Frosty Climate, Icy Relationships: Frosts and Intimate Partner Violence in Rural Peru

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Abstract

Violence against women — in particular, Intimate Partner Violence (IPV) — is a major health concern for women across the world. We study the impact of extreme cold on IPV among Peruvian women. Using a dataset that matches women to weather exposure, we find that overall, frost shocks increase IPV: 10 degree hours below -9°C increases the probability of experiencing domestic violence by 0.5 percentage points. These effects are larger for more extreme temperature thresholds. We provide evidence that frosts impact IPV through two main channels. First, extreme cold yields adverse consequences for income, which in turn affects IPV. Second, extreme cold limits time spent outside of the household, potentially increasing exposure of women to violent partners. To our knowledge, we are the first to measure relative significance of these two channels by using variation in frost timing to distinguish shocks that affect IPV through changes in income from those that act through time spent indoors. We find that the effect of frosts on IPV is mostly driven by frosts that occur during the growing season, when 10 degree hours below -9°C increase the probability of experiencing IPV by 1.5 percentage points. In contrast, we find that non-growing season frosts have no statistically significant effects on IPV.

1 Introduction

Violence against women — in particular, Intimate Partner Violence (IPV) — is a major health concern for women across the world, affecting one in three ever-partnered women worldwide (WHO, 2013; Sardinha et al., 2022). Extensive research demonstrates that IPV victims are more likely to suffer long-term physical health ailments, mental health problems, productivity losses (Campbell, 2022; Oram et al., 2022; Campbell, 2021), and economic suppression (Adams-Prassl et al., 2023) — all of which translate into aggregate economic losses. In low-income settings, IPV results in estimated costs of 1.5% to 4% of GDP (Ribero and Sánchez, 2005; Morrison and Orlando, 1999). Furthermore, IPV has intergenerational consequences; exposure in childhood increases the probability of becoming either a victim or perpetrator of IPV as an adult (Ehrensaft et al., 2003; Whitfield et al., 2003). These findings suggest that the negative consequences of IPV can self-perpetuate over time.

We are the first study the effect of extreme cold (temperatures below 0°C / 32°F) on IPV. We do so in the setting of the Peruvian Highlands, an area where IPV is unfortunately common[1] and where extreme cold events have become more frequent, affecting millions in recent decades (Keller and Echeverría, 2013; FAO, 2008).[2] We use nine rounds (2010-2018) of the Peruvian Demographic and Health Survey (DHS) to measure the incidence of IPV amongst women in the highlands. We match individual data from the DHS with hourly temperatures from the European Centre for Medium-Range Weather Forecasts (ECMWF) using highly localized (i.e., village or neighborhood block) GPS locations and household-specific month-of-interview. We calculate the cumulative degree hours in which households had experienced temperatures below alternative thresholds (e.g., 0°C, -1°C, -2°C,..., etc.) during the year prior to the survey. Our measure of degree hours takes into account both the duration (i.e., time spent below a predefined threshold) and intensity (i.e, by how much temperatures drop below that threshold) of frost: we calculate the extent by which temperatures drop below each threshold and aggregate this "excess cold" in the 12-month period prior to each household's participation in the DHS. Overall, we find that frost shocks increase IPV: 10 degree hours below -9°C increases the probability of experiencing domestic violence by 0.5 percentage points.

We explore two main channels through which frosts affect IPV. First, extreme cold can have adverse consequences for agricultural output (Snyder and Melo-Abreu, 2005) and thus income in rural settings. Previous research has found that income shocks can affect IPV, though there is no consensus about the direction of this effect. Some have found that negative income shocks can increase IPV (Schneider et al., 2016; Heath et al., 2020; Hidrobo et al., 2016; Díaz and Saldarriaga, 2022; Díaz and Saldarriaga, 2023; Abiona and Koppensteiner, 2018; Epstein et al., 2020) through

[1] Peru ranks in the top 20% of countries tracking IPV prevalence (WHO, 2021).

[2] In the southern hemisphere, the recent surge in extreme cold events is attributed to episodes of La Niña, which are projected to increase in both frequency and duration (Cai et al., 2015). La Niña has been linked to especially cold conditions in the Peruvian Highlands, with disastrous consequences (Barbier, 2010).

pathways of stress, anxiety, and impulsive decision-making (Mani et al., 2013; Haushofer and Fehr, 2014; Haushofer et al., 2020). However, others argue that there is a positive relationship between income and IPV: controlling husbands might want to exert instrumental violence to gain control over household resources (e.g., Eswaran and Malhotra, 2011; Bloch and Rao, 2002; Bobonis et al., 2013; Angelucci, 2008; Anderberg and Rainer, 2011).[3] To provide evidence that frost shocks affect IPV through economic status, we show that freezing temperatures — particularly those that occur during the growing season — lower agricultural income, total income, and household expenditure.

Second, extreme cold may confine individuals indoors. As people try to shield themselves from inclement weather, frosts can increase interactions between victims and perpetrators. More exposure to violent partners — e.g., through COVID-19 lockdown measures (e.g., Agüero, 2021; Arenas-Arroyo et al., 2021; Gibbons et al., 2021), prolonged male unemployment (Bhalotra et al., 2021), or lack of female employment (Chin, 2012) — has been found to increase domestic violence. Additionally, confinement during cold periods can lead to women's social isolation and sever them from support networks, which can increase IPV (Kim, 2019; Lanier and Maume, 2009). Anecdotally, extreme weather (and severe instances of cold in particular) have been linked to increases in partner violence; for example, both the Rape, Abuse and Incest National Network (RAINN) and the National Sexual Assault Online Hotline see higher call volume in the winter and especially during severe cold spells and storms (James, 2014), while police officers blame "cabin fever" induced by extreme weather for spikes in domestic violence cases (Whitehead, 2012). Consistent with this mechanism, we use Google location data to show that frosts reduce time spent in plausibly outdoor locations, as proxied by location pings in parks and on forms of transit.

Critically, we present the first evidence of the income and exposure channels' relative significance, using variation in frost timing to distinguish shocks that affect IPV through changes in income from those that act through time spent indoors. Specifically, we use data on sowing and harvest dates to construct growing calendars at the province level and then use these calendars to separate frosts that occur during the growing season — which affect both household income and time spent at home — from those occurring outside of the growing season, which primarily affect time spent at home. We find that frosts that occur during the growing season strongly affect IPV: experiencing 10 degree hours below -9°C increases the probability of IPV by 1.5 percentage points. In contrast, we find that non-growing season frosts have no statistically significant effects on IPV. A comparison of the exposure effect (the frost shock coefficient from the non-growing season) to the combined income and exposure effect (frost shock the coefficient from the growing season) suggests that the income channel accounts for nearly three quarters (74.1%) of the total effect of frost shocks.

Finally, we examine the role of access to social programs. As we find strong evidence that the

[3]Some other studies find no overall relationship between income shocks and violence against women (Blakeslee and Fishman, 2013; Iyer and Topalova, 2014). Though there is a growing literature on the effects of relative income of household members (e.g., male versus female income) on IPV, we do not focus on that literature here, as we do not have independent sources of variation in relative income.

income channel is the dominant channel through which frosts affect IPV, we hypothesize that access to social assistance may ameliorate these effects. To test this, we calculate social program coverage at the province level. Consistent with our expectations, the effects of frosts on IPV are large and significant in provinces where baseline social program coverage is low and is not significantly different from zero in provinces where the baseline social program coverage is high. We see these results as evidence that social assistance may play a key role in mitigating the adverse effects of extreme cold on women.[4]

Our results are consistent over a battery of robustness checks. We show that our results are not driven by any particular measure of frost shock we use (e.g., varying temperature thresholds or windows of frost shocks). We find no evidence that endogenous migration or other changes in sample composition explain our results. Our results are robust to allowing for other shocks that vary at the department level over time and to allowing for district-specific linear trends. Finally, through a falsification exercise we show that future shocks have no effect on IPV, illustrating that households do not anticipate future frost shocks and that frost shocks are not systematically related to other household- or district-level unobservables. Overall, these robustness checks give us confidence that frost shocks are truly exogenous.

This paper makes several contributions. First, by evaluating the effects of extreme cold on IPV, we add insight to the growing literature on the determinants of violence against women, especially with respect to the relationship between extreme weather and violence. Most of the literature has, so far, focused on the impact of droughts or heat waves on domestic violence, finding that both tend to increase IPV (e.g., Díaz and Saldarriaga, 2023; Abiona and Koppensteiner, 2018; Epstein et al., 2020; Sekhri and Storeygard, 2014; Cohn, 1993; Auliciems and DiBartolo, 1995; Sanz-Barbero et al., 2018; Zhu et al., 2023).[5] However, to our knowledge, we are the first to investigate whether *cold* temperatures also increase the incidence of IPV amongst women.[6] While climate change will increase global average temperatures, it is also expected to intensify weather variability leading to more frequent episodes of both extreme heat and extreme cold (Cai et al., 2015). Moreover, as average temperatures rise, plants bud earlier making crops more vulnerable to the effects of potential late-spring frosts and likely to fail (Limichhane, 2021).

Second, we are the first to assess the relative importance of the income and exposure effects of extreme weather on IPV. While several previous papers have also estimated reduced form effects of

[4]Relatedly, studies have found that households' access to public transfer programs reduces the incidence of IPV (Heath et al., 2020; Hidrobo et al., 2016; Díaz and Saldarriaga, 2022). Our findings differ from these in that we show how access to social assistance programs ameliorate the effects of cold weather events on IPV.

[5]However, it should be noted that some other papers do not find a clear association between rainfall shocks and violence against women (Iyer and Topalova, 2014; Blakeslee and Fishman, 2013).

[6]Perhaps the closest to our paper is Otrachshenko et al. (2021), who find that extreme heat (but not cold) increases the incidence of violent deaths in Russia, with larger impacts for women relative to men. A crucial difference between this paper and ours is that Otrachshenko et al. (2021) focus on *violent deaths*, which represent more infrequent and extreme situations. In contrast, we focus on IPV and investigate more general and prevalent types of aggression (physical aggression, emotional violence, sexual violence, and control issues) against women in their daily lives.

weather shocks on violence, the implications of these estimates are sometimes difficult to interpret. For this reason, we also provide detailed evidence for the mechanisms of these effects, addressing both income and exposure. The most traditional interpretation is that weather shocks affect violence through their impact on household incomes. However, extreme weather can also alter individuals' routine activities and the time they spend outdoors (Cohn, 1990; Cohn and Rotton, 2000).[7] We present novel evidence about the relative importance of the income and exposure channels, where we find that the income mechanism is the predominant one.[8]

Finally, our paper also contributes to the policy discussion around IPV reduction in developing countries. Poor households in developing countries have limited savings and access to credit. Thus, many rely on public support via social programs to withstand the adverse impacts of unexpected shocks. We show that expanding access to social programs in the face of weather shocks may not only help households meet basic needs in times of crisis but may also improve women's living conditions in developing countries.

2 Context

Peru is a setting where violence against women is unfortunately very common. Despite declining in the past decade, at the national level IPV remains prevalent: in 2019, 58% of Peruvian women experienced IPV (Agüero, 2021). Due to the nature and geographic scope of cold weather shocks in Peru, we focus on women living in the Peruvian Highlands that had been ever partnered (i.e., potentially subject to domestic violence). In this sample, the incidence of IPV is even higher than the national average; over the course of our sample period (2010-2018), 69% of women reported experiencing some form of IPV in the past year.[9]

Frosts and extreme cold events have become increasingly common throughout Peru over the last two decades, affecting millions of Peruvians (Keller and Echeverría, 2013; FAO, 2008). The Peruvian Highlands, located at elevated altitudes (between 500 and 6,798 meters above sea level), have been particularly susceptible to weather events including frosts and cold waves as well as droughts and floods (World Bank, 2008). In recent years, extreme cold temperatures have dipped as low as -20°C in some areas, affecting close to 200 thousand inhabitants (Centre for Research on

[7]A long line of literature examines the possibility that extreme temperatures evoke a biological response linked to increased aggression (e.g., Anderson, 1987, 1989; Simister and Cooper, 2005) and impair cognitive ability (Bain et al., 2015; Schlader et al., 2015; Cho, 2017). Theoretically, the body may respond to both extreme cold and extreme heat by producing stress hormones, though existing studies typically find a stronger link between hormone activation and heat than cold, perhaps because clothing acts as a mediator for cold weather (Anderson et al., 2000). This suggests that, in the case of extreme cold weather shocks, the "income" and "exposure" channels are the most relevant ones.

[8]Our results build on those in Abiona and Koppensteiner (2018) who investigate the possibility that drought can affect IPV by confining families indoors by examining whether controlling for the number of rooms in a dwelling (as a proxy for the size of living space) changes the estimated effect of drought on IPV. We provide more direct evidence of the exposure channel by estimating the impact of extreme cold on mobility; furthermore, we are able to quantify the relative importance of the exposure channel.

[9]We describe our measure of IPV in more detail in section 3.1.

the Epidemiology of Disasters, 2023). Most experts argue that this situation will continue to worsen in the future, as Peru is one of the most vulnerable countries to climate change (Stern, 2007; Tambet and Stopnitzky, 2021).

Extreme cold can have particularly severe consequences on agricultural output, an important economic activity in the highlands. The extent of the damage induced by frosts depends on the intensity of the frost (i.e., how far below 0°C the temperature drops), the frequency of these events, the type of crops, and the phenological state of the plants (Snyder and Melo-Abreu, 2005). More intense frost episodes can induce crop failure and significant economic losses. For example, a frost in 2008 destroyed 45% of potato production in several high-altitude Peruvian provinces (FAO, 2008). The continued threat of frosts is a concern for much of the highlands; CENEPRED (2021) estimates that there are 823 districts (encompassing around 1 million farmers and 3.3 million hectares of agricultural land) under high or very high risk of experiencing frosts.

3 Data and Variables

Our analysis uses five main data sources: the Peruvian Demographic and Health Survey (Encuesta Demográfica y de Salud Familiar), the Peruvian National Agricultural Survey (Encuesta Nacional Agropecuaria), weather data from the European Centre for Medium-Range Weather Forecasts (ECMWF) and the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS), and mobility data from Google.

3.1 Encuesta Demográfica y de Salud Familiar (Peruvian DHS)

The Peruvian Demographic and Health Survey (DHS - *Encuesta Nacional Demográfica y de Salud Familiar*) is a yearly survey collected by the Peruvian National Statistics Office (Instituto Nacional de Estadística e Informática, 2018a). The DHS collects data from a representative sample of females aged 15 to 49 years and boys & girls younger than 12 years. It includes information about their socioeconomic characteristics, basic housing features, access to social programs (health, nutrition, etc.), and health information (i.e., anthropometric measurements, hemoglobin levels, chronic conditions, diseases, illnesses, reproductive health, sexually transmitted infections, immunizations, etc.). Additionally, the DHS collects information on various types of domestic violence. For this purpose, one woman in the household (aged between 15 and 49 years) is randomly selected based on the last digit of the household's questionnaire ID code. Women chosen to participate in this section are asked about four different dimensions of IPV during the 12 months preceding the survey. First, they are asked about physical violence. This includes whether the woman has been pushed or had an object thrown at her; slapped; hit (with a fist or an object); kicked or dragged; attacked (or threatened) with a knife, gun, or other weapons; or at risk of being choked/burned. The second dimension is emotional violence: whether a woman's partner has threatened her with leaving home and taking away the kids; posed a threat to hurt her; or humiliated her. Sexual violence includes whether a woman's partner has forced her to have sex when she did not want to or forced her to do sexual acts she did not approve of. Finally, women are asked about control issues: whether a woman's husband gets jealous when she talks to another man; accuses her of infidelity; doesn't allow her to see her friends; limits her contact with relatives; insists on constantly knowing her whereabouts; or does not trust how she manages money. Our main dependent variable measures if a woman has experienced any of these types of abuse during the last year.

In this paper, we use nine repeated cross-sections (2010-2018) of the DHS. Our estimation sample is made up of ever-partnered women (aged 15-49) living in the Peruvian highlands. Importantly, the DHS data is collected throughout the year. In fact, each monthly round of the DHS is nationally representative for some key health and demographic variables; and each semester of data is representative of urban/rural areas. This design allows for areas to be sampled more than once during any given year. This is an important feature of the data considering that our empirical strategy (described in Section 4) exploits variation over time within districts.

Another important characteristic of the DHS is that (since 2010) it provides approximate geographical coordinates for households: it reports the longitude and latitude of the centroid of the household's village (in rural areas) or neighborhood block (in urban areas). Using this granular data, we are able to match each particular household with the weather shocks they have experienced.

3.2 Weather Data

We collect detailed hourly temperatures (i.e., at midnight, 1 AM, 2 AM,..., 11 PM) for every day between 2011 and 2018 from the European Centre for Medium-Range Weather Forecasts (2018) (ECMWF).[10] The ECMWF estimates temperatures from weather stations, satellites, and sondes, and processes this information at a geographic resolution of 0.25 degrees. We match household data from the ENAHO with the ECMWF weather data using two critical pieces of information: households' approximate GPS location (provided at the level of the primary sampling unit or the survey block) and each household's month and year of interview. This allows us to construct a household-specific measure of extreme cold exposure throughout the year prior to interview (the standard recall period for most survey questions), which takes into account both the location of the household and the timing of the interview.

We build on the widely used cumulative degree days measure from Schlenker and Roberts (2006) and estimate the number of cumulative degree *hours* in which a household experienced extreme cold temperatures. This measure aims to combine both the amount of time and the severity of a climatic shock — i.e., for how long and by how much a household experienced temperatures below a certain threshold. Therefore, this measure combines both the duration and intensity of frost events. Denote the temperature threshold λ, where λ= 0°C, -1°C, -2°C,... , -12°C. We begin by

[10]In particular, we use the ERA5 dataset, which provides the latest reanalysis data on global climate and weather for the past several decades.

defining harmful degree hours (i.e., hours of exposure to temperatures below the threshold λ) as:

$$DegreeHours(DH_{itmdh}) = \begin{cases} \lambda - h_{itmdh} & \text{if } h_{itmdh} < \lambda \\ 0 & h_{itmdh} \geq \lambda \end{cases} \tag{1}$$

where h_{itmd} is the temperature in household i's location, on year t, month m, and hour h. For example, if λ=-1°C, an hour of temperature at -3°C represents 2 degree hours; while an hour at a temperature of -2°C would lead to only 1 degree hour. Because there is no clear definition of a "harmful" threshold, we show our results using a wide range (from 0°C to -12°C) of temperature thresholds.

Our primary measure of extreme cold exposure is the *cumulative* degree hours (CDH) below threshold λ that household i interviewed in month m and year t experienced over the 12 months prior to the survey.

$$CumulativeDegreeHours(CDH_{it}) = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} DH_{itmdh} \tag{2}$$

Finally, we extract rainfall data from the Weather Hazards Group InfraRed Precipitation with Station Data (CHIRPS).[11] CHIRPS is a global dataset that provides high-resolution estimates of rainfall for 0.05 X 0.05 degree pixels. We match rainfall to households using GPS coordinates and interview dates from the ENAHO using the same procedure as we use for the temperature data.

3.3 Encuesta Nacional Agropecuaria (ENA)

We complement the weather data with data from the Peruvian ENA (National Agriculture Survey), also collected by the Instituto Nacional de Estadística e Informática (2018b). The ENA is a yearly cross-sectional dataset of agricultural households. Importantly, the ENA contains information about the timing of cultivation (sowing and harvesting). Information about when households grow crops is important because cold weather shocks could have a larger effect — at least in terms of agricultural income — during the months in which households grow their crops. We pool five rounds of the ENA (2014-2018) to build an agricultural calendar for each province. In particular, we calculate the share of households growing crops in each calendar month in each province, where we consider any months between sowing and final harvest as the growing period.[12]

[11] For a discussion of the CHIRPS dataset, please see Funk et al. (2015).

[12] For perennial crops (which do not have recurring sowing dates), we use the four months prior to harvest as the growing period.

3.4 Encuesta Nacional de Hogares (ENAHO)

The ENAHO is a detailed household survey collected annually by the National Statistics Office (*Instituto Nacional de Estadística e Informática* - INEI). The ENAHO collects detailed information about households' socioeconomic characteristics, and as in the DHS, provides households' approximate GPS location. We use the ENAHO for two purposes: to construct measures of agricultural and total income as well as expenditure, and to measure social program coverage.[13]

3.5 Mobility Data

In response to the COVID-19 pandemic, Google released province-level mobility measures aggregated from their users' location history data. Data were collected only for those users who opted into the location history feature and are only available starting in 2020. We use these data to demonstrate a relationship between cold weather shocks and daily mobility. For Peru, Google's mobility data include province-level changes in use of categorized places on Google Maps. We use data from the four types of categorized places with the most complete data during our time period: parks, workplaces, transit stations, and retail/recreational facilities. For each of these, we observe percent changes in the number of visitors relative to the median number of visitors observed during a pre-pandemic baseline (Jan. 3-Feb. 6, 2020). Baseline values are specific to the day of the week in which visitors were observed. To preserve anonymity, data are missing for any dates on which an insufficient number of visitors to a place category were observed. Data are most complete for parks (90% of province-days non-missing) and workplaces (78% non-missing).[14] We match temperature and rainfall data to the mobility data using the population-weighted average of weather measured at the centroids of all districts within each province.

Three features of the data and context are important for our purposes. First, the underlying set of users from whom data are collected are likely to change over time. Second, the set of categorized places may also change over time. Finally, Peru's government implemented strict mobility restrictions during the initial stages of the pandemic; these were largely eased a year into the pandemic. To limit the influence of these factors, we limit our sample period to the year of 2021.

3.6 Estimation sample

Our main estimation sample comes from nine repeated cross-sections of the DHS for 2010-2018. Due to the geographic concentration of frosts in higher altitudes, we restrict our data to the Peruvian highlands. To understand the role of extreme cold on IPV, our dataset includes women

[13]We consider whether households have access to a wide array of social programs: *Juntos* (the Peruvian Conditional Cash Transfer Program), *Pensión 65* (a non-contributory pension scheme for the poor elderly without access to social security transfers), INABEC (scholarship programs), job training programs (e.g., *Jóvenes a la Obra, Trabajando Perú, Vamos Perú*, etc.), and *Techo Propio* (soft loans for housing), etc.

[14]Google also publishes mobility data on grocery and residence locations; however, the coverage of these places is very low, and so we do not consider them here.

of reproductive age (i.e., 15-49 years old) that had ever been partnered. All in all, our estimation sample has information from 55,544 women (about 6,200 per survey year). We present some characteristics of our sample in the first column of Table 1. The average woman in the sample is 33 years old and has about 0.9 children under the age of five in her household. About 40% of those in the sample speak an indigenous tongue (i.e., different from Spanish), predominantly Quechua and Aymara. While about one fifth of women in the sample have some post-secondary education (e.g., technical or college); around one third of the sample had not even completed primary school and more than half had not completed their secondary education. Their households have on average 4.5 members and most of them (80%) have a male head. Our sample also reflects the high incidence of poverty in the Peruvian highlands. The DHS includes information about asset ownership from which a wealth index can be estimated.[15] Based on a national wealth index (calculated for *all* households in the DHS, and not only for those in the highlands), more than 40% of women in our sample fall into the poorest wealth quintile; and less than 15% are categorized in the wealthiest quintile.

Additionally, we also present summary statistics for several sub-samples in Table 1. In columns 2 through 6, we present the average characteristics of women who had not experienced any frosts (i.e., the temperature did not drop below 0°C) and those who had experienced frost shocks defined at different thresholds[16] (i.e., temperatures dropping below 0 °C, -4°C, -9 °C, or -12°C) during the last 12 months. The data suggest that women located in areas subject to alternative levels of climate shocks have different characteristics. For example, those in areas with higher incidence of frosts are more likely to have an indigenous language as their mother tongue and be in the bottom quintiles of wealth (also less likely to be in the top one). These compositional differences across areas inform our methodological approach (detailed in Section 4), where we condition our estimates on district-level fixed effects (and exploit *within* district variation over time) to estimate the causal effect of frost shocks on IPV.

[15] Similar to DHS data in other countries, the Peruvian DHS does not collect information about household incomes or expenditures.

[16] In other words, these are summary statistics for λ=0°C, -4°C, -9°C, and -12°C in Equation 2.

Table 1: Summary Statistics: Sample Characteristics

	Overall	Ever experienced frost shock at λ?				
		Never	$\lambda = 0$	$\lambda = -4$	$\lambda = -9$	$\lambda = -12$
Women characteristics						
Age	33.44	33.40	33.45	33.38	33.48	33.78
	(8.19)	(8.2)	(8.19)	(8.17)	(8.28)	(8.47)
Number of Children	0.87	0.87	0.87	0.87	0.84	0.81*
under 5	(0.73)	(0.74)	(0.73)	(0.73)	(0.75)	(0.77)
Native Spanish	0.62	0.71	0.59***	0.59***	0.55***	0.5***
speaker	(0.49)	(0.45)	(0.49)	(0.49)	(0.5)	(0.5)
Women's Education						
No education /	0.28	0.31	0.27	0.25**	0.26	0.29
Incomplete Primary	(0.45)	(0.46)	(0.45)	(0.43)	(0.44)	(0.45)
Complete Primary	0.14	0.18	0.13***	0.13***	0.14**	0.18
	(0.35)	(0.39)	(0.34)	(0.33)	(0.35)	(0.38)
Incomplete Secondary	0.15	0.13	0.15***	0.16***	0.16***	0.16***
	(0.36)	(0.33)	(0.36)	(0.37)	(0.37)	(0.37)
Complete Secondary	0.22	0.17	0.23***	0.24***	0.24***	0.25***
	(0.41)	(0.38)	(0.42)	(0.43)	(0.43)	(0.43)
College / Technical	0.21	0.21	0.21	0.23	0.2	0.13*
	(0.41)	(0.4)	(0.41)	(0.42)	(0.4)	(0.33)
Household characteristics						
Household size	4.49	4.50	4.49	4.47	4.35***	4.21***
	(1.62)	(1.62)	(1.61)	(1.61)	(1.6)	(1.57)
Household head is	0.82	0.83	0.81***	0.81***	0.78***	0.79***
male	(0.39)	(0.37)	(0.39)	(0.39)	(0.41)	(0.41)
Age of head of	39.99	40.95	39.75***	39.65***	39.57***	39.72***
household	(11.86)	(12.5)	(11.68)	(11.69)	(11.66)	(11.42)
Rural	0.56	0.65	0.54*	0.49**	0.57	0.66
	(0.5)	(0.48)	(0.5)	(0.5)	(0.49)	(0.47)
Household wealth						
Wealth group 1	0.42	0.49	0.4*	0.36**	0.42	0.46
(Poorest)	(0.49)	(0.5)	(0.49)	(0.48)	(0.49)	(0.5)
Wealth group 2	0.29	0.21	0.31***	0.33***	0.36***	0.39***
	(0.45)	(0.41)	(0.46)	(0.47)	(0.48)	(0.49)
Wealth group 3	0.15	0.12	0.16*	0.17**	0.13	0.11
	(0.36)	(0.33)	(0.36)	(0.38)	(0.34)	(0.32)
Wealth group 4	0.14	0.18	0.14	0.14	0.09	0.03***

... Continued

	Overall	Ever experienced frost shock at λ?				
		Never	λ=0°	λ=-4°	λ=-9°	λ=-12°
(wealthiest)	(0.35)	(0.38)	(0.34)	(0.35)	(0.28)	(0.18)
Spouse's education						
No education /	0.17	0.23	0.16***	0.14***	0.14***	0.16**
Incomplete Primary	(0.38)	(0.42)	(0.37)	(0.35)	(0.35)	(0.37)
Complete Primary	0.12	0.17	0.1***	0.09***	0.1***	0.1***
	(0.32)	(0.37)	(0.3)	(0.29)	(0.29)	(0.3)
Incomplete Secondary	0.21	0.20	0.22**	0.22**	0.23**	0.25***
	(0.41)	(0.4)	(0.41)	(0.41)	(0.42)	(0.43)
Complete Secondary	0.34	0.26	0.36***	0.38***	0.38***	0.38***
	(0.47)	(0.44)	(0.48)	(0.48)	(0.49)	(0.48)
College / Technical	0.16	0.14	0.16	0.18	0.16	0.11
	(0.37)	(0.35)	(0.37)	(0.38)	(0.37)	(0.31)
N	55544	11078	44466	32546	6564	2286

Notes: This table includes all women (aged 15-49) in the highlands who have responded to the domestic violence module of the DHS dataset between 2010-2018. We test whether each variable is significantly different between those that had experienced frost shocks (at $\lambda = 0, -4, -9, -12$°C) and those that had not. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.
† Asset-based household wealth index. The wealth index is calculated nationally for every round of the DHS.

In Table 2, we present the summary statistics for IPV incidence and extreme cold events in our dataset and outline the intuition behind our identification strategy. Considering an arbitrary threshold of λ=-9°C, we identify women in districts that did *not* experience any frost shocks (Column A) and those who experienced *at least* one frost episode (Column B) between 2010 and 2018. Among those with at least one shock, we separate those that had experienced shocks in the last 12 months (Column C) from those that report past or future shocks outside this time window (Column D). As suggested by Table 1, it is hard to interpret the variation in IPV between districts that never vs. ever experienced extreme cold events (B-A) because they are intrinsically different.[17] However, we can still compare how changes in IPV relate to exogenous fluctuations in temperature among women in a particular district that have experienced frost shocks in a given year relative to women that live in the same district but were interviewed in a different year without shocks. The results in Table 2 suggest that in districts that *ever* experience climatic shocks, overall IPV (and, especially, control issues) increases slightly in periods where there had been a frost in the past 12 months, relative to periods without such shocks (Columns C-D). In the subsequent sections, we

[17] Note that we still include data from districts that never experienced frost shocks in our regressions. While these observations do not identify the effect of the shock, they contribute to the identification of year effects and parameters related to our control variables.

test more rigorously for this possibility using the empirical approach described in Section 4.

4 Empirical Strategy

4.1 Estimating overall effects of frost shocks on IPV

To estimate the causal effects of extreme cold shocks on IPV, we employ a fixed effects strategy. Specifically, we estimate the following regression:

$$Y_{idmt} = \beta_1 CDH_{idmt} + \beta_2 AvgTemp_{idmt} + \beta_3 AvgRain_{idmt} + \beta_4 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt} \quad (3)$$

where Y_{idmt} is a measure of IPV in household i in district d interviewed in calendar month m of year t.[18] CDH_{idmt} is the number of degree hours below threshold λ that a household experienced in the 12-month period before being interviewed (as described in Section 3.2). Avg Temp$_{idmt}$ and Avg Rain$_{idmt}$ are the average temperatures and rainfall that household i experienced in the 12 months prior to the survey, respectively. Z_{idmt} is a vector of predetermined individual characteristics (respondent age and age squared, education level, mother tongue (to capture ethnicity)), household controls (sex and age of household head, indicators for wealth quintile, number of children under 5, a rural indicator), and husband's years of education.[19]

We include fixed effects at the district level (α_d), which account for spatial variation in the incidence of cold shocks and IPV that is constant over time. It is worth noting that even after conditioning on district fixed effects, there is still spatial variation in CDH, as weather data is matched to each household's approximate location (at a finer level than district) using the procedure described in Section 3.2.[20] We also include fixed effects at the interview year (γ_t) and month level (θ_m), which account for seasonality and general trends in IPV and cold shocks.

The coefficient of interest in is β_1. Our identification strategy assumes that – conditional on district, year, and month fixed effects (and other individual and household controls) – the incidence and intensity of cold shocks are exogenous with respect to IPV. While households might select into different districts (for example, wealthier households might choose to live in warmer areas), we exploit *within-district* variation in the intensity of cold shocks over time. In essence, we compare households within the same district who are interviewed at different times – and thus who are subject to different temperature fluctuations that vary randomly by the date of interview – while

[18]Our measures of IPV are binary, and so for these outcomes, equation 3 is a linear probability model. For ease of interpretation, the we multiply β_1 by 100 all tables where equation 3 is a linear probability model or where Y_{idmt} is transformed using the inverse hyperbolic sine. In Section 6 we also use versions of equation 3 to estimate the effects of frost shocks on intermediary variables, namely income and mobility.

[19]As described below, we regard CDH as exogenous (conditional on district-, year-, and month-fixed effects as well as average temperature). However, we include individual and household controls to improve precision. In section 5, we show that our results are not driven by the inclusion of covariates.

[20]Our data are cross-sectional in nature, so we are unable to include household-level fixed effects.

Table 2: IPV and Frost Shocks

		Households in districts...				Difference	
		without	who have experienced frost shocks ($\lambda = -9°C$)			with vs.	shock
	All	any frost shocks ($\lambda = -9°C$) **[A]**	All **[B]**	Shock prev 12 months **[C]**	No shock prev 12 months **[D]**	without shocks **[B]-[A]**	vs. no shock **[C]-[D]**
IPV (past 12 mos.)							
Any IPV	0.69	0.68	0.70	0.71	0.69	0.01	0.02
	(0.46)	(0.46)	(0.46)	(0.45)	(0.46)	(0.01)	(0.02)
Physical	0.13	0.12	0.15	0.15	0.15	0.02***	0.00
Violence	(0.33)	(0.33)	(0.35)	(0.35)	(0.36)	(0.01)	(0.01)
Emotional	0.16	0.15	0.19	0.18	0.19	0.03***	-0.01
Violence	(0.36)	(0.36)	(0.39)	(0.38)	(0.39)	(0.01)	(0.01)
Sexual	0.04	0.03	0.04	0.05	0.04	0.01**	0.01**
Violence	(0.19)	(0.18)	(0.21)	(0.23)	(0.19)	(0.00)	(0.01)
Control	0.66	0.66	0.67	0.68	0.67	0.01	0.02
Issues	(0.47)	(0.47)	(0.47)	(0.46)	(0.47)	(0.01)	(0.02)
Weather variables							
CDH ($\lambda = -9°C$)	0.60	0.00	5.04	14.24	0.00	5.04***	14.24***
	(8.27)	(0.00)	(23.58)	(37.93)	(0.00)	(1.07)	(2.39)
Average	9.34	9.73	6.45	5.22	7.13	-3.28***	-1.91***
Temperature	(3.24)	(3.17)	(2.13)	(1.54)	(2.10)	(0.37)	(0.45)
Total Rainfall	65.34	65.37	65.12	64.48	65.47	-0.24	-0.99
	(20.97)	(21.07)	(20.22)	(17.61)	(21.52)	(2.60)	(2.78)
N	55374	48829	6545	2318	4227		

Notes: Physical violence includes whether a woman has been: pushed or thrown something against; slapped; hit (with fist or object); kicked or dragged; threatened with a knife, gun, or other weapons; at risk of being chocked/burned; attacked with a knife, gun, or other weapons in the previous 12 months. Emotional violence includes whether a woman's partner has threatened her with leaving home and taking away the kids; posed a threat to hurt her; or humiliated her in the last 12 months. Sexual violence includes whether a woman's partner has forced her to have sex when she did not want to or forced her to do sexual acts she did not approve of. Control issues include whether a woman's husband gets jealous when she talks to another man, accuses her of infidelity, doesn't allow her to see her friends, limits her contact with relatives, insists on constantly knowing her whereabouts, or does not trust how she manages money. "Any IPV" captures whether a woman has experienced any physical, emotional, or sexual violence in the last 12 months.

[A]: Sample of households in districts that did not experience temperatures below -9°C between 2010 and 2018. **[B]**: Sample of households that have experienced at least one hour below -9°C between 2010 and 2018. The sample of households in **[B]** is further disaggregated into those that did experience frost events in the last 12 months (**[C]**) and those that did not (**[D]**).

Standard errors clustered at the district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

netting out general trends and seasonality in weather. As long as households are unable to anticipate fluctuations in the intensity of cold shocks, $\hat{\beta}_1$ will capture the causal effect of cold shocks.

4.2 Separately identifying income and exposure channels

In order to assess the relative importance of the income and exposure channels, we separate frost shocks that occur during the growing season versus the non-growing season. As described in Section 3.3, we use multiple rounds of a national agricultural survey to calculate the share of farmers actively growing crops in each calendar month for each province.[21] We consider the six months with the highest share of active farmers as the growing period in each province. This means that the months that constitute the growing period varies across provinces. Defining the growing period in this way also means that while we refer to "growing" and "non-growing" periods, there are some farmers who are actively growing crops during "non-growing" months and some farmers that are not actively growing crops during "growing" months. Nonetheless, we regard this distinction as important in separating frost shocks that will primarily affect time spent indoors versus both time spent indoors and agricultural income. This distinction appears meaningful, as according to this definition, nearly all (93.8%) farmers are actively growing crops during the "growing" season while only 57.2% of farmers do so during the "non-growing" season.[22]

We then construct modified versions of our CDH measure as follows:

$$\textit{Growing Season } CDH_{it} = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} Grow_{mp} \times DH_{itmdh} \tag{4}$$

$$\textit{Non-growing Season } CDH_{it} = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} (1 - Grow_{mp}) \times DH_{itmdh} \tag{5}$$

where $Grow_{mp}$ is an indicator of whether calendar month m is classified as a growing month for province p (as described above). we then run our main specification as in equation 3, but with separate growing and non-growing season CDH:

$$\begin{aligned} Y_{idmt} = {} & \beta_1 \textit{Growing Season } CDH_{idmt} + \beta_2 \textit{Non-growing Season } CDH_{idmt} + \\ & \beta_3 AvgTemp_{idmt} + \beta_4 AvgRain_{idmt} + \beta_5 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt} \end{aligned} \tag{6}$$

All controls and fixed effects are the same as in equation 3, but the parameters of interest in equation 6 are β_1 and β_2. Specifically, β_1 captures the effects of shocks that work through both the income and exposure channels, while β_2 captures (to a large extent) only those effects that

[21] In Peru, the province is the next administrative unit above (i.e. larger than) district. There are 196 provinces in all of Peru and 138 provinces in our sample.

[22] Authors' calculations based on 2014-2018 ENA data aggregated to the province-level.

work through the exposure channel. Thus we are also particularly interested in $\beta_1 - \beta_2$, which – assuming that the effects of frost shocks on exposure are the same in growing and non-growing seasons – captures the effects that work solely through the income channel.

5 Overall Effects of Extreme Cold on IPV

In Table 3, we show that extreme cold increases the probability that women experience IPV. We begin by running a basic version of equation 3 which includes only district, year, and month of interview fixed effects. We find that ten degree hours below the threshold of -9°C results in an increased likelihood of IPV of 0.42 percentage points, and this estimated effect is significant at the 10% level (column 1). In column 2, we add in basic woman and household controls, which adds precision; the estimate is now significant at the 5% level. Column 3 displays the results of our preferred specification, which adds in controls for husband characteristics (i.e., education levels). Here, we find that an additional 10 CDH below -9°C results in an increased likelihood of IPV of 0.52 percentage points. Note that controlling for husband characteristics drops about 600 observations from our sample because it limits the sample to women who are currently married. Nonetheless, the coefficient is nearly identical between columns 2 and 3, illustrating that this sample restriction does not substantively affect the results.

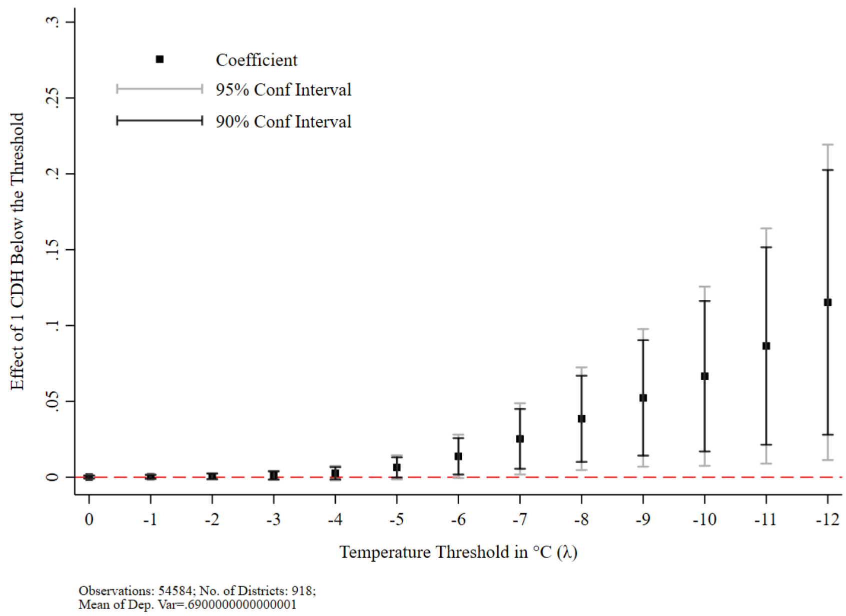
Table 3: Effects of Frost Shocks on Intimate Partner Violence

	Dep. Var.: Any IPV		
	Only Weather Controls	Including Woman Controls & HH	All Controls
	(1)	(2)	(3)
Cumulative Degree Hours (λ = -9°C)	0.042*	0.051**	0.052**
	(0.023)	(0.023)	(0.023)
Observations	55174	55174	54584
No. of Districts	918	918	918
Mean of Dep. Var	0.686	0.686	0.686

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2018. All specifications include average temperature and average rainfall at the household level in the past year as well as year, district, and month of interview fixed effects. Column 2 additionally includes individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), and household size. Column 3 adds fixed effects for husband's education level. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

In Figure 1, we illustrate the effects of frost shocks on IPV over a wide range of temperature thresholds (ranging from 0°C to -12°C). It appears that the frost shocks at low thresholds (above -5°C) have relatively small and statistically insignificant effects on IPV. However, with more extreme thresholds, the effects become statistically significant and grow considerably in magnitude. We find that an additional 10 hours below the most extreme threshold we consider (-12°C) increases the likelihood of experiencing IPV by 1.1 percentage points. For the remainder of the paper, we focus on the threshold of -9°C, the midpoint of thresholds that yield statistically significant effects.

Figure 1: Effect of Sub-zero Temperature Shocks on Intimate Partner Violence



Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2018. Controls include average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses.

The results in Table 3 and Figure 1 illustrate that overall IPV rises in response to occurrences of extreme cold. In Table 4, we examine the effects of frost shocks on individual components of overall IPV: physical, emotional, and sexual violence and controlling behavior. Extreme cold has the largest impacts on physical violence – such as being slapped, kicked, or attacked with a weapon — and on control issues – such as a husband limiting contact with friends and family. 10 additional CDH below -9°C increases the likelihood of physical violence by 0.33 percentage points (column 1) and control issues by 0.55 percentage points (column 4). Estimated effects on emotional violence (such as threats or humiliation) also increase by a considerable amount (0.3 percentage points), though the the effect is not statistically significant at conventional levels (p-value=0.128). Similarly, the point estimate is positive for effects on sexual violence (column 3), but smaller and not statistically significant (though still meaningful in magnitude, relative to the mean).

Table 4: Effects of Frost Shocks on Specific Dimensions of IPV

	Physical Violence (1)	Emotional Violence (2)	Sexual Violence (3)	Control Issues (4)
CDH (λ = -9°C)	0.033*	0.030	0.011	0.055**
	(0.019)	(0.019)	(0.020)	(0.026)
Observations	54778	54776	54778	54556
No. of Districts	918	918	918	918
Mean of Dep. Var	0.127	0.158	0.036	0.663

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2017. Controls include average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

6 Mechanisms

6.1 Effects on income and consumption

Extreme cold can have particularly severe consequences on agricultural output, an important economic activity in the highlands. Anecdotal evidence suggests that episodes of extreme cold can result in crop failures and livestock death, entailing significant economic losses in a variety of settings (Samora, 2021; Barbier, 2010; The Guardian, 2021; FAO, 2008; BBC News, 2015). This is further substantiated in the agronomy literature, which highlights that crops — including those that are most commonly grown in Peru, such as maize, potatoes, and *mashua* (a popular Andean tuber) — suffer when exposed to cold temperatures, especially for longer periods of time or during critical stages of growth (Lee and Herbek, 2012; Carter and Hesterman, 1990; Hijmans et al., 2001; Burrows, 2019; Janssen, 2004; Romero et al., 1989).

We estimate the effects of extreme cold shocks on income and expenditure using the strategy outlined in equation 3. We transform all monetary outcomes using an inverse hyperbolic sine transformation (IHST) to interpret the effects of extreme cold in terms of percentage changes while accounting for zero-valued observations. Table 5 shows that extreme cold substantially lowers agricultural income, total income, and consequently, expenditure. An additional 10 degree hours below -9°C in the past year lowers annual agricultural income by 1.25% (column 1) and total income by 0.78% (column 3). Total expenditure also falls by 0.25% (column 5), though the estimate is not significant at conventional levels. Consistent with earlier literature, we find that the effects of extreme weather shocks are smaller for total income and expenditure than for agricultural income, likely because households are able to mitigate the loss in agricultural income through secondary sources of employment in the non-farm sector, wage labor, credit access, migration and other consumption-smoothing mechanisms (Kubik and Maurel, 2016; Newman and Tarp, 2020). Nonetheless, even in light of these potential mitigation strategies, the net effects of cold shocks on income and expenditure are meaningful.

Table 5: Effects of Growing and Non-Growing Season Frost Shocks on Income and Expenditure

	Log(Agric. Inc.)		Log(Total Inc.)		Log(Expenditure)	
	(1)	(2)	(3)	(4)	(5)	(6)
CDH (λ = -9 °C)	-0.125***		-0.078*		-0.025	
	(0.043)		(0.047)		(0.034)	
Growing Season CDH (λ = -9 °C)		-0.421***		-0.143***		-0.144***
		(0.071)		(0.054)		(0.036)
Non-growing Season CDH (λ = -9 °C)		-0.062		-0.059		0.001
		(0.062)		(0.063)		(0.050)
p-value for Growing=Non-Growing		0.001		0.419		0.071
Observations	76202	76202	76202	76202	76202	76202
No. of Districts	944	944	944	944	944	944
Mean of Dep. Var	2481	2481	7804	7804	6077	6077

Notes: All income and expenditure variables have been transformed using the inverse hyperbolic sine function. The sample includes all households in the Highlands with agricultural revenue over the previous year using the 2007-2018 rounds of the ENAHO. Controls include (weighted) average temperature, average rainfall at the household level for over the same reference period as the frost shock, household head characteristics (sex, age, and age squared as well as education level and mother tongue fixed effects), log of total land (owned + rented), and household size fixed effects. All specifications include year, district, and month of interview fixed effects. District-level clustered standard errors in parentheses. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1. Mean of dependent variables are expressed in 2007 soles using the GDP deflator published by World Bank (2023).

We also separately estimate the effects of shocks occurring during in the growing season and non-growing season, following 6. As expected, the effects of extreme cold affect income and expenditure significantly in the growing season but not in the non-growing season. An additional 10 degree hours below -9°C in the past year lowers annual agricultural income by 4.21% (column 2), total income by 1.43% (column 4), and total expenditure by 1.44% (column 6), and all of these estimated effects are highly statistically significant. In contrast, shocks that occur outside of the growing season have much smaller and non-statistically significant effects on income and expenditure. For agricultural income and expenditure (columns 2 and 6), the effects of growing season and non-growing season shocks are statistically distinct from each other. Note that while a non-negligible share of farmers grow some crops during the non-growing season, the results in Table 5 illustrate that the non-growing season crops are either not significant contributors to household income, are invariant to cold shocks, or both. This insight will be useful in interpreting the effects of growing and non-growing season shocks on IPV, which we do below in Section 6.3.

6.2 Effects on mobility

We estimate the relationship between cold weather temperature shocks on mobility and find evidence that individuals forgo certain types of activities when it is cold. In Table 6, we find a

3.4 percentage point reduction in visits to parks (column 1), a 3.2 percentage point reduction in visits to retail and recreation locations (column 2), and a 3.8 percentage point reduction in visits to transit locations (column 3) for each degree-hour below -9°C. This pattern is consistent with extreme cold limiting time spent outdoors – e.g., in parks or waiting at outdoor bus or train stops. However, we do not find evidence that individuals change the likelihood of visiting a workplace when temperatures drop below -9°C (column 4).

Table 6: Effects of Frost Shocks on Mobility

	Dep. Var.: % Change in Number of Visitors from Baseline			
	Parks	Retail/Rec	Transit	Workplace
	(1)	(2)	(3)	(4)
Province-level CDH (λ = -9 °C)	-3.407***	-3.215***	-3.758***	0.227
	(1.165)	(1.164)	(1.238)	(0.231)
Observations	22447	9189	11432	19391
No. of Provinces	65	31	32	60
Mean of Dep. Var	-9.100	-11.629	-28.312	-5.572

Notes: The sample includes all provinces in the Peruvian Highlands for which Google released mobility data in 2021. All specifications include province, month, and day-of-week fixed effects. Province-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

6.3 Relative importance of income versus exposure channels

In sections 6.1 and 6.2, we showed that extreme cold has negative impacts on income and limits the mobility of individuals, particularly with respect to outdoor locations. This suggests that the impact of frost shocks on IPV may work through both income and exposure channels. To assess the relative importance of these channels, we separately identify the effects of shocks that occur during the growing and non-growing seasons (as described in Section 4.2). This is an important distinction, as extreme cold occurring during the growing season is likely to affect IPV through both channels, while extreme cold during the non-growing season should largely affect IPV through only the exposure channel. Indeed, as we showed in Section 6.1, non-growing season shocks have no statistically significant impacts on income or expenditure.

We estimate the effects of growing and non-growing season shocks in Table 7. In column 1, we reproduce our baseline estimate which gives the overall effect of frost shocks on IPV. In column 2, we only examine the effects of growing season shocks; in column 3, we examine only the effects of non-growing season shocks. Finally, in column 4, we include both types of shocks in the same specification. We find that the effects of extreme cold on IPV are driven almost exclusively by shocks occurring during the growing season. An additional 10 degree hours below -9°C during the growing season increases the probability of experiencing IPV by about 1.5 percentage points (column 4), and this effect is highly statistically significant. In contrast, the estimated effect is much smaller (0.4 percentage points) and not statistically significant for frosts taking place in the non-growing season. The two effects are statistically distinct; the p-value for the test that the effects are the same is 0.023.[23]

Table 7: Effects of Growing and Non-Growing Season Frost Shocks on Intimate Partner Violence

	Dep. Var.: Any IPV			
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.052**			
	(0.023)			
Growing Season CDH (λ = -9 °C)		0.153***		0.155***
		(0.047)		(0.048)
Non-growing Season CDH (λ = -9 °C)			0.039	0.040
			(0.026)	(0.026)
p-value for Growing=Non-Growing				0.023
Observations	54584	54584	54584	54584
No. of Districts	918	918	918	918
Mean of Dep. Var	0.686	0.686	0.686	0.686

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2018. Controls include average temperature and average rainfall at the household level in the past year (separately by growing and non-growing months in columns 2-4). We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

If we interpret the estimated effect during the non-growing season as largely capturing the effects working through the mobility channel, we would conclude that even though frost shocks limit outdoor time (shown in Section 6.2) and thus potentially increase exposure of women to violent partners, this has relatively small effects on IPV. To get a sense of the magnitude of the effect that works through the income channel, we can examine the difference in growing and non-growing season coefficients ($\beta_1 - \beta_2$ in equation 6). That difference suggests that the influence of frost shocks through the income channel is about 1.11 percentage points (for an additional 10 degree hours below -9°C); again, this difference is significant at the 5% level (p-value=0.023). Put another way, the income channel accounts for nearly three quarters (74.1%) of the total effect of frost shocks, with the exposure channel capturing about a quarter (25.9%).[24]

[23] To illustrate that our estimates are not an artefact of the way we define growing and non-growing seasons, we show that our results are robust to classifying the growing season using a more conventional definition of December through May (and a non-growing season of June through November) as in Aragón et al. (2021). These results (displayed in Appendix Table A1) are very similar to the growing calendar we construct using survey data.

[24] These calculations are based on the estimates in column 4 of Table 7 and the assumption that the total effect is captured by $\beta_1 = 0.155$, the exposure channel effect is captured by $\beta_2 = 0.040$, and the income channel effect is captured by the difference.

7 Heterogeneity by baseline social program coverage

To the extent that social assistance programs can mitigate the negative impacts of extreme cold on household income, they may also temper the effects of cold shocks on IPV. Many social programs are targeted at poor and marginalized populations and act as important sources of both steady income and "safety net" income in the case of adverse shocks. Thus access to these programs can be essential in facilitating income and consumption smoothing, potentially reducing financial stress that can act as a trigger for IPV.

To investigate the degree to which social assistance programs attenuate the effect of cold weather shocks on IPV, we construct a measure of social program coverage from the ENAHO. Specifically, we calculate the share of households in each province in which at least one member has been a beneficiary of a government-sponsored social program. As social assistance programs are targeted to poor households, we use the baseline share of *poor* (as opposed to all) households that receive government-sponsored social assistance. This measure automatically takes into account the underlying share of poor households. Because public programs can respond endogenously to frost shocks, we construct a baseline measure of coverage of social programs. Unfortunately, the ENAHO did not collect information about access to social programs prior to 2012. Thus, we estimate our measure of access to social programs based on this round.

As social program coverage data is only available starting in 2012, we restrict our analysis to the 2013–2018 rounds of the DHS (using 2012 coverage as our measure of baseline coverage). Thus, we begin by demonstrating that our main results in this restricted sample period (column 1 of Table 8) are similar to those using the full sample period, though they are not statistically significant (perhaps due to the nearly 30% reduction in sample size). In column (2), we add an interaction between CDH and the baseline share of social assistance beneficiaries. The results indicate that the effect varies greatly (and significantly) by baseline social program coverage. We find that, in provinces with low (10th percentile) social program coverage at baseline, extreme cold increases IPV: 10 degree hours below -9°C in the previous 12 months raises the likelihood of IPV by 0.72 percentage points (significant at the 95% level of confidence). In contrast, among households in provinces with high (90th percentile) baseline coverage, frost shocks appear to have no substantive effects on IPV.

8 Robustness Checks

8.1 Alternative measures of frost shocks

Throughout the paper, we generally focus on the effects of cumulative degree hours below -9°C in the 12 months prior to the date of interview. As discussed in Section 5, we find larger increases in IPV when we use colder temperature thresholds (λ) in our calculation of cumulative degree hours (Figure 1).

Additionally, we examine robustness to alternative windows of frost shocks in Appendix Table

Table 8: Heterogeneity by Baseline Social Program Coverage

	Dep. Var.: Any IPV	
	(1)	(2)
CDH (λ = -9°C)	0.036	0.089***
	(0.024)	(0.033)
CDH × Baseline Social Program Coverage		-0.069**
		(0.033)
Effect at the ... percentile of Baseline Coverage		
10th		0.072**
		(0.028)
90th		-0.008
		(0.034)
Observations	38841	38841
No. of Districts	801	801
Mean of Dep. Var	0.669	0.669

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2013-2018. Baseline coverage is defined as the share of poor households in the province receiving assistance from social programs in 2012 according to the ENAHO. Controls include average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

A2. Column 1 is our baseline result reflecting the effects of cumulative frost shocks experienced over the 12 months prior to the date of interview. Even though women are asked about IPV experienced over the past year, it is possible that women are more likely to recall more recent experiences of IPV and thus our dependent variable may be more likely to reflect (or more accurately reflect) IPV experienced in the months closer to the interview date. Consistent with this notion, columns 2 and 3 illustrate that the estimated effects are larger – though noisier – if we consider frost shocks over more recent windows (1 month and 6 months, respectively). Finally, in column 4, we show that our results are also similar when we consider a coarser binary indicator for whether a household has experienced any frost shocks over the year prior to the survey.[25] Experiencing a frost shock (regardless of the magnitude of the shock) increases the likelihood of experiencing IPV by 1.3 percentage points. However, the effects of this coarser measure are imprecisely estimated and are not statistically significant.

[25]In other words, this binary measure assigns a value of one to households that have experienced *any* positive values of CDH with a threshold of -9°C and zero otherwise.

8.2 Endogenous migration and changes in sample composition

One potential concern is that households may migrate in response to past shocks. This would mean that households who remain in areas experiencing relatively more frost shocks may be systematically different from those who live in areas with fewer shocks. To investigate this possibility, we begin by assessing whether household characteristics vary systematically with frost shocks. In Appendix Table A3, we find that there are no meaningful differences in observable characteristics according to frost shocks. Though there is a statistically significant relationship between frost shocks and one out of the eight characteristics considered (speaking Spanish, column 7), the magnitude of the relationship is very small. In addition, there is no association between frost shocks and fertility (as measured by the number of children under 5; column 8). In other words, there is no evidence that sample composition responds endogenously to frost shocks.

Next, we show that endogenous migration is unlikely to explain our results. In column 1 of Appendix Table A4, we show that the results are robust to restricting the sample to those who have always lived in their current residence (so-called "non-movers"). In columns 2-4, we assess whether households are likely to move in response to frost shocks (for example, to warmer areas with less extreme temperatures). We find no evidence that areas with fewer frost shocks have a larger proportion of migrant households.

8.3 Accounting for potential pretrends

Another potential concern is that there may be other unobserved shocks that vary temporally and spatially in ways that might be correlated with extreme cold. To illustrate that this is not the case, we first show that our results are robust to including department-by-year and department-by-calendar month fixed effects.[26] These fixed effects flexibly account for any shocks that vary by department and over time, such as other department-specific seasonal shocks and/or department-level economic conditions. Appendix Table A5 demonstrates that controlling for department-by-year and department-by-calendar month fixed effects (column 2) yields very similar estimates as the baseline specification (column 1). In column 3, we add district-specific (linear) trends in column 4 and find that even after accounting for these trends, extreme cold events increase IPV significantly.

8.4 Falsification exercise

As a final way to ensure that our measure of frost shocks captures exogenous weather shocks rather than systematic unobserved determinants of or prexisting trends in IPV, we perform a simple falsification test where we estimate the "effect" of future cold weather events. Specifically, we

[26] The department is the first administrative level, akin to a U.S. state. There are 26 departments in Peru (19 in the Highlands).

estimate a version of equation 3 where instead of focusing on CDH in the past 12 months to the survey, we include CDH in the 12 months *after* the interview date.

The results of this falsification exercise are displayed in Appendix Table A6. Because we estimate the "effects" of a 12-month lead of CDH and have weather data only through 2018, we begin by running our baseline specification (using shocks over the past 12 months) for the restricted sample period 2010-2017 in column 1. For this restricted time period, we confirm that frost shocks significantly increase IPV; if anything, the estimate is slightly larger for this restricted sample period. In column 2, we replace CDH over the past 12 months with CDH over the following (i.e., future) 12 months after the interview date. Here, we find no statistically significant relationship between IPV and future realizations of extreme cold temperatures. This null result helps us rule out the possibility that households can anticipate (and respond to) future frost shocks as well as the possibility that frost shocks simply capture unobserved determinants of IPV that vary systematically across households and/or geographic areas. They also help to dispel concerns about differential pre-trends in IPV that are related to frost shocks. Thus, we view the results in Appendix Table A6 as evidence that our main estimates capture the causal effect of extreme cold on IPV.

9 Conclusion

The findings in this paper highlight the importance of considering environmental factors in understanding and addressing violence against women. We show that extreme cold spells increase the likelihood of IPV, especially during the growing season, when they lower income and increase time spent indoors. Our findings suggest that climate shocks can have significant social and health implications for vulnerable populations, and that policies aimed at mitigating the adverse effects of frosts on income may help reduce IPV.

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A Appendix: Figures and Tables

Table A1: Effects of Frost Shocks on IPV: Dec.-May CDH vs. June-Nov. CDH

	Dep. Var.: Any IPV			
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.052**			
	(0.023)			
CDH Dec-May (λ = -9 °C)		0.181**		0.150**
		(0.070)		(0.071)
CDH June-November (λ = -9 °C)			0.055**	0.032
			(0.023)	(0.024)
p-value for Growing=Non-Growing				0.132
Observations	54584	54584	54584	54584
No. of Districts	918	918	918	918
Mean of Dep. Var	0.686	0.686	0.686	0.686

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2018. Controls include average temperature and average rainfall at the household level in the past year (separately by growing and non-growing months in columns 2-4). We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Alternative Definitions of Frost Shocks

	Dep. Var.: Any IPV in Past Year			
	(1)	(2)	(3)	(4)
CDH Past 12 months (λ = -9°C)	0.052**			
	(0.023)			
CDH Past 1 months (λ = -9°C)		0.117		
		(0.090)		
CDH Past 6 months (λ = -9°C)			0.072	
			(0.044)	
Any Frost in past 12 months (λ = -9°C)				1.349
				(1.754)
Observations	54584	54584	54584	54584
No. of Districts	918	918	918	918
Mean of Dep. Var	0.686	0.686	0.686	0.686

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2018. Controls include average temperature and average rainfall at the household level in the same window as the CDH. We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Frost Shocks and Sample Composition

	Household Size	Wealth Index	HH Head is Male	HH Head Age
	(1)	(2)	(3)	(4)
Cumulative Degree Hours (λ = -9°C)	0.001	0.000	0.006	-0.008
	(0.001)	(0.001)	(0.022)	(0.007)
Observations	54584	54584	54584	54584
No. of Districts	918	918	918	918
Mean of Dep. Var	4.496	2.028	0.819	39.919

	Age	Completed Secondary	Speaks Spanish	Number of Children Under 5
	(5)	(6)	(7)	(8)
Cumulative Degree Hours (λ = -9°C)	0.002	-0.009	-0.088*	0.000
	(0.003)	(0.029)	(0.047)	(0.000)
Observations	54584	54584	54584	54584
No. of Districts	918	918	918	918
Mean of Dep. Var	33.427	0.429	0.616	0.869

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2018; in column 1 (only), the sample restricted to women who have always lived in their current place of residence. Controls include average temperature and average rainfall at the household level in the past year. When not used as a dependent variable, we control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. For binary outcomes (only), coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Frost Shocks and Migration

		Migrated in last..		
	Any IPV	1 year	5 years	10 years
	(1)	(2)	(3)	(4)
Cumulative Degree Hours (λ = -9°C)	0.090***	0.000	0.002	0.021
	(0.033)	(0.006)	(0.015)	(0.022)
Observations	22544	53846	53846	53846
No. of Districts	882	918	918	918
Mean of Dep. Var	0.670	0.027	0.165	0.298

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2018; in column 1 (only), the sample restricted to women who have always lived in their current place of residence. Controls include average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Allowing for Differential Pretrends

	Dep. Var.: Any IPV in Past Year		
		Department-specific	District
	Baseline	Year and Month FE	Trends
	(1)	(2)	(3)
CDH (λ = -9°C)	0.052**	0.047**	0.052***
	(0.023)	(0.024)	(0.018)
Observations	54584	54584	54584
No. of Districts	918	918	918
Mean of Dep. Var	0.686	0.686	0.686

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2017. Controls include average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Falsification Test: Effects of Future Frost Shocks

	Dep. Var.: Any IPV in Past Year	
	(1)	(2)
CDH (λ = -9°C) in the *Previous* 12 Months	0.065***	
	(0.024)	
CDH (λ = -9°C) in the *Next* 12 Months		0.027
		(0.016)
Observations	46991	46991
No. of Districts	829	829
Mean of Dep. Var	0.691	0.691

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2010-2017. Controls include average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. All specifications include year, district, and month of interview fixed effects. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.