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

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Abstract

Violence against women — in particular, Intimate Partner Violence (IPV) — is a health concern for women across the world. We study the effect of cold exposure on IPV among Peruvian women. Using a dataset that matches women to weather exposure, we find that cold 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 then provide evidence that cold influences IPV through two main channels. First, extreme cold reduces income. 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 cold 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 cold on IPV is mostly driven by low temperatures that occur during the agricultural growing season, when income is most affected; 10 degree hours below -9°C during the growing season increases the probability of experiencing IPV by 1.6 percentage points. In contrast, we find that cold exposure outside of the growing season has no statistically significant effect on IPV.

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1 Introduction

Violence against women — in particular, Intimate Partner Violence (IPV) — affects one in three ever-partnered women worldwide (WHO, 2013; Sardinha et al., 2022). IPV victims suffer long-term physical and mental health problems, productivity losses (Campbell, 2022; Oram et al., 2022; Campbell, 2021), and economic suppression (Adams-Prassl et al., 2023). In low-income settings, IPV costs an estimated 1.5% to 4% of GDP (Ribero and Sánchez, 2005; Morrison and Orlando, 1999) and has intergenerational consequences, as 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; Hindin et al., 2008).

We are the first to study the effect of cold exposure on IPV. We do so in the Peruvian Highlands, where IPV is common (WHO, 2021) and where extreme cold events have become more frequent, affecting millions (Keller and Echeverría, 2013; FAO, 2008). We match women from nine rounds (2010-2018) of the Peruvian Demographic and Health Survey (DHS) to hourly temperatures from the European Centre for Medium-Range Weather Forecasts (ECMWF) using GPS coordinates and month of interview. Building on Schlenker and Roberts (2006), we calculate the cumulative degree hours in which households experienced temperatures below alternative thresholds (e.g., 0°C, -1°C, -2°C,..., etc.) during the year before the survey, taking into account both cold duration (i.e., time spent below a predefined threshold) and intensity (i.e, by how much temperatures dropped below that threshold). After conditioning on spatial and temporal fixed effects, we find that cold shocks increase IPV: 10 degree hours below -9°C increases the probability of experiencing domestic violence by 0.5 percentage points (pp).

We explore two channels through which cold can affect IPV: reduced income and increased time with a partner ("exposure"). Prior research suggests both negative and positive 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; Chong and Velásquez, 2024; Frankenthal, 2023) through negative-shock channels of increased stress, anxiety, and impulsive decision-making (Mani et al., 2013; Haushofer and Fehr, 2014; Haushofer et al., 2020) or through positive-shock channels of husbands' backlash against increased female-specific income and efforts to gain control over additional household resources (Bhalotra et al., 2021; Erten and Keskin, 2024, 2018; Bloch and Rao, 2002; Bobonis et al., 2013; Angelucci, 2008; Anderberg and Rainer, 2011; Lagomarsino and Rossi, 2023; Chin, 2012; Dhanaraj and Mahambare, 2022; Newiak et al., 2024).[1] Anecdotal evidence supports the exposure channel; assault hotlines report higher call volume during severe cold spells and winter storms (James, 2014), while police attribute spikes in domestic violence cases to weather-induced "cabin fever" (Whitehead, 2012). Evidence from other events that increase partner exposure – such as COVID-19 lockdown measures (e.g.,

[1] A smaller set of studies find no relationship between income shocks and violence against women (Blakeslee and Fishman, 2013; Iyer and Topalova, 2014; Kotsadam and Villanger, 2025).

Agüero, 2021; Arenas-Arroyo et al., 2021; Gibbons et al., 2021; Bhalotra et al., 2024; Erten et al., 2022), prolonged male unemployment (Bhalotra et al., 2025), or lack of female employment (Chin, 2012) – complement these observations.

We first provide evidence that both channels may be present during cold shocks. We use data from the Encuesta Nacional de Hogares (ENAHO) to demonstrate that cold exposure lowers agricultural revenue and total income, and Google location data to suggest that cold reduces time spent outside the home, proxied by location pings in parks, retail areas, and transit.[2] Then, critically, we present the first evidence of these channels' relative significance using variation in cold timing. Specifically, we use data on sowing and harvest dates to separate growing season cold shocks — which affect both household income and time spent at home — from non-growing season cold shocks, which primarily affect non-income mechanisms. Cold exposure during the growing season strongly affects IPV: experiencing 10 degree hours below -9°C increases the probability of IPV by 1.6 pp. In contrast, non-growing season cold has no statistically significant effects on IPV. Back-of-the-envelope calculations suggest that the income channel accounts for at least three quarters of the total effect of cold shocks.

Given the dominance of the income effect, we hypothesize that access to social assistance may mitigate these effects. We calculate *baseline* (before our period of analysis) regional social program coverage and interact this coverage with cold shocks. Effects of cold on IPV are large and significant where baseline coverage is low but not significantly different from zero where coverage is high. This suggests social assistance lessens the adverse effects of extreme cold on women.[3]

Our results are robust across a battery of specifications including alternative measures of cold (e.g., varying temperature thresholds or windows of shocks, accounting for spatial variation in defining cold shocks, and addressing the length of cold spells), and flexibly controlling for spatial heterogeneity in seasonality, pre-existing trends, and other spatially-specific temporal shocks. We find no evidence that endogenous migration or changes in sample composition explain our results. Finally, a falsification exercise shows that future shocks have no effect on IPV, illustrating that households do not anticipate cold shocks and that cold shocks are not systematically related to other unobservables.

This paper makes several contributions. We add insights to the growing literature on the determinants of violence against women, especially regarding extreme weather. While prior studies show drought and heat can increase IPV (Díaz and Saldarriaga, 2023; Abiona and Koppensteiner, 2018; Epstein et al., 2020; Sekhri and Storeygard, 2014; Henke and Hsu, 2020; Nguyen, 2024), we are the first to investigate whether *cold* temperatures affect IPV. In doing so, we also contribute to a small but growing literature on the effects of cold on violence more broadly (Anderson et al.,

[2] We do not distinguish between shocks to male and female income in this paper, as our data include only household (not individual) agricultural income.

[3] This aligns with recent studies finding cash transfers reduce IPV (Heath et al., 2020; Hidrobo et al., 2016; Díaz and Saldarriaga, 2022) and attenuate effects of *heat* on homicides (Garg et al., 2025).

2017; Zhang et al., 2006; Tol and Wagner, 2010; Otrachshenko et al., 2021). This literature is likely to become more salient over time; climate change increases average temperatures but is also expected to intensify weather variability, leading to more frequent extreme heat and cold episodes (Cai et al., 2015; Geng et al., 2023; Associated Press, 2025; Overland, 2016; Hanna et al., 2024; Nygård et al., 2023; Cohen et al., 2021). Indeed, though average temperatures have risen over time in Peru, minimum temperatures have remained steady (Appendix Figure A1), suggesting that cold temperature deviations from average temperatures are increasing. This may be particularly influential in agricultural communities as higher average temperatures cause plants to bud earlier, making crops more vulnerable to potential late-spring frosts (Limichhane, 2021).

We are also the first to quantify the relative importance of income compared to other mechanisms linking extreme weather to IPV. Whereas heat may additionally increase IPV through a biological or hormonal response (e.g., Anderson, 1987; Simister and Cooper, 2005) or impaired emotional and cognitive functioning (Bain et al., 2015; Schlader et al., 2015; Cho, 2017), evidence suggests no such biological link between cold and IPV (Anderson et al., 2000). As such, studying cold enables us to isolate the importance of income and exposure mechanisms. Among these mechanisms, we present novel evidence of the relative importance of income – one of the most oft-theorized causes of IPV.

Finally, our paper contributes to the policy discussion around IPV reduction in low-income countries. Poor households have limited savings and access to credit, often relying on public support to withstand unexpected adverse 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.

2 Context

Violence against women is unfortunately common in Peru; in 2019, 58% of Peruvian women experienced IPV (Agüero, 2021). Increasingly, Peru also experiences bouts of frosts and extreme cold events, affecting millions (Keller and Echeverría, 2013; FAO, 2008).[4] The Peruvian Highlands, located at elevated altitudes, are particularly susceptible to cold weather events (World Bank, 2008). In recent years, extreme cold temperatures dipped as low as -20°C in some areas, affecting close to 200,000 inhabitants (Centre for Research on the Epidemiology of Disasters, 2023). Most experts argue conditions will worsen, as Peru is one of the countries most vulnerable to climate change (Stern, 2007; Tambet and Stopnitzky, 2021).

Extreme cold can have severe consequences on agricultural output, an important economic activity in the highlands. For example, a frost in 2008 destroyed 45% of the potato production in several high-altitude Peruvian provinces (FAO, 2008). The damage induced by cold shocks depends on the intensity and the frequency of these events, the type of crops, and the phenological

[4] 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; Geng et al., 2023).

state of plants (Snyder and Melo-Abreu, 2005). The threat of frosts is a continual concern for much of the highlands: Peru's National Center for Disaster Risk Assessment, Prevention, and Reduction 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 frost (CENEPRED, 2021).

3 Data and Variables

Due to the nature and geographic scope of cold weather shocks in Peru, we focus our analysis on the Peruvian Highlands. Panel B of Appendix Figure A2 illustrates the geographic coverage of our sample, along with the average annual number of days with freezing temperatures. Our sample covers 918 districts, approximately half of the total districts in Peru. We outline our primary data below, with detailed supplements in Appendix A.1.

3.1 IPV Data

We obtain IPV and socioeconomic data from nine repeated cross-sections (2010-2018) of the Peruvian DHS, known as the Encuesta Demográfica y de Salud Familiar (Instituto Nacional de Estadística e Informática, 2018a).The DHS collects data annually from a representative sample of women aged 15 to 49 years, including four dimensions of partner abuse during the 12 months preceding the survey: physical, sexual, and emotional violence and a partner's control over a woman – such as whether he restricts contact with family or friends. Our main dependent variable captures whether a woman was a victim of any abuse during the past year.[5]

DHS data are collected throughout the year, with the exception of January and early February. Each monthly round of the DHS is nationally representative 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, which is important as our empirical strategy exploits variation in weather exposure over time within districts. Appendix Figure A3 confirms that interviews are conducted near uniformly throughout the year (except in January and February), in a way that is not correlated with the proportion of households in a growing season or experiencing extreme cold.[6]

Since 2010, the DHS provides the longitude and latitude of the centroid of the household's village or neighborhood block (in rural and urban areas, respectively) and the month and year of interview. Using these granular data, we match each household with the weather shocks experienced over the past year, aligning with the IPV recall period.

Our sample includes 54,555 ever-partnered women, with an average age of 33 and 8 years of completed education (Appendix Table A1). Nearly 70% experienced some form of partner abuse in

[5]Recent work illustrates that direct reporting of domestic violence in surveys is as reliable as more private, indirect methods (Agüero and Frisancho, 2022).

[6]Furthermore, in a household-fixed effects regression, interview timing is not related to cold exposure. Results available upon request.

the prior year. Almost all women who experienced abuse reported partner control problems (67% of the sample). Additionally, 13% of women experienced physical violence, 16% suffered emotional violence, and 4% reported sexual violence.

3.2 Weather Data

Our temperature data come from the ERA5 of the European Centre for Medium-Range Weather Forecasts (2018) (ECMWF), which estimates hourly temperatures from weather stations, satellites, and sondes at a geographic resolution of 0.25 degrees (31 km). These data are often used for reliable estimates of local weather; in our sample, they generate measures of cold that are very similar to those from Peru's Ministry of the Environment (Ministerio del Ambiente, SENAMHI) (see Appendix Figure A2).

We build on the widely used cumulative degree days measure from Schlenker and Roberts (2006) and calculate the number of cumulative degree *hours* in which a household experienced extreme cold. This measure combines both the duration and intensity of cold events — i.e., for how long and by how much a household experienced temperatures below a certain threshold, λ, where λ= 0°C, -1°C, -2°C,... , -12°C.

We begin by defining harmful degree hours (DH) for a given hour as:

$$\text{Degree Hours}(\text{DH}_{itmdh}) = \begin{cases} \lambda - h_{itmdh} & \text{if } h_{itmdh} < \lambda \\ 0 & h_{itmdh} \geq \lambda \end{cases} \tag{1}$$

where h_{itmd} is the temperature in household i's location, on year t, month m, day d, and hour h. This captures the extent to which the temperature in a given hour drops below a specific temperature threshold. Based on the agronomic literature, we choose a baseline threshold of -9°C, a temperature that is harmful for many crops grown in the highlands (Burrows, 2019; Lee and Herbek, 2012; Janssen, 2004; Hijmans et al., 2001; Carter and Hesterman, 1990; Romero et al., 1989). However, as sensitivity to cold can vary across crops, we show our results using a wide range of temperature thresholds (from 0°C to -12°C).

Our primary measure of extreme cold exposure — *cumulative* degree hours (CDH) — aggregates the DH experienced over the 12 months prior to the survey by household i interviewed in year t:

$$\text{Cumulative Degree Hours}(\text{CDH}_{it}) = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} \text{DH}_{itmdh} \tag{2}$$

We prefer CDH over coarser but easier to interpret measures – such as the number of days below a given temperature threshold – because the agronomic literature finds that both the extent and duration of cold exposure is harmful to crops. However, CDH does not distinguish between sustained exposure to cold and short-lived, more extreme dips in temperatures. We present results with alternative measures of cold in Appendix Table A9.

The average CDH at a threshold of -9°C in our sample is 0.6 (Appendix Table A1). However, this average masks substantial heterogeneity; among women living in areas that experienced cold below this threshold in a year (about 5% of women annually), the average CDH is 14.2 degree hours.

3.3 Income Data

To evaluate the mechanisms by which cold shocks affect IPV, we use income and social program coverage data from the Encuesta Nacional de Hogares (ENAHO). The ENAHO is a household survey collected annually by the Instituto Nacional de Estadística e Informática (2018c) that includes detailed information about households' socioeconomic characteristics and approximate GPS location. Using the ENAHO, we measure households' agricultural revenues, total income, and access to a wide array of social programs, including *Juntos* (a 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* (housing subsidies for low-income families).

4 Empirical Strategy

4.1 Estimating overall effects of cold shocks on IPV

To estimate the causal effects of extreme cold shocks, we employ a fixed effects strategy with the following regression model:

$$Y_{idmt} = \beta_1 \text{CDH}_{idmt} + \mathbf{\Gamma Z}_{idmt} + \alpha_d + \delta_t + \theta_m + \varepsilon_{idmt} \tag{3}$$

where Y_{idmt} is an outcome for woman/household i (typically a measure of IPV) in district d interviewed in calendar month m of year t. $\mathbf{Z}_{idmt}$ is a vector of predetermined individual, partner, and household characteristics (including altitude of the household) and other weather controls.[7] We include fixed effects at the district level (α_d) to account for spatial variation in cold shocks and inherent geographic differences in IPV[8] and at the interview year (δ_t) and month level (θ_m) to account for general trends and seasonality.

The coefficient of interest in Equation 3 is β_1. Our identification strategy assumes that — conditional on district, year, and month fixed effects — the incidence and intensity of cold shocks

[7] The full control set is listed in each table's notes and in Appendix A.2.

[8] We believe that district fixed effects are sufficient for several reasons. First, over 85% of the temperature variation in the sample takes place at the district-year level, i.e. little variation occurs at a level below the district. Second, we control for household-level altitude, which helps account for systematic variation in weather within districts. Finally, our results are unchanged when we match weather data by district centroid rather than household-specific location (column 1 of Appendix Table A7). In this specification, district fixed effects absorb all time-invariant heterogeneity in weather.

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 netting out general trends and seasonality in weather. As long as households cannot anticipate fluctuations in the intensity of cold shocks, $\hat{\beta}_1$ captures the causal effect of cold shocks.

4.2 Potential threats to identification

One concern is that households may migrate in response to shocks. We provide evidence in Appendix Tables A2 - A3 that systematic differences in sample composition and endogenous migration do not account for our results. Appendix Table A2 shows that households' observable characteristics do not systematically vary in response to extreme cold events. Importantly, cold shocks are not related to marital or partnership status, and thus do not affect selection into the sample. Appendix Table A3 shows cold shocks are also not related to migration behavior, and our primary results hold when we restrict the sample to "never-movers", i.e. those living in their district of birth.

To ensure that our measure of cold captures exogenous weather shocks rather than unobserved determinants of or preexisting trends in IPV, we show in Appendix Table A4 that there is no statistically significant relationship between IPV and *future* realizations of extreme cold temperatures. This helps us rule out the possibility that households respond to expectations of future shocks as well as the possibility that cold shocks capture unobserved determinants of IPV that vary systematically across households and/or geographic areas.

4.3 Separately identifying income and exposure channels

To assess the importance of the income channel relative to exposure and other channels, we separate cold shocks that occur during the growing season from the non-growing season.[9] We supplement the DHS data with multiple rounds of a large national agricultural survey conducted at the province level to calculate the share of farmers actively growing crops in each calendar month, detailed in Appendix A.2. We observe 138 provinces in our sample, and define the growing season for each province as the six months with the highest share of active farmers. We then separately estimate the effects of CDH occurring during the growing and non-growing seasons. To show that our results are not driven by endogenously constructed growing seasons, we show our results are robust to defining growing seasons nationally by calendar month as in Aragón et al. (2021). Importantly

[9] We view the effects of cold shocks in the non-growing season as primarily reflecting the exposure channel, though it may capture other non-income channels. Nonetheless, the *difference* in effects across the growing and non-growing seasons should measure the pure income (only) effect.

for identification purposes, cold shocks occur throughout the year in the highlands. Though they exhibit some seasonality, they occur during both growing and non-growing seasons; for example, they are about as likely to occur in September – a month in which virtually no households are growing crops – and December – a month in which the vast majority of households are growing crops (Appendix Figure A3).

Specifically, we separately calculate the CDH (-9°C) in the growing and non-growing seasons over the past year and estimate the following modified version of equation 3:

$$Y_{idt} = \beta_1 \text{Growing Season CDH}_{idmt} + \beta_2 \text{Non-Growing Season CDH}_{idmt} + \mathbf{\Gamma Z}_{idmt} + \alpha_d + \delta_t + \theta_m + \varepsilon_{idmt} \quad (4)$$

5 Overall Effects of Extreme Cold on IPV

In Table 1, we show that extreme cold increases the probability that women experience IPV. We find that each additional 1 CDH below -9°C over the past year increases the likelihood of IPV by 0.052 pp (column 1). Conditional on experiencing cold, average CDH is 14.2, implying that on average, women in households exposed to extreme cold are 0.72 pp more likely to be victims of IPV in a given year. This effect remains stable and statistically significant even when we consider a narrower definition of IPV that excludes controlling behavior, though the results are somewhat noisier. With this narrow definition, an additional CDH below -9°C increases IPV by 0.051 pp; alternatively, a one standard deviation increase in CDH leads to a 0.42 pp increase in the probability of IPV (a 2.1% increase over the mean). Columns 3-6 show that extreme cold is positively related to each component of overall IPV – physical, emotional, and sexual violence and controlling behavior – though the relationship is not statistically significant for sexual violence. Finally, in column 7, we find that extreme cold also increases IPV intensity, measured by the number of IPV types experienced by the woman. While our primary specification uses a -9°C threshold to measure CDH, Figure 1 illustrates the effects at alternative thresholds. Cold shocks at less severe thresholds have small effects on IPV, but the magnitudes of the estimated effects grow monotonically as the temperature threshold becomes more extreme.

To compare our results to other studies, we focus on the estimated effects on physical violence, which most closely aligns with the definition of IPV studied in other papers. Column 3 shows a one standard deviation increase in CDH leads to a 2.1% increase in the probability of physical violence at the mean. This is within the range of estimates from other studies; it is smaller than the estimated 4.4% increase in domestic violence for a 1-sd decline in rainfall in India from Sekhri and Storeygard (2014) and slightly larger than the estimated 1.8% increase in physical IPV for a 1-sd increase in a "dry shock" in Peru from Díaz and Saldarriaga (2023).[10]

[10] Calculated by dividing the "dry shock" coefficient from column 1 of Table 2 in Díaz and Saldarriaga (2023) by the sample mean, and multiplying by the imputed "dry shock" sd as implied from the mean of "dry shock" calculated from

Interestingly, we find evidence consistent with partner alcohol consumption as one proximate cause of IPV. In Appendix Table A5, an additional 10 CDH below -9°C increases the likelihood of a partner drinking alcohol by 0.3 pp, and the probability of getting drunk frequently by 0.27 pp.

5.1 Robustness Checks

In Appendix A.3, we show that our results are robust to a wide array of checks, including:

Alternative measures of temperature shocks. Our primary measure shows the effects of CDH below -9°C in the 12 months prior to the date of interview. In Appendix Table A7, we show that our results hold when defining CDH using district-specific thresholds based on historical temperature distributions to account for the possibility that harmful cold temperatures may functionally vary across districts. Additionally, our results are robust to considering alternative windows of cold shocks (Appendix Table A8), to using the more common measure of cumulative degree *days* (Appendix Table A9), and to focusing on the effects of extreme cold spells (defined as a continuous periods of time in which the temperature drops below the harmful threshold).

Extreme heat – while relevant for other contexts and in other studies – is exceedingly uncommon in the Peruvian Highlands. For example, Aragón et al. (2021) use 33°C as the harmful heat threshold when examining effects of heat on agricultural output and farmer behavior in Peru. Only 10 out of the 54,555 households in our sample experienced temperatures at or above 33°C in the year prior to being surveyed. Thus, we do not estimate the effects of extreme heat on IPV in our sample.

Administrative and timing-specific measures of violence. We use district-level police reports of violence against women to address two other potential concerns. First, self-reported IPV may reflect reporting bias if cold weather affects recall rather than actual experiences. However, we find a positive and significant relationship between extreme cold and police reports of violence (Appendix Table A6), suggesting the effect is not a recall artifact. Second, DHS measures only indicate *whether* (not when) IPV occurred in the past 12 months, making it impossible to establish precise timing between cold exposure and IPV. However, timestamped police data affirm that violence reports spike in the month when temperatures drop and are observed up to a year later (columns 1 and 2 of Appendix Table A6).

Flexibly controlling for spatial heterogeneity in seasonality, preexisting trends, and other spatially-specific shocks. In Appendix Table A10, we show that our results are robust to including month-by-year, district-by-month, and district-by-year fixed effects. This rules out any spurious correlation due to aggregate temporal shocks of almost any nature, district-specific seasonality, and district-specific shocks to or preexisting trends in weather and IPV.

columns 2 and 4 of Table 1.

6 Mechanisms

6.1 Effects on income and exposure

Evidence from supplementary data sources indicate that the impact of cold shocks on IPV may work through both income and exposure channels. First, Google Mobility data provide suggestive evidence that people in Peru forgo certain types of activities – such as visits to parks, retail and recreation locations, and transit locations – when it is cold.[11] This pattern is consistent with extreme cold limiting time spent outdoors – e.g., in parks or waiting at outdoor bus stops.[12]

Using ENAHO household finance data, we also find that extreme cold substantially reduces agricultural revenue. Table 2 shows an additional 10 degree hours below -9°C in the past year reduces annual agricultural revenue by 1.35% (statistically significant; column 1) and total income by 0.44% (not statistically significant; column 3).[13] Together with the results in column 1 of Table 1, these imply an income elasticity of IPV of -1.7. This is broadly consistent with other studies that find a negative relationship between income and IPV; for example, the implied elasticities from pandemic-induced income reductions in Peru and layoff-induced job loss in Brazil are -1.1 and -0.8, respectively (Agüero et al. (2024), (Bhalotra et al., 2025, p. 22)) while the implied income elasticity from cash and in-kind transfers in Ecuador is -2.7 (Hidrobo et al., 2016).[14] As with IPV, the effect of cold on agricultural revenue increases with more extreme temperature thresholds (Appendix Figure A5). The strikingly similar patterns across temperature thresholds for both IPV and agricultural revenue suggests that income is a likely mechanism linking cold exposure to IPV.

Importantly, extreme cold reduces agricultural revenue and total income significantly in the growing season but not in the non-growing season. Every 10 degree hours below -9°C during the growing season in the past year lowers annual agricultural revenue by 4.3% (Table 2, column 2) and total income by 2.3% (column 4). In contrast, shocks outside of the growing season have much smaller and non-statistically significant effects. For agricultural revenue, the effects of growing season and non-growing season shocks are statistically distinct from each other.

[11] Specifically, we find a 3.5 pp reduction in visits to parks, a 3.3 pp reduction in visits to retail and recreation locations, and a 3.8 pp reduction in visits to transit locations for each degree-hour below -9°C. We describe these data and results in Appendix A.1 and Appendix Table A11. We caution against over-interpretation of these results, as Google mobility data likely under-represents low-income individuals and is sensitive to changing user bases and geographic coverage in the underlying data.

[12] Neither Google Mobility nor ENAHO data suggest that individuals change the likelihood of visiting a workplace, working, or the number of hours worked when temperatures drop below -9°C. See Appendix Tables A11 and A12.

[13] We transform all monetary outcomes using an inverse hyperbolic sine transformation (IHST) to interpret estimates as percentage changes while accounting for zero-valued observations.

[14] Implied elasticity from Agüero et al. (2024) is calculated by the April-May effect of the lockdown on IPV (Table 2) by the April-May effect on household income, expressed in percent relative to the baseline mean (Table 3). Elasticity from Hidrobo et al. (2016) is calculated as the effect on physical IPV in percent relative to the control mean (Table 2) divided by the size of the transfer relative to baseline income as stated (p.287).

6.2 Relative importance of income versus exposure channels

We use the finding that non-growing season shocks have no statistically significant effects on income to assess the relative importance of the income and exposure channels. To do so, we separately identify the effects of shocks that occur during the growing and non-growing seasons. Extreme cold occurring during the growing season affects IPV through all channels, while extreme cold during the non-growing season affects IPV through only non-income channels. Thus, any difference in the magnitudes of these effects isolates income effects.

In practice, we find that the effects of extreme cold on IPV are driven exclusively by shocks occurring during the growing season. Table 3 shows an additional 10 degree hours below -9°C during the growing season increases the probability of experiencing IPV by about 1.6 pp (column 4), and this effect is highly statistically significant. In contrast, the estimated effect is much smaller (0.4 pp) and not statistically significant in the non-growing season. The two effects are statistically distinct (p-value=0.011).[15]

We find the income-only effect ($(\beta_1 - \beta_2)$ from Equation 4) is large and statistically different from zero (p-value = 0.011), indicating that the income channel increases IPV incidence by approximately 1.25 pp for each additional 10 degree hours below -9°C in the growing-season. By calculating the income share of the total growing-season effect ($\frac{\beta_1 - \beta_2}{\beta_1}$), we observe that the income channel accounts for at least three quarters (76.2%) of the total effect of cold shocks, with the exposure and other channels capturing at most a quarter (23.8%). This likely represents a conservative measure of the income channel, as the effect of non-growing season CDH is not statistically significant in Table 3. We confirm this result in Appendix Figure A6, in which income effect appears to dominate for any given temperature threshold. Interestingly, even if the income and exposure channels bind at *different* temperature thresholds – if, for example, the temperature that destroys crops is different than the temperature that makes it uncomfortable to leave the house – Appendix Figure A6 indicates that the income effect is likely to be at least as large as other effects. We show additional evidence that the income channel is the primary link between cold shocks and IPV in Appendix Table A14; the estimated effect of colds for households not reliant on agricultural income is close to zero, while the effect for households with agricultural earners is large (1.1 pp) and significant at the 95% confidence level.

7 Heterogeneity by baseline social program coverage

Because cold shocks affect IPV primarily through lost income, we next explore the extent to which social assistance programs can temper the effects of cold shocks on IPV. Many social programs act as important sources of both steady income and "safety net" income in the case of adverse shocks.

[15] Results are robust to classifying the growing season as December through May as in Aragón et al. (2021) in Appendix Table A13, affirming that they are not an artifact of our growing-season definition.

If access to these programs facilitates income and consumption smoothing, they may reduce the financial stress that can trigger IPV.

To investigate whether social assistance programs attenuate the effect of cold weather shocks on IPV, we construct a measure of social program coverage from the ENAHO: the share of *poor* households in each province in which at least one member has been a beneficiary of a government-sponsored social program. By construction, this measure accounts for the underlying share of poor households. Because program take-up may respond endogenously to cold shocks, we use data from 2012 (the earliest available year for this information) as the baseline measure of social program coverage and restrict our analysis to the 2013–2018 rounds of the DHS. We continue to include district fixed effects so that fixed differences across provinces (e.g., if some provinces are more progressive than others) do not confound the estimates.

We first show that our main results are robust to using this restricted sample period (column 1 of Table 4), 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 program coverage. The effect of cold exposure varies greatly (and significantly) by baseline social program coverage. In provinces with low (10th percentile) coverage at baseline, extreme cold increases IPV: 10 degree hours below -9°C in the previous 12 months increases IPV by 0.62 pp (p-value=0.027). In contrast, among households in provinces with high (90th percentile) baseline coverage, cold shocks appear to have no substantive effects on IPV (p-value=0.801). Column 3 illustrates that the patterns across growing and non-growing season shocks and social program coverage are also consistent. In Appendix Table A15, we show that these results are not driven by large districts or city capitals, differences in women's ages (which are related to social program eligibility), or political clout.

8 Conclusion

This paper highlights the importance of environmental factors in understanding and addressing violence against women. In a context in which climate change increases extreme weather events, we show that exposure to cold increases IPV victimization. Although cold can increase time spent inside with a potentially abusive partner, we find that lost income is far more influential, and households dependent on agriculture are particularly vulnerable to the effects of cold shocks during their crop growing season. Our findings suggest that climate shocks can have significant social and health implications for vulnerable populations. However, because lost income drives the effects, our results also indicate that policies aimed at mitigating the effects of adverse weather conditions on income may help reduce IPV.

While we do not have sufficient data to analyze *which* types of government support are best suited to this goal, recent evidence illustrates that increasing female labor productivity and access to women's justice centers, which provide police, legal, and medical services to women, can reduce gender-based violence in Peru (Sviatschi and Trako, 2024; Frankenthal, 2023). Our findings suggest that, at the margin, IPV is elastic; programs mitigating income shocks are likely candidates to reduce IPV.

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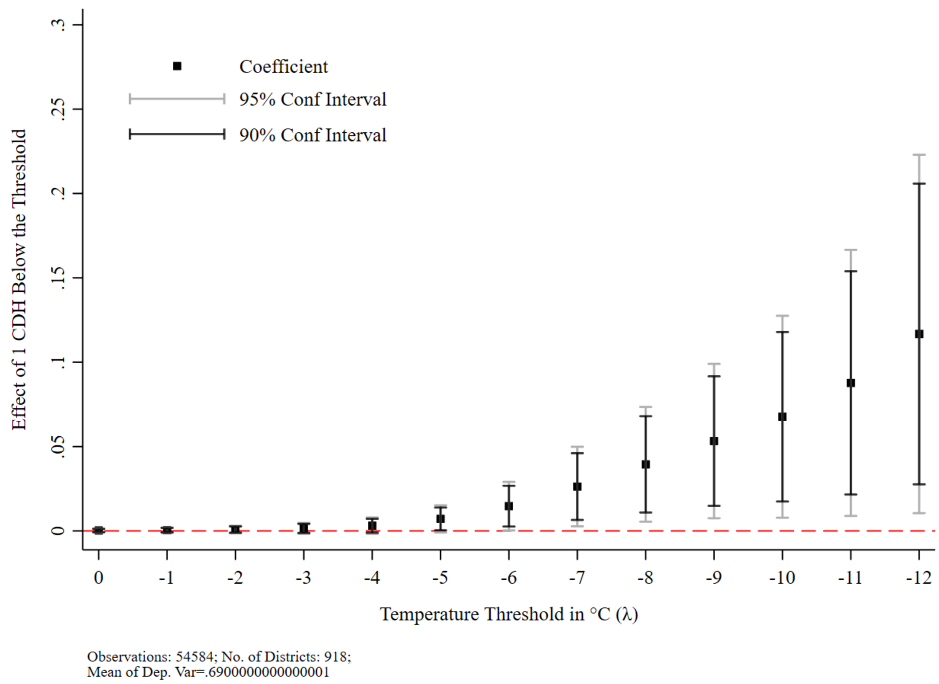
9 Figures and Tables

Figure 1: Effects of Cold Shocks on IPV across Temperature Thresholds



Notes: This figure displays the coefficients and associated 90% and 95% confidence intervals from regressions where the dependent variable is whether a woman has experience IPV in the past year. The explanatory variable is CDH at various thresholds, which capture cold shocks that occur in the past year. 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 altitude, average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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. Standard errors are clustered at the district-level.

Table 1: Effects of Cold Shocks on IPV

	Any IPV (Broad Def.)	Any IPV/Abuse (Narrow Def.)	Physical Violence Only	Emotional Violence Only	Sexual Violence Only	Control Issues Only	IPV Intensity (0-18)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CDH (λ = -9°C)	0.052**	0.051*	0.032*	0.032*	0.010	0.054**	0.224*
	(0.024)	(0.030)	(0.019)	(0.019)	(0.020)	(0.027)	(0.134)
Observations	54555	54555	54555	54555	54555	54555	54555
No. of Districts	918	918	918	918	918	918	918
Mean of Dep. Var	0.686	0.203	0.127	0.158	0.036	0.663	2.202

Notes: Cols 1-6: coefficients and standard errors have been multiplied by 100 for ease of interpretation. Col 7: IPV Intensity is the total number of IPV types that a woman has been the victim of in the past year. 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, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size fixed effects. All specifications include year, district, and month of interview fixed effects. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Effects of Growing and Non-Growing Season Cold Shocks on Agricultural Revenue and Total Income

	Value of Ag. Output		Total Income	
	(1)	(2)	(3)	(4)
CDH (λ = -9 °C)	-0.135***		-0.044	
	(0.042)		(0.055)	
Growing Season CDH (λ = -9 °C)		-0.432***		-0.229*
		(0.082)		(0.128)
Non-growing Season CDH (λ = -9 °C)		-0.084		-0.000
		(0.063)		(0.074)
p-value for Growing=Non-Growing		0.002		0.199
Observations	76642	76642	76642	76642
No. of Districts	944	944	944	944
Mean of Dep. Var	2747	2747	5552	5552

Notes: All dependent 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. Value of agricultural output in Cols. (1) & (2) is agricultural revenue. Total income excludes all extraordinary incomes and transfer amounts. Controls include average temperature, average rainfall at the household level for over the same reference period as the cold 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), altitude 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). Altitude is extracted using the Atlas (2022) data on World- Terrain Elevation Above Sea Level (ELE) GIS Data.

Table 3: Effects of Growing and Non-Growing Season Cold Shocks on Intimate Partner Violence

	Dep. Var.: Any IPV			
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.052**			
	(0.024)			
Growing Season CDH (λ = -9 °C)		0.162***		0.164***
		(0.046)		(0.047)
Non-growing Season CDH (λ = -9 °C)			0.037	0.039
			(0.026)	(0.026)
p-value for Growing=Non-Growing				0.011
Observations	54555	54555	54555	54555
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 altitude, 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, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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 4: Heterogeneity by Baseline Social Program Coverage

	Dep. Var.: Any IPV		
	(1)	(2)	(3)
CDH (λ = -9°C)	0.035	0.073**	
	(0.024)	(0.032)	
CDH × Baseline Social Program Coverage		-0.047*	
		(0.025)	
Growing Season CDH (λ = -9 °C)			0.685***
			(0.260)
Growing Season CDH × Baseline Coverage			-0.317
			(0.214)
Non-growing Season CDH (λ = -9 °C)			0.087***
			(0.031)
Non-growing Season CDH × Baseline Coverage			-0.068***
			(0.026)
Observations	38788	38788	38788
No. of Districts	796	796	796
Mean of Dep. Var	0.669	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 altitude, average temperature and average rainfall at the household level in the past year (separately by growing and non-growing months in columns 3-4). We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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.

A Online Appendix

A.1 Additional Data Sources

Weather Hazards Group InfraRed Precipitation with Station Data (CHIRPS). We extract daily rainfall data from the CHIRPS, a global dataset that provides high-resolution estimates of rainfall for 0.05×0.05 degree pixels (Funk, 2015). We match rainfall to households using GPS coordinates and interview dates using the same procedure as for the temperature data.

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). 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.[16]

Sistema Nacional de Denuncias Policiales (SIDPOL). To further validate our findings, we turn to another source of data: official police reports of domestic violence. Reports of physical and non-physical violence are collected by police stations and are made public via a dashboard by the Ministry of the Interior (Ministerio del Interior -Dirección de Gestión del Conocimiento, 2022). We scrape the dashboard to retrieve reports of violence against women at the district-month level for the years 2017-2022. We then normalize the number of reports by the number of women using the 2019 population estimates (Ministry of Health, Office of Information Management, 2022). Our final measure is the number of police reports per 100,000 women. These data are matched to weather data (from the ECMWF) measured at the centroids of districts, where the location of district centroids are calculated using QGIS and district shapefiles (The Humanitarian Data Exchange, The Humanitarian Data Exchange).

Mobility Data We use Google mobility data to provide additional evidence toward mobility as a potential mechanism for IPV increases (Google LLC, 2022). During the COVID-19 pandemic, Google began releasing 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

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

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).[17] 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. We use the official 2019 population estimates to calculate the weights (Ministry of Health, Office of Information Management, 2022).

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.

A.2 Additional Information about Primary Variables

Domestic violence. In the DHS, one randomly selected woman per household is asked about several dimensions of partner violence. First, she is 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 the 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 the 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.

Growing and non-growing seasons. We use the agricultural survey (ENA) to calculate the share of farmers actively growing crops in each calendar month for each province. 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 who are not actively growing crops during "growing" months. Nonetheless, we regard this distinction as important in separating cold shocks that will primarily affect time spent indoors versus both time spent indoors and agricultural income. This distinction appears meaningful: according to this definition, nearly all (93.8%) farmers are actively growing crops during the "growing" season while

[17] 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.

only 57.2% of farmers do so during the "non-growing" season.[18]

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

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

$$Non\text{-}growing\ Season\ CDH_{it} = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} (1 - Grow_{mp}) \times DH_{itmdh} \tag{6}$$

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 estimate Equation 4 with separate growing and non-growing season CDH, as described in the in Section 4.3.

Control set. The full control set for our main specification is altitude, age, age squared, an indicator for mother tongue is Spanish, household head characteristics (age and sex fixed effects), and fixed effects for education level, husband's education level, number of children under 5, and household size, as well as average temperature and rainfall over the previous year

A.3 Additional Results and Robustness Checks

Additional measures of partner abuse.

In Appendix Table A6 we show that there is a positive and significant relationship between extreme cold and police reports of violence against women. An additional 10 degree hours below -9°C in the current and previous month yields an additional 2.8 reports of violence against women per 100,000 women in the district (column 1), driven by reports of physical violence (column 2). Columns 4-6 illustrate that this relationship is robust to using CDH over the past 12 months, the same time frame as we use in our main specifications using the DHS. Moreover, we find a strikingly similar pattern of effects when we consider a range of harmful threshold temperatures in Appendix Figure A4 as when we use self-reported IPV from the DHS in Figure 1. Overall, we take the results in Appendix Table A6 and Appendix Figure A4 as validating the woman-level effects we present as our main results.

Alternative measures of cold shocks.

In Figure 1, we illustrate the effects of cold shocks on IPV over a wide range of temperature thresholds (ranging from 0°C to -12°C). Cold 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 1.2 pp. In the paper, we focus on the threshold of -9°C, the midpoint of thresholds that yield statistically significant effects.

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

In Appendix Table A7, we define CDH using district-specific thresholds that account for the possibility that the thresholds for harmful cold temperatures may vary substantially across districts. To do so, we define the harmful cold temperature using the historical distribution of hourly temperatures at the district- calendar month- level. In particular, we use the mean and standard deviations of hourly temperatures for each calendar month in each district separately for the time period 1996-2008 (the years leading up to our regression sample period). As we use district-level data to define these thresholds, we first show that our results are robust to matching households to district-level weather data using our baseline (fixed) threshold of -9°C (column 1). The estimated effect is smaller in magnitude (perhaps due to measurement error induced by matching at the district level) but still statistically significant. Columns 2 and 3 show that experiencing cold 2 and 3 standard deviations below the district- and calendar-month average temperatures increases IPV significantly.

Additionally, we examine robustness to alternative windows of cold shocks in Appendix Table A8. Column 1 is our baseline result reflecting the effects of cumulative cold 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 and thus not always statistically significant – if we consider cold 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 cold shocks over the year prior to the survey.[19] Experiencing a cold shock (regardless of the magnitude of the shock) increases the likelihood of experiencing IPV by 1.4 pp. However, the effects of this coarser measure are imprecisely estimated and are not statistically significant.

Appendix Table A9 shows that our results are also robust to using a measure of cumulative degree *days* (CDD), a commonly used measure in the literature. CDD are constructed similarly to cumulative degree hours and capture both the frequency and degree of extreme cold. A degree day is defined as the difference between the minimum temperature on a given day and the harmful temperature threshold and degree days are then aggregated over the previous 12 months to produce CDD. In column 2, we see that each additional degree day below -9°C increases the probability of experiencing IPV by 0.28 pp. If we instead use a simpler measure that only captures the number of days in which the minimum temperature dropped below -9°C (i.e., not accounting for the extent to which the minimum temperature dips below -9°C), we find that each additional day below -9°C increases the probability of IPV by 0.64 pp (column 2).

Columns 4 and 5 of Appendix Table A9 focus on the effects of extreme cold spells, where a cold

[19] 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.

spell is defined as a continuous period of time in which the temperature drops below the harmful threshold (for at least one hour). Column 4 shows that each additional cold spell over the past year results in a 0.61 pp increase in IPV. In column 5, we take into account the length of spells and find that longer cold spells are associated with larger increases in IPV. However, once we divide cold spells in this way, the estimated effects are no longer statistically significant.

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 year-by-month fixed effects (which flexibly capture any aggregate temporal shocks), district-by-calendar month fixed (to account for district-specific seasonality) and district-by-year fixed effects (to control for pre-existing trends in and district-specific temporal shocks to IPV).Appendix Table A10 demonstrates that controlling for these additional fixed effects yields very similar estimates (in both magnitude and significance) as the baseline specification.

Social Program Heterogeneity: Robustness.

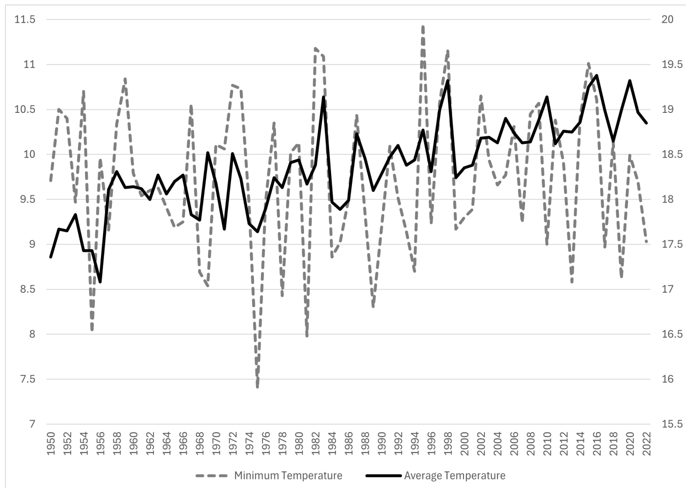
We rule out that our measure of social program coverage captures several other dimensions of heterogeneity in Appendix Table A15. We show that our results are not driven by department or city capitals (columns 2, 3), which tend to be the largest and most densely populated districts. In columns 4 and 5, we add in additional interactions to account for political clout as captured by the share of the province that voted for the winning party in the 2011 presidential election (column 5) and demographics - specifically, women's age, which could be related to social program eligibility[20] - in column 5. Across all of these specifications, we find point estimates that are very similar to our baseline estimates, though the estimates are not statistically significant in column 4.[21]

[20] Two of the largest social programs are Juntos (which targets children of school going age) and Pension 65 (which targets older men and women).

[21] In columns 4-5 we include the additional interactions after recentering the additional province variables to the sample mean for ease of interpretation.

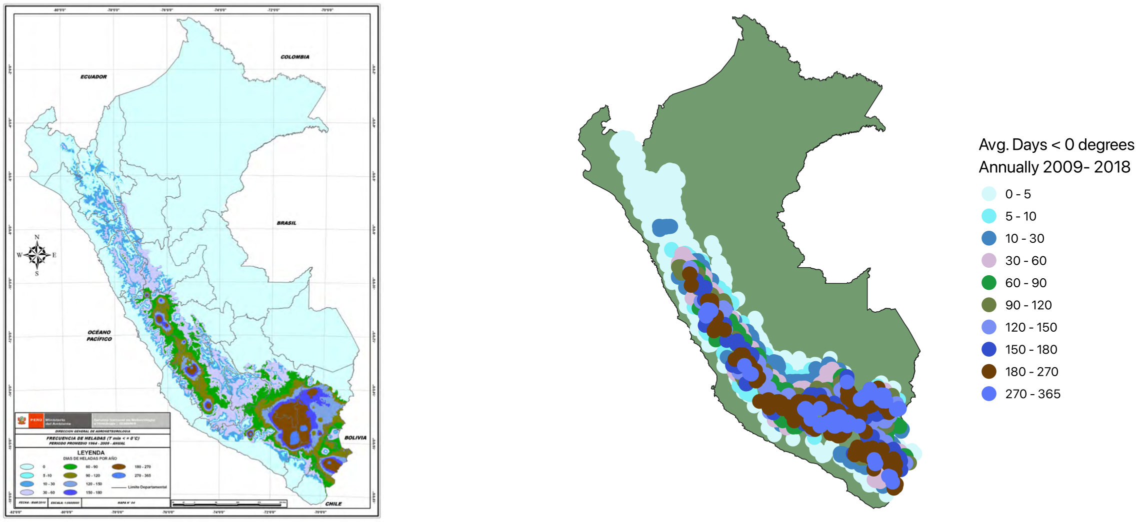
A.4 Appendix Figures and Tables

Figure A1: Average and Minimum Temperatures in Peru (1950-2022)



Notes: Data come from the ERA-5 as provided by the World Bank Climate Change Knowledge Portal (World Bank, 2025). Variables are the Average Mean Surface Air Temperature and the Minimum of Daily Min-Temperature (national averages).

Figure A2: Sample Area and Distribution of Freezing Temperatures

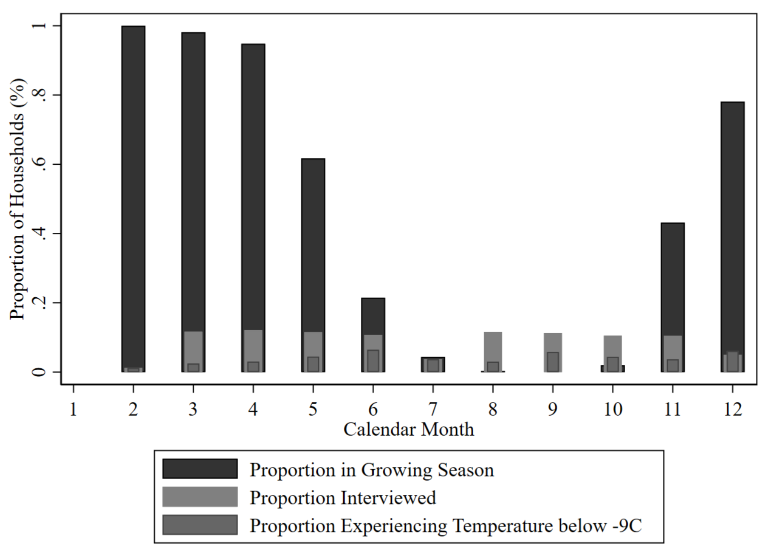


(a) Ministerio del Ambiente (1964-2009)

(b) ECMWF (2009-2018)

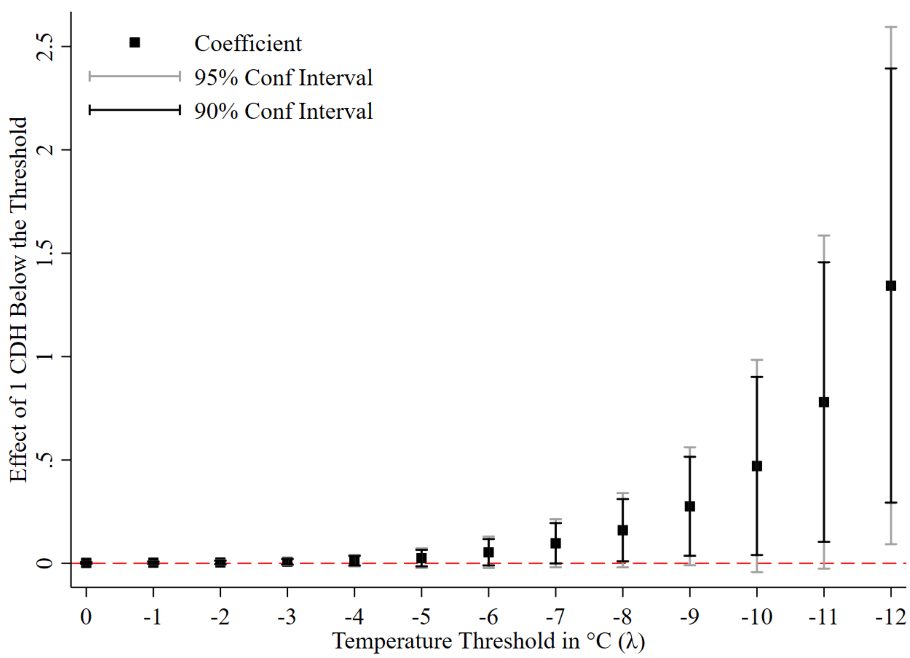
Notes: The above figure compares weather data from Peru's Ministerio del Ambiente (annual avg. 1964-2009) (SENAMHI, 2010) to the ECMWF data we use to evaluate cold shocks (annual avg. 2009-2018). Specifically, the Ministerio del Ambiente data use the count of days with a recorded minimum temperature below 0°Celsius, while using the ECMWF, we calculate the number days for which we observe at least one hour with an average temperature of below 0°Celsius.

Figure A3: Distribution of Interview Dates, Cold Shocks, and Growing Seasons



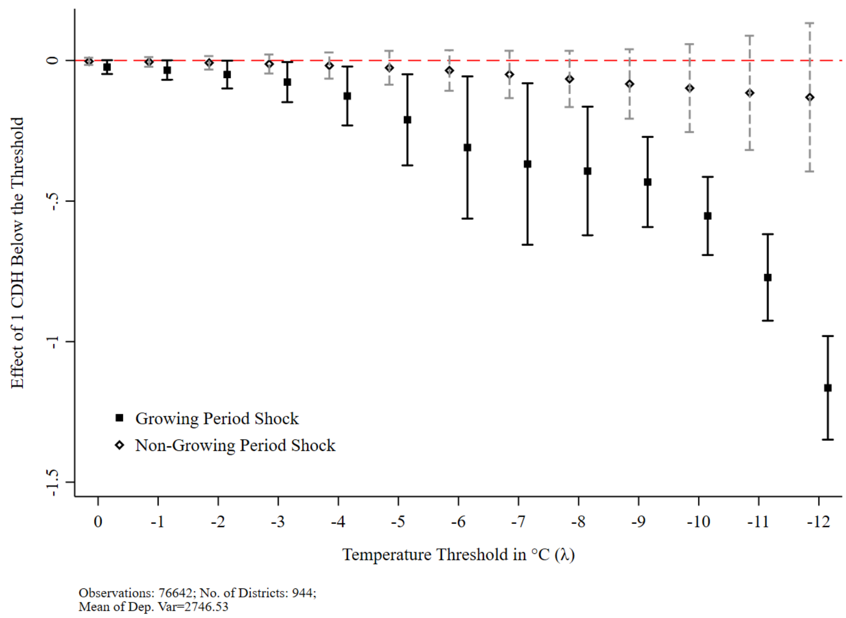
Notes: This figure displays the marginal effects and associated 90% and 95% confidence intervals from Poisson regressions where the dependent variable is the total police reports of violence against women of per 1,000 women by district and month between 2017 and 2022. The explanatory variable is CDH at various thresholds, which capture cold shocks that occur in the district over the current and previous month. All regressions include controls for average temperature and rainfall over the same reference period. Regressions also include district, month, and year by province fixed effects. Standard errors are clustered at the district-level.

Figure A4: Effects of Cold Shocks on Police Reports of Violence Against Women across Temperature Thresholds



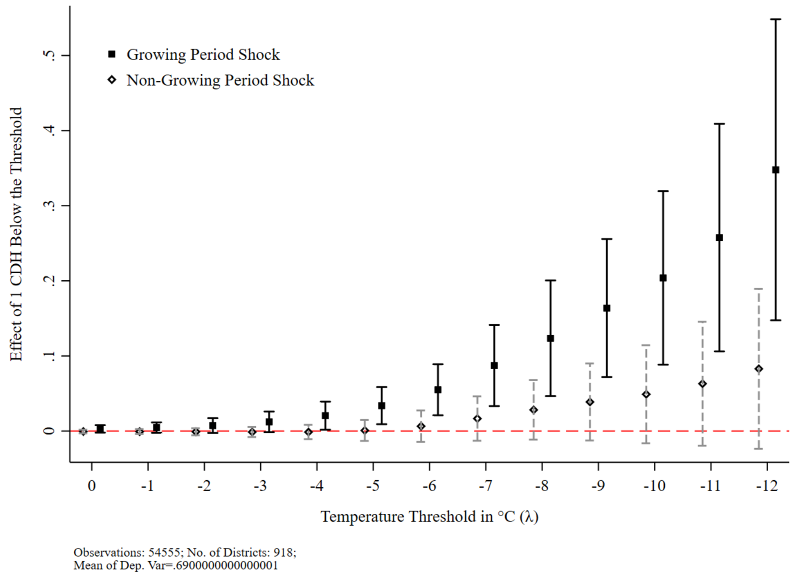
Notes: This figure displays the marginal effects and associated 90% and 95% confidence intervals from Poisson regressions where the dependent variable is the total police reports of violence against women of per 1,000 women by district and month between 2017 and 2022. The explanatory variable is CDH at various thresholds, which capture cold shocks that occur in the district over the current and previous month. All regressions include controls for average temperature and rainfall over the same reference period. Regressions also include district, month, and year by province fixed effects. Standard errors are clustered at the district-level.

Figure A5: Effects of Cold Shocks on Agricultural Revenue across Temperature Thresholds



Notes: This figure displays the coefficients and associated 90% and 95% confidence intervals from regressions where the dependent variable is (inverse hyperbolic sine-transformed) household agricultural revenue. The explanatory variables are CDH at various thresholds. 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 average temperature, average rainfall at the household level for over the same reference period as the cold 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), altitude and household size 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.

Figure A6: Effects of Growing and Non-Growing Season Cold Shocks on IPV across Temperature Thresholds



Notes: This figure displays the coefficients and associated 90% and 95% confidence intervals from regressions where the dependent variable is whether a woman has experience IPV in the past year. The explanatory variables are CDH at various thresholds, separately during the growing and non-growing seasons. 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 altitude, average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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.

Table A1: Sample Characteristics

IPV (past 12 months)		
	Any IPV	0.69
		(0.46)
	Physical Violence	0.13
		(0.33)
	Emotional Violence	0.16
		(0.37)
	Sexual Violence	0.04
		(0.19)
	Control Issues	0.66
		(0.47)
Weather variables		
	CDH 9	0.60
		(8.27)
	Average Temperature	9.34
		(3.25)
	Total Rainfall	65.34
		(20.98)
Women Characteristics		
	Age	33.43
		(8.17)
	Num. children under five	0.87
		(0.73)
	Native Spanish Speaker	0.62
		(0.49)
	Years of education	8.32
		(4.59)
Household Characteristics		
	Household size	4.50
		(1.61)
	Head of household is male	0.82
		(0.38)
	Age of head of household	39.92
		(11.80)
	Rural	0.56
		(0.50)
	Spouse's years of education	9.19
		(3.81)
	Wealth index (standardized)	0.00
		(1.00)
	Altitude (meters)	3161.8
		(678.2)
N obs		54555
N Districts		918

Table A2: Cold Shocks and Sample Composition

	Household Size (1)	Wealth Index (2)	HH Head is Male (3)	HH Head Age (4)	
Cumulative Degree Hours (λ = -9°C)	0.001	0.000	0.007	-0.008	
	(0.001)	(0.001)	(0.024)	(0.007)	
Observations	54555	54555	54555	54555	
No. of Districts	918	918	918	918	
	Age (5)	Completed Secondary (6)	Native Spanish Speaker (7)	Number of Children Under 5 (8)	Partnered or Married (ENAHO) (9)
Cumulative Degree Hours (λ = -9°C)	0.001	-0.007	-0.087*	0.000	-0.006
	(0.003)	(0.029)	(0.046)	(0.000)	(0.018)
Observations	54555	54555	54555	54555	91858
No. of Districts	918	918	918	918	953
Mean of Dep. Var	33.427	0.429	0.616	0.869	0.505

Notes: For columns 1-8, 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 altitude, 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. District-level clustered standard errors in parentheses. For column 9, we use data on women aged 15 and over (to match the DHS sample) from 2010-2018 rounds of the Peruvian National Household Survey (ENAHO). Controls include average rainfall (at the district-centroid level) and average temperature at the household level in the past year. We control for individual characteristics: age and age squared, years of education fixed effects, household size fixed effects, and whether the woman's mother tongue is an indigenous language. For all columns: 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. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Cold Shocks and Migration

		Migrated in last..		
	Any IPV (1)	1 year (2)	5 years (3)	10 years (4)
Cumulative Degree Hours (λ = -9°C)	0.092***	-0.001	0.003	0.023
	(0.034)	(0.006)	(0.015)	(0.023)
Observations	22534	53819	53819	53819
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 altitude, average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, mother tongue fixed effects, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), 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 A4: Falsification Test: Effects of Future Cold 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		0.028
		(0.017)
Observations	46965	46965
No. of Districts	829	829
Mean of Dep. Var	0.690	0.690

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 altitude, average temperature and average rainfall at the household level in the past year (and future year in column 2). We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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: Effects of Cold Shocks on Partner Alcohol Use

	Partner Drinks Alcohol	Partner Gets Drunk Frequently
	(1)	(2)
Cumulative Degree Hours (λ = -9°C)	0.032*	0.027***
	(0.017)	(0.009)
Observations	54777	54777
No. of Districts	918	918
Mean of Dep. Var	0.772	0.072

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. Controls include individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), household size, and 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.

Table A6: Effect of Cold on Police Reports of Violence Against Women

	All violence (1)	Physical violence (2)	Non-physical violence (3)	All violence (4)	Physical violence (5)	Non-physical violence (6)
CDH in current and previous month (λ = -9°C)	0.276*	0.229*	0.036			
	(0.146)	(0.118)	(0.071)			
CDH in the last 12 months (λ = -9°C)				0.300**	0.253***	0.049
				(0.127)	(0.098)	(0.045)
Observations	61548	60060	56352	61548	60060	56352
No. of Districts						
Mean of Dep. Var	68.079	41.307	30.331	68.079	41.307	30.331

Notes: This table reports the marginal effects of Poisson regressions where the dependent variables are the police reports for violence against women (total, physical, and non-physical) of per 1,000 women by district and month between 2017 and 2022. CDH captures cold shocks that occur in the district over the current and previous month (columns 1-3) or the previous year (columns 4-6). All regressions include controls for average temperature and rainfall over the same reference period. Regressions also include district, month, and year by province fixed effects. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Effects of Cold Shocks Defined using District- and Season-specific Thresholds

	Dep. Var.: Any IPV in Past Year (1)	(2)	(3)
Cumulative Degree Hours (λ = -9°C)	0.034***		
	(0.011)		
Cumulative Degree Hours (λ = 2 S.D.)		0.020**	
		(0.008)	
Cumulative Degree Hours (λ = 3 S.D.)			0.154***
			(0.055)
Observations	54555	54555	54555
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. We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size fixed effects. All specifications include altitude, 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 1 uses the district centroid temperature data. Column 2-3 use historical temperature data (1996-2008) to construct Cumulative Degree Hours using a relative harmful threshold (relative to a given district and month) defined as 2 and 3 standard deviations below the historical average temperature for a given district and calendar month. 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 A8: Effects of Cold Shocks over Various Time Frames

	Dep. Var.: Any IPV in Past Year			
	(1)	(2)	(3)	(4)
CDH Past 12 months (λ = -9°C)	0.052**			
	(0.024)			
CDH Past 6 months (λ = -9°C)		0.074*		
		(0.045)		
CDH Past 1 months (λ = -9°C)			0.116	
			(0.090)	
Any cold shock Past 12 months (λ = -9°C)				1.413
				(1.764)
Observations	54555	54555	54555	54555
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 altitude, average temperature and average rainfall at the household level in the same window as the CDH. We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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 A9: Effects of Cold Days and Spells

	Dep. Var.: Any IPV in Past Year				
	(1)	(2)	(3)	(4)	(5)
Cumulative Degree Hours$_($λ = -9°C)	0.052**				
	(0.024)				
Cumulative Degree Days (λ = -9°C)		0.284**			
		(0.113)			
Number of Days Below (λ = -9°C)			0.643*		
			(0.346)		
Number of Spells (λ = -9°C)				0.613*	
				(0.339)	
Number of Spells 1-4 hours (λ = -9°C)					0.381
					(0.423)
Number of Spells 5-8 hours (λ = -9°C)					1.306
					(1.680)
Number of Spells 9+ hours (λ = -9°C)					1.210
					(1.698)
Observations	54555	54555	54555	54555	54555
No. of Districts	918	918	918	918	918
Mean of Dep. Var	0.686	0.686	0.686	0.686	0.686

Notes: Cumulative degree days (CDD) in Column (2) are calculated based on minimum daily temperatures; we calculate daily shocks ($id = 0$ if $id > \lambda$, and $id = MinTemp_{id} - \lambda$ if $id \leq \lambda$) and aggregate them over the 12-month period prior to the household's interview date ($i = \sum_d Shock_{id}$). In Column (3) we calculate the number of days in which the minimum daily temperature fell below λ. Spells are defined as a continuous period of time in which the temperature drops below -9°C for at least one hour. 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 altitude, average temperature and average rainfall at the household level in the same window as the CDH. We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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 A10: Allowing for District-Specific Seasonality and Shocks/Pretrends

	Dependent Variable: Any IPV in Past Year			
	Baseline	Month-Year FE	District-specific Seasonality	District-specific Shocks/Trends
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.052**	0.054**	0.063**	0.066*
	(0.024)	(0.025)	(0.025)	(0.039)
Observations	54555	54554	54436	54544
No. of Districts	918	918	918	918
Mean of Dep. Var	0.686	0.686	0.686	0.686

Notes: For all columns: The sample includes all women (aged 15-49) in the Peruvian Highlands who responded to the domestic violence module of the DHS dataset between 2010-2018. Controls include altitude, average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size fixed effects. Column 1 includes year, district, and month of interview fixed effects. Column 2 includes year-by-month and district fixed effects. Column 3 includes district-specific month fixed effects and year fixed effects. Column 4 includes month fixed effects and district-specific year effects, which allow for both differential pre-trends by district and general yearly shocks that are specific to each district. 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 A11: Effects of Cold 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)	-3.498***	-3.298***	-3.784***	0.263
	(1.220)	(1.157)	(1.239)	(0.215)
Observations	22447	9189	11432	19391
No. of Districts	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. CDH is measured at the daily level for each province as the population weighted average of all district CDH in the province (population taken from official 2019 estimates (Ministry of Health, Office of Information Management, 2022)). 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.

Table A12: Effects of Cold Shocks on Daily Work

	Any Work (Indicator) (1)	Log Hours (Conditional) (2)
Daily Cumulative Degree Hours (λ = -9°C)	0.004	-0.102
	(0.084)	(0.131)
Observations	1882321	1207116
No. of Districts	268903	207283
Mean of Dep. Var	0.646	6.081

Notes: We use data from the Peruvian National Household Survey (ENAHO), which collects information about daily employment during the full calendar week prior to the individuals' interview date (e.g., if the survey takes place on a Wednesday, the questionnaire asks about employment between Monday and Sunday of the previous week). We restrict the sample to individuals 16 years or older, and estimate the regression $Y_{id} = \beta \text{DailyCDH}_{id} + \alpha_i + \gamma_d + \varepsilon_{id}$, where Y_{id} is either a binary variable that indicates whether individual i worked during day d or the logarithm of the number of hours worked. DailyCDH_{id} is the cumulative degree hours below a threshold of -9°C during a 24 hour-period. α_i are individual fixed effects; and γ_d are day-of-week fixed effects. In column 2, we estimate the effect of cold shocks on the number of hours of work. This sample is restricted to individuals who were employed during the reference week. Coefficients and standard errors have been multiplied by 100 for ease of interpretation. Individual-level clustered standard errors in parentheses. The mean reported in column 2 is for work hours (not log hours). Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Effects of Cold Shocks on IPV: Dec.-May CDH vs. June-Nov. CDH

	Dep. Var.: Any IPV			
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.052**			
	(0.024)			
CDH Dec-May (λ = -9 °C)		0.189***		0.160**
		(0.069)		(0.070)
CDH June-November (λ = -9 °C)			0.055**	0.031
			(0.024)	(0.025)
p-value for Growing=Non-Growing				0.096
Observations	54555	54555	54555	54555
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 altitude, 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, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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 A14: Heterogeneous Effects of Cold Shocks by Household Agricultural Status

	Baseline (1)	Including Interaction w/ Ag Earner Status (2)
Cumulative Degree Hours (λ = -9°C)	0.052**	0.031
	(0.024)	(0.024)
CDH $\times$ Agricultural Earners		0.083*
		(0.049)
Total effect for Ag HHs		0.114**
p-value for Total Effect		0.021
Observations	54555	54555
No. of Districts	918	918
Mean of Dep. Var	0.686	0.686

Notes: Agricultural Earner Status is a dummy variable for whether the woman's or her husband's primary occupation is in agriculture. 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 altitude, average temperature and average rainfall at the household level in the past year as well as year, district, and month of interview fixed effects. We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size fixed effects. Column 2 additionally controls for agricultural earner status. 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 A15: Heterogeneity by Baseline Social Program Coverage: Robustness

	Dep. Var.: Any IPV				
		Excluding Department	Excluding Province	Also Controlling for Interaction w/	
	Baseline	Capitals	Capitals	2011 Vote Shares	Woman's Age
	(1)	(2)	(3)	(4)	(5)
CDH (λ = -9°C)	0.073**	0.070**	0.070**	0.103*	0.075**
	(0.032)	(0.032)	(0.030)	(0.054)	(0.034)
CDH $\times$ Baseline Social Program Coverage	-0.047*	-0.046*	-0.060	-0.051	-0.051
	(0.025)	(0.025)	(0.037)	(0.033)	(0.032)
Observations	38788	34471	27151	38665	38788
No. of Districts	796	784	688	793	796
Mean of Dep. Var	0.669	0.671	0.672	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. The sample in column 2 excludes those living in department capitals and the sample in column 3 additional excludes those in province capitals. In addition to the controls listed below, column 3 includes an interaction with CDH and the share of poor households in the province (normalized to the sample mean); column 4 includes an interaction with CDH and the share of votes in the district in the 2011 presidential election that were cast for the winning party as reported by the Peruvian National Elections Commission (2011) (normalized to the sample mean); column 5 includes an interaction with age (normalized to sample mean). 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 altitude, average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, an indicator for mother tongue is Spanish, education fixed effects, number of children under five fixed effects); household head characteristics (age and sex fixed effects), fixed effects for husband's education level, and household size 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.