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 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 pp. 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 increases 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.

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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; Hindin et al., 2008), suggesting that IPV can self-perpetuate over time.

We are the first to 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 common[1] and where extreme cold events have become more frequent, affecting millions in recent decades (Keller and Echeverría, 2013; FAO, 2008). 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 GPS coordinates and household-specific month of interview. 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. Our measure takes into account both frost duration (i.e., time spent below a predefined threshold) and intensity (i.e, by how much temperatures dropped below that threshold). Conditional on spatial and temporal fixed effects, 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 (pp).

We explore two main channels through which frosts affect IPV. First, extreme cold can adversely affect agricultural output (Snyder and Melo-Abreu, 2005) and thus income. Previous research has found that income shocks can affect IPV, though there is no consensus about the direction of this effect. 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; Chong and Velásquez, 2024) through pathways of stress, anxiety, and impulsive decision-making (Mani et al., 2013; Haushofer and Fehr, 2014; Haushofer et al., 2020). However, there might be a positive relationship between income and IPV if controlling husbands exert instrumental violence to gain control over household resources (Erten and Keskin, 2024; Bloch and Rao, 2002; Bobonis et al., 2013; Angelucci, 2008; Anderberg and Rainer, 2011; Lagomarsino and Rossi, 2023).[2] To provide evidence that frost shocks affect IPV through economic status, we

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

[2] Other studies find no overall relationship between income shocks and violence against women (Blakeslee and

show that freezing temperatures — particularly those that occur during the crop-growing season — lower agricultural revenue and total income.

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; Bhalotra et al., 2024), 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, instances of extreme cold have been linked to increases in partner violence. For example, both the Rape, Abuse and Incest National Network 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 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 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 during the growing season strongly affect IPV: experiencing 10 degree hours below -9°C increases the probability of IPV by 1.5 pp. In contrast, non-growing season frosts have 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 frost shocks.

Given the dominance of the income effect, we hypothesize that access to social assistance may mitigate these effects. To test this, we calculate baseline (before our period of analysis) regional social program coverage and interact this coverage with frost shocks. Consistent with expectations, the effects of frosts on IPV are large and significant in provinces where baseline social program coverage is low, and not significantly different from zero in provinces where 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.[3]

Fishman, 2013; Iyer and Topalova, 2014). Though some study the effects of relative incomes of wives versus husbands on IPV (e.g., Frankenthal 2023), we do not focus on that literature here, as our data include only household (not individual) agricultural income.

[3] 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 in that we show how access to social assistance programs mitigates the effects of cold weather events on IPV.

Our results are consistent over a battery of robustness checks. Our results are not driven by any particular measure of frost (e.g., varying temperature thresholds or windows of 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 state 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 frost shocks and that frost shocks are not systematically related to other household- or district-level unobservables.

This paper makes several contributions to the existing literature. First, by evaluating the effects of extreme cold on IPV, we add insights to the growing studies on the determinants of violence against women, especially regarding the relationship between extreme weather and violence. Most of the literature has, so far, focused on the impact of drought or heat, 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; Henke and Hsu, 2020; Nguyen, 2024).[4] To our knowledge, we are the first to investigate whether *cold* temperatures also increase the incidence of IPV.[5] 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; Geng et al., 2023). Moreover, as average temperatures rise, plants bud earlier, making crops more vulnerable to the effects of potential late-spring frosts and more likely to fail (Limichhane, 2021). For these reasons, the effect of extreme cold on violence against women may become increasingly salient over time.

Second, we are the first to assess the relative importance of the income and exposure effects of extreme weather on IPV. While previous papers have estimated the effects of 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 behind these effects, addressing both income and exposure. While previous research has emphasized the role of income on violence, extreme weather can also alter individuals' routine activities and the time they spend outdoors (Cohn, 1990; Cohn and Rotton, 2000).[6] We present novel evidence about the relative importance of the income and exposure channels, where we find that the income mechanism dominates.[7]

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[4]However, others find no clear association between rainfall shocks and violence against women (Iyer and Topalova, 2014; Blakeslee and Fishman, 2013).

[5]Otrachshenko et al. (2021) find that extreme heat (but not cold) increases the incidence of violent deaths — relatively infrequent and extreme outcomes — in Russia, with larger impacts for women relative to men. In contrast, we focus on IPV, which includes more general and prevalent types of abuse against women.

[6]Both hot and cold extreme temperatures can theoretically evoke hormonal responses linked to increased aggression (Anderson, 1987, 1989; Simister and Cooper, 2005) and impair cognitive ability (Bain et al., 2015; Schlader et al., 2015; Cho, 2017). However, 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). Thus, for extreme cold weather shocks, the "income" and "exposure" channels are the most relevant ones.

[7]Our results build on Abiona and Koppensteiner (2018), who investigate 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. In contrast, 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.

Finally, our paper 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.

2 Context

Violence against women is unfortunately common in Peru; 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. 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 abuse in the past year.

Frosts and extreme cold events have become increasingly prevalent throughout Peru over the last two decades, affecting millions (Keller and Echeverría, 2013; FAO, 2008).[8] 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 (World Bank, 2008). In recent years, extreme cold temperatures have 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 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 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 frosts depends on the intensity and the frequency of these events, the type of crops, and the phenological state of plants (Snyder and Melo-Abreu, 2005). The threat of frosts is a continual 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 frost.

[8] 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). La Niña has been linked to frigid conditions in the Peruvian Highlands, with disastrous consequences (Barbier, 2010).

3 Data and Variables

3.1 Encuesta Demográfica y de Salud Familiar (Peruvian DHS)

We use nine repeated cross-sections (2010-2018) of the Peruvian DHS (Instituto Nacional de Estadística e Informática, 2018a).[9] The DHS collects data annually from a representative sample of women aged 15 to 49 years. It includes information about their socioeconomic characteristics, access to social programs, and health. Additionally, the DHS asks one randomly selected woman from each household about four dimensions of partner abuse during the 12 months preceding the survey: physical, sexual, and emotional violence as well as control issues (ways in which a woman's partner exerts control over her life, such as whether her partner restricts her contact with family or friends).[10] More details on these components of IPV are given in Appendix A.1. Our main dependent variable measures whether a woman was a victim of any of these types of abuse during the past year.

DHS data are collected throughout the year.[11] 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 in weather exposure over time within districts.[12]

Since 2010, the DHS provides approximate geographical coordinates for households: specifically, the longitude and latitude of the centroid of the household's village (in rural areas) or neighborhood block (in urban areas). The DHS also reports the month and year each household is interviewed. Using these granular data, we match each household with the weather shocks it has experienced over the past year (to match the IPV recall period).

Our sample includes 55,544 ever-partnered women (i.e., those potentially subject to domestic violence). Appendix Table A1 presents some basic characteristics of the sample. Women in the sample are 33 years old on average and about 40% report having an indigenous language as their mother tongue (as opposed to Spanish). Around one third of the sample has not completed primary and more than half has not completed secondary education. Nearly 70% of women experienced some form of partner abuse in the past year; much of this abuse related to partner control issues. Thirteen percent of women experienced physical violence, 16% suffered emotional violence, and 4% reported incidents of sexual violence.

[9] We describe additional sources of data in Appendix A.1.

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

[11] January is the only month in which the DHS does not conduct surveys.

[12] For example, this means that the data are not collected at a particular time based on the agricultural season.

3.2 Weather Data

We collect detailed hourly temperatures for each day between 2010 and 2019 from the ERA5 of the European Centre for Medium-Range Weather Forecasts (2018) (ECMWF). The ECMWF estimates temperatures from weather stations, satellites, and sondes at a geographic resolution of 0.25 degrees (31 km).[13] We match women from the DHS with the ECMWF weather data using each household's (approximate) GPS location and date of interview. This allows us to construct a household-specific measure of extreme cold exposure throughout the 12-month period prior to interview.

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 temperatures. This measure combines both the duration and intensity of frost events — i.e., for how long and by how much a household experienced temperatures below a certain threshold. Denote the temperature 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 (Lee and Herbek, 2012; Carter and Hesterman, 1990; Hijmans et al., 2001; Burrows, 2019; Janssen, 2004; 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 by a household interviewed in month m and year t experienced over the 12 months prior to the survey.

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

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

The average CDH over the past year at a threshold of -9°C for women in our sample is 0.6 (Appendix Table A1). However, this average masks substantial heterogeneity in weather across

[13]In terms of area, this is approximately equivalent to the average district size in Peru.

districts. For women who reside in districts that ever experience temperatures below this threshold (about 12% of the sample), the average CDH is 5 degree hours. Among women living in areas that experienced cold below this threshold in the past year (about 5% of women), the average CDH is 15 degree hours.

4 Empirical Strategy

4.1 Estimating overall effects of frost shocks on IPV

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

$$Y_{idmt} = \beta_1 \text{CDH}_{idmt} + \beta_2 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt} \quad (3)$$

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. Z_{idmt} is a vector of predetermined individual, partner, and household characteristics (including altitude of the household) and weather controls (average temperatures and rainfall over the previous year).[14] We include fixed effects at the district level (α_d) to account for spatial variation in cold shocks and inherent geographic differences in IPV[15] and at the interview year (γ_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 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.

[14] Covariates are listed in all table notes. In section 5, we show that our results are not driven by the inclusion of controls.

[15] Though there is some spatial variation in CDH at sub-district level, we believe that district fixed effects are likely to be 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 rather than household-specific location (column 1 of Appendix Table A6). In this specification, district fixed effects absorb all time-invariant heterogeneity in weather.

4.2 Separately identifying income and exposure channels

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 Appendix A.2, we use multiple rounds of a large national agricultural survey to calculate the share of farmers actively growing crops in each calendar month for each province. We consider the six months with the highest share of active farmers as the growing period in each province, such that the growing period varies across provinces. We then separately estimate the effects of CDH occurring during the growing and non-growing seasons.

5 Overall Effects of Extreme Cold on IPV

In Table 1, we show that extreme cold increases the probability that women experience IPV. We begin by including only district, year, and month-of-interview fixed effects. An additional ten degree hours (during the past year) below the threshold of -9°C increases the likelihood of IPV by 0.44 pp (significant at the 90% level of confidence, column 1).[16] In column 2, we add basic woman and household controls to improve precision; the estimate becomes significant at the 95% level. Column 3 displays the results of our preferred specification, which adds controls for partner education levels. Here, we find that an additional 10 CDH below -9°C results in an increased likelihood of IPV of 0.53 pp, or alternatively, a one standard deviation increase in CDH leads to a 0.43 pp increase in the probability of IPV.[17]

We explore the effects of shocks on individual components of partner abuse (physical, emotional, and sexual violence and control issues), as well as measures of IPV intensity and measures that focus solely on violence (omitting control issues) in Appendix Table A2. Overall, we find that extreme cold increases the likelihood and intensity of experiencing partner abuse across various measures. Furthermore, we find that extreme cold also increases a basic measure of IPV intensity (i.e., the number of IPV types experienced by the woman).

Interestingly, we find evidence that partner alcohol consumption is one proximate cause of IPV. In Appendix Table A3, an additional 10 CDH below -9°C increases the likelihood of a partner drinking alcohol by 0.3 pp (column 1) and the probability of getting drunk frequently by 0.27 pp (column 2).

[16]For ease of interpretation, we multiply β_1 by 100 in all tables where equation 3 is a linear probability model or where Y_{idmt} is transformed using the inverse hyperbolic sine.

[17]Controlling for partner education drops about 600 observations (women who are no longer partnered). Nonetheless, the coefficient is nearly identical in columns 2 and 3, illustrating that this sample restriction does not substantively affect the results.

5.1 Robustness Checks

In Appendix A.3, we show that our results are robust to a wide array of checks. Here, we briefly summarize those checks.

Administrative measures of violence. One potential concern is that self-reported IPV may reflect reporting bias – e.g., if cold weather does not affect experiences of IPV but changes whether women *recall* those experiences. To address this, we show that there is a positive and significant relationship between extreme cold and (district-level) police reports of violence against women (Appendix Table A5).

Alternative measures of frost shocks. 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). Frost shocks at low thresholds have relatively small effects on IPV; however, at more extreme thresholds, the effects grow considerably in magnitude. In Appendix Table A6, we show that our results hold when defining CDH using district-specific thresholds (using historical temperature distributions) to account for the possibility that what constitutes harmful cold temperatures may vary across districts.

Additionally, our results are robust to considering alternative windows of frost shocks (Appendix Table A7), to using the more common measure of cumulative degree *days* (Appendix Table A8), 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).

Endogenous migration, sample selection, and changes in sample composition

Another potential concern is that households may migrate in response to shocks. We provide evidence that sample composition and endogenous migration do not account for our results in three ways. First, Appendix Table A9 shows that households' observable characteristics do not systematically vary in response to extreme cold events. Frost shocks are also not related to marital or partnership status (column 9), ruling out the possibility that frost shocks affect selection into the sample. Second, our results are robust to restricting the sample to "never-movers", i.e. those living in their district of birth (Appendix Table A10, column 1). Finally, there is no relationship between CDH and migration behavior (Appendix Table A10, columns 2-4).

Accounting for potential pretrends and falsification exercise

In Appendix Table A11, we show that our results are robust to including department-by-year and department-by-calendar month fixed effects as well as to controlling for district-specific (linear) trends. As a final way to ensure that our measure of frost captures exogenous weather shocks rather than unobserved determinants of or preexisting trends in IPV, we show in Appendix Table A12 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 frost shocks capture unobserved determinants of IPV that vary systematically across households and/or geographic areas.

6 Mechanisms

6.1 Effects on income and exposure

We find that extreme cold substantially reduces agricultural revenue. An additional 10 degree hours below -9°C in the past year reduces annual agricultural revenue by 1.35% (Table 2, column 1) and total income by 0.44% (not statistically significant; column 3).[18] Together with the results in Table 1, these imply an income elasticity of IPV of -1.2. This is broadly consistent with other studies; for example, the implied elasticity from pandemic-induced income reductions in Peru is -0.9 (Hurtado et al., 2023). 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% (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. These results are useful in interpreting the effects of growing and non-growing season shocks on IPV (see Section 6.2).

Our primary method for disentangling income and exposure channels is to compare the effects of cold shocks on IPV in growing and non-growing seasons (described in the next section). However, using Google mobility data (detailed in Appendix A.1), we also find suggestive evidence that individuals forgo certain types of activities when it is cold. In Appendix Table A4, we find a 3.5 pp reduction in visits to parks (column 1), a 3.3 pp reduction in visits to retail and recreation locations (column 2), and a 3.8 pp 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 stops. However, we do not find evidence that individuals change the likelihood of visiting a workplace when temperatures drop below -9°C (column 4).[19] We caution against over-interpretation of these results, however, as Google mobility data likely under-represents low-income individuals and is sensitive to changing user bases and geographic coverage in the underlying data.

6.2 Relative importance of income versus exposure channels

The results in Section 6.1 suggest 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. This is an

[18] 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.

[19] Additionally, we estimate the effect of same-day CDHs on the probability of work and hours worked using individual- and day of the week- fixed effects regressions over a 7-day work period in the ENAHO. We find no relationship between labor outcomes and extreme cold events (Appendix Table A13).

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.[20] Indeed, as we showed in Section 6.1, non-growing season shocks have no statistically significant impacts on income or expenditure.

Table 3 shows 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 1.6 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=0.014).[21]

To understand the relative importance of the income channel, we examine the difference in growing and non-growing season effects[22], which suggests that the income channel accounts for about 1.22 pp (for each additional 10 degree hours below -9°C); this difference is significant at the 95% level of confidence. Thus, the income channel accounts for at least three quarters (75.3%) of the total effect of frost shocks, with the exposure channel capturing at most a quarter (24.7%), though this represents a conservative (liberal) measure of the income (exposure) channel, as the effect of non-growing season CDH is not statistically significant in Table 3.[23] We find additional evidence that the income channel is the primary link between cold shocks and IPV in Appendix Table A15. The estimated effect of frosts for households not reliant on agricultural income is close to zero (column 1), while the effect for households with agricultural earners is large (1.1 pp) and significant at the 95% confidence level (column 2).

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

[20] In theory, one could also separately estimate the effects of cold shocks that occur at different times throughout the day and night. In practice, CDH is very highly correlated within a 24-hour period – intuitively, because the coldest hours occur at night, we virtually never observe temperatures below -9°C during the day but not at night. Thus we cannot separately identify the effects of daytime versus nighttime cold shocks.

[21] To demonstrate that our estimates are not an artifact of the way we define growing and non-growing seasons, we show that our results are robust to classifying the growing season as December through May as in Aragón et al. (2021) in Appendix Table A14. Results are also robust to alternative harmful temperature thresholds (Appendix Figure A2).

[22] In particular, we estimate regression $Y_{idt} = \beta_1$Growing Season CDH$_{idmt} + \beta_2$Non-Growing Season CDH$_{idmt} + \beta_3 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt}$, and test whether $(\beta_1 - \beta_2)$ is different from zero (see Appendix A.2.)

[23] Calculations are based on the estimates in column 4 of Table 3 and the assumption that the total effect is captured by $\beta_1 = 0.162$, the exposure channel effect is captured by $\beta_2 = 0.040$, and the income channel effect is captured by the difference, $(\beta_1 - \beta_2)$.

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 Encuesta Nacional de Hogares (ENAHO). Specifically, we calculate 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 takeup can respond endogenously to frost shocks, we construct a baseline measure of coverage of social programs as of 2012 (the earliest year in which the ENAHO collects this information).

Since our baseline coverage measure is based on 2012 data, we restrict our analysis to the 2013–2018 rounds of the DHS. We first show that our main results in this restricted sample period (column 1 of Table 4) are similar to those using the full sample, 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. 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 increases IPV by 0.62 pp (p-value=0.027). In contrast, among households in provinces with high (90th percentile) baseline coverage, frost 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 A.3, we show that these results do not appear to be driven by large districts or city capitals, differences in women's ages (potentially related to social program eligibility), or political clout.

8 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.

While we do not have sufficient data to analyze *which* types of government support are best suited to mitigate the effects of adverse weather conditions, evidence from recent studies illustrates that access to women's justice centers (WJCs, which provide police, legal, and medical services to women) and increases in female labor productivity are effective in reducing gender-based violence in Peru (Sviatschi and Trako, 2024; Frankenthal, 2023). This suggests that increased provision of WJCs and support for women's work opportunities may help soften the blow of extreme cold on IPV.

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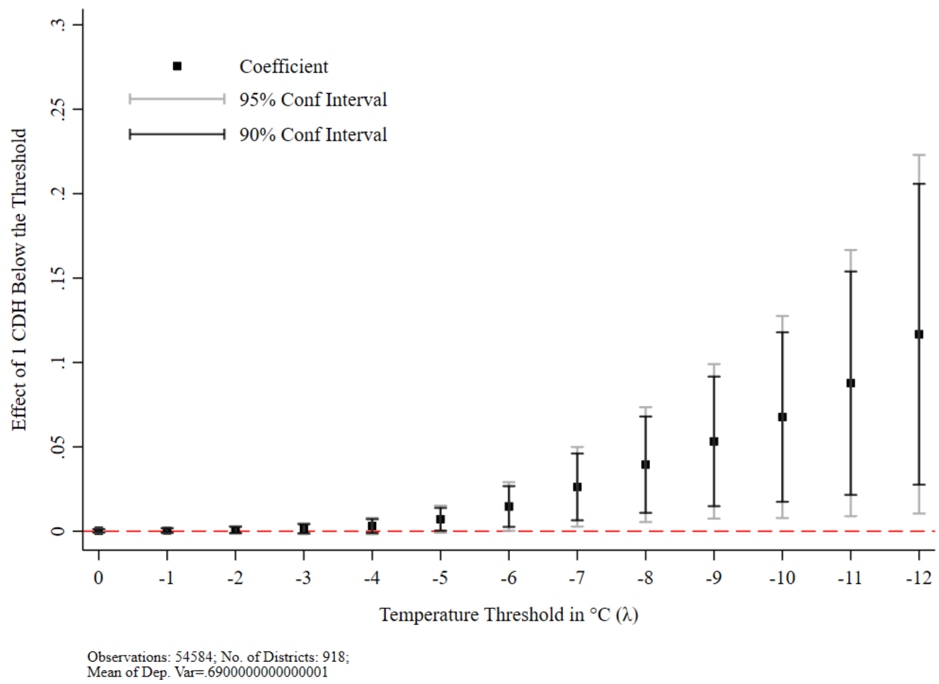
9 Figures and Tables

Table 1: 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)	0.044*	0.052**	0.053**
	(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 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 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.

Figure 1: Effects of Frost 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, 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. Standard errors are clustered at the district-level.

Table 2: Effects of Growing and Non-Growing Season Frost 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 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), 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 Frost Shocks on Intimate Partner Violence

	Dep. Var.: Any IPV			
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.053**			
	(0.023)			
Growing Season CDH (λ = -9 °C)		0.160***		0.162***
		(0.046)		(0.047)
Non-growing Season CDH (λ = -9 °C)			0.039	0.040
			(0.026)	(0.026)
p-value for Growing=Non-Growing				0.014
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 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, 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 4: Heterogeneity by Baseline Social Program Coverage

	Dep. Var.: Any IPV		
	(1)	(2)	(3)
CDH (λ = -9°C)	0.036	0.073**	
	(0.024)	(0.032)	
CDH $\times$ Baseline Social Program Coverage		-0.047*	
		(0.025)	
Growing Season CDH (λ = -9 °C)			0.672***
			(0.259)
Growing Season CDH $\times$ Baseline Coverage			-0.304
			(0.213)
Non-growing Season CDH (λ = -9 °C)			0.088***
			(0.031)
Non-growing Season CDH $\times$ Baseline Coverage			-0.069***
			(0.025)
Observations	38841	38808	38808
No. of Districts	801	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 column 3). 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: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A Online Appendix

A.1 Additional Data Sources

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).

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.[24]

Encuesta Nacional de Hogares (ENAHO). The ENAHO is a detailed household survey, also collected annually by the Instituto Nacional de Estadística e Informática (2018c). The ENAHO includes 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 revenue and total income and to measure social program coverage.[25] Household altitude is calculated based on the GPS coordinates of each households given in the ENAHO survey and elevation maps from Atlas (2022). Values of agricultural revenue and total income are deflated using the GDP deflator as reported by World Bank (2023).

Mobility Data To provide additional evidence toward mobility as a potential mechanism for IPV reductions, we conduct additional analyses using Google mobility data (Google LLC, 2022). During the COVID-19 pandemic, Google began releasing province-level mobility measures aggregated

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

[25]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.

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).[26] 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.[27]

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 Variables

Domestic violence variables. In the DHS, one randomly selected woman per household is asked about several dimension of partner violence. 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.

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

[26]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.

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

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.[28]

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:

$$\begin{aligned} Y_{idmt} = \beta_1 \textit{Growing Season } CDH_{idmt} + \beta_2 \textit{Non-growing Season } CDH_{idmt} \\ + \beta_3 AvgTemp_{idmt} + \beta_4 AvgRain_{idmt} + \beta_5 Altitude_{idmt} + \beta_6 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt} \end{aligned} \tag{6}$$

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 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.

A.3 Additional Results and Robustness Checks

Additional measures of partner abuse. In Appendix Table A2, we examine the effects of frost shocks on a measure that focuses on violence, individual components of overall abuse (physical, emotional, and sexual violence and controlling behavior), and a measure of IPV intensity. Column 1 repeats our baseline results. In column 2, we see that the estimated effect is similar in size and is statistically significant when we only consider overall violence, omitting control issues. Extreme cold has the largest impacts on physical violence (such as being slapped, kicked, or attacked with a weapon), emotional violence (such as humiliation or threats of violence), and on control issues

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

(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 pp (column 3), emotional violence by 0.31 pp (column 4), and control issues by 0.56 pp (column 6). The point estimate is positive for effects on sexual violence (column 5), but smaller and not statistically significant (though still meaningful in magnitude, relative to the mean). Lastly, in column 7, we use a simple measure of IPV intensity (Chong and Velásquez (2024)): the sum across all 18 individual indicators of IPV as asked in the DHS. This measure ranges from 0 to 18, with higher scores reflecting more affirmative answers to partner abuse and violence questions. We find that each degree hour below -9°C increases IPV intensity significantly.

In Appendix Table A5 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 6.1 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 A1 as when we use self-reported IPV from the DHS in Figure 1. Overall, we take the results in Appendix Table A5 and Appendix Figure A1 as validating the woman-level effects we present as our main results.

Alternative measures of frost shocks.

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). 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 1.2 pp. In the paper, we focus on the threshold of -9°C, the midpoint of thresholds that yield statistically significant effects.

In Appendix Table A6, 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 in 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 frost shocks in Appendix Table A7. 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 and thus not always statistically significant – 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.[29] Experiencing a frost 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 A8 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 0.29 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 A8 focus on the effects of extreme cold spells, where a cold 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.

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 A9, we find that there are no meaningful differences in observable

[29] 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.

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 A10, 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.

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.[30] 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 A11 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.

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 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 A12. 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

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

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 A12 as evidence that our main estimates capture the causal effect of extreme cold on IPV.

Social Program Heterogeneity: Robustness.

We rule out that our measure of social program coverage captures several other dimensions of heterogeneity in Appendix Table A16. In columns 2 and 3, we show that our results are not driven by department or city capitals, 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[31] - 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.[32]

A.4 Appendix Figures and Tables

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

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

Table A1: Sample Characteristics

	Full Sample	Ever experienced shock (λ=-9°C) Never	At least once	Diff
IPV (past 12 months)				
Any IPV	0.69	0.68	0.70	0.01
	(0.46)	(0.46)	(0.46)	(0.01)
Physical Violence	0.13	0.12	0.15	0.02***
	(0.33)	(0.33)	(0.35)	(0.01)
Emotional Violence	0.16	0.15	0.19	0.03***
	(0.36)	(0.36)	(0.39)	(0.01)
Sexual Violence	0.04	0.03	0.04	0.01**
	(0.19)	(0.18)	(0.21)	(0.00)
Control Issues	0.66	0.66	0.67	0.01
	(0.47)	(0.47)	(0.47)	(0.01)
Weather variables				
CDH (λ=-9°C)	0.59	0.00	5.02	5.02***
	(8.25)	(0.00)	(23.52)	(1.06)
Average Temperature	9.34	9.73	6.45	-3.28***
	(3.24)	(3.17)	(2.13)	(0.37)
Total Rainfall	65.34	65.37	65.11	-0.26
	(20.95)	(21.05)	(20.21)	(2.59)
Women Charact.				
Age	33.44	33.44	33.48	0.04
	(8.19)	(8.18)	(8.28)	(0.17)
Num. children	0.87	0.87	0.84	-0.03
under five	(0.73)	(0.73)	(0.75)	(0.02)
Native Spanish	0.62	0.62	0.55	-0.08***
Speaker	(0.49)	(0.48)	(0.50)	(0.03)
Years of	8.28	8.26	8.46	0.2
education	(4.60)	(4.62)	(4.43)	(0.50)
Household Charact.				
Household	4.49	4.51	4.35	-0.16***
size	(1.62)	(1.62)	(1.60)	(0.05)
Head of household	1.18	1.18	1.22	0.04***
is male	(0.39)	(0.38)	(0.41)	(0.01)
Age of head	39.99	40.05	39.57	-0.48
of household	(11.86)	(11.88)	(11.66)	(0.33)
Rural	0.56	0.56	0.57	0.02
	(0.50)	(0.50)	(0.49)	(0.08)
Spouse's years of	3.19	3.17	3.32	0.15
education	(1.32)	(1.33)	(1.25)	(0.11)
Wealth index	0.00	0.01	-0.06	-0.06
(standardized)	(1.00)	(1.01)	(0.91)	(0.08)
N obs	55544	48980	6564	
N Districts	919	809	110	

Table A2: Effects of Frost Shocks on Other IPV Measures

	Any IPV (Baseline)	Any IPV (Excluding Ctrl. Iss.)	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)	0.053**	0.050*	0.033*	0.031*	0.011	0.056**	0.251*
	(0.023)	(0.029)	(0.019)	(0.019)	(0.020)	(0.026)	(0.133)
Observations	54584	54776	54778	54776	54778	54556	54778
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	2.194

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, 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. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Effects of Frost Shocks on Partner Alcohol Use

	Partner Drinks Alcohol	Partner Gets Drunk Frequently
	(1)	(2)
Cumulative Degree Hours (λ = -9°C)	0.030*	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); household head characteristics (age and sex), 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 A4: 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)	-3.498***	-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

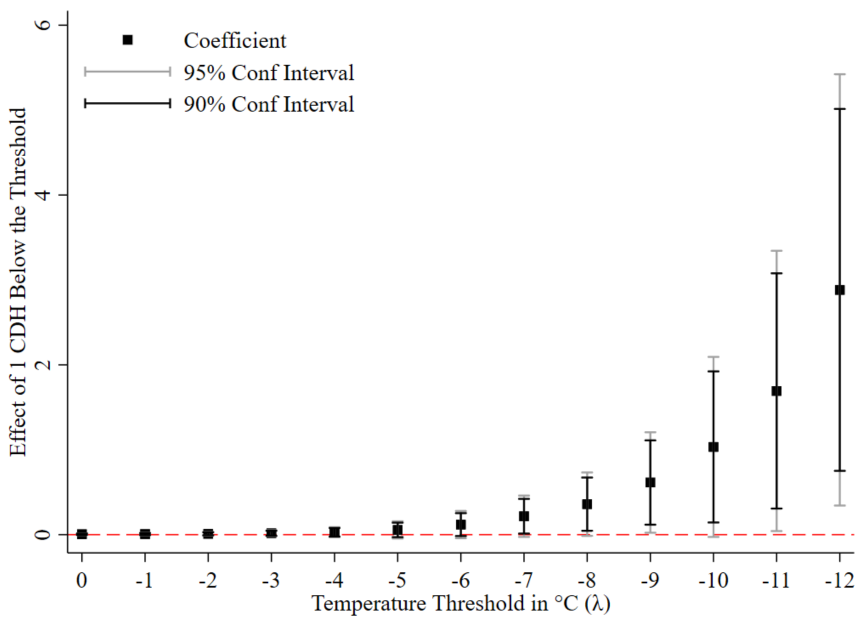
Notes: The sample includes all provinces in the Peruvian Highlands for which Google released mobility data in 2021. CDH is measured at the daily level for each province as the population weighted average of all district CDH in the province (population taken from official 2019 estimates (Ministry of Health, 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 A5: Effect of Frosts on Police Reports of Violence Against Women

	All violence	Physical violence	Non-physical violence	All violence	Physical violence	Non-physical violence
	(1)	(2)	(3)	(4)	(5)	(6)
CDH in current and prev. month (λ = -9°C)	0.614**	0.507**	0.086			
	(0.302)	(0.245)	(0.144)			
CDH in the last 12 months (λ = -9°C)				0.626**	0.531***	0.099
				(0.250)	(0.195)	(0.090)
Observations	61620	60132	56424	61620	60132	56424
No. of Districts	883	867	829	883	867	829
Mean of Dep. Var	140.485	85.823	61.959	140.485	85.823	61.959

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.

Figure A1: Effects of Frost 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.

Table A6: Effects of Frost Shocks Defined using District- and Season-Specific Thresholds

	Dep. Var.: Any IPV in Past Year		
	(1)	(2)	(3)
Cumulative Degree Hours (λ = -9°C)	0.035***		
	(0.011)		
Cumulative Degree Hours (λ = 2 S.D.)		0.020**	
		(0.008)	
Cumulative Degree Hours (λ = 3 S.D.)			0.153***
			(0.056)
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 2010-2018. 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. 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 A7: Effects of Frost Shocks Over Various Time Frames

	Dep. Var.: Any IPV in Past Year			
	(1)	(2)	(3)	(4)
CDH Past 12 months (λ = -9°C)	0.053**			
	(0.023)			
CDH Past 6 months (λ = -9°C)		0.074*		
		(0.044)		
CDH Past 1 months (λ = -9°C)			0.116	
			(0.089)	
Any Frost in past 12 months (λ = -9°C)				1.427
				(1.753)
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 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, 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 A8: Effects of Frost Days and Spells

	Dep. Var.: Any IPV in Past Year				
	(1)	(2)	(3)	(4)	(5)
Less than -9C	0.053**				
	(0.023)				
Cumulative Degree Days (Below -9C)		0.287***			
		(0.111)			
Number of days below -9C			0.642*		
			(0.347)		
Number of Spells (λ = -9°C)				0.612*	
				(0.340)	
Number of Spells 1-4 hours (λ = -9°C)					0.377
					(0.427)
Number of Spells 5-8 hours (λ = -9°C)					1.265
					(1.665)
Number of Spells 9+ hours (λ = -9°C)					1.336
					(1.682)
Observations	54584	54584	54584	54584	54584
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 (DD$_{id} = 0$ if MinTemp$_{id} \geq \lambda$, and DD$_{id} = \lambda -$ MinTemp$_{id}$ if MinTemp$_{id} < \lambda$) and aggregate them over the 12-month period prior to the household i's interview date (CDD$_i = \sum_d$ DD$_{id}$). In Column (3) we calculate the number of days in which the minimum daily temperature fell below λ. Spells (Columns 4 and 5) are defined as continuous periods 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. 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 A9: 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	0.005	-0.007	
	(0.001)	(0.001)	(0.023)	(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	Partnered or Married (ENAHO)
	(5)	(6)	(7)	(8)	(9)
Cumulative Degree Hours (λ = -9°C)	0.002	-0.008	-0.085*	0.000	-0.016
	(0.003)	(0.029)	(0.046)	(0.000)	(0.018)
Observations	54584	54584	54584	54584	91858
No. of Districts	918	918	918	918	953
Mean of Dep. Var	33.427	0.429	0.616	0.869	0.533

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, years of education, household size, 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 A10: 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)	0.092***	-0.000	0.003	0.023
	(0.034)	(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 altitude, 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 A11: Allowing for Differential Pretrends

	Dependent Variable: Any IPV in Past Year		
	Baseline	Department-specific Year and Month FE	District Trends
	(1)	(2)	(3)
CDH (λ = -9°C)	0.053**	0.048**	0.053***
	(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 2010-2018. Controls include altitude, average temperature and average rainfall at the household level in the past year. We control for individual characteristics (age, age squared, 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 A12: 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	0.066***	
	(0.024)	
CDH (λ = -9°C) in the *Next* 12 Months		0.027
		(0.017)
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 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, 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 A13: Effects of Frost 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

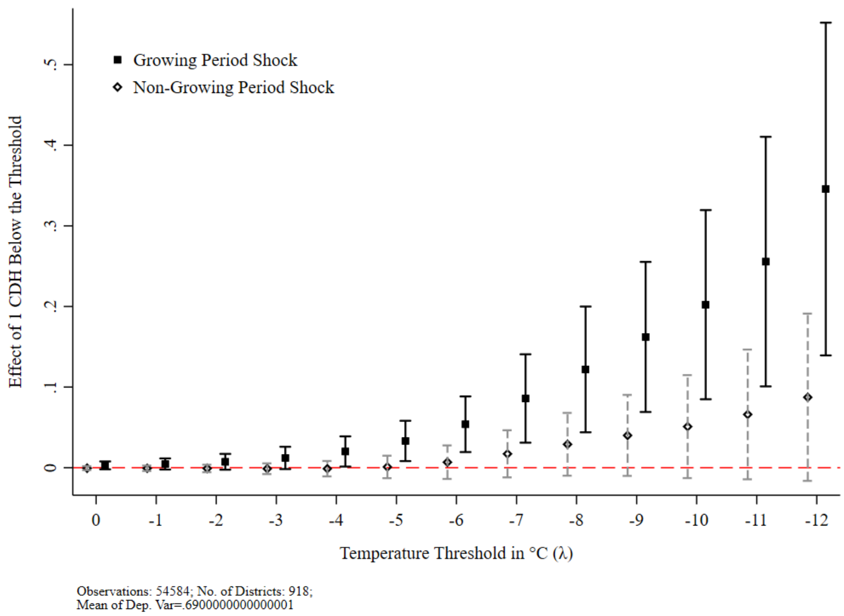
Notes: We use data from the Peruvian National Household Survey (ENAHO), which collects information about daily employment during the full calendar week prior to the individuals' interview date (e.g., if the survey takes place on a Wednesday, the questionnaire asks about employment between Monday and 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 frost 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 A14: 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)	0.053**			
	(0.023)			
CDH Dec-May (λ = -9 °C)		0.187***		0.156**
		(0.069)		(0.069)
CDH June-November (λ = -9 °C)			0.056**	0.032
			(0.024)	(0.024)
p-value for Growing=Non-Growing				0.108
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 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, 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.

Figure A2: Effects of Growing and Non-Growing Season Frost 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, 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.

Table A15: Heterogeneous Effects of Frost Shocks by Household Agricultural Status

	Baseline	Including Interaction w/ Ag Earner Status
	(1)	(2)
Cumulative Degree Hours (λ = -9°C)	0.053**	0.032
	(0.023)	(0.024)
CDH $\times$ Agricultural Earners		0.081
		(0.049)
Total effect for Ag HHs		0.113
p-value for Total Effect		0.021
Observations	54584	54584
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. Controls include individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size, and fixed effects for husband's education level. 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 A16: Heterogeneity by Baseline Social Program Coverage: Robustness

	Dep. Var.: Any IPV				
				Also Controlling for Interaction w/	
	Baseline	Excluding Department Capitals	Excluding Province Capitals	2011 Vote Shares	Woman's Age
	(1)	(2)	(3)	(4)	(5)
CDH (λ = -9°C)	0.073**	0.071**	0.072**	0.102*	0.077**
	(0.032)	(0.032)	(0.030)	(0.054)	(0.034)
CDH $\times$ Baseline Social Program Coverage	-0.047*	-0.046*	-0.065*	-0.052	-0.053
	(0.025)	(0.025)	(0.038)	(0.034)	(0.033)
Observations	38808	34489	27167	38684	38808
No. of Districts	796	784	688	793	796
Mean of Dep. Var	0.669	0.672	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, 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.