Notes. Results of a Poisson regression, where we control for different lengths of exposure between our 3 time periods (2019, April-May (2020) and July-August (2020)). Each column refers to a different measure of intimate partner violence from our survey. "Psychological" refers to psychological violence. "Physical" refers to acts of physical or sexual violence. "Any" refers to any type of violence, which is the sum of "Physical" and "Psychological".

g_i^{sector} refers to the percentage employment change in the main breadwinner's economic sector between the second quarter of 2020 and 2019, using the ENAHO labor force survey. For each economic sector we estimate the national employment counts using the provided survey weights, which we use to calculate the percentage change in employment for each sector.

April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.

Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

as well as possible reverse causality (mobility restrictions led to job loss in certain sectors). Unfortunately, the correlation between the two mechanisms makes it difficult to empirically isolate physical mobility impacts on IPV from income effects on IPV using this approach.

Table 5: Income by Employment Shocks

	(1) Household's Income	(2) Wife's Income	(3) Husband's Income	(4) Wife's Days Out
April-May (2020)	-381.9***	-192.6***	-210.2***	-2.714***
	(46.68)	(28.91)	(41.78)	(0.290)
July-August (2020)	-312.7***	-157.2***	-156.0***	-2.256***
	(46.82)	(32.77)	(31.71)	(0.209)
April-May (2020)×g_i^{sector}	6.685***	2.930***	4.132***	0.0165***
	(1.001)	(0.915)	(0.953)	(0.00554)
July-August (2020)×g_i^{sector}	4.214***	2.042***	2.470***	0.0116***
	(0.957)	(0.701)	(0.732)	(0.00393)
Outcome Mean (2019)	1488.1	632.8	939.3	5.252
Observations	3231	3167	2922	3231

Notes. Results of an OLS regression. For each partner, we ask what average monthly earnings were during 2019, April-May 2020 and July-August 2020. We then add the earnings of each partner together to calculate household income in Peruvian Soles. Wife's Days Out is the average number of days in a week the wife left to socialize or shop for groceries.

g_i^{sector} refers to the percentage employment change in the main breadwinner's economic sector between the second quarter of 2020 and 2019, using the ENAHO labor force survey. For each economic sector we estimate the national employment counts using the provided survey weights, which we use to calculate the percentage change in employment for each sector.

April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.

Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Controlling for COVID

A possible complication in our interpretation of our economic shocks is the extent to which the shocks are correlated with the likelihood of being infected with COVID-19. For instance, workers in the tourism sector may be more likely to be infected, and in turn these infections have impacts on domestic IPV. As a result, the real mechanism we capture may be disease related anxiety. To examine this concern we augment our regression to control for COVID-19 risk during April and May 2020 using administrative data on COVID-related deaths to proxy for *community level* risk. To do so, we calculate the district-level COVID-19 mortality rate for June of 2020.[13] We focus on death statistics, which do not depend on the district's testing capacity. The results can be seen in Table 6. The top panel reproduces the results from Table 4 to ease comparability, while the bottom panel shows estimates with the COVID-19 death rate control. The main estimates are virtually unchanged, while the June death rate coefficients are all statistically insignificant. We take this as evidence that anxiety due to COVID-19 is not the principal mechanism explaining our results.

5.4 Local labor market effects

Another potential concern is that our household employment shocks are correlated with local labor market conditions. A depressed local labor market may induce IPV by increasing economic anxiety. Our results may be biased by estimating the additional effect of a depressed local labor market. This is a salient concern if economic activity is specialized across geographic regions and if occupations cluster together.

To address this concern, we construct a high frequency measure of local labor markets based on a shift-share strategy (Bartik, 1992). We combine the occupational losses in the ENAHO between 2019 and Q2 2020 with district employment shares based on 2017 Population Census data.[14] This allows us to gauge employment levels at the district level, which is the smallest administrative unit in Peru. The results can be seen in Table 7.

Our main estimates of g_i^{sector} are still negative and retain their statistical significance. However, their estimated magnitudes decrease slightly. For instance the July-August coefficient for Physical violence shrinks from -0.0142 to -0.0117. The coefficients on the shift-share variable are negative as well, indicating that depressed local economic activity increases the risk of IPV. The shift-share effects are slightly nosier than the g_i^{sector}, which we would expect given that the g_i^{sector} are based directly on the household's occupation, instead of the more indirect effects captured by the shift-share variable. We take these results as evidence that our estimates are not capturing the effect of depressed local economic activity, and instead they reflect the effect of household economic conditions.

[13] We chose COVID-19 deaths in June because deaths trail infections. Hence the death rate in June would be indicative of infection risk in April or May.

[14] More details can be found in Appendix section A.1.

Table 6: IPV by Employment Shocks, with COVID-19 Controls

	(1) Psychological	(2) Physical	(3) Any Violence
April-May (2020)×g_i^{sector}	-0.00210	-0.00117	-0.00172
	(0.00159)	(0.00225)	(0.00169)
July-August (2020)×g_i^{sector}	-0.00492***	-0.0142***	-0.00864***
	(0.00187)	(0.00413)	(0.00211)
April-May (2020)×g_i^{sector}	-0.00189	-0.00112	-0.00157
	(0.00158)	(0.00222)	(0.00166)
July-August (2020)×g_i^{sector}	-0.00473**	-0.0143***	-0.00851***
	(0.00197)	(0.00424)	(0.00222)
April-May (2020)×June Death Rate	0.00105	0.00121	0.00113
	(0.000848)	(0.00144)	(0.000895)
July-August (2020)×June Death Rate	0.00105	0.00201	0.00128
	(0.00168)	(0.00217)	(0.00159)
Outcome Mean (2019)	1.985	2.223	3.042
Observations	981	606	1083

Notes. Results of a Poisson regression, where we control for different lengths of exposure between our 3 time periods (2019, April-May (2020) and July-August (2020)). Each column refers to a different measure of intimate partner violence from our survey. "Psychological" refers to psychological violence. "Physical" refers to acts of physical or sexual violence. "Any" refers to any type of violence, which is the sum of "Physical" and "Psychological".
g_i^{sector} refers to the percentage employment change in the main breadwinner's economic sector between the second quarter of 2020 and 2019, using the ENAHO labor force survey. For each economic sector we estimate the national employment counts using the provided survey weights, which we use to calculate the percentage change in employment for each sector.
April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.
June Death Rate refers to the death rate per 100000 inhabitants in June due to COVID-19 in the respondent's district. Inhabitant per district data comes from the 2017 Census, and COVID-19 deaths come from administrative data.
Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: IPV by Employment Shocks, with Shift-Share Controls

	(1) Psychological	(2) Physical	(3) Any Violence
April-May (2020)$\times g_i^{\text{sector}}$	-0.00210	-0.00117	-0.00172
	(0.00159)	(0.00225)	(0.00169)
July-August (2020)$\times g_i^{\text{sector}}$	-0.00492***	-0.0142***	-0.00864***
	(0.00187)	(0.00413)	(0.00211)
April-May (2020)$\times g_i^{\text{sector}}$	-0.000861	0.00146	0.0000912
	(0.00180)	(0.00311)	(0.00167)
July-August (2020)$\times g_i^{\text{sector}}$	-0.00377*	-0.0117***	-0.00689***
	(0.00210)	(0.00446)	(0.00223)
April-May (2020)$\times g_i^{\text{shift-share}}$	-0.00557	-0.0148*	-0.00882**
	(0.00582)	(0.00875)	(0.00446)
July-August (2020)$\times g_i^{\text{shift-share}}$	-0.00524	-0.0149	-0.00876*
	(0.00443)	(0.0118)	(0.00520)
Outcome Mean (2019)	1.985	2.223	3.042
Observations	981	606	1083

Notes. Results of a Poisson regression, where we control for different lengths of exposure between our 3 time periods (2019, April-May (2020) and July-August (2020)). Each column refers to a different measure of intimate partner violence from our survey. "Psychological" refers to psychological violence. "Physical" refers to acts of physical or sexual violence. "Any" refers to any type of violence, which is the sum of "Physical" and "Psychological".

g_i^{sector} refers to the percentage employment change in the main breadwinner's economic sector between the second quarter of 2020 and 2019, using the ENAHO labor force survey. For each economic sector we estimate the national employment counts using the provided survey weights, which we use to calculate the percentage change in employment for each sector.

$g_i^{\text{shift-share}}$ is our shift share variable constructed with employment changes by occupation between the second quarter of 2020 and the average of 2019. These changes are combined with district level occupational shares as described in Appendix Section A.1

April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.

Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.5 Effects on Mental Health

Our survey asks a series of mental health questions. These questions are of the form "In the months of April and May 2020, on average, did you feel more, same, or less [mental health issue] than an average month in 2019." In particular, we asked about anxiety, moodiness, loneliness, rage, urges to raise your voice and urges to act violently. These variables are coded as follows:

$$\Delta M_i = \begin{cases} 1, & \text{if the individual felt more anxiety} \\ 0, & \text{if the individual felt no change in anxiety} \\ -1 & \text{if the individual felt less anxiety} \end{cases}$$

Therefore, decreases in ΔM_i translate to reductions in anxiety and improvement in mental health. Since the mental health questions are about the changes instead of asking for levels pre- and during the pandemic, we modify the empirical strategy to be a first difference strategy of the type:

$$\Delta M_i = \alpha + \delta g_i^k + u_i \tag{4}$$

where g_i^k are the measured shocks. Recall that these shocks essentially capture changes in economic conditions between April-May 2020 and 2019, hence this strategy is akin to a conventional first difference strategy controlling for individual fixed effects. The results can be seen in Table 8. All the coefficients are negative, which indicate that the more economically protected households saw relative improvements (or less deterioration) in mental health. Because of the variable's coding, we can interpret these coefficients as reductions in the likelihood of experience negative mental health outcomes, akin to conventional panel estimates with binary outcomes. For instance, the median employment shock of -58.2 percentage points would yield a $-58.2 \times -0.00296 = 0.172$ increase in feelings of anxiety relative to 2019. However, since we only asked for the change we are not able to compare this coefficient to the overall mean of the mental health outcomes in 2019.

6 Conclusion

We conducted a large household survey and document a substantial and sustained increase in IPV during the COVID-19 pandemic in Peru. These results complement existing work

Table 8: Mental Health Outcomes

	(1) Anxiety	(2) Moodiness	(3) Loneliness	(4) Rage	(5) Raise Voice	(6) Violence	(7) Any Mental Health
g_i^{sector}	-0.00296**	-0.000840	-0.000334	-0.00142	-0.00128	0.0000889	-0.000879**
	(0.00119)	(0.000794)	(0.000664)	(0.00103)	(0.000864)	(0.000478)	(0.000361)
Outcome Mean (2020)	0.644	0.669	0.286	-0.0160	-0.0197	-0.416	0.894
Observations	1066	1072	1062	1065	1065	1048	1076

Notes. This table shows OLS regression results for mental health outcomes. The results are from two different regressions. Standard errors are shown below the estimates. The g_i^{sector} coefficients are clustered by economic sector, while the $g_i^{\text{shift-share}}$ coefficients are clustered by district.

The survey questions are of the form "In the months of April and May 2020, on average, did you feel more, same, or less anxiety than an average month in 2019." The table headers show the type of mental health feeling we ask about. Anxiety refers to feelings of anxiety. Moodiness refers to feelings of moodiness. Loneliness refers to feelings of loneliness. Rage refers to ability to control the respondent's anger. Raise Voice refers to feeling urges to raise your voice. Violence refers to urges to act violently. Any Mental Health refers to any mental health deterioration as measured in columns 1-6. It is the maximums across columns 1-6.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

showing similar increases in phone calls to victim helplines, indicating an enormous increase in IPV during the pandemic that was not simply a substitution towards phone-based assistance. Moreover we show that pandemic-related income shocks are strongly associated with changes in the incidence of IPV. While increases in IPV appear to be orthogonal to employment losses in the first two months of the pandemic, households most exposed to pandemic related job-losses suffered disproportionate and extremely large increases in physical IPV six months into the pandemic. This pattern is consistent with lockdown measures and uncertainty contributing to domestic violence at the onset of the shock, while income losses experienced by a subset of the population led to sustained levels of IPV several months later.

These results provide important additional empirical evidence that economic crises, in this case generated by COVID-19, produce violence through both the stress of economic uncertainty as well as through material losses to individual households.

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A Additional Results

Table A1: Employment Changes By Sector

Economic Sector	Employment Count		Percentage
	2019	Q2 2020	Change (%)
Art and Entertainment	176374	34253	-81
Hotel and Food Service	1284874	255782	-80
Household Employment	432118	110382	-74
Construction	1072992	301739	-72
Mining	200181	72742	-64
Water supply; sewerage, waste management	75938	28699	-62
Technical, Professional and Scientific Activities	387731	154740	-60
Manufacturing	1532773	624387	-59
Transportation and Storage	1308055	547316	-58
Fishing	97231	40867	-58
Administrative and support service activities	523687	224175	-57
Retail	3300452	1460108	-56
Other Service Activities	483815	244670	-49
Information and Communication	144148	83607	-42
Human health and social work activities	435638	272295	-37
Public administration and defence	708701	473513	-33
Real Estate	26502	18661	-30
Education	883133	664248	-25
Insurance and Financial Activities	133927	122273	-9
Agriculture	4091243	4633594	13
Electricity, gas, steam and air conditioning supply	15656	19034	22

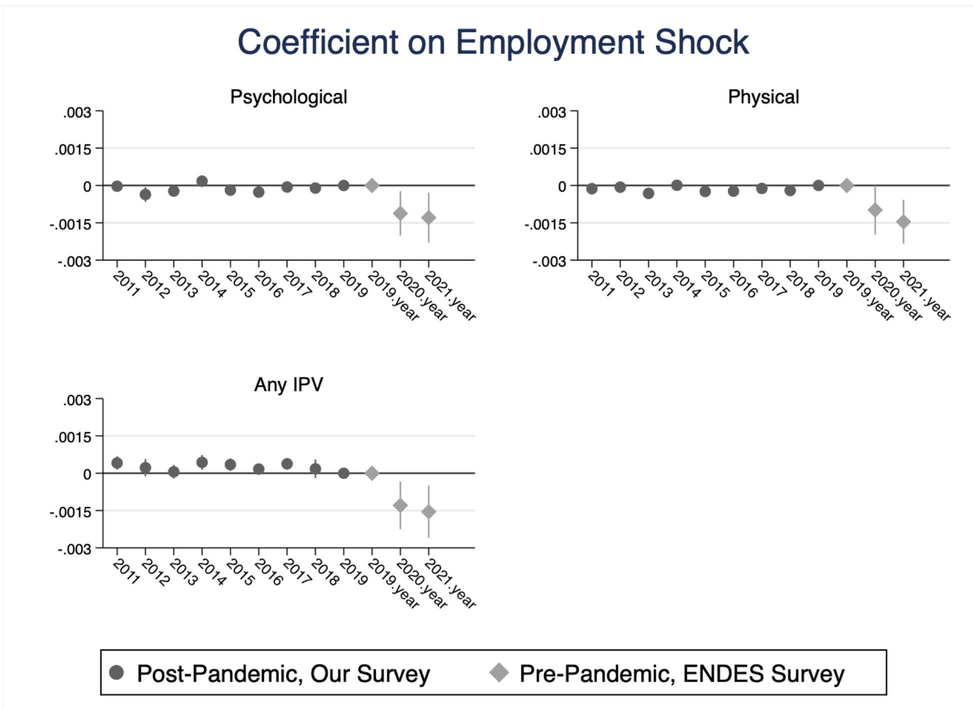
Notes: The table shows national employment estimates in 2019 and the second quarter of 2020 using the ENAHO surveys. The last column is the percentage change between Q2 2020 and 2019. These results use the sampling weights provided in the ENAHO.

Table A2: Summary Statistics of g_i^{sector}

	g_i^{sector}
p1	-80.1
p10	-71.9
p25	-60.1
p50	-58.2
p75	-49.4
p99	13.3
mean	-48.2
N	1077
Sectors	21

Notes. Summary statistics for the employment shocks, showing different percentiles and the mean. These statistics are generated using our final sample, hence they are weighted according to the distribution of households.

Figure A1: Pre-trends: Employment Change and IPV. All Outcomes.



Notes: Graph of pre-trend coefficients of equation 3, using ENDES data from 2011-2019. 2019 is the reference year. These results are based on an OLS linear probability model. Our estimates are incuded for comparison. Standard errors are clustered by the household's district.

Table A3: IPV by Employment Shocks, Linear Probability Model.

	(1) Psychological	(2) Physical	(3) Any
April-May (2020)	-0.203***	-0.145***	-0.226***
	(0.0339)	(0.0273)	(0.0316)
July-August (2020)	-0.246***	-0.181***	-0.275***
	(0.0289)	(0.0191)	(0.0231)
April-May (2020)$\times g_i^{\text{sector}}$	-0.00102	-0.00101*	-0.00121*
	(0.000663)	(0.000508)	(0.000619)
July-August (2020)$\times g_i^{\text{sector}}$	-0.00118*	-0.00146***	-0.00142***
	(0.000603)	(0.000345)	(0.000460)
Outcome Mean (2019)	0.273	0.162	0.305
Observations	3231	3231	3231

Notes. Results of an OLS regression, with an indicator for any amount of violence on the left hand-side. Each column refers to a different measure of intimate partner violence from our survey. "Psychological" refers to psychological violence. "Physical" refers to acts of physical or sexual violence. "Any" refers to any type of violence, which is the sum of "Physical" and "Psychological".

g_i^{sector} refers to the percentage employment change in the main breadwinner's economic sector between the second quarter of 2020 and 2019, using the ENAHO labor force survey. For each economic sector we estimate the national employment counts using the provided survey weights, which we use to calculate the percentage change in employment for each sector.

April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.

Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Employment Shocks on Savings Use

	(1) Used Savings Apr. May (2020)
g_i^{sector}	-0.000922**
	(0.000451)
Outcome Mean (2020)	0.852
N	1076

Notes. OLS regression with an indicator of any savings use during April or May 2020. On the right hand side is our economic sector shock.
Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.1 Geographic variation in exposure

In addition to our main specification, we construct a shift-share variable that captures the economic shock to the household's geographic district during the COVID-19 pandemic constructed from the ENAHO employment data and the 2017 Peruvian Population Census microdata. In particular, we calculate employment shares by district and industry from the 2017 Census to construct the shift-share variable defined as $\pi_{dn} = L_{dn}^{2017}/L_d^{2017}$, where L_{dn}^{2017} denotes total employment in industry n in district d in the 2017 Census, and L_d^{2017} denotes total employment in district d.

We then combine these shares with information on employment shocks during the COVID-19 pandemic, in a similar fashion to the economic sectors specification. We first calculate the changes in employment for each economic sector n as before. We then weight these employment changes with the district-sector shares from the census, yielding the expression:

$$g_i^{\text{shift-share}} = \sum_n \pi_{dn} \frac{L_{n1} - L_{n0}}{L_{n0}} \times 100 \tag{5}$$

$g_i^{\text{shift-share}}$ is therefore an industry-weighted average of employment changes in i's district. In these specifications, we cluster standard errors by district.

Table A5 shows summary statistics of local employment shocks at the district level. The median individual in the sample resides in a district that experienced a 50.95% drop in employment.

Table A6 reveals a pattern of IPV over the period similar to the main strategy based on household economic sector, in that negative local labor market shocks are associated with significant increases in reported IPV. Consistent with our previous estimates, the effects are stronger at later stages of the pandemic. For the median employment shock in the sample (-50.98 percentage points), the rate of any violence increases by 67.8% ($-50.98 \times -0.0133 = 0.678$) in July-August of 2020. The effects for each type of violence are less precisely estimated than in our main specification, which one would expect given that the shift-share shock measures local-labor market shocks rather than households' sector-specific shocks.

Table A5: Summary Statistics of $g_i^{\text{shift-share}}$

	$g_i^{\text{shift-share}}$
p1	-57.38879
p10	-56.49663
p25	-55.37397
p50	-50.98249
p75	-39.17353
p99	1.894225
mean	-44.47882
N	3231
Districts	305

Notes. Summary statistics for the shift-share shocks, showing different percentiles and the mean. These statistics are generated using our final sample, hence they are weighted according to the distribution of households.

Table A6: IPV by Shift-Share Shocks

	(1) Psychological	(2) Physical	(3) Any Violence
April-May (2020)	0.299	-0.111	0.155
	(0.220)	(0.449)	(0.216)
July-August (2020)	-0.0645	-0.614	-0.261
	(0.284)	(0.568)	(0.300)
April-May (2020)$\times g_i^{\text{shift-share}}$	-0.00617	-0.0135	-0.00871*
	(0.00500)	(0.00931)	(0.00478)
July-August (2020)$\times g_i^{\text{shift-share}}$	-0.00782	-0.0223*	-0.0133**
	(0.00631)	(0.0116)	(0.00665)
Constant	-0.893***	-0.685***	-0.328***
	(0.0253)	(0.0381)	(0.0254)
Outcome Mean (2019)	1.985	2.223	3.042
Observations	981	606	1083

Notes. Results of a Poisson regression, where we control for different lengths of exposure between our 3 time periods (2019, April-May (2020) and July-August (2020)). Each column refers to a different measure of intimate partner violence from our survey. "Psychological" refers to psychological violence. "Physical" refers to acts of physical or sexual violence. "Any" refers to any type of violence, which is the sum of "Physical" and "Psychological".

$g_i^{\text{shift-share}}$ is our shift share variable constructed with employment changes by occupation between the second quarter of 2020 and the average of 2019. These changes are combined with district level occupational shares as described in Appendix Section A.1

April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.

Standard errors are clustered by the household's district.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2 Analysis of Recall Bias

Since we rely on a retrospective panel for estimation, a natural concern is the extent to which there is recall bias in our the responses. Respondents may be systematically over or under-reporting IPV in a way that biases our results.

In this section, we leverage the sub-sample that was actually surveyed in 2019 to compare recalled 2019 values in our 2020 phone survey with baseline values surveyed in 2019. We can therefore analyze the extent of recall bias in our results within this sub-sample. We are limited in what we can do, however, since this sub-sample is very small. There are only 283 respondents for whom we have both baseline and recalled 2019 values.

For physical IPV, we repeated the exact same 4 sub-questions in both surveys. For psychological IPV, we only have the question "With what frequency has your partner said or done things to humiliate you in front of others" repeated in both surveys.

We first begin with a simple cross tabulation of the recalled versus baseline 2019 values in Tables A7 and A8. There is some evidence of overall under-reporting in Table A7 and there is no systematic difference in overall reporting rate in A8.

We then run a simple OLS with the recalled errors, defined as recalled value - baseline value, on the left hand side and our employment shocks on the right hand side, in Table A9. The coefficient on g_i^{sector} is insignificant, which is suggestive evidence that the recall error is not correlated with our main regressor of interest.

Finally, we conduct a sensitivity analysis where we replace the recalled 2019 values with the baseline values, and leave the other two time periods intact. We then repeat the main analysis. These are seen in Tables A10 and A11. In all cases, using the baseline values leads to coefficients with the same directions and similar magnitudes than using the recall values. While the poisson coefficients for psychological violence are positive, they are similar in size no matter if baseline or recalled values are used.

Table A7: Physical IPV: Cross Tabulation of Recalled Values and 2019 Baseline Values

	Recalled Value Physical = 0	Recalled Value Physical > 0	Total
Baseline Value Physical = 0	216	15	231
Baseline Value Physical > 0	31	21	52
Total	247	36	283

Table A8: Psychological IPV: Cross Tabulation of Recalled Values and 2019 Baseline Values

	Recalled Value Psychological = 0	Recalled Value Psychological > 0	Total
Baseline Value Psychological = 0	199	28	227
Baseline Value Psychological > 0	28	23	51
Total	227	51	278

Table A9: Correlation of Recall Error and Employment Shocks

	(1) Recall Error Physical	(2) Recall Error Psychological
g_i^{sector}	-0.00200	0.00159
	(0.00125)	(0.000988)
Error Mean	-0.233	-0.00722
N	283	277

Notes. OLS regression with the calculated 2019 recall error. On the right hand side is our economic sector shock.
Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Poisson Model: Comparison of Using Baseline Instead of Recalled Values of 2019 IPV

	(1) With Baseline Value Physical	(2) With Recalled Value Physical	(3) With Baseline Value Psychological	(4) With Recalled Value Psychological
April-May (2020)$\times g_i^{\text{sector}}$	-0.00332	-0.00262	0.00593*	0.00151
	(0.00440)	(0.00348)	(0.00335)	(0.00288)
July-August (2020)$\times g_i^{\text{sector}}$	-0.00929	-0.00783	0.00876**	0.00411
	(0.00631)	(0.00556)	(0.00407)	(0.00320)
Outcome Mean (2019)	2.450	2.025	1.508	1.654
Observations	180	120	175	155

Notes. Results of an Poisson model, with a count of IPV on the left hand-side.
The sample is limited to respondents with both recalled and baseline 2019 IPV values. We replace the reported 2019 value with the baseline value in columns 1 and 3, and only use recalled values in 2 and 4.
g_i^{sector} refers to the percentage employment change in the main breadwinner's economic sector between the second quarter of 2020 and 2019, using the ENAHO labor force survey. For each economic sector we estimate the national employment counts using the provided survey weights, which we use to calculate the percentage change in employment for each sector.
April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.
Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: LPM: Comparison of Using Baseline Instead of Recalled Values of 2019 IPV

	(1) With Baseline Value Physical > 0	(2) With Recalled Value Physical > 0	(3) With Baseline Value Psychological > 0	(4) With Recall Value Psychological > 0
April-May (2020)$\times g_i^{\text{sector}}$	-0.000673	-0.00170***	-0.000461	-0.000716
	(0.000548)	(0.000389)	(0.000446)	(0.000504)
July-August (2020)$\times g_i^{\text{sector}}$	-0.000852	-0.00188***	-0.000222	-0.000476
	(0.000545)	(0.000412)	(0.000519)	(0.000527)
Outcome Mean (2019)	0.184	0.127	0.183	0.183
Observations	849	849	842	842

Notes. Results of an OLS regression, with an indicator for any amount of violence on the left hand-side.
The sample is limited to respondents with both recalled and baseline 2019 IPV values. We replace the reported 2019 value with the baseline value in columns 1 and 3, and only use recalled values in 2 and 4.
g_i^{sector} refers to the percentage employment change in the main breadwinner's economic sector between the second quarter of 2020 and 2019, using the ENAHO labor force survey. For each economic sector we estimate the national employment counts using the provided survey weights, which we use to calculate the percentage change in employment for each sector.
April-May (2020) is a time dummy for April and May of 2020. July-August (2020) is a time dummy for July and August of 2020.
Standard errors are clustered by the main breadwinner's economic sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$