THREE ESSAYS ON THE IMPACT OF EXTREME WEATHER EVENTS IN PERU: STUDYING THE EFFECT ON PERCEIVED RELATIVE DEPRIVATION, INTIMATE PARTNER VIOLENCE, AND POLITICAL TRUST AND IDENTIFYING THE ROLE OF SOCIAL PROGRAMS AND PUBLIC GOODS AND SERVICES

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ABSTRACT

Previous literature has extensively studied the role of extreme weather events on various socio-economic outcomes. However, some important questions and underlying mechanisms remain unexplored. For example, do extreme weather shocks change perceptions of relative position among others within a neighborhood or community, even when the entire locality is exposed to an adverse weather shock? If weather shocks affect voting outcomes, then does changes in political beliefs work as a mediating factor? Can such shocks shape interpersonal behavior through intimate partner violence? Further, what is the role of social programs and access to public goods and services in attenuating the negative consequences of such adverse weather events? The general theme of this dissertation revolves around how weather shocks, specifically in the form of excess rainfall and extreme cold temperature shocks, affect perceptions of relative deprivation, political beliefs, and intimate partner violence. I study these in the context of a developing country- Peru.

The first chapter examines how covariate shocks – like excess rainfall- can shape perceptions of relative deprivation. Perceptions of relative deprivation or feelings of relative poverty affect a range of economic and behavioral outcomes, such as support for redistribution, political attitudes, hostility, and risky behavior. Using household-level longitudinal data for Peru, I provide novel evidence showing that exposure to excess rainfall shocks increases the likelihood that households perceive their standard of living to be worse off relative to the other households in the locality. Two fundamental mechanisms could explain this- firstly, the differential effect of excess rainfall shocks across objective outcomes suggests a widening economic gap reflected in standard relative deprivation measures, and secondly, misperceptions about the losses of other households within a locality could explain the increase in perceived relative deprivation. The impact is particularly larger for historically underprivileged and less developed communities. I show that social protection programs, such as conditional cash transfers and in-kind food assistance programs, can attenuate the effect of rainfall shocks on perceived relative deprivation. Finally, I show an association between perceived relative deprivation and political beliefs related to the functioning of democracy and support for authoritarian regimes in Peru.

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

The final chapter further examines how frost shocks can affect confidence in government and political institutions. Political trust or perceptions of government and political institutions can affect various outcomes, such as compliance with laws and demand for public goods. We examine how extreme weather affects individuals' political beliefs, such as how well democracy functions in Peru. We construct a unique dataset containing spatially and temporally specific cold temperature shocks and find that extreme cold reduces positive perceptions of democracy. We further find that extreme cold shocks reduce civic engagement in formal democratic institutions (as measured by participation in national elections), possibly due to increased political mistrust. However, participation in local neighborhood associations increases due to extreme cold shocks, possibly due to an adaptive coping strategy. We provide evidence that these effects work through several mechanisms: economic losses, increased incidence of illness, and higher crimes. Finally, we find that higher coverage of government-provided goods and services, namely, social programs, public hospitals, and police resources, can attenuate the adverse effects of extreme cold.

Dedicated to *Baba*, my father- my lifelong coach, teacher, and a friend.
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TABLE OF CONTENTS

CHAPTER 1

DOWNPOURS OF DEPRIVATION: EXPLORING THE IMPACT OF EXCESS RAINFALL SHOCKS ON PERCEIVED RELATIVE DEPRIVATION IN PERU

1.1 Introduction

Social positions relative to others matter to people. Kosec and Mo (2021) argue that equity theory, relative deprivation theory, and social comparison theory (Adams, 1965; Crosby, 1976; Walker and Smith, 2002; Festinger, 1954; Suls and Wheeler, 2000) advocate that individuals *"are acutely affected by comparison with others"*. While the literature from sociology and psychology has traditionally emphasized the importance of reference points, a recent growing body in economic research provides empirical evidence on how perceptions of social position or perceived relative deprivation [1] affect various critical outcomes. For example, perception of social position or relative deprivation can affect views on inequality (Hvidberg et al., 2021), shift political attitudes (Healy et al., 2017; Kosec and Mo, 2021), lead to poorer physical and mental health (Mishra and Carleton, 2015), increase hostility or aggressive behavior (Greitemeyer and Sagioglou, 2019), change risk tolerance (Mo, 2018), feelings of overall subjective well-being and life satisfaction (Ravallion and Lokshin, 2010), and support for redistribution policies (Alesina and La Ferrara, 2005; Clark and d'Ambrosio, 2015; Knell and Stix, 2020, 2021; Fehr et al., 2022; Hoy and Mager, 2021).

However, the evidence from recent literature is skewed towards developed countries. It primarily uses a combination of dedicated surveys with experimental set-ups alongside rich administrative records (e.g., income history, tax records, etc.). Importantly, this strand of research focuses on the effect of individual transitory income shocks (such as unemployment, disability, hospitalization, or promotions) on perceptions of social positions within a given reference group (Hvidberg et al., 2021). While a recent emerging literature does focus on developing countries, most of it provides evidence from *experimental* set-ups, showing the role of perceived relative deprivation in shaping political attitudes and risky behavior (Healy et al., 2017; Kosec and Mo, 2021; Mo, 2018). There is,

[1] Perceptions of social position in this context reflect individual perceptions of relative disadvantage. In particular, the literature in this area investigates whether an individual or a household perceives itself to be ranked lower (or worse off) than others in a given reference group. This is referred to as perceived relative deprivation or perceptions of relative poverty, defined in comparison to other people's standing in the economy (Eskelinen, 2011; Kosec et al., 2021).

however, very little evidence on determinants of perceived relative deprivation in a non-experimental or a real-world setting in developing country contexts. Moreover, less is known about whether covariate shocks can be an important determinant of perceived relative deprivation.

In this paper, I investigate whether covariate shocks — in particular, excess rainfall shocks — can affect perceived relative deprivation in the context of a developing country-Peru. With climate change, covariate shocks in the form of extreme weather shocks have become more widespread in recent decades. Extreme weather has adverse consequences for a wide range of economic, health, and social outcomes (Dell et al., 2012a; Zhang et al., 2017; Schlenker et al., 2009; Aragón et al., 2021; Deschênes and Greenstone, 2011; Iyer and Topalova, 2014; Blakeslee and Fishman, 2013). However, we know little about how these covariate shocks affect perceptions of relative deprivation. While one can argue that negative covariate shocks can increase both absolute and relative poverty, their effect on perceived relative deprivation is less straightforward. While idiosyncratic shocks could make households clearly worse off and thus make them perceive they are relatively deprived, this hypothesis in the context of covariate shocks is *ambiguous* as a covariate shock affects all contiguously placed households within a geographic area. In such a context, relative losses could be key in shaping perceptions of relative deprivation. Alongside relative losses, perceptions of possibilities of upward economic mobility or economic aspirations could be key in determining perceptions of relative deprivation through unmet aspirations (Genicot and Ray, 2017; Acemoglu et al., 2018; Healy et al., 2017).

I study the impact of excess rainfall shocks on perceived relative deprivation in the context of Peru, which is considered one of the most vulnerable countries to climate change in the world (Stern, 2007; Tambet and Stopnitzky, 2021). I focus on excess rainfall deviations due to their increasing relevance in recent decades, especially in Peru. Heavy abnormal rainfalls have increased the frequency of deadly landslides, mudslides, floods, flash floods, and other heavy rainfall-induced emergencies across Peru, resulting in heavy economic losses and casualties (USAID, 2017; French and Mechler, 2017). In general, it is important to understand the role of covariate shocks because they are more widespread than idiosyncratic shocks. Moreover, covariate shocks in the form of extreme weather shocks are becoming more frequent and intense in nature.

I use an unbalanced panel of households over a period of 13 years. Specifically, I use the 2007-2019 rounds of the Peruvian National Household Survey (*Encuesta Nacional de Hogares*, ENAHO), which includes a rich module on household perceptions of economic positions as well as confidence in public institutions. I create a measure of perceived relative deprivation using questions about households' perceptions of how their own standard of living has changed ("got worse", "same", or "got better") vis-à-vis other households in its locality ("got worse", "same", or "got better"), in the past 12 months from the time of interview. I match households' responses with local weather data. I use the geo-locations of each household (specific to the village centroid in rural areas and to the neighborhood block in urban areas) and the specific interview date of each household (to estimate weather shocks in the 12-month period prior to the survey date). My primary weather variable is a widely used measure of rainfall shock: an indicator variable for whether a household had experienced a cumulative rainfall over the previous 12 months that exceeded the average long-run (past 20 years) rainfall by more than some alternative harmful threshold (for example, Rosales-Rueda (2018); Riley (2018)). In particular, I consider thresholds of 1, 1.5, 2, 2.5, ..., 4 of the long-run standard deviation (S.D.) of rainfall. These indicator variables account for any potential non-linear effects of excess rainfall on perceived relative deprivation. My identification strategy exploits *within-household* variation in exposure to excess rainfall shocks, conditional on a set of household characteristics and district, year, and month-of-interview fixed effects.

I conceptualize that excess rainfall shocks could lead to changes in perceived relative deprivation through two key channels. First, it might be the case that rainfall shocks do have differential effects across households within localities, thus making a set of vulnerable households *actually* more deprived than other households within a locality. This could widen economic gaps within a locality and lead to perceived relative deprivation. In other words, perceived relative deprivation could indeed reflect households' objective losses. Second, given its covariate nature, excess rainfall shocks could similarly affect all households within a locality (i.e., no actual changes in relative well-being within communities). However, perceptions of relative deprivation could be guided by possible misperceptions about the losses of other households within a locality.

Conditional on household, month of interview, and year fixed effects, and controlling for a set of household characteristics, I find that exposure to extreme excess rainfall shocks increases the likelihood of households perceiving their standard of living to be worse off relative to other households in the locality or community. For example, I find that positive deviations in rainfall from the long-run mean by more than 2.5 times the long-run standard deviation increase the likelihood of perceived relative deprivation by 1.25 percentage points (6.2% increase). Importantly, the point estimates are larger and remain statistically significant when considering more intense shocks (i.e., when rainfall deviates by more S.D. from its mean).

I then explore possible mechanisms. I first show that excess rainfall shocks affect key objective outcomes. I show that rainfall shocks reduce household per capita expenditure[2]. For example, deviation in rainfall above its long-run mean by more than 2.5 (long-run) S.D. reduces household consumption by 2.11%. Then, I show that there is a differential effect amongst more vulnerable households. Using baseline household poverty status, I find that poorer households suffer a larger decline in household consumption. Furthermore, I find that this differential effect is reflected in standard measures of *objective* relative deprivation, such as the Yitzhaki or Stark indexes (Stark, 1984; Yitzhaki, 1979). Intuitively, these measures capture the average gaps between a household's consumption (or other welfare measure) with respect to the consumption of those in the same reference group (Hey and Lambert, 1980; Yitzhaki, 1979). I find that excess rainfall shocks actually widen the economic gap (in terms of household consumption) within localities, as measured by the Yitzhaki or Stark measures of relative deprivation.

Since poor households seem to experience larger losses than non-poor households objectively, I also test whether this translates into differential effects on perceived relative deprivation. Using baseline poverty status, I find that actually *both* poor and non-poor households perceive relative deprivation in the face of a shock, though the effects on non-poor households are somewhat smaller. While the differential losses and widening economic gap between the poor and non-poor households

[2]For convenience, I will refer to household per capita expenditure as household consumption throughout the paper.

could explain perceived relative deprivation for poor households, it does not fully explain increases in perceptions of relative deprivation amongst the better-off households.

Next, I look into the role of misperceptions of other households' losses in explaining the effect of excess rainfall shocks on perceived relative deprivation. Potentially households might under or overestimate how weather shocks affect neighbors (or others in their reference group), affecting how they perceive their status within their communities. First, I show that extreme positive rainfall shocks do not only affect individual households but negatively affect all others in their reference groups. In particular, I find similar negative effects of rainfall shocks on neighbors' consumption measured by leave-one-out average household per capita expenditure [3]. This explains that excess rainfall shocks also affect other households in the locality in terms of consumption losses, reassuring the covariate nature of the shock. However, I find that even with similar losses for other households within the locality in the face of a shock, a given household is more likely to perceive that the standard of living of others in their locality has remained the "same" or got "better" in the course of the last year. This evidence indicates that there are misperceptions about the losses of other households within a locality, and hence, possibly explains an increase in perceived relative deprivation due to an excess rainfall shock.

I document heterogeneous effects in terms of two key aspects- the indigenous population and low levels of local development. The indigenous population in Peru continues to face discrimination in various ways that potentially limit their capacity to smooth consumption in the face of a shock. Additionally, the ability to smooth consumption could be limited within areas with low levels of overall economic development and thus can shape perceived relative deprivation. Heterogeneity analyses point out that indigenous households are more likely to perceive relative deprivation in the face of a shock than non-indigenous households. Additionally, I find that households living in districts with a baseline Human Development Index (HDI) lower than the median HDI of all districts in Peru are more likely to perceive relative deprivation. This suggests that associations with historically isolated communities and lower levels of local development augment perceptions

[3]This is the mean household per capita expenditure of all sampled households within a district (rural or urban separately), excluding the household's consumption.

of relative deprivation in the face of a shock.

Next, I explore the role of social protection programs in mitigating perceived relative deprivation. For this, I look into the conditional cash transfer program *Juntos* [4] and access to the Food Assistance Programs. Based on the data in the ENAHO, I identify the households that had access to either Juntos or food assistance programs at the baseline year of the survey. I find that those without access to these programs are more likely to perceive relative deprivation in the face of a shock relative to beneficiary households. Thus, cash and in-kind transfer programs could be vital in helping mitigate perceptions of relative deprivation as households experience an excess rainfall shock.

I also show that my results are robust to several alternative specifications. The findings are robust to alternate measures of perceived relative deprivation. Second, the effect of excess rainfall-related shocks on perceived relative deprivation is robust to alternate shock measures. I use excess rainfall-related *emergencies* in Peru, like floods, mudslides, landslides, and heavy rainfall scenarios. I find that exposure to such emergency events that affect all households within a locality also leads to an increase in perceived relative deprivation. The effect of excess rainfall shocks on perceived relative deprivation is also robust to a range of potential harmful thresholds of rainfall (i.e., deviations in terms of the number of S.D. with respect to the long-term average rainfall) and measures of self-reported exposure to similar natural disaster events. I also do not find any evidence of changes in sample composition and endogenous migration. Finally, I also find that lead-year rainfall deviations do not affect changes in perceived relative deprivation. This suggests that areas that perceived relative deprivation had similar trends in areas that will experience *future* rainfall shocks relative to those that will not. This allows me to rule out that rainfall shocks capture unobserved determinants of perceived relative deprivation that vary systematically across households and/or geographic areas. It also suggests that households are unable to anticipate upcoming weather shocks and preemptively adjust to them.

[4] The Peruvian Juntos is a conditional cash transfer program with eligibility based on poverty scores. Transfers are conditional on households meeting certain educational attendance requirements (for children between 6-14 age) and health checkups (for children between 0-5 and pregnant women/nursing mothers). As of 2023, the program transfers 200 Peruvian Soles (roughly 54 USD) every other month to those meeting the required criteria.

Finally, I demonstrate the policy relevance and significance of perceived relative deprivation in the Peruvian context by providing evidence of a strong relationship between perceived relative deprivation and measures of political attitudes or trust- the belief that democracy functions well in Peru, as well as a preference for authoritarian regimes over a democratic regime. These outcomes are closely related to satisfaction of democracy, which is a widely used measure to capture political trust and confidence in institutions (Citrin and Stoker, 2018). Low levels of political trust indicate a lack of confidence in public institutions, affecting policy preferences, conflict, compliance with laws and civic participation, amongst other outcomes (Citrin and Stoker, 2018; Buhaug et al., 2015). Using a panel of households and a fixed-effects estimation strategy, thus exploiting within-household variations, I find that households perceiving relative deprivation are more likely to report democracy functions "poorly" or "very poorly" in Peru; additionally, these households are also more likely to prefer "authoritarian regimes over democratic ones, in some circumstances." These results help explain perceived relative deprivation as one of the alternate explanations for political mistrust in Peru.

My research provides new evidence and complements existing knowledge related to perceived relative deprivation through different aspects. To the best of my knowledge, this is the first paper to study perceived relative deprivation in a non-experimental set-up and in a developing country setting. This adds to the existing literature which studies perceived relative deprivation in developing countries through experimental set-ups (Kosec and Mo, 2021; Kosec et al., 2021; Healy et al., 2017).The recent experimental literature primarily relies on *poverty priming* [5]. One of the critical limitations of these studies is that they only *temporarily* create perceptions of relative deprivation, which could be very different from a situation where individuals or households are actually deprived in reality (Healy et al., 2017). Using a real-world setting, this paper shows that excess rainfall shocks can *also* lead to changes in perceived relative deprivation. This is most likely explained by an increase in relative deprivation through the differential impact of weather shocks

[5] Poverty priming involves inducing or "priming" a set of participants to feel relatively poor, and the other set is made to feel that their incomes are more typical or close to the median (Kosec and Mo, 2021; Kosec et al., 2021; Healy et al., 2017; Mo, 2018)

across the most vulnerable and less vulnerable households and misperceptions about the losses of other households within a locality.

Secondly, I study the role of *covariate shocks* in shaping household perceptions about relative social positions. This is key because the current literature studying perceptions of social positions attributes the role of idiosyncratic shocks in shaping perceptions of social positions (Hvidberg et al., 2021). It is relatively clear as to why idiosyncratic shocks may change perceptions of social positions as they are household-specific and make a household relatively worse off or better off than other neighboring households, depending on the nature of the shock. However, this is unclear in the case of covariate shocks, as all households within a locality experience this shock. Moreover, a major challenge with covariate or community-level shocks is that they impact all households in a given area, thereby significantly restricting the potential for mutual insurance. This is not the case with idiosyncratic shocks, which affect individual households and, therefore, can be mutually insured within communities (Günther and Harttgen, 2009; Bhattamishra and Barrett, 2008). However, it is easier to target covariate shocks as it is most often located within an easily identifiable geographic area or region (Günther and Harttgen, 2009).

Third, I contribute by studying the role of redistributive policies, such as cash transfers and food assistance programs, in attenuating perceived relative deprivation. There is scant evidence on whether access to redistribution can effectively mitigate perceived relative deprivation. Access to the Peruvian conditional transfer program Juntos and food assistance programs can effectively mitigate perceived relative deprivation in the face of extreme rainfall shocks. This is a key and novel result with regard to the role of redistributive policies in weakening perceived relative deprivation in a developing country setting.

Section 1.2 provides a context on the excess rainfall situation and its consequences, focusing on Peru, alongside a discussion on actual inequality in Peru. Section 1.3 discusses the various datasets that have been used. Section 1.4 describes the empirical strategy followed by the discussion of the main results in section 1.5. Section 1.6 explains the mechanisms, followed by evidence on the role of social programs in sections 1.7.1 and 1.7.2. Section 1.8 discusses the robustness checks.

Finally, section 1.9 provides evidence related to the role of perceived relative deprivation in shaping political attitudes in the context of Peru. Section 1.10 concludes.

1.2 Context

In recent times, extreme weather events have become a significant source of adverse covariate shocks, occurring more frequently and have become more widespread. One such common weather extreme has been *excess rainfall*-related events. Excessive rainfall-related emergencies such as floods, flash floods, and landslides have risen globally, affecting even some of the most developed and populous regions. Examples of such heavy rainfall-related emergencies include floods in Western Europe (Tradowsky et al., 2023), landslides in California, USA (Handwerger et al., 2019), and increased flood risks in Bangladesh, China, and India (Mukherjee et al., 2018; Kundzewicz et al., 2014). Though other meteorological, topographical, and other location-specific factors could augment the possibilities of a flood, flash flood, or landslide event, excess rainfall remains a key common factor behind such related hazards (Mukherjee et al., 2018; Tradowsky et al., 2023; Kundzewicz et al., 2014; Ávila et al., 2016; Maqtan et al., 2022; Vox, 2023).

Extreme weather events have become common and widespread in Peru as well. Peru is considered one of the most vulnerable countries to climate change in the world (Stern, 2007; Tambet and Stopnitzky, 2021). Extreme weather-related emergencies like heavy rainfall, floods, frost, cold waves, and droughts have increased in Peru in recent decades (World Bank, 2008). Peru has had much more excess rainfall-related weather emergencies like floods, flash floods, landslides, and mudslides, than other types of weather-related extreme events (Guha-Sapir, 2020). For example, figure A.1 shows that the share of specific weather related emergency responses, and excess rainfall related events tend to have higher emergencies than drought or frosts.

An extensive body of work highlights the negative consequences of heavy rainfall-related weather events. It affects populations both in rural and urban areas through channels of agricultural income, food security, child health and infectious diseases and vector-borne illnesses, human capital formation, armed conflict, and preventing people from working and destroying property (Oskorouchi and Sousa-Poza, 2021; Sajid and Bevis, 2021; Ghimire and Ferreira, 2016; Rosales-

Rueda, 2018; Dimitrova and Muttarak, 2020; Riley, 2018).

In the case of Peru, heavy rainfall-related events have had widespread consequences and have affected large sections of the population through losses in agriculture and damages in housing, water and sanitation, health, and even education and transportation sectors (French and Mechler, 2017). For example, the 2017 floods in Peru affected approximately 40,000 hectares of crops- affecting close to 7000 agricultural producers, a large majority of which were small farmers (USAID, 2017). Months of heavy rainfall have affected many urban and peri-urban populations through rainfall-related hazards like floods, mudslides, and landslides. Excessive rain has also restricted access to safe drinking water and sanitation infrastructure, increasing the chances of diseases like diarrhea, dengue, zika, and other harmful vector-borne diseases (USAID, 2017; French and Mechler, 2017). There is substantial evidence in the climate change literature suggesting heavy rainfall will become increasingly common in the future (Cai et al., 2014; Gründemann et al., 2022). This underscores the importance of studying the varied consequences of such extreme events, which affect a large section of the population worldwide.

Alongside increasing weather extremes, there has been a growing concern regarding inequality, particularly after the surge in economic inequality caused by the pandemic. Inequality has surged in recent years and remains prevalent in Peru (figure A.2). Peru has remained one of the most unequal countries in the world in the last three decades (figures A.3 and A.4). High inequality is often the breeding ground for political instability, lack of democratic consolidation, and fiscal volatility (Alesina and Perotti, 1996; Dutt and Mitra, 2008; Acemoglu and Robinson, 2001). Unfortunately, Peru has experienced all these issues in the last three decades. Corruption, political clashes, impeachments, and failed coup attempts have added to the uncertainty in the country, with Peru having one of the highest levels of political mistrust in Latin America (Bargsted et al., 2017). Despite being a democratic country, Peru has been classified as a "flawed democracy" or an "authoritarian regime" due to the continued political uncertainties over several decades. This classification is significant given its past history of suppressive autocratic and military regimes.

Negative economic shocks can exacerbate existing economic inequality. Since extreme weather events are increasingly becoming a major cause of negative economic shocks, studying their potential distributional consequences- both in terms of perceived relative deprivation and objective relative deprivation remains crucial.

1.3 Data

1.3.1 Encuesta Nacional de Hogares (ENAHO)

The ENAHO is a detailed household survey collected annually by the Peruvian National Statistics Office (*Instituto Nacional de Estadística e Informática* - INEI). In particular, my analysis is based on 13 rounds of the ENAHO (2007-2019). The ENAHO provides data on a panel (longitudinal) of households. In particular, the ENAHO provides these panel data in waves of 5 years. In this paper, I use 6 of these waves that span over 2007-2011 (wave-1), 2011-2015 (wave-2), 2012-2016 (wave-3), 2013-2017 (wave-4), 2014-2018 (wave-5) and 2015-2019 (wave-6). For this study, I use an unbalanced panel of households which are surveyed at least twice between 2007-2019. The households in the analytical sample are spread across the three main regions of Peru (the coastal region, the highlands, and the Amazonian jungle; see figure A.5).

The ENAHO collects rich data on a wide range of topics, including information on household and individual-specific characteristics; assets or dwelling characteristics; health outcomes; information on agricultural and livestock-related activities at the household level; income and wage information; and detailed information on governance-related attitudes and household perceptions.

In this paper, I calculate a perceived relative deprivation measure drawn from two particular questions asked to the household head in the governance module of the survey (see Table 1.1). The first question is: "In the course of the past year, has the standard of living of households in your locality or community got better, remained the same, or got worse?" (where "got better", "remained same" and "got worse" are provided as options to answer the question). The second question is: "In the course of the last year, has the standard of living of *your* household- got better, remained the same, or got worse?".

I construct a simple binary measure of perception of relative deprivation, which takes value one if the household perceives itself to be worse-off in terms of standard of living compared to the households in its locality or community, and zero if the household perceives its standard of living to remain the same or is better off in comparison to the households in the locality or community (Table 1.1). The resulting variable takes value one in three alternative situations: [1] if the household reports that its own standard of living has remained the same but has improved for other households in its locality or community; [2] if the household reports that its own standard of living has worsened in the past year but has improved for other households in its locality or community; or [3] if the household reports its own standard of living has worsened in the past year but has remained the same for other households in its locality or community. The binary measure takes a value of zero in all other possible cases [6].

Table 1.1 Constructing Perceived Relative Deprivation Measure

Perception of Relative Deprivation		In the course of the last year, the standard of living of households in your locality or community		
		got better	same	worse
In the course of last year, the standard of living of your household?	got better	same (=0)	hh perception-better off (=0)	hh perception-better off (=0)
	same	*hh perception-worse off (=1)*	same (=0)	hh perception-better off (=0)
	got worse	*hh perception-worse off (=1)*	*hh perception worse off (=1)*	same (=0)

1.3.2 Weather Data

Next, to construct the weather shock measure, I extract rainfall data from the Weather Hazards Group InfraRed Precipitation with Station Data (CHIRPS).[7] CHIRPS is a global dataset that provides high-resolution estimates of rainfall for 0.05×0.05-degree pixels. I match rainfall to households using GPS coordinates and interview dates from the ENAHO, thus constructing household-specific rainfall shocks.

[6]Specifically, this is the case when either of the following holds: [1] a household perceives its standard of living has remained the same while others have remained the same or worsened; [2] a household perceives its standard of living to have improved over the course of the past year, notwithstanding the perceived positions of other households.

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

Using the daily rainfall data, I construct the following excess rainfall shock measure-

$$ExcessRainfall_{idmt} = (R_{idmt} - LRMean_{idmt})/\sigma_{idmt} \tag{1.1}$$

where, R_{imdt} is observed cumulative rainfall in the past 12 months from the time of interview of household i, in district d, interviewed in month m of year t; $LRMean_{idmt}$ is household i's corresponding long-run mean (past 20 years) from the time of interview of the household; and σ_{idmt} is the corresponding long-run standard deviation.

$$Shock_{idmt} = \begin{cases} 1 & \text{if } ExcessRainfall_{idmt} \geq \lambda \\ 0 & \text{if } ExcessRainfall_{idmt} < \lambda \end{cases} \tag{1.2}$$

where λ takes alternative values (i.e., λ= 1, 1.5, 2, 2.5,.. 4 S.D.) that represent different harmful thresholds in terms of deviations of contemporaneous rainfall. As noted earlier, I am primarily interested in excess rainfall shocks as it is key to some of the weather-induced extreme hazards like floods, landslides, and mudslides (Ávila et al., 2016; Maqtan et al., 2022; Tradowsky et al., 2023; Vox, 2023). Such hazards are becoming increasingly prevalent in Peru. I also show that the measure of shock here is a strong predictor of exposure to heavy rainfall, floods, mudslides, and landslide-related emergencies in Peru.

In addition to using actual weather shock measures for excess rainfall shocks, as a robustness check, I also examine the impact of households' self-reported exposure to natural disasters. The governance module of the ENAHO asks respondents whether they had experienced natural disaster events in the past 12 months from the time of the interview. I use this response to create a binary variable of self-reported exposure to natural disasters. Since this measure can raise endogeneity concerns, I additionally construct a binary measure of exposure to natural disaster events which takes a value of one if at least 50% (i.e., the majority) of the households within a district in a given year report being exposed to a natural disaster.

1.3.3 Other Data Sources

Emergency Maps Data- The Peruvian Government provides detailed locations of emergency responses related to various emergency-related events like heavy rainfall, floods, mudslides, flash floods, landslides, fires, earthquakes, strong winds, environmental pollution, volcanic eruptions, and so on. The Instituto Nacional de Defensa Civil- INDECI (or National Institute of Civil Defense of Peru) is a public body under the Peruvian Government that coordinates emergency responses across Peru and is tasked with planning relief and rehabilitation responses alongside coordinating with local and regional governments to assess the extent of damage and supply relief and services in the case of an emergency. The institute of civil defense of Peru provides data on all such emergency responses since the year 2003 in the form of geographic coordinates (latitudes and longitudes) of all emergency responses and by type of emergency. This data allows us to test whether the measure of excess rainfall shock is a good proxy for heavy rainfall, floods, mudslides, flash floods, and landslide emergencies. As a part of the robustness check, I also examine the impact of exposure to such related emergency events on perceptions of relative deprivation.

Human Development Index (HDI) - The United Nations Development Program (2021) has published data of their calculations of the HDI at the district level for several years. In particular, it compiles data on three components of the HDI- life expectancy (as a proxy for general health conditions), average years of education (human capital), and per capita household expenditures (economic conditions). I use district-level HDI for the year 2007 as the baseline HDI in this case.

Table 1.2 provides summary statistics for households' relative deprivation and exposure to rainfall shocks.

1.4 Empirical Strategy

The main outcome of interest is how households change their perception of relative deprivation with exposure to excess rainfall shocks. I employ a household-level fixed effects estimation strategy to account for household-level unobserved time-fixed confounders that may affect exposure to weather shocks as well as perceptions of relative deprivation simultaneously, thus exploiting *within-household* variation in exposure to extreme rainfall shocks. Specifically, the following regression

Table 1.2 Descriptive Statistics

	Household Panel 2007-2019
Perceived Relative Deprivation (Dummy)	0.203
Excess Rainfall Shocks (Dummy)	
Rainfall Shock ≥ 1 S.D.	0.343
Rainfall Shock ≥ 1.5 S.D.	0.222
Rainfall Shock ≥ 2 S.D.	0.132
Rainfall Shock ≥ 2.5 S.D.	0.078
Rainfall Shock ≥ 3 S.D.	0.049
Rainfall Shock ≥ 3.5 S.D.	0.033
Rainfall Shock ≥ 4 S.D.	0.025
Mechanisms	
Annual Household Per Capita Expenditure	4643
Poor (Dummy, =1 if poor)	0.252
Relative Deprivation (Stark Measure)	0.315
Perception- other households in locality worse-off	0.117
Household Head Characteristics	
Male	0.510
Age (in years)	50.863
Education	
No education	0.095
Incomplete Primary	0.225
Complete Primary	0.172
Incomplete Secondary	0.127
Complete Secondary	0.189
Incomplete Technical	0.027
Complete Technical	0.069
Incomplete College	0.026
Complete College or higher	0.069
N. of obs.	139,587
N. of Households	44,193

is estimated:

$$Y_{idmt} = \beta_1 Shock_{idmt} + \boldsymbol{X_{idmt}\delta} + \alpha_i + \gamma_t + \theta_m + \varepsilon_{idmt} \tag{1.3}$$

where Y_{idmt} is a binary measure of perceived relative deprivation- the main outcome of interest, as discussed above, of household i, in district d, interviewed in month m and year t. I also look into the effect of the excess rainfall shock on objective measures, like actual relative deprivation and consumption expenditure per capita, as a part of the mechanisms and to explain the effect of excess rainfall shock on perceived relative deprivation. $Shock_{idmt}$ is an indicator variable that equals 1 if the household experiences a excess rainfall shock in the past 12 months and 0 otherwise. X_{idmt} is a vector of household-level control variables. These controls include sex, age, age square, and education level fixed effects. α_i, γ_t and θ_m captures household, year and month fixed effects. Standard errors are clustered at the household level.

The coefficient of interest is β_1. The expected sign of β_1 is ambiguous in this case. Given the nature of the shock is covariate in this case, i.e., all households within the locality are exposed to a weather shock of similar intensity, which could potentially affect everyone economically. The identification strategy assumes-conditional on household, month of interview and year fixed effects, and other household-level controls– the incidence of excess rainfall shocks is exogenous to the perceived relative deprivation outcome. In summary, I exploit *within-household* variation, i.e., I compare the same household across years with and without excess rainfall shocks. As long as households are unable to anticipate fluctuations in extreme rainfall shocks, $\hat{\beta}_1$ will capture the causal effect of excess rainfall shocks on perceived relative deprivation.

1.5 Results

Effect on Perceived Relative deprivation

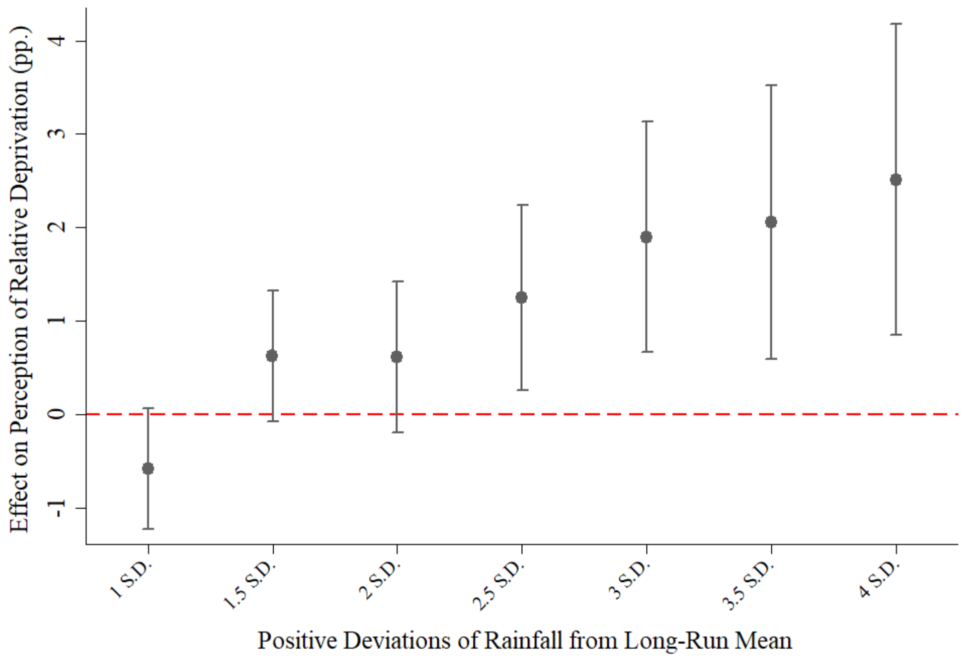
I find that exposure to positive rainfall shocks increases the likelihood of a household perceiving itself to be worse off than other households in the locality or community. For example, Table 1.3 shows that if rainfall in the past year deviates by more than 2.5 S.D. from its long-run mean, then the likelihood of the household perceiving its own standard of living to be worse off relative to other households in the locality or community increases by 1.25 percentage points (pp.). This is a large effect size: considering the sample average of the dependent variable, this translates into a 6.1% increase in the probability of feeling relatively deprived. Additionally, the magnitude of this effect increases as we choose more harmful thresholds, i.e., deviations greater than 3, 3.5, and 4 S.D. (figure 1.1). For instance, severe positive rainfall shocks of 4 S.D.s or more increase the likelihood of a household perceiving its standard of living to be worse off relative to other households in their locality or community by 2.5 percentage points.

Table 1.3 Effect on Perceived Relative Deprivation

	Dep. Var.: Perceived Relative Deprivation	
	(1)	(2)
Rainfall Shock	1.251**	1.249**
Deviation >= 2.5 S.D.	(0.506)	(0.505)
N. of obs.	139,587	139,587
N. of Households	44,193	44,193
Mean Dep Var	0.203	0.203
R2	0.367	0.368

Notes: Column (1) is without any controls. Column (2) includes controls- household head specific characteristic like sex of respondant (hh head), age, age square, education level fixed effects. All specifications include household, month of interview and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Figure 1.1 Effect of Positive Rainfall Shocks on Perceived Relative Deprivation



No. of observations: 139,587; Households: 44,193; Mean of Perceived Relative Deprivation: 0.20

1.6 Potential Mechanisms and Heterogeneity

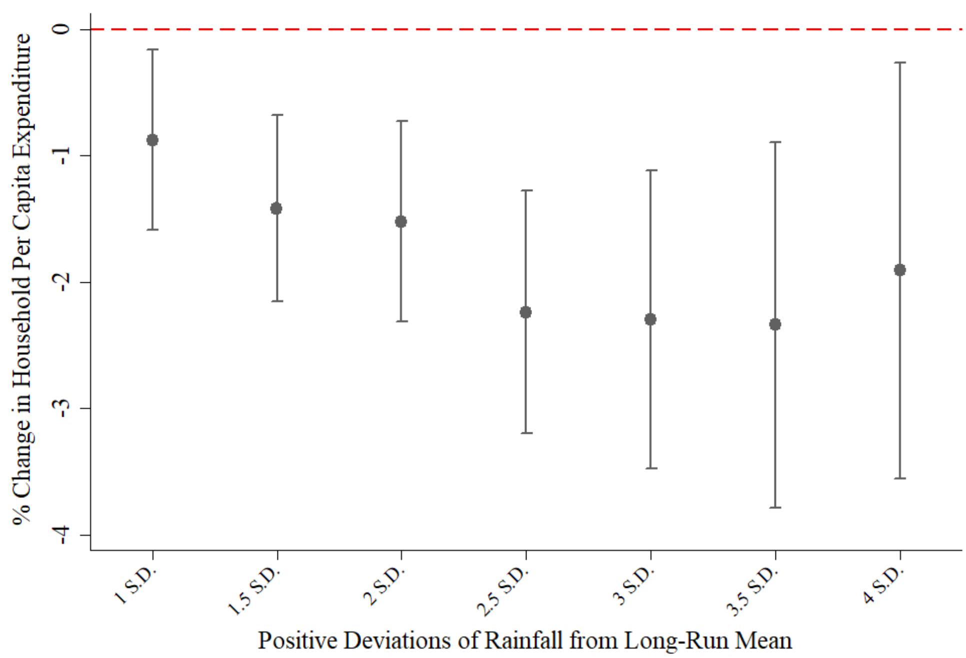
I conceptualize that the changes in perceived relative deprivation could be guided through two potential mechanisms. First, I examine whether rainfall shocks can increase *actual* relative deprivation. Rainfall shocks could potentially have differential effects and make some households objectively worse off than other households in the locality (altering their actual economic position within the community). Thus, the increase in *perceived* relative deprivation could be an artifact of an increase in actual relative deprivation. Second, an alternative channel could be that the weather shock of interest could affect all households similarly within a locality, but misperceptions about the losses of other households could guide perceptions of relative deprivation. I discuss these potential mechanisms in this section.

1.6.1 Effect on Objective Outcomes and Differential Effect by Baseline Economic Status

To explore the first potential mechanism (i.e., shocks affecting *perceived* relative deprivation through *actual* relative deprivation), I start by analyzing the effect of rainfall shocks on key objective outcomes, such as household per capita expenditure (household consumption). Next, I test whether rainfall shocks have differential impacts on objective outcomes that could affect perceived relative deprivation within communities.

I find that excess rainfall shocks reduce household per capita expenditure, one of the most widely used measures of economic welfare. This is in line with the literature exploring the effect of extreme weather shocks on income or consumption levels. Specifically, a deviation in contemporaneous rainfall from the long-run mean by 2.5 SDs, reduces household consumption by 2.13 % (Table 1.4).[8] The effect size increases in magnitude for higher harmful thresholds of deviations (figure 1.2).

Figure 1.2 Effect of Positive Rainfall Shocks on Household Per Capita Expenditure



No. of observations: 139,587; Households: 44,193; Mean of Household Per Capita Expenditure: 4643

As previously discussed, even when rainfall shocks affect all households within a given community, they can alter perceived relative deprivation if they affect households *differentially*; i.e., some households might experience more negative effects on objective outcomes than their neighbors. This could be because households might have different levels of vulnerability, especially across

[8]This corresponds to an increase in the likelihood of a household falling below the poverty line by 1.3 percentage points (figure A.6). Compared to the sample average of households below the poverty (25%), this translates to a 5.2% increase in poverty, which is a large effect.

Table 1.4 Effect on Household Per Capita Expenditure

	Log Household Per Capita Exp. (1)
Rainfall Shock	-2.110***
Deviation >= 2.5 S.D.	(0.529)
N. of obs.	139,587
N. of Households	44,193
Mean Dep Var	4643
R2	0.855

Notes: Controls include household head specific characteristics like sex of respondent (hh head), age, age square, education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

poor and non-poor households. To investigate this possibility, I test whether rainfall shocks have heterogeneous effects by households' baseline poverty status [9]. Columns (1) of table 1.5 suggest that poor households (i.e., below the official poverty line) at baseline are more negatively affected by excess rainfall shocks than the non-poor households along objective outcomes. Specifically, for households classified as poor at baseline, a positive deviation in rainfall from its long-run mean by 2.5 SDs reduces household consumption by 3.2%. In comparison, a shock of similar intensity does not seem to affect non-poor households, suggesting that excess rainfall shocks disproportionately affect poor households. This differential effect on household consumption across poor and non-poor households hold across all thresholds of excess rainfall shock (figure A.7).

Next, I investigate whether the differential effect of extreme rainfall shocks on objective out-

[9]For this regression, I calculate households' "baseline" based on their poverty status in the first year in which they appear in the panel. Thus, I drop the observations from this baseline year from the regression sample. Because the empirical strategy discussed in Section 3.4 is based on *within* household variation, I also drop the observations from households that only appear once (besides the baseline year) in the panel. Therefore, this analysis only includes households that were surveyed for at least 3 years.

comes translates into changes in *perceptions* about relative deprivation; i.e., are the poor also more likely to perceive they are relatively worse off? Column (2) of table 1.5 shows that *both* poor and non-poor households (by baseline poverty status) are more likely to perceive relative deprivation in the face of an extreme positive rainfall shock. However, poor households experience larger effects. Specifically, the probability that poor households perceive they are relatively deprived increases by 3.7 percentage points upon experiencing a shock. In contrast, the probability that non-poor households feel relatively deprived increases by 1.4 percentage points. In fact, this pattern of both poor and non-poor households perceiving relative deprivation is consistent for the other severe thresholds of excess rainfall shocks (figure A.8). These findings are consistent with poor households experiencing larger losses across objective measures of well-being (such as consumption). However, given that non-poor households do not seem to experience objective losses, it does not explain why this group would also feel more relatively deprived [10].

Additionally, to determine whether extreme excess rainfall shocks widen the economic gap within the locality or community and lead to *actual* relative deprivation, I look into the effect of rainfall shocks on standard measures of relative deprivation (Stark, 1984; Yitzhaki, 1979). These standard measures of relative deprivation are based on using income differences within a reference group. However, alternate outcomes of interest like household consumption or wealth index could be used as well (Kafle et al., 2020). Since the perceived relative deprivation measure is based on perceived differences in the standard of living between the household and other households within a locality, I believe that using household consumption would be in line with our perception measure.

Following Stark (1984), let $F(y)$ denote the cumulative distribution of consumption y, and the $1 - F(y)$ is the percentage of households with higher consumption than y. The measure of relative

[10] It can be possibly argued that this increase in perceived relative deprivation for non-poor households is driven by the relatively vulnerable non-poor households (at baseline) that perhaps slip below poverty due to exposure to excess rainfall shocks. To address this, figures A.9 and A.10 show the effect of excess rainfall shocks on perceived relative deprivation on two separate sub-samples. Separately for households that *always* remain non-poor or above the poverty line and a combined sub-sample of households that always remain poor, as well as, *switch* status at least once, i.e., switch between non-poor and poor status. But fig. A.9 shows that even households which remain always non-poor or above the poverty line *also* tend to perceive relative deprivation in the face of a shocks. This is suggesting that the increase in perceived relative deprivation for non-poor households are not just driven by the specific vulnerable non-poor households that possibly slip into poverty in the face of a shock.

Table 1.5 Differential Effect with Baseline Poverty Status

	Log Household Per Capita Exp. (1)	Perceived Relative Deprivation (2)
Rainfall Shock	-3.241**	3.686**
Deviation >= 2.5 S.D.	(1.654)	(1.430)
× Baseline Poverty Status	2.843	-2.267
[=1 if household is non-poor in baseline]	(1.777)	(1.595)
Effect for non-poors at Baseline	-0.398	1.419*
	(0.689)	(0.743)
N. of obs.	78,884	78,884
N. of Households	26,941	26,941
Mean Dep Var	4679	0.201
R2	0.869	0.391

Notes: Since I use the baseline poverty status, I leave out the baseline year of the household, thus, the number of observations reduces. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

deprivation for household i in a reference group n is defined as :

$$RD_{in}(y) = \int_{y_n^i}^{y_n^h} [1 - F(x)]\, dx \tag{1.4}$$

Here RD_{in} is the measure of relative deprivation for household i in reference group N. y_n^i is the consumption for household i, y_h^i is the highest consumption value in the reference group N, and $F(x)$ is the cumulative distribution of consumption in the reference group. Reference group in this context is defined as all households sampled within a given district in a given year (either all households within rural or urban areas, depending on the location of the household). Equation 1.4 can be written as the following:

$$RD_{in} = \mu_n[1 - \phi(Y_{in})] - Y_{in}[1 - F((Y_{in}))] \tag{1.5}$$

Here μ_n is the average consumption in the reference group, $\phi(Y_{in})$ is the proportion of households in the reference area with a consumption level higher than Y_{in} to the total consumption of all households in the reference area. $F(Y_{in})$ is the cumulative distribution of consumption in the reference group.

A similar measure of relative deprivation is the Yitzhaki measure of relative deprivation (Yitzhaki, 1979; Hey and Lambert, 1980; Podder, 1996). In this case, the Yitzhaki measure of relative deprivation for household i with N other households in its reference group [11] is defined as the following:

$$RD_i = 1/N \sum_{i \neq j} [ln(c_j) - ln(c_i)] ... \forall c_j > c_i \tag{1.6}$$

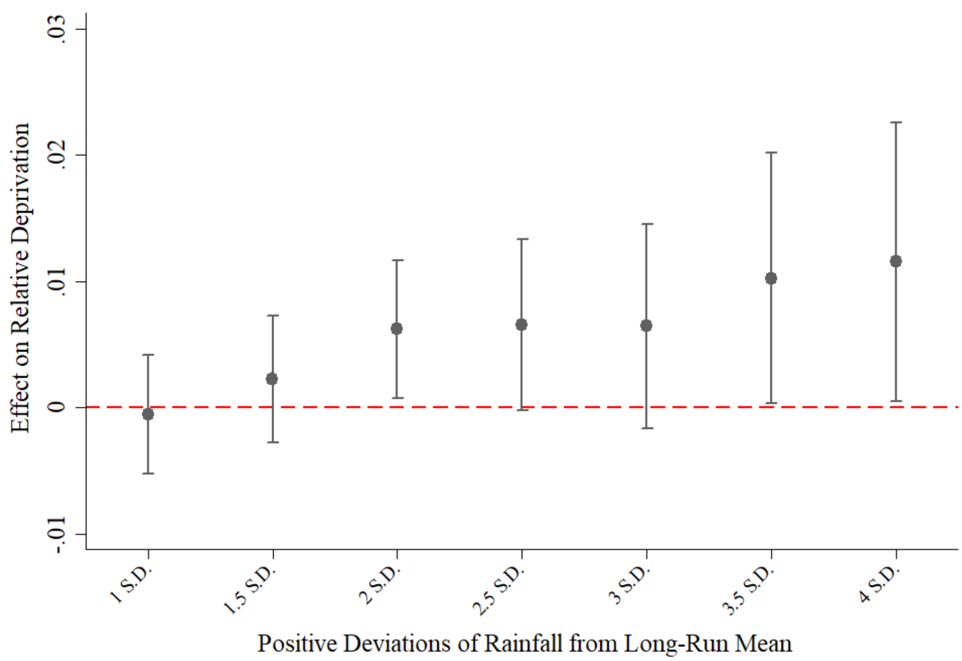
Here c is household per capita expenditure. Both these measures capture that the relative deprivation for household i is driven by the households with higher consumption than c_i. Using differences in log consumption expenditure per capita makes the measure scale-invariant, and dividing the size of the reference group makes the measure invariant to the reference group, and it also adjusts for the probability of making a comparison (Eibner and Evans, 2005; Podder, 1996; Hey and Lambert, 1980). Using this measure of relative deprivation, I find that heavy rainfall shocks widen the economic gap between households within its locality- as measured by per capita consumption expenditure (figure 1.3). Considering the sample average of the dependent variable, an excess rainfall shock above 2.5 S.D. from the long-run mean increases this objective measure of relative deprivation by 2.1%. The effect size is positive, statistically significant, and increases with higher harmful thresholds of the shock.

Overall, this explains that the differential effect of the excess rainfall shock across the poor and non-poor households translates into widening economic gaps within a locality- as measured by the

[11] The reference group here is similar to the Stark measure of relative deprivation. I consider all other households sampled within the district in a given year, either rural or urban, as the reference group of household i

measures of relative deprivation using objective outcomes like household per capita consumption. While this possibly explains the increase in perceptions of relative deprivation for poor households, it is unclear as to why the non-poor perceive relative deprivation (column (2) of table 1.5). Thus, we next look into the possible misperception channel as an additional mechanism to explain this finding alongside an increase in actual relative deprivation.

Figure 1.3 Effect of Positive Rainfall Shocks on Relative Deprivation (Stark measure)



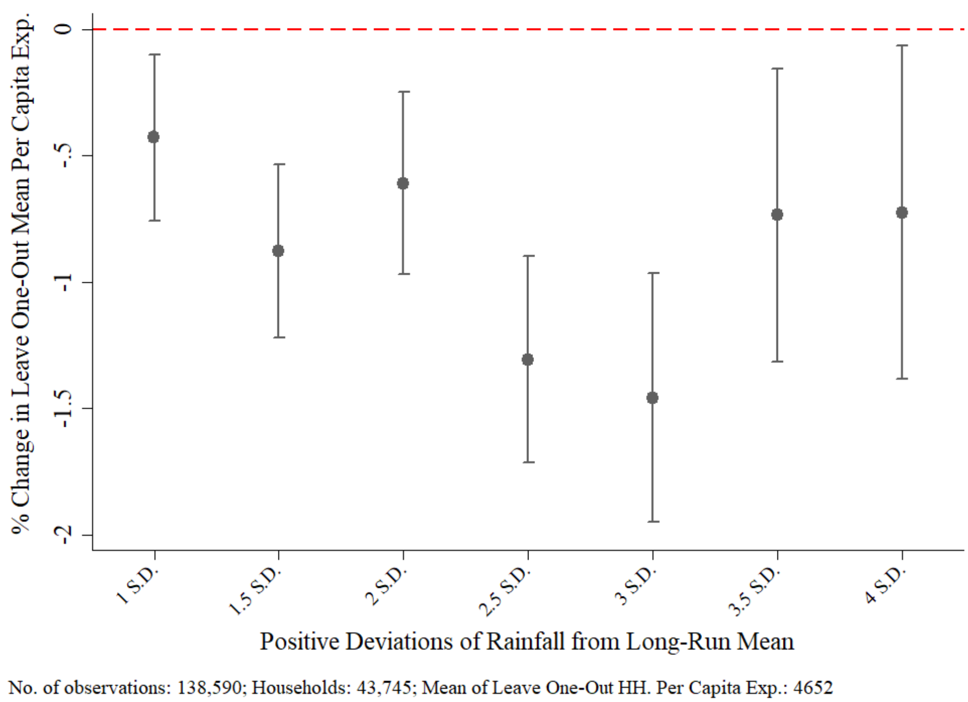
No. of observations: 134,848; Households: 42,523; Mean of Relative Deprivation: 0.32

1.6.2 Role of Misperceptions of Other Households' Outcomes

As discussed earlier, excess rainfall shocks can affect perceived relative deprivation through another mechanism: households might feel relatively worse off if they have an incorrect sense of how these shocks affect others in their communities. For example, even if a household has only experienced mild objective losses from a rainfall shock, it might (incorrectly) believe that others around it have been completely unscathed and that its social standing in its community has been diminished.

To examine the role of possible misperceptions, I first check the impact of excess rainfall shocks on other households within a locality. For this, I construct a measure of relative consumption: the leave-one-out mean of per capita expenditure. The leave-one-out mean of household i is the average outcome of all other households within a community *excluding* household i. I estimate equation 1.3 using the leave-one-out mean of per capita expenditure (in logs). I find that the other households within a locality are also affected negatively due to a heavy rainfall shock. This can be seen in figure 1.4. Heavy rainfall shocks negatively affect the leave-one-out mean of per capita expenditure within a locality [12].

Figure 1.4 Effect of Positive Rainfall Shocks on Leave One-Out Mean Per Capita Exp. (in Log)



Next, I test whether there are misperceptions about the losses of other households within the locality. For this, I use the question related to households' perception of how the standard of living has changed for other households within its community over the course of the previous year. I create a measure of perception of other households' conditions which takes value of one if a household perceives that the standard of living of other households is "worse" and zero if it perceives it remained "same" or got "better". I estimate equation 1.3 using this binary variable of

[12] Correspondingly, this increases leave-one-out average poverty in the locality (Figure A.11)

perceptions about the standard of living of other households as the dependent variable. Despite objective losses among neighbors (as shown in figure 1.4), it is possible that households are unable to gauge these losses and systematically perceive that the standard of living of other households within its reference group has remained "same" or "got better".

Table 1.6 provides some support for the potential role of misperceptions in shaping increased feelings of relative deprivation. Column (1) in Table 1.6 shows that in the face of a shock, households are actually more likely to report that the standard of living of other households in their community has remained "same" or "got better". This is contrary to what we observe in terms of the effect of the shock on measures of actual losses of other households. Specifically, exposure to positive rainfall deviation, which is above the long-run mean by 2.5 times the long-run standard deviation, reduces the likelihood of reporting other households in their community are "worse-off" by 0.66 percentage points. This suggests that, regardless of how households perceive their *own* losses, they tend to underestimate the effect of shocks on *others* in their communities. This could lead to increased perceptions of relative deprivation. In figure A.12 it can be observed that at more severe excess rainfall shocks, households are less likely to report other households have remained "same" or "got better". This suggests that misperceptions about the losses of other households weaken at more severe excess rainfall shock, but it does not reduce in a way that would have an effect on perceived relative deprivation.

1.6.3 Heterogeneity by Indigenous Households and Human Development Index

Belonging to historically alienated communities or living in regions with lower levels of local development could augment perceptions of relative deprivation. I test this with heterogeneity by indigenous households and the human development index, which is used as a measure of local development.

Indigenous households are those whose household heads' mother tongues are indigenous languages (i.e., Quechua, Aymara, or other native languages). There is evidence related to discrimination against indigenous households in Peru that limits their economic opportunities, even outside the realms of poverty and asset holdings. Alongside evidence of historical discrimination that

Table 1.6 Effect of Rainfall Shock on Perceptions of Standard of Living of other Households

	Dep. Var.: Perceptions about Other Households
	(1)
Rainfall Shock	-0.660*
Deviation >= 2.5 S.D.	(0.374)
N. of obs.	139,587
N. of Households	44,193
Mean Dep Var	0.116
R2	0.392

Notes: The dependent variable is a binary variable which take value 1 if the household perceives that the standard of living of other households has become "worse" and 0 if it perceives it remained "same" or "got better", in the course of last year. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

affects current objective economic outcomes (Dell, 2010), there is evidence of economic discrimination against indigenous households even in current times. Galarza and Yamada (2014) found that indigenous job applicants with similar qualifications to white applicants must send 80% more applications to get a callback chance. They used fictitious resumes with indigenous surnames to apply to actual job vacancies. There is also evidence of indigenous people being exploited through debt bondage, where laborers are trapped in debt they cannot repay through wage advances and other manipulations (International Labor Organization, 2008). In addition, there are other taste-based discrimination against the indigenous people- for example, discrimination based on even *beauty* (Castillo et al., 2010). In summary, these indicate the presence of a persistent pattern of discrimination against the indigenous population in current times. These patterns of discrimination could essentially limit the ability of indigenous households with opportunities to smooth consumption in the face of a shock. There is similar evidence of disparities by race in the ability to smooth consumption in the face of a shock in the U.S.- Black and Hispanic households smooth consumption less than white households in the face of an income shock due to less access to credit, different debt obligations, liquid wealth amongst other factors (Ganong et al., 2020).

Alternatively, I test for heterogeneity using the district-level human development index (HDI). I use the human development index as a measure to capture local development. Low levels of local development can indicate low living standards and fewer economic opportunities, which could also hinder the ability to smooth consumption, shaping perceptions of relative deprivation. Another explanation could be that the salience of deprivation or inequality could be higher within less developed or poorer districts. For example, Fafchamps and Shilpi (2008) shows that isolated communities and households actually care more about relative consumption, contrary to the idea that market interaction fuels invidious comparison. One of the suggested reasons behind this is the salience of inequality- relative differences are more glaring when a homogeneous poor community starts differentiating economically. Relative differences in losses and consumption smoothing in the face of a shock could thus shape perceptions of relative deprivation even within locally less developed or poorer regions. The heterogeneity with respect to the human development index at the district level attempts to capture the effect of the excess rainfall shock on perceived relative deprivation within a region that is less developed.

Table 1.7 shows the heterogeneity results. I find that indigenous households experiencing an excess rainfall shock are more likely to perceive they are relatively more deprived. Similarly, households inhabiting in districts with lower levels of development captured by the district-level human development index are also more likely to perceive relative deprivation in the face of an excess rainfall shock. This suggests that belonging to historically alienated communities or residing in regions with low levels of development could augment the likelihood of perceived relative deprivation upon experiencing severe excess rainfall shock.

1.7 Examining the Role of Social Assistance Programs

The results in Section 1.6.1 suggest that objective losses (e.g., actual household consumption) can partly explain the effect of rainfall shocks on perceived relative deprivation. Importantly, the

Table 1.7 Heterogeneity by Indigenous Households and Human Development Index

	Dep. Var.: Perceived Relative Deprivation		
	(1)	(2)	(3)
Rainfall Shock	1.245**	2.435**	2.462**
Deviation >= 2.5 S.D.	(0.506)	(1.021)	(1.161)
× Dummy for Indigenous Household		-1.574	
[=1 if household non-indigenous]		(1.155)	
× Dummy for Districts with HDI ≥ Median HDI			-1.365
[=1 if District HDI ≥ Median HDI in Baseline year-2007]			(1.277)
Effect for non-indigenous HH.		0.860	-
		(0.573)	-
Effect for hhs. in districts			1.097**
with above median HDI			(0.558)
N. of obs.	139,213	139,213	129,626
N. of Households	44,096	44,096	41,748
Mean Dep Var	0.203	0.203	0.205
R2	0.369	0.369	0.375

Notes: Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. In column (3), I use baseline HDI for the year 2007; for this purpose, the analytical sample in this case contains households surveyed in rounds 2008-2019. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

differential effect of the shock across more vulnerable (poor) *vis-à-vis* less vulnerable (non-poor) households could be an important channel through which excess rainfall shocks affect households' perceptions about relative social positions. If this could explain some of the change in perceived relative deprivation, then government programs that partly offset such losses could mitigate the effect of these shocks on perceived relative deprivation. Therefore, I explore the heterogeneous impact of the excess rainfall shock by access to social programs. Specifically, I test whether access to cash or in-kind assistance can mitigate households' negative perceptions about their relative well-being.

1.7.1 Role of Direct Cash Transfer Program- Juntos

To test whether cash transfer programs have mitigating effects, I focus on the *Programa de Apoyo Directo a los más Pobres - Juntos* (or Direct Support Program for the Poorest – Juntos). This program was launched in April 2005. It provides households with cash transfers to reduce current poverty and prevent intergenerational poverty patterns through increases in human capital investments (i.e., health and education). Through Juntos, eligible poor households receive cash transfers of 200 soles (about US $55) every other month[13], *conditional* on meeting the following conditions: households having children aged 6-14 should attend at least 85% of school days; children aged 0-5 should visit healthcare centers for checkups; and finally, pregnant or nursing women must visit healthcare centers for antenatal and postnatal care, respectively. Juntos is the most widely available government-run assistance program for poor households in Peru (Díaz and Saldarriaga, 2019; Morel Berendson and Girón, 2022).

Unfortunately, ENAHO only started recording households' access to social programs (including Juntos) from 2012 onwards. Thus, I test for the role of this program on a limited sample of households (that excludes data before 2012). Since access to government programs (such as direct cash transfers) could be potentially endogenous to excess rainfall shocks (e.g., as a government response to local calamities), I construct an indicator variable for whether households had access to Juntos in the baseline year (i.e., the first year in which a household appears in the panel). Thus, my restricted sample also excludes information from this baseline year.

Column (1) of Table 1.8 shows the effect of the excess rainfall shock on perceived relative deprivation in the restricted sample of households. Though the effect is still positive, its magnitude is larger than the one found with the full sample (in Table 1.3). In column (2) of Table 1.8, I include the interaction of the rainfall shock with an indicator variable that captures access to Juntos at baseline. I find that households without access to Juntos are more likely to perceive relative deprivation in the face of an excess rainfall shock. Specifically, excess rainfall shocks increase households' probability of perceiving relative deprivation by 2.4 percentage points for

[13]Though originally, this program made a monthly transfer of 100 soles to its beneficiaries, later in 2010 this changed to a bimonthly payment of 200 soles.

those without access to this program. In contrast, for households with access to Juntos at baseline, rainfall shocks do not seem to affect their perception of relative deprivation: the effect is small and not statistically different from zero. The difference between non-beneficiaries and beneficiary households is large, but not statistically significant.

Table 1.8 Heterogeneous Effect on Perceived Relative Deprivation by Access to Direct Cash Transfer Program in Baseline Year of Survey

	Dep. Var.: Perceived Relative Derpivation	
	(1)	(2)
Rainfall Shock *Deviation >= 2.5 S.D.*	2.195** (0.879)	2.393** (0.926)
× Baseline Access to Juntos *[=1 if household has access in baseline year]*		-1.938 (2.788)
Effect for households with access in baseline year		0.455 (2.646)
N. of obs.	43,295	43,295
N. of Households	14,660	14,660
Mean Dep Var	0.198	0.198
R2	0.390	0.390

Notes: Since I use the baseline information of access to direct cash transfer program, I leave out the baseline year of the household. Additionally, since the record of social programs was started by ENAHO only in 2012, the analytical sample contains households surveyed in rounds between 2013 and 2019. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

1.7.2 Role of Food Assistance Programs

I also look into the role of in-kind food assistance programs in mitigating perceptions of relative deprivation. Theoretically, access to in-kind assistance also allows for smoothing own consumption losses and thus attenuates the effect of excess rainfall shocks on perceived relative deprivation. Similar to Juntos, I explore the potential heterogeneous impacts of excess rainfall shocks by access to food assistance programs. Peru has several food assistance programs [14], most targeting to improve mother's and children's nutrition. The ENAHO includes information about access to these programs throughout the entire analysis period (2007-2019). Across all years in the sample, on average, around 35% households had access to different kinds of food assistance programs. Some of the popular assistance programs are Vaso de leche (Glass of Milk), Desayunos o Almuerzos Escolares en Instituciones Educativas de Primaria, or Qali Warma (School breakfasts or lunches in primary educational institutions). The Vaso de leche program is one of Peru's most active and oldest assistance programs that operates locally and provides milk servings complemented with oats, rice, quinoa flour, or other food items (Zavaleta et al., 2017). The Qali Warma on the other hand is a national school feeding program that aims to provide food service to children above the age of 3 years in public schools. It serves breakfast in some schools, and breakfast and lunch in some- depending on the district poverty rates (Zavaleta et al., 2017). Like the cash transfer program, the idea here is that access to food assistance programs would help the household smooth a part of their consumption in the face of a shock.

Similar to Juntos (Section 1.7.1), access to food assistance programs could also be endogenous to extreme rainfall shocks (which can create food shortages and foster government aid). I construct a variable that captures whether households have access to *any* food assistance programs listed in the ENAHO in their baseline year (i.e., the first year a household was interviewed in the panel dataset). Therefore, I use a similar sample to the one in Table 1.3 but exclude observations from households' baseline year. Column (1) of Table 1.9 shows the baseline effect of the shock on

[14]Popular food assistance programs include- Vaso de leche (Glass of Milk), Comedor popular (incluye club de madres) (Popular dining room), Canasta en Establecimientos de Salud para Niños y Niñas menores de 3 años (Food assistance in health establishments for boys and girls under 3 years of age), Canasta en Establecimientos de Salud para Madres Gestantes (Food assistance in health establishments for pregnant mothers), Canasta en Establecimientos de Salud para Madres que dan de Lactar (Food assistance in health establishments for breastfeeding mothers), Refrigerios o Almuerzos Escolares en Instituciones Educativas de Inicial o PRONOEI (Snacks or school Lunches in initial educational institutions or pre-School initiatives), Desayunos o Almuerzos Escolares en Instituciones Educativas de Primaria (School breakfasts or lunches in primary educational institutions), Atención Alimentaria Wawa Wasi / Cuna Más (Centers for impoverished children aged six to 48 months), INABIF (CEDIF-Centro Comunal Familiar) (Family Community Center)

perceived relative deprivation in the restricted sample of households. This effect is slightly larger but overall consistent with the results in Table 1.3 based on the full sample. In column (2) of Table 1.9, I add the interaction of the rainfall shock with an indicator variable that captures whether the household had access to any food assistance programs at baseline. I find that households without access to such assistance are more likely to perceive relative deprivation in the face of a shock: excess rainfall shocks increase the likelihood of perceiving relative deprivation by 2.1 percentage points among these households. Alternatively, for households with access to in-kind food assistance at baseline, rainfall shocks do not seem to affect their perception of relative deprivation; the effect is not statistically different from zero. However, the difference in the effect size for households with and without access to in-kind food assistance is not statistically significant.

In summary, the heterogeneous impacts among those with access to cash transfers and in-kind assistance programs suggest that public policies could be critical in attenuating perceptions of relative deprivation in the face of a covariate shock.

1.8 Robustness Checks

In this section, I test whether my results are robust to alternate measure of perceived relative deprivation; exposure to emergency events like floods, mudslides, landslides, and heavy rainfall-related emergencies and alternative measures of covariate shocks- like self-reported exposure to natural disasters; changes in sample composition, and endogenous migration and falsification tests with leads (i.e., future) of the rainfall shocks.

1.8.1 Alternative Measure of Perceived Relative Deprivation

As table 1.1 shows, in the preferred definition of dependent variable of interest, we have a binary measure of perceived relative deprivation which takes value one *only* when households perceive *strict* relative deprivation. However, this may mask a lot of information and so I construct a categorical variable of perceived relative deprivation with strictly better-off, same as others, and strictly worse-off categories (in that order), as shown in table A.1. Following, this I estimate an ordered probit model and report the marginal effects for this regression in table A.2. Using this alternate definition we have consistent results, it shows that with exposure to an excess rainfall

Table 1.9 Heterogeneous Effect on Perceived Relative Deprivation by Access to Food Assistance Program in Baseline Year of Survey

	Dep. Var.: Perceived Relative Deprivation	
	(1)	(2)
Rainfall Shock	1.836***	2.135***
Deviation >= 2.5 S.D.	(0.670)	(0.831)
× Baseline Access to Food Assist. Progs.		-0.832
[=1 if household has access in baseline year]		(1.354)
Effect for households with access in baseline year		1.303
		(1.093)
N. of obs.	78,116	78,116
N. of Households	26,633	26,633
Mean Dep Var	0.201	0.201
R2	0.391	0.391

Notes: Since I use the baseline information of access to food assistance programs, I leave out the baseline year of the household. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

shock above 2.5 S.D. from the long-run mean significantly increases the probability of perceiving strictly *worse-off* than others in the locality or community, and there is a corresponding decrease in the likelihood of perceiving strictly better-off, as well as, perceiving to be same as others with exposure to an excess rainfall shock of this intensity.

1.8.2 Exposure to heavy rainfall related emergency events

As discussed earlier, I use excess rainfall shocks to proxy for extreme events like floods, mudslides, landslides, and other heavy rainfall-related emergencies. The National Institute of Civil Defense of Peru provides geographic coordinates (latitude and longitude) of emergency responses by type of emergency events. I match these geographic coordinates with the household locations provided by the ENAHO for a given year, and I categorize a household as exposed to a heavy rainfall-related emergency if it is located within a 500-meter radius from the geographic coordinate of the emergency response provided in the National Civil Defense dataset, and the emergency occurred within the 12 months from the time of interview. The National Institute of Civil Defense of Peru provides emergency response for a wide range of emergency event categories, like- heavy rainfall, floods, mudslides, landslides, storms, fires, droughts, frost/cold waves, hail, earthquakes, epidemics, volcanic eruptions, spillover of harmful substances, environmental pollution and other types of emergencies. I consider only heavy rainfall, floods, mudslides (huaycos), and landslides as these are closely connected to excess rainfall shocks, and so I consider the exposure of households to these types of emergencies only in this case.

Figure A.13 shows the locations of huaycos or mudslide-related emergencies in Peru in 2019, alongside the locations of households surveyed in the ENAHO in 2019. Figure A.14 shows an illustrative example of the case of the Puacartambo district in Pasco province in Pasco, where the emergency illustrated here is related to a huaycos or mudslide situation that occurred on 21st January 2019. The households located within a radius of 500 meters are considered to be exposed to this emergency as they are in close proximity to this emergency; importantly, these households were interviewed in February 2019 (and the emergency exposure is within the past 12 months from the time of interview) [15]. Alongside huaycos or mudslides, I consider heavy rainfall, floods, and landslide emergencies as documented by the National Institute of Civil Defense of Peru, considering these are most closely related to instances of heavy rainfall.

This also allows us to test if the measure of excess rainfall shock used in this case is a good proxy for exposure emergencies related to heavy rainfall, floods, landslides, and mudslides. Table A.3 shows that an excess rainfall shock above 2.5 S.D. from the long-run mean increases the likelihood of being exposed to an *emergency event* related to heavy rainfall, floods, landslides, or mudslides by 3.1 percentage points. This is a large effect size, considering the sample average of the dependent

[15] Similar to the rainfall shock, I categorize emergency exposure as a *binary variable* which takes value 1 if the household is located within the 500-meter radius from the location of a relevant emergency and also if it occurs within the past 12 months from the time of interview; and 0 otherwise.

variable; this translates into a 21.3% increase in the probability of exposure to an emergency event related to heavy rainfall, floods, landslides, or mudslides.

Table A.4 shows the direct effect of exposure to excess rainfall-related emergency events on perceived relative deprivation. I find that exposure to such emergency events in the past 12 months from the time of the interview increases the likelihood of perceived relative deprivation by 1.06 percentage points. The effect size is quite similar to table 1.3.

1.8.3 Alternative Measures: Self-Reported Exposure to Natural Disasters

Next, I check whether exposure to natural disasters (and not just excess rainfall) provides similar consistent findings on perceived relative deprivation. For this, I use self-reported exposure to natural disasters in the past 12 months from the time of the interview (from the governance module of ENAHO).

In Column (1) of Table A.5, I reproduce my main results (from Table 1.3) to ease comparison with estimates using alternative variables to identify similar covariate shocks. Columns (2) and (3) of Table A.5 show that exposure to extreme events in the form of natural disasters indeed increases the likelihood of households perceiving their standard of living to be worse off in comparison to other households in the locality. Specifically, conditional of household, year, month of interview fixed effects and a set of household level controls, self-reported exposure to natural disaster events increases the likelihood of perceiving own household status adversely relative to other households in the locality by 2.58 percentage points. Alternatively, a self-reported measure of exposure to natural disaster events could have endogeneity concerns, so I construct an additional measure of natural disaster indicator, which assigns value 1 to all households within a district only if the majority of the respondents (more than 50% of the respondents within a district) report exposure to natural disasters in the past 12 months from the time of the interview. Using this measure of exposure to natural disasters increases the likelihood of perceived relative deprivation by 1.44 percentage points (column (3) of table A.5) [16].

[16]Table A.6 shows the effect of negative rainfall shocks on perceived relative deprivation. I consider deviations below 0.8 S.D. and 1.6 S.D., as these are considered moderate and extreme dry conditions (Tambet and Stopnitzky, 2021; Zhang et al., 2011). The effect of exposure to negative rainfall shock on perceived relative deprivation is

1.8.4 Changes in Sample Composition and Endogenous Migration

It could be possible that households who experience relatively more excess rainfall shocks could be different from households experiencing relatively lower excess rainfall shocks. Therefore, I test if household characteristics vary systematically by excess rainfall shocks. In table A.7, I find that there is no meaningful differences in observable characteristics by exposure to excess rainfall shocks. Additionally, I show that there is no indication of endogenous migration in this case. From 2014 onwards the ENAHO survey data records information on whether 5 years ago the household lived in the same district as during the time of interview. Figure A.15 checks whether households are likely to move in response to excess rainfall shocks, possibly to areas with less extreme rainfall shocks. We do not find any evidence suggesting that there is a differential exposure to excess rainfall shocks between households who migrated and those who did not.

1.8.5 Falsification Exercise

Overall, my identification strategy exploits within-household variation over time, comparing outcomes in years with rainfall shocks relative to periods with relatively average weather patterns. However, it might still be possible that areas with rainfall shocks would be on differential pre-trends (in terms of perceived relative deprivation) relative to those without such shocks. It could also be that households are able to anticipate (and respond to) future rainfall shocks. Additionally, it is possible that rainfall shocks simply capture unobserved determinants of perceived relative deprivation that vary systematically across households and/or geographic areas.

To rule out these possibilities, I perform a simple falsification test where I estimate the "effect" of *future* excess rainfall shocks. Specifically, I estimate equation 1.3 where — instead of focusing on exposure to rainfall shocks in the past 12 months to the survey — I use rainfall shocks in the 12 months *after* the interview date. I find that the lead year rainfall shock has no effect on perceived relative deprivation. As shown in Figure A.16, all coefficients are small and statistically insignificant. Thus, this suggests that the main estimates do capture the causal effect of extreme rainfall shocks.

similar, even with moderate dry conditions. However, the effect is positive but statistically insignificant for extreme dry conditions, possibly due to only 2% of the sample are exposed to extreme dry shocks.

1.9 Does Perceived Relative Deprivation Shape Political Attitudes in the Context of Peru?

Recent experimental evidence have established a relationship between perceived relative deprivation and political attitudes (Kosec and Mo, 2021). As noted earlier, alongside shaping political attitudes, perceived relative deprivation also shapes other important outcomes like physical and mental health, hostile and aggressive behavior, subjective well-being or life satisfaction, and support for redistribution.

In this section, I draw a relationship between perceived relative deprivation and political trust, specifically, belief in the functioning of democracy and preference for democratic vis-à-vis autocratic regimes. The measure of belief in the functioning of democracy is most closely related to a widely used measure-"satisfaction of democracy," which is used as a summary measure of political trust or confidence in government institutions (Citrin and Stoker, 2018; Norris, 2011a). This measure most likely captures both "diffuse" attitudes towards the political system (i.e., democracy as a principle or as a broad institution) and "specific" satisfaction with or confidence in the current or recent government regimes (i.e., how democracy works in practice and citizens' evaluation of the performance of different government bodies and different levels of the government- central, regional, provincial, and district level). Studying the effects of perceived relative deprivation on political trust can have important policy relevance as political trust and confidence in government institutions shape policy preferences, compliance with laws, political participation and voting behavior, and the use of public goods and services (Fairbrother, 2019; Citrin and Stoker, 2018; Bélanger, 2017; Christensen et al., 2021; León-Ciliotta et al., 2022).

ENAHO collects political beliefs and confidence in public institutions in the first part of the governance module which could be responded by an randomly chosen adult individual within the household. The two key measures of political attitudes are discussed in more detail as follows. Firstly, whether households believe "democracy functions well in Peru?" I code the responses to this question as one to those who believe democracy works "well" or "very well" and zero otherwise (see below). This measure is widely considered to be a summary measure of political trust.

$$Y_{idt} = \begin{cases} 1 & \text{if response is "very well" or "well"} \\ \\ 0 & \text{if response is "very poorly" or "poorly"} \end{cases} \tag{1.7}$$

I also examine the relation between perceived relative deprivation and preference for authoritarian regimes over democratic regimes. For this, I use the question asked in the governance module- "With which of the following opinions do you agree- a) A democratic government is always preferable; b) In some circumstances, authoritarian government is preferable to a democratic one, and c) I don't care if it is an authoritarian or democratic government"

$$Y_{idt} = \begin{cases} 1 & \text{if response is (a) or (c)} \\ \\ 0 & \text{if response is (b)} \end{cases} \tag{1.8}$$

I estimate the following equation: the dependent variable is these two measures of political trust, and the main variable of interest is perceived relative deprivation. I control for α_i, γ_t and θ_m capturing household, year and month of interview fixed effects respectively [17]. Standard errors are clustered at the household level.

$$Y_{idmt} = \beta_1 PerceivedRel.deprivation_{idmt} + \alpha_i + \gamma_t + \theta_m + \varepsilon_{idmt} \tag{1.9}$$

Exploiting within-household variation in perceived relative deprivation, I find that households that perceive relative deprivation are more likely to report democracy functions "poorly" or "very poorly" in Peru; additionally, these households are also more likely to prefer "authoritarian regimes over democratic ones, in some circumstances". Specifically, perceived relative deprivation increases the likelihood of perceiving democracy functions "poorly" or "very poorly" by 1.15 percentage points and expressing support for autocratic regimes over democratic ones, in some circumstances, by 0.79 percentage points (table 1.10). Considering the sample average, these translate to a 2.1%

[17] Since the political beliefs could be reported by any adult individual within the household (and not just household head), I do not control for respondent specific characteristics in this case, as these are most likely captured by household fixed effects. In table A.8 , I restrict the sample where both perceived relative deprivation and the political perception are responded by the household head. The results are quite similar. In column (3) of table A.8, we drop the "don't know" responses in constructing preference for Democracy v/s Autocratic Regime variable, and the results hold.

Table 1.10 Association between Perceived Relative Deprivation and Belief that Democracy Functions Well in Peru & Preference between Authoritarian v/s Democratic Regimes

	Democracy Functions Well (1)	Authoritarian v/s Democracy Preference (2)
Perceived Relative Deprivation	-1.146***	-0.785**
	(0.415)	(0.315)
N. of obs.	112,422	113,049
N. of Households	37,275	37,458
Mean Dep Var	0.432	0.858
R2	0.459	0.397

Notes: All specifications include household, month of interview and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

and 5.5% increase in negative perception related to the working of democracy and preference for democratic regime, respectively. Overall, these results provide evidence that perceived relative deprivation matters for determining political attitudes that could be key in the Peruvian context.

1.10 Conclusion

This paper provides important evidence on the effects of covariate shocks- in the form of excess rainfall shocks on perceptions of relative deprivation. I find that exposure to excess rainfall shocks in the past year (from the time of interview of the household) can bring about large changes in perceptions of relative deprivation. This is potentially explained by the differential effect of excess rainfall shocks on objective welfare outcomes across the poor and the non-poor households. Further, I find that this differential effect translates into an increase in actual relative deprivation, as measured by the Stark or Yitzhaki measures of relative deprivation. Additionally, I show that this could also be guided by misperceptions about the losses of other households within a locality.

This study also explores the role of social protection programs in weakening the effect of heavy rainfall shocks on perceived relative deprivation. I find that both direct cash transfers and in-kind transfers can possibly play an important role in attenuating the effect of excess rainfall shocks on perceived relative deprivation. This is an important contribution to literature related to the role of redistributory policies in mitigating perceived relative deprivation.

Overall, this study makes novel contributions through these findings, especially given that it is in a developing country context with a non-experimental, real-world setting. A key takeaway is that subjective perceptions about relative economic position could be different from objective economic losses. The findings could also generate potential interest amongst the literature linking changes in income levels with political attitudes, instability and conflict, by identifying that changes in levels of income may not be the only channel through which weather shocks could affect these outcomes and there could be alternate channels like changes in perceived relative deprivation.

CHAPTER 2

FROSTY CLIMATE, ICY RELATIONSHIPS: FROSTS AND INTIMATE PARTNER VIOLENCE IN RURAL PERU

2.1 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 the negative consequences of 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 locations and household-specific month of interview. We calculate the cumulative degree hours in which households had experienced temperatures below alternative thresholds (e.g., 0°C, -1°C, -2°C,..., etc.) during the year before the survey. Our measure takes into account both the duration (i.e., time spent below a predefined threshold) and intensity (i.e, by how much temperatures dropped below that threshold)

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

of frost. 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.

We explore two main channels through which frosts affect IPV. First, extreme cold can have adverse consequences for agricultural output (Snyder and Melo-Abreu, 2005) and thus income. Previous research has found that income shocks can affect IPV, though there is no consensus about the direction of this effect. Some have found that negative income shocks can increase IPV (Schneider et al., 2016; Heath et al., 2020; Hidrobo et al., 2016; Díaz and Saldarriaga, 2022; Díaz and Saldarriaga, 2023; Abiona and Koppensteiner, 2018; Epstein et al., 2020; 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, others argue that there is a positive relationship between income and IPV, as controlling husbands might exert instrumental violence to gain control over household resources (e.g., 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 show that freezing temperatures — particularly those that occur during the crop-growing season — lower agricultural revenue, total income, and household expenditure.

Second, extreme cold may confine individuals indoors. As people try to shield themselves from inclement weather, frosts can increase interactions between victims and perpetrators. More exposure to violent partners — e.g., through COVID-19 lockdown measures (e.g., Agüero, 2021; Arenas-Arroyo et al., 2021; Gibbons et al., 2021; 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, extreme weather (and severe instances of cold in particular) have

[2]Other studies find no overall relationship between income shocks and violence against women (Blakeslee and Fishman, 2013; Iyer and Topalova, 2014). Though some study the effects of relative income of household members (e.g., male versus female income) on IPV (e.g., Frankenthal 2023), we do not focus on that literature here, as our data include only household (not individual) income.

been linked to increases in partner violence. For example, both the Rape, Abuse and Incest National Network (RAINN) and the National Sexual Assault Online Hotline see higher call volume in the winter and especially during severe cold spells and storms (ABC News, 2014), while police officers blame "cabin fever" induced by extreme weather for spikes in domestic violence cases (Whitehead, 2012). Consistent with this mechanism, we use Google location data to show that frosts reduce time spent in plausibly outdoor locations, as proxied by location pings in parks and on forms of transit.

Critically, we present the first evidence of the income and exposure channels' relative significance, using variation in frost timing to distinguish shocks that affect IPV through changes in income from those that act through time spent indoors. Specifically, we use data on sowing and harvest dates to separate frosts that occur during the growing season — which affect both household income and time spent at home — from those occurring outside of the growing season, which primarily affect time spent at home. We find that frosts that occur during the growing season strongly affect IPV: experiencing 10 degree hours below -9°C increases the probability of IPV by 1.5 percentage points. In contrast, we find that non-growing season frosts have no statistically significant effects on IPV. Back of the envelope calculations suggest that the income channel accounts for nearly three quarters (74.1%) 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) social program coverage at the province level and interact this coverage with our measure of frost shocks. Consistent with expectations, the effects of frosts on IPV are large and significant in provinces where baseline social program coverage is low, though they are 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]

Our results are consistent over a battery of robustness checks. We show that our results are

[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 from these in that we show how access to social assistance programs mitigate the effects of cold weather events on IPV.

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

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 with respect to the relationship between extreme weather and violence. Most of the literature has, so far, focused on the impact of droughts or heat waves, 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).[4] To our knowledge, we are the first to investigate whether *cold* temperatures also increase the incidence of IPV amongst women.[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 several previous papers have also estimated the effects of weather shocks on violence, the implications of these estimates are sometimes difficult to interpret. For this

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

[5] Related to our results, Otrachshenko et al. (2021), find that extreme heat (but not cold) increases the incidence of violent deaths in Russia, with larger impacts for women relative to men. However, Otrachshenko et al. (2021) focus on violent deaths — relatively infrequent and extreme outcomes — whereas we focus on IPV, which represent more general and prevalent types of abuse against women (physical, emotional, and sexual violence, as well as control issues).

reason, we also provide detailed evidence for the mechanisms behind these effects, addressing both income and exposure. The most traditional interpretation is that weather shocks affect violence through their impact on household incomes. However, extreme weather can also alter individuals' routine activities and the time they spend outdoors (Cohn, 1990; Cohn and Rotton, 2000).[6] We present novel evidence about the relative importance of the income and exposure channels, where we find that the income mechanism dominates.[7]

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

2.2 Context

Peru is a setting where violence against women is unfortunately very common. Despite declining in the past decade, IPV remains prevalent: in 2019, 58% of Peruvian women experienced IPV (Agüero, 2021). Due to the nature and geographic scope of cold weather shocks in Peru, we focus on women living in the Peruvian Highlands that had been ever partnered (i.e., potentially subject to domestic violence). In this sample, the incidence of IPV is even higher than the national average; over the course of our sample period (2010-2018), 69% of women reported experiencing some form of IPV in the past year.[8]

Frosts and extreme cold events have become increasingly common throughout Peru over the

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

[7] Our results build on those in Abiona and Koppensteiner (2018) who investigate the possibility that drought can affect IPV by confining families indoors by examining whether controlling for the number of rooms in a dwelling (as a proxy for the size of living space) changes the estimated effect of drought on IPV. We provide suggestive 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.

[8] We describe our measure of IPV in more detail in section 2.3.1.

last two decades, affecting millions of Peruvians (Keller and Echeverría, 2013; FAO, 2008).[9] The Peruvian Highlands, located at elevated altitudes (between 500 and 6,798 meters above sea level), have been particularly susceptible to weather events including frosts and cold waves as well as droughts and floods (World Bank, 2008). In recent years, extreme cold temperatures have dipped as low as -20°C in some areas, affecting close to 200 thousand inhabitants (Centre for Research on the Epidemiology of Disasters, 2023). Most experts argue that this situation will continue to worsen in the future, as Peru is one of the most vulnerable countries to climate change (Stern, 2007; Tambet and Stopnitzky, 2021).

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

2.3 Data and Variables

2.3.1 Encuesta Demográfica y de Salud Familiar (Peruvian DHS)

We use nine repeated cross-sections (2010-2018) of the Peruvian Demographic and Health Survey (DHS - *Encuesta Nacional Demográfica y de Salud Familiar*), a yearly survey collected by the Peruvian National Statistics Office (Instituto Nacional de Estadística e Informática, 2018a). The DHS collects data from a representative sample of women aged 15 to 49 years. It includes information about their socioeconomic characteristics, access to social programs, and health information. Additionally, the DHS collects information on various types of domestic violence experienced in

[9] 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).

the year prior to the survey.[10] One randomly selected woman from each household is asked about four different dimensions of partner abuse during the 12 months preceding the survey: physical, sexual, and emotional violence as well as control issues, which capture ways in which a woman's partner exerts control over her life. More details on these components of IPV are given in Appendix B.1.2. 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 2.4) 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). Using this granular data, we are able to match each particular household with the weather shocks they have experienced over the past year (the same time frame as the IPV recall period).

Due to the geographic concentration of frosts in higher altitudes, we focus on ever-partnered women residing in the Peruvian highlands, resulting in a sample of 55,544 women (about 6,200 per survey year). Appendix Table B.1 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 school and more than half has not completed secondary education. Nearly 70% of women have experienced some form of partner abuse in the past year; much of this abuse is related to partner control issues (e.g., whether a woman's partner does not allow her to see her family or friends). 13% of women experienced physical violence 16% suffered emotional violence, and 4% reported

[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.

incidents of physical violence in their households.[13]

2.3.2 Weather Data

We collect detailed hourly temperatures (i.e., at midnight, 1 AM, 2 AM,..., 11 PM) for every day between 2010 and 2019 from the European Centre for Medium-Range Weather Forecasts (2018) (ECMWF).[14] The ECMWF estimates temperatures from weather stations, satellites, and sondes; and processes this information at a geographic resolution of 0.25 degrees. We match household data from the DHS with the ECMWF weather data using two critical pieces of information: households' approximate GPS location (i.e., the centroid of the village or neighborhood block) and each household's month and year of interview. This allows us to construct a household-specific measure of extreme cold exposure throughout the 12-month period prior to interview (the standard recall period for most survey questions), which takes into account both the location of the household and the timing of the interview.

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

$$\text{Degree Hours}(DH_{itmdh}) = \begin{cases} \lambda - h_{itmdh} & \text{if } h_{itmdh} < \lambda \\ 0 & h_{itmdh} \geq \lambda \end{cases} \tag{2.1}$$

where h_{itmd} is the temperature in household i's location, on year t, month m, day d, and hour h. For example, if λ=-1°C, an hour of temperature at -3°C represents 2 degree hours; while an hour at a temperature of -2°C would lead to only 1 degree hour. Based on the agronomy literature, we

[13]We describe additional sources of data in Appendix Section B.1.1.

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

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, we recognize that sensitivity to cold can vary across crops and livestock types and, thus, we show our results using a wide range (from 0°C to -12°C) of temperature thresholds in figure 2.1.[15] Importantly, some of the major frost-sensitive crops also account for the majority of the value of agricultural output. For example, maize and potato, which are also frost-sensitive crops, alone account for close to half of the agricultural value of output [16].

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

$$\text{Cumulative Degree Hours}(CDH_{it}) = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} DH_{itmdh} \tag{2.2}$$

Finally, we extract rainfall data from the Weather Hazards Group InfraRed Precipitation with Station Data (CHIRPS).[17] CHIRPS is a global dataset that provides high-resolution estimates of rainfall for 0.05 X 0.05 degree pixels. We match rainfall to households using GPS coordinates and interview dates from the DHS using the same procedure as we use 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 B.1). However, this average masks substantial heterogeneity in weather across 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 experience cold below this threshold in the past year (about 5% of women), the average CDH is 15 degree hours.

[15] Additionally, there is no single temperature threshold considered harmful for human exposure. For example, temperatures in the range of 30-50°F (-1-10°C) put individuals at risk for hypothermia (National Weather Service, 2022).

[16] Some of the major crops include Maize, Potato, Beans, Pumpkin, Quinoa, Barley, and Wheat. In total, these account for close to two-third of the agricultural revenue.

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

2.4 Empirical Strategy

2.4.1 Estimating overall effects of frost shocks on IPV

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

$$Y_{idmt} = \beta_1 CDH_{idmt} + \beta_2 AvgTemp_{idmt} + \beta_3 AvgRain_{idmt} + \beta_4 Altitude_{idmt} + \beta_5 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt} \tag{2.3}$$

where Y_{idmt} is a measure of IPV in household i in district d interviewed in calendar month m of year t.[18] CDH_{idmt} is the number of degree hours below threshold λ that a household experienced in the 12-month period before being interviewed (as described in Section 2.3.2). Avg Temp$_{idmt}$ and Avg Rain$_{idmt}$ are the average temperatures and rainfall that household i experienced over the same time period. Altitude$_{idmt}$ is measured at the household level (the same level as weather variables). Z_{idmt} is a vector of predetermined individual characteristics (respondent age and age squared, education level, mother tongue), household controls (sex and age of household head, indicators for wealth quintile, number of children under 5, a rural indicator), and husband's years of education.[19] We include fixed effects at the district level (α_d), which account for spatial variation in the incidence of cold shocks and IPV that is constant over time.[20] We also include fixed effects at the interview year (γ_t) and month level (θ_m), which account for seasonality and general trends in IPV and cold shocks.

The coefficient of interest in equation 2.3 is β_1. Our identification strategy assumes that —

[18]Our measures of IPV are binary, and so for these outcomes, equation 2.3 is a linear probability model. For ease of interpretation, we multiply β_1 by 100 all tables where equation 2.3 is a linear probability model or where Y_{idmt} is transformed using the inverse hyperbolic sine. In Section 2.6 we also use versions of equation 2.3 to estimate the effects of frost shocks on intermediary variables, namely income.

[19]As described below, we regard CDH as exogenous (conditional on district-, year-, and month-fixed effects as well as average temperature). However, we include individual and household controls to improve precision. In section 2.5, we show that our results are not driven by the inclusion of covariates.

[20]Since we match weather data to each household's approximate location (at a finer level than district), there is some spatial variation in CDH at sub-district level. However, we believe that district-level fixed effects are likely to be sufficient in this case for several reasons. First, over 85% of the temperature variation in the sample takes place at the district-year level, i.e. very little variation occurs at a level below the district. Second, we control for household-level altitude, which helps account for systematic variation in weather (and IPV) related to altitude within district. Finally, we run specifications where we match weather data by district centroid rather than the household-specific location. For this, district fixed effects absorb all time invariant heterogeneity in weather. The results of the district-level matching (displayed in column 1 of Appendix Table B.6) are very similar to those in our main results (positive and significant).

conditional on district, year, and month fixed effects (and other individual and household controls) — the incidence and intensity of cold shocks are exogenous with respect to IPV. While households might select into different districts (for example, wealthier households might choose to live in warmer areas), we exploit *within-district* variation in the intensity of cold shocks over time. In essence, we compare households within the same district who are interviewed at different times — and thus who are subject to different temperature fluctuations that vary randomly by the date of interview — while netting out general trends and seasonality in weather. As long as households are unable to anticipate fluctuations in the intensity of cold shocks, $\hat{\beta}_1$ captures the causal effect of cold shocks.

2.4.2 Separately identifying income and exposure channels

In order to assess the relative importance of the income and exposure channels, we separate frost shocks that occur during the growing season versus the non-growing season. As described in Appendix Section B.1.2, 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.

2.5 Overall Effects of Extreme Cold on IPV

In Table 2.1, we show that extreme cold increases the probability that women experience IPV. We begin by running a basic version of equation 3.4 which includes only district, year, and month of interview fixed effects. We find that ten degree hours below the threshold of -9°C lead to an increased likelihood of IPV of 0.44 percentage points, and this estimated effect is significant at the 90% level of confidence (column 1). In column 2, when we add basic woman and household controls to improve precision; our estimate becomes significant at the 95% level. Column 3 displays the results of our preferred specification, which adds in controls for husband characteristics (i.e., education levels). Here, we find that an additional 10 CDH below -9°C results in an increased likelihood of IPV of 0.53 percentage points.[21]

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 B.2. Overall, we find that extreme cold increases the likelihood and intensity of experiencing partner abuse across various measures. Furthermore, we construct a basic measure of IPV intensity and find that extreme cold also has negative effects on the intensive margin.

Interestingly, we find evidence that partner alcohol consumption is one proximate cause of IPV. In Appendix Table B.3, an additional 10 CDH below -9°C increases the likelihood a partner drinks alcohol by 0.3 percentage points (column 1) and the probability he gets drunk frequently by 0.27 percentage points (column 2).

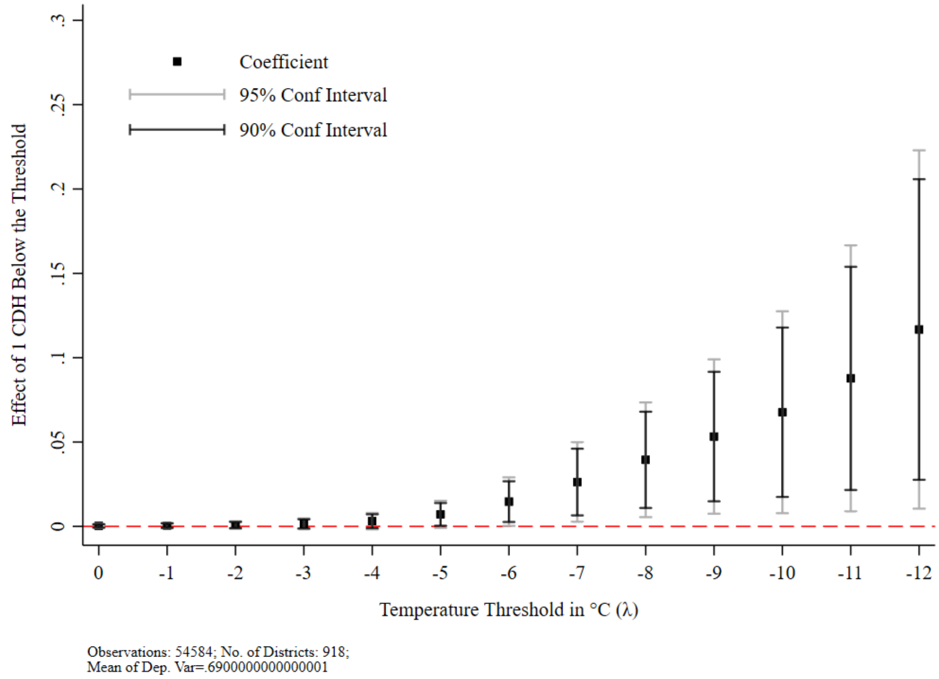
Table 2.1 Effects of Frost Shocks on Intimate Partner Violence

	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.

[21]Note that controlling for husband characteristics drops about 600 observations from our sample because it limits the sample to women who are currently married. Nonetheless, the coefficient is nearly identical between columns 2 and 3, illustrating that this sample restriction does not substantively affect the results.

Figure 2.1 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.

2.5.1 Robustness Checks

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

Alternative measures of violence. While the Peruvian DHS collects following the similar approach of other international health surveys, one might suspect that these data might be subject to reporting bias (arising from social desirability bias, shame, or similar). For this reason, we explore an alternative dataset based on police reports of violence against women at the district level. In Appendix Table B.5 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).

Alternative measures of frost shocks. Throughout the paper, we focus on the effects of CDH below -9°C in the 12 months prior to the date of interview. In figure 2.1, 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. In Appendix Table B.6, we define CDH using district-specific thresholds that account for the possibility that what constitutes harmful cold temperatures may vary across districts. When we define CDH using district- and season-specific historical temperature distributions — such as experiencing temperatures 2 standard deviations below the district- and calendar-month average — we similarly find that extreme cold increases IPV.

Additionally, we show our results are robust to considering alternative windows of frost shocks (Appendix Table B.7) to allow for the possibility that our IPV measure may capture more recent experiences of IPV, which are then more heavily affected by more recent bouts of extreme cold. Appendix Table B.8 shows that our results are also robust to using a measure of cumulative degree *days* (CDD), a commonly used measure in the literature, 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). Both CDD and cold spells have significant positive effects on IPV, and longer spells are associated with larger effects on IPV (though not significantly so).

Endogenous migration, sample selection, and changes in sample composition

One potential concern is that households may migrate in response to past shocks. We provide evidence that sample composition and endogenous migration do not account for our results in three ways. First, in Appendix Table B.9, we find that there are no meaningful changes in observable characteristics related to frost shocks. Exploiting within-district variation, we find that the observable characteristics of households do not systematically vary in response to extreme cold events. In the same table, we also show that frost shocks are not significantly related to marital or partnership status (column 9). This helps us rule out a case in which frost shocks impact selection into our sample, as IPV can only occur when a partner is present. Second, we show that our results are robust to restricting the sample to "never-movers", i.e. those living in their district of birth (Appendix Table B.10, column 1). Finally, we show that there is no relationship between CDH and migration behavior (Appendix Table B.10, columns 2-4).

Accounting for potential pretrends and falsification exercise

In Appendix Table B.11, we show that unobserved shocks that vary temporally and spatially in ways that might be correlated with extreme cold are unlikely to explain our results. More specifically, 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.[22]

As a final way to ensure that our measure of frost shocks captures exogenous weather shocks rather than unobserved determinants of or preexisting trends in IPV, we show in Appendix Table B.12 that there is no statistically significant relationship between IPV and future realizations of extreme cold temperatures. This null result 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.

2.6 Mechanisms

2.6.1 Effects on income and exposure

We find that extreme cold substantially reduces agricultural revenue.[23] Table 2.2 shows that overall an additional 10 degree hours below -9°C in the past year lowers annual agricultural revenue by 1.35% (column 1).[24] The effects of extreme cold affect income and expenditure significantly in

[22]The department is the first administrative level, akin to a U.S. state.

[23]One limitation of the data is that we cannot separately identify the effects of shocks on individual household members' (e.g., male versus female) income.

[24]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.

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), total income by 2.3% (column 4), and total expenditure by 1.7% (column 6). Importantly, these effects translate into an increase in the likelihood of a household falling below the poverty line by about 0.8 percentage points (column 8). In contrast, shocks that occur outside of the growing season have much smaller and non-statistically significant effects. For most outcomes, 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 2.6.2).

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 B.1.1), we also find suggestive evidence that individuals forgo certain types of activities when it is cold. In Appendix Table B.4, 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).[25] 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.

[25] 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 B.13).

Table 2.2 Effects of Growing and Non-Growing Season Frost Shocks on Income and Expenditure

	Val. of Ag. Output		Total Income (Constructed)		Expenditure		Poverty	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDH (λ = -9 °C)	-0.135***		-0.044		-0.026		0.011	
	(0.042)		(0.055)		(0.022)		(0.022)	
Growing Season CDH (λ = -9 °C)		-0.432***		-0.229*		-0.174***		0.079***
		(0.082)		(0.128)		(0.031)		(0.014)
Non-growing Season CDH (λ = -9 °C)		-0.084		-0.000		0.001		-0.002
		(0.063)		(0.074)		(0.035)		(0.031)
p-value for Growing=Non-Growing		0.002		0.199		0.003		0.032
Observations	76642	76642	76642	76642	76642	76642	76642	76642
No. of Districts	944	944	944	944	944	944	944	944
Mean of Dep. Var	2747	2747	5552	5552	6117	6117	49	49

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 includes annualized gross income from main monetary activity (dependent), income from main independent activity, gross income from dependent secondary activity and net income from independent secondary activity. Constructed 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 in this case is extracted using the Atlas (2022) data on World- Terrain Elevation Above Sea Level (ELE) GIS Data.

2.6.2 Relative importance of income versus exposure channels

The results in Section 2.6.1 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 (as described in Section 2.4.2). This is an important distinction, as extreme cold occurring during the growing season is likely to affect IPV through both channels, while extreme cold during the non-growing season should largely affect IPV through only the exposure channel.[26] Indeed, as we showed in Section 2.6.1, non-growing season shocks have no statistically significant impacts on income or expenditure.

We estimate the effects of growing and non-growing season shocks in Table 2.3. In column 1, we reproduce our baseline estimate which gives the overall effect of frost shocks on IPV. In column 2, we only examine the effects of growing season shocks; in column 3, we examine only the effects of non-growing season shocks. Finally, in column 4, we include both types of shocks in the same specification. We find that the effects of extreme cold on IPV are driven almost exclusively by shocks occurring during the growing season. An additional 10 degree hours below -9°C during the growing season increases the probability of experiencing IPV by about 1.6 percentage points (column 4), and this effect is highly statistically significant. In contrast, the estimated effect is much smaller (0.4 percentage points) and not statistically significant for frosts taking place in the non-growing season. The two effects are statistically distinct; the p-value for the test that the effects are the same is 0.014.[27].

If we interpret the estimated effect during the non-growing season as largely capturing the effects working through the mobility channel, we would conclude that even though frost shocks may limit

[26]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.

[27]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 using a more conventional definition of December through May (and a non-growing season of June through November) as in Aragón et al. (2021). These results (displayed in Appendix Table B.14) are very similar to the growing calendar we construct using survey data. Our results are also robust to alternative harmful temperature thresholds. In Appendix Figure B.2, we show that the difference in effects of frost shocks is apparent using various levels of λ in Equation 2.1.

outdoor time (shown in appendix table B.4) and thus potentially increase exposure of women to violent partners, this has relatively small effects on IPV. To get a sense of the magnitude of the effect that works through the income channel, we can examine the difference in growing and non-growing season coefficients ($\beta_1 - \beta_2$ in equation B.3). That difference suggests that the influence of frost shocks through the income channel is about 1.22 percentage points (for an additional 10 degree hours below -9°C). Again, this difference is significant at the 95% level of confidence (p-value=0.014). Put another way, the income channel accounts for nearly three quarters (75.3%) of the total effect of frost shocks, with the exposure channel capturing about a quarter (24.7%).[28] We find additional evidence that the income channel is the primary link between cold shocks and IPV in Appendix Table B.15. We find that the effects of cold shocks are larger for households that rely on agricultural income (column 2) from the effect for households that do not depend on agriculture, though the difference is not statistically significant (p-value = 0.101).[29] However, the estimated effect for non-agricultural households is close to zero and not significant, while the effect for agricultural households is large (1.1 percentage points) and significant at the 95% confidence level. These results align with existing work that points to negative income shocks as an important proximate cause of IPV, even specifically in the case of Peru (Chong and Velásquez, 2024).

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 that can act as a trigger for IPV.

To investigate the degree to which social assistance programs attenuate the effect of cold

[28] These calculations are based on the estimates in column 4 of Table 2.3 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.

[29] We define households as being reliant on agriculture if either the woman's or her husband's primary occupation is in agriculture.

Table 2.3 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.

weather shocks on IPV, we construct a measure of social program coverage from the ENAHO. Specifically, we calculate the share of households in each province in which at least one member has been a beneficiary of a government-sponsored social program. As social assistance programs are targeted to poor households, we use the baseline share of *poor* (as opposed to all) households that receive government-sponsored social assistance. This measure automatically takes into account the underlying share of poor households. Because 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 begin by demonstrating that our main results in this restricted sample period (column 1 of Table 2.4) are similar to those using the full sample period, though they are not statistically significant (perhaps due to the nearly 30% reduction in sample size). In column (2), we add an interaction between CDH and the baseline share of social assistance beneficiaries. The results indicate that the effect varies greatly (and significantly) by baseline social program coverage. We find that, in provinces with low (10th percentile) social program coverage at baseline, extreme cold increases IPV: 10 degree hours below -9°C in the previous 12 months raises the likelihood of IPV by 0.71 percentage points (significant at the 95% level of confidence). In contrast, among households in provinces with high (90th percentile) baseline coverage, frost shocks appear to have no substantive effects on IPV. Column 3 illustrates that the patterns across growing and non-growing season shocks and social program coverage are also consistent: the effects are much larger in the growing season than in the non-growing season and are counteracted by social program coverage. In the Appendix, we show that these results do not appear to be driven by large districts or city capitals, province poverty levels, differences in women's ages (which could be related to social program eligibility), or political clout.

2.8 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.

Table 2.4 Heterogeneity by Baseline Social Program Coverage

	Dep. Var.: Any IPV		
	(1)	(2)	(3)
CDH (λ = -9°C)	0.036	0.088***	
	(0.024)	(0.033)	
CDH × Baseline Social Program Coverage		-0.067**	
		(0.033)	
Growing Season CDH (λ = -9 °C)			0.695***
			(0.255)
Growing Season CDH × Baseline Coverage			-0.341
			(0.222)
Non-growing Season CDH (λ = -9 °C)			0.101***
			(0.033)
Non-growing Season CDH × Baseline Coverage			-0.089***
			(0.031)
Observations	38841	38841	38841
No. of Districts	801	801	801
Mean of Dep. Var	0.669	0.669	0.669

Notes: The sample includes all women (aged 15-49) in the Peruvian highlands who have responded to the domestic violence module of the DHS dataset between 2013-2018. Baseline coverage is defined as the share of poor households in the province receiving assistance from social programs in 2012 according to the ENAHO. Controls include altitude, average temperature and average rainfall at the household level in the past year (separately by growing and non-growing months in columns 3-4). We control for individual characteristics (age, age squared, mother tongue, education fixed effects, number of children under five); household head characteristics (age and sex), household size and husband education fixed effects. 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.

CHAPTER 3

WHEN THE TEMPERATURE DROPS, PERCEPTIONS WORSEN: EFFECTS OF EXTREME COLD ON PERCEPTIONS OF GOVERNMENT AND CIVIC PARTICIPATION IN THE PERUVIAN HIGHLANDS

3.1 Introduction

A growing body of empirical evidence illustrates the role of trust and confidence in government in determining a myriad of important political economy outcomes, such as policy preferences (Fairbrother, 2019; Marien and Hooghe, 2011), compliance with laws (Citrin and Stoker, 2018), political participation (Grönlund and Setälä, 2007; Bélanger and Nadeau, 2005; Bélanger, 2017), voting behavior (Dalton and Weldon, 2005; Citrin and Stoker, 2018; Guiso et al., 2020; Bélanger, 2017), and the use of public goods and services (Christensen et al., 2021; Alsan and Wanamaker, 2018; Lowes and Montero, 2021; Martinez-Bravo and Stegmann, 2022; León-Ciliotta et al., 2022). However, much of the current literature focuses on the consequences of political trust in rich countries; few study the context of low- and middle-income countries (LMICs). Moreover, less is known about what determines sentiments towards government and political systems at the individual level.[1] Additionally, there is a lack of clarity regarding what could attenuate political mistrust.

In this paper, we study the effect of extreme cold spells or frost shocks on the belief that democracy works well in Peru. This outcome captures an overall perception of the way democracy functions in Peru, both in terms of "diffuse" attitudes towards the political system (i.e., democracy as a regime) and "specific" satisfaction with or confidence in government in practice (i.e., citizens' evaluation of the performance of government bodies).[2] Peru is an ideal context to study this for several reasons. Peru is one of the countries with the lowest levels of political mistrust in Latin America (Bargsted et al., 2017), with a significant history of political instability in the recent past. Peru is also considered one of the most vulnerable countries to climate change in the world (Stern,

[1] We are aware of only four economics papers that study the determinants of political trust. Stevenson and Wolfers (2011) document the strong pro-cyclicality of confidence in public institutions. Blanco and Ruiz (2013) and Blanco (2013) show that crime and insecurity can affect trust in democracy and institutions in Colombia and Mexico, respectively. Malásquez and Salgado (2023) finds that perceptions of democracy is affected by exposure to the Peruvian Conflict.

[2] We discuss the interpretation of this variable in more detail in Section 3.3.1.

2007; Tambet and Stopnitzky, 2021). Especially in the context of the Peruvian Highlands– the main agricultural region of Peru — extreme cold events are particularly important. Frost and cold waves have become increasingly common and devastating, highlighting the region's vulnerability to weather volatility (Painter, 2008; Tambet and Stopnitzky, 2021; Keller and Echeverría, 2013; FAO, 2008). Extreme weather has adverse consequences for agricultural income, assets, and consumption (Dell et al., 2012b; Skoufias et al., 2012; Zhang et al., 2017; Schlenker et al., 2009; Aragón et al., 2021); health (Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011); and crime (Simister and Cooper, 2005; Simister, 2001; Miguel, 2005; Ranson, 2014; Iyer and Topalova, 2014; Blakeslee and Fishman, 2013). Thus, in many ways, exposure to extreme weather shocks can test the capacity and efficacy of the government system. Extreme cold spells represent a broad negative shock that could meaningfully test the state's capacity for citizens. Intuitively, we expect negative shocks to worsen perceptions of government and democracy in circumstances where government programs and services cannot meet the needs of citizens adversely affected by extreme cold or frost shocks. Therefore, in this paper, we also study whether access to social programs and public provisions can attenuate political mistrust.

This paper has three main findings. Using a large repeated cross-section of agricultural households in the Peruvian Highlands over 12 years, we first show that extreme cold temperature shocks significantly lower the belief that democracy works well. In particular, we use the 2007-2018 rounds of the Peruvian National Household Survey (ENAHO), which collects individuals' perceptions of government and democracy. We match these data to local hourly weather data from the European Centre for Medium-Range Weather Forecasts (ECMWF). To do so, we use the GPS location of each household and the specific date each household is interviewed.[3] Our primary measure of extreme cold is the cumulative degree hours (CDH) below a given temperature threshold, which captures the number of hours in the relevant window that a household experienced temperatures below a specific threshold and the extent to which the temperature was below the threshold. Conditional on district, year, and month-of-interview fixed effects, an additional ten hours below the threshold

[3] The recorded GPS location of each household is specific to the village centroid in rural areas and the neighborhood block in urban areas.

of -9°Celsius (C) over the previous year *lowers* the probability that an individual sees democracy functioning well in Peru by 0.38 percentage points. Given that the sample average for this measure is 0.51, we see these results as illustrating that extreme weather can meaningfully impact perceptions of government and democracy. The point estimates are *larger* in magnitude and statistically significant for colder temperature thresholds. Our main results are robust to using alternate samples from other data sources (i.e., the Americas Barometer (LAPOP) and the Latinobarómetro), testing alternative measures of frost shocks, including fixed effects at more disaggregated levels, and accounting for potential endogenous migration.

We explain this relationship between extreme cold and our measure of political trust, i.e., belief in poor functioning of democracy through three key mechanisms- significant economic losses that also worsen subjective perceptions regarding the economy, increased health hazards, and higher exposure to crimes. We first confirm that extreme cold acts as a significant negative shock to income in our setting, mainly through the lower value of agricultural output. Specifically, 10 additional degree-hours below the threshold of -9°C in the past year reduces the value of agricultural output by 1.35%. This same shock during the growing season has a larger impact. It reduces the value of agricultural output by 4.32%, which translates into a significant drop in total income and expenditure. Additionally, we find supporting evidence that extreme cold shocks lead to the loss of productive assets in the form of livestock assets in the Peruvian Highlands. Further, we could even confirm that such objective economic losses worsen subjective perceptions related to the economy. Second, we show that extreme cold increases illness among children in these agricultural households. 10-degree hours below -9°C increases the probability that a young child in the household has been ill in the past 4 weeks by 2.66 percentage points and has been "severely ill" (requiring a medical consultation) by 1.92 percentage points. Third, we use a district-level yearly panel to show that frost shocks increase certain types of crime. 10 CDH below -9°C increases economic crimes (e.g., burglary, theft, fraud, sales of illicit goods, etc.) per capita by 2.04% and overall crime by 1.22% but does not lead to more violent crime (e.g., assaults, murder, kidnapping, etc.).

Based on this evidence about the multiple ways extreme cold affects households' well-being, we posit that frosts highlight the extent to which government institutions can (or cannot) effectively serve their citizens in times of need. In other words, we argue that negative shocks are detrimental to perceptions of how democracy functions in circumstances where government programs and services do not meet the needs of the affected citizens. Conversely, government-led programs that help smooth or ease negative shocks could be key in weakening the effect of cold shocks on political mistrust.[4]

As our second main finding, we further document other downstream effects of extreme cold, specifically on electoral participation and participation in local informal neighborhood associations. We hypothesize that exposure to extreme cold shocks would reduce electoral participation, and we see this as a *consequence* of political mistrust. This is motivated by previous evidence in developed countries' context suggesting political mistrust as an important factor behind voting abstention (Bélanger, 2017). We also test the effect of extreme cold shock on participation in local informal community-based associations. We see it as an adaptive coping strategy to interact with neighborhood communities in the face of the negative consequences of extreme cold; this also paves the way for higher interpersonal or social trust (Buggle and Durante, 2021).

Extreme cold indeed reduces participation in national elections. The share of absent voters (registered voters who do not show up at the polling stations) and blank votes (votes that are cast but are left blank) is higher in districts that experience cold weather shocks leading up to presidential elections. The extent to which extreme cold affects voter abstention is found to be highly meaningful if contextualized with the winning margin in the presidential elections, thus, indicating the importance of this relationship. This suggests that, as cold weather erodes the belief that democracy functions well, individuals are less likely to participate in national electoral

[4]Previous literature has explored the role of public policy in attenuating the negative consequences of weather shocks on citizenship-related outcomes. For example, Fetzer (2014) shows that public workfare programs like the National Rural Employment Guarantee Act (NREGA) weakened the relationship between rainfall shocks and conflict in India, primarily by providing an option for income smoothing. Sarsons (2015) finds that public infrastructure (i.e., dams) attenuates the impact of rainfall shocks on Hindu-Muslim violence in India. Garg et al. (2020) find a positive relationship between heat waves and homicides in Mexico. However, homicide rates in locations that benefit from conditional cash transfers are less sensitive to higher temperatures, suggesting a role for income-support programs in reducing violence.

institutions directly linked to democracy. Second, we also show that individuals are more likely to engage with local institutions (such as community-based associations) in the wake of cold shocks.[5] Thus, our results are consistent with negative shocks resulting in citizens turning away from formal national institutions to less formal and more local institutions.

Finally, our third main finding brings more clarity to our understanding of how access to public provisions may attenuate political mistrust. In order to identify relevant public provisions that can attenuate political mistrust, we need to understand the specific drivers of political mistrust. Our earlier discussion on the mechanisms through which extreme cold affects political mistrust-economic losses, health hazards, and higher exposure to crimes sheds light on this. Thus, access to government-led social programs, public health provisions, and public safety that can provide insurance to income losses and weaken health hazards and crime exposure can attenuate political mistrust.

To substantiate this claim, we conduct heterogeneity analyses that focus on the role of government institutions in serving citizens in the presence of extreme cold shocks. We create a composite indicator of public provisions using three key baseline measures of access to social programs (a measure of social program coverage), access to public health facilities (a measure of access to public health), and access to police stations (a measure of access to public safety). Based on this composite indicator, we identify the provinces with high and low public provision. We, therefore, study whether the effect of cold weather shocks on political trust is mediated by access to government-led social programs, public health, and public safety provisions. Indeed, we find that in provinces that have historically higher access to public goods and services (at baseline), the effect of a cold weather shock on political trust is smaller. However, the effect is large and negative in areas with a lower coverage of public goods and services. Although the effect is much larger in places with a lower public provision than in places with a higher public provision at baseline, we do not find this difference statistically significant. We also test the heterogeneous impact of frost shock on electoral abstention by coverage of public provision. Since we expect political mistrust

[5] These results are consistent with recent work by Buggle and Durante (2021), who find that historical climate variability fostered interpersonal trust in Europe with lasting impacts on norms and institutions.

to drive voter abstention in the face of a crisis, we expect higher coverage of public provisions to reduce voter abstention through improved political trust. We find statistical evidence that higher coverage of public goods and services reduces voter absenteeism in the second, more decisive round of presidential elections. Finally, we do not find any heterogeneous effect of frost shocks by coverage of public provisions on local neighborhood participation. In fact, we find that the increase in participation in local informal neighborhood associations is driven by provinces with already higher coverage of public provisions. This suggests that higher coverage of government-provided goods and services does not necessarily crowd out informal participation in this setting.

It is worth noting that though we study extreme cold as a relevant weather shock for our context, our results are useful for understanding the effects of other extreme weather conditions. This is because our results indicate that the mechanisms of interest — income, health, and crime — respond similarly to extreme cold as they do to other measures of extreme weather, such as extreme heat, drought, and floods (see, for example, Dell et al., 2012b; Skoufias et al., 2012; Zhang et al., 2017; Schlenker et al., 2009; Aragón et al., 2021; Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011; Simister and Cooper, 2005; Simister, 2001; Miguel, 2005; Ranson, 2014; Iyer and Topalova, 2014; Blakeslee and Fishman, 2013). Thus we expect perceptions of government and downstream outcomes to be similarly impacted by events like heat waves and extreme rain episodes.

Our research makes important strides in understanding both the causes and consequences of changes in the way citizens view democracy and government. Evidence on the determinants of confidence and trust in government institutions in economics is scarce and outside of economics, the evidence is heavily skewed toward rich economies (Citrin and Stoker, 2018; Zmerli and Van der Meer, 2017). Our results yield novel insight into one factor that is important for determining beliefs about how democracy functions in LMICs: extreme cold. We are able to explore the pathways through which extreme cold impacts perceptions of democracy and government and illustrate the extent to which government provision of goods and services mitigates the impact of negative shocks on political perceptions. Moreover, we demonstrate the importance of perceptions in key, tangible outcomes, such as voter participation, and highlight that extreme cold lowers participation in national institutions, and there is a corresponding increase in participation in local, community-based institutions. As such, these results provide policy insights into improving political trust and civic participation in unstable democracies or regions with high political mistrust, like Peru.

Our results also complement the extensive body of work linking extreme weather to conflict and political instability.[6] Though previous work has examined the roles of income and health as mediating factors through which weather impacts conflict and instability (see, for example, Miguel et al., 2004; Burke et al., 2009; Dell et al., 2012b; Hsiang et al., 2011; Harari and La Ferrara, 2018; Ranson, 2014; Maystadt and Ecker, 2014; Sarsons, 2015; Hsiang et al., 2013), our findings shed light on the role of perceptions of and participation in democracy, which are thus far largely unstudied. We show that weather shocks erode the beliefs that democracy functions well at the individual level and that this, in turn, translates into changes in electoral behavior at an aggregate level, with potential implications for political instability and conflict.[7]

Finally, we build on the previous literature evaluating the effects of extreme weather by focusing on a novel measure: extreme cold. Though the adverse effects of floods, droughts, and extreme heat have been well documented, to our knowledge, we are the first to establish the effects of extreme cold on economic and political outcomes in a low-income setting. Interestingly, though average temperatures are expected to rise globally with climate change, there is evidence that extreme cold events may also become more common. In the northern hemisphere, this is attributed to the polar vortex or the "accelerated Arctic warming", which has induced more severe cold-air outbreaks in North America and Eurasia (Cohen et al., 2018; Kim et al., 2017).[8] In the southern hemisphere, the recent surge in extreme cold events is attributed to episodes of La Niña, which are projected to

[6]While the research relating climate change and conflict is relatively recent, evidence suggests that weather has affected governance and political stability throughout human history. A growing strand of the literature analyzes long-term historical consequences of changes in climatic patterns on conflict in ancient civilizations (Chaney, 2013; Kung and Ma, 2014; Jia, 2014; Yancheva et al., 2007).

[7]For example, Engvall (2010) shows that low pre-conflict trust in government is a strong determinant of contemporaneous incidence of violence and casualties in Southern Thailand while Buhaug et al. (2015) argues that preexisting political mistrust could provide "breeding ground" for political violence.

[8]It is hypothesized that Artic amplification or "accelerated Arctic warming" is a key underlying mechanism behind increased extreme cold weather events in the northern hemisphere. In other words, "as the Arctic warms the continent becomes colder" (Cohen et al., 2018).

increase in both frequency and duration (Cai et al., 2015).[9]

3.2 Background

Formally, Peru is a democracy, where the president and members of Congress are elected by popular vote every five years. However, its political system has been plagued by individualistic leaders and unstable environments in the last three decades. These circumstances have led The Economist Intelligence Unit (2023) to classify Peru as a *hybrid regime*, somewhere between a "flawed democracy" and an "authoritarian regime". Political parties collapsed in the 1990s — a phenomenon that Tanaka (2005) coined as a "party-less democracy" — and have remained weak. Clashes between the executive and legislative branches have prevented the implementation of any meaningful reforms during the last decades. In the last six years (2016-2022), tensions between the two branches have escalated: Congress has impeached three presidents, one president dissolved Congress, and another one staged a failed *coup d'état*.

Furthermore, Peruvian politics have been deeply entrenched in systemic corruption: every elected president since 1985 has either faced jail time for corruption or has had credible corruption allegations against them (Bristow, 2022). Former president Fujimori (who ruled Peru between 1990 and 2001) has been ranked as one of the most corrupt leaders in the world, having embezzled an estimated $600 million (Transparency International, 2004). Peru has continued to be plagued by subsequent corruption scandals. One case — considered to be the "largest foreign bribery case in history" (US Department of Justice, 2016) — involved millions of dollars in bribes to Peruvian political leaders, including large campaign donations to several presidential candidates. Members of Congress have also faced corruption accusations. They are perceived to favor powerful lobbies, act based on personal economic interests, and shield themselves from accountability through congressional immunity (Wall Street Journal, 2020). The judiciary has not been exempt from corruption either. In 2018, wiretap transcripts uncovered a vast corruption network where judges in high courts and members of the National Board of Justice (a council that appoints and removes judges from office) received bribes and political favors from businessmen and politicians in exchange

[9] La Niña is a weather pattern characterized by cooler sea-surface temperatures in the southern Pacific off the coast of South America. It is the "opposite" phase of the El Niño, which increases the sea temperature in this region.

for favorable sentences (IDEHPUCP, 2020; La República, 2021). Thus, it is not surprising that Peru is one of the countries with the lowest levels political trust in Latin America. Bargsted et al. (2017) shows that, in a sample of 17 Latin American countries, Peruvians' trust in democratic institutions (i.e., the national congress, political parties, and the government) is the lowest, with the exception of Ecuador.

Despite this political instability, Peru's economy has experienced considerable and sustained economic growth; in 20 years (2000-2019), GDP per capita doubled. Economic growth allowed for a large reduction in poverty (which dropped from 48.4 % to 20.5% during this period). While there was some reduction in inequality (the Gini index reduced by 15%, from 49.1 to 41.6), Peru is still a country with large inequalities. While the top 10% of the population concentrates 31.6% of total income in Peru, the share of the bottom 10% is only 1.8%. There are also significant regional gaps in Peru. In this paper, we focus on the rural highlands of Peru, a region that has been left behind despite the significant overall progress that Peru experienced in the last decades. By 2018, 13.1% of the population in Metropolitan Lima was poor. In contrast, the poverty rate in the rural highlands (the poorest region in the country) was 49% (INEI, 2019). There are also large regional gaps in terms of access to public services: while access to sanitation is almost universal in Metropolitan Lima (97%), only about half of households in the rural highlands (54.1%) have access to such utilities.[10]

Compounding this vulnerable situation, the rural highlands in Peru are also subject to considerable weather shocks (e.g., droughts, floods, frosts, cold waves, etc.; World Bank 2008). 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). Frosts and extreme cold events have become increasingly common in Peru over the last two decades, affecting millions of Peruvians (Keller and Echeverría, 2013; FAO, 2008), particularly those in the highlands, which are located at elevated altitudes (between 500 and 6,798 meters above sea level). In recent years, extreme cold temperatures have dipped as low as -20°C in some areas, affecting close to 200

[10]Calculations based on the 2018 Peruvian National Household Survey (ENAHO).

thousand inhabitants (Centre for Research on the Epidemiology of Disasters, 2023).

Extreme cold can have particularly severe consequences on agricultural output, an important economic activity in the highlands. The extent of the damage induced by frosts depends on the intensity of the frost (i.e., how much below 0°C the temperature drops), the frequency of these events, the type of crops, and the phenological state of the plants (Snyder and Melo-Abreu, 2005). More intense frost episodes can induce crop failure and significant economic losses. For example, a frost in 2008 destroyed 45% of potato production in several high-altitude Peruvian provinces (FAO, 2008). Frost damage is not limited to Peru. A 2021 frost caused an estimated US$ 1 billion losses to coffee farmers in the Brazilian state of Minas Gerais (Samora, 2021), while another frost in 2021 generated around 2 billion Euros in losses in French wine production (The Guardian, 2021). The continued threat of frosts is a concern for much of the highlands; CENEPRED (2021) estimates that there are 823 districts (encompassing around 1 million farmers and 3.3 million hectares of agricultural land) under high or very high risk of experiencing frosts.

Extreme cold can also have detrimental effects on livestock. Livestock are valuable assets for rural households in the Peruvian Andes (Kristjanson et al., 2007). They are sources of food, energy, fiber, fertilizer, and transport (León-Velarde and Quiroz, 2003). Additionally, they "can be sold to finance investments such as school fees or in time of need such as illness or drought" (Herrero et al., 2013). For example, *alpacas* (a South American camelid) are one of the most important types of livestock in the Peruvian highlands. Alpacas can be directly affected by frosts, as they can experience hypothermia and frostbite when subject to sudden reductions in temperature. The effects of frosts can be quite severe: during 2015, temperatures in the state of Puno reached -20°C. The extreme cold shock killed 170 thousand alpacas and had negative impacts on the livelihoods of several communities that depend upon sales of alpaca fiber (BBC News, 2015).

In addition to its negative impact on farm income, extreme cold weather can potentially also have severe health consequences. Previous research has found a significant association between cold weather and the incidence of respiratory tract infections (Zhao et al., 2021; Kephart et al., 2022; Sheridan and Allen, 2015). In 2010, extreme cold temperatures related to a *La Niña* event killed 250 children (mostly under the age of 5) in Peru due to "cold-related respiratory diseases, mostly pneumonia" (Kirkland, 2012).

A less-explored channel through which extreme cold can affect rural households is a potential increase in crime and violence. Previous literature has found that *hotter* temperatures can increase violence and crime (Blakeslee and Fishman, 2018; Mukherjee and Sanders, 2021; Colmer and Doleac, 2022; Mares and Moffett, 2019; Garg et al., 2020; Simister, 2001; Simister and Cooper, 2005). Income losses and physiological responses to extreme weather shocks can lead to increases in crimes. However, there is scant research testing whether *colder* temperature can also affect crime rates.

All in all, the Peruvian highlands are vulnerable to frosts that can have negative impacts on agricultural production, incomes, productive assets (such as livestock), health outcomes, and crimes. We hypothesize that such shocks can potentially translate into political mistrust, in a country that has faced long-standing governance crises.

3.3 Data and Variables

Our analysis uses two main data sources: the Peruvian National Household Survey (*Encuesta Nacional de Hogares* - ENAHO) and weather data from the European Centre for Medium-Range Weather Forecasts (ECMWF) and the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS).

3.3.1 Encuesta Nacional de Hogares (ENAHO)

The ENAHO is a detailed household survey collected annually by the National Statistics Office (Instituto Nacional de Estadística e Informática 2018c - INEI). We use twelve rounds of the ENAHO (2007-2018) and focus on several dimensions of the survey. The first is a module on households' perceptions of governance, which solicits individuals' confidence in democracy, political parties, and institutions. Only one randomly chosen adult (18 years or older) in each household is sampled for this module.

Our primary outcome variable measures whether citizens believe that democracy works well in Peru. Specifically, we focus on a question that asks the following: "In Peru, does democracy work..?" We code our variable as one to those who believe democracy works "well" or "very well" and zero otherwise.[11]

$$Y_{idt} = \begin{cases} 1 & \text{if response is "very well" or "well"} \\ 0 & \text{if response is "very poorly" or "poorly"} \end{cases} \tag{3.1}$$

We believe that this variable represents an overall perception of the way democracy functions in Peru, both in terms of so-called "diffuse" attitudes towards the political system (i.e., democracy as a principle or as a broad institution) and "specific" satisfaction with or confidence in the current or recent government regimes (i.e., how democracy works in practice and citizens' evaluation of the performance of government bodies).

Indeed, we find empirical support for both interpretations of this measure. Table 3.1 displays conditional correlations between our primary outcome measure (the belief that democracy works well in Peru) and a battery of other measures of political trust and confidence in specific institutions.[12] We find that the belief democracy works well is most highly correlated with evaluations of how well different levels of government (central, regional, provincial, and district) are managed. Our outcome variable is also correlated with confidence in specific government bodies, such as the national Congress, the Judiciary, and Political parties. However, it also reflects more general beliefs about democracy as a system: it is highly correlated with the belief that democracy is always the most preferred form of government and the belief that democracy is important.

In this way, we see our outcome as being similar to the widely used "satisfaction with democracy" (SWD) measure. SWD is typically elicited with questions very similar to the one included in the ENAHO, along the lines of: "On the whole, are you very satisfied, fairly satisfied, not very satisfied, or not at all satisfied with the way democracy works in [country]?" SWD has been interpreted as a measure of either support for democratic principles (for example, see Norris 2011b) or for specific

[11] The questionnaire includes an option for "do not know". About 24% of individuals respond with "do not know". In our main analysis, we drop these observations from our sample; in Section 3.5.1, we show that our results are robust including these observations as a neutral, middle category.

[12] The correlations in Table 3.1 are coefficients from separate regressions that include district, year, and month-of-interview fixed effects.

Table 3.1 Conditional Correlations between Evaluation of Democracy and Evaluation and Confidence in Specific Institutions

	Dep. Variable: Believes democracy works well
Supports management of central government †	0.235***
	(0.006)
Supports management of regional government †	0.224***
	(0.007)
Supports management of provincial government †	0.225***
	(0.006)
Supports management of district government †	0.211***
	(0.006)
Confidence in political parties	0.140***
	(0.007)
Confidence in Congress	0.129***
	(0.005)
Confidence in regional government	0.119***
	(0.005)
Confidence in municipal government	0.116***
	(0.005)
Confidence in provincial government	0.106***
	(0.005)
Confidence in the Judiciary	0.110***
	(0.005)
Believes democracy is preferable	0.102***
	(0.006)
Confidence in Police	0.101***
	(0.005)
Confidence in Armed Forces	0.050***
	(0.005)
Confidence in the Catholic Church	0.042***
	(0.005)

Note: Each coefficient comes from separate regressions with district, year, and month-of-interview fixed effects and "Believes Democracy Works Well" as the dependent variable. The sample in the regressions includes the 2007-2018 rounds of ENAHO. † However, due to lack of data availability, the top four variables (management of the central, regional, provincial, and district governments) are only analyzed for the 2012-2018 rounds of the ENAHO. District-level clustered standard errors in parentheses. Significance levels denoted by: *** p<0.01, ** p<0.05, * p<0.1.

support (for example, see Linde and Ekman 2003), or both (Kölln and Aarts, 2021; Clarke et al., 1993; Christmann, 2018; Kosec and Mo, 2023). Along these lines, SWD can be interpreted as "an expression of citizen‘s evaluation of how the democratic regime procedures function in practice, so it reflects a rational response to the working and outputs of political systems" (Christmann, 2017, p. 10). The ENAHO does not explicitly ask about citizens' SWD, but instead has a similar question about how democracy "works".

The ENAHO also collects detailed information about households' socioeconomic characteristics, such as demographics, education, expenditures, and dwelling characteristics. Importantly, INEI provides households' approximate GPS location: in rural areas, the ENAHO reports GPS coordinates for the village in which the household lives, and in urban areas, it reports coordinates for the centroid of the neighborhood block.

We use ENAHO's health module to collect information about child health status. In particular, we focus on illnesses and medical consultations of children below five years of age (an age group that is particularly vulnerable to respiratory infections when exposed to frosts). We also use the ENAHO to collect information about household members' membership in local associations. Lastly, we use the ENAHO agricultural module, where households report their crop income, input usage, and other relevant agricultural information in the twelve-month period before their interview. Appendix figure C.1 shows the location of all farming households surveyed within the Peruvian Highlands in the ENAHO between 2007-2018, the sample which we use for our study. Importantly, these households are located precisely in the regions of Peru that are more susceptible to experiencing frosts (see SENAMHI (2010), p.47).

3.3.2 Weather Data

We collect hourly temperatures (i.e., recorded daily, at each hour from midnight to 11 PM) between 2006 and 2018 from the European Centre for Medium-Range Weather Forecasts (2018) (ECMWF).[13] ECMWF processes information from weather stations, satellites, and sondes to provide temperature estimates at a geographic resolution of 0.25 degrees. To align this weather data

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

with household data from ENAHO, we used two crucial pieces of information: the households' approximate GPS locations (specified at the primary sampling unit or survey block level) and household's month and year of the interview. This matching enabled us to create a measure of extreme cold exposure specific to each household, covering the year prior to the interview—the standard recall period for most survey questions.

We extended the widely adopted cumulative degree days metric from Schlenker and Roberts (2006) to estimate cumulative degree hours of extreme cold experienced by a household. This approach integrates both the duration and severity of temperature exposure, indicating how long and by how much temperatures fell below a certain threshold. We choose a range of sub-zero temperature thresholds denoted by λ, including 0°C, -1°C, -2°C, and so on, down to, -12°C. Harmful degree hours (hours of exposure to temperatures below the threshold λ) are defined as follows:

$$DegreeHours(DH_{itmdh}) = \begin{cases} \lambda - h_{itmdh} & \text{if } h_{itmdh} < \lambda \\ 0 & h_{itmdh} \geq \lambda \end{cases} \tag{3.2}$$

Here h_{itmd} is the temperature in household i's location, on year t, month m, day d and hour h. For instance, if λ is set at -4°C, an hour of temperature at -6°C represents 2 degree hours; while an hour with a temperature of -5°C would contribute only 1 degree hour. Given the lack of clarity of "harmful" threshold, we present our findings across a broad spectrum of sub-zero temperature thresholds, ranging from 0°C to -12°C.

Our main measure for extreme cold exposure is the cumulative degree hours (CDH) below the threshold λ that household i, interviewed in month m and year t, experienced over the 12 months preceding the survey. This is calculated as follows:

$$CumulativeDegreeHours(CDH_{it}) = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} DH_{itmdh} \tag{3.3}$$

In some of our regressions, we use a shorter window of time instead of a 12-month period (e.g., for morbidity outcomes, which have a shorter recall period). Agriculture-related activities are most often conducted during specific months of a calendar year, thus for agricultural value, income and expenditure outcomes alongside using cumulative exposure to frost shocks in the past 12 months from the time of interview, we also use the "growing" and "non-growing" season CDH separately. This is to affirm that the losses in agriculture are primarily due to frost shocks in the "growing" season. For this we calculate a modified version of this above index where we identify province specific "growing" and "non-growing" months based on the provincial crop calendar (described below in 3.3.4 and more details in appendix sub-section C.1.1).

In addition, we also extract rainfall data from the Weather Hazards Group InfraRed Precipitation with Station Data (CHIRPS) [14]. CHIRPS provides global, high-resolution rainfall estimates for 0.05 X 0.05 degree pixels. Similar to the temperature data, we match the rainfall data with the households using GPS coordinates and interview dates from the ENAHO.

3.3.3 Main Estimation Sample

In this paper, we pool 12 survey rounds of the ENAHO (2007-2018). Due to the nature and geographic scope of cold weather shocks in Peru, we restrict our sample to farming households in the highlands. With these restrictions, we obtain a sample of 57,159 households across 938 districts in the Peruvian highlands.[15] Table 3.2 presents the summary statistics for our sample.

About 63% of the sample has completed at most primary school and over half of the sample speaks Quechua (the most prominent indigenous language in Peru) at home (column 1). Though the average household has experienced less than one harmful degree hour at the threshold of -9°Celsius, this is because only 5% of households experience temperatures below this threshold (Appendix figure C.2). Conditional on having been exposed to temperatures below this threshold, the average CDH in the sample is about 15.

Strikingly, only about half of the individuals in our full sample believe that democracy works well in Peru. When we break down the sample into households that face and do not face frost shocks (columns 2 and 3), we see that those who face frost shocks are about 2.5 percentage points less likely to report that democracy works well. Households facing frost shocks also tend to have lower agricultural and total income, and they are more likely to have sick children in the household.

[14]Please check Funk et al. (2015), for more detailed information about CHIRPS.

[15]There are 1,873 districts in Peru, so our sample covers around half of all districts in the country.

Table 3.2 Descriptive Statistics

	Full Sample (1)	Households Facing Frost Shocks (2)	Households Not Facing Frost Shocks (3)
Believes Democracy Works Well	.511	.487	.512
Weather Variables			
CDH (λ = -9°C)	.755	14.981	0
Average Temperature	9.542	5.318	9.766
Average Rainfall	65.303	65.314	65.302
Mechanisms			
Total Agricultural Income	3039.5	1696.8	3110.7
Total Income	9209.4	8776.4	9232.3
Total Expenditure	6799.3	6826.6	6797.8
Value of Livestock Losses	751.6	242.2	781.3
Livestock Death (dummy)	.342	.488	.334
Biggest Problem: No Agric. Support	.083	.069	.084
Biggest Problem: Lack of Employment	.076	.09	.075
Child Has Been Ill (prev. 4 weeks)	.333	.387	.332
Child Required Medical Attention	.316	.319	.316
Individual and Household Characteristics			
Male	.509	.498	.51
Age	46.724	47.632	46.676
Household Size	4.014	3.88	4.021
Education			
Primary or Less	.628	.626	.628
Secondary	.285	.286	.285
Technical	.05	.057	.049
College	.037	.032	.038
Mother Tongue			
Quechua	.518	.830	.501
Spanish	.428	.096	.445
Amarya or Other Indig.	.055	.075	.054
Observations	57159	2880	54279

Notes: All monetary variables are expressed in 2007 soles using the GDP deflator published by World Bank (2023). The main sample (column 1) includes individuals in all farming households in the Highlands in the ENAHO 2007-2018 . We further split the sample into households that have experienced frost shocks (column 2) and those that have not (column 3). The exception is the sample for child health variables, which are reported for a restricted sample of children ages 0-5 living in the main sample households.

In terms of predetermined individual and household characteristics, households that have and have not faced frost shocks are largely similar, with the exception that those facing frost shocks are more likely to speak Quechua as their mother tongue.

3.3.4 Other Data Sources

Encuesta Nacional Agropecuaria (ENA). We complement the ENAHO data by incorporating information from the Peruvian ENA (National Agriculture Survey), which is also provided by Instituto Nacional de Estadística e Informática (2018b). The ENA offers a yearly cross-sectional data on agricultural households. A key feature of the ENA is its detailed information on cultivation timings, including sowing and harvesting periods. This data is crucial as cold weather shocks might have a more significant impact on agricultural income during the specific months when crops are being grown. By combining five years of ENA data (2014-2018), we create an agricultural calendar for each province. Specifically, we calculate the proportion of farmers actively cultivating crops each month within each province. We then specify a calendar month as a "growing" month in a province if in the given month the share of farmers actively growing crops is higher than the province specific *median* of the share of farmers actively growing crops for all the calendar months in the given province. Alternatively, the calendar month is a "non-growing" month if the share of farmers actively growing crops is lower than the province specific *median* of the share of farmers actively growing crops for all the calendar months in the given province. We use this to construct separate measures of the CDH for the growing and non-growing season, as given in equations C.1 and C.2 respectively in appendix sub-section C.1.1.

Organismo Nacional de Procesos Electorales (ONPE). We obtain data on voting outcomes at the district level from the Peruvian National Elections Commission (2016). We focus on the 2011 and 2016 Peruvian presidential elections, the two presidential elections that occur during our sample period. Presidential elections in Peru proceed in two rounds; all parties/candidates openly compete in the first round, and if no party claims an overall majority (50 % or higher), the two parties with the highest first-round votes compete in a run-off in the second round. Our data capture voting participation in both rounds. For each district, we are able to observe the number of registered voters and the number of votes cast. Within the votes cast, we observe how many of them are valid or blank/invalid.

Registro Nacional de Denuncias de Delitos y Faltas. The Registro Nacional de Denuncias de

Delitos y Faltas (National Registry of Crimes and Misdemeanors) collects crime-level information from each police station in Peru (Instituto Nacional de Estadística e Informática, 2017). Importantly, the registry includes information on the type of crime (e.g., violent versus economic crimes) and the district where each crime occurs. We use this to create a district-level panel of crimes per 10,000 residents for the years in which the Registro is available (2011, 2013, 2014, 2016, and 2017).[16]

Registro Nacional de Municipalidades (RENAMU). The RENAMU (Municipality Registry) is an annual survey that collects information on the universe of municipalities (districts) in Peru (Instituto Nacional de Estadística e Informática, 2007b). We use it to compute the number of public hospitals per 10,000 residents at the province level in 2007, the baseline year of our main estimation sample.

Censo Nacional de Comisarías (CENACOM). The CENACOM (National Census of Police Stations) is an annual census that collects information on police stations throughout Peru Instituto Nacional de Estadística e Informática (2012). We use the CENACOM to measure the number of police stations per 10,000 residents at the province level in 2012, the earliest available round of the census.

Latin American Public Opinion Project (LAPOP) and Latinobarómetro. We use data covering Peru from two similar, nationally representative surveys: the AmericasBarometer of the LAPOP (LAPOP Lab, 2017) and Latinobarómetro (Latinobarómetro Corporation, 2017). Both collect information on a variety of topics, including citizens' satisfaction with democracy. We use the 2014 and 2017 rounds of the LAPOP and the 2008-11, 2013, and 2015-2017 rounds of the Latinobarómetro. For both surveys, we restrict our attention to individuals in the Highlands as we do in our main regression sample.

[16]District population data is taken from the 2007 National Census.

3.4 Empirical Strategy

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

$$Y_{idmt} = \beta_1 CDH_{idmt} + \beta_2 AvgTemp_{idmt} + \beta_3 AvgRain_{idmt} + \beta_4 Altitude_{idmt} + \beta_5 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt} \tag{3.4}$$

where Y_{idmt} is a measure of political trust for a randomly chosen individual from household i in district d interviewed in calendar month m of year t. As discussed earlier, the main measure of extreme cold temperature shock is cumulative degree hours, denoted as CDH_{idmt}. It captures the number of degree hours below threshold λ that a household experienced in the past 12-months from the time of interview (as described in Section 3.3.2). We also control for average temperature (Avg Temp$_{idmt}$) and rainfall (Avg Rain$_{idmt}$) that household i experienced in the 12 months prior to the survey. Altitude$_{idmt}$ is measured at the household level (the same level as weather variables). We control for a vector of predetermined individual characteristics (i.e., respondent sex, age, education level, mother tongue, relationship to the head of the household, and household size), this is denoted by Z_{idmt}.

We include fixed effects at the district level (α_d), which account for any time-invariant spatial heterogeneity in the incidence of cold shocks and political trust. We also include fixed effects at the interview year (γ_t) and month level (θ_m), which accounts for seasonality and general trends in political trust and cold shocks.

The coefficient of interest in equation 3.4 is β_1. Our identification strategy assumes that — conditional on district, year, and month fixed effects (and other individual and household controls) — the incidence and intensity of cold shocks are exogenous with respect to political trust. 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[17] — while netting out general trends and seasonality in weather. As long as households are unable to anticipate fluctuations in the intensity of cold shocks, $\hat{\beta}_1$ will capture the causal effect of cold shocks. We report our results for this specification below. To simplify their interpretation, we have multiplied the coefficients and standard errors in the tables below by 100 (so they directly reflect changes in terms of percentage points).

3.5 Results

We find that cold weather shocks negatively affect individuals' perceptions of democracy. Exposure to an additional 10 degree hours below -9°C in the previous year reduces the probability an individual believes democracy works well (or very well) by 0.38 percentage points (Table 3.3). The effects of cold weather shocks are larger if we consider more extreme thresholds of harmful temperatures (see figure 3.1). For example, 10 degree hours below -12°C over the period of previous one year reduces the likelihood that a respondent believes democracy works well by 1.03 percentage points.

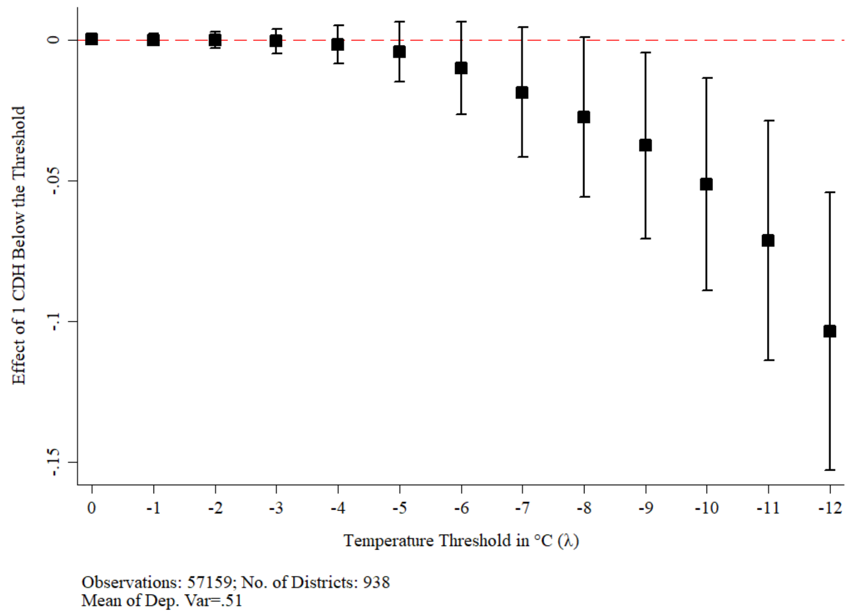
[17] It is worth noting that the ENAHO is not collected during particular months. Instead, it is collected continuously throughout each survey year, in such as way that each quarterly dataset provides a nationally representative sample. This provides us with random variation in the survey dates.

Table 3.3 Effects of Frost Shocks on the Belief that Democracy Works Well

	Dep. Var.: Believes Democracy Works Well
Cumulative Degree Hours (λ = -9°C)	-0.038**
	(0.017)
Observations	57159
No. of Districts	938
Mean of Dep. Var	0.511

Notes: The sample includes individuals in all farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, individual characteristics (respondent sex, age, age squared, education level, and mother tongue), and household size. 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.

Figure 3.1 Effect of Sub-zero Temperature Shocks on the Belief that Democracy Works Well



Notes: The sample includes individuals in all farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, individual characteristics (respondent sex, age, and age squared as well as education level, mother tongue fixed effects, and household size). 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.

3.5.1 Robustness Checks

We find the effect of extreme cold shocks on individuals' perceptions of democracy robust to many alternate checks. First, we check this on alternative samples and similar other measures of political trust. To retain the full variation in the potential responses (with and without "don't know" responses to perceptions of democracy), we estimate an ordered probit and report the marginal effects of this regression in Appendix Table C.1. We find similar results; frost shocks increase the likelihood of reporting democracy functions "poorly" or "very poorly" (Panel A). In Panel B, we again estimate an ordered probit, but now we include individuals who responded "don't know" in a neutral middle category (i.e., between poorly and well). Results suggest a minimal increase in "don't know" responses with frost shocks. In addition to using the full ENAHO sample, we also use alternate datasets and a definition of confidence in democracy. Namely, we use the Latin American Public Opinion Project (LAPOP) and the Latinobarómetro. From these, we use the satisfaction of democracy question, which is a commonly used measure of confidence and trust in government and political institutions. We also match the weather data using the geographic centroid of the district where survey participants reside and the year and month of the interview (considering shocks in the previous 12 months to the interview); this is because geo-locations of the surveyed household are not collected [18]. We find similar results in these alternate samples- specifically, in the LAPOP and Latinobarómetro data, an additional 10-degree hours below -9°C lowers the probability that an individual in the Highlands is satisfied with democracy by 8.4 percentage points and by 7.4 percentage points respectively (Appendix Table C.2 column 1 and column 2 respectively).

Next, we also use alternate measures of the frost shock. In Appendix Table C.3, we have the results with alternate measures of the frost shock. We find that the effect is larger if we construct the frost shock over more recent windows from the time of the interview, i.e., 6 months or 3 months, respectively. We also find similar results to two other measures, first, choosing a coarser but more common measure of temperature shocks: cumulative degree days, i.e., the number of degree days

[18] Additionally, the LAPOP and Latinobarómetro are much smaller surveys that with lower coverage of districts (about 5% or less of districts in our main sample).

in the previous year that the household experienced temperatures below -9°C [19]; and second, a binary indicator for whether a household has experienced any frost shocks over the year prior to the survey [20].

Next, we use alternate identifying variations. In our main specification, to account for potential endogenous variation in frost shocks, we used district fixed effects, which were meaningful mainly because districts are typically small in Peru. However, to further control for unobserved spatial heterogeneity, we include conglomerate [21] fixed effects column 2 of Appendix Table C.4. We find similar results; the estimated effects of frost shocks are even larger when we include conglomerate fixed effects. Additionally, we also use household fixed effects (in column (3)), thus dropping spatial variation and restricting the identifying variation to differences in frost shocks that occur over time within a household (i.e., within the same GPS location) [22]. Our estimate using household fixed effects is smaller but still negative and meaningful in magnitude. The standard errors are larger (arguably due to the dramatic reduction in our sample size); thus, the estimate with household fixed effects is not statistically significant.

Another potential concern could be that households migrate as a response to past frost shocks. This can mean that households who remain in areas experiencing relatively more frost shocks may systematically differ from those living in areas with fewer shocks. However, we do not find any meaningful differences in household characteristics. Table Appendix Table C.5 shows no systematic differences in observable characteristics, except for a statistically significant relationship between frost shocks and having primary education or less (column 4); the magnitude of this relationship is very small. Additionally, in column 2 of Appendix Table C.6, we show that the results are robust to restricting the sample to those who are currently living in their district of birth (so-called

[19]Similar to our primary measure (cumulative degree hours), cumulative degree days capture both the number of days temperatures dipped below a given threshold and by how much below the threshold the temperature fell.

[20]In other words, this binary measure assigns a value of one to households that have experienced *any* positive values of CDH; and zero otherwise.

[21]Conglomerates are generally smaller than districts (though they constitute primary sampling units and not official administrative areas); our sample includes 2,985 conglomerates (compared to 938 districts).

[22]This is possible because the ENAHO contains a much smaller sub-sample made up of an unbalanced panel of households. This sample includes 7,291 households and covers only about a third of our baseline observations and 200 fewer districts.

"non-movers"). We also assess whether households are likely to move in response to frost shocks (most likely to warmer areas with less extreme temperatures). We find no evidence that areas with fewer frost shocks have more migrant households (column 3 of Appendix Table C.6).

Finally, to ensure that our measure of frost shocks captures exogenous weather shocks rather than systematic unobserved determinants or pre-existing trends in perceptions of democracy, we perform a simple falsification test where we estimate the "effect" of future cold weather events. Specifically, we estimate a version of equation 3.4 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 [23]. Column 2 of Appendix Table C.7 shows no statistically significant relationship between perceptions of democracy and future realizations of extreme cold temperatures. This helps us rule out any possibility that households can anticipate future frost shocks, as well as the fact that the frost shocks capture unobserved determinants of perceptions of democracy that systematically vary across households and geographic areas. Finally, it also rules out the role of any possible differential pre-trends in perceptions of democracy that are related to frost shocks.

3.5.2 Mechanisms

This section explores potential pathways through which frost shocks can influence perceptions of democracy. We focus on three fundamental mechanisms: economic losses in income, expenditure, and productive assets, adverse health hazards like the likelihood of illnesses, and increased exposure to criminal activities.

Objective Economic Losses and Subjective Perceptions of the Economic Environment- First, we focus on how exposure to extreme cold temperature shocks leads to economic losses, primarily through loss of agricultural produce and productive livestock assets. Anecdotal evidence suggests that episodes of extreme cold can result in crop failures and livestock death, thus entailing significant economics losses amongst agricultural households in various settings (Samora, 2021; Barbier, 2010; The Guardian, 2021; FAO, 2008; BBC News, 2015). To corroborate this, we borrow significantly from the agronomy literature, which highlights that crops — including those that are most commonly

[23] Because we estimate the "effects" of a 12-month lead of CDH and have weather data only through 2018, for this analysis we have a restricted sample period from 2007-2017

grown in Peru, such as maize and potatoes — suffer when exposed to cold temperatures, especially for longer periods or during critical stages of growth (Lee and Herbek, 2012; Carter and Hesterman, 1990; Hijmans et al., 2001; Burrows, 2019; Janssen, 2004; Romero et al., 1989) [24]. Additionally, exposure to extreme cold temperatures can also be fatal for livestock, leading to economic losses. Livestock provide transportation and help with plowing equipment, products and byproducts for sale or self-consumption and can be sold to cushion unexpected shocks, making them crucial assets for agricultural households (Escobal et al., 1999; Herrero et al., 2013).

We find that extreme cold lowers agricultural revenue substantially. Table 3.4- column 1 shows an additional 10 degree hours below -9°C in the past year lowers annual agricultural revenue by 1.35% (column 1).[25] We believe that this is mainly driven due to extreme cold temperatures during specific growing seasons in a calendar year. For example, every 10 degree hours below -9°C during the growing season in the past year lowers annual agricultural revenue by 4.3% (column 2 in table C.8), total income by 2.3% (column 4 table C.8), and total expenditure by 1.7% (column 6 table C.8). Results in column 2 of table 3.4 show that 10-degree hours below a threshold of -9°C in the previous 12 months translates into a 2.5 percent increase in monetary losses due to livestock deaths, this is extensive margin, i.e., households' self-reported monetary value of dead animals[26].

We are further interested in understanding whether these objective economic losses influence households' understanding of broad economic issues for which they may hold governments accountable. The governance module of the ENAHO collects citizen sentiments on a variety of areas through the question *"What are the main problems of the country?"*. Respondents rank several issues in order of importance. We test whether extreme cold impacts the likelihood that individuals report *lack of agricultural support* or *lack of employment opportunities* as the top-priority issue

[24]Some of the major frost-sensitive crops also account for the majority of the value of agricultural output. For example, Maize and Potato, which are frost-sensitive crops, account for nearly half the agricultural output value. Along with Maize and Potato, other major crops include Beans, Pumpkin, Quinoa, Barley, and Wheat. In total, these account for close to two-thirds of the agricultural revenue.

[25]All monetary outcomes (in column 1 and 2 table 3.4) is transformed using the inverse hyperbolic sine transformation (IHST) to interpret the effects of extreme cold in terms of percentage changes, while accounting for zero-valued observations.

[26]The same shock increases the likelihood of a reported livestock death by 0.45 percentage points (column 1, Appendix Table C.9); this is an intensive margin.

for the country. Our findings reveal that exposure to extreme cold increases the likelihood of reporting these issues as main problems in Peru (Columns 3 and 4 of Table 3.4). This suggests that economic losses influence citizens' perceptions of the country's economic state, this could be crucial in evaluating the government's capacity and shaping perceptions related to the government and the democratic system.

Health- Next, we test the effect of extreme cold on increased health hazards. Extreme cold can be harmful to health in terms of both population morbidity (Zhao et al., 2021; Kephart et al., 2022; Sheridan and Allen, 2015) and mortality (Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011). In this case, we focus on child health, which is motivated by evidence from Peru suggesting that children are a particularly vulnerable population to extreme cold exposure. In 2010, extreme cold events reportedly resulted in increases in infant mortality due to cases of chronic pneumonia and cold-related respiratory diseases (Kirkland, 2012). To the extent that cold weather shocks affect child health, they may lower individuals' trust in the government's ability to aid citizens in times of need. This is especially salient in low-income settings, where public health facilities and access to quality medical care are often scarce or insufficient. Indeed, Costello et al. (2015) find that child mortality rates were a significant predictor of violent and non-violent protests that took place as part of the "Arab Awakening".

We test this on two indicators of health: the incidence of child illness (due to flu, fever, cough, etc.) and the severity of child illness as captured by illnesses that require a medical consultation (both of which are dummy variables in the ENAHO). We restrict our analysis to the subset of households in our main sample from Table 3.3 that contain children aged five and younger. Illness is reported within the 4 weeks prior to the survey interview, so we match the household's weather data from the 8 weeks prior to the interview date to allow for extreme cold conditions to affect health with a lag. Columns (5) and (6) of Table 3.4 shows that 10-degree hours below a harmful threshold of -9°C increases the likelihood of any child illnesses and more "severe" illness by 2.66 and 1.92 percentage points, thus confirming earlier findings. These are meaningful effects on infant health, given that about a third of households in our sample have a child who has been ill in the past month.

Crime and Violence- Earlier studies show exposure to crime and victimization shape (mis)trust in democracy and institutions (Blanco and Ruiz, 2013; Blanco, 2013). Motivated by these findings, we test if extreme cold shocks can spur crime. In this context, we see increased crime as an additional channel that tests the government's ability to enforce law and order and provide citizens with a better quality of life, a lack of which can, in turn, lower trust in government and public institutions. The relationship between extreme cold and crimes is plausible because, as shown earlier, extreme cold events can lead to significant economic losses; such losses can plausibly spur crimes by increasing the value of crime as an alternate source of income (e.g., Iyer and Topalova (2014); Blakeslee and Fishman (2018); Mehlum et al. (2006)). Similar reasoning is used to show that extreme heat can spur violence and crime (see for example Blakeslee and Fishman (2018); Mukherjee and Sanders (2021); Colmer and Doleac (2022); Mares and Moffett (2019); Garg et al. (2020); Simister (2001); Simister and Cooper (2005)).

Significantly less is known about whether extreme cold can spike crimes. To test this, we construct a panel of district-level crimes per 10,000 residents for the years in which the National Registry of Crimes and Misdemeanors (see Section 3.3.4) was conducted (2011, 2013, 2015, and 2017).[27] We focus mainly on two types of crime, which we believe are most likely to respond to extreme weather based on prior work: economic crimes (such as robbery and theft, extortion, fraud, and the sale of illicit goods) and violent crimes (such as murder, assaults, kidnapping, and rape) [28]. We match weather data to the crime data using the geographic coordinates of each district's centroid and consider cumulative frost shocks 12 months prior to the calendar year of the crimes. We find that economic crimes rise by 2% and total crimes by 1.2% for an additional 10-degree hours below -9°C (columns (7) and (9) in table 3.4). In contrast, we find no discernible effects on violent crimes (column 8), though the point estimate is positive. We expect crimes to be underreported; given this additional noise in the (reported) crime data, we expect that the estimates in columns 7-9 of table

[27]The National Registry of Crimes and Misdemeanors does not include information about population. To calculate our measure of crimes per capita, we use district-level population from the 2007 National Census in the denominator.

[28]We transform all crime variables using the inverse hyperbolic sine function to account for zeros (which are common for crime counts in smaller districts)

3.4 will likely represent lower bounds of the actual effects of frost shocks on crime.

3.6 Effect of Extreme Cold on Electoral Participation and Participation in Local Neighborhood Associations

The previous section shows robust empirical evidence on how frost shocks can reduce political trust in the Peruvian Highlands. We also discuss the fundamental mechanisms through which frost shocks can affect political trust- economic losses in the form of reduced agricultural income, loss of productive assets like livestock, increased likelihood of child illness, and increased exposure to crimes. In summary, these negative consequences of extreme cold test the ability of public institutions to provide sufficient insurance, public provisions, and services to the affected population.

In this section, we are interested in documenting the other downstream effects of extreme cold. Specifically, we want to test the reduced-form relationship between exposure to extreme cold temperature shocks and two key outcomes of interest: electoral participation and participation in local neighborhood associations. We see this relationship between frost shocks and electoral participation or voting abstention as a plausible *consequence* of low trust in political institutions. With regard to electoral participation, we hypothesize that frost shocks could mean distrusting voters choose the "exit" option or abstention to express discontent with the most democratic institution (i.e., voting). This is most likely true in scenarios with already high levels of political mistrust, high political fragmentation, or lack of political consolidation, like Peru. In recent decades, there has been some evidence linking political distrust with voting abstention in Western societies and established democracies (Bélanger and Nadeau, 2005; Bélanger, 2017), though this topic remains less explored in the context of developing countries.

Moreover, individuals may seek *additional* sources of support from informal community-based institutions as an adaptive coping strategy to mitigate the negative consequences of extreme cold. We draw the motivation for this relationship from prior work that suggests that in the face of economic shocks, agricultural households may use alternative strategies to cope with economic uncertainties and consumption losses when state and market-led opportunities for consumption smoothing are lacking (Bhattamishra and Barrett, 2010). Though some alternative strategies can

Table 3.4 Effects of Frost Shocks on Economic Outcomes, Subjective Perceptions, Child Health, and Crimes

	Economic Outcomes		Subjective Perceptions		Child Health		Crimes		
	Val. of Ag. Output	Val. of Livestock Deaths	Lack of Ag. Support	Lack of Employment	Child Has Been Ill	Child Needed Medical Attention	Economic Crimes	Violent Crimes	Total Crimes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CDH (λ = -9°C)	-0.135***	0.251*	0.017***	0.014***	0.266***	0.192***	0.204***	0.090	0.122**
	(0.042)	(0.141)	(0.005)	(0.006)	(0.056)	(0.064)	(0.063)	(0.075)	(0.058)
Observations	76642	63028	75632	75632	29240	29240	5390	5390	5390
No. of Districts	944	922	940	940	887	887	1072	1072	1072
Mean of Dep. Var	2746.530	582.943	0.076	0.063	0.333	0.316	19.700	14.553	40.275

Notes: Value of agricultural output and livestock death have been transformed using the inverse hyperbolic sine function. The sample includes all households in the Highlands with agricultural revenue over the previous year using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, and columns (1) & (2) include household head characteristics (sex, age, and age squared as well as education level and mother tongue fixed effects), log of total land (owned + rented), and household size fixed effects. Columns (3) & (4) include individual characteristics (respondent sex, age, and age squared as well as education level and mother tongue fixed effects), and household size fixed effects. The sample in Columns (5) & (6) includes all children under the age of 5 living in farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, household head characteristics (sex, age, age squared, education level, and mother tongue), child sex and age fixed effects, and household size.All specifications (1)-(6) include year, district, and month of interview fixed effects. District-level clustered standard errors in parentheses.In Columns (7)-(9) all crime variables have been transformed using the inverse hyperbolic sine function. The sample includes all districts in the Highlands using all available crime data from the 2011, 2013, 2015, 2016, and 2017 rounds of the National Registry of Crimes and Misdemeanors. All specifications (7)-(9) include year and district fixed effects as well as province-specific time trends. Controls include average temperature and rainfall. District-level clustered standard errors in parentheses. All 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.

be household-specific (like diversifying own income channels), others can involve a higher degree of engagement both within and outside local communities. Higher cooperation, interaction, and participation in neighborhood and nearby communities are key pathways for risk coping, mutual insurance, and, in turn, raising social trust (Buggle and Durante, 2021).

In summary, we find that a crisis lowers political trust. We hypothesize that this low political trust may lead individuals to abstain from engaging with formal institutions, such as voting. Moreover, such abstention may be more in places with weaker formal institutions, i.e., places with lower coverage of public goods and services. On the other hand, we also hypothesize that this crisis can lead to a corresponding increase in engagement in local informal community-based associations, which can lead to higher social trust.

Electoral Participation- First, to study the effect of exposure to extreme cold shocks on electoral participation, we consider two indicators at the district level: the share of absent votes (i.e., the share of eligible voters in a district that did not cast a vote)[29] and the share of votes that are either absent or blank (where blank votes are those that are cast but that are left blank).[30] Both voting behaviors capture disengagement with the most basic democratic institution (i.e., voting), and previous research suggests that they might reflect protest voting (Alvarez et al., 2018).

We use district-level voting data from ONPE for the 2011 and 2016 Presidential Elections (the two races during our study period)[31]. Therefore, we focus on four different voting rounds. We match weather data to district-level voting data using the GPS location of the district centroid. We measure extreme weather shocks as those that occur in the year previous to the election, taking into account the date at which each voting round occurs. As in our main specification (equation 3.4), we

[29]An important characteristic of the Peruvian political system is that voting is mandatory for all citizens aged 18–70. Those who do not show up to the polling stations on election day face a monetary fine that ranges from approximately US$ 6 (in poorer districts) to approximately US$ 25 (in wealthier districts). Therefore, absenteeism imposes economic costs on those that decide not to participate in elections.

[30]In the results below, we do not consider spoilt votes (null votes where individuals choose more than one presidential candidate, make drawings in their ballot, physically deforms the ballot, etc.). While some spoilt votes may reflect protest voting, others might have unintentionally voided their ballots. In any case, our results are robust to including spoilt votes in our measure of civic disengagement.

[31]As mentioned previously, the Peruvian Presidential election typically includes two rounds: a general election (with several candidates) and a run-off race between the two top candidates (when no candidate reaches more than 50% of the votes in the general election).

include district- and year-fixed effects. To make the results more representative, the only difference in this case is that we weigh the regression with district level number of registered voters in each election.

We find that extreme cold shocks in the year before a presidential election decrease voter participation: 10-degree hours below -9°C in the 12 months prior to the election increases the share of absent voters by 0.08 percentage points in the 1st round and by 0.10 percentage points in the 2nd round of the elections (Table 3.5, columns 1 and 2). These results are robust to including blank votes as an additional measure of non-participation (columns 3 and 4).[32] Though the effect size is modest, we believe that these results have important implications for voting outcomes for Peru, where the margin of victory in national elections tends to be very small. For example, a 10-degree hour shock translates into an increase in 22,766 absent voters in the second round, just from the Peruvian Highlands.[33] In total, the margin of victory in the 2016 presidential elections was only 41,057, suggesting that the effect of extreme cold on absent voters could potentially play a meaningful role in election outcomes. Moreover, appendix figure C.3 shows the effect size is larger for higher thresholds of the shock, thus translating into absent voters, which is even more than the 2016 winning margin [34]. These results are very similar with the unweighted specification as well (appendix table C.10). Finally, we also use the alternate LAPOP dataset to demonstrate that our voting results are robust by using an individual-level indicator for whether a respondent abstained from voting in the presidential election prior to the survey (column 3 of appendix table C.2). Consistent with the results using official district level voting data, we find that individuals are more likely to report that they did *not* vote if they experienced frost shocks in the year prior to the election; an additional degree hour below -9°C lowers the probability that an individual in the

[32] Recent literature has interpreted blank, null, or spoiled ballots as a manifestation of disillusionment with the existing political system, rejection of incumbent politicians, and/or discontent with current conditions (Alvarez et al., 2018, p. 144). To demonstrate that blank votes can be interpreted as intentional "protest votes" rather than accidental errors in casting votes, Cohen (2017) compares self-reported null votes cast in ex-post surveys' to official electoral results in 14 Latin American countries. She finds that a large proportion of official null votes corresponds to self-reported ones, suggesting that these votes are intentional.

[33] The total number of eligible voters for the entire country in 2016 was 22,016,988.

[34] For example, a 10-degree hour shock for a -12°C harmful threshold translates into an increase in 48,547 absent voters in the second round in total.

Highlands abstains from voting by 2.2 percentage points. Overall, these results align with recent findings in other contexts, where awareness of weak public service delivery reduces the likelihood of voting (Cox et al., 2024). These results also provide key insights into how exposure to a crisis can lower voter turnout even in contexts with compulsory voting rules.

Table 3.5 Effects of Frost Shocks on Electoral Participation

	Share of Absent Votes		Share Absent & Blank	
	First Round	Second Round	First Round	Second Round
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.008***	0.010***	0.007***	0.011***
	(0.001)	(0.002)	(0.001)	(0.002)
Observations	12,496,220	12,496,220	12,496,220	12,496,220
No. of Districts	1278	1278	1278	1278
Mean of Dep. Var	0.187	0.211	0.297	0.220

Notes: Shares are calculated with respect to the total eligible voters in each district. The sample includes all districts in the Highlands and covers the 2011 and 2016 presidential elections. Weather variables are measured at the district centroid and measures weather in the year prior to the date of each election. All specifications include year and district fixed effects. District-level clustered standard errors in parentheses. Regression weighted by district-level number of registered voters in each election. 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.

Participation in Local Neighborhood Associations- To investigate this possibility, we examine whether extreme cold shocks impact engagement in local institutions. Namely, we use data from ENAHO, where individuals report whether they participate (as leaders or members) in different types of local associations and groups. We classify these institutions into three categories[35]: political (e.g., political parties, municipal management committees, citizen round tables, etc.), professional and agricultural (e.g., worker associations, trade guilds, professional associations, agricultural associations, etc.), and community-based (e.g., peasant communities in charge of communal land administration, *Rondas Campesinas* or rural self-defense groups[36], *Juntas de*

[35]Our measure of participation in local organizations aims to highlight how citizens self-organize to cope with adverse shocks. Therefore, our variable excludes participation in government-run social assistance programs (such as *Vaso de Leche* and *Comedores Populares*), which require communities' in-kind provision of labor.

[36]Prior to the 2012 round of the ENAHO, participation in *Comunidades Campesinas* (a historical and widespread

Regantes or local irrigation management boards, neighborhood associations, etc.). We test whether exposure to frost shocks increases the likelihood that (at least one member of) these agricultural household report participation in any local organizations. We follow a similar specification for this, as in equation 3.4.

Overall participation in local associations increases by 0.23 percentage points when households face 10-degree hours below -9°C (Table 3.6, column1). This estimated effect does not appear to be driven either by participation in political (column 2) or professional and agricultural associations (column 3) but rather by community-based associations (column 4). As with our main results, we find that the effects of cold weather shocks on participation in local organizations are larger when we consider more extreme temperature thresholds (see Appendix figure C.4). In addition to these results, we also test with our alternate LAPOP dataset. The LAPOP data does not provide information on participation in local neighborhood associations but collects information on social or interpersonal trust indicators. We use the 2014 and 2017 LAPOP rounds, in which respondents are asked- "Would you say that people in your community are trustworthy?" we use this as an indicator of interpersonal trust. We find similar results: exposure to extreme cold temperature shocks in the previous year from the survey increases the likelihood that respondents report more trustworthy people in their community, indicating higher interpersonal trust. For example, an additional degree hour below -9 °C increases the likelihood of trusting people in community by 0.6 percentage points (column 4 of appendix table C.2). These results are consistent with the findings of Buggle and Durante (2021). This also indicates a possible divergence in political and social trust in the face of a crisis. The closest literature in this context is a very recent paper by Aassve et al. (2024), which uses both experimental and observational data to provide evidence of such a divergence in the context of the US with exposure to the COVID-19 crisis.

Overall, these evidence is consistent with the possibility that, *on average*, extreme cold shocks can make individuals choose to abstain from engaging with formal, national institutions (such as voting) and engage more toward local, informal institutions related to identity, kinship, and social

community-based group) was not asked about directly, but was included in the category "Other". As a result, we include the "Other" category prior to 2012 in the community-based definition.

proximity.

Table 3.6 Effects of Frost Shocks on Participation in Local Associations

	All Local Assoc.	Political & Government	Professional & Agricultural	Community-Based
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.024**	0.000	0.004	0.031**
	(0.010)	(0.001)	(0.017)	(0.014)
Observations	76471	76471	76471	76471
No. of Districts	944	944	944	944
Mean of Dep. Var	0.816	0.012	0.182	0.703

Notes: The sample includes individuals in all farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, household head characteristics (sex, age, age squared, education level, and mother tongue), and household size. 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.

3.7 Can Access to Public Goods and Services Improve Political Trust and Electoral Participation? Examining the Role of Access to Social Assistance Programs, Public Health Care Facilities and Public Safety

Previously, we identified economic losses in the form of lower agricultural income, loss of productive assets like livestock, increased health hazards amongst children, and increased exposure to crimes as possible mechanisms by which frost shocks can lower evaluations of democracy in the Peruvian Highlands. To provide further evidence that these mechanisms at least partly explain our main findings, we now examine the extent to which the effects of extreme cold on political trust are heterogeneous by access to government-provided means of mitigation. Suppose public provisions like government-provided programs, facilities, and other resources protect households from the adverse effects of cold weather. In that case, the effects should be strongest for those who lack access to relevant public goods and services. With this in mind, we now explore the heterogeneous impacts of frost shocks by an aggregate measure of public provisions or, specifically, a composite indicator of access to social assistance programs, public hospitals, and police stations. Thus, we test the heterogeneous impact of frost shocks by coverage of public goods and services on political mistrust and electoral non-participation.

Several studies find that redistributive programs such as cash transfers can foster support for government (Evans et al., 2019; Kosec and Mo, 2023), though effects may be short-lived (Zucco Jr, 2013). To the extent that social assistance programs can mitigate the negative impacts of extreme cold on households, they may also temper the effects of cold shocks on political trust. Many social programs are targeted at poor and marginalized populations, and access to these programs can facilitate income and consumption smoothing, potentially inspiring confidence in public institutions and increasing political trust. Similarly, access to public health facilities and police resources can also improve confidence in public institutions through reduced health hazards and lower crimes in the face of extreme cold shocks.

To operationalize this heterogeneity analysis we use three components of public goods and services, namely, access to social programs, public hospitals, and police stations. First we construct the measure for social program coverage from the ENAHO. This measure is the share of households in each province in which at least one member has been a beneficiary of a government-sponsored social program. Because public programs can respond endogenously to frost shocks (or even shift due to low levels of government approval), we construct a baseline measure of coverage of social programs. Unfortunately, the ENAHO did not collect information about access to social programs prior to 2012. Thus, we estimate our measure of access to social programs based on the 2012 round. Second, to measure access to public hospitals, we calculate the number of public hospitals per 10,000 residents at the provincial level using the 2007 Peruvian Municipality Registry (RENAMU). Similarly, using data from the 2012 CENACOM, the earliest available census of police stations, we calculate the number of police stations per 10,000 province-level residents in 2012. Finally, we construct a composite indicator of public provisions at the province level using principal component analysis of these three separate measures of access to social programs, public hospitals, and police stations. For simplicity, we construct an indicator variable, identifying high public provision provinces as those with an above-median value of the composite indicator and low public provision provinces as those with a below-median value of this composite indicator.

Since we use information prior to 2013 to construct this composite indicator of public provisions, we restrict our analysis to the 2013 - 2018 rounds of the ENAHO to explore the heterogeneous impact of frost shocks on our political trust outcome. However, such a sample restriction is not feasible to study the heterogeneous effects of public provisions on electoral participation because we use only two rounds of election data (2011 and 2016) [37]. Thus, we use both 2011 and 2016 election data for our heterogeneity analysis, and this raises a concern of endogeneity and remains a limitation for this part of the analysis.

We begin by demonstrating that our main results in this restricted sample period (column 1 of table 3.7) are nearly identical to those using the full sample period (table 3.3). In column (2) of table 3.7, we present heterogeneous impacts of CDH across provinces with lower and higher levels of public goods and services. We find that the negative impact of CDH on political trust is lower in places with a higher coverage of public goods and services. For example, in provinces with a low baseline coverage of public goods and services, 10-degree hours below -9°C in the previous 12 months reduces political trust by 0.65 percentage points. In contrast, the same shock in provinces with a higher baseline coverage of public goods and services reduces political trust by 0.27 percentage points. Although this difference is not statistically significant.

Similar to the effects on political trust, we find that overall access to higher levels of public provisions in the face of a shock can lower voter abstention in the decisive second round of Presidential elections in Peru. For example, in provinces with lower coverage of public goods and services, a 10-degree hours below -9°C in the previous 12 months from the time of the second round election can increase voter absenteeism by 0.16 percentage points (column 4 of table 3.7). In contrast, this shock has a lower effect on voter absenteeism in provinces with higher coverage of public goods and services (0.09 percentage points). The results are similar if we include blank votes as well (column 6 of table 3.7). This difference is also statistically significant. However, these results do not hold in the first round of general elections with several candidates (columns (3) and

[37] For the electoral participation results, we use electoral data from 2011 and 2016; thus, restricting the sample to only 2016 data (the only round after 2012) will leave us with a cross-section of districts.

(5) of table 3.7). Overall, we find some evidence that access to public goods and services in the face of a shock can attenuate political mistrust, which translates into lowering voter absenteeism and improved participation in the more decisive second round election.

Finally, we check for heterogeneity of extreme cold by coverage of public goods and services on participation in local neighborhood associations. We find that the increase in local neighborhood participation is, in fact, driven by provinces with already higher coverage of public goods and services (appendix table C.11). In other words, higher public provision of goods and services does not necessarily crowd out participation in local informal networks in this setting. This may need further examination, but it could be driven by multiple factors, like participation in local networks could help in collectively seeking access to social programs. Moreover, the findings from the emerging literature on crowd-out of private transfers or informal networks due to access to formal social programs and public goods and services are mixed (Banerjee et al., 2024). Studies seem to suggest that the findings are primarily dependent on context and features of the economy and vary with the characteristics of the programs studied (Albarran and Attanasio, 2003; Strupat and Klohn, 2018; Takahashi et al., 2019; Huang and Zhang, 2021). Additionally, both informal and formal consumption smoothing channels could be helpful, especially with spatially correlated income shocks in a rural-agrarian context (Banerjee et al., 2024).

3.8 Conclusion

This study sheds light on the impact that extreme weather conditions have on individuals' perceptions of democracy. Extreme cold temperature shocks significantly decrease in the belief that democracy functions well in Peru. This, in turn, reduces civic engagement in formal, national institutions, as reflected by lower participation in national elections. We also observe a corresponding increase in participation in local associations, suggesting households look for alternative forms of civic involvement in an attempt to seek additional sources of support from more informal community-based institutions in the face of a shock.

Furthermore, our research explores the underlying mechanisms through which extreme cold affects perceptions. We find that decreased income, assets, and expenditure, along with an increased

Table 3.7 Heterogeneous Effects by Coverage of Public Goods and Services

	Believes Democracy Work Well		Share of Absent Voters		Share of Absent + Blank Voters	
			First Round	Second Round	First Round	Second Round
	(1)	(2)	(3)	(4)	(5)	(6)
CDH (λ = -9°C)	-0.036**	-0.065**	0.009***	0.016***	0.007***	0.016***
	(0.018)	(0.032)	(0.003)	(0.004)	(0.002)	(0.004)
CDH (λ = -9°C) X Above Median Coverage of Public Goods and Services		0.038	-0.001	-0.007*	-0.000	-0.007*
		(0.036)	(0.003)	(0.004)	(0.002)	(0.004)
Effect in Provinces with Higher Public Goods and Services		-0.027*	0.008***	0.009***	0.007***	0.0095***
		(0.016)	(0.0013)	(0.0012)	(0.0007)	(0.001)
Observations	34295	34089	12,454,805	12,454,805	12,454,805	12,454,805
No. of Districts	890	883	1256	1256	1256	1256
Mean of Dep. Var	0.555	0.555	0.187	0.211	0.297	0.220

Notes: – For Columns (1) & (2) the sample includes individuals in all farming households in the Highlands using the 2013-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, individual characteristics (respondent sex, age, and age squared, education level, and mother tongue), and household size. All specifications include year, district, and month of interview fixed effects. District-level clustered standard errors in parentheses. All Coefficients and standard errors have been multiplied by 100 for ease of interpretation.

For Columns (3)- (6): Shares are calculated with respect to the total eligible voters in each district. The sample includes all districts in the Highlands and covers the 2011 and 2016 presidential elections. Weather variables are measured at the district centroid and measures weather in the year prior to the date of each election. All specifications include year and district fixed effects. District-level clustered standard errors in parentheses. Regression weighted by district-level number of registered voters in each election. 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.

incidence of illness and crimes, contribute to the negative effects on individuals' beliefs about democracy and government.

Importantly, our findings indicate that government provision of goods and services can mitigate the adverse effects of extreme cold. Higher coverage of public goods and services in the form of access to social programs, public hospitals, and police resources play a crucial role in attenuating political mistrust due to impact of extreme weather shocks and even translating to improved engagement with formal institutions through a higher electoral participation.

Overall, these results emphasize the importance of considering weather-related factors when examining the dynamics of citizens' beliefs about how well democracy functions. These findings underscore the need for governments to be attentive to extreme weather events and to prioritize the provision of essential services during such periods of crisis, as this can help maintain or restore confidence in democratic processes and institutions.

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APPENDIX A

APPENDIX A FOR CHAPTER 1

A.1 Appendix A

Figure A.1 Weather Related Emergency Responses in Peru

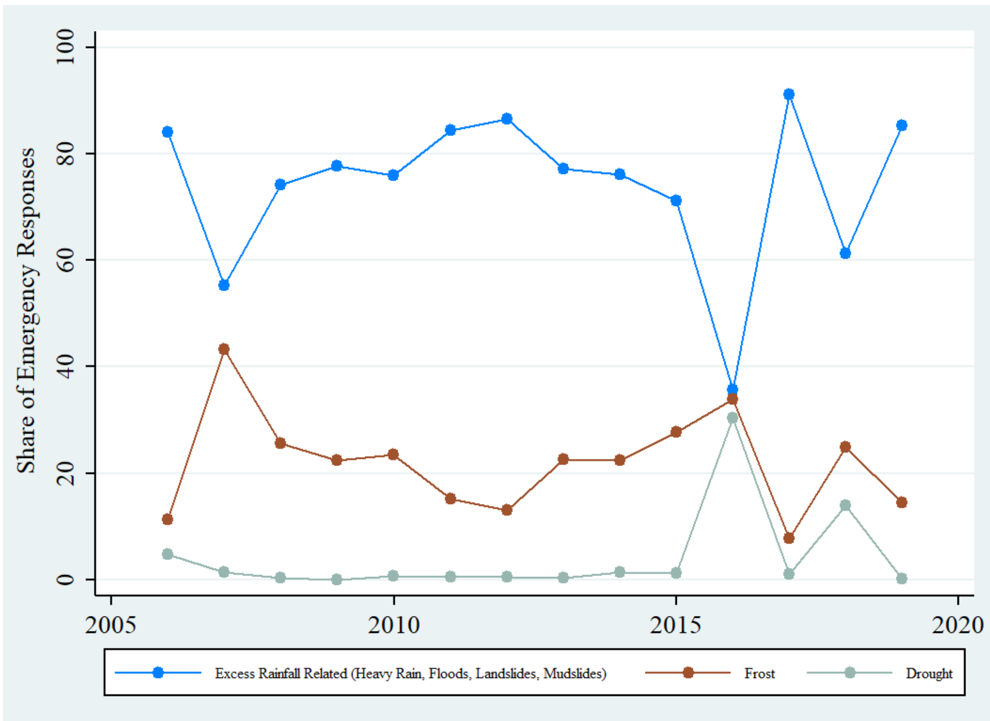
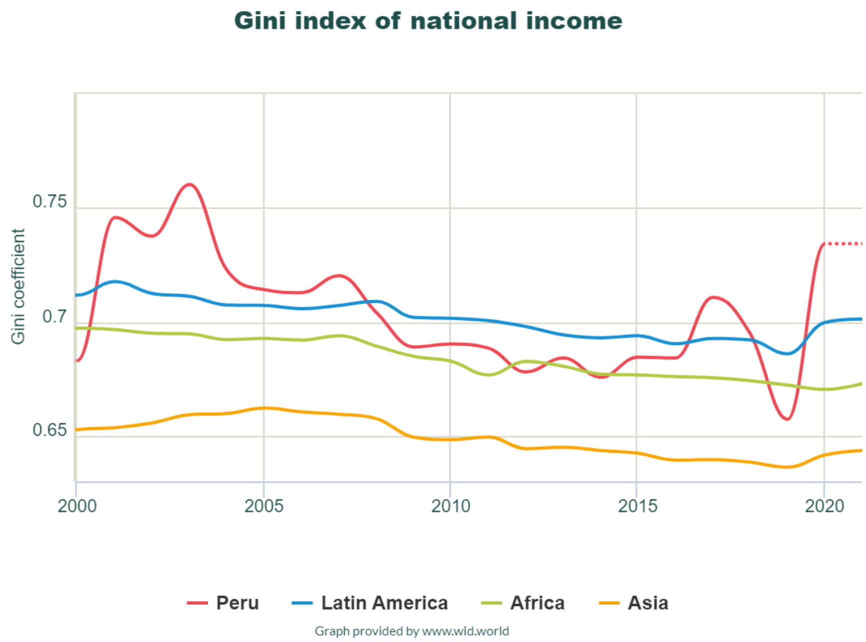
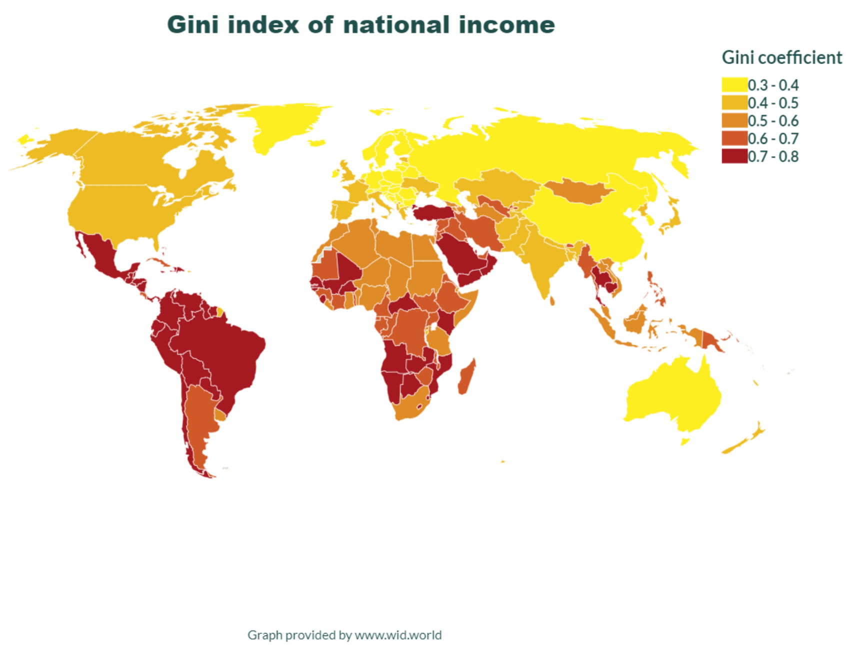


Figure A.2 Income Inequality in Peru, Latin America, Africa, and Asia



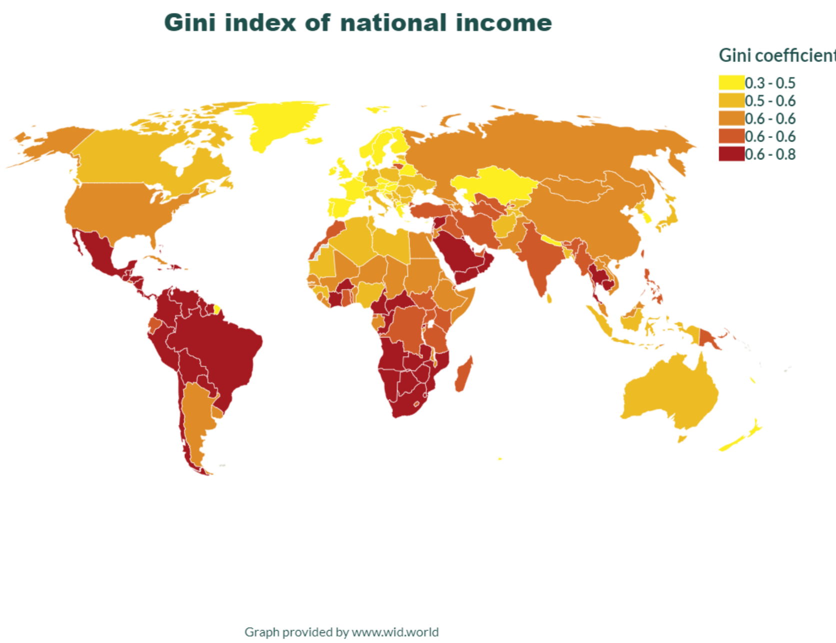
Source: Author's Illustration using Data from World Inequality Database

Figure A.3 Income Inequality by Countries, 1990



Source: Author's Illustration using Data from World Inequality Database

Figure A.4 Income Inequality by Countries, Latest Year



Source: Author's Illustration using Data from World Inequality Database

Figure A.5 Location of households used in the analytical sample

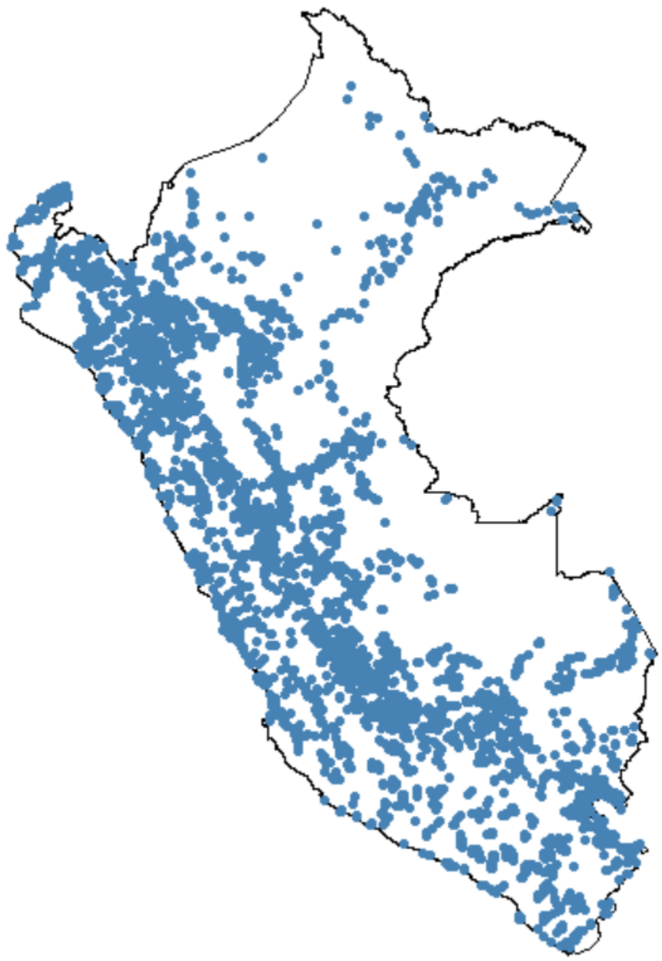
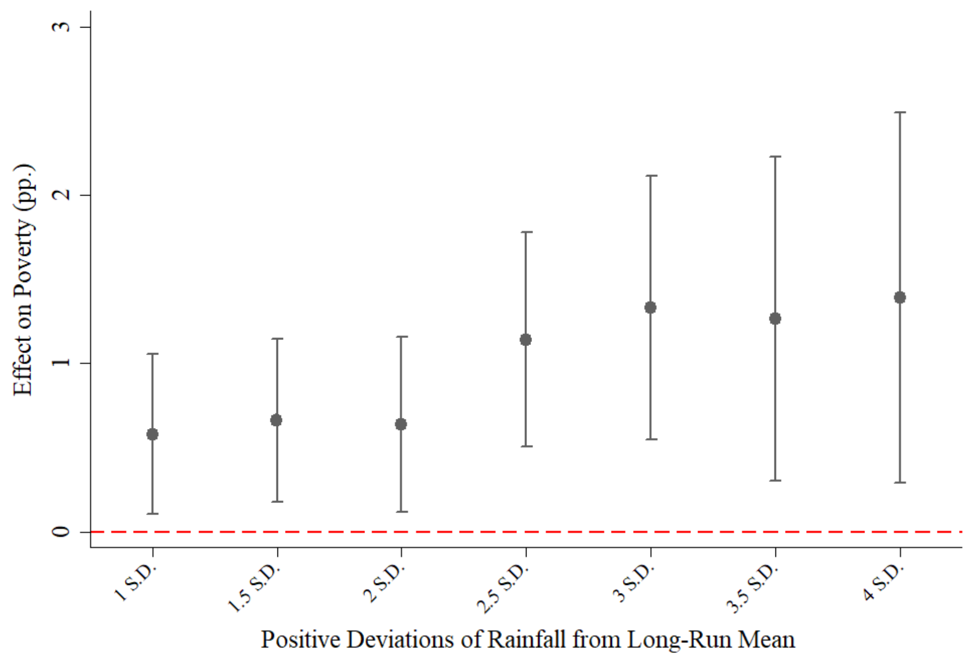
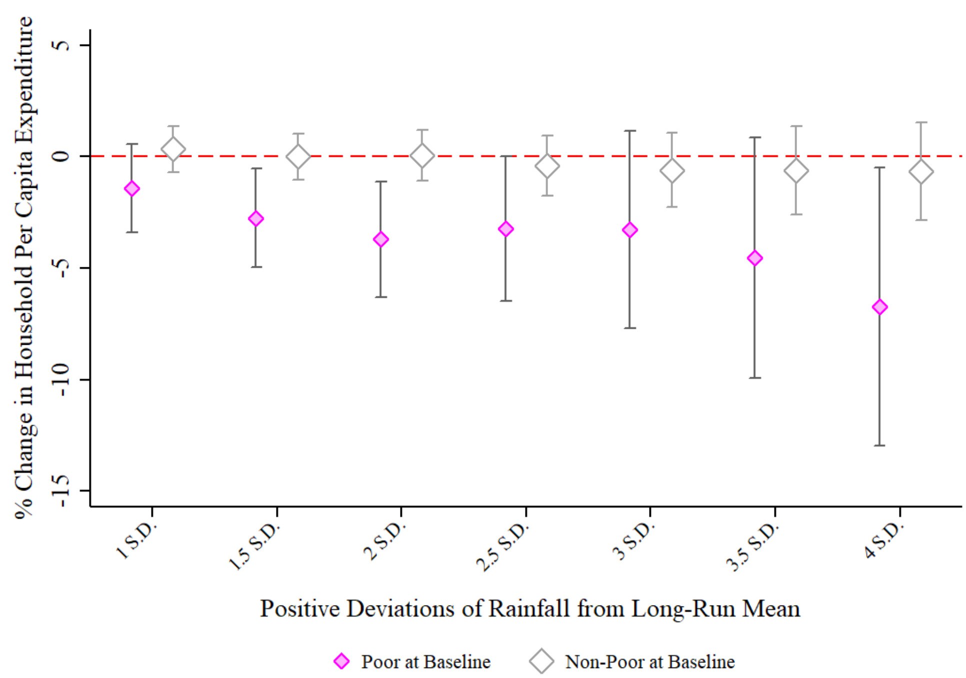


Figure A.6 Effect on Poverty



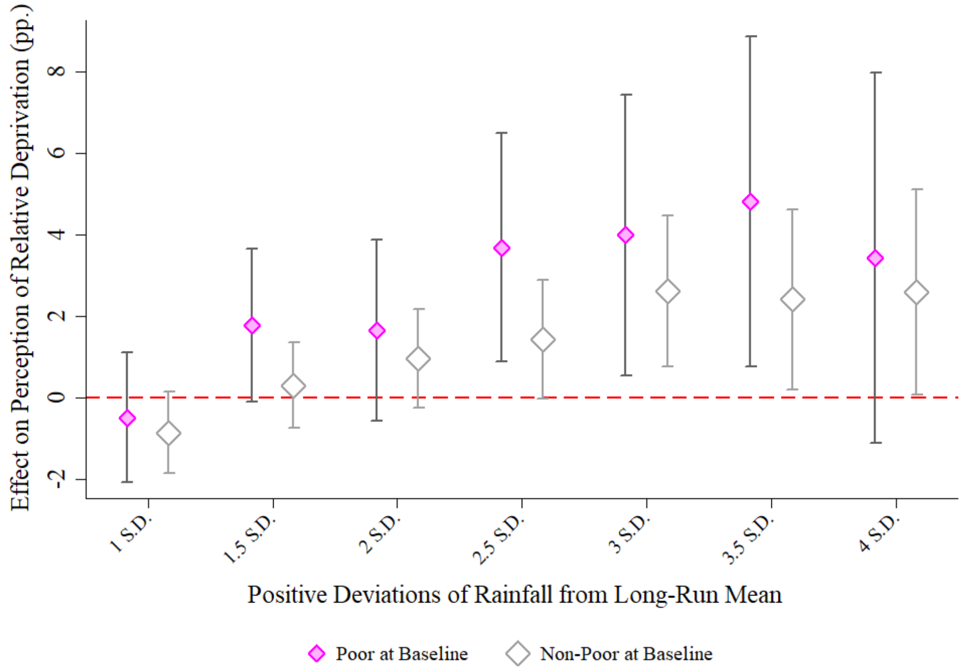
No. of observations: 139,587; Households: 44,193; Mean of Poverty: 0.25

Figure A.7 Differential Effect on Household Per Capita Expenditure



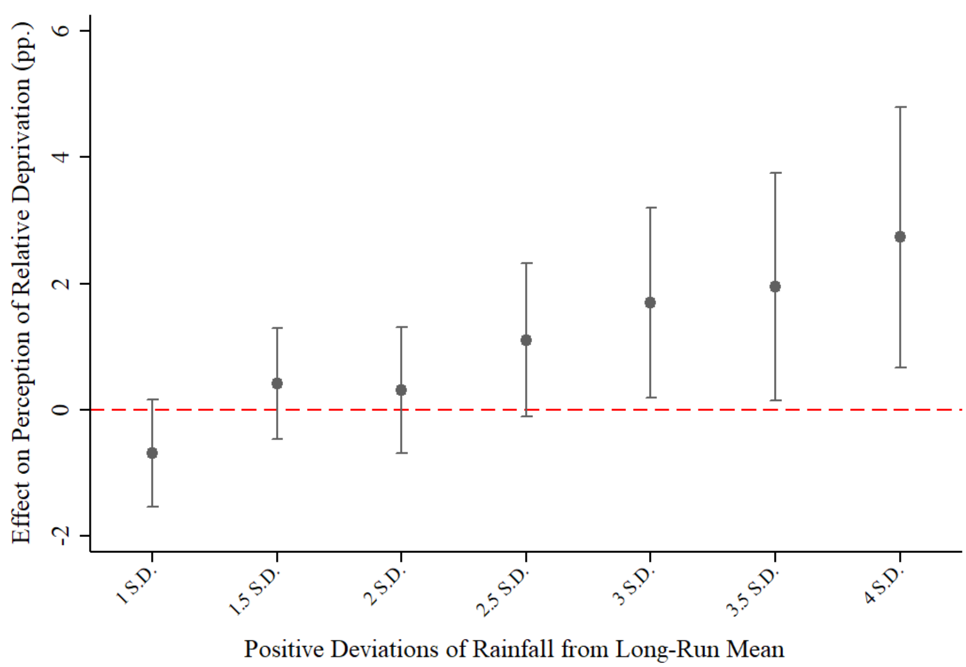
No. of observations: 78,884; Households: 26,941

Figure A.8 Differential Effect of Perceived Relative Deprivation



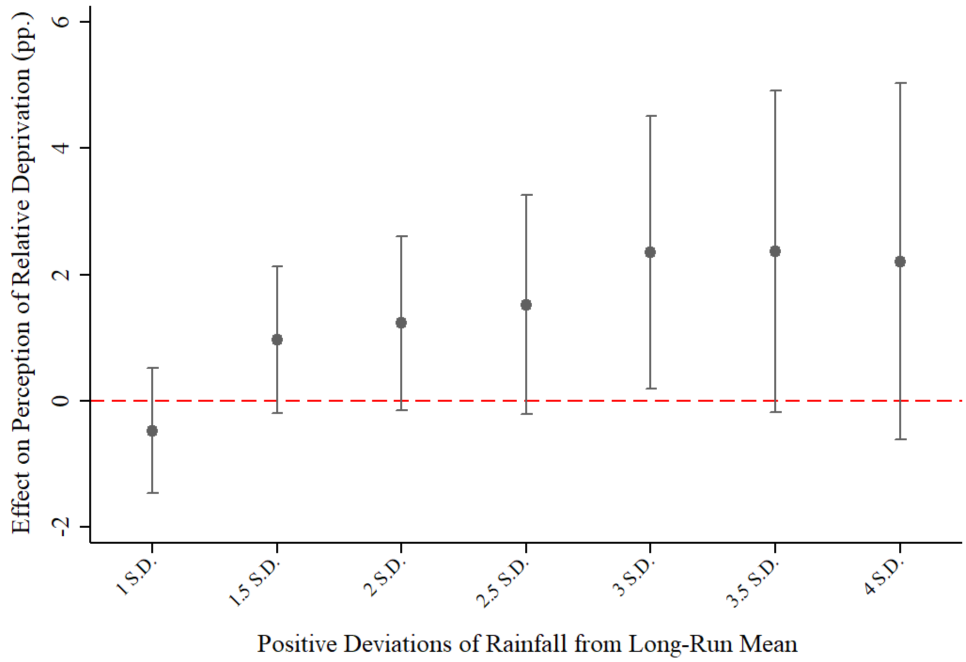
No. of observations: 78,884; Households: 26,941

Figure A.9 Effect of Perceived Relative Deprivation (On Sub-Sample of Always Non-Poor)



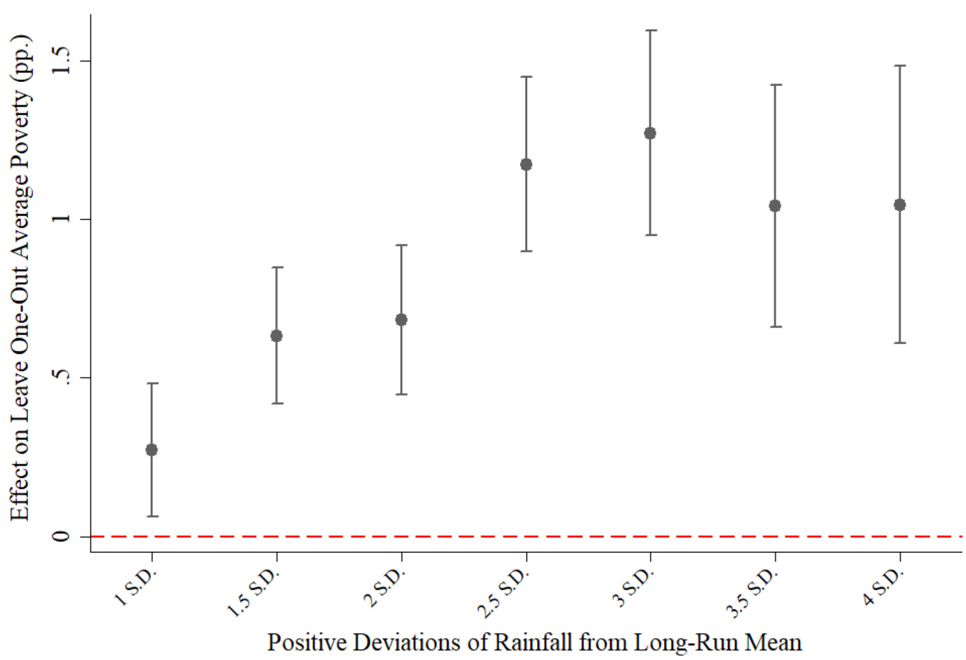
No. of observations: 81,635; Households: 26,658 ; Mean of Perceived Relative Deprivation: 0.21

Figure A.10 Effect of Perceived Relative Deprivation (On Sub-Sample of Always Poor + Switchers/Atleast once Poor)



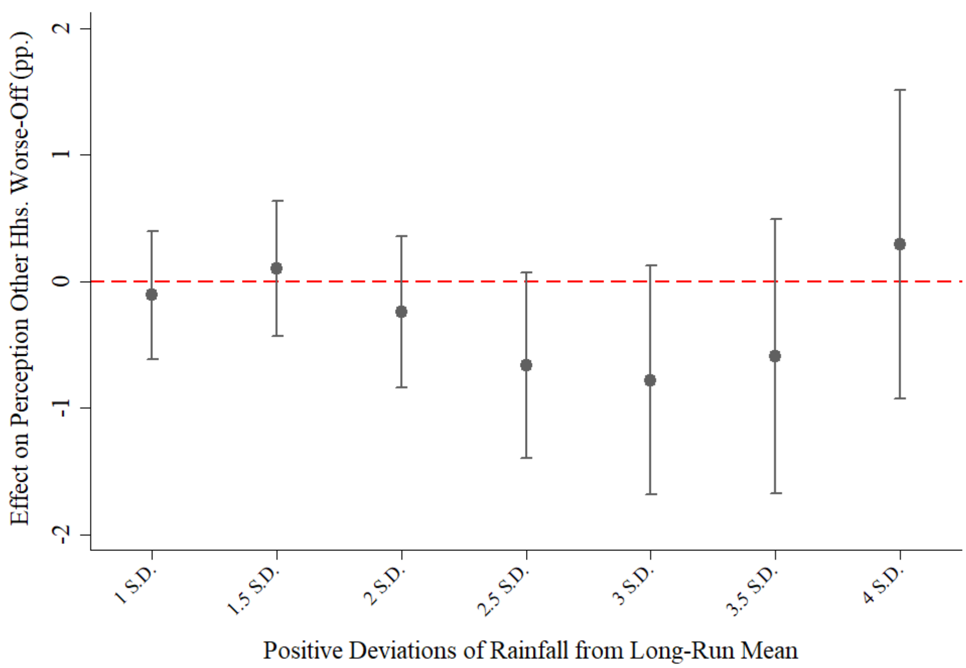
No. of observations: 57,952; Households: 17,535 ; Mean of Perceived Relative Deprivation: 0.19

Figure A.11 Effect on Leave-one-out Average Poverty



No. of observations: 138,590; Households: 43,745; Mean of Leave One-Out Average Poverty: 0.25

Figure A.12 Effect on Perceptions of Other Households being Worse-Off



No. of observations: 139,587; Households: 44,193; Mean of Perceiving Other Hhs. Worse-Off: 0.12

Table A.1 Perceived Relative Deprivation (Alternate Measure)

Perception of Relative Deprivation		In the course of the last year, the standard of living of households in your locality or community: got better	same	worse
In the course of last year, the standard of living of your household?	got better	same (=2)	hh perception-better off (=1)	hh perception-better off (=1)
	same	*hh perception-worse off (=3)*	same (=2)	hh perception-better off (=1)
	got worse	*hh perception-worse off (=3)*	*hh perception worse off (=3)*	same (=2)

Table A.2 Ordered Probit Model (Marginal Effects)

	Better-Off than others (=1)	Same as others (=2)	Worse-Off than others (=3)
Rainfall Shock	-0.786***	-0.277***	1.063***
Deviation ≥ 2.5 S.D.	(0.306)	(0.108)	(0.414)
N. of obs.	139,587	139,587	139,587
N. of Households	44,193	44,193	44,193
Mean Dep Var	0.1279	0.6688	0.2032

Notes: Dependent variable is a categorical variable and takes 3 distinct values: 1 for strictly better-off, 2 for same as others and 3 for strictly worse-off. Controls include household head specific characteristics like sex of respondent (hh head), age, age square, education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Figure A.13 Location of households surveyed in 2019 and all Huaycos-related emergencies in 2019

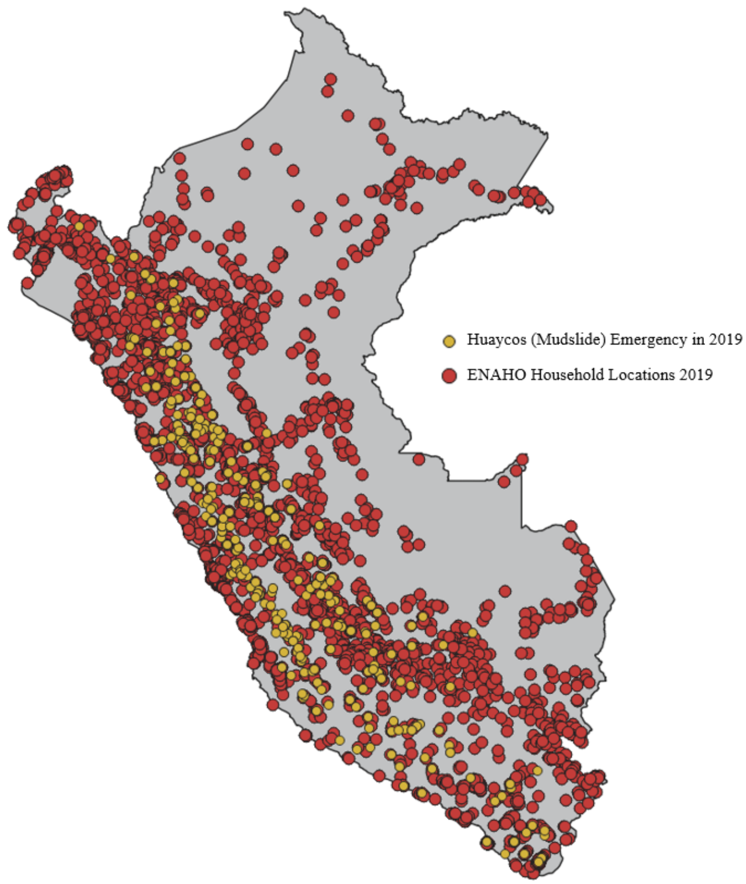
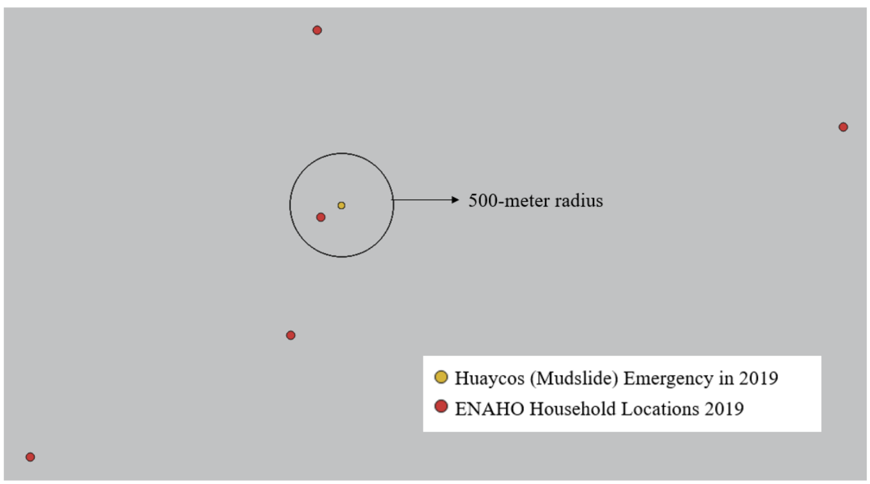


Figure A.14 Illustrative example of households exposed to mudslides in Puacartambo District in Pasco Province, Pasco in 2019



The households with a location within the 500-meter radius are considered to be exposed to a mudslide emergency. The locations outside the radius are not considered to be exposed.

Table A.3 Effect of Rainfall Shock on Exposure to Emergency Events

	Dep. Var.: Exposure to Emergencies
	(1)
Rainfall Shock	3.094***
Deviation >= 2.5 S.D.	(0.351)
N. of obs.	139,587
N. of Households	44,193
Mean Dep Var	0.145
R2	0.613

Notes: The dependent variable is a binary variable that takes value 1 if the households are located within a 500-meter radius of heavy rainfall, flood, landslide, or mudslide-related emergency in the past 12 months from the time of interview and 0 otherwise. I control for household, month of interview, and year fixed effects in this specification. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Table A.4 Effect of Exposure to Emergency Events on Perceived Relative Deprivation

	Dep. Var.: Perceived Relative Deprivation
	(1)
Exposure to Emergencies	1.059**
heavy rainfall, floods, landslides, mudslides	(0.471)
N. of obs.	139,587
N. of Households	44,193
Mean Dep Var	0.203
R2	0.368

Notes: The explanatory variable of interest is a binary variable that takes value 1 if the households are located within a 500-meter radius of heavy rainfall, flood, landslide, or mudslide-related emergency in the past 12 months from the time of interview and 0 otherwise. Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Table A.5 Effect on Perceived Relative Deprivation

	Dep. Var.: Perceived Relative Deprivation		
	(1)	(2)	(3)
Rainfall Shock	1.249**		
Deviation >= 2.5 S.D.	(0.505)		
Self-Reported Natural Disaster		2.583***	
		(0.481)	
Natural Disaster Indicator			1.436**
=1 if >= 50% of hhs. reported exposure to a natural disaster in a district			(0.660)
N. of obs.	139,587	139,582	139,587
N. of Households	44,193	44,192	44,193
Mean Dep Var	0.203	0.203	0.203
R2	0.368	0.368	0.368

Notes: Notes: Controls include household head specific characteristics like sex of respondent (hh head), age, age square, education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Table A.6 Effect of Negative Rainfall Shock on Perceived Relative Deprivation

	Perceived Relative Deprivation	
	(1)	(2)
Rainfall Shock	1.054**	
Deviation ≤ 0.8 S.D.	(0.484)	
Rainfall Shock		0.697
Deviation ≤ 1.6 S.D.		(0.923)
N. of obs.	139,587	139,587
N. of Households	44,193	44,193
Mean Dep Var	0.203	0.203
R2	0.368	0.368

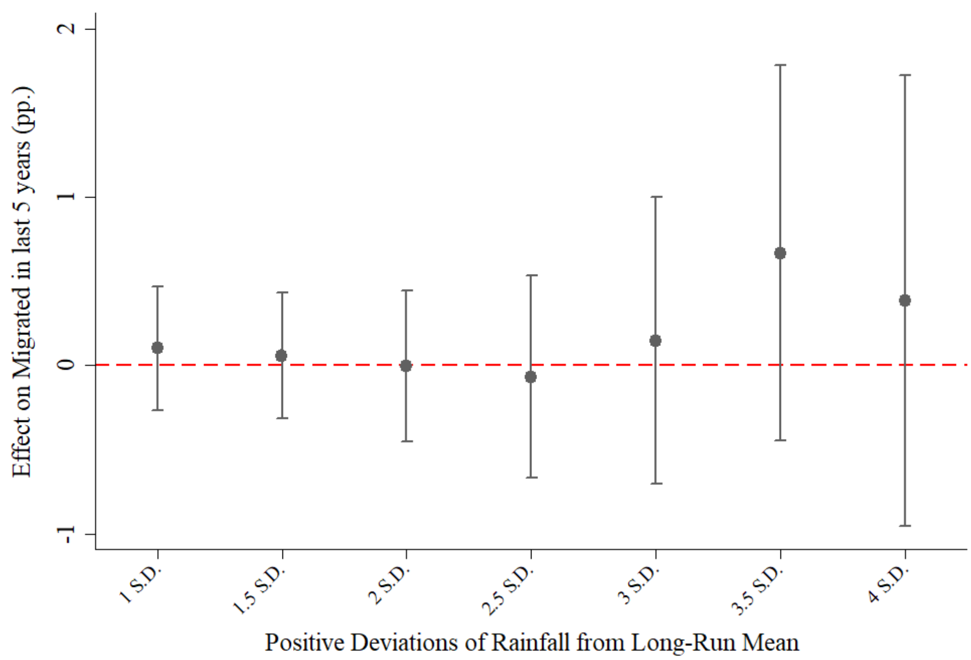
Notes: Controls include household head-specific characteristics like sex of respondent (hh head), age, age square, and education level fixed effects. All specifications include household, month of interview, and year fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Table A.7 Excess Rainfall Shock and Sample Composition

	Male	Age	Primary Education
Rainfall Shock	-0.0065	-0.0017	-0.0010
Deviation $\geq$ *2.5 S.D.*	(0.0046)	(0.0738)	(0.0019)
N. of obs.	139,587	139,587	139,587
N. of Households	44,193	44,193	44,193
Mean Dep Var	0.490	50.864	0.095

Notes: Except when used as an outcome, controls include household head specific characteristics like sex of respondent (hh head), age, age square, education level fixed effects. All specifications include household, month of interview, and year fixed effects. Standard errors clustered at the household level *** p<0.01, ** p<0.05, * p<0.1.

Figure A.15 Endogenous Migration



No. of observations: 70,459 ; Households: 23,744; Mean of Migrated in last 5 years: 0.04

Figure A.16 Effect of Lead Rainfall Shocks on Perceived Relative Deprivation

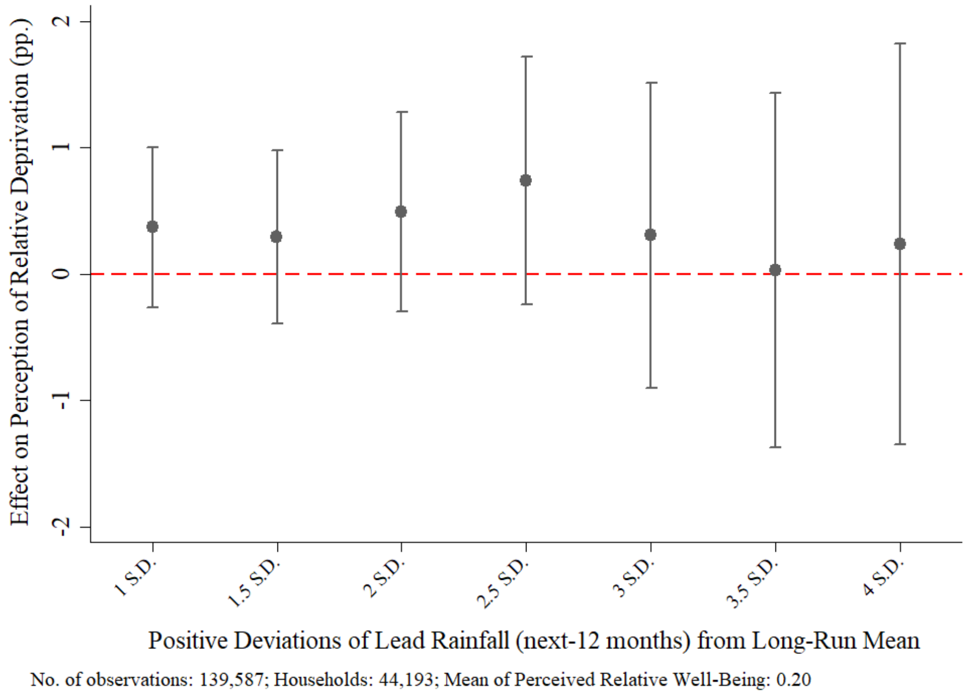


Table A.8 Perceived Relative Deprivation and Political Attitudes

	Democracy Functions Well	Democracy v/s Authoritarian Preference	Democracy v/s Authoritarian Preference
	(1)	(2)	(3)
Perceived Relative Deprivation	-1.298**	-0.878**	-0.993***
	(0.576)	(0.435)	(0.383)
N. of obs.	59,085	59,409	88,109
N. of Households	21,802	21,927	30,977
Mean Dep Var	0.423	0.862	0.832

Notes: Restricted sample in Column (1) and (2)- respondent for perceived relative deprivation and political perception are same (hh. head). Column (3) does not consider "don't care" option in constructing preference for Democracy v/s Autocratic Regime variable. Controlling for household, year, and month of interview fixed effects. All coefficients and standard errors (in parentheses) have been multiplied by 100 for easy interpretation.

APPENDIX B

APPENDIX B FOR CHAPTER 2

B.1 Appendix B

B.1.1 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 aged 15-49 using the 2007 Census data (Instituto Nacional de Estadística e Informática, 2007a), the most recent round of the Census that occurs prior to the start of our analysis period. Our final measure is the number of police reports per 100,000 women.

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.[1]

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

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

measures of agricultural and total income as well as expenditure, and to measure social program coverage.[2]

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 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).[3] We match temperature and rainfall data to the mobility data using the population-weighted average of weather measured at the centroids of all districts within each province.

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

[2] 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.

[3] 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.

B.1.2 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 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.[4]

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

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

$$Non\text{-}growing\ Season\ CDH_{it} = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} (1 - Grow_{mp}) \times DH_{itmdh} \tag{B.2}$$

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

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 3.4, but with separate growing and non-growing season CDH:

$$Y_{idmt} = \beta_1 Growing\ Season\ CDH_{idmt} + \beta_2 Non\text{-}growing\ Season\ CDH_{idmt} \quad \text{(B.3)}$$
$$+\beta_3 AvgTemp_{idmt} + \beta_4 AvgRain_{idmt} + \beta_5 Altitude_{idmt} + \beta_6 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt}$$

All controls and fixed effects are the same as in equation 2.3, but the parameters of interest in equation B.3 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.

B.1.3 Additional Results and Robustness Checks

Additional measures of partner abuse. In Appendix Table B.2, 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 (such as a husband limiting contact with friends and family). 10 additional CDH below -9°C increases the likelihood of physical violence by 0.33 percentage points (column 3), emotional violence by 0.31 percentage points (column 4), and control issues by 0.56 percentage points (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 B.5 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 B.1 as when we use self-reported IPV from the DHS in figure 2.1. Overall, we take the results in Appendix Table B.5 and Appendix figure B.1 as validating the woman-level effects we present as our main results.

Alternative measures of frost shocks.

In Figure 2.1, 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 percentage points. In the paper, we focus on the threshold of -9°C, the midpoint of thresholds that yield statistically significant effects.

In Appendix Table B.6, 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 B.7. 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.[5] Experiencing a frost shock (regardless of the magnitude of the shock) increases the likelihood of experiencing IPV by 1.4 percentage points. However, the effects of this coarser measure are imprecisely estimated and are not statistically significant.

Appendix Table B.8 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 percentage points. If we instead use a simpler measure that only captures

[5] 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.

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 percentage points (column 2).

Columns 4 and 5 of Appendix Table B.8 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 percentage point 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 B.9, we find that there are no meaningful differences in observable characteristics according to frost shocks. Though there is a statistically significant relationship between frost shocks and one out of the eight characteristics considered (speaking Spanish, column 7), the magnitude of the relationship is very small. In addition, there is no association between frost shocks and fertility (as measured by the number of children under 5; column 8). In other words, there is no evidence that sample composition responds endogenously to frost shocks.

Next, we show that endogenous migration is unlikely to explain our results. In column 1 of Appendix Table B.10, 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.[6] 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 B.11 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 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 2.3 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 B.12. Because we estimate the "effects" of a 12-month lead of CDH and have weather data only through 2018, we begin by running our baseline specification (using shocks over the past 12 months) for the restricted sample period 2010-2017 in column 1. For this restricted time period, we confirm that frost shocks significantly increase IPV; if anything, the estimate is slightly larger for this restricted sample period. In column 2, we replace CDH over the past 12 months with CDH over the following (i.e., future) 12 months after the interview date. Here, we find no statistically significant relationship between IPV and future realizations of extreme cold temperatures. This null result helps us rule out the possibility that households can anticipate (and respond to) future frost shocks as well as the possibility that frost shocks simply capture unobserved determinants of IPV that vary systematically

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

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 B.12 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 B.16. 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 4-6, we add in additional interactions to account for poverty (column 4), 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[7] - in column 6. 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.[8]

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

[8]In columns 4-6 we include the additional interactions after recentering the additional province variables to the sample mean for ease of interpretation.

B.1.4 Appendix Figures and Tables

Table B.1 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 B.2 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 B.3 Effects of Frost Shocks on Partner Alcohol Use

	Partner Drinks Alcohol (1)	Partner Gets Drunk Frequently (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 B.4 Effects of Frost Shocks on Mobility

	Dep. Var.: % Change in Number of Visitors from Baseline			
	Parks (1)	Retail/Rec (2)	Transit (3)	Workplace (4)
Province-level CDH (λ = -9 °C)	-3.498***	-3.298***	-3.784***	0.263
	(1.222)	(1.157)	(1.239)	(0.215)
Observations	22447	9189	11432	19391
No. of Provinces	65	31	32	60
Mean of Dep. Var	-9.100	-11.629	-28.312	-5.572

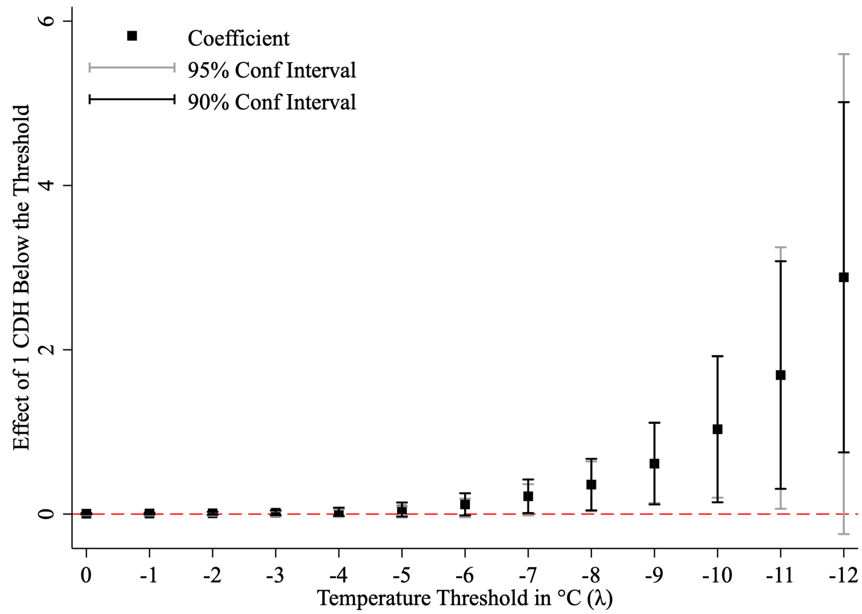
Notes: The sample includes all provinces in the Peruvian Highlands for which Google released mobility data in 2021. CDH is measured at the daily level for each province as the population weighted average of all district CDH in the province (population taken from official 2019 estimates (Ministry of Health, Office of Information Management, 2022)). All specifications control for rainfall and includes 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 B.5 Effect of Frosts on Police Reports of Violence Against Women

	All violence (1)	Physical violence (2)	Non-physical violence (3)	All violence (4)	Physical violence (5)	Non-physical violence (6)
CDH in current and previous month (λ = -9°C)	0.614**	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						
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 of violence against women (total, physical, and non-physical) of per 1,000 women aged 15-49 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 B.1 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 aged 15-49 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 B.6 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) efined 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 B.7 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 B.8 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 B.9 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	-0.013
	(0.003)	(0.029)	(0.046)	(0.000)	(0.017)
Observations	54584	54584	54584	54584	144654
No. of Districts	918	918	918	918	955
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 B.10 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 B.11 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 B.12 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 B.13 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

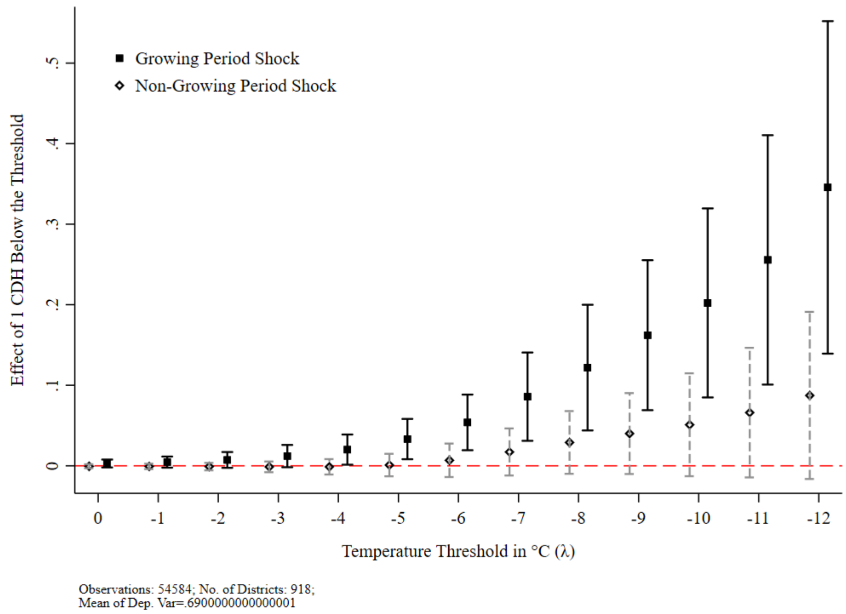
Notes: We use data from the Peruvian National Household Survey (ENAHO), which collects information about daily employment during the full calendar week prior to the individuals' interview date (e.g., if the survey takes place on a Wednesday, the questionnaire asks about employment between Monday and Sunday of the previous week). We estimate regression $Y_{id} = \beta DailyCDH_{id} + \alpha_i + \gamma_d + \varepsilon_{id}$, 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. $alpha_i$ are individual fixed effects; and γ_d are day-of-week fixed effects. 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 B.14 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 B.2 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 B.15 Heterogeneous Effects of Frost Shocks by Household Agricultural Status

	Baseline (1)	Including Interaction w/ Ag Earner Status (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 B.16 Heterogeneity by Baseline Social Program Coverage: Robustness

	Dep. Var.: Any IPV					
		Excluding	Excluding	Also Controlling for Interaction w/		
		Department	Province	Poverty	2011 Vote	Woman's
	Baseline	Capitals	Capitals	Share	Shares	Age
	(1)	(2)	(3)	(4)	(5)	(6)
CDH (λ = -9°C)	0.088***	0.086**	0.086**	0.078	0.116**	0.092***
	(0.033)	(0.033)	(0.034)	(0.091)	(0.054)	(0.033)
CDH $\times$ Baseline Social Program Coverage	-0.067**	-0.067**	-0.087*	-0.059	-0.071*	-0.075**
	(0.033)	(0.033)	(0.050)	(0.074)	(0.038)	(0.037)
Observations	38841	34522	27200	38841	38717	38841
No. of Districts	801	789	693	801	798	801
Mean of Dep. Var	0.669	0.672	0.672	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. 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 (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.

APPENDIX C

APPENDIX C FOR CHAPTER 3

C.1 Appendix C

Figure C.1 Location of Households in this Study, from ENAHO

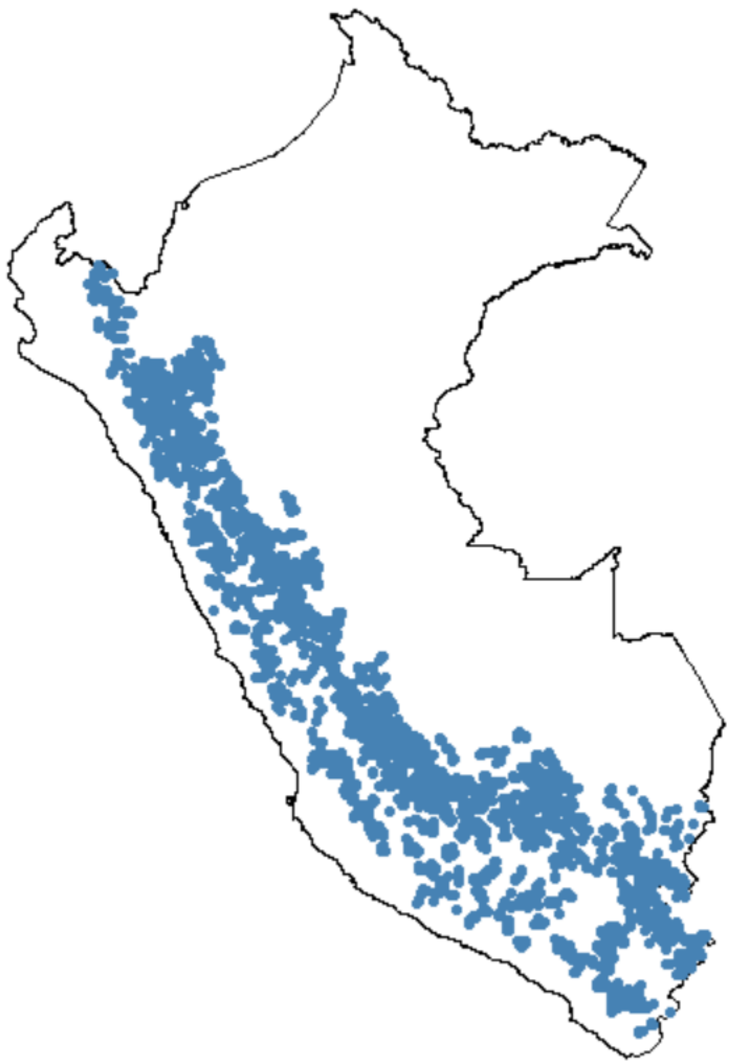


Figure C.2 Percentage of Households Facing Shocks at Different Temperature Thresholds

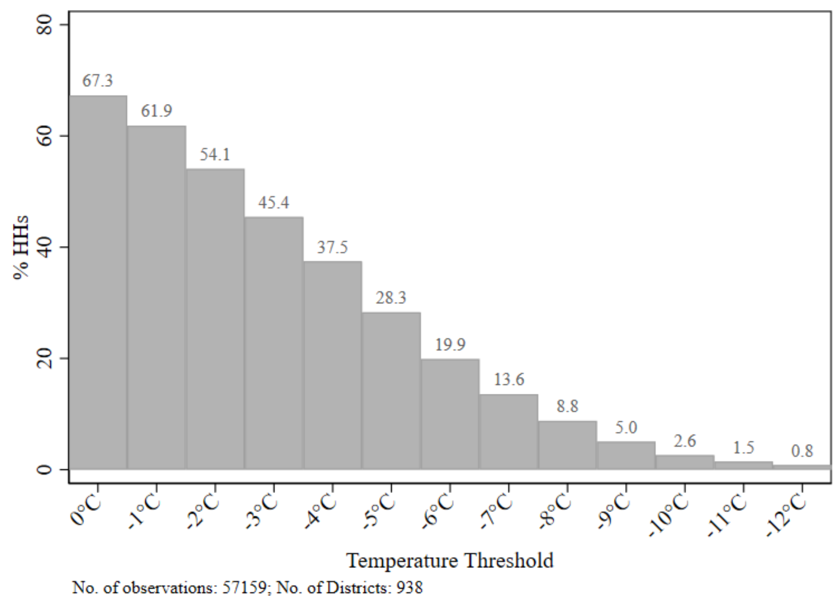


Table C.1 Ordered Probit Models (Marginal Effects)

	A. Dep. Var.: Believes Democracy Works Well (categories)				
	Very Poorly	Poorly	Don't Know	Well	Very Well
	(1)	(2)	(3)	(4)	(5)
CDH (λ = -9 °C)	0.010***	0.024***	–	-0.004***	-0.001***
	(0.003)	(0.006)	–	(0.001)	(0.0003)
N. of obs.			57159		

	B. Dep. Var.: Believes Democracy Works Well (categories)				
	Very Poorly	Poorly	Don't Know	Well	Very Well
	(6)	(7)	(8)	(9)	(10)
CDH (λ = -9 °C)	0.005*	0.014*	0.0002*	-0.017 *	-0.002*
	(0.003)	(0.008)	(0.0001)	(0.009)	(0.0013)
N. of obs.			75632		

Notes: Columns 1-5: Dependent variable is categorical and takes 4 distinct values (omitting "Don't Know"). Columns 6-10: Dependent variable is categorical and takes 5 distinct values (including "Don't Know" as a "middle" category). The sample includes individuals in all farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, individual characteristics (respondent sex, age, age squared, education level, and mother tongue), and household size. All specifications include year, district, and month of interview fixed effects. District-level clustered standard errors in parentheses. Marginal Effects 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 C.2 Using Alternative Datasets

	Is Satisfied with Democracy		Did Not Vote in Last Presidential Election	Trust People in Community
	LAPOP	Latinobarometer	LAPOP	LAPOP
	(1)	(2)	(3)	(4)
CDH (λ = -9°C) in Year Prior to Survey	-0.835***	-0.742***		0.591*
	(0.243)	(0.216)		(0.324)
CDH (λ = -9°C) in Year Prior to Election			2.198*	
			(1.146)	
Observations	1053	2819	1544	1096
No. of Districts	47	33	84	47
Mean of Dep. Var	0.324	0.199	0.087	0.485

Notes: Sample is restricted to districts in the Highlands and includes the 2014 and 2017 rounds of the LAPOP in column 1; the 2008-2011, 2013, 2015-2017 rounds of the Latinobarometer in column 2; the 2006, 2012, and 2017 rounds of the LAPOP in column 3; and 2014 and 2017 rounds of LAPOP for column 4. Weather variables are measured at the district centroid and measures weather in the year prior to the interview month and year in columns 1 and 2 and in the year prior to the election month and year in column 3. Controls include respondent sex, age, and age squared as well as education level fixed effects. Columns 1 and 2 include year, district, and month of interview fixed effects; column 3 includes election year and district 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.

Table C.3 Effects Using Alternate Measures of Frost Shocks

	Dep. Var.: Believes Democracy Works Well				
	(1)	(2)	(3)	(4)	(5)
CDH over past 12 months (λ = -9°C)	-0.038**				
	(0.017)				
CDH over past 6 months (λ = -9°C)		-0.055***			
		(0.018)			
CDH over past 3 months (λ = -9°C)			-0.040***		
			(0.015)		
Cumulative Degree Days (λ = -9°C)				-0.186*	
				(0.103)	
Any shock over past 12 months (λ = -9°C)					-3.206*
					(1.674)
Observations	57159	57159	57159	57159	57159
No. of Districts	938	938	938	938	938
Mean of Dep. Var	0.511	0.511	0.511	0.511	0.511

Notes: The sample includes all individuals in farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, individual characteristics (respondent sex, age, and age squared as well as education level and mother tongue fixed effects), 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.

Table C.4 Effects Using Alternate Fixed Effects

	Dep. Var.: Believes Democracy Works Well		
	District FE (Baseline)	Conglome FE	Household FE
	(1)	(2)	(3)
Cumulative Degree Hours (λ = -9°C)	-0.038**	-0.066***	-0.021
	(0.017)	(0.019)	(0.022)
Observations	57159	56823	20934
No. of Districts	938	932	748
No. of Groups for FE	938	2985	7291
Mean of Dep. Var	0.511	0.512	0.513

Notes: The sample includes all individuals in farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, household head characteristics (sex, age, age squared, education level, and mother tongue), and household size. 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.

Table C.5 Frost Shocks and Sample Composition

	Male	Age	Household Size	Primary Education	Speaks Quechua
	(1)	(2)	(3)	(4)	(5)
CDH (λ = -9°C)	0.0000	-0.0012	0.0005	0.0003***	0.0000
	(0.0001)	(0.0032)	(0.0005)	(0.0001)	(0.0001)
Observations	57159	57159	57159	57159	57159
No. of Districts	938	938	938	938	938
Mean of Dep. Var	0.509	46.724	4.014	0.628	0.518

Notes: The sample includes individuals in all farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Except when used as an outcome, controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, individual characteristics (respondent sex, age, age squared, education level fixed effects, mother tongue); and household size. 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 C.6 Assessing Endogenous Migration

	Dep. Var.: Believes Democracy Works Well		Dep. Var.: Migrated
	Full Sample	Non-movers	Full Sample
	(1)	(2)	(3)
CDH (λ = -9°C)	-0.038**	-0.033*	-0.009
	(0.017)	(0.018)	(0.010)
Observations	57159	46907	57151
No. of Districts	938	913	938
Mean of Dep. Var	0.511	0.518	0.179

Notes: The sample includes individuals in all farming households in the Highlands using the 2007-2018 rounds of the ENAHO; in column 2, the sample is further restricted to individuals who reside in their district of birth (non-movers). Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, individual characteristics (respondent sex, age, age squared, education level fixed effects, mother tongue); and household size. 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.

Table C.7 Falsification Test: Effects of Future Frost Shocks

	Dependent Variable: Believes Democracy Works Well	
	(1)	(2)
CDH (λ = -9°C) in the *Previous* 12 Months	-0.043***	
	(0.016)	
CDH (λ = -9°C) in the *Next* 12 Months		0.011
		(0.012)
Observations	50701	50701
No. of Districts	902	902
Mean of Dep. Var	0.515	0.515

Notes: The sample includes all individuals in farming households in the Highlands using the 2007-2017 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, individual characteristics (respondent sex, age, and age squared as well as education level and mother tongue fixed effects), 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.

C.1.1 Additional Information about Growing and Non-Growing Seasons

Agriculture-related activities like sowing, growing, and harvesting crops are most often conducted during specific months of a calendar year. Therefore, we hypothesize that the losses in agricultural revenue would be primarily driven by frost shocks in the growing season. Thus, alongside using cumulative exposure to frost shocks in the past 12 months from the time of interview, we also use the growing season CDH given in equation C.1 below and the non-growing season CDH given in equation C.2 below separately, as this will help us disentangle the losses from the growing and non-growing seasons separately.

We construct modified versions of our CDH measure as follows:

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

$$Non\text{-}growing\ Season\ CDH_{it} = \sum_{m=-12}^{-1} \sum_{d=1}^{30} \sum_{h=1}^{24} (1 - Grow_{mp}) \times DH_{itmdh} \tag{C.2}$$

where $Grow_{mp}$ is an indicator of whether calendar month m is classified as a growing month for province p (as described below in 3.3.4). Specifically, for these economic outcomes- value of agricultural output, income, expenditure and poverty status, we run our main specification as in equation 3.4, but with separate growing and non-growing season CDH:

$$Y_{idmt} = \beta_1 Growing\ Season\ CDH_{idmt} + \beta_2 Non\text{-}growing\ Season\ CDH_{idmt} \tag{C.3}$$
$$+\beta_3 AvgTemp_{idmt} + \beta_4 AvgRain_{idmt} + \beta_5 Altitude_{idmt} + \beta_6 Z_{idmt} + \alpha_d + \gamma_t + \theta_m + \varepsilon_{idmt}$$

All controls and fixed effects are the same as in equation 3.4, but the parameters of interest in equation C.3 are β_1 and β_2. Specifically, β_1 captures the effects of shocks that work through the growing months, while β_2 captures the effect for the non-growing months. The results are given below in table C.8.

Table C.8 Effects of Growing and Non-Growing Season Frost Shocks on Income and Expenditure

	Val. of Ag. Output		Total Income (Constructed)		Expenditure		Poverty	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDH (λ = -9 °C)	-0.135***		-0.044		-0.026		0.011	
	(0.042)		(0.055)		(0.022)		(0.022)	
Growing Season CDH (λ = -9 °C)		-0.432***		-0.229*		-0.174***		0.079***
		(0.082)		(0.128)		(0.031)		(0.014)
Non-growing Season CDH (λ = -9 °C)		-0.084		-0.000		0.001		-0.002
		(0.063)		(0.074)		(0.035)		(0.031)
p-value for Growing=Non-Growing		0.002		0.199		0.003		0.032
Observations	76642	76642	76642	76642	76642	76642	76642	76642
No. of Districts	944	944	944	944	944	944	944	944
Mean of Dep. Var	2747	2747	5552	5552	6117	6117	49	49

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 includes annualized gross income from main monetary activity (dependent), income from main independent activity, gross income from dependent secondary activity and net income from independent secondary activity. Constructed 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 in this case is extracted using the Atlas (2022) data on World- Terrain Elevation Above Sea Level (ELE) GIS Data.

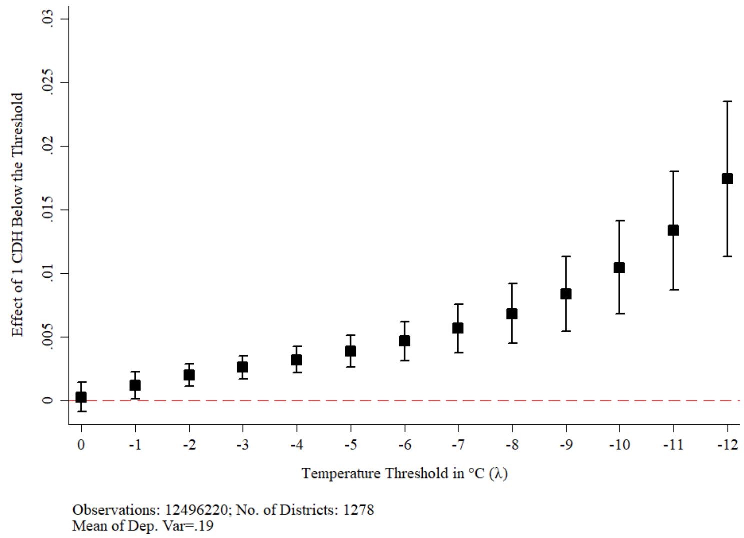
Table C.9 Effects of Frost Shocks on Livestock Assets

	Any Livestock Death (1)	Log Value of Livestock Deaths (2)
CDH (λ = -9°C)	0.045*	0.251*
	(0.025)	(0.141)
Observations	63028	63028
No. of Districts	922	922
Mean of Dep. Var	0.339	582.943

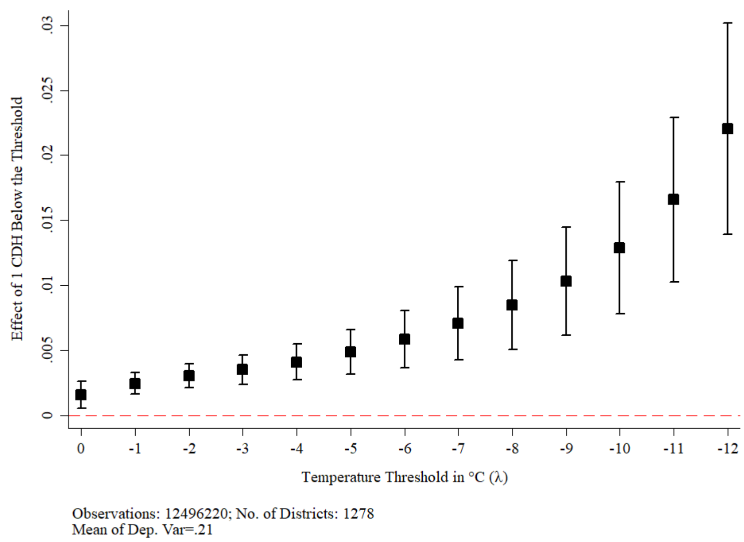
Notes: Value of livestock deaths has been transformed using the inverse hyperbolic sine function. The sample includes all farming households using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, household head characteristics (sex, age, and age squared, education level and mother tongue), log of total land (owned + rented), and household size. 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 value of livestock deaths are expressed in 2007 soles using the GDP deflator published by World Bank (2023).

Figure C.3 Effect of Sub-zero Temperature Shocks on the Share of Absent Voters in Presidential Elections

(a) First Round



(b) Second Round



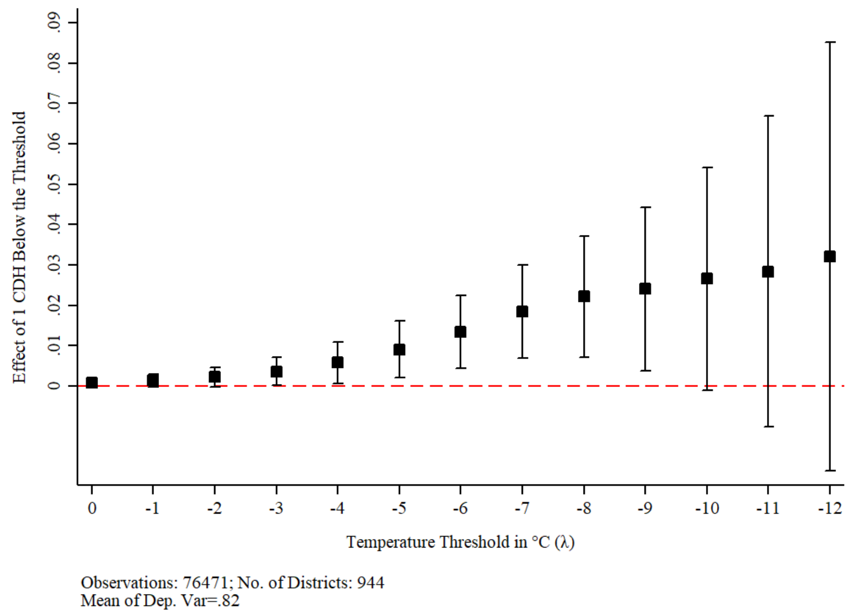
Notes: Shares are calculated with respect to the total eligible voters in each district. The sample includes all districts in the Highlands and covers the 2011 and 2016 presidential elections. Weather variables are measured at the district centroid and measures weather in the year prior to the date of each election. All specifications include year and district fixed effects. District-level clustered standard errors in parentheses. Regression weighted by district-level number of registered voters in each election. Coefficients and standard errors have been multiplied by 100 for ease of interpretation.

Table C.10 Effects of Frost Shocks on Electoral Participation

	Share of Absent Votes		Share Absent & Blank	
	First Round	Second Round	First Round	Second Round
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	0.008***	0.013***	0.007***	0.013***
	(0.002)	(0.003)	(0.002)	(0.003)
Observations	2536	2536	2536	2536
No. of Districts	1268	1268	1268	1268
Mean of Dep. Var	0.235	0.263	0.363	0.273

Notes: Shares are calculated with respect to the total eligible voters in each district. The sample includes all districts in the Highlands and covers the 2011 and 2016 presidential elections. Weather variables are measured at the district centroid and measures weather in the year prior to the date of each election. All specifications include year and district 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.

Figure C.4 Effect of Sub-zero Temperature Shocks on Participation in Local Associations



Notes: The sample includes individuals in all farming households in the Highlands using the 2007-2018 rounds of the ENAHO. Controls include average temperature, average rainfall , altitude at the household level for over the same reference period as the frost shock, household head characteristics (sex, age, age squared, education level, and mother tongue), and household size. 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.

Table C.11 Heterogeneous Effects of Participation in Local Associations by Public Provision Coverage

	All Local Assoc.	Political & Govt.	Professional & Argic.	Community-based
	(1)	(2)	(3)	(4)
CDH (λ = -9°C)	-0.006	-0.002	0.047	-0.025
	(0.025)	(0.002)	(0.074)	(0.054)
CDH (λ = -9°C) X Above Median	0.030	0.003	-0.059	0.052
Coverage of Public Goods and Services	(0.025)	(0.003)	(0.074)	(0.054)
Effect in Provinces with Higher	0.024***	0.001	-0.012	0.028***
Public Goods and Services	(0.0064)	(0.002)	(0.009)	(0.006)
Observations	43648	43648	43648	43648
No. of Districts	890	890	890	890
Mean of Dep. Var	0.823	0.009	0.180	0.703

Notes: Since we use the 2012 social program coverage, along with 2007 coverage of public hospitals, and the 2012 coverage of police resources to construct this composite indicator of public provisions, we restrict our analysis to the 2013 - 2018 rounds of the ENAHO. The sample includes individuals in all farming households in the Highlands. Controls include average temperature, average rainfall, altitude at the household level for over the same reference period as the frost shock, household head characteristics (sex, age, age squared, education level, and mother tongue), and household size. 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.