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Quantifying Vulnerability to Poverty in El Salvador

Britta Rude
Monica Robayo-Abril

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Abstract

El Salvador is marked by high vulnerability to risks and hazards, such as crime, natural disasters, and migration. Therefore, it is crucial to understand the vulnerability patterns of its population. This paper applies an innovative approach to estimate the population's vulnerability to poverty and analyze its underlying drivers. The findings show that ex-ante vulnerability to poverty decreased over 2016 to 2019, a parallel trend to the poverty reduction observed in the country during this period. This finding comes hand in hand with an increase in the importance of risk factors relative to a low accumulation of assets driving vulnerability. Additionally, household-level shocks play a more significant role than community-level shocks. To address vulnerabilities in the country, the government should invest in adaptive safety nets and risk mitigation strategies.

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Quantifying Vulnerability to Poverty in El Salvador[1]

Britta Rude

Monica Robayo-Abril

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1. Introduction

Many scholars have stressed that pure poverty measures might fall short of our understanding of how to create sustainable long-term growth paths for developing countries. Traditionally, poverty and development economists have mainly focused on poverty and inequality measures when analyzing developing countries' growth paths. Recently, many scholars have stressed that this approach might fall short of understanding how to create long-term, sustainable development trajectories. In a more recent context, the COVID-19 outbreak and the war in Ukraine have shown how easily many households can fall back into poverty. Against this background, there is a need to understand not only poverty and inequality globally, but also vulnerability to poverty.

While many households might currently not live in poverty, they could be easily pushed into it through the occurrence of natural or human-made hazards. Vulnerability is the inability of an individual or group to encounter a natural or human-induced hazard. These households are considered to be vulnerable to poverty. Their probability of becoming poor due to external shocks, such as an economic downturn, natural disasters, personal illness, or job loss, is elevated. Especially under recent global developments, which are marked by an increase in the occurrence of hazards worldwide, it is vital to quantify countries' vulnerability. The UNDRR (2020) classifies hazards as biological, environmental, geological, hydrometeorological, technological, and societal hazards. These hazards, then again, increase population growth, urbanization, environmental degradation, natural disasters, and climate change (Makoka and Kaplan, 2005). International organizations and academic scholars increasingly stress the importance of understanding hazards and risks, on the one hand, and of risk-informed decision-making and strategies to reduce these risks and hazards, on the other hand.

In this paper, we apply an innovative methodology to identify a forward-looking (ex-ante) measure of vulnerability to poverty in El Salvador, a country marked by high exposure to natural and human hazards. We follow an innovative approach to vulnerability developed by Gao et al. (2020), and estimate the vulnerability rate in El Salvador. The innovative approach applied in this paper follows a probabilistic understanding of vulnerability, which takes into account the average level of welfare across many periods and the deviation of welfare across these periods (that is, the variance of welfare). Studying vulnerability to poverty from an ex-ante perspective is highly relevant in the context of El Salvador. El Salvador is characterized by high risk exposure. It scores 4.7 out of 10 in the INFORM Global Risk Index 2021 and ranks 58th (DRMKC, 2021). It is especially vulnerable to natural hazards, such as tsunamis, earthquakes, and volcanos (ibid), but also faces a number of human hazards, such as high crime rates, a high population density, and one of the highest emigration rates. Given the significant number of shocks to which the population is exposed, studying vulnerability to poverty is highly relevant in the context of El Salvador.

Using household survey data from El Salvador, we show that the country's vulnerability rate is higher than its poverty rate; our analysis also reveals important differences between rural and urban areas. We estimate a vulnerability rate of 23.7 percent for 2019. This number is higher than the poverty rate, standing at 21.7 percent.[2] In addition, vulnerability patterns differ for the rural and urban populations. While the overall vulnerability rate is only slightly higher than the overall poverty rate, the rural population is especially prone to falling back into poverty. Among the rural population, 41.2 percent is affected by vulnerability to poverty, while this only applies to 13.5 percent of the urban population. The vulnerability rate in rural areas is 1.3 times the poverty rate.

Our paper reveals that the vulnerability rate in El Salvador decreased constantly over 2016-2019, in both rural and urban areas. Our findings demonstrate that the vulnerability rate decreased from 39.4 percent in 2016 to 23.7 percent in 2019. This is in line with recent poverty developments in the country but different from developments in the operational vulnerability measure. Operational vulnerability,[3] which is purely monetary, increased in El Salvador during the period under consideration, from 34.6 percent in 2000

[2] This is the poverty rate measured by the vulnerability model applied in this paper, and not the one observed from household data. Poverty is measured in 2011-PPP-US$, and relying on the 5.5 US$/day threshold.

[3] The "operational" definition widely used in the LAC region defines vulnerable households as those with daily incomes between $5 and $13 a day (in 2011 PPP dollars).

to 48.2 percent in 2019.[4] These developments show that insights vary depending on the approach used to understand vulnerability to poverty. When relying on an income-based measure of vulnerability, there is evidence of a translation of the poor into the vulnerable group instead of a steady middle-class. Contrary to that, when relying on a probabilistic approach towards vulnerability, vulnerability has decreased in parallel to poverty. Consequently, considering probabilistic approaches to vulnerability creates valuable insights in addition to evidence generated from purely static views of poverty and vulnerability. The decrease in vulnerability to poverty observed from our probabilistic measure took place both in rural and urban areas.

Our analysis demonstrates that vulnerability in El Salvador is driven by household-level shocks instead of community-level shocks. We show that vulnerability is mainly due to idiosyncratic shocks, such as personal illness or job loss, instead of aggregate shocks, such as natural disasters or epidemics. The relative importance of these individual-level shocks is especially marked in urban areas, with a ratio of 3.3 (compared to a relative ratio of 2.2 in rural areas).

We find that risk factors play a more significant role in vulnerability to poverty than a low accumulation of assets, which is in line with the country context. We demonstrate that risk-induced vulnerability is relatively more important than poverty-induced vulnerability. This means that individual risk exposure, such as the probability to fall victim to a crime, plays a more significant role than households' low accumulation of assets, such as human capital. Our findings reveal that risks seem to play a critical role in urban areas. The ratio of risk-induced to poverty-induced vulnerability is 1.7 in total, 1.4 in rural areas, and 2.7 in urban areas. These findings are evidence of the different realities of the urban and rural populations in El Salvador. The decreasing vulnerability rate in rural and urban areas comes hand in hand with a decrease in the relative importance of poverty-induced vulnerability for 2016-2019. This development was more marked in urban areas. These results align with available evidence showing that rural areas lack access to critical infrastructure, economic opportunities, and human capital accumulation (Robayo-Abril and Barroso, 2022).

Our work makes a significant contribution to the economic literature. To the best of our knowledge, we are the first ones to apply the probabilistic measure of vulnerability to an income-based measure of welfare. Previous approaches relied on consumption-based measures. In addition, we are the first ones to investigate the robustness of this new approach to a number of model specifications and investigate the influence of accounting for potential measurement errors. Our paper adds to a number of papers studying vulnerability to poverty in other countries (Chaudhuri et al. (2002); Kamanou and Morduch (2002); Chaudhuri (2003); Azam and Imai (2010); Dutta et al. (2011); Barrientos (2013); Klasen and Herman (2015); Ward (2016); Skoufias et al. (2021)). Our work also contributes to the current discussion on how to best measure vulnerability to poverty (Pritchett et al. (2000); Celidoni (2013); Gallardo (2017)).

The paper at hand makes a valuable contribution to the policy agenda in El Salvador, given that the country is characterized by high risk exposure. Further analyzing and quantifying the country's vulnerability to poverty can bring policy makers valuable insights. Identifying those vulnerable to falling into poverty can assist in determining which policies should be prioritized and developed. The analysis can also inform the design and implementation of adaptive social safety net systems that protect households when shocks arise. Additionally, it can provide evidence on how to best achieve sustainable growth patterns. To the best of our knowledge, we are the first ones to estimate the vulnerability rate in El Salvador via a probabilistic approach.

To address vulnerabilities in El Salvador, the government should invest in adaptive social safety nets and risk mitigation strategies. Our analysis reveals that vulnerability in El Salvador is higher than poverty, especially in rural areas. Additionally, households' exposure to individual-level risks plays a critical role in both rural and urban areas. Therefore, it is recommended that policy makers invest in risk mitigation and coping strategies. It is vital to reduce households' exposure to risks, such as crime, illness, or job losses, in the first place and to increase their access to mitigation and coping mechanisms in the second place. One possibility to do so is enhancing the adaptiveness of El Salvador's social safety net and developing a

[4] Own estimations from El Salvador's household survey.

comprehensive and targeted risk mitigation strategy. Finally, the government should pay special attention to rural areas. Doing so would contribute to a forward-looking poverty reduction strategy in El Salvador, potentially allowing for a more sustainable development trajectory.

The paper is organized as follows. Section 2 describes the country context. Section 3 details the definitions and summarizes the recent literature. Section 4 presents the methodology applied. Section 5 presents the empirical results, which include our estimates and their drivers, as well as temporal trends. Section 6 presents several robustness tests and a sensitivity analysis to investigate the validity of our main messages. Finally, section 7 concludes and presents policy insights.

2. Country Context

Studying vulnerability in El Salvador is highly relevant, given that the country is marked by a variety of different hazards. The country is exposed to several hazards, which is reflected when comparing the country in its vulnerability globally. El Salvador scores 4.7 out of 10 in the INFORM Global Risk Index 2021 and ranks 58th (DRMKC, 2021). One important dimension of the country's vulnerability is its high emigration rate. In mid-2020, 1.6 million El Salvadorians lived abroad, representing one-fourth of the country's total population, one of the highest numbers worldwide (Migration Data Portal 2021). This significant emigration rate and a slowing demographic dividend pose challenges to the country's development trajectory. It also creates a high dependency on remittances (Robayo-Abril and Barroso, 2022). In general, El Salvador is highly dependent on the US economy, with one-third of its imports originating in the US (Trading Economics, 2022). Similarly, 40 percent of its exports flow to the US (ibid).

Moreover, the country is vulnerable to the spread of epidemics, and crime rates are high. The country's high population density makes it prone to epidemics and the spread of illness (Robayo-Abril and Barroso, 2022). Additionally, crime rates are high. In 2018, El Salvador was the country with the highest homicide rate globally (World Development Indicators, 2021). The intentional homicide rate is 52.0 per 100,000 people (ibid). Property crimes are also prevalent in the country, accounting for 47 percent of all crimes (OSAC, 2021). Additionally, El Salvador is marked by violent, well-armed street gangs, further increasing individuals' vulnerability (ibid). All these characteristics add up to a generally high exposure to human hazards.

In addition, El Salvador has high exposure to natural hazards. El Salvador is vulnerable to natural hazards, with an INFORM Index of 6.5 out of 10 (DRMKC, 2021). Earthquakes are especially pertinent, with an index of 9.7, followed by Tsunamis with an index of 8.2. Also, El Salvador is highly vulnerable to climate change, and vulnerability has increased over the years. The country ranks 106 out of 181 on the ND-GAIN Index[5] (World Bank Group, 2021a). This exposure is mainly due to its location, which increases the probability of extreme weather events. The complex environmental, social and institutional situation adds to the overall challenging situation. El Salvador's economic dependency on climate-sensitive economic activities, such as agriculture, forestry, and economic activities in coastal areas, further exacerbates the situation.

When compared to other countries in the region, El Salvador is marked by high levels of vulnerability. At a subnational level, several of El Salvador's departments report high vulnerabilities compared to Latin America and the Caribbean (World Bank Group, 2021b). El Salvador's subnational vulnerability index varies between 17.4 and 33.7 on the subnational Socioeconomic Vulnerability Index (SEVI).[6] Twelve of the country's 14 departments are located among the most vulnerable half of subnational

[5] The ND-Gain index is a summary index about a country's vulnerability to climate change and other challenges as well as its resilience to tackle them.

[6] The SEVI Index is a subnational index measuring the socioeconomic vulnerability of subnational regions in Latin-America and the Caribbean in 2019. It ranks from 0 to 100, with 100 being the highest possible exposure to vulnerability. In 2019, the highest obtained value on the SEVI Index was 50.1 by Alta Verapaz in Guatemala. The lowest value was 8.6 for Antofagasta in Chile.

regions in Latin America and the Caribbean, and 7 of 14 are among the most vulnerable third. The Morazan department scores 33.7 on the index and ranks 47 out of 248, followed by the Cabanas region ranking 59 out of 248, and La Union ranking 62 out of 248.

Since 2012, there have been slight improvements in El Salvador's capacity to cope with the variety of hazards faced; still, it ranks only 82 out of 192 with respect to its coping capacity on the 2021 INFORM index (DRMKC, 2021). El Salvador scores 4.6 out of 10 on the 2021 INFORM Index on lack of coping capacity, similar to Peru or South Africa (DRMKC, 2021).[7] This same index was 5.2 in 2012. The lack of coping capacity is to a larger extent driven by institutional factors rather than factors related to inadequate infrastructure. While the institutional risk index is 5.8, the infrastructure risk index is only 3.2. On the other hand, the institutional risk index is mainly driven by a high governance risk index. El Salvador scores 6.3 on the governance risk index. This value is similar to the Arab Republic of Egypt, Mexico, or the Dominican Republic. Consequently, there is still room for institutional improvements to encounter the challenges created by climate change and natural hazards.

Given the multiple vulnerabilities faced by its population, understanding vulnerability to poverty can bring essential insights to policy makers in El Salvador. The country context and institutional setting of El Salvador demonstrates that studying vulnerability is highly relevant in this case. To the best of our knowledge, this is the first paper creating a probabilistic vulnerability measure in El Salvador. Consequently, our paper makes a valuable contribution to the country's poverty agenda.

3. Vulnerability to Poverty – Definition and Current State of the Literature

Understanding vulnerability to poverty helps to understand the future trajectory path of poverty, particularly in developing countries. Vulnerability is a concept that goes farther than pure income poverty. While pure income poverty is an important driver of social policy, a broader approach to understanding different types of vulnerabilities is needed to inform public policies. This applies especially in environments marked by high risks of shocks like natural disasters, crime, or price volatility, like El Salvador. Public policies should have the capacity to help societies cope with these shocks and prevent them. In particular, safety nets that are designed to protect the poor and vulnerable and increase their resilience against idiosyncratic and systemic shocks will need to be flexible and adaptive. This can contribute towards increasing a country's resilience to poverty. Public policies should have the capacity to be scaled up rapidly and expand their coverage during unanticipated shocks. To do this, policy makers need to have a clear idea of who the vulnerable population is. Looking at vulnerability from a systematic perspective allows for a better understanding of the needs of households and thus better designed policies. Also, the effectiveness of targeting households when designing policies can improve.

There are two different definitions of vulnerability, one defining vulnerability from a pure income perspective and the other one from a probabilistic viewpoint. Traditionally, vulnerability to income poverty is based on a monetary income threshold, similar to those used to define poverty from an income perspective. The World Bank often uses the population with a daily per capita income between 5.5 2011-PPP-US$ and 13 2011-PPP-US$ to identify the vulnerable population. The concept of probabilistic vulnerability, on the other hand, is based on two subcomponents: The average level of welfare across many periods and the deviation of welfare across these periods (that is, the variance of welfare). Vulnerability is defined as the probability of becoming poor in the future or the "poverty risk." It is, therefore, a forward-looking extension of the static concept of poverty at a given point in time (Skoufias and Baez, 2021). Instead of considering poverty from a purely ex-post viewpoint, it incorporates a forward-looking perspective on poverty.

Especially in countries with high fluctuations and income volatility, looking at the current state of poverty falls short of painting a complete picture of the situation. High fluctuations mean that a poor

[7] The coping capacity dimension of the INFORM risk index measures which issues the government has addressed to increase the resilience of the society and how successful their implementation is.

household today might not necessarily be poor in the future and vice versa. Therefore, a household's current poverty status is not a good indicator of a country's poverty risk.[8] This vulnerability is influenced by the incidence of hazards present in a country. Vulnerability can be poverty-driven or risk-driven. Poverty-driven vulnerability refers to a high probability of falling back into poverty due to a low accumulation of productive assets, such as housing, human capital, or financial resources. Risk-driven vulnerability occurs whenever a household has a high chance of becoming poor due to high exposure to risks, such as falling victim to a crime or illness, or natural disasters. On the other hand, these risks can occur at the individual level, such as a personal illness or job loss, or at the community level, such as a regional economic downturn or epidemic. Depending on which is relatively more important, policy makers should adapt their risk-mitigation strategy and coping mechanisms.

Several scholars have addressed the need to quantify vulnerability to poverty over the last decades in various countries, but there is currently no consensus on how to best measure vulnerability to poverty. The empirical discussion about the estimation of vulnerability to poverty is not new and has a long history. In 2000, Pritchett et al. took a probabilistic view on vulnerability to poverty and calculated the overall vulnerability rate for Indonesia. They define a household to be vulnerable as soon as it has a 50-50 odd ratio or worse to fall into poverty. In 2002, a literature review by Kamanou and Morduch found that, while there is a large consensus on the need to measure vulnerability to poverty, there is no consensus on how to measure it. They introduce an empirical strategy that combines Monte Carlo and bootstrap statistical techniques and applies their measure to the case of Côte d'Ivoire. Related work by Celidoni (2013) compares the performance of several measures of individuals' vulnerability to poverty. A more recent review by Gallardo (2017) shows that there is still no consensus on measuring vulnerability to poverty

There are a number of studies applying different measures of vulnerability to poverty to a number of countries, but empirical applications are still relatively limited. Several papers have further elaborated the measurement of vulnerability to poverty, but the number of empirical applications is still relatively low.[9] Recently, several scholars have made an effort to make the measurement of vulnerability to poverty more accessible to a broader range of development economists (Gao et al., 2020). In this line of research, a recent application by Skoufias et al. (2021) shows that vulnerability is 1.6 times higher than poverty in Ethiopia and is especially high in drought-prone lowlands.

We tie in with the current line of research and apply a novel vulnerability measure developed by Gao et al. (2020) to the context of El Salvador. This paper is the first to quantify an ex-ante measure of vulnerability to poverty in El Salvador. There is currently no overall estimation of vulnerability to poverty available for the country. Additionally, to the best of our knowledge, this paper is also the first to apply the tool developed by Gao et al. (2020) to an income-based welfare measure. It is crucial to characterize vulnerable in El Salvador, as the challenges created through natural and human hazards and climate change in El Salvador might reverse the positive trend in poverty experienced by the country in recent years.

Evidence from other countries shows that natural and human hazards disproportionately affect poor people (Hallegatte, 2020), further fostering the case for studying vulnerability to poverty in these settings. Poor people are often more exposed to natural hazards, more vulnerable to them (when exposed, they lose a more significant fraction of their assets), and have a lower socioeconomic resilience (a lower ability to cope with its impacts). This can create a vicious circle between poverty and disasters (Hallegatte, 2020). Therefore, disaster risk management can be part of a poverty reduction strategy and vice versa. Similarly, human hazards and poverty are intertwined. To give an example, crime may induce poverty traps under low levels of modernization and high levels of production (Mehlum et al., 2005). Poverty, on the other hand, can trigger crime (McCrea, 2019). Based on this evidence, it is crucial to understand the relationship between both and design adequate policies to address these.

[8] Analyzing three waves of data from Nigeria, for example, shows that households are unlikely to remain in poverty over time. Only 7 percent of households were always below the poverty line while 35 percent were never below it. The rest of households reported a switching poverty status (Skoufias and Baez, 2021).

[9] Further examples are studies by Chaudhuri et al. (2002), Chaudhuri (2003), Azam and Imai (2010), Imai et al. (2011), Dutta et al. (2011), Barrientos (2013), Klasen and Waibel (2015), Ward (2016).

4. Methodology

The World Bank Equity Policy Lab (EPL) and the Global Solutions Group on the Welfare Implications of Climate Change, Fragility, and Conflict Risks have developed a novel tool to systematically estimate vulnerability, applying a "simulation approach" to vulnerability (Gao et al., 2020). The tool predicts vulnerability before a shock (ex-ante vulnerability) and decomposes the different vulnerability sources, allowing the identification of the main drivers behind vulnerability. Vulnerability can be poverty-induced (also called structural or chronic and related to low physical and human assets) or risk-induced (due to high volatility). The tool draws from two sources of information: a household's mean level of welfare (consumption or income) and a household's variance of welfare. For example, if a household experiences a mean welfare level below the poverty line, its vulnerability is poverty-induced. While in a good year, they might be above the poverty line, on average, meaning in most years, they might be located below the poverty line. Their location above the poverty line is then more of an outlier than a steady-state. In contrast, if a household's mean welfare is on average above the poverty line, but due to the type of variance it is located below the poverty line in some states of the world, it is vulnerable to poverty mostly due to risks (risk-induced). Households that are never below the poverty line are considered non-vulnerable.

The advantage of the tool is that it does not rely on panel data and that one cross-section is sufficient to calculate the persistence of vulnerability. Traditionally, to analyze a household's exposure to shocks and consequently its vulnerability, it would be best to follow this same household over time and analyze its location above and below the poverty line each year. One can then draw valuable insights on vulnerability through analyzing common patterns in the characteristics of those households often located below or above the poverty line but subject to outliers. Often, panel data is not available in developing countries and development economists rely on cross-sectional data to draw valuable insights. This is also the case in El Salvador. The World Bank Vulnerability Tool makes it possible to apply vulnerability analyses to cross-sectional data, as it draws information from similar households instead of following the same household over time.

The methodology also helps distinguish between idiosyncratic and covariate shocks, as community-level shocks or household-level shocks are drivers behind risk-induced vulnerability. Idiosyncratic shocks are those experienced by a household independent of what is experienced by other households in the community, such as an accident, experiencing crime, or individual disease. In addition, covariate shocks affect many households in a region or community simultaneously, such as droughts, floods, earthquakes, and other natural disasters, increases in food prices, and epidemics.

A predefined vulnerability threshold characterizes the vulnerable based on the probability of falling into poverty. The vulnerable are those with a higher probability of falling into poverty than a predefined vulnerability threshold in this other state of the world. This means that the vulnerable group consists of households who nowadays can be poor, but also non-poor. Intuitively, the total number of non-poor households classified as vulnerable to poverty increases when one decreases the probability threshold used to classify a household as vulnerable to poverty.

The tool originally embarks from a consumption-based perspective and applies a multilevel statistical modeling approach. The model regresses the per capita log household consumption (or in our case income) lnc_{ij} on a set of household characteristics X_{ij} for households i living in community j, and Z_j (community j's characteristics). It also controls for two error terms accounting for the unexplained variation of consumption (or income) across communities and captures the impact of community-specific shocks on household consumption or income. Lastly, e_{ij} stands for an idiosyncratic shock on consumption or income (the unexplained variation of consumption/income within a household).

$$\boldsymbol{lnc_{ij} = y_{00} + y_{01} Z_j + (y_{10} + y_{11} Z_j) X_{ij} + u_{0j} + u_{1j} X_{ij} + e_{ij} \; (1)}$$

We base our vulnerability rate on a threshold equal to a 50 percent probability of falling below the poverty line over the next two years.[10] This measure is equivalent to a 29 percent chance or higher of falling into poverty in a given year. The vulnerability rate is the share of the population having a higher probability of falling into poverty. If the probability of falling above the probability threshold is driven by a mean household consumption/income below the mean, vulnerability is poverty-induced. If the probability is driven by high consumption/income volatility, vulnerability is risk-induced. The combination of both is the overall vulnerability rate.

Due to a lack of panel data in the country, we rely on repeated cross-sections. The El Salvador Multipurpose Household Survey (EHPM) is a cross-sectional survey collected by Dirección General de Estadística y Censos (DIGESTYC) since 1975. There is no longitudinal survey of individuals or households in the country. Therefore, we rely on repeated cross-sections, which provides less information than panel data. Ideally, for the methodology, we would also draw from a community-level survey, which is not available in El Salvador. Instead, we rely on household surveys from 2016 to 2019 and average our variables of interest at the municipality level. We focus on the period 2016 to 2019, as data on self-reported hazards was only collected for the years 2016 onwards. We do not consider the post-COVID period (2020 onwards) due to data limitations. Due to the pandemic, the survey round collected in 2020 is not fully comparable with previous survey rounds.

In contrast to previous studies applying the vulnerability tool, we employ an income-based and not consumption-based approach, given that poverty is officially measured via income-based measures in El Salvador. Our primary outcome is overall household per capita income and not per capita consumption, as poverty is measured in El Salvador using income. The tool draws from three sets of parameters: i) A set of covariates, measuring variables of interest at the household or community level, ii) parameters measuring vulnerability and poverty, as well as the threshold for vulnerability and the poverty line, and iii) a set of subgroups of interest (e.g., the rural and urban population as well as the distinctive departments).

We use a variety of control variables and the international poverty line as parameters in our model. In this paper, we measure poverty using the international moderate poverty line of 5.5 2011-PPP-US$ and a 29 percent chance or higher of falling into poverty in a given year to characterize vulnerability. We introduce the following control variables at the individual level: gender, marital status, age, homeownership, overall years of schooling, labor activity status, self-employment status, public/private sector employment, informal employment status,[11] and urban/rural status. We also control for the number of household members, the number of children below 15 years old in the household, the number of children aged 3 to 15 years attending school, and the number of household members out of the labor force. Additionally, we control for municipality characteristics: the employment rate, the unemployment rate, the share of self-employed and entrepreneurs, the share of public sector employees, the share of children attending school, and the share of the population with secondary education. Moreover, we create three indices to measure the individual exposure to crime, insecurity, and natural hazards.[12] Table 1 shows the summary statistics.

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[10] To test the validity of our main messages, we decrease our probability threshold, which defines if a person is vulnerable or not to 25 percent.

[11] Informality is defined as all workers who do not have health insurance or a signed working contract.

[12] In order to measure these hazards we take advantage of questions asked on each three of these risks in the national household survey. For each of these three hazards, we calculate a risk index. The risk index is the sum of all subtypes of hazards falling into the respective category. More specifically, we create a dummy variable for each subtype of hazard. This dummy variable is equal to one as soon as a household experiences one form of, for example, crime, and zero otherwise. We then add up the number of, for example, crimes experienced. This then is our respective risk index. In case a household experiences five different forms of crimes, for example, the index has a value of five. In case the household experiences zero crimes, it has a value of zero, and so on. We opt for an index to measure risk exposure to also account for the serverity of hazards. For a detailed overview of the indices see Annex 5.

Table 1: Descriptive Statistics of main explanatory variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Urban	74448	0.617	0.486	0	1
Male	74448	0.471	0.499	0	1
Single	74448	0.393	0.488	0	1
Age	74448	32.511	21.784	0	98
Ownership	74448	0.675	0.468	0	1
Highest grade obtained	42613	7.181	3.554	1	15
Employed	68609	0.478	0.5	0	1
Self-Employed	33580	0.271	0.445	0	1
Public sector	33580	0.072	0.258	0	1
Informal	17884	0.584	0.493	0	1
No. of Children	74448	1.157	1.151	0	8
Number of children attending school	74448	0.756	0.908	0	6
Number of members in main household	74412	4.322	1.893	1	17
Number of household members out of labor force	74448	1.492	1.173	0	8
Crime Index	71044	0.096	0.359	0	10
Security Index	71011	3.473	1.769	0	5
Environmental Index	74448	0.015	0.155	0	4
Financial literacy	74448	0.225	0.418	0	1
Occupation rate	74448	0.545	0.051	0.279	0.75
Unemployment rate	74448	0.043	0.027	0	0.27
Share of self-employed	74448	0.274	0.066	0.133	0.789
Share of entrepreneurs	74448	0.043	0.025	0	0.498
Share of public sector employees	74448	0.071	0.037	0	0.333
Share of children attending school	74448	0.66	0.071	0.143	1
Share of people with secondary education	74448	0.214	0.118	0	0.62

Notes: The table shows summary statistics at the individual level in El Salvador for survey data collected in 2019. The number of observations varies with the number of people eligible to the respective survey questions. We define informality as all employed people who do not have any health insurance or have no signed work contract. The number of observations is low in this case, given that only 17,884 people responded to the question on if they have a signed work contract or not. The crime index reflects the number of crimes a person reports to have been subject to and ranges from 0 to 10. Similarly, the security index reflects the personal restrictions, such as not going out at night, a person is subject to due to perceived insecurities. This index ranges from 0 to 5. The environmental riks index ranges from 0 to 4. For a detailed overview of the indices see Annex 5. Source: World Bank estimates based on EHPM (2019).

Relying on the variables as they are reported in Table 1 could result in a biased estimator of vulnerability to poverty due to missing observations. As soon as individuals report a missing observation in one of the variables included in the model, they are excluded from the estimation due to listwise deletion. This selective deletion of individuals might result in biased observations, which could be especially pronounced in the case of labor market variables, but also the share of children attending school. We therefore replace missing observations with zeros in these cases (Annex 6 presents the respective Summary Statistics). We verify the validity of our findings in a robustness check. There is one variable, which still reports a higher number of missing observations: the highest grade obtained. While we include this variable in our main empirical specification, we exclude it in one of our validity tests.

We estimate results for the overall population but also distinguish between rural and urban areas; we also analyze the development of vulnerability to poverty over time and at the department level. We estimate vulnerability to poverty at the yearly level for the overall population, but also the rural and urban populations. This distinction is of interested, as there are significant gaps between urban and rural areas in El Salvador (Robayo-Abril and Barroso, 2022). In addition, we estimate vulnerability to poverty for all of the 12 departments included in the household survey. This analysis might generate important insights on where investments in resilience and adaptive responses to shocks are most needed.

As the model relies on several assumptions, our findings are subject to a number of caveats. First, the model assumes that household consumption/income variation over time can be proxied by the variation in household consumption/income observed for households with the same characteristics. Moreover, it assumes that there is no measurement error in the measurement of consumption/income.[13] The downside of the approach is that it cannot identify the effects of specific shocks, like a drought or flood. Moreover, the vulnerability tool applied in this paper falls short of identifying which exact shocks are the specific drivers behind vulnerability in the country.

5. Results

Table 2 shows the results of the multilevel mixed-effects estimation.[14] Nearly all variables besides the occupation rate, share of employed in the public sector, and child assistance rate at the municipality level are significant at the 1-percent level. The unemployment rate, being female, self-employment, the number of children, informality, the number of household members out of the labor force, and perceived security, as well as environmental damages, have a negative correlation with per capita household income. The share of self-employed entrepreneurs, human capital accumulation, working in the public sector, and having a financial account positively influence the per capita household income. The number of children attending school is also positively correlated with per capita household income. Higher exposure to crime goes hand in hand with higher per capita household income. This could be due to those with more income being more exposed to crime.

Table 2: Multilevel Mixed Effects Estimation Results

Variable	Per Capita Household Income
Occupation rate	0.372
	(0.237)
Unemployment Rate	-2.321***
	(0.480)
Share (Self-employed)	0.696***
	(0.145)
Share (Entrepreneurs)	2.457***
	(0.352)
Share (Public Sector)	0.299
	(0.260)
Child Assistance Rate	0.179
	(0.123)
Secondary Schooling	1.008***
	(0.151)
Dummy for residency area	0.513***
	(0.118)
Sex	-0.057***
	(0.006)
Single	0.253***
	(0.061)
Age	0.011***
	(0.002)

[13] Due to consumption smoothing, measurement error is generally more prevalent and varies more across households in income than in consumption. We test our findings to the inclusion of measurement errors. Our main results are robust to measurement errors. While the vulnerability rate decreases when accounting for measurement errors, our main messages persist across the different specifications.
[14] We do not report the respective interaction terms.

Ownership	0.007
	(0.012)
Schooling completed	0.020***
	(0.002)
Dummy of activity status: employed	0.133***
	(0.012)
Self-employed	-0.123***
	(0.008)
Public Sector	0.244***
	(0.015)
Informal employment	-0.808***
	(0.114)
Number of children	-0.310***
	(0.029)
Number of children attending schooling	0.072***
	(0.005)
Number of members in the **main household**	0.199***
	(0.019)
Number out of labor force	-0.219***
	(0.012)
Crime Rate	0.114***
	(0.015)
Security	-0.021***
	(0.003)
Environmental damages	-0.036**
	(0.016)
Financial account	0.308***
	(0.013)
Constant	5.057***
	(0.169)
Observations	40,573
Number of groups	226
Standard errors in parentheses	
***** p<0.01, ** p<0.05, * p<0.1**	

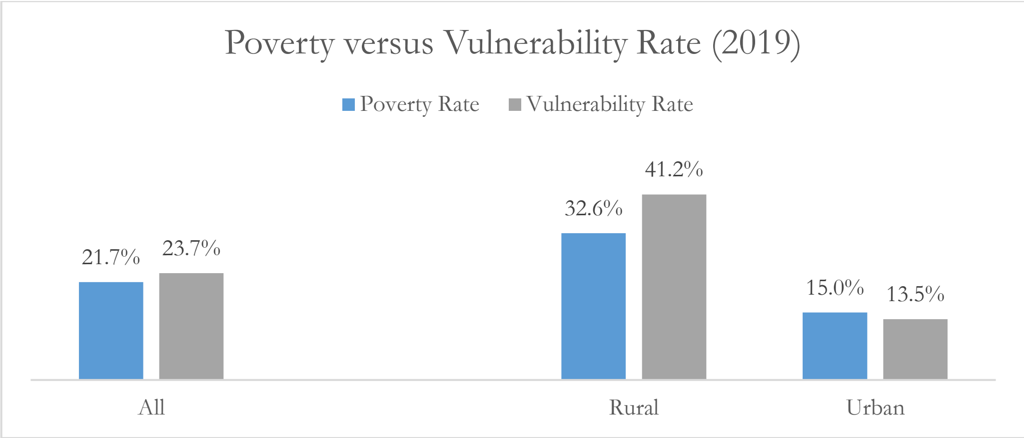
Source: World Bank estimates based on EHPM (2019). The number of observations is driven by missing variables in the variable indicating the highest grade obtained. For all other variables, we replace missing values with zeros to avoid a selective deletion of these individuals from the model estimation. See Annex 6 for the details.

5.1. Vulnerability to Poverty: Recent Estimate and Drivers

Our estimates show that vulnerability to poverty in El Salvador in 2019 was slightly higher than poverty, with 24 percent of households being vulnerable; vulnerability is mainly driven by risk-induced vulnerability. The overall vulnerability rate in El Salvador in 2019 was 23.7 percent and, therefore, slightly higher than the poverty rate.[15] The vulnerability rate was higher in rural areas with 41.2 percent and only 13.5 percent in urban areas (see Figure 1). In addition, risk-induced vulnerability played a more significant role in overall vulnerability in El Salvador, mainly driven by urban areas (see Figure 2). The ratio of risk-induced to poverty-induced vulnerability was 1.7 in total, 1.4 in rural areas, and 2.7 in urban areas. These results suggest that vulnerability in the country is mainly driven by climate and environmental shocks or crime rather than by low access to assets and low human capital.

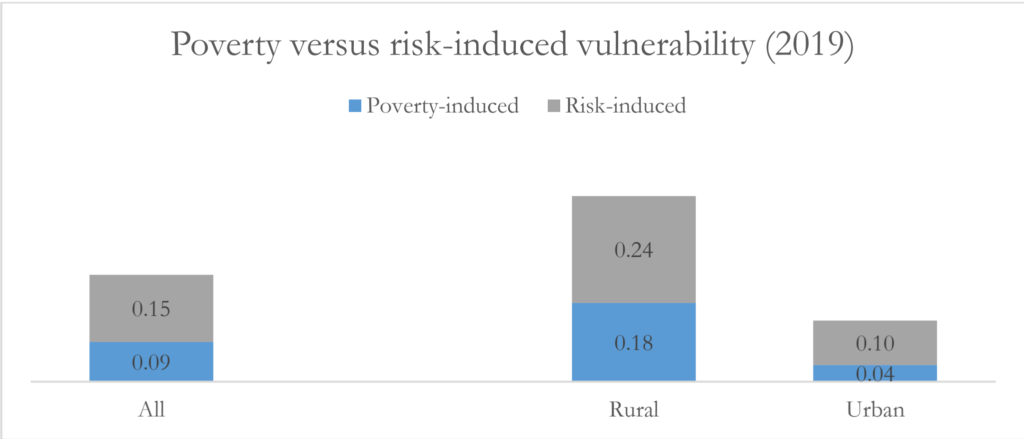
[15] This is the poverty rate estimated by the model, and not the one observed in the data.

Figure 1: Poverty versus vulnerability to poverty in El Salvador, 2019



Note: The poverty rate reported here is the estimated poverty rate from the model and not the observed poverty rate. Source: World Bank estimates based on EHPM (2019).

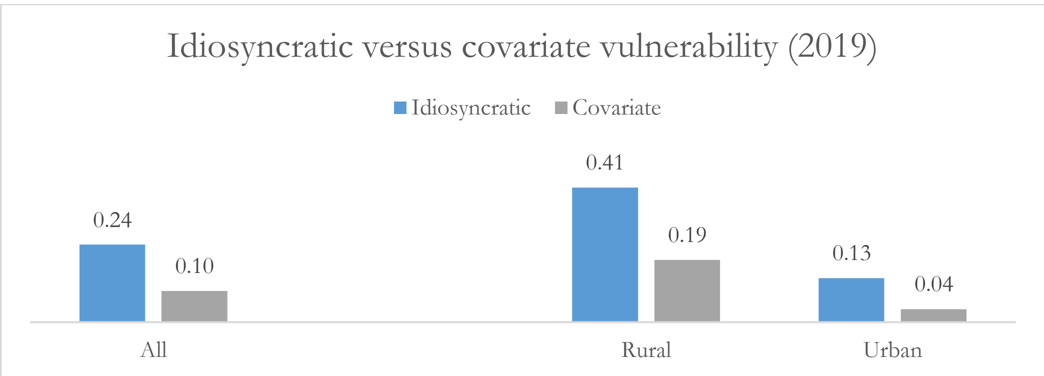
Figure 2: Vulnerability Decomposition



Source: World Bank estimates based on EHPM (2019)

Idiosyncratic shocks are more prevalent in El Salvador than covariate shocks. Risk-induced vulnerability can arise from idiosyncratic or covariate shocks. The ratio of idiosyncratic to covariate vulnerability is 2.5 in El Salvador (see Figure 3). The ratio of idiosyncratic to covariate vulnerability is 2.2 in rural areas and 3.4 in urban areas. These results suggest that shocks at the household level are more marked for urban areas than municipality-level shocks. In addition, households in urban areas are relatively more vulnerable to crime, illnesses, or price increases than rural households. Still, rural households are also more affected by these individual shocks than those happening at the municipality level.

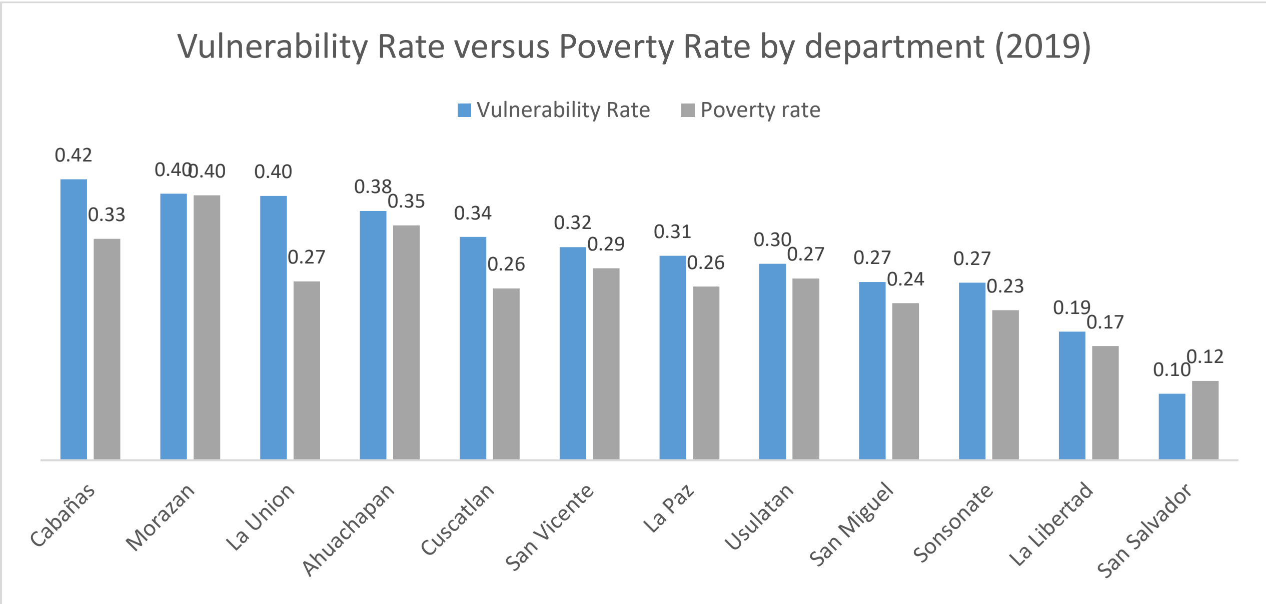
Figure 3: Sources of vulnerability



Source: World Bank estimates based on EHPM (2019)

Vulnerability and poverty vary significantly at the department level. Figure 4 shows the vulnerability rate by department in 2019. The graph shows that there is a large variation in vulnerability by department. As shown, there are significant deviations with respect to poverty and vulnerability levels in the different departments. While Morazán is the department with the highest poverty rate in 2019 (with a rate of 40.0 percent), Cabañas is the department with the highest vulnerability rate (with a rate of 42.0 percent). These differences further stress the importance of differentiating between poverty and vulnerability.

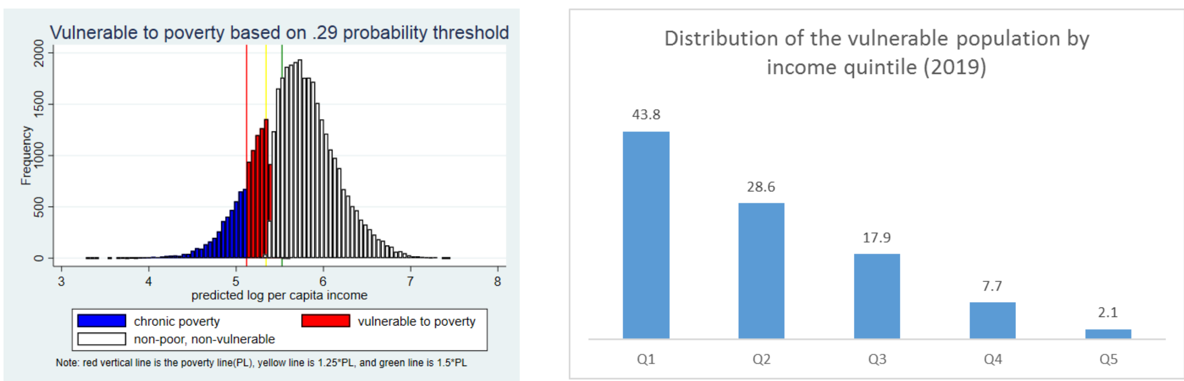
Figure 4: Vulnerability versus poverty rate by department (2019)



Source: EHPM (2019). Note: Poverty is defined by the international 5.5 2011-PPP-US$ poverty line. The poverty rate shown in this graph is the estimated one by the model and might therefore deviate from the direct poverty measures.

Nearly half of the vulnerable population is currently not poor but at risk of becoming poor. In 2019, nearly half of the vulnerable population has a per capita income below the international moderate poverty line of 5.5 2011-PPP-US$. Moreover, in 2019, 43.8 percent of the vulnerable population belonged to the lowest income quantile (see Figure 5). More than one-fourth of the vulnerable population belongs to the upper three income quintiles (27.7 percent). Therefore, there is a relatively large overlap between income poverty and vulnerability to poverty. Still, nearly half of the vulnerable population is currently not poor but at risk of becoming poor. These insights have implications for social policies that aim to protect households from becoming poor when a future shock hits.

Figure 5: Income quintiles of the vulnerable population



Source: World Bank estimates based on EHPM (2019)

Table 3 compares the vulnerable to the poor population. The table shows that the poor and vulnerable are similar among several dimensions. Still, there are some systematic differences. First, a lower share of the vulnerable than poor live in urban areas (36.6 percent versus 42.5 percent). Surprisingly, a higher share of the poor are employed (33.1 percent versus 29.1 percent). Also, nearly the full universe of the vulnerable population are informally employed compared to 9 out of 10 poor people. The vulnerable have, on average, more children, more household members, and a higher exposure to criminal activity. When designing targeting mechanisms, these differences should be taken into consideration.

Table 3: Descriptive Statistics – Vulnerable versus poor (2019)

Variable	Vulnerable population			Poor population		
	Observations	Mean	Standard Deviation	Observations	Mean	Standard Deviation
Urban	22196	0.366	0.482	18321	0.425	0.494
Male	22196	0.469	0.499	18321	0.464	0.499
Single	22196	0.373	0.484	18321	0.342	0.474
Age	22196	27.905	19.247	18321	27.389	21.166
Ownership	22196	0.656	0.475	18321	0.664	0.473
Highest grade obtained	11110	6.653	3.382	8600	6.453	3.39
Employed	22196	0.291	0.454	16288	0.331	0.471
Self-Employed	6858	0.377	0.485	5947	0.341	0.474
Public sector	6858	0.004	0.063	5947	0.008	0.091
Informal	3046	0.963	0.189	2447	0.895	0.307
No. of Children	22196	2.006	1.203	18321	1.816	1.298
Number of children attending school	22196	1.298	1.048	18321	1.131	1.051
Number of members in main household	22196	5.409	2.006	18321	5.038	1.957
Number of household members out of labor force	22196	2.203	1.307	18321	1.977	1.305
Crime Index	21363	0.064	0.326	17557	0.052	0.246
Security Index	21349	3.683	1.787	17535	3.648	1.755
Environmental Index	22196	0.018	0.161	18321	0.02	0.16
Financial literacy	22196	0.172	0.377	18321	0.18	0.384

Source: World Bank estimates based on EHPM (2019)

5.2. Vulnerability to Poverty: Recent Trends

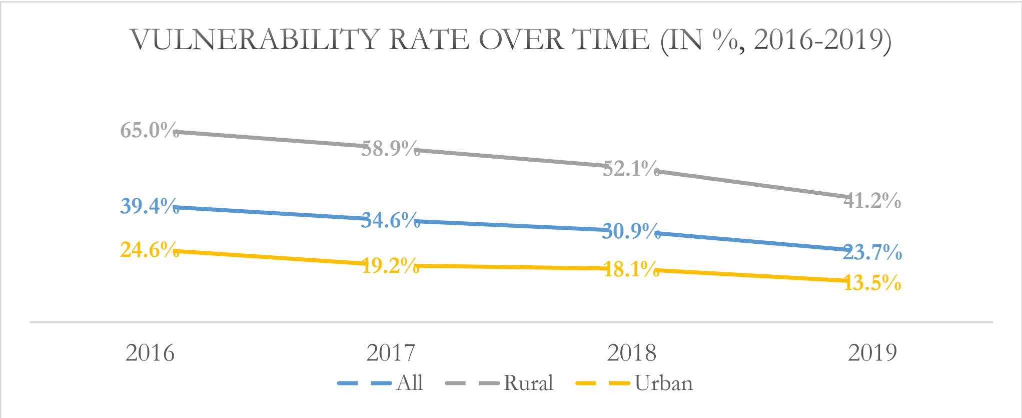
This subsection presents estimates of ex-ante vulnerability to poverty over time in the more recent period 2016-2019. These estimates rely on the household surveys available at the time of this publication. Even though the 2020 data was publicly available, the collection of the 2020 data was affected by the COVID-19 pandemic, potentially affecting the comparability of the income aggregates over time. The statistical office (DIGESTYC) continuously collects the household survey from January to December. Still, in 2020 data was not collected from March to July (the period of strict confinement in which labor incomes probably fell the most); therefore, the entire sample was not covered.

Our estimates show that the vulnerability rate nearly halved during the period 2016-2019 in El Salvador from a total vulnerability rate of 0.39 in 2016 to 0.24 in 2019, with decreases in both rural and urban areas. The decrease in vulnerability is 23.8 percentage points in rural areas and 11.1 percentage points in urban areas (see Figure 6). The decline in vulnerability to poverty is mainly related to a parallel decrease in poverty (falling from 31.4 percent in 2016 to 22.3 percent in 2019, when measured in 2011-PPPs). Therefore, the share of households close to the poverty line is lower, and a lower share of households switched their poverty status, which then also lowers the rate of households being vulnerable.

The decline in vulnerability to poverty comes along with an increase in the role of risk factors; this could be due to parallel poverty decreases in the country. As poverty also fell over time, the increased importance of risk factors in vulnerability comes as no surprise. The ratio of risk-induced to poverty-induced vulnerability increased from 1.1 to 1.7 between 2016 and 2019 (see Figure 7). Especially in rural areas, risks have started to play a larger role. While in 2016, vulnerability to poverty was to a larger extent driven by low access to assets, it is the risks that drive vulnerability in 2019. In urban areas, risk factors have started to play an increasing role between 2016 and 2019.

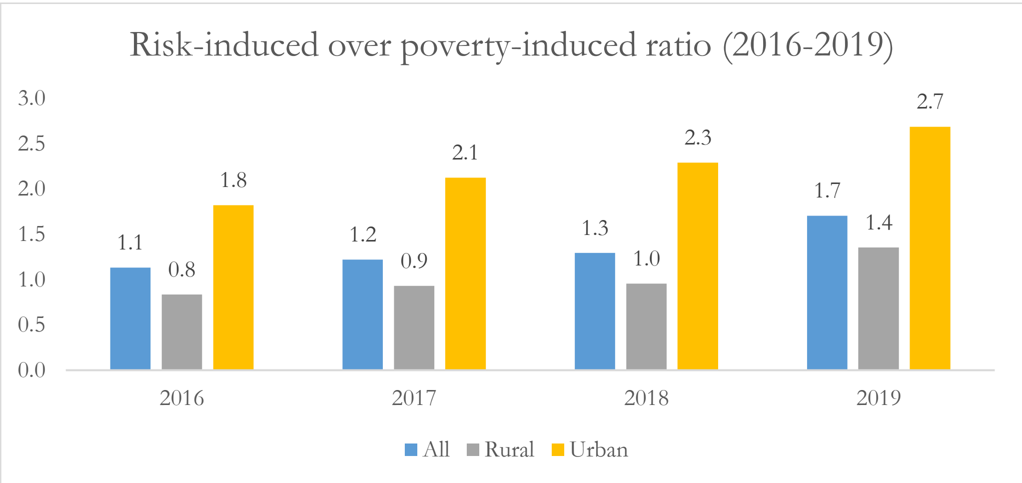
Additionally, idiosyncratic factors increasingly became more critical than covariate shocks. This applies to the population as a whole, for which the ratio of idiosyncratic to covariate shocks increased from 1.9 in 2016 to 3.4 in 2019, but also the urban and rural population (see Figure 8). The increasing importance of household-level shocks relative to community-level shocks was more significant in urban areas. This means that, especially in urban areas, households are more subject to individual shocks, such as crime, employment losses, or illnesses.

Figure 6: The development of vulnerability over time



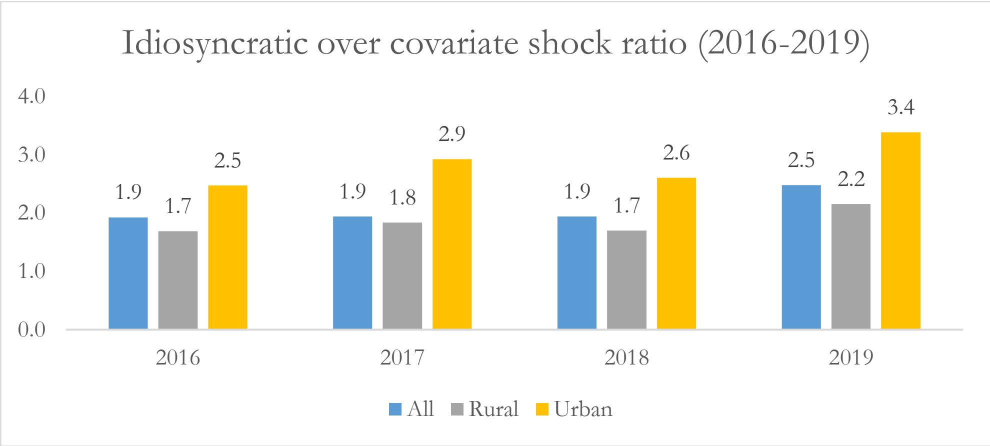
Source: World Bank estimates based on EHPM (2016-2019)

Figure 7: The development of risk-induced versus poverty-induced vulnerability over time



Source: World Bank estimates based on EHPM (2016-2019)

Figure 8: The development of idiosyncratic versus covariate shocks



Source: World Bank estimates based on EHPM (2016-2019)

To sum up, the decrease in vulnerability to poverty over time is connected to a parallel decrease in poverty. Given the decrease in poverty, the share of households close to the poverty line is lower. Related to this development, a lower share of households switched their poverty status, which then also lowers the rate of households being vulnerable. Poverty-induced vulnerability decreased and risk-factors play a more significant role in vulnerability to poverty. These developments are not in contrast to parallel increases in operational vulnerability (Robayo-Abril and Barroso, 2022), given that operational vulnerability takes a static perspective towards vulnerability to poverty. Operational vulnerability and ex-ante vulnerability therefore do not reflect the same group of people.

6. Robustness Tests and Sensitivity Analysis

To validate our findings, we conduct several robustness tests and a sensitivity analysis. First, we estimate several model specifications and compare their results to each other. Next, we account for potential measurement errors in the underlying income variable. We then take advantage of the fact that 50 of the included municipalities are autorrepresentative, meaning direct estimates from the household survey are representative for these 50 municipalities, given their sample size. This analysis is useful for the estimation of covariate vulnerability. Lastly, we conduct a sensitivity analysis by applying an alternative probability threshold, which defines if a person is vulnerable or not. The following subsection details the main findings and conclusions from these validity checks.

6.1. Different Model Estimations and Vulnerability Estimates

We investigate the robustness of our findings to different model specifications. These model specifications account for some of the shortfalls of our baseline specification. Table 4 illustrates the results. We conduct these robustness tests for the 2019 survey year. The first colum reports the baseline estimate. We first present the total vulnerability rate for the overall population, and those for the urban and rural populations separately. Column 2 refers to a model specification which excludes the educational variable in order to increase the underlying sample size. Row 1 reveals that the vulnerability rate is slightly higher than the one from the baseline specification (29.5 percent versus 23.7 percent). These differences remain when restricting the sample by urban/rural status.

Our risk measures are self-reported and could be subject to reporting biases; we account for this potential shortcoming by measuring exposure to hazards via external data sources. There are two possibilities to measure hazards. First, one can rely on self-reporting of exposure to shocks by households. Second, it is possible to rely on data collected externally, as for example weather or remote-sensed data. Both approaches are subject to potential limitiations and biases. While external data sources might suffer from so-called basis risks, self-reporting is endogenous and subjective (Nguyen & Nguyen, 2020). Column 3 presents results for a model specification which relies on external data sources to measure risk exposure and excludes the educational variable. Column 4 relies on external data sources to measure risk exposure and includes the educational variable. We draw from the subnational INFORM Risk Index to measure a municipality's exposure to natural hazards. We rely on administrative data on homicides to proxy for human hazards. The estimates are very similar to the ones relying on self-reported risk exposure.

Lastly, column 5 reports results for a model specification which pools several survey waves. More specifically, we pool data for the years 2016-2019 and estimate our model relying on the pooled data set. We control for year fixed effects and exclude the educational variable. This specification demonstrates that vulnerability is much higher when pooling several survey waves. The higher vulnerability rate is not surprising, given our findings on decreasing vulnerability over time. Importantly, it is not possible to compare vulnerability estimates from pooled data to the one relying on one single year.

Table 4: Diffrent model specifications and estimates of the total vulnerability rate

Model Specification	Baseline	Robustness Test 1	Robustness Test 2	Robustness Test 3	Robustness Test 4
All	0.237	0.295	0.294	0.234	0.410
Rural	0.412	0.492	0.498	0.413	0.627
Urban	0.135	0.164	0.172	0.139	0.265
Educational variable	*Yes*	*No*	*No*	*Yes*	*No*
Self-reported hazard exposure	*Yes*	*Yes*	*No*	*No*	*Yes*
Survey rounds	*2019*	*2019*	*2019*	*2019*	*2016-2019*

Note: The table presents empricial estimates of the total vulnerability rate relying on different model specifications. The first colum presents the baseline estimate. Column 2 refers to a model specification which excludes the educational variable. Column 3 presents results for a model specification which relies on external data sources to measure risk exposure and excludes the educational variable. Column 4 relies on external data sources to measure risk exposure and includes the educational variable. Lastly, Column 5 considers pooled data from survey years 2016 to 2019. Source: World Bank estimates based on EHPM (2019), INFORM (2019).

6.2. Accounting for Potential Measurement Errors

The income-based measure of welfare employed in this paper is subject to important empirical limitations. There are two main approaches to measure material well-being of the poor. One approach relies on income while a second approach draws from consumption data. Both approaches have important advantages and disadvantages (Meyer and Sullivan, 2003). While income is easier to measure, it might be inaccurately measured for the poor due to measurement error and under-reporting as well as high levels of informality among those with lower income levels. In addition, consumption might more accurately reflect material well-being. These limitations are an important caveat and could influence the results presented in this paper.

We test if our results are robust to the inclusion of measurement errors. One of the weaknesses of the vulnerability tool is that it assumes no measurement errors. Especially in the case of income, measurement errors are not uncommon. As the vulnerability rate draws from the idiosyncratic errors, measurement errors could inflate our vulnerability rate (measurement errors form part of the idiosyncratic error). Therefore, we assume that 25-50 percent of the overall volatility, which we observe across households when looking at their income, stems from measurement errors. We apply this exercise to our tool using the 2019 cross-section of the household data for El Salvador.

When assuming that half of the total variance is due to measurement errors of income, the vulnerability rate decreases to 18.4 percent. Therefore, it is lower than when we assume no measurement error. This means that the vulnerability rate is lower than the poverty rate, with a 50 percent measurement error. Still, several of our main findings hold. First of all, rural vulnerability is much higher than the urban one. The vulnerability rate of the rural population is 0.336 compared to 0.095 in urban areas (see Figure

A1). Moreover, vulnerability is mainly risk-induced and not poverty-induced, with a ratio of 1.1 (see Figure A2). Still, this ratio is considerably lower than in the case without measurement errors (a ratio of 1.7). Additionally, contrary to our previous results, poverty-induced vulnerability outweighs risk-induced vulnerability in rural areas, where this same ratio is 0.9 (compared to 1.4 in the case without measurement errors). Idiosyncratic vulnerability remains more persistent than covariate vulnerability, but the difference is smaller than in the case without measurement error (see Figure A3). In addition, the large variation with respect to vulnerability across departments persists (see Figure A4).

Assuming that 50 percent of the variation stems from measurement errors is assuming a substantial measurement error. Therefore, we alternatively assume that 25 percent of the observed variation is due to measurement errors in our income data. The vulnerability rate, in this case, is 0.21 and poverty-induced vulnerability plays a lower role in overall vulnerability than risk-induced vulnerability (see Annex 2 for the detailed results). This applies to rural as well as urban areas. The vulnerability rate is much larger in rural (0.38) than urban areas (0.12), similarly to the case without measurement error. Idiosyncratic vulnerability persists to be relatively more critical than covariate vulnerability. In the case of one-third of variation stemming from measurement errors, the vulnerability rate is 0.20. Risk-induced vulnerability is still the main driver, both for rural and urban areas. Idiosyncratic vulnerability plays a more significant role than covariate vulnerability.

Given the above results, our main findings are robust to measurement errors. While the vulnerability rate decreases when accounting for measurement errors, our main messages persist across the different specifications. Thus, risk-induced vulnerability remains the main driver behind vulnerability, and idiosyncratic vulnerability plays a more significant role than covariate vulnerability. Additionally, there is substantial variation in vulnerability across departments. While some of our main messages fall when increasing the measurement error to 50 percent, the occurrence of a measurement error of this scale is highly unlikely.

6.3. Relying on 50 Autorepresentative Municipalities

We take advantage of the fact that 50 of the included municipalities are autorrepresentative and reestimate vulnerability to poverty using this restricted sample. This robustness test is useful for estimating covariate vulnerability, especially as the estimation might suffer from the lack of representativeness in the rest of the municipalities. Our findings on the relative importance of idiosyncratic and covariate shocks hold (see Annex 4). The ratio of idiosyncratic to covariate vulnerability is very similar to our baseline results (2.5 versus 2.9). Still, covariate vulnerability is slightly lower when only considering the 50 auto-representative municipalities (0.052 versus 0.095). Overall, the vulnerability rate is lower under this model specification than under the full model specification. This is mainly because the 50 auto representative municipalities are not representative of the overall country in many aspects, and the underlying estimation should not be taken as a reference.

6.4. Decreasing the Probability Threshold

To test the validity of our main messages, we decrease the probability threshold, which defines if a person is vulnerable or not, to 25 percent. This means that a person is vulnerable if their probability of falling into poverty is higher than 25 percent in the next two years, or a yearly probability of 14.5 percent. Similarly to our robustness check on measurement errors, we apply this robustness check to the 2019 cross-section of the underlying household data.

Under this threshold, the vulnerability rate in El Salvador is much higher and our main messages reinforce themselves. Vulnerability is high under a 25 percent vulnerability threshold, with an overall rate of 44.2 percent. Moreover, all of our messages reinforce themselves under this vulnerability threshold (for a detailed overview of the results, see Annex 3). First, the rural population is more affected than the urban one (0.672 versus 0.307). Next, vulnerability is more risk- than poverty-induced, with an overall rate of 4.0. Additionally, this holds for both rural and urban areas. In addition, vulnerability is mainly based on idiosyncratic and not covariate shocks. The variation of vulnerability is high in this case. We can therefore conclude that our main results are robust to alternative thresholds.

7. Conclusion and Policy Insights

This paper applies an innovative approach to estimate the population's vulnerability to poverty in El Salvador and analyzes potential underlying drivers. We apply a novel ex-ante approach to vulnerability developed by the World Bank to the context of El Salvador to measure ex-ante vulnerability and its components. In addition, we take advantage of household-level data from 2016 to 2019 to show trends over time. We also analyze the components behind these trends, distinguishing between poverty- and risk-induced vulnerability and idiosyncratic and covariate vulnerability. Our analysis is based on an income measure of welfare.

Our main results show that ex-ante vulnerability to poverty decreased over time, in parallel to the poverty reduction observed in the country. This development comes hand in hand with an increase in the importance of risk-factors relative to factors related to assets driving vulnerability. The importance of risks in overall vulnerability increased over time. Although the vulnerability rate decreased since 2016, this might be a hint for shocks playing a more significant role in the overall development path of El Salvador. The analysis at hand finds that risk-induced vulnerability is mainly driven by idiosyncratic (household-level) shocks and not covariate (municipality-level) shocks. Consequently, shocks occurring to individual households (such as crime, unemployment, or illnesses) should receive special attention from policy makers. Still, it is essential to note that covariate shocks (such as a drought or flood at the municipality level) can lead to idiosyncratic shocks (an illness or employment loss of an individual household). While about half of the vulnerable also suffer from poverty, the vulnerable do not coincide entirely with the poor.

Furthermore, our work reveals that vulnerability rates are higher in rural than urban areas, and risk factors have become relatively more important in rural areas over time. Our paper demonstrates that, while vulnerability was mainly poverty-induced in rural areas in 2016, this dynamic shifted over the last few years. In 2019, risk factors played a more significant role than poverty assets in overall vulnerability. The relative importance of risk-induced to poverty-induced vulnerability in urban areas also increased since 2016. As vulnerability is higher in rural areas, public policies should pay special attention to rural populations.

These findings are important from a policy standpoint, given that the design of a flexible and adaptive social protection system depends on the magnitude and type of welfare shocks. Under a scenario in which vulnerability is mostly poverty-induced, policies strengthening social assistance and cash transfer programs should be prioritized. In addition, there is a need for improving service delivery, and increasing the human capital accumulation (education and health) of vulnerable populations. Under this scenario, households do not have sufficient financial, physical, or human capital to escape poverty. In these circumstances, disasters caused by climate shocks and other adverse shocks only exacerbate an already difficult situation and can contribute to increasing the depth of poverty. Policies prioritizing the establishment of social assistance programs targeting the chronically poor, such as unconditional or conditional cash transfer programs (such as Comunidades Solidarias and Rurales in El Salvador), are likely to be effective in contributing to the reduction of short-term poverty and the accumulation of financial, physical, and human capital in the medium to longer-term) (Laws, 2016).

By contrast, when vulnerability is mostly risk induced, as in the case of El Salvador, policies that increase the availability of social insurance mechanisms should be prioritized. When vulnerability is predominantly risk-induced, shocks push households below the poverty threshold, as they do not have the ability to protect their consumption or income. Social insurance mechanisms can assist households in coping with and recovering from adverse shocks. Under risk-induced vulnerability, the preferred policy action is the enhancement of access to savings, insurance, credit, and other mechanisms that allow affected households to access resources to better cope and recover faster from negative impacts on their consumption and income. Alderman and Haque (2006) point out that social protection programs can provide an insurance function when their targeting is based on transitory rather than more chronic correlates of poverty, in addition to the need for a flexible implementation strategy for faster response. The widespread dominance of idiosyncratic shocks across countries and regions within countries suggests that, for effective protection (and insurance), targeting should be based on the potentially adverse welfare impacts of shocks experienced by individual households and not on the chronic correlates of poverty. Risk-sharing mechanisms might be appropriate here (Alderman and Paxson, 2016).

Mitigation strategies which focus on risk reduction might secure a sustainable poverty reduction path in El Salvador. Policy instruments in El Salvador should focus on social insurance mechanisms that help households cope and recover from adverse shocks if the country aims to reduce vulnerability. The pandemic and the war in Ukraine demonstrated the importance of understanding the vulnerable population and of having instruments at hand to protect them against shocks.

The literature identifies an evidence gap on how idiosyncratic shocks can be addressed most effectively, but making existing social assistance programs more flexible could be an important mechanism (Laws, 2016). Among the little empirical evidence in this field, scholars have identified social assistance programs as effective mechanisms to decrease negative coping strategies during shocks (Laws, 2016). Cash transfers are one way to make households more resilient to negative shocks (Skoufias, 2007). The literature also points out that social assistance programs are often not flexible enough to provide the assistance needed when idiosyncratic shocks occur (Laws, 2016). Increased flexibility implies increasing the level of assistance when needed (Fiszbein and Schady, 2009).

Additional mechanisms include public work programs and special social protection and labor strategies. Public work programs might be more effective in addressing vulnerability, as they are more short-term focused than Cash Transfer Programs (Fiszbein et al., 2009). Still, these programs have to be well designed as they might have adverse effects (McCord, 2013). Additionally, increased access to savings, insurance, credit, and other mechanisms that allow affected households to access resources to better cope and recover faster from negative impacts on their consumption and production could be alternative ways to cope with risk factors (Skoufias and Baez, 2021). Governments can also introduce social protection and labor strategies working in tandem to protect the poor and vulnerable (World Bank, 2021). Finally, they can orient themselves to best practices used in the field of social protection as responses against natural disasters (World Bank, 2013).

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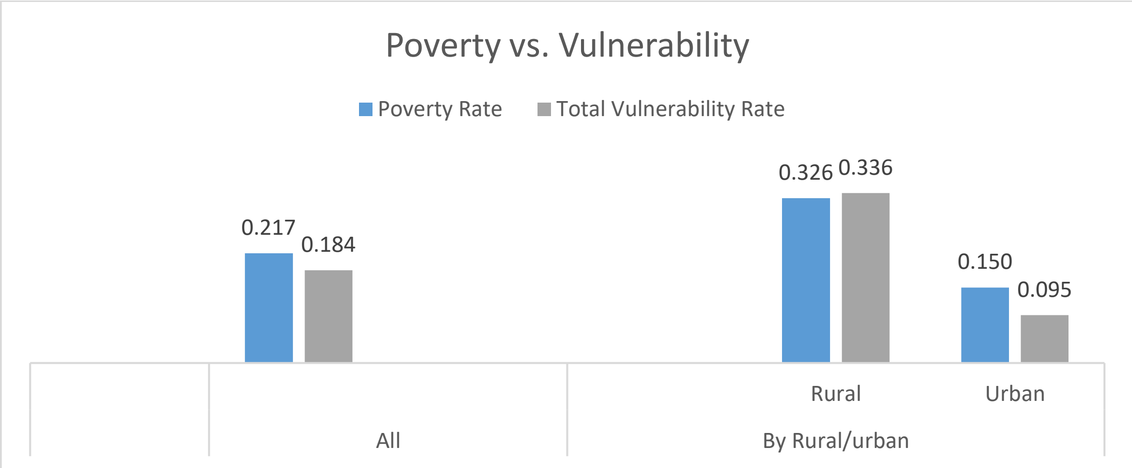
Annex

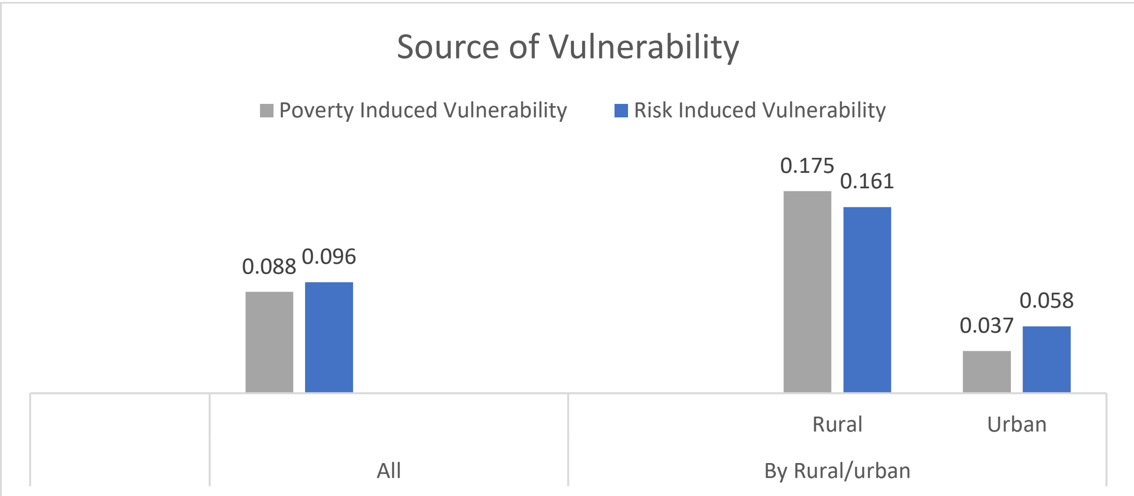
Annex 1 – Accounting for 50 percent measurement errors

Figure A 1: Poverty and vulnerability estimates under a 50 percent measurement error (2019)



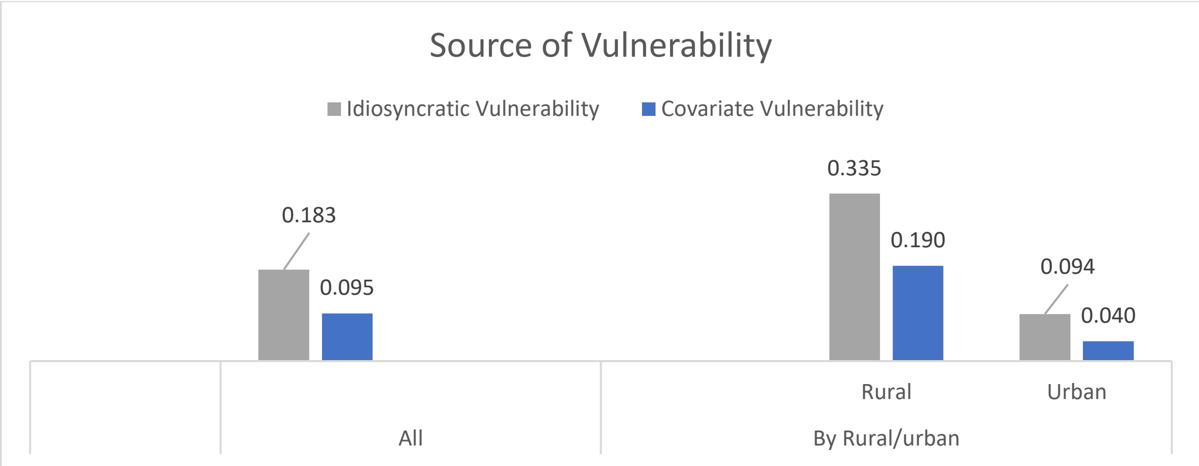
Source: World Bank estimates based on EHPM (2019)

Figure A 2: Sources of vulnerability (poverty versus risk-induced, 2019)



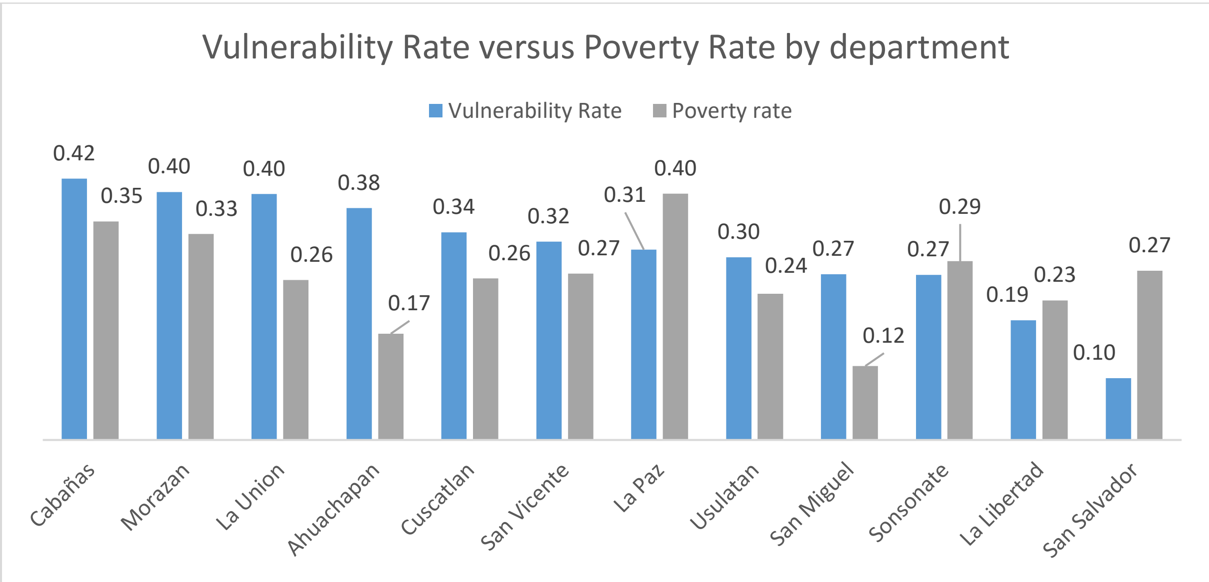
Source: World Bank estimates based on EHPM (2019)

Figure A 3: Sources of vulnerability under a 50 percent measurement error (2019)



Source: World Bank estimates based on EHPM (2019)

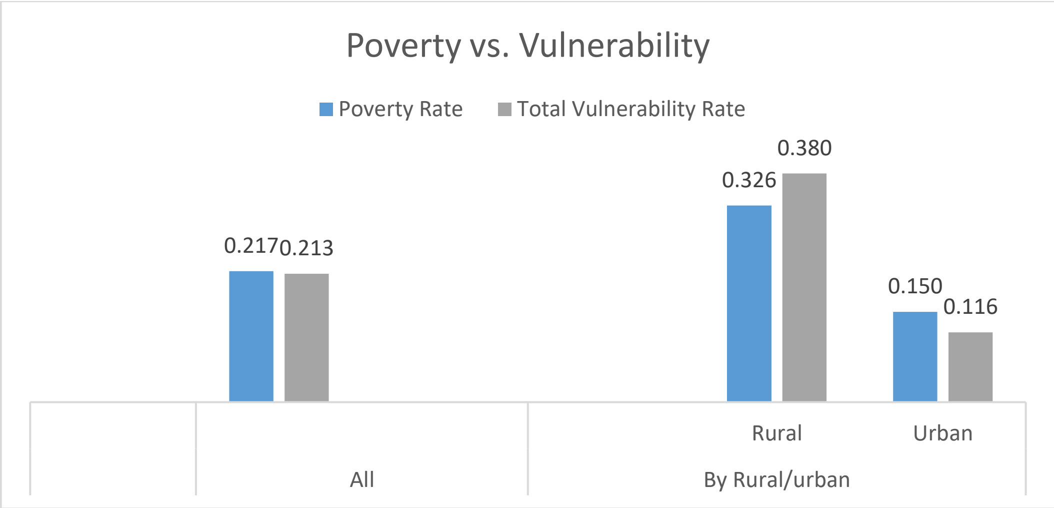
Figure A 4: Vulnerabiliy and poverty by department under a 50 percent measurement error (2019)



Source: World Bank estimates based on EHPM (2019)

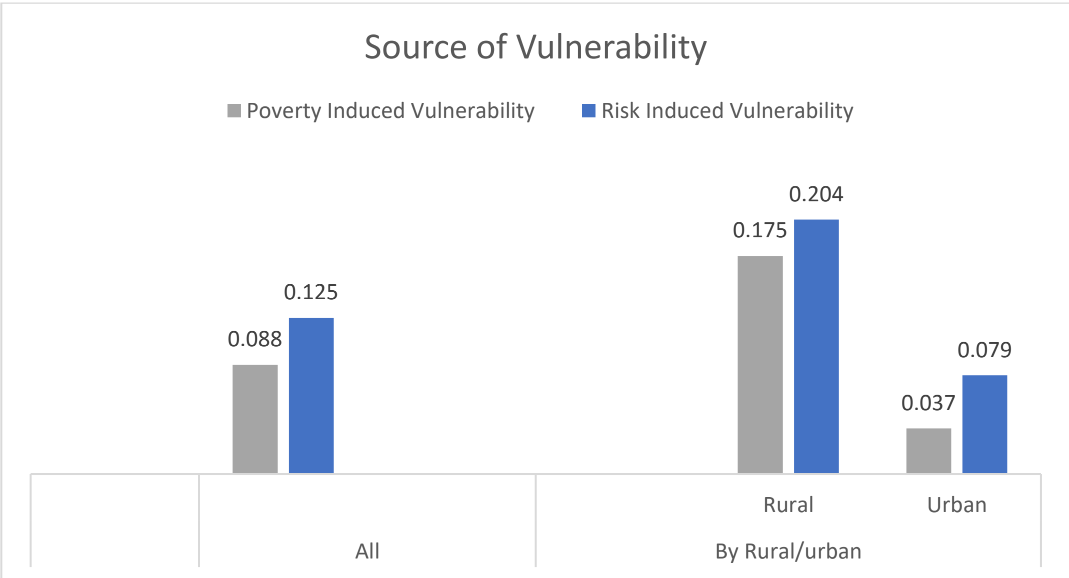
Annex 2 – Accounting for a 25 percent measurement error

Figure A 5: Poverty and vulnerability estimates under a 25 percent measurement error (2019)



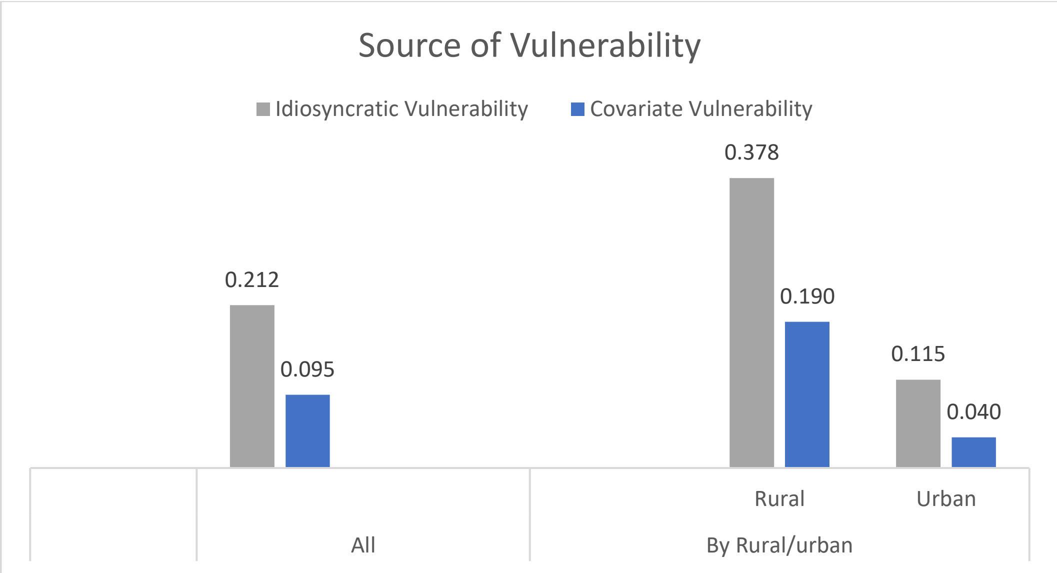
Source: World Bank estimates based on EHPM (2019)

Figure A 6: Sources of vulnerability under a 25 percent measurement error (2019)



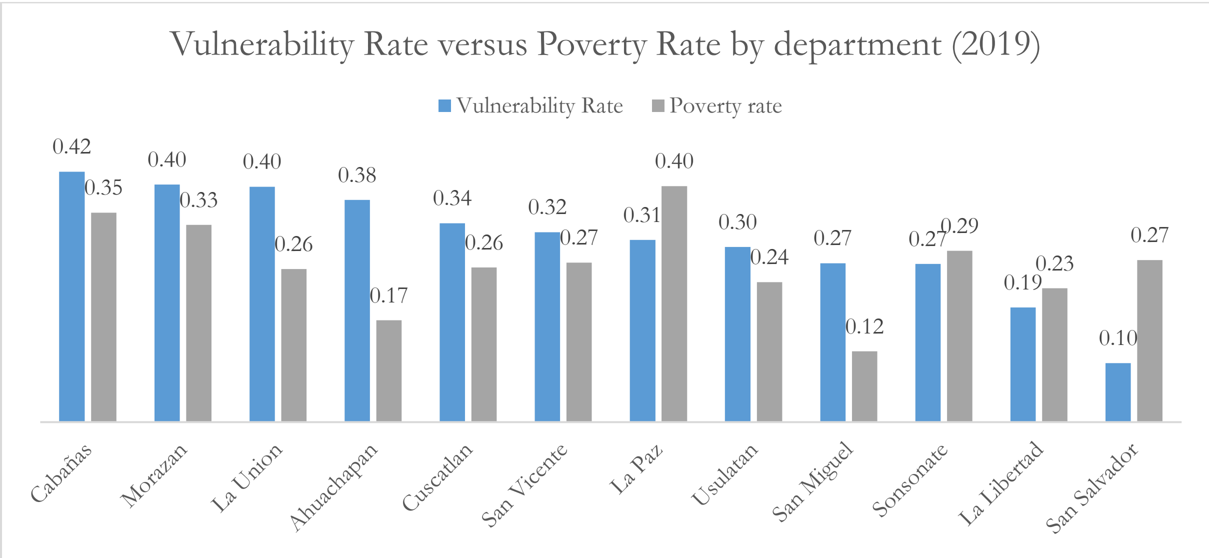
Source: World Bank estimates based on EHPM (2019)

Figure A 7: Sources of vulnerability under a 25 percent measurement error (2019)



Source: World Bank estimates based on EHPM (2019)

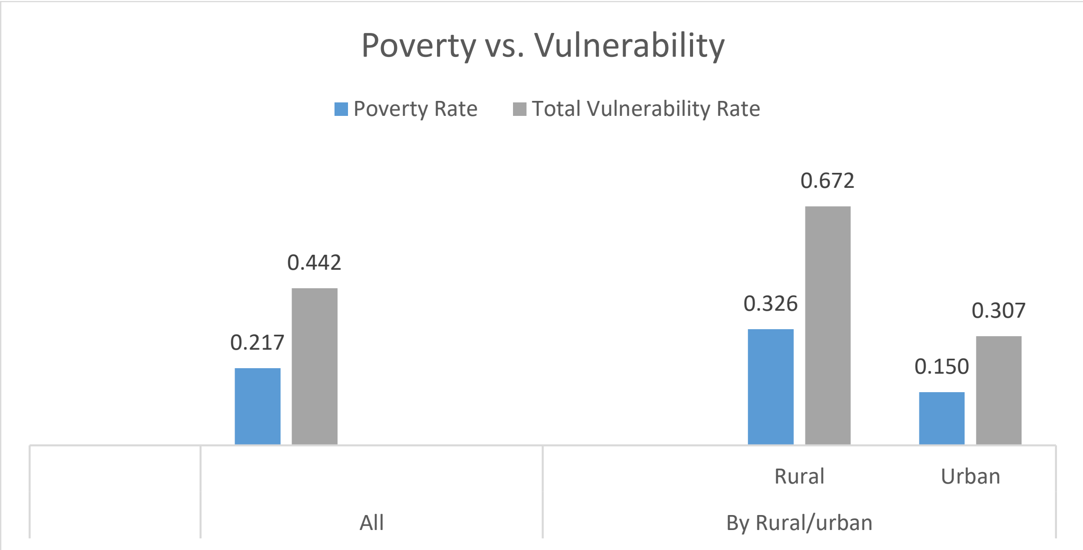
Figure A 8: Vulnerability and poverty by department under a 25 percent measurement error (2019)



Source: World Bank estimates based on EHPM (2019)

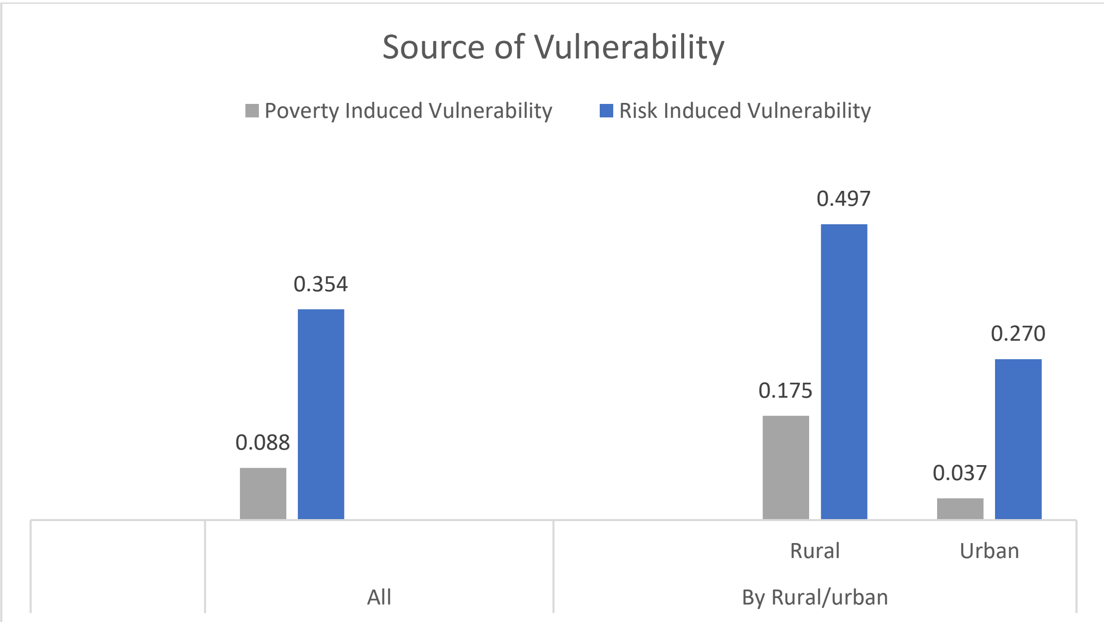
Annex 3 – Using an alternative probability threshold

Figure A 9: Poverty and vulnerability estimates under a 25 percent probability threshold (2019)



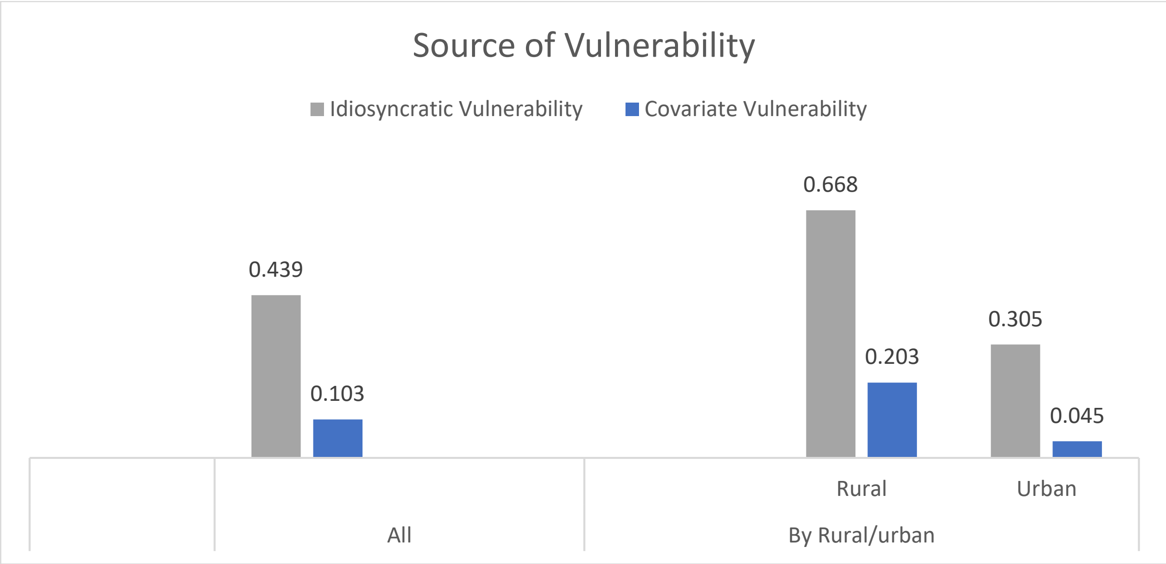
Source: World Bank estimates based on EHPM (2019)

Figure A 10: Sources of vulnerability estimates under a 25 percent probability threshold (2019)



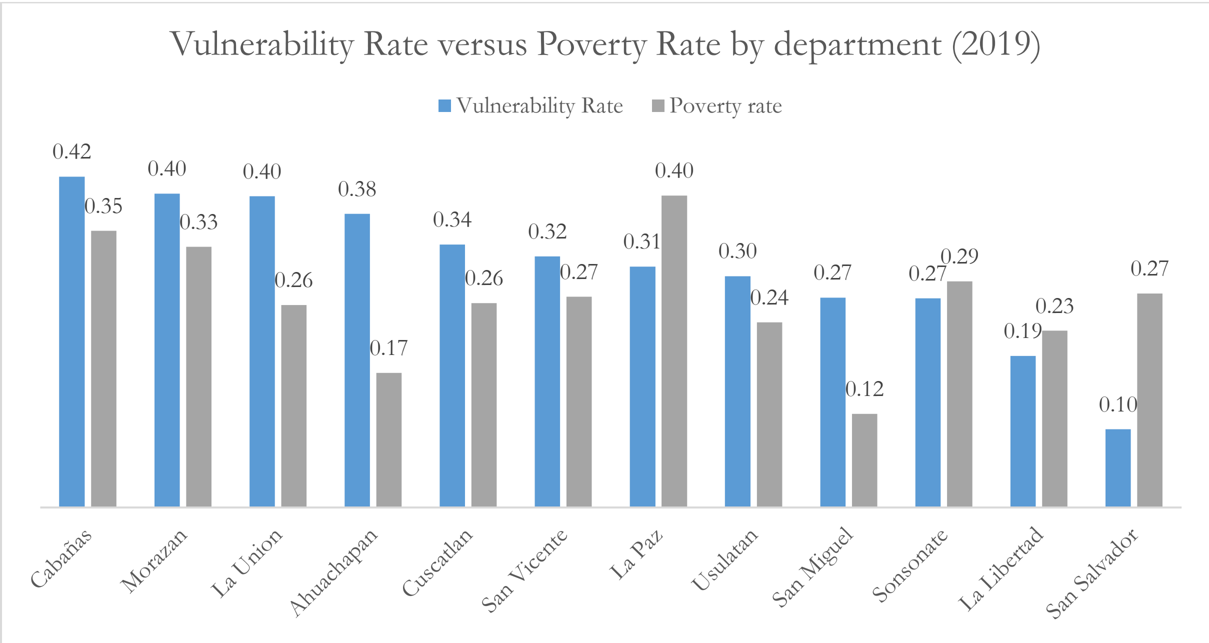
Source: World Bank estimates based on EHPM (2019)

Figure A 11: Sources of vulnerability estimates under a 25 percent probability threshold (2019)



Source: World Bank estimates based on EHPM (2019)

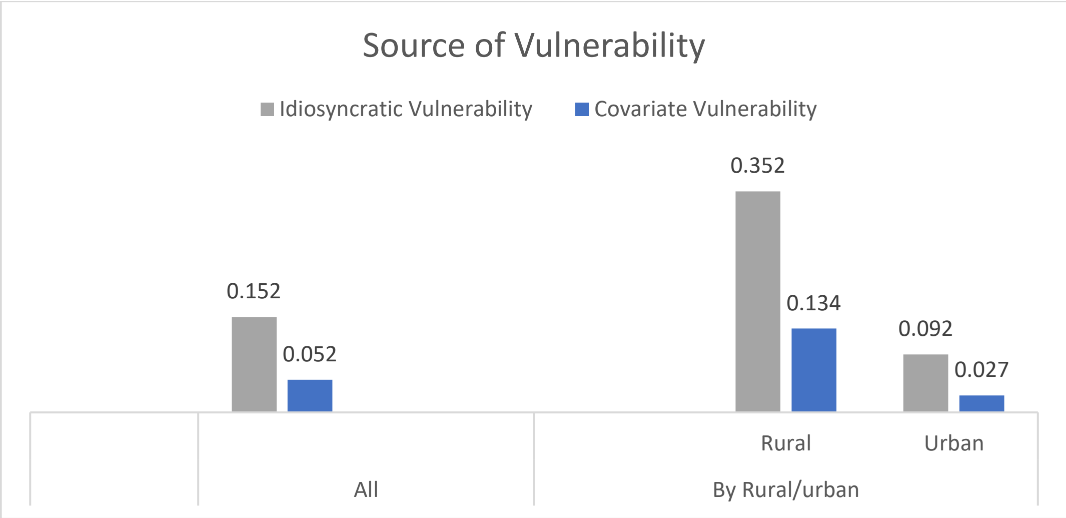
Figure A 12: Vulnerabiliy and poverty by department under a 25 percent vulnerability threshold (2019)



Source: World Bank estimates based on EHPM (2019)

Annex 4 – Relying on 50 auto representative municipalities

Figure A 13: Sources of vulnerability - Restriction to 50 auto representative municipalities (2019)



Source: World Bank estimates based on EHPM (2019)

Annex 5 – Construction of risk indices

In this paper, we construct three different risk indices to measure a person's exposure to natural hazards. For this purpose, we rely on a number of questions about each individual's exposure to different hazards included in the household survey data. We first construct an index measuring exposure to crime. The questionnaire considers 11 different types of crimes, which are robbery at home, robbery on the streets, robbery of vehicles, destruction of property, fraud, extortion, threats, physical violence, abduction, sexual violence, and all other crimes. The index could theoretically range from zero to 11, but only assumes values from zero to 10. Higher values reflect higher crime exposure. Figure A14 reveals that most people report low levels of criminal exposure in 2019.

Similarly, we construct an index, which measures a person's level of insecurity. The following questions form part of our index: if an individual can go out at night in their neighborhood, if they could theoretically have a business in their neighborhood, if they can leave their house empty when going out, if their children can play outside alone, if women can transit safely in their community. This index assumes a value from zero to 5. A higher value reflects a higher perceived feeling of security. Figure A15 demonstrates that around 40 percent do not restrict themselves due to perceived insecurities while around 15 percent of respondents experience very high levels of insecurity in 2019.

Figure A14: Histogram of Crime Index (2019)

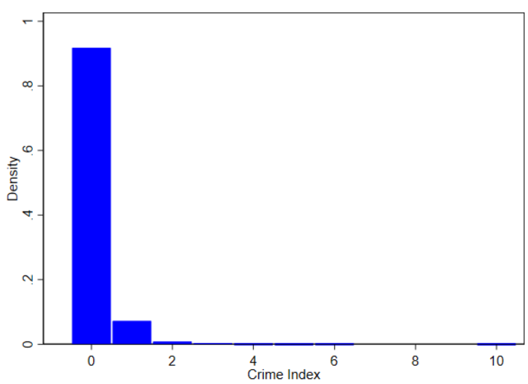
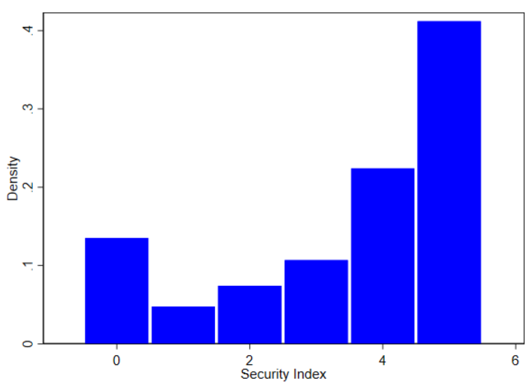


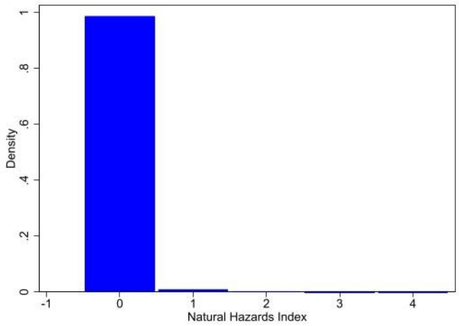
Figure A15: Histogram of Security Index (2019)



Source: World Bank estimates based on EHPM (2019)

Lastly, we construct a measure for people's exposure to natural hazards. We draw from a set of questions asking about people's property damage: if they experienced damages to their housing, material goods, food, animals, or if a household member got injured. Due to the low response rate (standing at 1,527 out of 74,447 possible responses) we treat missing observations as zeros. The index could theoretically range from zero to 5, but only assumes values from zero to 4 in the data collected. Higher values reflect a higher exposure to natural hazards. Figure A16 illustrates that nearly the full universe of respondents does not report any damages as a consequence of environmental hazards.

Figure A16: Histogram of Natural Hazard Index (2019)



Source: World Bank estimates based on EHPM (2019)

Annex 6 – Summary Statistics of adapted variables for the estimation of vulnerability

The table below presents summary statistics when replacing missing observations with zeros due to listwise deletion. We also report the community level variables in this case, which reflect labor market and human capital characteristics at the municipality. Importantly, these rates might suffer from low sample biases. Only 50 out of the 262 municipalities included in the survey report representative data at this level of geographic aggregation. This limitation is another caveat in our underlying analysis. Table A1 presents the results. The table reveals that there is still one variable reporting a large share of missing observations, namely the one indicating the highest educational grade obtained. These missing variables are mainly driven by children below 17 years old. Still, given that replacing this variable with zeros would be misleading, we decide to include this variable in the main model specification, and exclude it as a robustness test.

Table A 1: Summary statistics of adapted variables forming part of the estimation strategy (2019)

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Urban	74448	0.617	0.486	0	1
Male	74448	0.471	0.499	0	1
Single	74448	0.393	0.488	0	1
Age	74448	32.511	21.784	0	98
Ownership	74448	0.675	0.468	0	1
Highest grade obtained	42613	7.181	3.554	1	15
Employed	68609	0.478	0.5	0	1
Self-Employed	74448	0.126	0.331	0	1
Public sector	74448	0.033	0.179	0	1
Informal	74448	0.764	0.424	0	1
No. of Children	74448	1.157	1.151	0	8
Number of children attending school	74448	0.756	0.908	0	6
Number of members in main household	74412	4.322	1.893	1	17

Number of household members out of labor force	74448	1.492	1.173	0	8
Crime Index	71044	0.096	0.359	0	10
Security Index	71011	3.473	1.769	0	5
Environmental Index	74448	0.015	0.155	0	4
Financial literacy	74448	0.225	0.418	0	1
Occupation rate	74448	0.545	0.051	0.279	0.75
Unemployment rate	74448	0.043	0.027	0	0.27
Share of self-employed	74448	0.274	0.066	0.133	0.789
Share of entrepreneurs	74448	0.043	0.025	0	0.498
Share of public sector employees	74448	0.071	0.037	0	0.333
Share of children attending school	74448	0.66	0.071	0.143	1
Share of people with secondary education	74448	0.214	0.118	0	0.62

Source: World Bank estimates based on EHPM (2019)