LUND UNIVERSITY
School of Economics and Management

Master's Program in Economic Development

Natural disasters, unnatural consequences?

Characterizing the causes of natural disaster's vulnerability in Chile

by

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Reducing inequality in Chile has long been a priority of policymakers because of its negative impacts over political representation, spatial segregation and distribution of opportunities. Through the framework of vulnerability, this research suggests that an unexpected impact of inequality in Chile is an increased likelihood of experiencing losses due to natural disasters. By using logistic multilevel regressions based on household survey data, this study finds that disaster-related losses are more likely among households with less economic capacity and entitlements, less mechanisms of political and social power, in more economically unequal settings. At the national and regional level, poverty, rurality and having experienced discrimination are found to be positively significantly associated with increases in likelihoods of losses due to natural disaster. In presence of all the studied factors of vulnerability, it is shown that the likelihood of experiencing losses due to natural disasters increases in 11 percentage points at the national level, and between 9 and 15 percentage points, depending on the region.

Keywords: *natural disasters; inequality; vulnerability; Chile; multilevel logistic regression; household data*

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List of Abbreviations

CASEN: Encuesta Nacional de Caracterización Socioeconómica – National socio-economic charaterization survey
CRED: Centre for Research on the Epidemiology of Disasters
GDP: Gross domestic product
OECD: Organization for Economic Co-operation and Development
ONEMI: Oficina Nacional de Emergencias del Ministerio del Interior – National Office of Emergency of the Ministry of the Interior
PAR: Pressure and Release Model
UNISDR: United Nations International Strategy for Disaster Reduction

1 Introduction

In recent years, the relationship between disaster management and economic development has become a relevant public policy priority in both the developing and developed world. Almost all regions of the world are struck by the natural occurrence of windstorms, floods, droughts, cold spells and heat waves, landslides, earthquakes and other hazardous phenomena. However, in the past 30 years the number and intensity of natural hazards has quadrupled resulting in increased human and economic losses: while in 1998 the world's estimated economic cost associated to natural disasters was of USD$125 billion, in 2017 the number swelled to USD$450 billion used in reconstruction, humanitarian aid, relocation, livelihood recovery and heritage rescue (UNISDR & CRED, 2018; UNISDR, 2018). Climate change scenarios have predicted increases in both frequency and severity of extreme weather events due to global warming, which could imply an elevation of these numbers even further (IPCCC, 2012).

While several natural phenomena occur on everyday basis, not all of them are considered natural disasters. According to the Centre for Research on the Epidemiology of Disasters (CRED), natural disasters are defined as events that have natural causes and lead to 10 or more fatalities, affect 100 or more people, or result in a call for international assistance or the declaration of a state of emergency (UNISDR & CRED, 2018). This difference is made clear when separating the concepts of *hazards* and *disasters*: while the former alludes to extreme geophysical events to which humans are exposed, the latter refers to the adverse effects caused by hazard themselves (Alexander, 2000; Paul, 2011).

There is a common belief stating that natural hazards do not discriminate. Nevertheless, this does not seem to be the case for disasters: economic and human losses are unevenly distributed among and within countries, nations, communities and genders (Yoon, 2012). A way to understand this relates to the fact that disasters' consequences and impacts are very contingent on cultural, economic and social relationships (Neumayer & Plümper, 2007). Social processes that articulate societies generate unequal exposure to disaster risks, making some groups of the population more likely to be affected by disasters than others; an relationship that reflects inequalities of power in societies (Hilhorst & Bankoff, 2004). Therefore, the extent to which communities are vulnerable– or prone to suffer losses (Cutter, 1999) – to disasters does not seem to only be determined by its proximity to sources of risk, but by the characteristics that influence the capacity to prepare, respond and recover from disasters, which are very closely related to income, education and the context to which they are subject (Cannon, 1994). In that sense, it is possible to argue that hazards are natural, but disasters are, instead, socially constructed; even a function of income and social inequality (Cannon, 1994).

Overall, it seems that exposure to natural hazards is not enough to explain the differences in losses, but instead, some function of economic development is part of the equation. Income, ethnicity, age, rurality and education seem to be crucial in determining who is affected the most by hazards and to whom they turn into disasters. To explore this puzzle, this research pretends to examine the distribution of natural hazards' caused damage, focusing on the country of Chile, attempting to identify the factors that increase vulnerability to natural disasters. Chile represents an especially compelling case of study for exploring exposure and impacts of natural disasters and how different population groups are affected by them. Located between the Andes and a long coastline with the Pacific Ocean in the so-called 'Pacific Ring of Fire', Chile is one of the countries with the highest volcanic and seismic activity in the world, registering in the past 100 years three of the top-five strongest earthquakes in history (Bronfman et al., 2016). Among the OECD countries, Chile is classified as the most exposed to natural hazards, with 13% of its area and 54% of its population exposed to 3 or more different types, which vary geographically and regionally (Dilley et al., 2005). This provides the opportunity to analyze a broad scope of risks and hazards, ensuring that the results are not disaster-specific.

Besides the abundant geographic diversity, great social and economic inequalities characterize Chile. The country exhibits the second highest income inequality within the OECD, with a Gini Index of 45%, with the closest follower, Turkey, almost 5 percentage points behind (OECD, 2019). This degree of income distribution's skewness permeates most aspects of social interactions. More than 28% of Chileans feel they belong to a group that is discriminated against, the highest rate in Latin America (Latinobarómetro, 2015). High levels of inequality have also been documented on access to education, health, housing quality, regional disparities and urban-rural gaps, which may enhance differences in vulnerability even further (Cociña, Frei & Larrañaga, 2017; Parro & Reyes, 2017; UNDP, 2014; Valenzuela, Bellei & De los Ríos, 2014).

Therefore, this research aims to explore the relationship between inequality and natural disaster vulnerability by surveying the impact that differences geographic, social and economic characteristics have on the likelihood of being affected by natural hazards in Chile. Since the concept of vulnerability is a dynamic one which is determined by the variety of risk and structures of inequality in different countries, this research will attempt to answer to the question of *which households' factors have an impact on disaster vulnerability in Chile,* or, in other words, which empirical characteristics increase disaster vulnerability. Through this question, this research pretends to specifically contribute to the study of social vulnerability, but also to that of the consequences of inequality in a broad sense. Empirically, I will show that mechanisms related to economic capacity and entitlement, social and political power and structure of income inequality are significant in impacting the likelihood of experiencing losses because of natural disasters.

In the Chilean context, while the research in the causes and consequences of inequality is vast, little previous research has addressed the unequal impacts of natural hazards, and when so, it has been done at the local level (Sandoval Henríquez, 2017; Sandoval & Voss, 2016; Vasquez et al., 2008; Vásquez & Salgado, 2009). No research has been carried out at the national level, which is allowed by the existence new data provided by the use of the Socio-economic Characterization National Survey – *Encuesta Nacional de Caracterización Socioeconómica CASEN* -, a nationally representative survey gathering information of over 200.000 Chile inhabitants. For the Chilean context, this research will empirically contribute by expanding case-studies to a national perspective, including a large, nationally representative sample.

Although this is a single-country study, its consequences may be understood in a broader scheme by relating to non-traditional consequences of inequality, in which way I pretend to contribute theoretically. By linking disaster risk to inequality in vulnerability, the Chilean case is just an example that can be applied to other countries in which similar structures of inequality are present. The Chilean case represents an exception in terms of its high exposure to disaster risk, but other countries with high social inequality may find similar distributions of losses concentrated in specific groups to different extents. In this sense, this research pretends to link the literature of disaster risk management, economic and social inequality and vulnerability in an empirical study.

This research will be organized as follows. Section 2 reviews the theoretical framework on vulnerability, its relationship with disaster risk and its determinant factors. Previous research on the topic is surveyed. This section includes a background analysis on Chile, its social and economic inequality history and disaster risk policies. Hypotheses are presented at the end of this chapter. Section 3 presents the CASEN survey, proxy and control variables, as well as data limitations. Section 4 introduces multilevel logistic regression models, and the empirical models that this research will test. Section 5 presents the results of multilevel logistic regressions for within-cluster and between-cluster analyses, as well as its discussion. Concluding remarks and implications are examined in Section 6.

2 Theory and background

2.1 Theoretical Approach

Disasters are multidimensional and all-encompassing occurrences that extend across various aspects of human life impacting environmental, social, economic, political and biological conditions. When studying its effects, this multidimensionality needs to be reflected into an analytical arena, and the concept of vulnerability has become key in understanding what impacts communities' likelihood to become endangered or affected by natural hazards (Oliver-Smith, 2004). This section, therefore, will first examine the relationship between vulnerability and natural disasters, and the factors to which it is related. The Chilean context in natural disasters will be presented afterwards.

2.1.1 Vulnerability and natural hazards

The disaster management literature has introduced a variety of concepts that are useful for asserting who is more and less likely to be affected by natural disasters. In the first place, 'hazard' refers to the natural events that affect places at different times (Wisner et al., 2004: pp. 7). Hazards have different degrees of intensity and severity, and weather and climate statistics allow for the estimation of hazard occurrences as a general trend (Wamsler, 2014). However, these are not enough to estimate the losses, which come from the concept of risk of disaster. The concept of risk of disaster is an interaction term of the natural hazard and the number of vulnerable people, which could be schematized in a semi-equation like, as argued by Wisner et al., (2004: p.49) and Wamsler (2014):

$$\textit{Risk of Disaster} = \textit{Hazard} * \textit{Vulnerability}$$

A disaster, then, can be defined as a 'serious disruption of the functioning of a community involving widespread human, material, economic or environmental losses and impacts exceeding the ability of the affected community or society to cope using its own resources' (UNISDR, 2009: p9). This definition refers to the different scales of impact, but also to the way communities are capable to cope with it in terms of preparedness and response, a model that has been referred to as the Pressure and Release (PAR) model (Wisner et al., 2004). Overall, the basis for the PAR model is that a disaster originates because of the intersection of two forces: those that generate vulnerability on one side – risk factors -, and the natural hazard event on the other side. The 'release', instead, may come from reducing vulnerability through addressing its 'root causes', or the risk factors that increased it in the beginning (Adger, 2006). In other words, the likelihood of disaster in a community is a function of both their biophysical exposure and their social dimension, as shown in Figure 1:

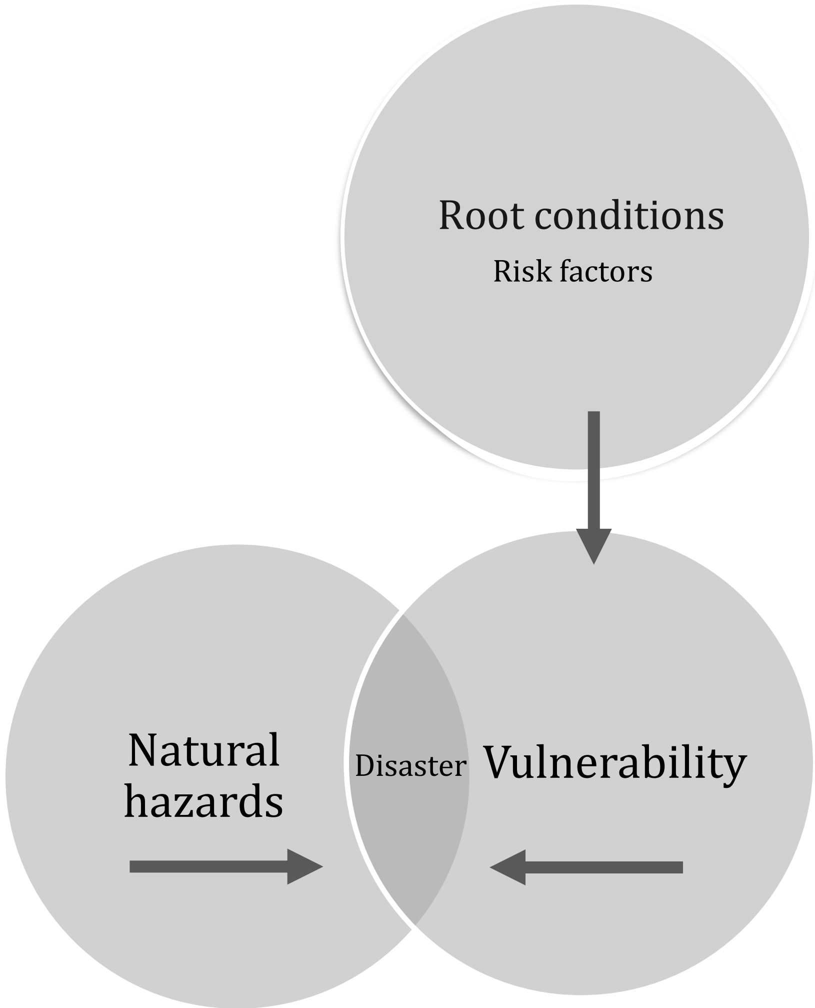

Figure 1: Pressure and Release Model

Source: Author's based on Adger (2006)

In all these definitions, vulnerability is at the core of the definition of who is at risk of experiencing disasters. The concept of vulnerability has been used across different fields and disciplines including disaster management, development studies, economics, anthropology, geography, and environmental studies (Alwang, Siegel & Jørgensen, 2001; Bergstrand et al., 2015). Because of its widespread use, a consensus on a definition has not been reached. However, as noted by several authors (Cutter, 1996; Cutter, Boruff & Shirley, 2003; Füssel & Klein, 2006), two opposing strands of literature arise in this regard: one that identifies vulnerability as the material conditions that make people or places potentially more likely to losses in case of extreme weather events; and one that understands it as a social condition that measures societal resilience to hazards. In that sense, vulnerability has been understood as a context, but also as an outcome, i.e. societal resilience.

Following the economics and disaster management tradition, in opposition to the human and political ecology one, this research will adopt the definition of vulnerability that understands it as the traits and conditions that make humans vulnerable in coping with disasters which go beyond the risk exposure itself (Alwang, Siegel & Jørgensen, 2001; Cutter, 1996; Wisner et al., 2004). In this definition, vulnerability refers to a group of pre-existing conditions of the population that influences its ability to prepare, respond, and recover from hazards, therefore making them more likely to be affected and disrupted by them (Roncancio & Nardocci, 2016).

Specifically, in the PAR approach, factors or conditions that generate vulnerabilities are accumulated producing differentiated environmental and disaster risk through social structures and inequalities which influence the ability of groups to respond to disasters, but also, characteristics which difficult access to information, knowledge and technology, limit access to political power and representation, and diminish the quality of infrastructure (Wisner et al., 2004). These factors that can be summarized in three processes of inequality: entitlement, or economic capacity; social power and political economy, or historical and structural class-based patterns of social reproduction; and the interaction of these two, or mechanisms related to income inequality (Cutter, 2001; Cutter, Boruff & Shirley, 2003). All of these social processes that may generate unequal exposure to risk by mirroring power relations in society are different components of vulnerability (Cannon, 1994; Hilhorst & Bankoff, 2004; Watts & Bohle, 1993), and will be explored in the following section.

2.1.2 Factors affecting vulnerability: who is at risk of disaster?

Factors related to mechanisms of economic capacity and entitlement

From the definition presented above, it can be inferred that the concept of social vulnerability is closely linked to poverty. However, they are not perfect correlates: not all socially vulnerable people are poor, and not all poor are vulnerable to natural disasters (Bandyopadhyay, 2016; Yoon, 2012). Instead, unlike poverty, vulnerability is a dynamic concept that expresses changing social and economic conditions concerning the nature of hazards (Huafeng, 2016), which is more related to socio-economic conditions, incorporating race, gender, age, and other marginalized groups in an intersectional way. Disaster vulnerability arises out of the social and economic circumstances of everyday living (Morrow, 1999), therefore there is no universal checklist of vulnerable groups that may apply for all cases. Poor people are generally the most vulnerable, but an understanding of vulnerability rests on a disaggregation of the structure of poverty itself (Swift, 1989).

The mechanisms under which marginalized groups are more vulnerable than others are multiple. A first one comes straight from the lack of material and economic resources. Poor households have limited financial reserves for supplies before an announced natural hazard and for buying reconstruction materials in the aftermath (Morrow, 1999). Non-poor households' asset damage can sometimes be greater in monetarized value, but the proportion of assets damaged for the poor is usually larger (Sawada & Takasaki, 2017). Therefore, the impact is likely to affect them disproportionately, including higher mortality rates and housing damage: they are built with worse materials and are usually overcrowded, enhancing the difficulty for evacuation (Wisner et al., 2004). Poorer households will recover slowly or not entirely at all, which will increase their future vulnerability as well (Watts & Bohle, 1993). Moreover, poorer households are often located in more vulnerable locations, which may threaten the household itself but also belongings in the case of floods, earthquakes or landslides; and difficult the access to public transport for evacuations (Bolin & Stanford, 1998).

Factors related to mechanisms of social and political power

As stated before, not only the lack of resources impacts the likelihood of disaster impact. Households possess different human resources and capabilities, such as health and physical ability, education and skills, which may be related to income but have different causal mechanisms (Morrow, 1999). Age-wise, the vulnerability of the elderly varies significantly with age, health, family and economic circumstances. However, the elderly usually lack independent physical and economic resources for appropriate responses, are more likely to suffer health consequences and will recover slowly (Bolin & Klenow, 1983; Donner & Rodriguez, 2008). On the opposite, children's vulnerability is also higher than adults, since they lack the ability to handle their own evacuation and recovery. Additionally, disasters have a gendered nature. Traditionally, women's roles have been related to look after and protect children and elder relatives, as well as to maintain and take care of the family's property, which hampers their own rescue effects (Neumayer & Plümper, 2007). Relief efforts rely on existing structures of resource distribution, which usually implies that women are marginalized in access and so are households led by them (West & Orr, 2007).

Living arrangements also have disaster-related consequences, given that the material and non-material resources available to any household are affected by the ratio of productive adults to dependents. Moreover, the personal experience, education and skills possessed by the adults in a household can significantly influence its resiliency. The problems posed by illiteracy or poor language management are great when seeking information, understanding evacuation routes and alerts (Bolin & Kurtz, 2018).

Lack of family and social networks can also be a risk-increasing factor. Fast-growing communities are more likely to contain isolated households with limited social and family networks to activate in times of crisis (Christian et al., 2019). Similarly, discriminated groups like immigrants and ethnic and racial minorities may lack connections to the larger community and hesitate to seek assistance outside their immediate contact group for a variety of reasons, including a fear of government officials and of discrimination, while simultaneously be denied of such assistance (Donner & Rodriguez, 2008).

Another important factor in a household's exposure to disaster is the degree to which it lacks autonomous control over its circumstances: vulnerability is also dependent upon a household's relation to community decision-makers, impacting the speed of recovery and distribution of aid, but also placement of early warning systems and other prevention factors (Cannon, 1994). In this regard, the recovery of a community can be tied to its position in the local or national political power structure. For example, isolated and/or rural areas can be ignored in the politicized environment surrounding a disaster, and they are usually correlated with poverty (Gillis Peacock, Gladwin & Morrow, 2012).

Factors related to mechanisms of income inequality

Because of the factors outlined above, the definition of vulnerability is built upon the notion of inequality, of which one representation is income inequality. All of the mechanisms that impact vulnerability are, in some way or another, related to the use of resources and the extent to which communities and households are entitled to make use of them in order to determine their ability to cope with and adapt to disasters (Cannon, 1994; Sen, 1990). In this sense, by understanding the use of resources as a function of entitlement, an underlying premise states that institutions are moderating its access: as argued by Kammerbauer & Wamsler (2017) the status quo structure of entitlements determines which groups bear unwanted costs and which ones are able to confide in the power of the state to protect interests. This implies, for example, that some groups may get better access to assistance, recovery funds and reconstruction than others, reinforcing or reshaping patterns of poverty. Moreover, inequality acts as a catalyzer of other factors determining vulnerability: for example, richer people will tend to reside in areas that are less prone to disasters, whereas poor people will not be able to choose to do so in areas that are safe, increasing their exposure (Yamamura, 2015).

Specifically, there is a body of research that has analyzed the impacts of natural disasters over income inequality. This builds on the idea that when a natural disaster strikes, it is poor people in a larger proportion who are more likely to be injured or unable to work, suffering through infrastructure destruction. Therefore, their incomes are overly-likely to be impacted, whereas the same will not usually happen to those who are better off, widening income disparities and income inequality. However, the inverse relationship has also been researched: in particular, as argued by Anbarci, Escaleras & Register (2005), higher income inequality hinders the rationale for collective action that creates the base for mitigation and preparedness for natural hazards, which, in a way, helps them turn into disasters. Moreover, in a society with high income inequality, informational asymmetries are high and politicians are less accountable for prevention and mitigation efforts, which hinders efforts for disaster prevention (Besley & Burgess, 2002).

Overall, all of these impacts are crossed by each other empirically. Poverty is likely a more definitive marginality but is compounded by membership in other groups. On average, poor people are more likely to be female, which implies they will be more affected by disasters. Rurality and disenfranchisement are usually highly correlated (Hilhorst & Bankoff, 2004; Morrow, 1999). Moreover, when these factors are combined with high inequality, whether as a cause or as a consequence, effective policy for recovery and rebuild is likely to be segmented and therefore increase vulnerabilities further.

Vulnerability has become a strong orienting principle for the field of disaster studies in the sense that it is able to encompass a variety of aspects crossed related to economic positionality or the position society determined by income and other factors (Oliver-Smith, 2009). It is in that sense that it is possible to argue that disasters and its consequences are deeply enrooted in history and political economy, since exposure and vulnerability, as part of the conceptual equation of 'hazard × vulnerability = risk → disaster', are a combination of complex social, economic, political, and cultural relations. Understanding the role each one of these factors has in determining the likelihood of disaster will be the main aim of the empirical part of this research.

2.1.3 Previous research

The empirical research of the economic impacts of natural disasters has several layers. First, some research has dealt with the effects of natural disasters on macroeconomic indicators. There are no clear causal mechanisms for this reduction: from a Schumpeterian point of view, creative destruction could even bring growth rates up, but traditional neo-classical growth models predict that the destruction of capital would lower it (Cavallo et al., 2013). Indeed, empirical evidence has found evidence for both of these claims. Meta-analytic works have found that natural disasters usually bring an immediate contraction in economic output, a deterioration of a country's balance of trade and fiscal balances, and an increase in poverty and income disparities (Felbermayr & Gröschl, 2014; Klomp & Valckx, 2014). Time-wise, it has been found that reductions in the growth of GDP typically occurs in the year that the event occurs, with the potential for sharp increases in subsequent years. Alternatively, Skidmore & Toya (2002) find that although disasters reduce the expected rates of return to physical capital, it increases relative returns to human capital which promotes investments, forces the update of new technologies and overall improves total factor productivity.

In relevance for this study, the relationship of natural disasters and vulnerability has been also been tested empirically, in two different types of research. A first group is comprised of qualitative and small-N studies, usually from the field of sociology, which deal with the mechanisms adopted by communities with specific needs in recovering and responding to disasters. Usually, this literature is disaster-specific, and argues that specific community vulnerability is not applicable for other cases, therefore does not intend to generalize in any way. Building on the PAR model, examples of this are found in Christian et al.'s work (2019), who analyze the impact of rural livelihoods programs in India over cyclone impacts; Besley & Burguess (2002) who do so with government first-responses over flood damage in the Bengal region; and Bolin & Stanford (1998) who study the needs of the elderly in Californian communities for earthquake responses. Differently, Graif (2016) found that a group of Hurricane Katrina's single-mothers victims experienced upward mobility by forced resettlement, which created new networks and job opportunities. While the advantage of these approaches is that they see vulnerability as shifting, contingent, and spatio-temporally variable, they impede cross-country and time comparison.

A second type of research is quantitative and examines national or global impacts of different components and definitions of vulnerability over natural disasters-related losses. Some research has focused on the impact of specific factors over disaster risk. Anbarci, Escaleras & Register (2005) find that a positive relationship between income inequality and earthquake deaths in a worldwide sample. Kellenberg & Mobarak (2008) find the effect of income over household vulnerability to be marginally decreasing after USD$4,000 per year. Finally, Neumayer & Plümper (2007) study the gendered impacts of natural disasters, and find that most disasters decrease the life expectancy of women more than men's and have higher mortality rates for women, a relationship that is mediated by income.

The single-factor literature, however, has a strong weakness: understanding vulnerability as a single-factor determinant, which does not build on societal relationships. Instead, another approach which has been common in the economics and geography literature builds on the PAR theoretical development of accumulated vulnerabilities coming from different factors. Usually these rely on the creation of composite indices or multilevel models for addressing global vulnerability to disasters, focusing on the community-level or household level. The better-known case is the Social Vulnerability Index (SoVi) (Cutter, Boruff & Shirley, 2003), which uses a normalized set of 42 United States' census variables to measure vulnerability for 3000 counties, including variables for dimensions of age, income, race distribution, rates of poverty, population change, housing stock and infrastructure dependence. This was found to be significantly correlated with presidential declarations of disaster at the county level (Cutter, Boruff & Shirley, 2003). A great number of indices has been created based on this approach for specific hazards: Boruff et al. (2005) for coastal erosion, Myers et al. (2008) for hurricanes in the US, and Fekete (2009) for flooding in Germany.

In the case of single-year measurements, multilevel regression modeling has been the more common approach. Examples of this can be found in Huafeng's work (2016), which developed a vulnerability analysis of Chinese provinces relying on different accounts of poverty at the household level, by building multilevel models with measurements at the household and community levels. Rasch (2017) finds similar results for Brazil's vulnerability to floods focusing on the relevant impact of income inequality as a mediator variable for all levels.

The limitation of composite and quantitative approaches is that they understand vulnerability as a fixed condition, inherent in a certain fraction of the population. However, it allows for large-N analyses and the quantification of impacts of different factors. Overall, despite the approach, all vulnerability to disaster literature seems to refute the randomness of natural disaster and understands them as social events.

2.2 Background: Chile's inequality structure and disaster management history

Chile is located in the Southern Cone in South America, bordering the Pacific Ocean, the Republics of Peru and Bolivia, the Andes mountain range and Argentina. It has over 18 million inhabitants over 750.000 km^2 of land, of which 6.5 million live in the capital city, Santiago. Administratively, the country is divided into 16 regions and 345 municipalities, and 88% of its population lives in urban areas. 65% of the Chilean labor force is employed in services, although most of its GDP is attributed to mining activities, especially from copper and non-metallic materials (UN Statistics, 2019). Currently, the average GDP per capita is around US$15.000, the highest in Latin America.

Figure 2: Administrative divisions of Chile

Source: Biblioteca del Congreso Nacional de Chile (2019)

Chile has long been considered the most stable country in Latin America. In economic terms, GDP grew steadily since 1990 increasing by 149% and reaching USD$227.1 billion in 2018 (The World Bank, 2018). Poverty reductions efforts have done so from 68.6% in 1990 to 11.7% in 2017 (CASEN, 2017), and access to education and health have increased, elevating HDI by 20% to a value of 0.843 – similar to Portugal (UNDP, 2018). Politically, since the return of democracy in 1989 after a 17-year dictatorship, the country has been politically stable and showcased Latin America's most institutionalized party system, as well as strong and reliable institutions, strong party discipline, and low levels of corruption and voting shares for populisms (Roberts, 2015).

However, together with the advances the country has experienced in the past couple of decades, inequality has also been a characteristic of Chilean's development. As argued by Rodríguez-

Weber (2017), this has been an Achilles heel since independence, which could be attributed to a historical malapportionment of land in favor of the Spanish elite in the early XVII century. As the author estimates, the Gini Index follows a similar trend to Milanovic' Kuznets inequality waves (Milanovic, 2016) for the 1850-2010 period (see Figure 2). However, the trend has not gone down since the 1980's, but rather has stabilized at a high point. Since 1990, the Gini Index has fallen only 0.52 to 0.48 (CASEN, 2017). While this reduction has been credited to improvements in education which have improved wages, recent analyses suggest that the premium skill is exhausted (Parro & Reyes, 2017), giving little reason to believe the downturn will continue.

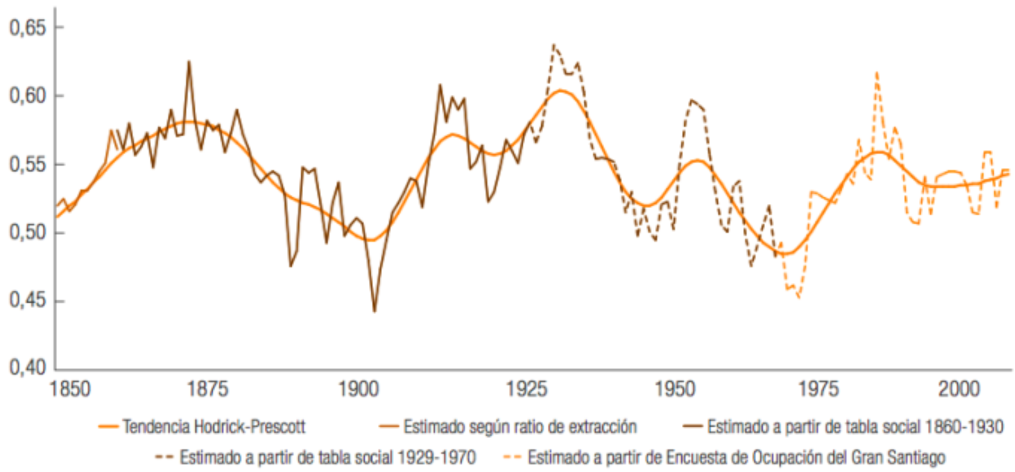

Figure 3: Historic estimated Gini Index

Source: Rodriguez Weber (2017)

In line with Milanovic's argument showing the rise of global plutocrats since the 2000's, income in Chile is highly concentrated in the 1% and 0.1% top earners, which maintain over 33% of the national income and 19.5% respectively (The World Bank, 2015). Overall, this has implied that relative inequalities have reduced, but the absolute income distance between the richest and poorest has grown. Since 2000, the 1st income decile has seen increases in salaries of 145%, whereas the top 10% has by 30%, bringing down the Gini Index. However, in absolute terms, the per capita real gain has been of USD$43 for the lowest 10%, and USD$372 for the highest 10%, almost 9 times higher (Cociña, Frei & Larrañaga, 2017).

The current status of income inequality also has effects over perceived justice and democracy. Most Chileans feel that society's retribution is not in line with their individual effort, in what has been referred to as the 'qualitative aspect of income inequality' (Espinoza, 2012). In particular, 41% of Chileans feel that they have been discriminated against, most because of their social class or gender (PNUD-DES, 2017)

However, it is not only a matter of perceived inequality. Chile holds the highest HDI in Latin America, ranking 38th in the world. However, adjusting it by inequality, which considers how the poorer in society live, makes the country drop 32 positions in the ranking and lose 18% of its value (UNDP, 2018). In concrete terms, the worse living conditions of the poorer, fostered by worse educational and health infrastructure, imply low levels of inter-generational mobility and spatial segregation (Espinoza & Núñez, 2014). According to the PISA indicators, students of the 1st and 5th quintile show the largest differences in Latin America (UNDP, 2017). The Chilean state capacity – understood as the ability to effectively exert sovereignty by providing basic services (Luna & Soifer, 2017) -, has been documented to be extremely limited in rural settings, as well as in poor communities, unable to provide access to primary education for all children, health services within the reach of emergency care time, and housing beyond emergency settings.

Moreover, segregation of specific groups has characterized the latest trends of Chilean social development. Rural population in Chile holds most of the poor and indigent incomes, characterized by temporary and informal employment and low educational levels (RIMISP, IDRC & IFAD, 2018). However, even in areas where income is within the national averages, rural population suffers from under provision of basic public services, isolation, and lack of telecommunications coverage. Indigenous people also suffer from severe segregation: on average, indigenous households, which constitute around 10% of the total population, earn less than half the income of those who are not. They are also heavily excluded in terms of land ownership, water rights and educational access (Agostini, Brown & Roman, 2010).

The preservation of Chilean inequality cannot be understood without focalized social policy. Overall, state's action has been insufficient to reverse income inequality, by means of deficient and insufficient public spending, but also by failing to guarantee access to services non conditioned to payment capacity. During the military dictatorship of Augusto Pinochet, Chile experienced a strong process of social policy retrenchment, when the Junta adopted radical market-oriented reforms in most areas. In this period, most social programs' execution were delegated to subnational or private actors, incorporating market mechanisms such as demand subsidies, educational vouchers, and health services payment (Castiglioni, 2018; Ocampo, 2008). With these, a network of direct poverty subsidies was created, incorporating the concept of 'focalization' in public policy, or the directionality of social policy to priority groups, accompanied with a heavy reduction of public expenditure in education, health and housing (Parro & Reyes, 2017). Great varieties existed and persist between and within subnational entities in terms of income and capacities, which has led to enormous differences in results and coverage of basic needs and services, creating inequalities in life quality.

After democratization, most market-oriented and decentralized policies persisted until well into the 2000, and a large majority is still in place. Instead of a comprehensive welfare or social policy, Chilean's has been characterized as a constellation of subsidies and social help that intervene fragmentarily without creating a sense of entitlement to it (Ceballos, 2015). For example, only in 2008 a pension system was established for those with salaries below the minimum, which coverage was raised to include the 60% poorer and house-workers. Women who are registered in the social protection system are entitled to receive 'care packages' for born children; and public schools are not guaranteed funding, but rather students are through a system of vouchers (Bellei, 2015).

In housing policy, particularly relevant for disaster risk management, the subsidiary nature of state policy has also been present. While vouchers and private offer have helped reduce the quantitative demand for housing, which has implied that more than 70% of Chileans own their houses, the quality of housing has decreased (Brain & Mora, 2012). With social housing being subject to private offer, it has to compete for location with better payers, which has derived into its agglomeration in peripheric areas of cities, where services are worse, and more disaster risk has been reported (Cociña & Boano, 2013).

In conclusion, the entrenchment of structural inequality given by income, social class and other social factors, and the lack of effective redistributive policy contribute to the establishment of segmented life qualities, impacting access to health, education, housing, and as will be argued next, disaster risk safety.

2.2.1 Natural disasters in Chile: Impacts and institutional responses

In year 2017, the years analyzed by the survey that this research employs, the National Emergency Office (ONEMI) registered 41,457 affected households due to natural disasters.

Within these, almost 4 million Chileans were registered to have suffered from some source of natural hazard, as shown in Table 1.

Table 1: Number of affected inhabitants according to type of disaster, 2017

Type of hazard	Number of affected people
Wildfires	289,643
Flood	4,266
Drought	6,805
High tides	68
Snowstorms	407,690
Rainstorm	397,229
Earthquakes	6,588
Storms	2,568,826
Tornados	16,633
Wind storms	28,159

Source: Author's based on ONEMI (2018)

During this year, ONEMI characterized four events as major disasters: 1028 wildfires in the Maule region in January 2017; a low-pressure front and snowstorm in the Northern regions of the country followed by landslides; a snowstorm in the Metropolitan region of Santiago; and a landslide product of a snowstorm in the Chaitén municipality, in the 10^{th} region of Los Lagos (ONEMI, 2018). Overall, 2017 costed the Chilean state around USD$150 million in disaster and emergency management and risk, about half of the of the decade's average.

The regional distribution of affected inhabitants is shown in Table 2.

Table 2: Distribution of inhabitants affected by natural disasters by region

Number	Region	Number of affected inhabitants	Total inhabitants	Share
I	Tarapacá	2124	330558	1%
II	Antofagasta	49874	607534	8%
III	Atacama	395317	286168	138%
IV	Coquimbo	231489	757586	31%
V	Valparaíso	135557	1815902	7%
VI	O'Higgins	13054	914555	1%
VII	Maule	1049428	1044950	100%

VIII	Biobío	567177	1556805	36%
IX	Araucanía	596722	957224	62%
X	Los Lagos	95652	828708	12%
XI	Aysén	8129	103158	8%
XII	Magallanes	28143	166533	17%
XIII	Metropolitana	391020	7112808	5%
XIV	Arica	22988	226068	10%
XV	Los Ríos	6820	384837	2%

Source: Author's based on ONEMI (2018)

Note: Shares may show over 100% given that disasters are not mutually exclusive. Therefore, these are presented just as an illustrative measure

As has been argued before, Chile's geographic characteristics imply that almost all its territory is exposed to natural hazards. The variety of climates in the national territory also bring a variety of hazards: the north contains the driest desert in the world, whereas the south is crossed by large ice fields and strong winds, both with very deficient communication systems towards the center. In particular, the crossing of the Andes mountains – an intense seismic and volcanic activity area – and the long line of coast line make the country vulnerable to a large variety of disasters, some of which may be prevented but others which are harder to.

As shown in Figure 4, 100% of its population is subject to considerable earthquake damage; almost 80% to winter storm's damage, and more than half to that produced by droughts. Historically, indeed, between 1980 and 2017, the average annual losses due to natural disasters in Chile reached 1.3% of the country's GDP (UNISDR, 2018). Between 2000 and 2016, an average of 2 natural hazards occurred every year, with an economic cost of US$1 billion. In all of these cases, more than 50% of costs were absorbed by the state. In particular, the 2010 Maule earthquake and tsunami, the largest catastrophe in the last years, caused losses of over US$30 billion, or 18% of Chilean GDP (Brain & Mora, 2012).

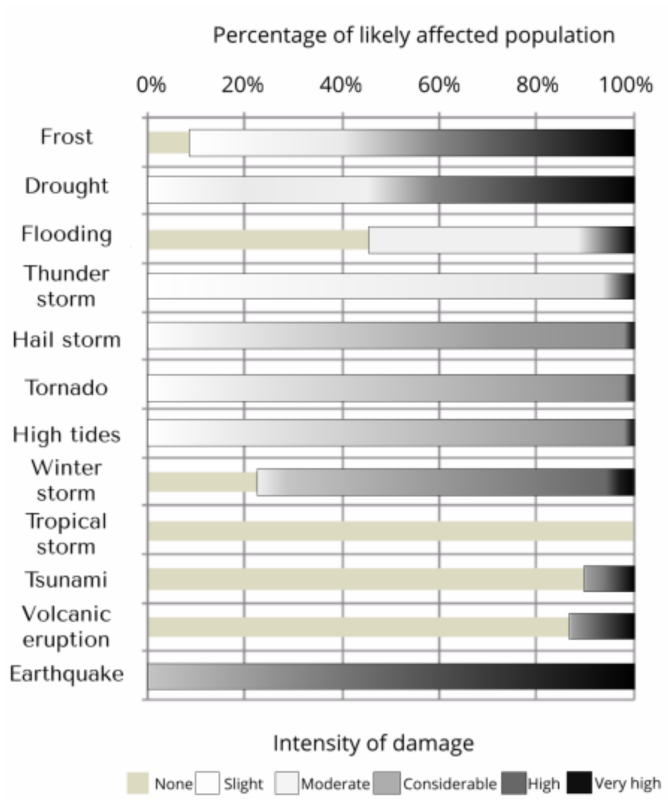

Figure 4: Natural hazard exposure and likelihood of damage, Chile, 2017

Source: Author's based on MunichRE (2018)

Because of these characteristics, the state of Chile has developed a large set of policies and institutions tasked with the coordination of disaster action, framed under the 5th article of the National Constitution, which states that it is the State's duty to provide safety to the population. Currently, the main instrument in disaster risk management is the National Disaster Risk Reduction Policy (RESDAL, in Spanish), established in 2014. This was the product of a joint assessment between the Chilean government under Michelle Bachelet, and an external evaluation provided by the United Nations International Strategy for Disaster Risk' Hyogo Action Plan, which will be reviewed ahead (ONEMI, 2014a).

Although this is the first national coordinated effort to respond to disasters, previous policies existed spread throughout Chilean institutions. Usually, these have come as a response to large disaster events. For example, after the greatest earthquake registered in history hit the southern city of Valdivia in 1905, the University of Chile established a monitoring system for seismic activity in 1908. The first concrete actions towards disaster risk management came in the early

1930's, with publication of the first building code in 1931 regulating high edification and anti-seismic measures, as well as with an analytical effort to identify disaster-prone areas in the General Law of Construction and Urbanization (Sandoval & Voss, 2016).

However, an integral policy was not established until 1964: after a strong earthquake and tsunami in the south and center of Chile, the National Emergency Office (ONEMI, in Spanish) was created, which would act as the articulator of all prevention, response and recuperation against disasters. In 1977, the first organic plan involving all ministries and undersecretaries was created, which was held in place until 2002, when the National Plan of Civil Protection replaced it, considering pre-existing conditions as part of the risk and disaster management policy for the first time. In 2010, the Maule earthquake and tsunami promoted the reorganization of ONEMI into a National System of Civil Protection and Emergency Plan, which included the implementation of a National Agency of Civil Protection.

The current policy, established in 2014, recognizes the human aggravated nature of natural disasters, and attempts to take action for three levels: for families, productive systems and social entrenchments. Because of this, it is built on three main principles: complementarity between private and public actors; decentralization, with the objective of strengthening local capacities and relying on closer-to-source information; and coordination between all levels (ONEMI, 2014b). In practical terms, it implies that each administrative level (regions and municipalities) must have a Civil Protection Committee (CPC), which must create a 'plan' to implement prevention and mitigation actions. CPCs are composed of private and public representatives from a great diversity of local and intermediate government agencies. The costs of these actions are covered by the regional offices budget, meaning that there is great variability within and between regions (Sandoval & Voss, 2016).

Nevertheless, lower and upper levels of administration do not always coordinate their plans, which implies that, at the time of emergency, directives at the local or municipal level can be overridden by upper levels. In addition, despite the declaration of ONEMI as a risk and disaster management agency, its focus has mainly been set on emergency management and response, perhaps as a continuation of its legacy from its initial structure in 1974. Evidence has also found that decision-making has been strongly based on political and mediatic considerations instead of technical ones (Sandoval Henríquez, 2017).

While the policy of disaster management and emergency response has usually been positively highlighted by Chilean press and authorities because of the relatively little number of casualties in the aftermath of disasters, there is strong evidence showing large deficiencies that have enhanced the uneven distribution of disaster impacts. Navia (2010) shows that poor coordination between local, regional and national level, especially in rural areas effectively slowed down first responders and alert systems. Structurally, it has been asserted that the pre-existing conditions of inequality between regions and municipalities regarding economic resources and political tensions have contributed to enhancing impacts over poor and isolated areas, especially those disconnected from centers of power (Elnashai et al., 2010).

Overall, this generates a complex dilemma: the local sphere is the one that handles better and closer information about the reality it is set on, and the one to which citizens go to when they are in emergency situations. However, the disparities between them, the lack of adequate coordination, and the inexistent installed capacities at these levels generate a limited ability to respond to emergencies and disaster policy. In this sense, the policy of disaster and risk management can also be understood as a reproduction of territorial and economic inequalities.

2.2.2 Empirical research

While the empirical research on Chileans' vulnerability has not been extensive, there are some studies that have addressed differentiated distribution of disaster damages, most of which is related to the 2010 Maule earthquake and tsunami. Larrañaga & Herrera (2011) analyze a CASEN survey subsample performed after this disaster in the 5 impacted regions. The authors find that because of localization in more risky areas as well as poorer housing conditions, lower income households were 3 times more exposed to losses and damages from the earthquake and tsunami than higher income ones: overall, 12% of the 1st quintile houses were affected and only 4.6% of the 5th. They conclude that this disaster did not only caused a stronger economic impact in poorer households, but also that they struggled more with post-traumatic stress disorders, delayed school years and water supply problems (Larrañaga & Herrera, 2011).

Within the vulnerability framework, Engel analyzes the effect of the 2010 earthquake in recovery plans in the municipality of Talcahuano. She argues that the middle-classes, and not the poorest groups, struggled the most because they were not eligible for financial assistance, yet still did not make enough money to insure their property (Engel, 2016). Within the same theoretical standpoint, and using a qualitative analysis of the municipality of Chaiten, Sandoval & Voss (2016) argue that the decentralization of policies acts as a catalyzer for uncoordinated responses and mistrust in public authorities, therefore summing to root conditions of vulnerability posed by poverty, rurality and isolation. This result is corroborated by Valdivieso Fernández (2017) for three municipalities in the region of Maule, who by the use of a mixed methods approach, finds that the amount of resources that municipalities spend in disaster risk prevention is a significant predictor of the number Vasquez et al. (2008) map vulnerabilities using compound indicators based on Cutter (2008) for two municipalities, San Pedro de la Paz and Peñalolen, and find that the biggest predictor for hazard risk is socioeconomic status, and although some richer areas have had evidence of disaster risk, they have been effectively handled in advanced – a process that is not found in poorer neighborhoods.

2.3 Hypotheses

As was exposed before, the aim of this research is to study the relationship between inequalities and vulnerability, by exploring the impact that different factors have over vulnerability to natural disasters and answering to which empirical characteristics increase disaster vulnerability. Based on the reviewed literature and proposed theoretical framework, as well as in the background provided by the Chilean context, this study will seek to evaluate hypotheses regarding the three types of exposed factors and mechanisms (economic entitlement; social and political power; and income inequality).

1. *Economic capacity and entitlement variables are inversely associated with the likelihood of suffering losses due to natural disasters*
    a. Household poverty will be positively associated with likelihood of suffering losses due to natural disasters
    b. Household income will be negatively associated with the likelihood of suffering losses due to natural disasters
    c. Household over-crowdedness will be positively associated with the likelihood of suffering losses due to natural disasters
2. *Social and political power variables are inversely associated with the likelihood of suffering losses due to natural disasters:*

    a. Educational level of the household's head will be positively associated with the likelihood of being affected by natural disasters;
    b. Household's discrimination status will be positively associated with the likelihood of suffering losses due to natural disasters
    c. Household's physical isolation and status of rurality will be positively associated with the likelihood of suffering losses due to natural disasters
    d. Household's social isolation will be positively associated with the likelihood of suffering losses due to natural disasters
3. *Inequality mechanisms are positively associated with the likelihood of suffering losses due to natural disasters*
    a. Gini indices will be positively associated with the likelihood of suffering losses due to natural disasters

Because of the expected causal mechanism operating behind these hypotheses, the first two sets are related to the household level, whereas the last set is more related to the regional and municipal level. This is empirically captured through the use of a multilevel logistic model, which will be presented in Section 4.

3 Data

All the data used in this research is part of the Chilean National Socioeconomic Characterization Survey, CASEN, on its 2017 round. The following section will describe the survey's characteristics, as well as the used and constructed variables.

3.1 The CASEN Survey

The National Socioeconomic Characterization Survey of Chile, CASEN, is a cross-sectional survey that has been implemented by the Social Development Ministry since the year 1990 in 12 rounds. Its general objectives are to provide the Chilean state with information regarding poverty and its development, and it focuses particularly in groups defined as a priority by the national social policy. In particular, it has two goals: first, to estimate the magnitude of the country's poverty status as well as income distribution, identifying gaps separating social groups (Ministerio de Desarrollo Social y Familia, 2018); and second, to evaluate the impact of state's social policy estimating coverage, focalization and distribution of fiscal expenditure of the main social programs among households, as well as its distribution across the income range (Ministerio de Desarrollo Social y Familia, 2018).

CASEN is a face-to-face household survey focused in private houses across the Chilean territory, with the smallest unit being a household – or, as defined by the survey, a shared food budget unit. Sampling units are houses, which are sampled in a bi-staged, probabilistic and stratified manner according to geographic area (urban-rural) and population size. Variance strata are built by an area-municipality pair. In the case of one house containing more than one household, all households are surveyed given that the sampling unit is the house.

The key informant of each household is, ideally, the head of household– the person providing main income -, or any adult present in its absence (Ministerio de Desarrollo Social, 2018). Households are then divided into nuclei if necessary, which are defined according to dependency relationships, although no differentiating questions are asked at the nuclear level.

The 2017 round is built in 8 modules: registry, education, work, income, health, identity, networks and participation, and house and environment, with different questions at the house and household level.

The 2017 round was carried between December 2017 and January 2018. Overall, 94.222 houses were sampled estimating a non-response rate of 26,6%, with a maximum of 43% non-response for the Metropolitan region of Santiago. 68.466 houses were kept in the final dataset, adjusting by income ventile (1/20), geographic area and municipality. The survey has national and regional representativeness; and municipal representativeness through expansion factors. All work was performed used provided variance strata.

Table 1 shows the distribution of houses surveyed in each region, according to geographic zone.

Table 3: Sample size according to region and geographic zone, CASEN 2017

Region number	**Region name**	**Houses**	**Urban**	**Rural**
I	Región de Tarapacá	2.974	2733	241
II	Región de Antofagasta	2.511	2348	163
III	Región de Atacama	2.331	2054	277
IV	Región de Coquimbo	3.028	2390	638
IX	Región de La Araucanía	5.136	3622	1514
V	Región de Valparaíso	6.717	5621	1096
VI	Región de O'Higgins	5.099	3585	1514
VII	Región del Maule	5.007	3610	1397
VIII	Región de Biobío	6.901	5761	1140
X	Región de Los Lagos	4.129	2927	1202
XI	Región de Aysén	1.862	1484	378
XII	Región de Magallanes	2.301	2168	133
XIII	Región Metropolitana	12.954	12227	727
XIV	Región de Los Ríos	3.624	2487	1137
XV	Región de Arica y Parinacota	2.408	2155	253
XVI	Región de Ñuble	2.834	1915	919
Total	National	69.816	57087	12729

Source: Author's based on CASEN 2017

3.2 Variable description

3.2.1 Response variable: Experience of loss due to natural disasters

The main variable used for this research constitutes a proxy for natural disaster impact. It is a CASEN survey question introduced in 2017, as a state attempt to assess the full scope of natural disaster's impact in welfare and poverty, and it is part of the final module of the survey, 'House and Environment' (Ministerio de Desarrollo Social, 2017). In spite of the phrasing asking about the house, the question is asked at the household level. The question specification and response categories as well as its distribution are shown in Table 2.

Table 4: Response variable specification and categories, count and percentage

In the last year, did any of the following disasters caused your house any losses or damages?		
Type of disaster	**Count**	**Percent**
Earthquake or tsunami	7,951	3.70%
Flood, alluvium or waterlogging	7,143	3.30%
Drought	1,682	0.80%
Wildfires	2,032	0.90%
Urban fires or explosions	403	0.20%
Volcanic eruption	38	0.00%
Landslide or land collapse	113	0.10%
Frost or snowstorms	2,161	1.00%
Sanitary emergency or chemical disasters	476	0.20%
Other; specify	1,105	0.50%
No, I did not have any losses.	193,217	89.30%
Non response	118	0.10%

Source: Author's based on CASEN 2017

As shown in Table 2, the majority of surveyed households were not damaged from natural disasters, but a total of 23,104 houses was, which constitutes over 10% of the total sample. Within those, earthquake and tsunamis, as well as floods concentrate the bulk of causes, with other hazards having relatively small impacts. A residual category for other disasters is also included, although upon further examination, most of the responses were re-categorized in pre-existing categories. However, the severity of the impact is not assessed by the survey, neither is a quantification of the damage and houses are not allowed to answer if they have been hit more than once. Because of this, all disasters are included in order to offer a pseudo-control for differences in intensity and event recurrence. Because of the small count of some disasters, they were recoded into a dummy variable. Non responses were included in the '0' values.

Table 5: Dependent variable categories and distribution

Category	Code	Distribution
Household experienced losses	1	10.6%
Household did not experience losses	0	89.4%

As expected, there are relevant differences in geographic concentration of this variable, as shown in Table 6. Regions II, III and XI show the higher percentage of affected houses, all with shares over 20% of surveyed houses; although because of population concentration, the majority of impacted houses locate in the Metropolitan Region of Santiago.

Table 6: Regional distribution of dependent variable, count and percentage

Region		House did not experience losses		House experienced losses	
		Count	**Percent**	**Count**	**Percent**
I	Región de Tarapacá	9,429	92.90%	717	7.10%
II	Región de Antofagasta	6,615	77.80%	1,888	22.20%
III	Región de Atacama	5,140	73.90%	1,816	26.10%
IV	Región de Coquimbo	8,491	85.40%	1,448	14.60%
V	Región de Valparaíso	17,734	90.40%	1,887	9.60%
VI	Región del O'Higgins	14,676	92.50%	1,182	7.50%
VII	Región del Maule	12,935	85.10%	2,265	14.90%
VIII	Región del Biobío	19,995	92.90%	1,524	7.10%
IX	Región de La Araucanía	14,165	91.60%	1,307	8.40%
X	Región de Los Lagos	11,288	90.70%	1,153	9.30%
XI	Región de Aysén	4,012	79.50%	1,033	20.50%
XII	Región de Magallanes	5,806	87.60%	824	12.40%
XIII	Región Metropolitana	38,620	90.70%	3,957	9.30%
XIV	Región de Los Ríos	9,792	96.30%	377	3.70%
XV	Región de Arica y Parinacota	7,071	89.80%	806	10.20%
XVI	Región de Ñuble	7,448	89.00%	920	11.00%

Source: Author's based on CASEN 2017

Some regions did not experience any disasters in the examined period, and only show responses in the residual category. Because of this reason, regions in which natural disasters did not occur (as shown in Section 2.2) or were not captured by the survey, were excluded of the analyzed sample. These are Region 1 (Tarapacá), Region VI (O'Higgins), Region 14 (Los Ríos) and Region XVI (Ñuble). The overall working sample included 86% of total affected houses in 2017, and 84% of the total sampled houses.

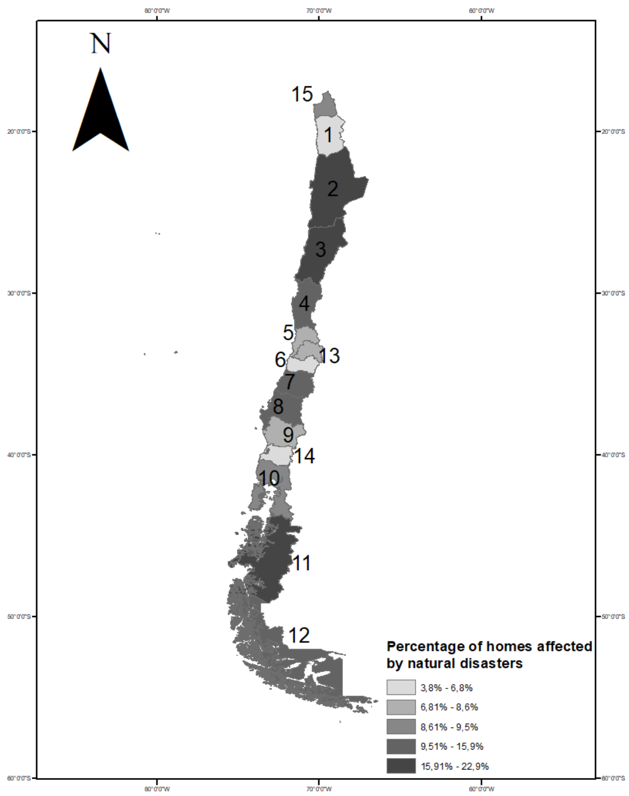

Figure 5: Percentage of houses affected by natural disasters, regional level

Source: Author's based on CASEN 2017

In the final working sample, relevant differences in the distribution of affected houses were found also across income levels. Geographically, although the absolute number of households affected by disaster was larger in urban areas due to the greater proportion of population in this zone, rural areas' households were statistically significantly more prone to losses: while 12% of sampled urban houses experienced losses, 20% of rural ones did. As shown in Figure 6, 15% of the total affected households are located in the 1^{st} income decile, and that share decreases as income increases. However, it is worth noting that the decrease is not perfectly linear nor proportional: in particular, the highest income decile seems to have a relatively large proportion of affected households.

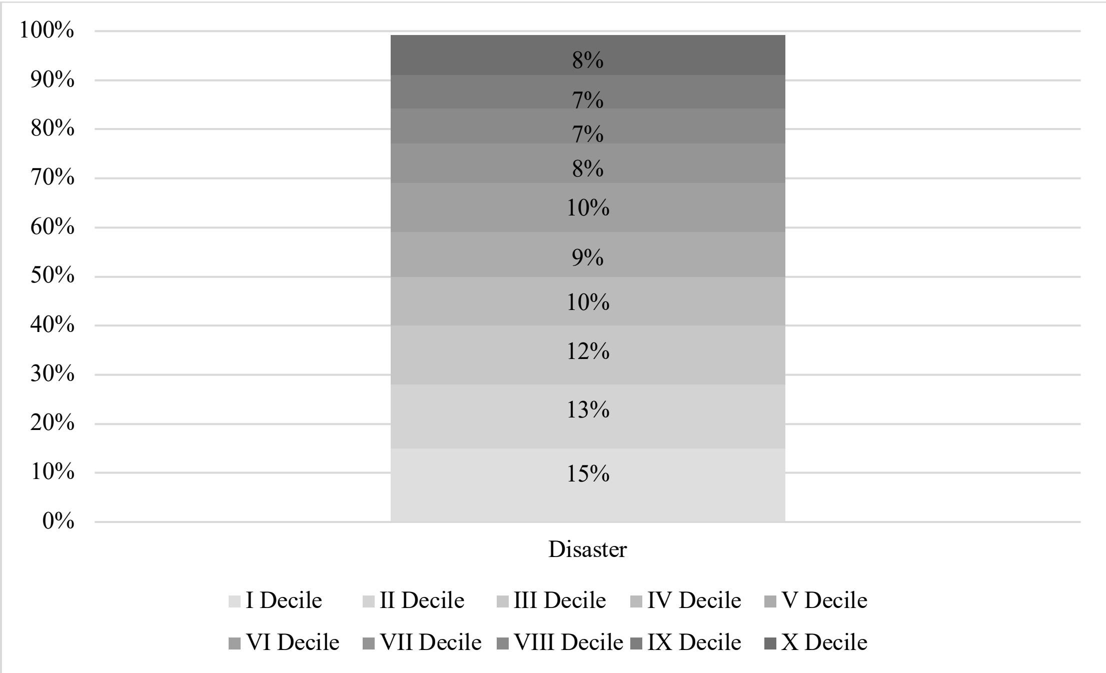

Figure 6: Distribution of household's houses experiencing losses due natural disasters according to national income deciles

Source: Author's based on CASEN 2017

3.2.2 Other variables

In order to characterize vulnerability of households which experienced losses due to natural disasters, factors based on a list of theoretically informed variables was included in the analysis. Because this research uses a multilevel logistic regression, these were organized in a household level, and a regional and municipal level.

At the house-household level, 12 variables were recorded. Regarding mechanisms of economic entitlement, the household's total income was included, as well as its income decile characterized at the regional level. A dummy variable for multidimensional poverty was also included, using the Chilean Ministry of Social Development's definition of poverty. This is a composite index with components of income, educational access, health access and basic house services such as running water and basic pipelines, which is used to define poverty lines in Chile (Ministerio de Desarrollo Social, 2018). Additionally, dummy variables for deficient house status and over-crowdedness were incorporated, based on assessment by the surveyors.

Regarding mechanisms of political and social power, 5 variables were recorded. First, a characterization of the geographic zone of the house-household in regard of urban or rural location, under the assumption that it captures political and economic exclusion, as well as worse communication infrastructure and slower emergency responses (Gillis Peacock, Gladwin & Morrow, 2012; Sandoval Henríquez, 2017). Also, a variable recording if the household had the status of 'isolated' from state-provided social services was included, as well as one recording if the household lacked social networks – attempting to measure social isolation. Because of the negative effect of illiteracy in emergencies described before, a dummy variable regarding the achievement of primary education of the respondent (the household head) was included. Although this is an individual variable, it functions under the assumption that if the main household income holder has not achieved primary education, then probably the remaining adult members have not either. A variable asking if members of the household had been discriminated against was included, incorporating all factors of discrimination that the question surveyed. A dummy variable recording belonging to indigenous population was recorded, given Chilean's particular history of indigenous people's economic and political discrimination and isolation.

At the municipal and regional level, regarding mechanisms of inequality, the Gini Index at the regional and municipal level were calculated and recorded. A variable recording the share of population in the most basic social program – Permanent Family Subsidy -, as a proxy for the municipal and regional's level of income and capacity to dedicate resources to natural disasters' response was added, following Sandoval & Voss (2016). Also, as contextual variables, in this level regions and municipalities were included in the model as second level variables. Table 7 shows the summary of included variables, and summary statistics and categories can be found in Appendix A.

Table 7: Variables summary

Mechanism	Factor	Categories	Type	Record level	Expected impact
Economic capacity and entitlement	Total income		Continuous	Household	-
	Total income (log)		Continuous	Household	-
	Regional income decile	1-10	Ordinal	Household	-
	Poverty status	Non-poor (0), poor (1)	Categorical	Household	+
	Deficient housing status	Non-deficient (0), deficient (1)	Categorical	Household	+
	Over-crowdedness status	Non overcrowded (0), Overcrowded (1)	Categorical	Household	+
Political and social power	Geographic zone	Urban (0), rural (1)	Categorical	Household	+
	Physical isolation status	Non-isolated (0), Isolated (1)	Categorical	Household	+
	Social isolation status	Non-isolated (0), Isolated (1)	Categorical	Household	+
	Educational level	non below primary (0), Below primary (1)	Categorical	Household	+
	Discrimination status	Non discriminated (0), discriminated (1)	Categorical	Household	+
	Indigenous population belonging	Does not belong (0), belongs (1)	Categorical	Household	+
Inequality	Municipal Gini Index		Continuous	Municipal	+
	Regional Gini Index		Continuous	Regional	+
	Share of houses in family subsidy		Continuous	Municipal	+
Context	Region		Categorical	Regional	
	Municipality		Categorical	Municipal	

3.2.3 Data limitations

Regarding the response variable, an important limitation comes from the lack of quantification in the level of damage due to natural disasters. While some houses may have experienced little dysfunctions, others may have been completely destroyed and they would be coded in the same way for surveying processes. In the same matter, houses affected more than once were not able to register this, which could be under-reporting the damage of particularly exposed territories.

Other limitations come from the survey design and its field work, in particular, from the exclusion criteria for sampling, which could cause coverage bias. According to the sampling design, two criteria are used in order to exclude areas from being selected: first, 22 municipalities that are remote and do not house more than 10.000 inhabitants; and second, blocks that have less than 7 houses. This generates a bias excluding two relevant groups of the performed analysis: the most spatially isolated segments of the population, and the wealthier sectors, who live in bigger houses that even in urban areas, are more sparsely distributed. Because of this, the 10^{th} income decile is comparatively much smaller than the remaining ones and reaches only 63% of the number of sampled houses in the $1\text{-}5^{th}$. Specifically, concerns regarding the representativeness of the 10^{th} decile have been risen regarding the sample size, but also, regarding who answers the questionnaire, a task that has been documented to fall in house staff in higher income households. Overall, the representation quality of the highest decile is usually worse than the remaining income brackets. Nevertheless, if anything, the exclusion of these groups would likely cause an underestimation of the results.

On the other hand, there are limitations coming from working at the household and house level. Most people experience and respond to disasters as members of households and houses (Morrow, 1999), and damages are usually experienced in collective levels as well, which makes it the smallest level prone to analysis. Nevertheless, some information is lost from the analysis at this level, like the specific influences of gender and women-led houses, as well as the dependence composition of the household, which could increase vulnerability and risk significantly, as has been studied by individual-level case studies (Bolin & Klenow, 1983; Neumayer & Plümper, 2007). However, addressing these issues is only possible in small-N studies, and diminishes some of the generalization of the analysis.

Finally, the use of survey data, and specially government-produced one, brings around several respondent's bias. Non-responses could be more frequent among people who do not trust the government, those who hold illegal immigration status or live in illegally established housing communities, for example. Moreover, an income survey brings insecurities regarding cross-referencing of information which could lead to underestimations of salaries and other measurements. Other measurements bias could come from mishandling information, as well. In spite of these limitations, CASEN has been proven a tested survey that has been the base for Chilean social policy for decades which has attempted to minimize these risks by using an overestimated sample.

4 Methodology

4.1 Multilevel logistic regressions

This research employs a quantitative approach based on a multilevel logistic regression model. Multilevel regression models are based on the assumption that context is relevant in understanding social phenomena, but since group observations may not always hold for individuals, econometric modelling should be adjusted to prevent ecological fallacies (Freedman, 1999). The traditional approach for tackling this issue has been to disaggregate group-level information in order to tie all predictors to the individual level of analysis; however, this leads to several problems. First, the contextual error term gets pooled into the single individual error term of the model, and individuals in the same context will have correlated errors violating basic assumptions of regression modeling. Moreover, ignoring context implies that regression coefficients apply to all individuals in the same way, which may bias results (Shiverdecker & LeBreton, 2018).

In the case of this research, context is hardly overestimated. Regional and municipal location of houses determine physical closeness to natural hazards risk, but also other variables relevant in establishing vulnerability such as isolation, geographical zones and income levels. In particular for the Chilean case, deployment of first responders and emergency signals are managed at the municipal and regional level, which implies that national territories may have different speeds of response as well as effectiveness in doing so (Valdivieso Fernández, 2017).

Therefore, after checking that single-level logistic regression produced biased and clustered error terms, a multilevel regression model was found to be most useful for this analysis and will be used in analyzing the likelihood of experiencing losses due to natural disasters. Multilevel regressions, also called random coefficient models or variance components models, are a hierarchical system of equations in which the intercept and slope are allowed to vary across the different groups of the higher level. In this sense, the first level of the regression equation is a fixed-effects models, whereas the upper level acts as a random effect regression model (Luke, 2011). Therefore, the single prediction equation is a mixed-effects models.

For this research, the response variable is binary, so a logistic multilevel method was employed, using a maximum likelihood estimation. These models attempt to estimate the odds or likelihood of an event's occurrence, or the conditional probability of an outcome variable = 1 at a certain point, given by:

$$P(Y_i = 1) = \frac{\exp(\beta_0 + \beta_1 X_1 \dots)}{1 + \exp(\beta_0 + \beta_1 X_1 \dots)}$$

The implication of using a multilevel approach in a logistic model is that the log-odds that the outcome variable equals 1 instead of 0 may vary according to different groups, allowing for the interaction of regional and municipal variables to determine the household components: instead of estimating the probability of experiencing losses due to natural disasters in Chile, the multilevel model does estimate the probability in Chile, in each individual region or municipality. Statistically, this is defined by

$$P(Y_i = 1) = logit^{-1}\left(X_i G_{j[i]} + X_i \alpha_{j[i]}\right),$$

where X_i represents the measurements on the individual level variables – house/household -, and G_j does so at the second level variables – region. Empirically, this is measured by the intra-class correlation coefficient (ICC), defined as:

$$ICC = \frac{var(\mu_{0j})}{var(\mu_{0j}) + (\frac{\pi^2}{3})}$$

Overall, the higher the ICC, the more residuals are dependent upon cluster membership. In this case, ICC has a value of 0.22 for regions and 0.26 for municipalities, which means that 22% and 26% of the likelihood of experiencing loss due to a natural disaster is marginally explained by regional differences, justifying the need for a multilevel approach. This is shown in Figures 4 and 5, where the random effects for each municipality and region is graphed: as can be seen, most of the municipalities and all regions but Region 8 – Biobío - have a statistically different from 0 impact on the estimation of likelihood of loss over natural disasters.

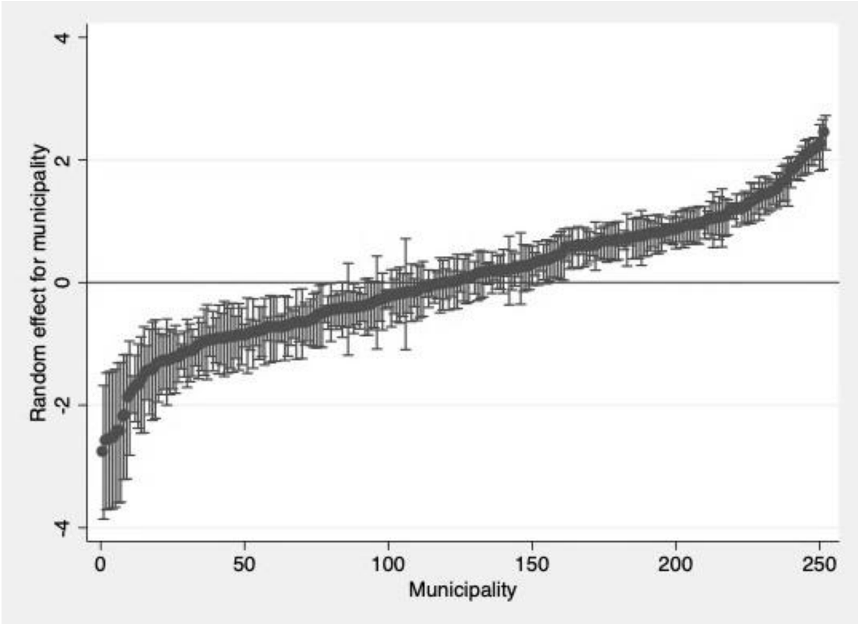

Figure 7: Random effect slope margin of municipal belonging, Municipality as second-level variable.

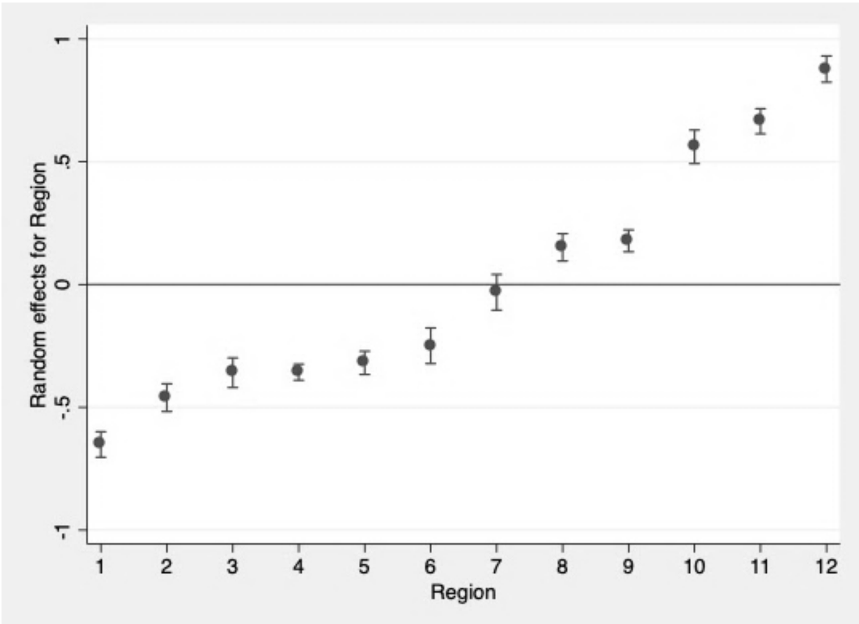

Figure 8: Random effect slope margin of regional belonging, Region as second-level variable.

Following the theoretical reasoning presented in Section 2, and data availability given in Section 3, this research will work with four models' specification. Models 1, 2 and 3 will be tested at the national level, and Model 4 will be tested for all included regions individually.

All models include variables at the household (fixed) and regional/municipal (random) level, denoted β and μ, respectively. Models 1 includes total logarithmic household income, whereas Models 2 and 3 include income decile. Model 1 includes the regional Gini index, and Model 3 includes the municipal Gini. All other variables are kept constant. For the analysis of each region, the same specification of Model 3 is used, replacing variables recorded at the regional level for those at the municipal level.

Model 1

$$\begin{aligned}\pi_{nat.dis.loss} = {} & \beta_{Income(\log)} + \beta_{Poverty} + \beta_{Deficient\ housing} + \beta_{Over-crowdedness} + \beta_{Zone} \\ & + \beta_{Physical\ isolation} + \beta_{Social\ isolation} + \beta_{Educational\ level} + \beta_{Discrimination} \\ & + \beta_{Indigenous} + \mu_{Regional\ Gini} + \mu_{Region} + \varepsilon\end{aligned}$$

Model 2

$$\begin{aligned}\pi_{nat.dis.loss} = {} & \beta_{Income\ Decile} + \beta_{Poverty} + \beta_{Deficient\ housing} + \beta_{Over-crowdedness} + \beta_{Zone} \\ & + \beta_{Physical\ isolation} + \beta_{Social\ isolation} + \beta_{Educational\ level} + \beta_{Discrimination} \\ & + \beta_{Indigenous} + \mu_{Regional\ Gini} + \mu_{Region} + \varepsilon\end{aligned}$$

Model 3

$$\begin{aligned}\pi_{nat.dis.loss} = {} & \beta_{Income\ Decile} + \beta_{Poverty} + \beta_{Deficient\ housing} + \beta_{Over-crowdedness} + \beta_{Zone} \\ & + \beta_{Physical\ isolation} + \beta_{Social\ isolation} + \beta_{Educational\ level} + \beta_{Discrimination} \\ & + \beta_{Indigenous} + \mu_{Municipal\ Gini} + \mu_{Region} + \varepsilon\end{aligned}$$

For regional analysis,

Model 4

$$\begin{aligned}\pi_{nat.dis.loss} = {} & \beta_{Income\ Decile} + \beta_{Poverty} + \beta_{Deficient\ housing} + \beta_{Over-crowdedness} + \beta_{Zone} \\ & + \beta_{Physical\ isolation} + \beta_{Social\ isolation} + \beta_{Educational\ level} + \beta_{Discrimination} \\ & + \beta_{Indigenous} + \mu_{Municipal\ Gini} + \mu_{Region} + \varepsilon\end{aligned}$$

4.1.1 Methodological limitations

For this type of data and research question, multilevel models provide a stronger basis for statistical analysis than traditional, single-level models. However, the use of multilevel modelling does not come without limitations. By introducing regions and municipalities as second-level variables, the relevance of context is being addressed allowing for difference intercepts to vary. However, variation could be occurring within these levels due to non-random errors due to omitted variables. The use of a wide variety of disasters attempts to control this error, but it is possible that in some regions or municipalities some disasters were concentrated within municipalities affecting a specific population. Because of this, within-cluster margins are also estimated and presented in the following section. Finally, another consideration may come from the fact that municipalities and regions may not be relevant for context in natural disasters' associated losses at all (Gelman, 2006; Wooldridge, 2002). While there are theoretical reasons to believe so in this particular research, this concerned is also addressed empirically by analyzing variance shares.

5 Empirical Analysis

The general purpose of a multilevel logistic regression is to estimate the odds of an event occurring, while simultaneously considering the dependency of data. In this case, this implies that the likelihood of natural disasters' related losses is also dependent on the belonging to a region or municipality, due to the fact that disasters are not equally distributed across the territory, but also because, as exposed before, regions and municipalities determine reactions to disasters. In this context, results for multilevel regression models are presented in Tables 8 and 10. Outcomes are presented as odds, or as the likelihood of losses occurring/losses not occurring. Diagnostic tests for all models in this section are presented in Appendix B.

5.1 National level analysis

Table 8 shows the results for the national analysis. Variables' odds are to be interpreted as in comparison to households altering the selected variable but keeping all remaining characteristics at mean values; and as a multilevel model, the regional grouping implies that estimations and comparisons are valid for households within the same region.

The model predicts that 11% of the sample suffered losses due to disasters, which is close to sample ratio of 10.4%. Regarding factors of economic entitlement, Model 1 shows that for two households located in the same region and with the same characteristics, being poor will give a 30% increase in odds, which is statistically significant at a 1% level. This implies a large practical effect, in which poverty increases likelihood of disaster losses between 23% and 31%. This result seems to be robust across all model specifications: models 2 and 3 also result in significant and positive odds increases between 44% and 51%.

The effect of income in Model 1, however, shows that there is a positive and statistically significant association with natural disaster's damage, which is contrary to the expected effects and what is suggested by the literature. When examining the marginal effect of this variable, as shown in Figure 9, it is found that the effect stays relatively flat until an approximate income of CLP$1,000,000, which is over the threshold for the 10th decile. Therefore, it seems that it is the richest share of the population for which income has an increasing effect, able to skew the results of the income variable. Indeed, analyzing Models 2 and 3, in which specifications include income decile instead of income, it is found that deciles 2-8 show a decrease of odds in comparison to the 1st decile, and only the 10th implies an increase in odds in similar households.

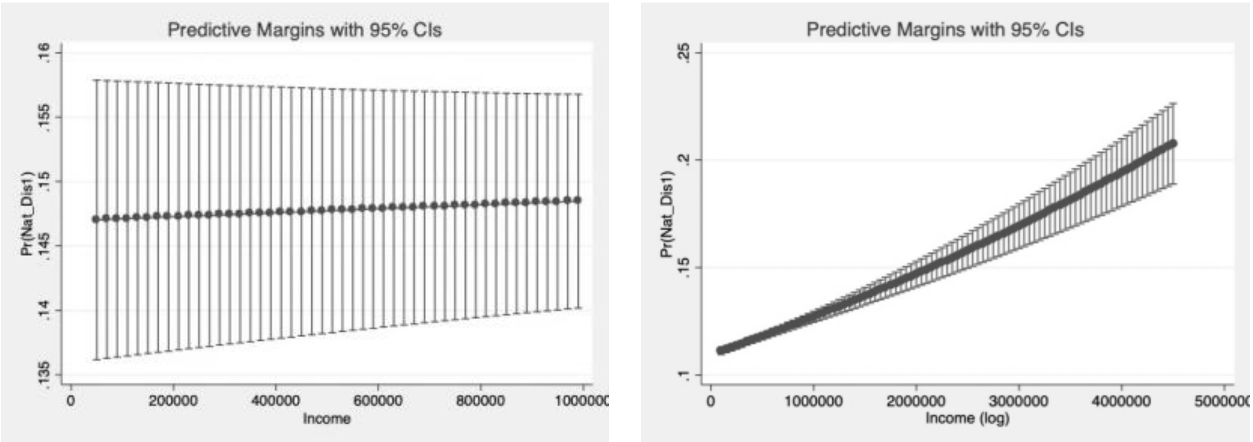

Figure 9: Marginal effect of income over natural disaster's losses likelihood

Two more variables are included in the economic capacity mechanisms, but only one of them is statistically significant; deficient housing status, which shows similar coefficients across model specifications. Compared to similar households in the same region, houses in deficient status will, expectedly, experience a 20% odds' increase in likelihood of disaster losses. Over-crowdedness is not statistically significant.

When it comes to mechanisms related to social and political power, results are consistent with expectations and they seem to show that lower power is associated with higher likelihood of losses due natural disasters. The greatest impact is given by geographic zone. A rural household, in comparison to a similar one in the same region, will increase the odds of losses by 75%, with confidence interval between 65% and 80%, the largest impact in the model. This is consistent across all models and implies an estimated increase in probabilities of around 42-48%. However, all three models show a number of relevant variables in this category. Physical isolation is also statistically significant and is associated with an 11% increase in odds of suffering losses due to disasters in all models, compared to houses within the same cluster. So is belonging to a household that has experienced discrimination, which brings an increase of odds by 27% in average among similar households in the same region. Finally, belonging to an indigenous people is also positively and significantly associated with odds increases of 8% in Model 1 and of 8,5% in Models 2 and 3, however, in practical terms, it implies a probability increase of around 5%, smaller than other variables.

Regarding income inequality variables, only the inclusion of municipal level Gini is statistically significant and has the expected directionality. However, Gini recorded at the regional level as shown in models 1 and 2 are not statistically significant. Since this variable is a second-level variable, its effect impacts on the slope and not directly on the estimation. Figure 10, however, shows the marginal effects.

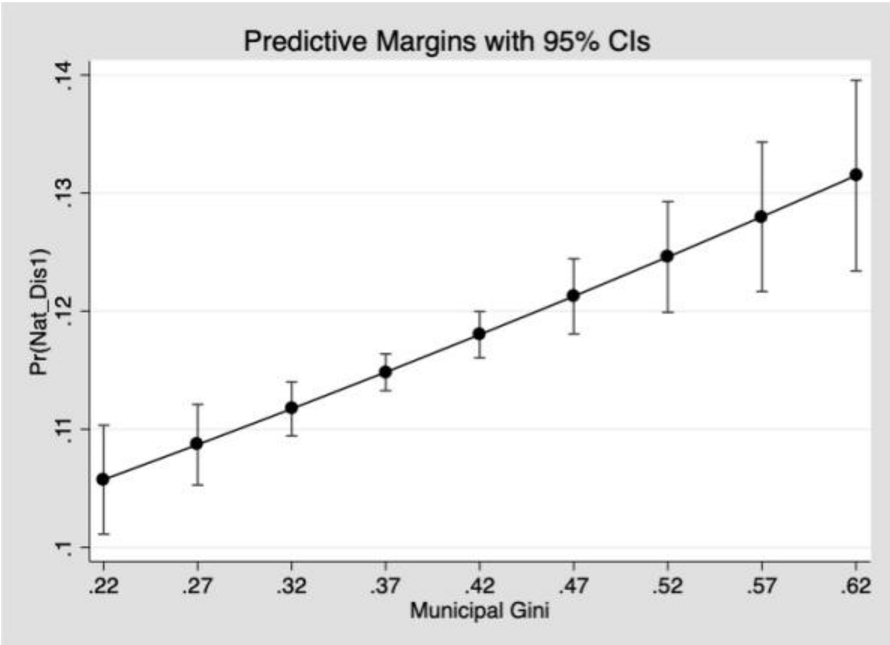

Figure 10: Marginal effect of Gini Index over natural disaster's losses likelihood

Finally, as was argued before, regional grouping is statistically significant across model specifications, which shows evidence for the validity of multilevel modelling as a methodological strategy.

Table 8: Multilevel logistic regression estimation over likelihood of loss due to natural disaster – House/household as base level, region as context level

		Model 1		**Model 2**		**Model 3**	
Level	**Variables**	Estimates	Odds Ratio	Estimates	Odds Ratio	Estimates	Odds Ratio
Household	Income (log)	0.099*** (0.012)	1.104*** (0.013)				
	Regional income decile = 2			-0.117*** (0.033)	0.890*** (0.029)	-0.117*** (0.033)	0.890*** (0.029)
	Regional income decile = 3			-0.017 (0.033)	0.983 (0.032)	-0.017 (0.033)	0.984 (0.032)
	Regional income decile = 4			-0.100*** (0.034)	0.905*** (0.031)	-0.099*** (0.034)	0.905*** (0.031)
	Regional income decile = 5			-0.001972	0.944* (0.032)	-0.0019652	0.944* (0.032)
	Regional income decile = 6			-0.117*** (0.035)	0.890*** (0.031)	-0.117*** (0.036)	0.890*** (0.031)
	Regional income decile = 7			-0.039 (0.036)	0.961 (0.034)	-0.040 (0.036)	0.961 (0.034)
	Regional income decile = 8			-0.088** (0.037)	0.916** (0.034)	-0.090** (0.037)	0.914** (0.034)
	Regional income decile = 9			0.038 (0.037)	1.039 (0.038)	0.034 (0.037)	1.034 (0.038)
	Regional income decile = 10			0.166*** (-0.038)	1.081*** (0.044)	0.159*** (0.038)	1.073*** (0.044)
	Poverty status = 1	0.1099*** (0.024)	1.304*** (0.026)	0.1840*** (0.024)	1.488*** (0.026)	0.184*** (0.024)	1.487*** (0.026)
	Deficient housing status = 1	0.181*** (0.023)	1.199*** (0.028)	0.174*** (0.023)	1.190*** (0.027)	0.175*** (0.023)	1.191*** (0.027)
	Over-crowdedness status = 1	-0.083 (0.030)	0.920 (0.027)	-0.113 (0.023)	0.893 (0.027)	-0.113 (0.030)	0.893 (0.027)
	Zone = Rural	0.551*** (0.023)	1.736*** (0.040)	0.545*** (-0.023)	1.752*** (0.040)	0.552*** (0.023)	1.737*** (0.040)
	Physical isolation = 1, Isolated	0.114*** (0.029)	1.120*** (0.032)	0.109*** (0.030)	1.116*** (0.033)	0.108*** (0.029)	1.114*** (0.032)
	Social isolation = 1, Isolated	-0.001 (0.018)	0.999 (0.018)	0.002 (0.018)	1.002 (0.018)	0.003 (0.019)	1.003 (0.019)
	Educational level = 0, Below primary education	0.017 (0.018)	1.017 (0.018)	0.007 (-0.018)	1.007 (0.018)	0.007 (0.018)	1.007 (0.018)
	Discrimination status = 1, Discriminated against	0.239*** (0.023)	1.270*** (0.029)	0.235*** (0.023)	1.265*** (0.029)	0.234*** (0.023)	1.263*** (0.029)
	Belongs to indigenous people = 1, Belongs	0.081*** (0.025)	1.084*** (0.027)	0.076*** (-0.025)	1.078*** (0.026)	0.076*** (0.025)	1.079*** (0.026)
Region	Municipal Gini					0.290* (0.164)	
	Regional Gini	-4.794 (4.440)		-4.565 (4.563)			
	Constant	-1.408 (1.819)		-0.221 (1.865)		-2.193*** (0.161)	
	Regional constant	0.222** (0.091)		0.235** (0.096)		0.254** (0.104)	
	Observations	164,973	164,973	165,076	165,076	165,076	165,076
	Number of groups	12	12	12	12	12	12

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5.2 Within-regions analysis

Table 10 shows the results for the national analysis. Variables' odds are to be interpreted as in comparison to households changing the selected variable and keeping all remaining characteristics at mean values; and as a multilevel model, the municipal grouping implies that estimations and comparisons are valid for households within the same municipality. Only odds are shown, but coefficients can be found in Appendix B. Table 9 shows the goodness of fit of all regional models.

Table 9: Predicted and observed values of the dependent variable across regions

	Predicted Probability at means	Observed	Difference
Region 2	22.40%	22.20%	-0.002
Region 3	26.10%	26.20%	0.001
Region 4	14.79%	14.57%	-0.002
Region 5	9.49%	9.62%	0.001
Region 7	14.79%	14.90%	0.001
Region 8	7.03%	7.08%	0.001
Region 9	8.23%	8.45%	0.002
Region 10	9.38%	9.27%	-0.001
Region 11	20.25%	20.48%	0.002
Region 12	12.41%	12.43%	0.000
Region 13	9.25%	9.29%	0.000
Region 15	9.99%	10.23%	0.002

Regarding factors of economic entitlement, the majority of regions show a significant and positive impact of being poor over the likelihood of experiencing losses due to natural disasters, with the exception of Region XII (Magallanes); and Region XV (Los Ríos). For all 9 remaining ones, the impact varies between 34% odds increase in Region XI (Aysén), to 8% increase in Region VIII (Biobío). This is related to a 38% increase in likelihood in Aysén to a much more limited increase of 9% in Biobío. Deficient housing status and over-crowdedness are both statistically significant and have the expected direction, showing that the presence of both factors increase likelihood of losses due to disasters. In four regions – Valparaíso (V), Biobío (VIII), Aysén (XI) and Metropolitana (XIII) -, they are both statistically significant. However, keeping all factors constant, the magnitude of the effects varies greatly: in Region III (Atacama), the impact of deficient housing increases odds by 103%, which only reaches 20% in Region XV (Los Ríos). Unlike poverty, over-crowdedness shows the highest probability increase in Region XI (Aysén), with an expected odds-increase of 80%, and the lowest in Region III (Atacama). In urban regions like Region XIII (Metropolitana) and V (Valparaíso), this factor has the largest positive impact over odds.

As the national analysis suggested, the effect of income decile is not linear, and it varies greatly between regions. For example, while Regions III (Atacama) and VII (Maule) show an inverse relationship between this factor and losses' likelihood, Regions XV and V show that almost all income deciles have a higher likelihood of losses than the first decile. In Region II (Tarapacá), the impact is concentrated in the middle of the distribution. Overall, as shown at the national level, the effect of this variable is not robust across regions and is greatly subject to variation.

For factors related to mechanisms of social and political power, the results of rurality confirmed what was found at the national level. In households within the same municipality, and across all regions, the impact of belonging to a rural house instead of an urban one increases the likelihood of experiencing losses due to natural disasters. The magnitude varies between regions: while Regions V (Valparaíso), XI (Aysén) and XV (Los Ríos) show moderate increases of 20% in odds, Regions XI, IX and X evidence a marginal effect increase of odds by 180%, 150% and 138% on average, respectively. The only region for which this variable is not significant is Region III (Atacama), for which the coefficient of physical isolation is much higher than for the other regions, which implies that it could be taking some of that impact. Indeed, physical isolation at is significant for half of the regions (the ones with smaller impacts in geographic zone) and shows similar odds increases than the ones found at the national level, around 20% increase with an interval between 13% and 28%. In the same mechanism, the discrimination factor is also found significant for several regions; in particular those highly urbane, and the contrary is true for belonging to an indigenous people. For the first case, the largest impacts increase odds by 90% and 75% in Regions IV and VIII for similar households within the same municipality.

Finally, regarding the inequality variable, its specification as a second-level variable implies that its effect is a slope shifting one, not one over odds ration. However, unlike the national level, the impact of income inequality is not significant for most of the regions, and for those in which it is, it is extremely small. The municipal constant is significant for all regions, implying that differences attributable to municipal characteristics are relevant for the model.

Table 10: Multilevel logistic regression estimation for regional models over likelihood of loss because of natural disaster - Household as base level, municipality as context level. Odds ratios

Variables	Region 2	Region 3	Region 4	Region 5	Region 7	Region 8	Region 9	Region 10	Region 11	Region 12	Region 13	Region 15
Regional income decile = 2	1.033	0.644***	0.758**	1.191*	0.698***	0.677***	1.344**	0.683***	0.866	1.219	0.876	1.524**
	(0.118)	(0.081)	(0.095)	(0.126)	(0.069)	(0.074)	(0.176)	(0.100)	(0.138)	(0.200)	(0.072)	(0.251)
Regional income decile = 3	1.042	0.609	1.169	1.048	0.802**	0.686***	1.115	1.058	1.057	0.876	1.144*	1.424**
	(0.122)	(0.113)	(0.142)	(0.115)	(0.077)	(0.081)	(0.156)	(0.145)	(0.166)	(0.153)	(0.091)	(0.240)
Regional income decile = 4	1.105	0.675***	0.894	1.203*	0.567***	0.975	1.603***	1.054	0.713**	1.022	0.774***	1.192
	(0.130)	(0.0874)	(0.114)	(0.134)	(0.0589)	(0.108)	(0.217)	(0.145)	(0.119)	(0.170)	(0.0686)	(0.206)
Regional income decile = 5	1.400***	0.647***	0.912	1.426***	0.572***	0.781**	1.182	0.615***	1.055	0.875	1.043	1.054
	(0.160)	(0.0837)	(0.120)	(0.156)	(0.060)	(0.093)	(0.171)	(0.094)	(0.172)	(0.152)	(0.084)	(0.190)
Regional income decile = 6	1.057	0.653***	1.014	1.083	0.522***	1.056	1.451***	0.995	1.167	0.761	0.840**	0.716*
	(0.127)	(0.0862)	(0.136)	(0.128)	(0.0581)	(0.121)	(0.207)	(0.147)	(0.191)	(0.141)	(0.073)	(0.144)
Regional income decile = 7	0.918	0.538***	0.936	1.091	0.648***	0.769**	1.362**	1.146	1.265	1.343*	0.937	1.565***
	(0.119)	(0.0744)	(0.126)	(0.131)	(0.0704)	(0.0958)	(0.204)	(0.173)	(0.203)	(0.227)	(0.082)	(0.312)
Regional income decile = 8	1.059	0.460**	0.705**	1.485***	0.708***	0.578***	1.366**	0.781	0.651**	0.800	0.942	0.819
	(0.137)	(0.104)	(0.103)	(0.176)	(0.0785)	(0.0823)	(0.211)	(0.127)	(0.118)	(0.148)	(0.082)	(0.168)
Regional income decile = 9	1.017	0.339	0.931	1.457***	0.780**	0.804	1.068	0.728*	0.779	0.897	0.961	1.166
	(0.141)	(0.130)	(0.130)	(0.178)	(0.0884)	(0.109)	(0.175)	(0.128)	(0.140)	(0.169)	(0.083)	(0.223)
Regional income decile = 10	1.189	0.272	0.734**	1.357**	0.629***	1.065	1.355*	1.064	0.992	0.892	1.042	0.874
	(0.184)	(0.133)	(0.115)	(0.179)	(0.0791)	(0.153)	(0.229)	(0.189)	(0.184)	(0.167)	(0.090)	(0.181)
Poverty status = 1	1.228**	1.169*	1.113**	1.139*	1.136*	1.078*	1.177*	1.128*	1.342***	0.814	1.157**	0.850
	(0.082)	(0.095)	(0.074)	(0.080)	(0.079)	(0.081)	(0.102)	(0.094)	(0.151)	(0.117)	(0.062)	(0.105)
Deficient housing status = 1	1.444***	2.389***	1.076	1.371***	0.900	1.371***	0.913	1.022	1.781**	1.550***	1.196***	1.122
	(0.119)	(0.176)	(0.085)	(0.097)	(0.065)	(0.106)	(0.080)	(0.115)	(0.091)	(0.206)	(0.072)	(0.124)
Over-crowdedness status = 1	0.972	0.886	1.453***	1.714***	1.072	1.503***	0.928	0.818	1.580***	1.126	1.802***	1.084
	(0.097)	(0.096)	(0.146)	(0.080)	(0.099)	(0.153)	(0.103)	(0.111)	(0.102)	(0.185)	(0.057)	(0.152)

Zone = Rural	2.186***	0.860	1.769***	1.240***	1.690***	2.004***	2.370***	2.155***	1.248*	2.779***	1.484***	1.283***
	(0.405)	(0.092)	(0.157)	(0.095)	(0.103)	(0.162)	(0.193)	(0.181)	(0.152)	(0.451)	(0.155)	(0.158)
Physical isolation = 1, Isolated	0.851	1.460***	1.243**	1.336***	1.180**	1.172	1.023	1.164*	1.093	0.828	1.309***	0.729
	(0.121)	(0.146)	(0.089)	(0.117)	(0.094)	(0.122)	(0.091)	(0.105)	(0.159)	(0.163)	(0.080)	(0.159)
Social isolation = 1, Isolated	1.193*	1.080	0.974	1.009	0.970	1.105	0.962	1.081	0.934	1.044	1.006	0.873
	(0.081)	(0.077)	(0.066)	(0.057)	(0.054)	(0.073)	(0.067)	(0.084)	(0.077)	(0.096)	(0.040)	(0.077)
Educational level = 0, Below primary	0.986	1.019	1.022	1.039	0.964	0.997	1.007	1.056	0.916	1.173*	0.990	0.857*
	(0.064)	(0.067)	(0.066)	(0.061)	(0.051)	(0.062)	(0.066)	(0.077)	(0.073)	(0.104)	(0.042)	(0.078)
Discrimination status = 1, Discriminated	1.173*	1.472***	1.902***	1.192**	1.056	1.756***	1.174*	1.057	1.424***	0.843	1.235***	1.113
	(0.099)	(0.129)	(0.173)	(0.086)	(0.0853)	(0.138)	(0.110)	(0.123)	(0.160)	(0.131)	(0.057)	(0.132)
Belongs to indigenous people = 1, Belongs	0.959	1.371***	0.515***	1.074	1.060	0.802**	0.861**	1.235***	0.929	0.989	1.021	1.208**
	(0.106)	(0.107)	(0.083)	(0.143)	(0.156)	(0.085)	(0.064)	(0.095)	(0.079)	(0.093)	(0.080)	(0.108)
Coefficient of Municipal Gini	0.001	3.4e-^{7}***	6.474	0.0872	0.975	5.291	2.689	0.194	1.288	$1.37e^{-5}$**	16.65	9.711
	(0.004)	($1.77e^{-6}$)	(0.34)	(0.228)	(2.583)	(4.002)	(0.412)	(0.971)	($8.691e^{7}$)	($2.82e^{-5}$)	(15.094)	(0.143)
Coefficient of Constant	3.053	99.97**	0.0553	0.149**	0.216	0.0262***	0.0331***	0.0809	0.001***	11.08***	0.026***	0.040
	(5.620)	(187.1)	(0.111)	(0.140)	(0.202)	(0.0271)	(0.0388)	(0.159)	(0.00106)	(9.097)	(0.0189)	(0.099)
Coefficient of Municipal Constant	1.733*	1.262**	2.238**	2.215***	1.904***	3.094***	1.611***	17.05***	1.197	1	2.093***	1
	(0.492)	(0.149)	(0.791)	(0.520)	(0.342)	(1.000)	(0.212)	(17.75)	(0.143)	(0)	(0.323)	(0)
Observations	7,826	6,502	9,484	19,004	14,602	20,989	14,927	12,092	4,907	6,309	41,040	7,394
Number of groups	8	9	15	36	30	33	32	25	6	3	52	3

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5.3 Between-region analysis

While the previous analyses show the impact of different individual variables within regions and municipalities, multilevel regressions also allow for analyses in which the household and context level interact. For this, the probability margins of natural disaster related losses at the mean values of the regional samples according to all factors was estimated. Then, probability margins for models including all factors at risk values at household levels were estimated. Appendix B has the specification for these calculations, and the results of these estimations are shown in Figure 11.

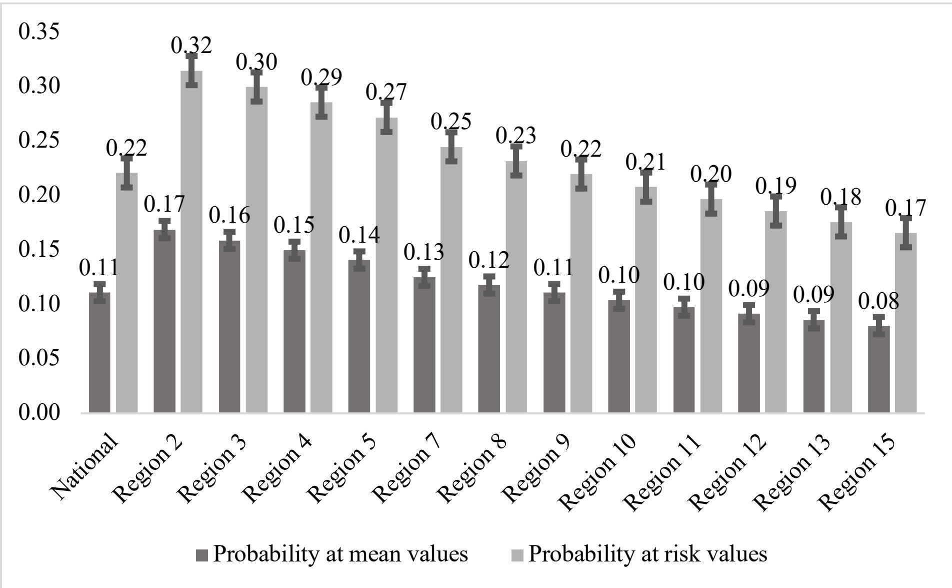

Figure 11: Probability of household experiencing loss due to natural disasters at model mean values and model risk values

These results show that the analyzed factors have significant and large impacts over the likelihood of experiencing losses due to natural disasters. At the national level, the interaction of all risk factors is associated with a statistically significant probability increase of 11 percentage points. A household that is simultaneously poor, with deficient, overcrowded housing, living in a rural area, physically isolated, without social networks, in which the household head did not reach primary education, that has experienced discrimination and that belongs to an indigenous people, has a 22% likelihood of experiencing losses due to a natural disaster, whereas an average one does so at an 11% rate. While the likelihood of this scenario occurring is extremely low (less than 2% of the sample), it shows that the interaction of these variables has a significant impact in establishing vulnerabilities. At the regional level, the differences are great as well, with the largest difference between mean and risk values showed in Region II (Tarapacá), in which it reaches an average of 15 percentage points. Regions XIII (Metropolitana) and XV (Los Ríos) show the smallest difference, of an average of 9 percentage points.

5.4 Discussion

This research is grounded within the inequalities of vulnerabilities literature, which is a perspective that understands structural factors or root conditions —economic, political, social—, like 'social relations' and 'structures of domination' as a constitutive element of disasters and risks (Hilhorst & Bankoff, 2004; Wisner et al., 2004). This starting fundamental to position the exposed results within the literature and in a broader empirical context.

In this regard, this research had 3 main hypotheses. The first one stated that *economic capacity and entitlement variables are inversely associated with the likelihood of suffering losses due to natural disasters*. The conducted empirical research found that most of the factors related to economic capacity were indeed inversely associated with losses from natural disasters, with the exception of income. In particular, poverty was found to be consistently increasing the likelihood of experiencing losses consistently at the national level and for almost all regions. Overall, this finding is consistent with the theoretical framework, but also with the previous research of disaster damage distribution in Chile. Poorer households have little financial reserves for supplies prior to an announced natural hazard, and for buying reconstruction materials in the aftermath of a sudden one. Even within the municipal and regional controls, in Chile poorer households tend to be located in less safe areas; and they have more chance of being informal and therefore not in conformance with anti-seismic building regulations. In this sense, this research has found evidence that poverty is an increasing factor in natural disaster vulnerability.

Regarding income, the results seem to be less clear. At the national level, the effect of income is found to be positive. At the regional level, it seems that the distribution of income is even less straightforward than at the national level: some regions even show a statistically significant increase in odds for higher deciles. This result is contrasting with that of poverty. While this result is contrasting with the macro and multi-country literature, poverty being significant and income not being so is consistent with the analysis of Kellenberg & Mobarak (2008), who argue for the decreasing impact of income over disaster risk. In the case of Chile in particular, a possible explanation can be found in the distribution of property: while the average household has a 12% likelihood of experiencing losses due to disasters, this number increases to 17% among those who own more than 1 property. 98% of those who own more than 1 property are indeed located in the 10th decile, which could be over-estimating their likelihood of experiencing losses. Moreover, as was argued before, the representativeness of this decile is somewhat inferior to that of the rest of the sample, which could speak of this group's data quality. It is also likely that the magnitude of damage may come into play when reporting to the survey. Overall, and while there are several possible explanations in addressing this issue, it is not possible to assure that household income is negatively associated with likelihood of suffering losses due to natural disasters.

Finally, there seems to be empirical evidence to back up the hypothesis that household over-crowdedness is positively related to disaster risk losses, but with some nuances regarding the interaction with house material conditions. Although at the national level this variable was not found significant, the regional level showed that groups in which deficient housing conditions was significant would not be significant in this factor and vice-versa; which may provide evidence to think that these two factors are related and capturing the same phenomena of material conditions of housing and living. Moreover, the regional analysis showed that over-crowdedness was the largest predictor for more urbanized regions concentrating the greater metropolitan areas of the country, which suggests that as an urban concern, it could be related to the decreased quality product of housing policy exposed in Section 2.

The second hypothesis stated that *social and political power variables are inversely associated with the likelihood of suffering losses due to natural disasters*. At the national level, it is possible to find evidence supporting the claims that belonging to rural areas and being isolated were positively associated with likelihood of disaster-related losses. The first one of these factors was the biggest predictor of the national level model, which was also confirmed at the regional level. This is a claim supported by the theoretical framework, which states that there is less political pressure to acknowledge the needs of rural and isolated population, but also that isolated groups will have less access to information technology, relief aid and other mechanisms that can decrease their losses. Qualitative studies in Chile have also recorded that isolated areas have less resources and are rescued slower than urban areas. In this sense, rurality and isolation can be understood as relevant causes of vulnerability to natural disasters.

Social isolation and educational level of the household's head were not found to be significant, and therefore, there is not enough evidence to support the claim that they are positively associated with likelihood of suffering losses due to natural disasters. However, being discriminated was found to increase likelihood of experiencing natural disasters' related losses at the national and the individual level. This factor's impact has not been addressed by any other Chilean research, but it is consisted with the American and Brazilian studies which have shown similar inequalities distribution (Bandyopadhyay, 2016; Rasch, 2017).

As it is expected, all of these factors are related to the structures that generate income inequality, which is reflected in the Gini index variable significance. Although this is not a household factor so its direct impact cannot be calculated, its coefficients show that at both the national and some of the regions, the context of higher income inequality will significatively shift the slope for the whole region or municipality: meaning that households in higher inequality settings are more likely to experience natural disasters than other households. In that sense, higher income inequality will positively impact natural disasters' vulnerability.

The inclusion of municipal and regional grouping, finally, provided controls for addressing the differences in these administrative groups' capacity in dealing with natural disasters. As was argued, the policy environment of Chile has been deficient at addressing general root causes of vulnerability, but in particular, the decentralization of disaster risk policy has acted as a booster of inequalities of disaster-related losses. While this has not been tested empirically in this research, these effects have been extensively addressed by the literature (Engel, 2016; Sandoval Henríquez, 2017; Sandoval & Voss, 2016; Valdivieso Fernández, 2017).

With the evaluation of these results, it is necessary to address the question of whether disasters and risks respond to social constructions. In this concern, and in the line that the literature of inequalities of vulnerabilities has stated, it seems that disasters and its related damage have evidence of being socially mediated, therefore so is disaster vulnerability. As the results of this research suggest, there are fundamental issues related to root causes that mediate the likelihood of disaster damage, both at the household level and at the contextual level.

However, although this research has made an effort to empirically differentiate the factors building disaster vulnerability, both the theoretical revision and the results of the within-region analysis show that it is the interaction of these factors that create the greatest differences. Understanding vulnerability and its inequality through the PAR approach, factors or conditions that generate vulnerabilities are accumulated producing differentiated disaster risk. This has been confirmed by the final section of the analysis, showing that combinations of factors generate statistically significant differences between risk and average Chilean households.

6 Conclusion

In a climate change world, the risk of natural disaster in the world has shown evidence of only be increasing. In Chile, one of the most hazard-exposed countries in the world, disaster risk has been characterized as a strong obstacle for development, and its costs have been estimated to reach around 1.2% of the country's annual GDP. This research has provided empirical evidence showing that costs and impacts of natural disasters are far from naturally distributed: instead, they are to a great extent a reflection of social relationships and structures of power that generate inequality. In a way, hazards are natural, but disasters are to great measure, a function of income and social inequality.

Through the analysis of three mechanisms creating inequalities – economic entitlements, social and political power, and income inequality –, it has been found that vulnerability to natural disasters is unequally distributed among the Chilean population, an empirical contribution to this body of literature. Poor, rural, isolated, discriminated against households are significantly more likely to experience losses due to natural disasters. At the municipal and regional level, it has been found that households set in contexts with higher income inequality are also at more risk. Although these results must consider that this sample only considers the distribution of disasters for a single year, they are consistent with theoretical and empirical research in the subject.

As has been exposed throughout this research, these root conditions interact also with its environment. However, in Chile the context of a social policy that does not hinder inequality in conjunction with great territorial inequalities and capacities to generate responses to disasters, bolster inequalities of vulnerability that are generated through root conditions.

These results have relevant public policy implications, which arise from the PAR framework. First, they suggest that by tackling social root causes, it is possible to reduce natural disaster vulnerability, and therefore release budget for other social expenditures. The specific effects of expenditure and specific planning for reducing disaster risk are subject to future research. Second, it has been argued that differences at the municipal and regional level in terms of disaster and emergency response may enhance vulnerabilities even further. Specific analyses of what are appropriate disaster risk and disaster response policies should be researched further, but it seems that these processes interact with the household levels in increasing root causes for progressions of vulnerabilities.

While this research has provided with a differentiation of factors to which vulnerability responds to, it has also been showed that vulnerability has different characteristics under different contexts, understanding it as a dynamic characteristic of communities. The understanding of vulnerability allows for a deeper understanding of the extent to which Chilean's inequality structure permeates its environment but is its understanding that allows for tackling its root causes and setting the path for establishing resilient communities.

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Appendix A: Summary statistics and variable construction

Table 11: Summary statistics for continuous variables

Mechanism	Variable	Obs	Mean	Std. Dev.	Min	Max
Economic capacity and entitlement	Total income	171780	361,459	522,838.4	0	4.89E+07
	Total income (log)	171663	12.4506	0.7656	6.2146	17.7052
Inequality	Regional Gini	171780	0.4245	0.0439	0.3712	0.4983
	Municipal Gini	171780	0.3804	0.0533	0.2214	0.6190

Table 12: Categories, count, percentage and source of categorical variables

Mechanism	Variable	Categories	Count	Percentage	Source
Economic capacity and entitlement	Regional income decile	1	17432	10.16	CASEN
		2	20928	12.2	
		3	20162	11.75	
		4	18984	11.06	
		5	18369	10.7	
		6	17182	10.01	
		7	16249	9.47	
		8	15031	8.76	
		9	14322	8.35	
		10	12939	7.54	
	Poverty status	Non-poor	133198	80.69	CASEN
		Poor	31878	19.31	
	Deficient housing status	No	145,961	85.18	CASEN
		Yes	25,396	14.82	
	Over-crowdedness status	No	155,728	90.98	CASEN
		Yes	15,433	9.02	
Political and social power	Geographic zone	Urban	143,206	83.37	CASEN
		Rural	28,574	16.63	
	Physical Isolation status	Non isolated	157,861	91.9	Constructed
		Isolated	13,919	8.1	
	Social Isolation status	Non isolated	111,309	65.67	CASEN
		Isolated	581,777	34.33	
	Educational level	Below primary education	52,388	30.5	Constructed
		Above primary education	119,392	69.5	

	Discrimination status	No	150,480	88	CASEN
		Yes	21,118	12.31	
	Indigenous population belonging	Does not belong	149,963	87.3	Constructed
		Belongs	21,817	12.7	

Appendix B: Models diagnostics tests

Correlation test

Table 13 shows that the utilized variables do not present high correlation rates.

Table 13: Variable correlation matrix

	Inc.	Inc. Dec-	Pov.	Hou	Crowd	Zone	Ph.Is	Soc. Is	Educ	Disc	Indig	Mun. Gini	Reg. Gini
Inc. Decile	0.52	1.00											
Poverty	-0.15	-0.25	1.00										
Deficient housing	-0.10	-0.17	0.35	1.00									
Over-crowdedness	-0.11	-0.19	0.31	0.10	1.00								
Zone	-0.09	-0.13	0.17	0.04	0.00	1.00							
Physical isolation	-0.05	-0.07	0.11	0.03	0.01	0.48	1.00						
Social isolation	-0.09	-0.09	0.35	0.05	0.06	0.07	0.04	1.00					
Educational level	0.13	0.21	-0.16	-0.07	-0.10	-0.13	-0.08	-0.03	1.00				
Discrimination	0.00	-0.03	0.06	0.07	0.04	-0.04	-0.02	0.03	0.00	1.00			
Indigenous people	-0.08	-0.10	0.10	0.04	0.04	0.13	0.08	0.06	-0.07	0.03	1.00		
Mun. Gini	0.15	0.16	-0.06	-0.04	-0.03	-0.15	-0.05	-0.04	0.05	0.02	0.02	1.00	
Reg. Gini	0.16	0.02	-0.02	-0.05	0.03	-0.15	-0.09	0.02	0.05	0.06	-0.07	-0.06	1
Fam. Subsidy	-0.07	-0.12	0.04	0.03	0.04	0.05	0.02	0.03	0.05	0.01	0.04	-0.03	-0.022

ROC Tests

In a ROC curve the true positive rate (Sensitivity) is calculated in function of the false positive rate (100-Specificity). The area under the ROC curve (AUC) is a measure of how well a parameter can distinguish between two groups (1/0). A test with perfect discrimination has an area closer to 1, and areas above 0.50 are usually classified as good predictors (Gelman, 2006). As shown, all models score values above 0.60 as point estimators, and no confidence interval goes below 0.60, which shows that models are reasonably good in predicting results.

Table 14: ROC Estimations

Analysis	Model	Area	Std. Error	Interval	
National	Model 1	0.6411	0.0015	0.64404	0.63816
	Model 2	0.6627	0.0021	0.666816	0.658584
	Model 3	0.6532	0.0032	0.659472	0.646928
Regional	Model 4	0.6718	0.0069	0.685324	0.658276
	Model 5	0.7012	0.0071	0.715116	0.687284
	Model 6	0.6811	0.0096	0.699916	0.662284
	Model 7	0.7193	0.0041	0.727336	0.711264
	Model 8	0.7242	0.0022	0.728512	0.719888
	Model 9	0.6925	0.0039	0.700144	0.684856
	Model 10	0.7312	0.0032	0.737472	0.724928
	Model 11	0.7122	0.0049	0.721804	0.702596
	Model 12	0.6632	0.0054	0.673784	0.652616
	Model 13	0.6788	0.0076	0.693696	0.663904
	Model 14	0.7026	0.0068	0.715928	0.689272
	Model 15	0.7039	0.0031	0.709976	0.697824

AIC and BIC

Akaike's information criterion and Bayesian information criterion are selection tests. The general interpretation is that models showing smaller values better fit the data than those with larger values, which lead to the selection of Model 2 and 3 as the specification for the regional models.

Table 15: AIC and BIC tests

Model	Obs.	ll(model)	df	AIC	BIC
Model 1	164973	-56826.01	13	113678	113808.2
Model 2	165076	-56839.06	21	113720.1	113930.4
Model 3	165076	-56837.98	21	113718	113928.3

Table 16: Estimation of probability margins for within-cluster effects, at population average and risk values

	Mean values		**Risk values**	
	Constant	**Standard Errors**	**Constant**	**Standard Errors**
National	0.11***	(0.0001)	0.22***	(0.0076)
Region 2	0.17***	(0.0030)	0.32***	(0.0100)
Region 3	0.16***	(0.0025)	0.30***	(0.0100)
Region 4	0.15***	(0.0020)	0.29**	(0.0096)
Region 5	0.14***	(0.0016)	0.27***	(0.0092)
Region 7	0.13***	(0.0010)	0.25***	(0.0083)
Region 8	0.12***	(0.0008)	0.23***	(0.0079)
Region 9	0.11***	(0.0008)	0.22***	(0.0076)
Region 10	0.10***	(0.0008)	0.21***	(0.0074)
Region 11	0.10***	(0.0001)	0.20***	(0.0071)
Region 12	0.09***	(0.0011)	0.19***	(0.0069)
Region 13	0.09***	(0.0012)	0.18***	(0.0066)
Region 15	0.08***	(0.0013)	0.17***	(0.0064)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1