Three Essays on Energy and Environmental Economics

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ABSTRACT

Three Essays on Energy and Environmental Economics

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This dissertation considers three empirical essays: two covering the nexus between energy and environmental economics and one addressing economic aspects regarding environmental monitoring, enforcement, and compliance.

The first essay explores the consequences of different energy poverty definitions and measures for identifying the energy poor. A Perception-based Multidimensional Energy Poverty Index (PMEPI) is proposed and compares the identification outcomes with the monetary index applying the ten percent rule index (TPRI) for the case of Chile. Coincidentally, both classify 15.5% of the population as energy poor. However, they select different energy-poor households while producing diverging energy-poverty rankings across the territory. Moreover, the TPRI neglects supply-side constraints captured by the PMEPI. These results suggest that both types of measures should not be used as substitutes but rather as complements in the energy policy debate and implementation of energy poverty alleviation actions.

The second essay estimates the key private benefits of a program to improve ambient air quality during winter in central Chile by replacing inefficient wood-fired home heating stoves with more efficient pellet stoves. By combining electronic stove surface temperature and air pollution monitoring with household surveys, this work shows that pellet stoves users

enjoy 14% lower indoor air pollution concentrations and more stable indoor temperatures than traditional wood-burning stoves users. In addition, lower-income and energy-poor households receive much greater improvements in indoor air pollution than those with higher incomes, indicating that the program is progressive in this dimension. However, these have significantly higher operating costs, and we found that these costs are most salient for low-income and energy-poor households. The results of this work represent an additional value for driving the energy transition.

The third essay empirically analyzes the complete sequence of enforcement and compliance in Chile, including inspections, compliance, submission of compliance programs, size of fines, payment of fines, and delay of payment of fines. These analyses are conducted for the case of facilities that belong to different economic sectors and are regulated by the Chilean Superintendency of Environment. This work demonstrates that monitoring efforts are relatively low, inspections are conducted differently across different sectors and are related to some specific facilities' characteristics. Compliance is also conducted differently across sectors, and it is positively related to the enforcement activities carried out by the regulators. This work also displays that fines increase the probability of compliance, and that is transmitted as a spillover effect to facilities sharing the same firm owner and in facilities that belong to the same sector located in the same commune. Furthermore, this work shows that presenting a compliance program is less likely on the small size facilities, the severity of the violation correlates positively with the size of the fine, and finally, the fine's payment positively correlates with the size of the facility.

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I. INTRODUCTION

The Sustainable Development Goals (SDGs) recognize that eradicating poverty, in all forms, is currently the most significant global challenge (United Nations, 2015). The SDGs are an urgent call to shift the world onto a sustainable and resilient path. They also represent a critical framework for envisioning a prosperous future where economic, social, and technological progress occurs in harmony with nature. The SDGs motivate the research I present in this thesis. This research considers two essays covering the nexus between energy and environmental economics and one essay addressing economic aspects regarding environmental monitoring, enforcement, and compliance. Consequently, the first two essays refer to SDG 7, "Affordable and clean energy," and the third essay refers to SDG 12 "Responsible consumption and production."

Recently, the World Bank has classified Chile into a group of high-income economies, which is the result of the economic growth experienced by the country in the last decades. However, it is still relevant to study whether this economic prosperity has been transmitted to other dimensions, such as energy transition and compliance with environmental regulations. My dissertation focuses on households and firms behind Chile's path to sustainable development. In the first part of my thesis, I focus on families classified as energy-poor by considering a broad set of energy dimensions beyond the prices of energy services (Essay 1). Secondly, I study the impact of transitioning to cleaner stoves and fuels on different outcomes showing that the poorest face the highest benefits (Essay 2). Finally, the last part of my thesis identifies facilities from the sectors of Fishing-Aquaculture and Housing-Construction as the ones having more difficulties complying with environmental regulations (Essay 3). Therefore, this dissertation also represents three opportunities where

Chile must continue advancing in green and equitable growth by providing evidence for each problem. The comprehensive purpose of this thesis is to analyze Chile's path towards sustainable development under the lens of environmental economics.

The first essay, titled “Energy Poverty Measures and the Identification of the Energy Poor in Chile Through a Multidimensional Approach,” explores the consequences that different energy poverty definitions might have for identifying the energy poor. Using the 2017 National Survey of Public Energy Perception applied to a sample of 3,500 households in Chile, this study compares the respective identification outcomes of applying the ten percent rule index (TPRI) and our proposed Perception-based Multidimensional Energy Poverty Index (PMEPI) against the monetary poverty identification outcome. Coincidentally, both measures classify 15.5% of the population as energy poor. However, they select different energy-poor households while producing diverging energy-poverty rankings across the territory.

This first essay contributes to the existing literature on energy poverty in three different aspects. First, based on the association level that the different energy poverty measures have, we propose a classification for energy poverty definition/measures. Second, this work is the first one that is devoted to researching multidimensional energy poverty at the household level in a recently classified high-income country. Finally, this essay explores the level of association between other measurements of poverty providing an empirical support to the proposed new index.

The second essay titled “The Impacts of More Efficient Biomass Heating Technologies: Evidence from Urban Households in Chile,” aims to estimate the effects of adoption of pellet stoves on household fuel expenditures, indoor temperatures, and indoor air pollution concentrations ($PM_{2.5}$). The fieldwork of this research considered a sample of 325 households that are participants of the stove replacement program in the city of Talca. Our work suggests that users of pellet stoves, on average, enjoy 14% lower indoor $PM_{2.5}$ concentrations compared with those who have traditional wood burning stoves. Lower-income and energy-poor households receive a much greater-than-average improvement in their indoor air pollution than those with higher incomes, driving the overall sample estimate and indicating that the program is progressive in this dimension. This work shows that improved heating stoves have significantly higher operating costs, and we found that these costs are most salient for low-income and energy-poor households.

This second essay contributes to the existing literature by providing empirical evidence, based on physical measurements, about the effects on households of the main economic incentives under implementation for controlling air pollution in central-southern Chile. Thus far, the Chilean government has replaced over 51,000 inefficient stoves during the last decade and, until now, there is a lack of knowledge about potential welfare effects after households have received the new stove. This essay contributes to narrowing this gap. This work also extends the literature to the case of a new high-income country, complementing the extensive literature on improved biomass cookstoves in low- and middle-income countries.

The third essay titled "What Drives Monitoring, Enforcement, and Environmental Compliance? An Empirical Investigation in Chile," empirically analyses the complete sequence of enforcement and compliance within Chilean firms. This includes inspections, compliance, submission of compliance programs, size of fines, payment of fines, and delay in payment of fines in a sample of 6,790 Chilean facilities. This work recognizes that the inspection decisions of the Chilean Superintendence of Environment (on who to inspect) are not independent of the compliance decisions of the facilities (to comply or not to comply).

This essay also analyzes what determines to present a compliance program as an intermediate alternative to fulfill the regulations for the facilities found in violation.

The third essay contributes to producing new empirical evidence on environmental monitoring, enforcement, and compliance in the context of a transitional economy. This work explores the driving factors of fines being imposed on non-compliant facilities and related payments, which have received little attention in existing empirical literature. Another contribution from this work to the literature is the exploration of spillover effects of monitoring and enforcement on facilities that belong to the same firm using the ownership structure of facilities included in the sample.

This document is structured as follows: Section II presents Essay 1, section III contains Essay 2; section IV presents Essay 3, and finally, section V presents the Conclusions.

II. ESSAY 1. ENERGY POVERTY MEASURES AND THE IDENTIFICATION OF THE ENERGY POOR IN CHILE THROUGH A MULTIDIMENSIONAL APPROACH [1]

1.1 Introduction and Background

According to the United Nations, energy is an essential resource to face the challenges of today's society. The Agenda for Sustainable Development requires, by 2030, to ensure universal access to affordable, reliable and modern energy services, to increase substantially the share of renewable energy in the global energy mix, and to double the global rate of improvement in energy efficiency. A proper definition of energy poverty could guide us to achieve these targets. Introducing the energy-related welfare dimensions, allows us to link the energy poverty to the poverty reduction strategies and to the national development (Birol, 2018; Kuzemko et al., 2017; Smith, 2018; UNDP, 2018).

Traditionally, energy poverty has been defined by how it has been measured (Bazilian et al., 2010). Given this development, it is not yet clear whether a consensus on its definition is going to be reached and the consequence of that is the emergence of many different energy poverty definitions. This issue has been critically reviewed by recent literature with focus on their policy implications (see Castaño-Rosa et al., 2019; Charlier and Legendre 2019; Deller, 2018; González-Eguino, 2015; Heindl and Schuessler, 2015; Romero et al., 2018; Thomson et al., 2016, 2017; Tirado Herrero, 2017).[2] One can argue that the differences in scope and

[1] This essay is based on Villalobos, Carlos, Carlos Chávez, and Adolfo Uribe. (2021). "Energy poverty measures and the identification of the energy poor: A comparison between the utilitarian and capability-based approaches in Chile." *Energy Policy* 152: 112146. https://doi.org/10.1016/j.enpol.2021.112146.

[2] Some authors already use certain energy poverty measurement classifications. For instance, Tirado Herrero (2017) identifies a direct approach when comparing the level of domestic energy services against a pre-defined standard, an income/expenditure approach, and definitions based on a household's self-assessment of energy

purpose of the many energy poverty definitions in current use run the risk of downgrading the concept: a consequence of the differing ways the term is understood by researchers and practitioners. On the other hand, one could also argue that the lack of consensus is advantageous, since this reflects how the circumstances determining energy-related wellbeing vary between and within societies. On that basis, there is value in defining energy poverty in a way that clearly relates to the context of evaluation.

In developing countries, current energy poverty measures focus primarily on the access to modern forms of energy (Malla, 2013; Nussbaumer et al., 2012; Sadath and Acharya, 2017; Tang and Liao, 2014; Zhang et al., 2019). Contrarily, in developed countries the focus lies prominently on the issue of economic affordability (Boardman, 1991; Bouzarovski and Petrova, 2015; Hills, 2012; Moore, 2012; Robinson et al., 2018), and in comparing the level of domestic energy achievements versus some standards (Besagni and Borgarello, 2019; WHO, 1987). In transition countries, energy poverty measures have been focused on emerging issues, such as tracking rural electrification (see Giannini et al., 2011 for the case of Brasil), on fuel switching for the case of Hungary (Bouzarovski et al., 2016) and on transition related issues in former east European countries (see Tirado Herrero and Ürge-Vorsatz, 2012).

In Chile, the government has neither adopted a definition of energy poverty nor conducted a systematic effort to measure it. Based on these agendas, the United Nations Development Program (UNDP) (2018) recommends that Chile first defines energy poverty and, secondly, goes beyond the issues of generating and accessing electricity. According to this recommendation, energy poverty is recognized as a multidimensional phenomenon

related living conditions. González-Eguino (2015) identify three approaches based on technological, physical, and economic thresholds.

including the availability of alternative sources of energy, their attributes such as quality, reliability, and its interaction with other contextual factors.

In this essay, we aim to examine the viability of introducing a new classification of the concept, with the new classification based on the impact that energy poverty may have on the household's overall wellbeing. On the one hand, first order energy poverty definitions/measures exhibit a relatively high level of association with an overall welfare index. On the other hand, second-order energy poverty definitions/measures show a relatively low association level. This new classification is empirically tested based on the level of association between these energy poverty measures and an overall welfare measure. For the empirical test, as a first-order energy poverty measure, we employ a utilitarian, income-related energy poverty measure such as the ten percent rule index (TPRI).[3] As a second order measure we propose a Perception-based Multidimensional Energy Poverty Index (PMEPI), which is based on the capability approach advocated by Sen (1999) and estimated using the Alkire-Foster (AF) method.[4] As a reference point, the indicator of household's overall wellbeing corresponds to the standard income poverty measure (FTG_0), which serves to assess the pertinence of the proposed energy poverty classification.[5]

We use a unique data set based on a survey applied to 3,500 households across the country during 2017. Firstly, we identify first and second-order energy poor households as well as income poor households. Secondly, we assess the level of association of the different measures. Thirdly, we decompose the indices across population subgroups to assess their distributional patterns (by macrozones, socio-economic levels, indigenous status, formal

[3] See Boardman (1991).
[4] See Alkire and Foster (2011), Nussbaumer et al., (2013).
[5] See Foster et al. (1984). Alternative indices of household's overall wellbeing are not available due to data constraints.

schooling of the household head, and the urban-rural divide). Finally, we explore the role of households' socio-economic and demographic characteristics as determinants of the level of association between the different energy poverty measures.

This essay contributes to the existing literature on energy poverty in three different aspects. First, based on the level of association that the different energy poverty measures have, we propose a classification for energy poverty definition/measures. By doing so, we aim to clarify the expectations (for researchers, policymakers, and practitioners) associated to the use of one energy poverty definition/measure. Second, our work is the first one that is devoted to researching multidimensional energy poverty at the household level in a recently classified high-income country.[6] This is relevant since, until now, the Chilean government has avoided the implementation of an energy poverty definition/measure beyond the issues of generating and accessing electricity. This is important since there are many low income and lower-middle income countries that are likely to follow a similar pattern of development in the years ahead. Finally, we explore the level of association between the mentioned measurements of poverty (TPRI, PMEPI, and FTG_0) providing an empirical support to our energy poverty classification.

The essay is structured as follows. Section 1.2 provides a theoretical discussion for the proposition of an empirical classification of the many energy poverty definitions/measures (first and second order) along with an extensive literature review around this. Moreover, this section reviews the scarce empirical evidence on the association between energy poverty measures. Lastly, to give the necessary context to this study, this section presents the empirical studies on energy poverty in Chile. The methodology in section 1.3

[6] In this country, the GDP per capita PPP rose from 10,438 in 1992 to 22,767 in 2017 (Figures in 2011 international Dollars. Data from the World Development Indicators).

briefly presents the datasets used in this work, the Alkire-Foster method and the capability approach in which our multidimensional energy poverty measure is embedded. Additionally, we describe the imputation procedure to allow the estimation of TPRI, as well as the analytical description of a measure of redundancy for our empirical assessment of our energy poverty classification. In the same section, we formulate our 2017 Perception-based Multidimensional Energy Poverty Index (PMEPI) for Chile. Results are presented in section 1.4. Section 1.5 concludes.

1.2 Theoretical Discussion on a Classification for the Definitions of Energy Poverty

1.2.1 First Order Energy Poverty Definitions and Measures

According to our classification, first-order definitions of energy poverty are those based on the direct impact that the energy underachievement has on the overall household's wellbeing. That is, energy poverty increases the likelihood of being poor (income or multidimensionally, etc.). In this category, one can classify energy poverty definitions aiming to capture households unable to access energy services at home up to a socially- and materially-necessitated level (Bouzarovski et al., 2012; Robinson et al., 2018). The empirical test consists of assessing the level of redundancy between the identification of the poor based on an energy poverty measure and an overall poverty measure. If the dentification of the poor based on both measures is highly correlated, then energy poverty can be treated as an (overall) poverty predictor.

First in this category and relevant to this work is the "Ten Percent Rule Index" (TPRI) proposed by Boardman (1991) who took the concept of fuel poverty to cover those households in the United Kingdom whose financial expenditure exceeds 10% of their net income.[7] Other first-order measures are the Low Income-High Costs index (LIHC) proposed by Hills (2012), and the Minimum Income Standard (MIS) indicator by Moore (2012).

The limitations of these energy poverty measures have been critically analyzed by Tirado-Herrero (2017). Among others, his analysis includes the arbitrariness of setting of thresholds and energy poverty lines, the diversity of domestic energy services to account for, the distinction between required and actual domestic energy expenditures, the way how household income and energy expenditures are equivalized, and how housing costs are accounted. First-order definitions of energy poverty have inspired several studies overseas. For instance, Bouzarovski et al. (2012) in Bulgaria, Boltz and Pichler (2014) in Austria, Miniaci et al. (2014) and Miazga and Owczarek (2015) in Poland, Legendre and Ricci (2014) and Imbert et al. (2016) in France, and Papada and Kaliampakos (2016) in Greece, Heindl and Schuessler (2015) in Germany, and Mbewe (2018) in South Africa.

1.2.2 Second Order Energy Poverty Definition and Measures

We move from the overall well-being space to an energy-related subset of it. That is, we focus exclusively on energy-related achievements. From a sectoral policy perspective, this type of indicator should be more informative and useful as they provide information on deficits in energy dimensions that could be addressed by the design and implementation of specific public policies (Bazilian et al., 2010). Since energy-related achievements go beyond the income-expenditure relation, measures in this category may consider a broader set of information when assessing the energy poverty status. Nussbaumer et al. (2012) measures

[7] Although one can claim that there are differences between fuel poverty and energy poverty, under this utilitarian framework, both concepts have been used interchangeably as they rely on the relationship between income and energy/fuel expenditure.

energy poverty using the Alkire and Foster method (Alkire and Foster, 2011) throughout the Multidimensional Energy Poverty Index (MEPI). This multidimensional index focuses on the joint deprivation in accessing modern energy services.[8]

Several studies have been developed using multidimensional indices. Ogwumike and Ozughalu (2015) find that about 75% of the population is energy poor in Nigeria.[9] In the same country, Ozughalu and Ogwumike (2019) find that energy poverty it is more pronounced in the rural sector and in the northern regions of Nigeria. Bersisa (2019) using estimates of the MEPI for Ethiopia in 2011 and 2014 finds that a large part of households living in rural and small towns are identified as energy poor. Crentsil et al. (2019) study the dynamics of multidimensional energy poverty in Ghana between 2008 and 2014 and find that even though multidimensional energy poverty was reduced in Ghana from a MEPI value of 0.505 to 0.363 between 2008 and 2014, energy poverty is still biased against female-headed and rural households. Finally, Mbewe (2018) estimates the MEPI for South Africa and finds declining levels of energy poverty. In Pakistan, Sher et al. (2014) find that more than the half of the population lives in an energy poverty condition, being the situation much worse in rural areas. Olang et al. (2018) using a MEPI explores the interaction between energy poverty and the determinants of household energy choice in Kisumu City, Kenya.

In the developed world, Okushima (2017) uses the MEPI approach considering three dimensions: energy costs, income, and energy efficiency of housing revealing the consequences of the Fukushima accident on the energy poverty level in Japan. Delugas and

[8] MEPI is part of the family of multidimensional measures. They are different from the composite indices since multidimensional measures capture the joint distribution of deprivations.

[9] Sanusi and Owoyele (2016) employ a complementary approach. The authors developed an Energy Development Index (EDI) ranging between 0 and 1, where 1 means maximum energy wellbeing and 0 the lowest energy wellbeing.

Brau (2018) measure multidimensional energy poverty using data from dwelling conditions and sources of energy inefficiency in Italy. Their results show negative effects of energy poverty on subjective wellbeing.

Finally, Gouveia et al. (2019) estimate the Energy Poverty Vulnerability Index (EPVI) in Portugal by combining socio-economic indicators of the population with buildings' characteristics and energy performance. The authors show higher energy poverty vulnerability in the inland region and the islands, especially in rural areas. A different group of energy poverty definition/measures within this category relies on a household's self-assessment of its living conditions (For instance, see Healy and Clinch, 2002).

1.2.3 Association between Welfare Indicators

Few studies have looked at the association level between different energy poverty measures. Robinson et al. (2018) finds spatial divergence in the distribution of fuel poverty in England using TPRI and LIHC indicators (first-order definition). Robinson et al. (2018) find divergence when identifying who is energy poor between the TPRI, LIHC and MIS measures in European countries. Using the MEPI in developing countries, some studies have found significant correlation between energy poverty and other income and non-income indicators. Olawumi Israel-Akinbo et al. (2018) find that low-income households in rural areas are more multidimensionally energy deprived than those in South African urban areas. In India, Sadath and Acharya (2017) find that energy poverty comes hand-in-hand with income poverty and gender gap, since women manage the domestic activities such as the collecting firewood and cooking. Moreover, they also find a significant association between energy poverty and health issues due to the incomplete combustion of fuels. Mendoza et al. (2019) find that income poverty and other socio-economic indicators are strongly correlated with multidimensional energy poverty in Philippines. Contrarily, in the developed world, Charlier and Legendre (2019) find that a multidimensional fuel poverty index (FPI), considering the dimensions of income, residential energy efficiency, and heating, has a low level of association with the TPRI and LIHC indices in France.

1.2.4 Energy Poverty in Chile

Only a few measures of energy poverty are available in the case of Chile. To the extent of our knowledge, only Cerda and González (2017) provide empirical measures of energy poverty at the household level, all of them based on energy-income-expenditure-related metrics (first-order measures). By using data from the 2013 Chilean Expenditure Survey (EPF2013), they found an energy poverty rate of about 5.2% under the Low Income and High Cost (LIHC) measure. The energy poverty rate could go up to 15.7% under the Minimum Income Standard measure (MIS).[10]

The issue of energy poverty has recently also been explored due to the severe air pollution problems caused by households burning wood for heating in urban areas of central-southern regions of Chile. Reyes et al. (2018; 2015) have examined the effects of air pollution control policies on energy poverty. Based on case studies in the city of Valdivia, a medium size city located in southern Chile, they found that due to the relevance of households' expenditure on energy for heating and the poor thermal insulation of the current stock of households' dwellings, policies intended to reduce emissions from households should focus on improving thermal efficiency.

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[10] Cerda and González (2017) also explored the impacts of a tax on CO_2 emissions on energy poverty in Chile and found that, because of the relevance of energy expenditure, any policy that targets emissions but increases the price of energy will increase energy poverty in the country.

1.3 Methodology

In this section, first we present the data used in this study. Second, we show the capability Approach and the Alkire-Foster Method. Third, we present the Perception-based Multidimensional Energy Poverty Index (PMEPI). Fourth, the Estimation of TPRI Energy Poverty in the ENE 2017 and finally, the redundancy Between Energy Poverty Measures.

1.3.1 Data

The information used to implement our energy poverty measures comes from the 2017 National Energy Survey (ENE2017) designed by the Ministry of Energy. The survey considers a total sample of 3,500 households distributed in statistically representative macrozones. One thousand households were surveyed in the metropolitan region of the country (MET) and 500 households in each of the following macrozones: NGR (the northernmost region), NCH (northern region), CEN (central region), CES (central southern region), SUR (the southernmost region). The survey is also representative by socio-economic level as defined by the social grades system of demographic classification for Chile (high-middle-class families (ABC1), middle-class families (C2), low-middle-class families (C3), and poor and working-class families (D+E). According to the Ministry of Energy (2017), the survey respondents were selected following the Kish selection method aiming to avoid respondent selection bias (Kish, 1949).[11]

The ENE2017 considers the demographic, socio-economic, and geographic information of its respondents as well as energy-related information from objective questions, quizzes, and perceptions. It also includes income information that can be used to

[11] This method uses a pre-determined table of random numbers to find the person to be interviewed.

estimate the monetary poverty status of a household and the monetary poverty headcount ratio (FTG_0).[12] As the ENE2017 does not contain any information on energy expenditure, we rely on the 2017 Chilean Expenditure Survey (EPF2017) to impute the energy expenditure status of the households surveyed in the ENE2017. This procedure is feasible since similarly to ENE2017, the EPF2017 contains equivalent household level demographic information, socio-economic characteristics, and geographic information.

In this section, we present the methodology employed to develop the analysis on our classification of energy poverty measures. First, we present The Capability Approach and the Alkire-Foster (AF) method and then our second-order Perception-based Multidimensional Energy Poverty Index (PMEPI), which is estimated using the AF method.

1.3.2 The Capability Approach and the Alkire-Foster Method

The capability approach advocated by Sen (1999) is a welfare evaluation framework that rejects the view that the commodity holdings (resources) are adequate for judging the freedom that individuals enjoy when pursuing their life purpose. According to this approach, the problem of assessing the quality of life consists in evaluating the functionings (doings and beings that are valuable for the individual) and the capability to function (Sen, 1985). Then, poverty is ultimately a matter of capability deprivation (Dreze Jean, 1995). In this framework, we define energy poverty as the condition of a household experiencing systematic underachievement in energy-related dimensions that, because their simultaneity, have the potential to negatively affect different functionings (education, health, etc.) and the

[12] The FTG_0 measure relies on the official poverty line set at 155,443 Chilean pesos in 2017. Following the official procedures, we set the parameter of the household economies of scales at 0.7 used to adjust total per capita income figures.

capability to function. The magnitude of this potential is what distinguishes first and second-order energy poverty definitions.

The Alkire-Foster (AF) method is a straightforward multidimensional extension of the Foster-Greer-Thorbecke poverty measures (Foster et al., 1984). Consider a population of interest of n individuals measured across j indicators of achievement. Then, the n x j dimensional achievement matrix X might have cardinal, ordinal and dichotomous information of the achievement of individual i in indicator j (x_{ij}). Each indicator j has a corresponding deprivation cutoff z_j,. Then, an individual is deprived in indicator j if its achievement in that indicator is below z_j.[13] The entries $g^0{}_{ij}$ of the deprivation matrix g^0 takes the value of 1 if $x_{ij} < zj$ and 0 otherwise. Normalized weights (w_j) can be used to represent the relative importance of each dimensional deprivation. The weighted sum of deprivations $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$ can take a value between zero (representing an individual with no deprivation) and the unity (representing an individual simultaneously deprived in all dimensions). An individual (or household) is identified as poor if its sum of weighted deprivations ci is higher than a poverty cutoff denoted by k.

An AF Multidimensional Poverty Index requires aggregating deprivations across dimensions of those already identified as multidimensional poor while neglecting deprivations of those non-poor (with $c_i < k$). The censoring of the deprivation score vector originates the censored deprivation score vector $c_i(k)$, which preserves the entries of $c_i(k)$, when $c_i > k$ and takes the values of zero for all individuals when $c_i < k$. Being q the number of individuals identified as poor, and n the total number of individuals, one possible analytic

[13] The individual refers to the unit of analysis. It can be people or households, in which case, the deprivations suffered by the household members are aggregated at the household level.

definition of the AF Multidimensional Poverty Index is $M_0 = \frac{q}{n} \times \frac{1}{q} \sum_i^q c_i(k)$. This is a convenient way to decompose the index in a (multidimensional) poverty headcount ratio ($H = q/n$) and in an intensity factor (A), which is the mean deprivation of those multidimensionally poor. Consequently, the Multidimensional Poverty Index M_0 is a multidimensional headcount ratio (H) adjusted by the deprivation intensity (A) suffered by the poor ($M_0 = H \times A$). These partial indices are of interest to policymakers.

The index can be decomposed by population sub-groups using population shares as weights and it is possible, using the censored headcount ratios, to assess the contribution of dimensional deprivations to overall poverty (dimensional breakdown). The censored headcount ratio of an indicator corresponds to the population share who are energy poor and simultaneously deprived in that indicator. Formally, if j is a given welfare indicator, then the censored headcount ratio is defined as $h_j(k) = \frac{1}{n} \sum_{i=1}^n g_{ij}^0(k)$, being $g_{ij}^0(k)$ the censored deprivation matrix.

1.3.3 Perception-based Multidimensional Energy Poverty Index (PMEPI)

Our proposed energy poverty measure follows the AF method and considers five energy-related achievement dimensions maximizing the use of information from the ENE2017 household survey. In the adoption of the normative decision for the PMEPI (dimensions, weights, dimensional cutoffs and an energy poverty cutoff) expressed in Table 1-1, we consider first the issues mentioned by UNDP (2018). In this report devoted to Chile, any energy poverty measure should not be restricted exclusively to the assessment of the affordability of energy services.[14] The measure should also include an assessment of the access to other energy sources, their qualitative attributes as well as their sustainability. The key role that UNDP (2018) attaches to affordability justifies to put this dimension first in the weighting hierarchy. However, the implicit message is that energy poverty is more than only an affordability problem. This led us to set the (i) affordability weight in (1/3) and the energy poverty line *k* above it at 0.44.[15]

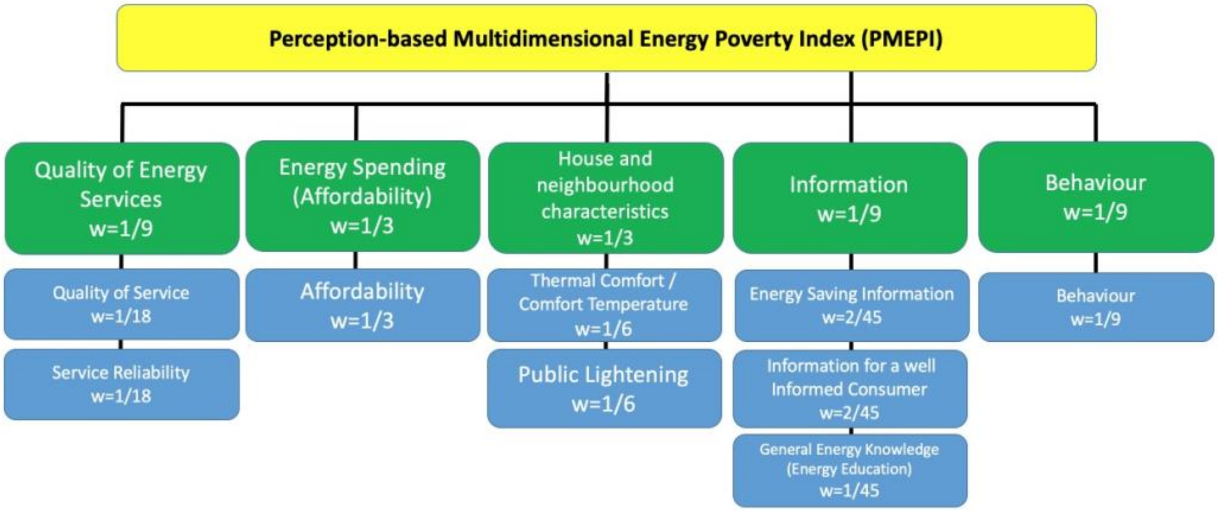
The remaining dimensions considered in the PMEPI are weighted following according to hierarchy discussion: (ii) energy-related households and neighborhood characteristics: thermal comfort (1/6) and public lighting (1/6), (iii) energy demand behavior (1/9) (iv) quality of energy services: service quality (1/18) and service reliability (1/18), and (v) Information: energy-saving information (2/45), information for a well-informed consumer (2/45), and energy education (1/45).

Finally, PMEPI is SDGs sensitive. It means that progress in each indicator translates into a reduction in the gap between the current situation and the achievement of Targets 7.1, 7.2 and 7.3 (see Table 1-1). The PMEPI is shown in Figure 1-1.

[14] According to the Chilean household survey (‘*Encuesta Nacional de Caracterización Socio Económica’* – CASEN), in 2017, electrical coverage reached 99.47% in the country (99.7% and 97.6% in urban and rural areas, respectively). In the ENE2017 household survey, 100% of households reported having access to electrical services.

[15] The assumptions used in this study for the definition of dimensions and weights were discussed in a working session held with members of the Division of Prospective and Regulatory Impact Analysis of the Ministry of Energy, January 2019. Additionally, an equal-weights estimation was performed to test the robustness of our results. The conclusion is that our results are not affected by the weighting structure of the PMEPI.

Figure 1-1. Dimensions and Weights selected for PMEPI



Source: Own elaboration.

Table 1-1. Deprivation Indicators, Cutoffs and Weights of PMEPI for Chile 2017

Dimensions	Deprivation indicators (People who live in households with the following characteristics)	Weights	Related SDG Target
	Energy Spending (Affordability)	**1/3**	
Affordability	Households where their adjusted household per capita income is less than two times the poverty line and perceive that, in relation with the quality of services, BOTH services, electricity and natural gas, are found to be expensive.	1/3	Target 7.1
	Energy-related House and Neighborhood Characteristics	**1/3**	
Thermal Comfort	Households where their members perceive that they cannot maintain an adequate temperature during winter.	1/6	Target 7.3
Public Lighting	Households where their members are not satisfied with the Public Lighting in their neighborhood (less than four in the 1-7 scale).	1/6	Target 7.1
	Behavior	**1/9**	Target 7.3
Behavior	Households where their members have adopted up to five (out of 11) of the energy saving measures listed in question P42 of the ENE2017 questionnaire.	1/9	Target 7.3
	Quality of Energy Services	**1/9**	
Service Quality	Households where their members are generally not satisfied with the electricity service OR the natural gas service (from 1 to 3 in the satisfaction scale out of 7). If they are satisfied, they are still deprived if their assessment of the quality of the electricity service is bad AND it is also bad for the natural gas service.	1/18	Target 7.1
Service Reliability	Households where their members are not confident that, in the case of an earthquake, fire, alluvium, volcanic eruption, etc., the fuel supply will be enough to satisfy the needs of the population AND that the electricity service will be restored shortly AND that the natural gas supply will be enough to satisfy the needs of the population.	1/18	Target 7.1
	Information	**1/9**	
Energy-Saving Information	Households where their members know up to five (out of 11) of the mentioned possible domestic actions to save energy listed in question P41 of the ENE2017 questionnaire.	2/45	Target 7.2 & 7.3
Information for a Well-informed Consumer	Households where their members know up to two (out of 5) key energy-related information listed in questions P7 and P29 (price, saving measures, electricity bill, electricity consumption of an electronic device) of the ENE2017 questionnaire.	2/45	Target 7.2 & 7.3
General Energy Knowledge (Energy Education)	Households where their members know up to five (out of 11) of the non-key energy-related concepts listed in questions P17, P7, P5 and P22 of the ENE2017 questionnaire.	1/45	Target 7.3

Source: Own elaboration.

1.3.4 Estimation of TPRI Energy Poverty in the ENE 2017

Measuring TPRI requires information on energy expenditure and income. Although the ENE2017 contains information on households' income, the dataset does not contain any information regarding energy expenditure. Therefore, we rely on regression imputation to predict the point estimates of the household energy expenditure in the ENE2017. If the regression equation in EPF2017 is well specified, estimates are unbiased since the relevant data in ENE2017 is missing completely at random. For predictive purposes, the regression equation in EPF2017 maximizes the use of information that is available in both surveys (ENE2017 and EPF2017). The set of explanatory variables considered for the imputation model are the household's total disposable income, the occupation of the household head, the level of education of the household head, the type of dwelling, the household size, and locality.

1.3.5 Redundancy Between Energy Poverty Measures

To assess the matches and mismatches between the (energy) poverty measures, we use the overlap R^0 (Alkire et al., 2015). For instance, entries $\mathbb{P}_{00}^{jj'}$ and $\mathbb{P}_{11}^{jj'}$ in Table 1-2 show the percentages of people being classified simultaneously as PMEPI non-poor and TPRI non-poor, and PMEPI poor and TPRI poor, respectively. $\mathbb{P}_{10}^{jj'}$ and $\mathbb{P}_{01}^{jj'}$ show the population shares classified as TPRI poor but not PMEPI poor and vice versa, respectively. The marginal distributions are $\mathbb{P}_{1+}^{\cdot j}$ for the TPRI poor, $\mathbb{P}_{0+}^{\cdot j}$ for the TPRI non-poor, $\mathbb{P}_{+1}^{\cdot j'}$ for the PMEPI poor and $\mathbb{P}_{+0}^{\cdot j'}$ for the PMEPI non-poor. The same two-way contingency table is employed to assess the level of association between PMEPI and FTG_0, and between TPRI and FTG_0.

Table 1-2. Two-way Contingency Table for TPRI and PMEPI Energy Poverty.

		PMEPI Energy Poverty (j')		
		Non-poor	**Poor**	**Total**
TPRI Energy Poverty (j)	Non-poor	$\mathbb{P}_{00}^{jj'}$	$\mathbb{P}_{01}^{jj'}$	$\mathbb{P}_{0+}^{\cdot j}$
	Poor	$\mathbb{P}_{10}^{jj'}$	$\mathbb{P}_{11}^{jj'}$	$\mathbb{P}_{1+}^{\cdot j}$
	Total	$\mathbb{P}_{+0}^{\cdot j'}$	$\mathbb{P}_{+1}^{\cdot j'}$	**1**

Source: Own elaboration based on Alkire et al. (2015).

Suppose both poverty measures are correlated, and at least one of the headcount ratios is higher than zero. In this case, this measure shows the poverty identification matches as a proportion of the minimum of the marginal poverty rates. By construction, R^0 ranges between zero to one and it is defined as follows in equation 1.1:[16]

$$R^0 = \frac{\mathbb{P}_{11}^{jj'}}{min\,[\mathbb{P}_{+1}^{\cdot j'}, \mathbb{P}_{1+}^{\cdot j}]} \qquad (1.1)$$

A low redundancy level is an indication of a low degree of substitution between both TPRI and PMEPI. Since TPRI is an income-related measure, a low level of substitution between TPRI and PMEPI implies that a reduction of energy prices and/or increasing household income will not translate into a proportional PMEPI reduction.

[16] As an example, if the monetary poverty headcount ratio is 10% and the energy poverty headcount ratio is 15%, then R^0= 0.5 implies that 50% of the income poor population is simultaneously energy poor. For robustness purposes, we additionally use the Cramer's V coefficient of association. It is defined as the product of the matches minus the product of the mismatches divided by the square root of the product of the marginal distributions or: $\frac{(\mathbb{P}_{00}^{jj'} \times \mathbb{P}_{11}^{jj'}) - (\mathbb{P}_{10}^{jj'} \times \mathbb{P}_{01}^{jj'})}{(\mathbb{P}_{+1}^{\cdot j'} \times \mathbb{P}_{1+}^{\cdot j} \times \mathbb{P}_{+0}^{\cdot j'} \times \mathbb{P}_{0+}^{\cdot j})^{1/2}}$.

Aiming to investigate the factors behind the R^0 level between both energy poverty measures, we estimate a probit model. In the selection of explanatory variables, we follow Klasen and Villalobos (2019) who investigate the level of association between multidimensional and income poverty in Chile. They find that household education, rurality and household size explain the divergent identification pattern between both poverty measures to a great extent. Consequently, our model includes education level of the household head, macrozones, indigenous status of a household, household size, and rurality.

1.4 Results

In this section, we present the main results. First, we show results of the national Perception-based Multidimensional Energy Poverty. Second, we present an analysis on the spatial distribution of the welfare measures. Third, we present our results by population subgroups, including socioeconomic level, rural-urban divide, education, and indigenous status.

1.4.1 Energy Poverty in Chile

Our results in Table 1-3 show that 15.5% of the population lives in a household classified as multidimensionally energy poor (PMEPI-H) with an average deprivation of 56.3% (PMEPI-A), which results in a Perception-based Multidimensional Energy Poverty Index (PMEPI) of 0.087. Coincidentally, our estimate of TPRI classifies 15.5% of the population as energy deprived while 16.9% of the population is found to be monetarily poor. Although the headcount ratios are very similar in level, we show later in our redundancy analysis that there is a high level of discrepancy among individuals classified as energy poor across these measures. It implies that the selection of a type of energy poverty measure (first or second order) goes hand in hand with a selection of a different set of energy poor households. Thus, this issue is not trivial since it has a potentially relevant impact when using poverty statistics for the purpose of elaborating energy poverty reduction plans.

Regarding our proposed multidimensional energy poverty measure, by construction, if deprivations were randomly allocated across households, the dimensional contribution to the level of PMEPI would reflect the structure of the weighting vector. At the country level, the dimension of affordability is by far the most important contributing dimension to energy poverty, explaining 57.6% of its level. This dimension is the only one whose contribution to energy poverty exceeds its random expectation of 33.3%.[17]

Our results in Table 1-3 also support our expectations about the level of association between first and second-order energy poverty measures with an overall household's wellbeing index. On the one hand, the level of association between TPRI and the income poverty headcount (FTG_0) is high (R^0=0.94 and Cramer's V=0.81). On the other hand, the level of association between PMEPI and FTG_0 is low (R^0=0.37 and Cramer's V=0.23), and the redundancy between PMEPI and TPRI is also low (R^0=0.35 and Cramer's V=0.21). These results are congruent with the findings by Charlier and Legendre (2019) in the case of France. The policy implication is that TPRI and PMEPI are complementary energy welfare indicators, while TPRI can be proxied by the use of a standard monetary poverty measure. These results sustain the idea that the utilitarian measure (TPRI) corresponds to a first-order measure, while the multidimensional index (PMEPI) is a second-order measure of energy poverty.[18]

[17] See the Dimensional contribution to PMEPI section in Table 1-3. Household and neighborhood's characteristics contribute with 29.72% (expectation of 33.3%), quality of service with 5.62% (expectation of 11.1%), information with 6.6% (expectation of 11.1%), and behavior with 0.44% (expectation of 11.1%).

[18] Table 1-3 also shows the levels of association between first and second-order energy poverty measures across macrozones. These results confirm the complementarity between first and second-order energy poverty measures.

Table 1-3. Indices and Dimensional Contribution by Country Level and Macrozones.

Indices	Country	Macrozones					
		NGR	NCH	CEN	CES	SUR	MET
PMEPI	0.087	0.070	0.140	0.067	0.090	0.136	0.074
s.e. PMEPI	0.006	0.019	0.033	0.012	0.013	0.024	0.011
Headcount (H)	0.155	0.124	0.251	0.123	0.160	0.245	0.130
s.e. H	0.011	0.032	0.059	0.022	0.023	0.042	0.018
Intensity (A)	0.563	0.568	0.559	0.548	0.560	0.555	0.575
s.e. A	0.005	0.009	0.012	0.014	0.013	0.008	0.007
Dimensional contribution to PMEPI (%)							
Quality	5.62	4.94	7.54	4.53	6.16	6.56	4.65
Spending	57.63	52.86	58.38	57.62	59.01	57.71	57.04
House	29.72	32.23	28.04	28.30	28.75	28.30	31.84
Information	6.60	8.29	5.62	8.48	5.91	7.17	6.15
Behavior	0.44	1.68	0.43	1.07	0.17	0.26	0.32
Ten Percent Rule Index (TPRI) and Monetary Poverty (FTG-0)							
TPRI	0.155	0.149	0.172	0.249	0.190	0.196	0.081
s.e. (TPRI)	0.012	0.065	0.049	0.042	0.032	0.053	0.010
FTG-0	0.169	0.158	0.199	0.264	0.214	0.233	0.082
s.e. (FTG-0)	0.014	0.070	0.064	0.053	0.036	0.061	0.014
Overlap R^0 Measure							
TPRI & FTG0	0.940	0.956	0.927	0.969	0.899	0.985	0.935
s.e. (TPRI-FTG0)	0.018	0.039	0.036	0.029	0.044	0.012	0.041
PMEPI-H & TPRI	0.347	0.295	0.593	0.450	0.358	0.515	0.358
s.e. (PMEPI-H & TPRI)	0.033	0.119	0.072	0.081	0.088	0.085	0.088
PMEPI-H & FTG0	0.374	0.365	0.607	0.476	0.407	0.510	0.323
s.e. (PMEPI-H & FTG0)	0.031	0.128	0.065	0.103	0.086	0.095	0.062
Cramer's V Coeffcient							
TPRI & FTG0	0.807	0.853	0.819	0.843	0.786	0.839	0.720
PMEPI-H & TPRI	0.212	0.172	0.357	0.196	0.192	0.300	0.160
PMEPI-H & FTG0	0.225	0.203	0.413	0.166	0.198	0.344	0.175

Source: Own elaboration based on ENE2017 and EPF2017 household surveys.
Note: s.e. = Standard errors.

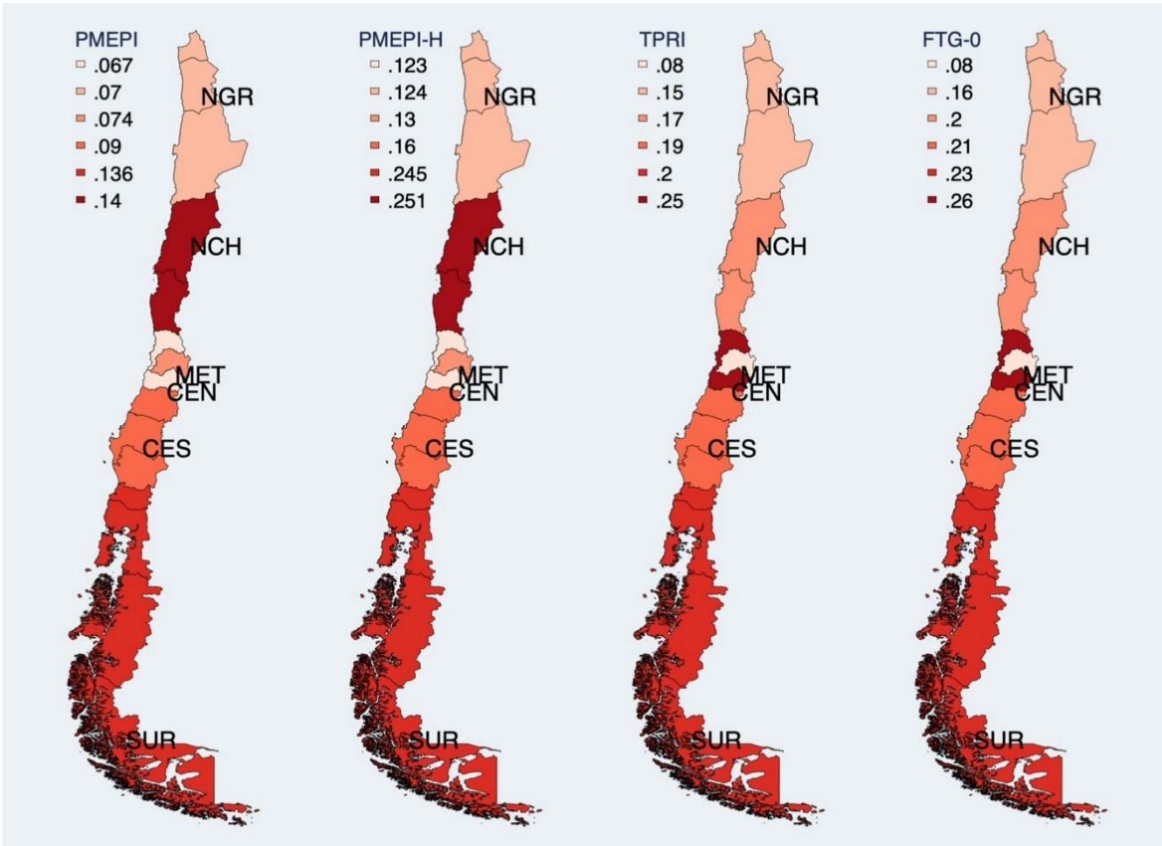
1.4.2 Spatial Patterns of Energy Poverty in Chile

Figure 1-2 displays the spatial distribution of the welfare measures. From left to right, it shows the distribution of the PMEPI, its headcount ratio (PMEPI-H), TPRI and FTG_0.[19] The FTG_0 and TPRI indices produce exactly the same deprivation ranking across macrozones.[20] From the most to the least deprived macrozones, we find: CEN, SUR, CES, NCH, NGR, and MET. Contrarily, PMEPI-H and PMEPI rank from the most to the least energy deprived macrozones as follows: NCH, SUR, CES, MET, NGR, and CEN. The least deprived macrozone by PMEPI-H and PMEPI is ranked as the most deprived one following the TPRI and FTG_0 measures. Similarly, while NCH is the macrozone with the second lowest monetary poverty prevalence, it ranks as the most deprived one based on our second-order energy poverty measure. These results reveal the distributive spatial consequences when designing interventions based on one or another energy poverty measure.

By macrozone, affordability is still the most important contributing dimension to PMEPI, ranging from 52.9% in NGR to 59.0% in the CES macrozone. In this macrozone, although it has the lowest level of multidimensional energy poverty, affordability contributes the most to PMEPI. These results confirm that our measure goes beyond affordability, and therefore, other dimensions related to sustainability, quality, and comfort play a significant role in shaping energy-related wellbeing across the country.

[19] In general, intensity of the PMEPI (PMEPI-A) does not explain the variation of PMEPI across the different population sub-groups including macrozones (see Appendices 1.1, 1.2 and 1.3).
[20] This is somewhat expected as TPRI is a first-order energy poverty measure.

Figure 1-2. Energy and Poverty Indicators, Chile, 2017



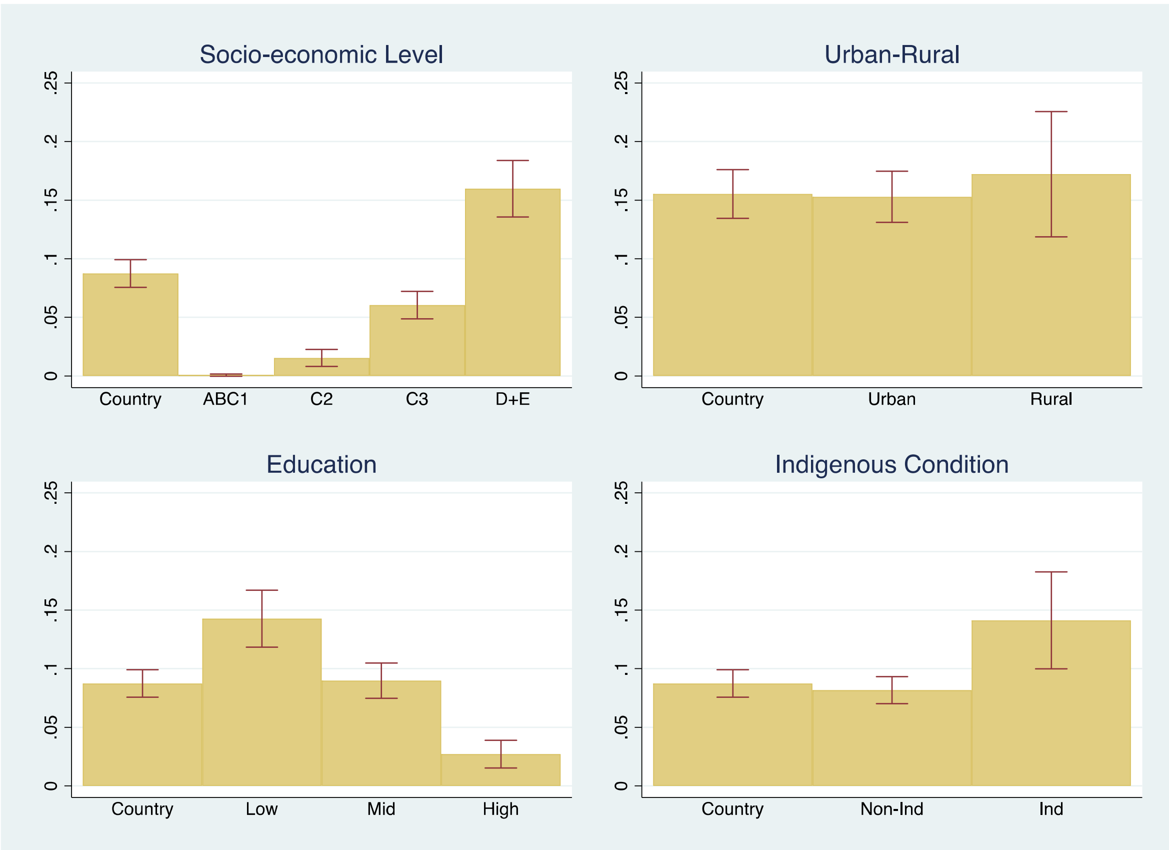
Source: Own elaboration.

1.4.3 Energy Poverty in Chile by Population Subgroups

Figure 1-3 presents our results by population subgroups, including socio-economic level, rural-urban divide, education, and indigenous status of the households. We find statistically significant energy gaps for most subgroups of the population. The higher the socio-economic classification and education level of the household head is, the lower the PMEPI. A similar pattern is reported by Olawumi Israel-Akinbo et al. (2018), Sadath and Acharya (2017), and Mendoza et al. (2019).

Contrarily to the findings by Ozughalu and Ogwumike (2019), Bersisa (2019), Crentsil et al. (2019), Sher et al. (2013), and Gouveia et al. (2019), we did not find sufficient statistical evidence supporting the urban-rural energy poverty divide. The high variability of the information of rural households compared to the number of observations do not allow us to statistically confirm urban-rural gap in our multidimensional energy poverty measure.[21]

Figure 1-3. Energy Poverty Index Chile, 2017



Source: Own elaboration.

Although indigenous people might face different state regimes and laws around the world, they can share some energy-related disadvantages in accessing energy services. To the best of our knowledge, there is no study devoted to detecting and explaining the causes

[21] More data and further research could help to investigate the existence of the rural-urban divide. However, our results suggest that the gap would be in any case small in size.

of energy underachievement in indigenous communities. In this regard, and in spite of the high variability of the indigenous estimates, Figure 1-3 shows that the indigenous households experience statistically significantly higher levels of multidimensional energy poverty. This finding is consistent with the scarce literature on energy poverty and indigenous populations (see Carpenter and Jampolsky, 2015).

1.4.4 Explaining the PMEPI Differences Across Population Subgroups

PMEPI differences across population subgroups are explained by the level and distribution of the censored headcount ratios (the average deprivation by indicator of those multidimensionally energy poor) presented in Table A1 and Table A2 in Appendices. Compared against the macrozone with the lowest energy poverty (CEN macrozone), NCH has significantly higher censored headcount ratios for the dimensions of service reliability, affordability, thermal comfort, and energy education (10, 13, 12, and 5 more percentage points than CEN, respectively). Similarly, the SUR macrozone has significantly higher censored headcount ratios for the dimensions of service reliability, affordability, thermal comfort, information for efficiency, and energy education (8, 12, 9, 6, and 7 more percentage points than CEN, respectively). Thus, the gap is not only an issue of affordability; service reliability and thermal comfort, in this order, also play an important role in explaining this spatial discrepancy.

Higher deprivation levels across all indicators mean PMEPI gaps can be explained by socio-economic and education levels. Although our results do not statistically confirm the existence of a PMEPI gap relating to the urban-rural divide, there are differences in the dimensions of behavior and service reliability, which are still statistically significant at the

5% and 10% level, respectively.[22] Appendix 1.2 shows that the energy underachievement of indigenous communities is mostly explained by the dimensions of (in order of relevance): Affordability, Thermal Comfort, and Service Quality. Note that with the exception of the energy savings information indicator, all gaps are statistically significant.[23]

1.4.5 Overlap Between Energy Poverty Measures and their Determinants

We explore the overlap between energy poverty measures and its determinants. Our results show significantly lower R^0 levels among households with tertiary educated heads. Klasen and Villalobos (2019) find the same when assessing the association level between income and multidimensional poverty between 1992 and 2017 in Chile. Our results suggest higher overlap levels in NCH and SUR macrozones as well in rural areas. On the contrary, the indigenous status of a household seems be uncorrelated with the association measure. Appendix 1.3 details the redundancy measure between PMEPI-H and TPRI.

The probit model results investigating the factors behind the overlap between PMEPI and TPRI at the household level are presented in Appendix 1.4.[24] Among TPRI poor households, the dependent variable takes the value of 1 if the household is additionally PMEPI poor and 0 otherwise.

We find that low education is positively associated with the overlap between both energy poverty indices. The transmission channel works as follows: low education affects negatively the income generation capacity of the household, its energy behavior, and

[22] On average, the urban-rural gaps reach about 2%-3% in the censored deprivation ratios in the dimensions of service reliability, thermal comfort, affordability, and information.
[23] The gaps in the dimensions of affordability, behavior, and service quality are significant at the 1% level. The gaps in thermal comfort, and public lightning are significant at the 5% level. Finally, the gaps in service reliability, information for a well-informed consumer, and energy education are significant at the 10% level.
[24] Appendix 1.4 also reports estimates for the overlap between PMEPI and FTG_0.

performance in the information dimension (all demand side factors). Therefore, it increases the probability that PMEPI and TPRI go hand-in-hand in these households. However, neither household size nor rurality play a significant role in explaining the overlap level. A higher conditional overlap expectation is also found for the NCH and SUR macrozones.

The strong association between the macrozones and the overlap reveals that there are territory-linked (supply side) factors that are beyond the control of TPRI poor families, affecting their probability of being PMEPI poor. In the NCH and SUR macrozones, high levels of TPRI poverty are followed by relative deficiencies in the quality of service, service reliability, and thermal comfort of dwellings, which results in a high energy poverty overlap. On the contrary, in the CEN macrozone, high levels of TPRI poverty are juxtaposed with high achievements in the same dimensions. This juxtaposition explains the apparent paradox between both energy poverty measures since the CEN macrozone ranks as the most deprived in TPRI poverty and the least poor according to PMEPI.

1.5 Conclusions and Policy Implications

In this essay, we proposed a classification of energy poverty definitions/measures. To show evidence supporting this classification, our empirical exercise relied on the estimation of a Perception-based Multidimensional Energy Poverty Index (PMEPI) using a unique data set for the case of Chile. Additionally, we identified the ten percent rule energy poor (TPRI) and the monetarily poor (FTG_0). Then, we decomposed these welfare indices by population subgroups to assess their distributional patterns. Furthermore, we provided association measures between PMEPI, TPRI, and FTG_0. Finally, we explored the role of households' socio-economic and demographic characteristics as determinants of the association level between the different measures.

Based on the results of our multidimensional energy poverty measure, we found that 15.5% of the population lives in energy poverty. PMEPI differences across population subgroups are explained by the headcount poverty ratio rather than the energy poverty intensity suffered by the households. The PMEPI poverty is higher among those households with lower education living in the NCH and SUR macrozones. Although we did not find evidence supporting the existence of an urban-rural energy poverty divide, there are statistically significant urban-rural deprivation gaps among the energy poor. Therefore, policymakers should observe the dimensions in which rural households appear to be significantly worst-off. In the same vein, we do observe an energy poverty gap based on the household's indigenous background. Policy actions should aim to close the gap putting attention to economic disadvantages amongst the indigenous population, while fighting energy suppliers' discriminatory behavior.

Although the affordability deprivation plays an important role in explaining PMEPI poverty, the joint distribution of deprivations in other dimensions (quality of energy services, service reliability, public lighting, and thermal comfort) contributes to shaping the distribution of the PMEPI poor across different population subgroups.

Contrarily to the high association between TPRI and FTG_0, we find a low degree of association between both, PMEPI and TPRI and also between PMEPI and FTG_0. These empirical analyses confirm the pertinence of our energy poverty classification and suggest that first and second-order energy poverty measures cannot be used as substitutes but as complements. The fact that about 15% of the population is energy poor according to both TPRI and PMEPI, but only about 21% of them correspond to the same population, reveals the importance of this issue. Consequently, policymakers should be aware that, by construction, just by selecting an energy poverty definition/measure (from first or second order), a different set of households will be identified as energy poor. From this analysis, it is clear that the diverging identification of the first- and second-order energy poor has a territorial dimension. At the same time, it also depended on the education level of the household.

The main policy conclusion for Chile is that given the relatively higher correlation between TPRI and FTG_0 (which are widely available), to fight energy poverty, the government needs first to implement second-order energy poverty definition/measure.

To the best of our knowledge, PMEPI is the unique multidimensional second-order energy poverty measure implemented in Chile, a recently classified high-income country. By discussing the drivers of the divergence between PMEPI and TPRI, we improve our understanding of the complementarity between different types of energy poverty measures. We show that energy poverty reduction strategies that only considered the TPRI can be misleading. For example, if the policy interventions prioritize CEN (the macrozone with the highest TPRI), it would do it in the macrozone with the lowest multidimensional energy poverty while neglecting macrozones with the highest PMEPI levels. This lesson can be relevant for other transition countries that are increasing their income levels and that are evaluating the implementation of energy poverty measures and subsequent policies.

The empirical test of household-level determinants of the divergence between TPRI and PMEPI provides useful insights for policymakers. Among the variables under control of the families, we only find that education supports this divergence. However, the discrepancy is mostly explained by territory-linked factors. Consequently, energy-related wellbeing is not just about income or reducing energy cost, but more fundamentally about improving supply side factors such as public lighting, service quality, service reliability, and the quality of building materials to foster thermal comfort.

Finally, there are several ways to extend our work. For example, further research should consider investigating the level of association between the family of multidimensional energy poverty indices (MEPI) and multidimensional poverty measures (MPI). This research would improve our understanding of the transmission channels and consequences that energy poverty might have on the wellbeing of the population beyond income or the issue of affordability. Additionally, the finding of higher levels of energy poverty among indigenous populations is of interest as we show that the underachievement is not necessarily determined by the predominantly rural condition of these households. Additionally, a more disaggregated spatial analysis could also help to improve identification and target of public policies intended to reduce energy poverty at local levels.

III. Essay 2. The Impacts of More Efficient Biomass Heating Technologies: Evidence from Urban Households in Chile [25]

2.1 Introduction

Air pollution control policies seek to reduce ambient air pollution levels and generate public benefits, such as reduced premature mortality (Lelieveld et al., 2015), less acid rain (Grennfelt et al., 2020) and lower greenhouse gas emissions (Allen et al., 2018). Therefore, the raison d'être for air pollution policies is to produce shared rather than privately appropriated air quality benefits. This is certainly the case in south and central Chile, which is attempting to improve ambient air quality by reducing small particle emissions from biomass combustion by small residential heating sources.

Reducing small, residential non-point air pollution sources is believed to be critical to reducing excess human mortality from outdoor air pollution. Leilieveld et al. (2015), for example, estimate that outdoor air pollution emissions of fine particles ($PM_{2.5}$) and ground-level ozone (O_3) kill approximately 3.3 million people per year, and about one-third of those deaths are due to biomass burning in residential heating and cooking sources, mainly in Asia, but also in Africa and South America. Biomass stoves are also major sources of black carbon,

[25] This essay is based on Uribe, Adolfo, Carlos Chávez, Walter Gómez, Marcela Jaime, and Randy Bluffstone. (2022). “Private Benefits from Air Pollution Reduction Policies: Evidence from the Household Heating Stove Replacement Program in Chile”. *Environment for Development: Discussion Paper Series. EfD DP 22-18.* https://www.efdinitiative.org/publications/private-benefits-ambient-air-pollution-reduction-policies-evidence-household-heating
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which is a short-lived but potent greenhouse gas (Bond et al., 2013). On a global scale, curbing outdoor air pollution from inefficient residential biomass stoves is therefore a critical international issue.

Biomass burning for cooking is most common in low-income countries, where such fuels may make up well over 2/3 of primary energy usage. For example, IEA (2020) estimates that three-quarters of the energy used in Sub-Saharan Africa – mainly for cooking - comes from biomass, and without major policy changes an overwhelming majority of people will rely on biomass fuels for the foreseeable future. Households in temperate regions, which generally have higher incomes, also often rely on biomass, though these fuels are mainly used for heating. The 2009 European Union Renewable Energy Directive required member states to derive 20% of their energy from renewable sources by 2020, and offered incentives to convert fossil fuel heating systems to biomass. In a comprehensive review, Miguez et al. (2012) find that the European Union alone had 186 companies producing 995 different biomass stoves and boilers with capacities less than 200 kW (more than 80% from Germany and Austria). Such stoves use a variety of fuels and have technical specifications that affect performance, which can vary air pollution emissions by several orders of magnitude (Johansson et al., 2003).

Reducing outdoor emissions from residential sources can offer not only improvements in ambient air quality, but can also potentially generate private benefits that accrue to households. Examples of such possible benefits include better indoor air quality (Wyss et al. 2016; Ward and Noonan 2008; Noonan et al. 2012), possibly lower fuel costs, if combustion becomes more efficient (Wassie and Adaramola 2021), higher average and more stable room temperatures and better overall performance (Howden-Chapman et al. 2009; Buso et al. 2017).

It is important to consider the private benefits of biomass emission reductions, because households make adoption decisions, and high levels of private benefits have been found to spur regular use of improved biomass stoves (Jeuland and Pattanayak, 2012; Mobarak et al., 2012). Indeed, Boso et al. (2019) find that in Chile reducing indoor air pollution (IAP) is a critical reason households adopt improved biomass stoves.

Access to high quality energy is not equally distributed within or across countries, with the poor tending to use less, lower quality, more polluting fuels for cooking and heating and obtaining fewer services from those fuels. This so-called "energy poverty" is most pronounced when comparing households across countries with very different per capita income levels (Rockefeller Foundation, Undated; Jeuland et al., 2021), but energy poverty exists everywhere in the world (Bouzarovski and Petrova, 2015; Kelly et al., 2020), with significant within-country variation (Bouzarovski et al., 2012).

In this essay, we present the results of field research to estimate the key private benefits from a program in central Chile to replace inefficient wood-burning home heating stoves with more efficient pellet stoves. Though the goal of the stove replacement program is to improve ambient air quality, which is a critical problem in southern and central Chile (Chávez et al., 2011; Reyes et al., 2015; Schueftan et al., 2016; Gomez et al., 2017; Jaime et al., 2020), we find that the program also reduces indoor air pollution (IAP), measured as the one-hour household-averaged $PM_{2.5}$ concentration, by an average of 14%. Critically, we find that lower-income and energy-poor households receive a substantially greater reduction in IAP than those with higher-incomes, which suggests that such programs can help disadvantaged households.

We also find that households who adopt the technology have more stable indoor temperatures (i.e., lower variance) during the hours when stoves are in use, which may increase comfort (Li et al., 2020), but average indoor temperature is not affected by switching to more efficient heating technologies. Finally, we estimate that adoption of the improved heating stove is more costly for households, increasing fuel costs by an average of about US$1.40 per day regardless of income level. As a US$1.40 increase is more salient for low-income and energy-poor households, we find that the improved biomass heating technology is not progressive with regard to cost.

This essay proceeds as follows: Section 2.2 discusses the study area and key literature on adoption and use of improved biomass cooking and heating technologies. We also provide an overview of the key issues related to air pollution and biomass stove replacement in southern and central Chile. Section 2.3 presents the details of our field research design. Section 2.4 discusses the empirical strategy. Section 2.5 presents the results. Section 2.6 concludes and discusses the key implications of our findings.

2.2 Key Literature and the Study Area

In addition to a reduction in unhealthy outdoor air pollution, residential polluters in Chile may receive private benefits from adopting technologies that reduce ambient air pollution. For example, due to more efficient burning, those adopting improved biomass cooking and home heating technologies may use less fuel which reduces costs (Bensch and Peters, 2015; Ludwinski et al., 2011). They may also experience reduced indoor air pollution which may enhance child development (LaFave et al., 2021). On a worldwide basis, IAP is estimated to result in the premature deaths of over 4 million people per year, mainly in lower-income countries (Lim et al., 2012) and recent estimates suggest that willingness to pay to reduce IAP in China, and perhaps other middle income countries, is significant (Ito and Zhang, 2020). Advanced biomass heating stoves, such as pellet stoves, not only offer lower outdoor emissions, because of higher efficiencies (Miguez et al., 2012), they may also reduce IAP, because of lower fuel use and the combustion chamber not having to be opened every time they are refilled with fuel.

Adopting more efficient biomass heating technologies, potentially along with building insulation, may offer higher and more stable indoor temperatures, which is an important aspect of reduced energy poverty in colder regions. Indoor temperatures may be affected using pellet stoves, because they are controlled electronically, offering users more control, to maintain temperatures and reduce variability.

Healy and Clinch (2002) find that two-thirds of those with inadequate access to energy in Ireland have chronic exposure to low ambient indoor temperatures, potentially leading to a physiological condition called "cold strain," which is linked to energy poverty, illness and even mortality; they find that the homes of half of all the elderly had low indoor temperatures during winter. Milne and Boardman (2000) note that about 30% of the efficiency improvements from a building insulation program in the UK were translated into increased temperatures. In recent studies conducted in Chile, over two-thirds of households did not achieve an average indoor temperature of 21 degrees Celsius (Reyes et al., 2019), and significant portions did not even achieve 15.25 degrees Celsius (often called the lower comfort limit or LCL) for 65% of the winter period, leading to higher self-reported illness and medical expenses (Porras-Salazar et al., 2020). These findings and other literature (e.g., Buso et al., 2017; Fang et al., 2012; Healy and Clinch, 2002) suggest that especially for energy-poor households in colder areas of the world, comfortable indoor temperatures are significant benefits of improved heating and better insulation.

In central Chile, which is the setting for this study, inefficient home heating is a critical driver of poor ambient air quality (Celis et al., 2004, 2006; Chávez et al., 2011;

Gómez et al., 2014), and is responsible for as much as 94% of $PM_{2.5}$ emissions in some cities (IQAir, 2021). The top three most polluted cities in Latin America, as measured by average annual $PM_{2.5}$, are in Chile (IQAir, 2021) and the Chilean government estimates that more than 9 million inhabitants (48% of the population) are exposed to poor air quality. Around 3,600 people die in Chile each year from cardiopulmonary diseases associated with chronic exposure to air pollution, the majority in central and southern Chile (Ministry of Environment [MMA], 2014; 2019).

Chile also has significant issues with energy poverty, which Urquiza et al. (2019) argue are primarily related to the quality of energy services rather than access. Using multidimensional indices, they find that 12% - 15% of households in Chile are energy poor, which corresponds with the results of other studies (e.g., Villalobos et al., 2021). The outcome variables we examine in this paper, energy costs and fuel consumption, comfort related to indoor temperatures during winter, as well as IAP, have all been highlighted as key aspects of energy poverty in Chile (e.g., see Schueftan et al., 2016).

The Government of Chile has developed a strategy to reduce air pollution in urban areas caused by households that burn wood for heating. Since 2011, the Ministry of Environment (MMA) has replaced over 51,000 inefficient stoves in more than 30 cities at a cost of more than US$85 million (MMA, 2020). This policy is regarded as a central element of national air pollution control plans (DIPRES, 2019).[26] The replacement programs, which are open to all income levels, promote a variety of technologies using several different subsidy schemes. Appendices 2.1 and 2.2 provide details on the national stove replacement

[26] Policies to reduce air pollution from wood heating stoves in Chile include subsidies for adoption of cleaner and more efficient heating technologies and for retrofitting, enforcement of fuelwood quality standards, and restrictions/bans on burning wood for heating during critical pollution days during winter.

program and the number of stove replacements by type of technology/fuel between 2011 and 2019.

Despite its policy centrality and scope, there is limited evidence regarding the effects of promoting improved heating stoves in Chile. Key exceptions include Ruiz-Tagle and Schueftan (2021) and Mardones (2021), who examine metrics that are related to the hypotheses we test. Although offering important insights, none of these evaluations analyze the effect of the stove program on the outcomes that are central to our analysis or evaluate the implications of heating stove replacements for energy poverty.

Our study significantly extends the limited existing literature. In the remainder of this essay, we derive causal effects of a stove replacement policy implemented in Talca, which is in central Chile, on fuel costs, IAP, and indoor temperatures. To our knowledge, this study is one of the first causal analyses of the key private benefits heating stove replacements offer those who make the adoption decisions that are critical to air quality in Chile and around the world.

2.3 Research Design

2.3.1 Introduction to Research Goals and Implementation of the Stove Program

The objective of our field research is to estimate the key private benefits generated by a program to replace inefficient wood-burning heating stoves with more efficient pellet stoves. In this section, we describe our population, sampling, assignment of households to treatment, the procedures we follow for the intervention and collection of field data, and our questionnaire.

We conducted our field research in the city of Talca, the capital of the Maule region in central Chile. This city has a population of about 210,000 people, with approximately 50%

of households in the city using wood as a source of energy (Jaime et al., 2020). This city has been declared a “saturated area” by the MMA, implying that air pollution is a major policy problem. The stove replacement program in Talca provides around 1,300 replacement subsidies each year and is open to all income levels. Pellet stoves make up approximately 90% of the total subsidy value.[27] The widespread acceptance of this technology is driven by its enhanced caloric power, compared with other cleaner technologies offered by the program.

Each year MMA published application instructions and selection criteria and invited applications via social media. Applicants had to fill out a questionnaire, which included information on (*i*) household members, (*ii*) type of traditional stove[28], (*iii*) dwelling characteristics and (*iv*) location, which were then used as selection dimensions. MMA assigned points based on criteria applied to each of these four dimensions. For example, all else being equal, households in more polluted areas received more points, as did those with less efficient baseline stoves and larger household sizes. Subsidies were distributed to those who scored the most points, until the budget was exhausted. Only applications with high scores were accepted for funding, and in this regard successful applicants were like each other. Appendices 2.3, 2.4 and 2.5 detail the selection process and offer pictures of stoves and typical houses.

[27] At the time of data collection, the program was in the fifth year of a ten-year program. Stove replacement programs in Talca and the nearby town of Maule were promoting pellet stoves as the main technology to replace old wood burning heating stoves. During 2019, 1,322 households received 1,082 subsidies for pellet stoves and 240 for kerosene stoves (https://calefactores.mma.gob.cl/region/9).

[28] Stoves are divided into three categories: 1) one or two chamber; 2) homemade and 3) “salamander” stoves. The salamander stove is a traditional small metal-lined stove with only one main combustion chamber. These stoves are classified as low-efficiency and high-emission stoves. Salamander stoves have similar characteristics to the Franklin stove or the potbelly stove. Please see Appendix 2.3 for a photo.

2.3.2 Population, Sampling and Assignment to Treatment

To conduct our field study, we used a list of 3,290 households participating in the stove program in Talca during 2019 and 2020. From this list, 898 households received a pellet stove in 2019, and 2,029 households were applicants for a pellet stove in 2020. During July 2020 we drew a random sample of 169 households that had received the subsidy for a pellet stove in 2019 and had the new technology in place at the time of the study. These households were defined as our treatment group. We also randomly drew a control group, which consisted of 156 households who had applied for a pellet stove subsidy in 2020 and at the time of our data collection in August/September 2020 were still using their traditional stoves.[29] There was little change in selection criteria across the two years, making the treatment and control groups similar based on program selection criteria.

In sum, our treatment households were those who in 2019 received sufficient points when they applied for the program to be selected for a subsidy and by the time of our sample selection and data collection had a pellet stove installed in their homes and no traditional wood stove. Control households applied for the 2020 round subsidy, met the selection criteria, and were waiting for notification that they were beneficiaries. At the time of the data collection in July/August 2020, these households were still using their traditional stove and did not yet have a pellet stove.[30] The official MMA selection criteria and points by criterion for 2019 and 2020 are provided in Appendix 2.6.

[29] This sample size was chosen to achieve a power of 0.80 and to identify a minimum detectable effect of at least a 14% reduction in indoor $PM_{2.5}$ concentration.

[30] Although we acknowledge that our design based on whether households had a replacement stove involved self-selection, the objective, applicable-to-all 2019 treatment assignment criteria followed by MMA in Talca were such that households were comparable with regard to the selection procedure.

These data were collected during the COVID-19 pandemic in central Chile. We therefore contacted households and gathered survey data by mobile phone using mobile phone numbers provided by the local office of the MMA and a local company (QSE), which was responsible for implementing the stove replacement program in Talca. QSE was also trained by the research team to collect the on-site measurement data used in this study. Appendix 2.7 provides details about participants in our study distributed across the city of Talca, the timing of the visits, the devices used, and the COVID-19 safety protocols followed.

All randomly sampled households accepted the invitation to participate in the study (i.e., there were no refusals) and all respondents provided written informed consent. COVID-19 protocols recommended by the Ministry of Health and the Ministry of the Environment were strictly followed by QSE to ensure protection of respondents, the research team and QSE staff members. Households agreed to be visited and to follow these protocols.[31]

Though treatment and control households were similar in selection criteria, it is possible that there were differences within individual scoring categories. We therefore test for balance using detailed household information received from the local office of MMA, which included household and dwelling characteristics. As shown in Appendix 2.18, we compare the treatment and control groups based on 13 variables divided across the above categories, which could potentially be related to selection into the treatment (i.e., received a stove in 2019). We find that only household size is associated with assignment to treatment at the 5% significance level, suggesting a very high degree of balance across the treatment

[31] During the 2020 field research, the city of Talca was not in a total lockdown as was the case in other cities in Chile. According to regional authorities, the city of Talca had 1,863 inhabitants infected with COVID-19 on August 13, 2020; by the end of the field work, on September 13, 2020, this number had increased to 2,688 people. This infection rate represented 1.3% of the population in the city.

and control groups. We nevertheless include household size as a control in all models unless household fixed effects are used.

2.3.3 The Intervention

We visited households twice during the period August 13, 2020, to September 13, 2020. During the first visit, informed consent was obtained, and electronic sensors were installed to measure 1) indoor temperature (ambient and stove surface); 2) outdoor temperature and $PM_{2.5}$ and 3) indoor $PM_{2.5}$. A two-page form like those used in a standard kitchen performance test was given to households to record fuel consumption during the 48-hour measurement period. $PM_{2.5}$ and temperature monitoring devices were installed in the living room, where stoves were placed, as well as outside. To measure stove usage, we employed iButton temperature loggers with a measurement range from 0°C to +125°C (model DS1922T), which recorded stove surface temperatures every hour over a 48-hour period.[32] During the second visit, we removed all measurement equipment and collected the completed fuel log form.

In sum, during these visits, we measured $PM_{2.5}$ concentrations (inside and outside), number of hours the stove was used based on surface temperature, fuel consumption, and air temperature (inside and outside). We also asked households to write down whether they were using another stove in the same room, which might impact our measurements, and to note whether problems arose during the measurement period.

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[32] The air quality sensors were assembled using the open-source electronics platform Arduino. It includes a PM sensor model SDS011 Nova Fitness, and a DTH22 temperature-humidity sensor. Both devices are joined to an Arduino Uno microcontroller using a data shield that has a SD memory card and a real time clock. An external battery (10,000 mAh) was included to make this device independent of other sources of energy in the household. The battery runs continuously for 50 hours. The data collected by SUMs were processed using the Platform for Integrated Cookstove Assessment (PICA) developed by the Berkeley Air Monitoring Group.

In addition to the household visits, we conducted a mobile phone (due to COVID-19) survey of respondents. The survey took about 20 minutes and the questionnaire had four sections. The first section collected general information necessary for the study. The second focused on characteristics of the heating stove, fuel consumption (including costs) and use of the heating equipment. The third part of the questionnaire gathered information on dwelling characteristics, including descriptions of building materials, year of construction or renovation and descriptions of windows, walls, and insulation. The last section collected data on characteristics of household members. [33]

2.4 Empirical Strategy

2.4.1 Effects on Indoor Air Quality and Temperature

We estimate the effects of using pellet stoves on indoor air quality and temperature using fixed-effects panel data regression models. Because our monitoring devices were started at different times, our panel is unbalanced. Our main specification follows equation 2.1:

$$Y_{it} = \alpha ON_{it} + \mu\, PELLET_i\, ON_{it} + X_{it}\beta + g_d + s_p + c_i + \varepsilon_{it} \quad i = 1,\ldots,325;\ t = 1,\ldots,749 \qquad (2.1)$$

where Y_{it} denotes the outcome variable (i.e., IAP or indoor temperature), i denotes the household, t represents the hour of each measurement, ON_{it} is a dummy variable that denotes whether the stove was operated during the measuring period t, $PELLET_i\, ON_{it}$ is an interaction term denoting whether a pellet stove was operated during the measuring period t, X_{it} is a vector of explanatory variables, including log of outdoor temperature, log of outdoor $PM_{2.5}$

[33] Survey instruments (questionnaires and logging forms) (in both English and Spanish) to collect household level information necessary for the study are available as an online supplement at https://osf.io/4xkma/.

and whether a second stove was used (from self-report annotations). We also control for household size when appropriate. The "outdoor" variables are included as controls to adjust for ambient environment, which could affect indoor measurements via infiltrations. We include g_d to denote day fix effects (31 days), s_p for period of the day fix effect (4 periods per day: 0.00–6.00; 6.00–12.00; 12:00–18:00; 18:00–24:00), and c_i for households' time-invariant unobserved effects. α, μ, β are parameters to be estimated, and ε_{it} are errors.

We are primarily interested in the estimates of μ, which capture the average treatment effect of the stove replacement program on the outcome variables. As our study was conducted in the central Chile winter, when all houses require heat, our baseline comparator controls for whether any stove is in operation as measured by our iButtons. We are therefore only interested in μ and not ($\alpha + \mu$). Variable definitions and expected signs of the estimated parameters are presented in Appendices 2.16 and 2.17.

2.4.2 Effects on the Variance of Indoor Temperature and Fuel Consumption

We analyze the effect of the pellet stoves on the cost of fuels and the variance in indoor temperature during the hours that the stoves were in use. For both outcomes, we estimate cross-sectional models according to the following specification in equation 2.2:

$$Z_i = v\ PELLET_i + X_i \gamma + \sum_{\{j=1,..,4\}} \theta_j * Di + d + \eta_i\ , \quad i = 1,\ldots,325 \qquad (2.2)$$

where Z_i is the outcome variable for household i, and $PELLET_i$ is a dummy variable equal to one if a household received a pellet stove in 2019, and zero otherwise. X_i is a vector of explanatory variables, including reported or measured hours stoves were used, whether a second stove was used, household size, and whether households had wall and/or ceiling insulation. These variables are included because they affect fuel use, fuel costs and variance in temperatures independent of whether the household used pellet stoves. D_i is a set of dummy variables controlling for week-invariant unobserved effects, v, γ and θ_j are parameters to be estimated, d is the constant term, and η_i are idiosyncratic errors. We are mainly interested in the parameter v, which denotes the average effect of the replacement program, measured as intent to treat, on the outcome variables. Control variable definitions and expected signs are presented in Appendices 2.16 and 2.17.

2.5 Results[34]

2.5.1 Descriptive Statistics

Table 2-1 presents descriptive statistics of outcome variables by treatment status. Descriptive statistics of controls can be found in Appendix 2.18. For the group with traditional stoves (i.e., our control group), the mean $PM_{2.5}$ concentration during our measurement period is higher than for the group with pellet stoves (i.e., our treatment group) (23.69 vs 19.41, $p < 0.01$), but there is no difference in mean temperature (18.41 vs. 18.37). The variance in temperature experienced by traditional stove users is greater than for pellet stoves (3.61 vs 2.56, $p < 0.05$), though the main heating stove is used about 38% of the time by both groups. Second stoves are used 2% and 6% of the time for treatment and control groups, respectively, suggesting that those with traditional stoves are three times more likely to use second stoves. Average fuel consumption costs during the 48-hour measurement period are lower for traditional stove users than for those with pellet stoves (Ch$ 1,786.1 vs Ch$ 4,001.9, $p < 0.01$).[35]

[34] Data, statistical code, and outputs are available as an online supplement at https://osf.io/4xkma/.
[35] At the time of our study the exchange rate was US$1 = Ch$790.

Table 2-1. Measurements across Treatment and Control sub-samples

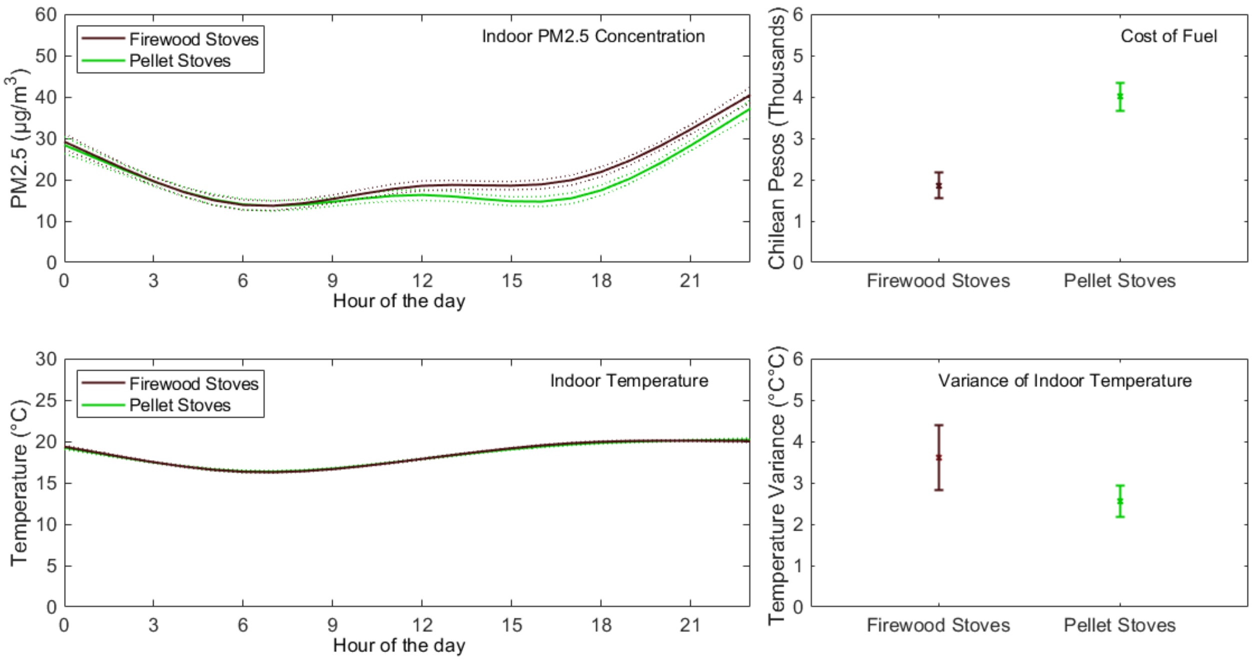
Variable	N	(1) Control Mean/SE	N	(2) Treatment Mean/SE	*t*-test Difference (1)-(2)
Hourly measurements:					
Indoor PM2.5 concentration (μg/m^3)	7576	23.688	7933	19.407	4.282***
		(0.479)		(0.309)	
Outdoor PM2.5 concentration (μg/m^3)	7297	24.427	8043	24.951	-0.524
		(0.395)		(0.371)	
Indoor Temperature (°C)	7625	18.414	8088	18.371	0.042
		(0.040)		(0.035)	
Outdoor Temperature (°C)	8185	10.372	8785	10.245	0.127**
		(0.046)		(0.042)	
Indoor Relative Humidity (%)	7576	57.239	7886	56.833	0.406***
		(0.116)		(0.099)	
Outdoor Relative Humidity (%)	7297	73.510	8036	74.357	-0.847***
		(0.178)		(0.167)	
Stove use ON (% time)	8185	0.384	8785	0.386	-0.002
		(0.005)		(0.005)	
Other stove ON (% time)	8185	0.065	8785	0.022	0.043***
		(0.003)		(0.002)	
Aggregated measurements:					
Use of stove in 48 h (hours)	156	18.760	169	18.740	0.020
		(1.175)		(0.867)	
Cost of fuel per 48 h (10^3 CLP)	156	1.786	169	4.002	-2.216***
		(0.155)		(0.175)	
Variance Indoor Temp. in 48 h	154	5.403	165	5.025	0.378
		(0.442)		(0.403)	
Variance Indoor Temp. only if ON = 1	129	3.610	157	2.560	1.049**
		(0.395)		(0.195)	

Source: Own elaboration.
Note: The value displayed for t-tests are the differences in the means across the groups.
* $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

Figure 2-1 in the upper left corner shows the mean indoor $PM_{2.5}$ concentration during each hour of the day over the whole period of our study for treatment and control households. In both groups, from 00.00 to 12:00 hours, the concentration remains mostly below 20 $\mu g/m^3$. During the afternoon hours it is around 20 $\mu g/m^3$, and then increases from 17:00 until 23:00 hours, reaching around 40 $\mu g/m^3$, which is substantially above the WHO 24-hour guide value of 15 $\mu g/m^3$. Average indoor $PM_{2.5}$ concentrations are higher for those with traditional stoves compared with treatment households from 9:00 onward. The bottom left figures in the table are the mean indoor temperature during each hour of the day. We do not find differences in mean temperatures across treatment and control groups. As shown in the figures bottom right, during the hours that the stoves were in use, the variance in temperature for pellet stoves was lower than for traditional stoves. The figures in the upper right of the table suggest that fuel consumption costs during the 48-hour measurement period are, on average, higher for pellet stove users.[36]

[36] Prices for fuel are self-reported in the survey. Fuel consumption is based on logs of kitchen fuel type, collected using the logging form. Based on this information, we find that firewood users paid on average Ch$ 106.3 (about US$ 0.14) per kilogram of fuel, with a standard deviation of Ch$ 68.4 (US$ 0.09), which is 0.64 times the mean. Pellet users paid a mean of Ch$ 200.70 (about US$ 0.26) per kilogram (with a standard deviation of Ch$ 19.7 (US$ 0.03) (0.1 times the mean). Energy content per kilogram differs by fuel type.

Figure 2-1. Air Quality, Fuel Cost, and Comfort



Source: Own elaboration.
Note: Upper left corner: Splines for 1 hour mean of indoor $PM_{2.5}$ during the whole day and 95% confidence intervals by treatment and control. Bottom left corner: Splines for 1 hour mean of indoor temperature during the whole day and 95% confidence intervals by treatment and control. Upper right corner: Mean for cost of fuel for each group. Bottom right corner: Variance of the indoor temperature for the hours that the stoves were in use during the study.

2.5.2 Effects of Stove Replacement Program on Indoor Air Quality and Temperature

Table 2-2 presents results of fixed-effects regression models for indoor air pollution and indoor temperature. We identify a statistically significant average reduction of 14% in indoor $PM_{2.5}$ concentration for users of pellet stoves, compared with households operating traditional stoves. At the control group mean, this implies that having a pellet stove reduces average indoor $PM_{2.5}$ concentrations by 3.32 μg/m^3, or from a control mean of 23.69 μg/m^3 to 20.37 μg/m^3 We do not find statistically significant differences in indoor air temperature for those using pellet stoves, indicating that on average households do not increase temperatures after receiving improved stoves.

Not surprisingly, we find that due to infiltration outside air pollution and temperature positively affect indoor air pollution and temperature respectively, as does using a second stove. As robustness checks, we run simple OLS models, apply a Mundlak (1978) adjustment to random effects models (Imbens and Wooldridge, 2007) and also use propensity score matching. These results are presented from Appendix 2.24 to Appendix 2.32, and we show that they are fully consistent with those in Table 2-2.

Table 2-2. Fixed Effects Models for Indoor Air Pollution and Indoor Temperature

Variable	(1) Log PM indoor	(2) Log Temp indoor
ON	0.0970***	0.123***
	(0.0351)	(0.00855)
PELLET * ON	-0.135***	0.00234
	(0.0461)	(0.0129)
Other Stove ON	0.0712**	0.0303***
	(0.0320)	(0.0110)
Log outdoor PM	0.662***	
	(0.0153)	
Log outdoor Temperature		0.0718***
		(0.00968)
Constant	0.245	2.786***
	(0.264)	(0.0631)
Observations	14,484	15,711
R-squared	0.507	0.474
Number of ID	302	319
Household FE	YES	YES
Day FE	YES	YES
Period FE	YES	YES

Source: Own elaboration.
Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$. The baseline comparator is adjusted for whether any of the main stoves is in operation as measured by our iButtons. We are therefore only interested in μ from PELLET*ON and not (α + μ), that is adding α from ON.

2.5.3 Effects on Variance in Indoor Temperature and Total Fuel Cost

Table 2-3 shows the cross-section estimates for variance in indoor temperature (Column 1) and fuel costs (Column 2). In addition to the control variables, both models also include a set of week dummy variables, which indicate the week households were visited. These variables allow us to control for special weather conditions and ambient air pollution regulations in place at the time each household was measured over the data collection period. Columns (3) and (4) present models for monthly and annual costs of operating the heating stoves based on data from our household survey.

We find that, compared with using a traditional heating stove, having a pellet stove decreases the variance in temperature during the hours that the stoves are in use and increases the cost of heating homes. Those who have pellet stoves experience almost one standard deviation less variance than those using traditional stoves. However, they are estimated to pay an additional Ch$ 2,215 (about US$ 2.80) per 48-hour period, which implies that, on average, using pellet stoves for an additional hour costs Ch$ 46 (about US$ 0.06) more than traditional stoves. As expected, households operating stoves for longer periods of time have higher heating costs, and we also find that they have greater temperature variance. We do not find effects of insulation or of having a second stove on temperature variance or fuel cost.

Table 2-3. Cross-Sectional Estimates for the Variance of Indoor Temperature and Fuel Cost

Variable	(1) Var Ti ON	(2) Cost 48h	(3) Cost 1 month	(4) Cost 1 year
Pellet	-0.882**	2,215***	13,382***	22,521**
	(0.428)	(221.2)	(2,359)	(9,206)
Number of family members (persons)	-0.0393	43.67	956.3	7,742**
	(0.176)	(82.13)	(797.4)	(3,189)
High insulation (1 if yes, 0 if no)	0.0268	352.5	-2,859	-7,777
	(0.454)	(238.2)	(2,252)	(9,231)
Use of main stove (measured)	0.0503***	66.69***		
	(0.0170)	(10.33)		
Use of second stove (measured)	0.0122	372.8		
	(0.593)	(357.5)		
Use of main stove (survey reported)			1,497***	4,622***
			(292.2)	(1,269)
Use of second stove (survey reported)			1,154	14,761
			(2,506)	(10,640)
Constant	3.049***	191.8	9,615**	69,733***
	(0.881)	(434.5)	(4,636)	(18,675)
Observations	286	325	313	314
R-squared	0.075	0.376	0.158	0.099
Week Fixed Effect	YES	YES	NO	NO

Source: Own elaboration.
Note: Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$. Model 1 and Model 2 consider the information from our 48-hour visits. Model 3 and Model 4 are based on information from our household survey.

2.5.4 Distributional Effects of the Improved Stove Program

The replacement program is open to all income levels in areas with high levels of ambient air pollution. To analyze the distributional effects of the stove replacement program, we divide the sample into three income groups: (1) households with total income lower than Ch$ 450,000 (about US$ 577) per month; (2) households with total income between Ch$ 450,001 and Ch$ 900,000 (US$ 577 – US$ $1,154) per month; and (3) households with total income over Ch$ 900,000 (> US$ 1,154) per month.

As an alternative metric for distributional effects, we analyze results based on whether households were experiencing energy poverty. First, we compute the Ten Percent Rule index (TPR) proposed by Boardman (1991), who classifies a household as energy poor if its expenditure on fuels exceeds 10% of net income. Second, we calculate the Minimum Income Standard (MIS) indicator proposed by Moore (2012), which classifies a household as energy poor if it cannot afford energy costs after deducting its minimum living cost. The procedure used to calculate these measures and their underlying assumptions are presented in Appendices 2.21 and 2.22. We find that 68% of the sample is classified as energy poor using the TPR index, and only a slightly lower percentage are energy poor based on the MIS, with energy poverty largely concentrated in our three lower-income categories. These descriptive results are highly consistent with the results of Reyes et al. (2019).

Table 2-4, Panel A shows the effects of the treatment on indoor air pollution across our four income classifications. We find that using pellet stoves rather than traditional stoves reduces indoor air pollution mainly for the poorest group, with IAP on average falling by 28% for the poorest group ($p < 0.01$).[37] It is notable that effects of the treatment on indoor $PM_{2.5}$ concentrations are not statistically significant for other income categories, suggesting that it is the lower-income group that drives our sample-wide finding that using a pellet stove reduces IAP on average by 14%. Panel B shows the estimated parameters for the model of indoor temperature, and we find no evidence of heterogeneous effects. Results using Mundlak's adjustment for each income group are presented in Appendix 2.24 and confirm there are significant indoor air pollution effects on the poorest group only.

As shown in Appendix 2.29, our estimates of the progressive effects of the treatment on indoor air pollution are robust to define households based on energy poverty rather than income category. We find that the treatment reduces indoor air pollution by 15% only for the

[37] The larger IAP effects for lower-income households could be due to less efficient baseline technologies. In Appendix E we present regression results supporting the hypothesis that among our 156 control households, those in the low-income category are more likely to have the least efficient traditional stoves, such as salamander, potbelly or Franklin, or homemade stoves.

relatively large subsample of households (total of 193) who experience energy poverty. Consistent with our other panel data model results, we do not find effects on average indoor temperature.[38]

Table 2-5 presents estimates of the effects of the treatment on fuel costs by income category. Panel A shows the effects for our 48-hour measurement period. Regardless of the income category, we find that pellet stoves increase average fuel costs by approximately Ch$ 2,200 per 48-hour period (Panel A), and between Ch$ 10,000 and Ch$ 17,000 per month (US$ 12.7 - US$ 21.5 per month) (Panel B) based on our survey results. These effects are regressive, because these amounts are higher percentages of total estimated income for lower income households.[39]

[38] As shown in Appendix 2.29, using pellet stoves rather than traditional stoves reduces the variance in indoor temperature only for the highest income group, but this finding is marginally significant ($p < 0.10$). These results also hold when energy poverty is defined using the TPR index.

[39] These findings are robust to parsing the sample based on energy poverty status (Appendix 2.29). We find that all households face similar increases in energy costs when they adopt pellet stoves.

Table 2-4. Fixed Effects Models for Indoor Air Pollution and Indoor Temperature by Income

PANEL A Variable	(1) Log indoor PM *Lower Income*	(2) Log indoor PM *Middle Income*	(3) Log indoor PM *High Income*
ON	0.259***	0.0196	-0.0602
	(0.0635)	(0.0466)	(0.0565)
PELLET * ON	-0.283***	-0.0373	-0.0135
	(0.0817)	(0.0711)	(0.0732)
Other Stove ON	0.0997	0.0183	0.170**
	(0.0729)	(0.0320)	(0.0842)
Log outdoor PM	0.680***	0.684***	0.578***
	(0.0267)	(0.0234)	(0.0276)
Constant	0.576**	0.0449	0.387**
	(0.290)	(0.257)	(0.164)
Observations	5,159	5,790	3,535
R-squared	0.515	0.542	0.474
Number of ID	106	122	74
Household FE	YES	YES	YES
Day FE	YES	YES	YES
Period FE	YES	YES	YES
PANEL B Variable	(1) Log indoor Temp. *Lower Income*	(2) Log indoor Temp. *Middle Income*	(3) Log indoor Temp. *High Income*
ON	0.110***	0.144***	0.0941***
	(0.0117)	(0.0147)	(0.0115)
PELLET * ON	0.0343*	-0.0151	0.00349
	(0.0191)	(0.0222)	(0.0156)
Other Stove ON	0.0272	0.0147	0.0633*
	(0.0167)	(0.0150)	(0.0326)
Log outdoor Temp.	0.0638***	0.0922***	0.0543***
	(0.00986)	(0.0208)	(0.0115)
Constant	2.710***	2.498***	2.739***
	(0.0937)	(0.0601)	(0.0411)
Observations	5,674	6,248	3,789
R-squared	0.529	0.470	0.491
Number of ID	114	128	77
Household FE	YES	YES	YES
Day FE	YES	YES	YES
Period FE	YES	YES	YES

Source: Own elaboration.
Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$. Lower Income: income lower than Ch$ 450,000 (about US$ 577) per month; Middle Income: income between Ch$ 450,001 and Ch$ 900,000 (US$ 577 – US$ $1,154) per month; High Income: income over Ch$ 900,000 (>US$ 1,154) per month.

Table 2-5. Cross-Sectional Estimates for Fuel Cost by Income Level

PANEL A Variable	(1) Cost 48 hours *Lower Income*	(2) Cost 48 hours *Middle Income*	(3) Cost 48 hours *High Income*
Pellet	2,228***	1,909***	2,728***
	(385.6)	(295.1)	(403.3)
Num. family members (persons)	-52.47	144.3	133.1
	(118.0)	(135.3)	(181.3)
High insulation (1 if yes, 0 if no)	305.7	1,141***	-343.4
	(424.9)	(374.4)	(404.8)
Use of main stove (measured)	96.23***	57.43***	52.34***
	(24.06)	(9.668)	(17.32)
Use of second stove (measured)	556.6	577.8	-537.7
	(657.9)	(496.6)	(651.2)
Constant	247.3	-319.0	61.50
	(728.6)	(571.5)	(975.3)
Observations	119	128	78
R-squared	0.368	0.432	0.507

PANEL B Variable	(1) Cost 1 month *Lower Income*	(2) Cost 1 month *Middle Income*	(3) Cost 1 month *High Income*
Pellet	16,994***	10,029***	15,714***
	(3,370)	(3,461)	(5,736)
Num. family members (persons)	-714.4	2,309**	825.5
	(1,196)	(1,133)	(1,571)
High insulation (1 if yes, 0 if no)	1,330	-9,595***	-73.11
	(2,947)	(3,289)	(5,339)
Use of main stove (reported)	1,159***	1,373***	1,331**
	(419.8)	(442.1)	(656.4)
Use of second stove (reported)	819.0	3,516	-3,978
	(3,671)	(3,917)	(5,581)
Constant	12,259**	10,293	15,605
	(6,149)	(6,564)	(13,970)
Observations	116	122	75
R-squared	0.199	0.200	0.125

Source: Own elaboration.
Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$. Lower Income: income lower than Ch$ 450,000 (about US$ 577) per month; Middle Income: income between Ch$ 450,001 and Ch$ 900,000 (US$ 577 – US$ $1,154) per month; High Income: income over Ch$ 900,000 (>US$ 1,154) per month.

2.5.5 Cost-Effectiveness of the Stove Program

We now present back-of-the-envelope calculations to estimate the cost-effectiveness of the stove program related to indoor air quality improvements. Using data from MMA (2014) and our survey results, we compute the fixed and variable costs of replacing 13,000 stoves in Talca by 2025, as planned by the Ministry of Environment. We estimate that the annual program cost per household is US$ 252, with approximately half being fixed costs and the other half variable costs.[40]

The average household enjoys a reduction in $PM_{2.5}$ of 14% (equivalent to 3.3 μg/m^3), implying that the social cost per μg/m^3 reduction based on the one-hour average is about $76 per household per year. As households receive significant subsidies, they actually pay about US$ 42 per year μg/m^3 reduced. Our lowest-income households show a much higher average $PM_{2.5}$ reduction (28%, which is equivalent to 6.6 μg/m^3) and have marginally lower fuel costs than the average household. We therefore, estimate that the average social cost for low-income households is only US$ 38 per year per μg/m^3 reduction and low-income households pay only about US$ 21 per year per μg/m^3 reduced due to the government subsidies they receive. For all income groups, ambient air quality improvements are in addition to IAP benefits.

[40] All estimates are at the mean, including our estimated additional pellet stove fuel cost, which we use along with MMA estimates of additional annual maintenance costs (Ch$ 10,0000/stove/year), to calculate the additional variable cost of the pellet stove (Ch$ 100,000/stove/year for overall sample and Ch$ 80,000 for low-income households). Based on Ministry of Environment-provided program information, stoves are assumed to cost Ch$ 950,000 and have twenty-year lifespans, which are discounted at 6% /stove/year. The cost to install is assumed to be Ch$ 25,000/stove and to remove and recycle old stoves costs Ch$ 15,000/stove, with administrative costs/stove of 10% of direct costs.

2.6 Conclusions and Policy Implications

In this essay, we use field research conducted in central Chile to evaluate the impact of a program to replace traditional wood burning heating stoves with more efficient pellet stove technologies. We find that the program, which is intended to improve ambient air quality, generates important private benefits that may encourage adoption. We identify statistically significant reductions in indoor $PM_{2.5}$ concentrations and find that lower-income households and energy-poor households are the main beneficiaries. These findings suggest that, regarding household air pollution, biomass heating stove replacement programs may be a progressive policy.

We do not identify any treatment effects on average indoor temperature, but we find a statistically significant average effect on the variance in indoor temperature, which has been found in the literature to be a benefit of adopting improved heating or home insulation technologies. These temperature variance benefits do not appear to be progressive, however, as they seem to mainly accrue to higher income households. Regardless of income category or energy poverty status, pellet stoves are more expensive to operate than traditional stoves, and the average effect on fuel costs is similar across income groups, which is a regressive effect. Because the additional costs are economically significant (about US$1.40 per day), the increased costs of adoption could call into question the economic sustainability of the stove replacement program.

Our findings regarding additional fuel costs have important implications for the design and implementation of such stove programs. Programs should consider variable running costs as well as fixed costs, such as the cost of the stove and installation, and take steps to promote thick and competitive fuel markets to drive down prices. Attending pellet supply issues is particularly important at the time of writing, because of serious supply chain problems experienced by the local pellet industry. Ignoring this problem may exacerbate affordability issues, especially for low-income households.

Setting aside such pellet supply issues, which did not appear to be significant at the time we conducted our research, the pellet stove substitution program appears to offer important benefits, especially for low-income and energy-poor households. This is to the extent that households sufficiently value improvements in IAP, as suggested by Boso et al. (2019). This finding could be highlighted by government officials to promote adoption, but officials should be candid about the additional fuel costs – and market dependence - associated with adopting pellet stoves.

Our research can be extended in various ways. We do not know why we observe larger IAP effects on lower-income households, but present preliminary evidence that perhaps it is due to less efficient baseline technologies. This point could be further explored, particularly in light of legislation that allows local authorities to ban homemade "salamander" stoves and makes those households ineligible for stove replacement programs. Delving into differing baseline technologies could be a useful avenue for further investigation. Although we control for the existence of home insulation, we do not examine the effects of complementary programs to improve energy efficiency. Evaluating the synergistic effects of stove replacement and insulation on our outcomes of interest could be very important.

Finally, our study took place during the peak of the COVID-19 pandemic. Thus, an interesting avenue for future research would be to collect post-COVID-19 pandemic data and use estimators that account for the behavior of treated and control households before and after the replacement took place. These approaches could reduce selection problems, providing cleaner estimates of the effects of the treatment on outcomes of interest. Moreover, it is possible that the public health crisis generated systematically different behaviors than found in non-COVID times, which may have magnified or depressed effects of the improved stove program. Comparing our findings on the effects of the stove replacement program during the pandemic with those after the pandemic could help us better understand the effects of COVID-19 on heating behaviors and outcomes. We consider such a post-pandemic evaluation to be an especially fruitful extension of our research.

IV. ESSAY 3. WHAT DRIVES MONITORING, ENFORCEMENT AND ENVIRONMENTAL COMPLIANCE? AN EMPIRICAL INVESTIGATION IN CHILE

3.1 Introduction

Monitoring and enforcement are critical components of environmental regulatory compliance. The existing literature supports the idea that enforcement actions, such as inspections and sanctions, affects positively the environmental performance of regulated entities (Gray and Shimshack, 2011; Laplante and Rilstone, 1996; Nadeau, 1997; Shimshack, 2014; Shimshack and Ward, 2005). Most of these studies have been carried out in the developed world. Unfortunately, for the case of low- and middle-income countries, the empirical literature that has addressed monitoring, enforcement, and compliance with environmental regulations is scarce. In the context of developing countries, Blackman et al., (2018) points out that regulatory monitoring and enforcement are affected by weak institutions, inconsistency in the written legislation, a high number of informal firms, and lack of access to abatement alternatives to decrease emissions. For example, the related literature in Latin America presents a few empirical studies conducted in Colombia, Uruguay, and Mexico (Briceño and Chávez, 2010; Caffera, 2004; Chakraborti, 2022; Dasgupta et al., 2000; Escobar and Chávez, 2013). These works support the idea that as well as in developing countries enforcement has a significant impact to explain compliance behavior among industrial firms. However, the empirical studies face the challenge of obtaining credible data that is barely verified by the regulator.

In this essay, we analyze empirically the drivers of inspections, compliance, and imposition of sanctions in the context of environmental regulations in Chile. We start our analysis by identifying drivers of inspections carried out by the Chilean Superintendence of Environment (SMA by its Spanish acronym) over the regulated facilities; then, we study drivers of environmental compliance behavior of the regulated facilities; and finally, we identify drivers of imposition of sanctions carried out by SMA and explore the payment over the regulated sanctioned facilities. The analysis is conducted for the case of facilities that belong to different economic sectors that are regulated by the SMA. The facilities must comply with different environmental regulations in addition to what is established in each environmental operating permit. Our work includes several sectors such as Agroindustry, Fishing, Aquaculture, Mining, Energy, Industrial Factories, Environmental Sanitation, Housing, and Construction. We consider a total of 6,790 facilities belonging to all the geographical areas of continental Chile between the years 2013 and 2019. The SMA carries out a monitoring plan yearly and must prioritize which facilities to visit, given the fact that the number of resources is limited. From the total sample considered in our study, each year the SMA has inspected less than 3% of the total facilities.

Our work is an empirical analysis of the complete sequence of enforcement and compliance in Chile, including inspections, compliance, submission of compliance programs, size of fines, payment of fines, and delay in payment of fines. In conducting our analysis, we recognize that the inspection decisions of the SMA (who to inspect) are not independent of the compliance decisions of the facilities (comply or not comply). Because non-compliance facilities can either face a fine or submit a compliance program to fulfill the environmental regulations during the first stage of the sanctioning procedure, we also analyze what determines to present a compliance program as an intermediate alternative to fulfill the regulations for the facilities found in violation.

Our work contributes to producing new empirical evidence on environmental monitoring, enforcement, and compliance in the context of a transitional economy.[41] We first estimate together both decision of inspection and compliance and then we link that to the imposition of fines, for the same data set. We explore the drivers of fines being imposed on non-compliant facilities and related payments, which have received little attention in the existing empirical literature. We also add to the literature that has explored spillover effects of monitoring and enforcement within sectors and locations. We do so by considering also the possibility of spillover effects on facilities that belong to the same firm. To that purpose, we use the information on the ownership structure of facilities included in our sample.

Our research has produced several new and important results. We find that inspections are carried out differently across sectors and are related to some specific facilities' characteristics. Facilities from Agroindustry, Energy, and Mining sectors are more likely to be inspected than facilities from the sectors of Fishing-Aquaculture and Housing-Construction. Small and large facilities are less likely to be inspected than middle-size. Also, inspections correlate negatively with the age of the facility. The enforcement actions of SMA, as past monitoring and fine imposed, have a positive correlation with developing a new inspection.

Regarding compliance, we found that facilities that belong to Agroindustry, Energy, and Industrial sectors have a higher probability of compliance compared with facilities in the Fishing-Aquaculture and Housing-Construction sectors. We also find that the SMA

[41] World Bank classifies Chile in the group of High-Income Economies. GDP per capita PPP rose from 10,438 in 1992 to 22,767 in 2017 (Figures in 2011 international Dollars. Data from the World Development Indicators https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups). However, we consider Chile as a country still in transition in many aspects, especially in the implementation of the institutional environmental framework that is the topic of this study.

monitoring activities increase the probability of compliance. Another driver of compliance is having received a fine in the past, which also impacts the compliance behavior of facilities sharing the same firm's owner and facilities sharing the same sector and location, as a spillover effect.

We also find that once detected in violation, presenting a compliance program is less likely for small-size facilities than middle and large-size facilities. The severity of the violation correlates positively with using the option of presenting a compliance program. With respect to the impositions of fines, we show that the severity of the violation correlates positively with the size of the fine, and the fine payment positively correlates with the size of the facility.

This essay proceeds as follows: Section 3.2 briefly discusses the key literature and describes monitoring and enforcement activities to induce environmental compliance carried out by the SMA in Chile. Section 3.3 presents the details of our methodology and data. Section 3.4 presents the results. In section 3.5 we discuss the results and conclude.

3.2 Key Literature on Monitoring and SMA's Monitoring and Enforcement

In this section, by following the existing literature, we present key aspects of the relationship between an enforcement agency's actions and regulated firms' compliance behavior. Then we describe the monitoring and enforcement activities carried out by SMA in Chile.

3.2.1 Key Aspects of the Relation Between the Enforcement Actions and Regulated Firms' Compliance

Monitoring and enforcement strategies are key components of environmental regulations. The enforcement agency has limited resources, inspections and sanctioning procedures are costly, then in practice, it must select which facilities and firms to inspect. The existing empirical literature suggests that inspections are related to the compliance history of the facilities, the action of citizen complaints, and the facilities' characteristics (Earnhart, 2004; Eckert and Eckert, 2010; Helland, 1998b; Shimshack, 2014).

The facilities' compliance is affected by the expected actions of the regulator (Cohen, 1987; Dasgupta et al., 2000; Dasgupta et al., 2001). Firms deal with private costs to comply with the regulations and face the probability of being inspected and detected as non-complier. The conventional economic analysis suggests that an individual firm has the incentive to not comply as long as the marginal savings (marginal gains from non-compliance) are larger than the marginal expected cost (fines) of being caught as non-complier (Blackman, 2010). This hypothesis has been evaluated by the empirical literature that has suggested that firms adjust environmental behavior by reacting to inspections, sanctions, or motivated by the fear of being in the sights of the regulator (Shimshack, 2014). Therefore, for a given level of monitoring and enforcement from the regulator, facilities with higher abatement costs have higher incentives to violate regulations, and consequently are likely to exhibit lower environmental compliance (Stranlund, 2013).

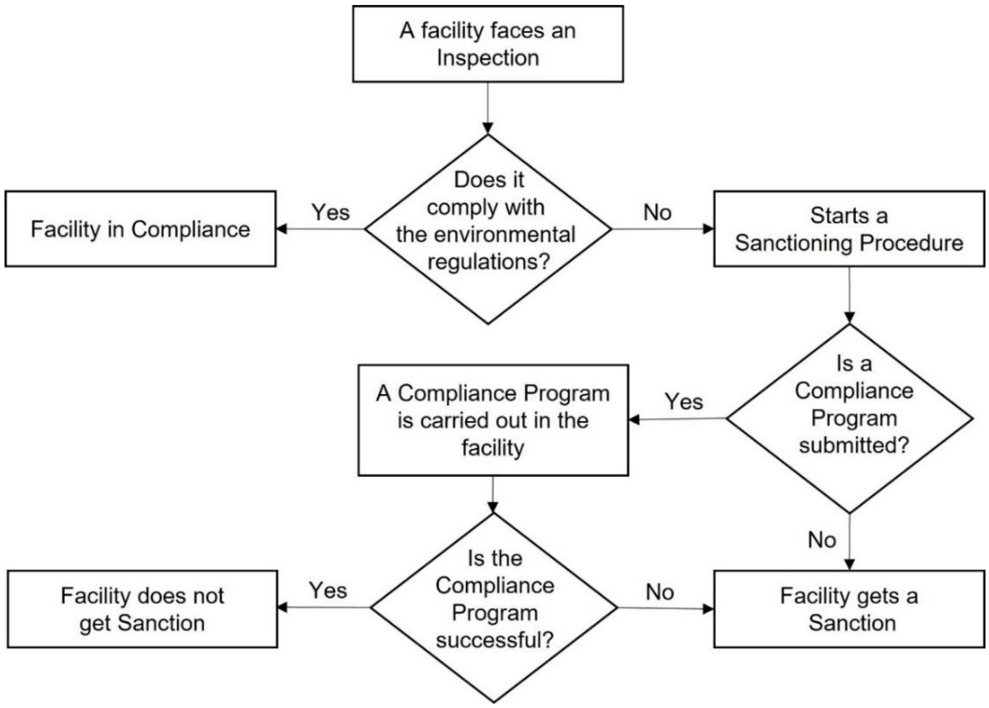
The regulator might impose sanctions after detecting violations of environmental regulations. The sanctioning procedures vary according to specific administrative law and regulations. For example, from the experience documented in The United States and by the EPA guidelines, penalties need to be severe enough in order to serve as a deterrent but also need to treat violators fairly and equitably (US Agency Environmental Protection, 2020). In support of the EPA's actions, light sanctions such as warning letters, phone calls, and notices of violation are developed by lower-level authorities. Instead, more severe sanctions can be carried out by courts at the regional, state, or federal level (Shimshack, 2014). The impositions of sanctions depend on factors such as facility characteristics, the damage caused by the violations, and the economic benefits obtained from that (Earnhart, 2009; Shimshack, 2014). Rousseau (2019) also shows that fines are higher for relapsed violators as well as for intentional offenses. To the best of our knowledge, there is a gap in the existing literature regarding what determines the payment of fines from sanctioned facilities.

3.2.2 Description of the Enforcement Activities Carried out by SMA in Chile

The SMA is responsible for executing, organizing, and coordinating the monitoring of environmental regulation in Chile. The SMA began its activities in 2010 but its sanctioning activities started at the end of 2012 (SMA, 2018). The SMA carries out environmental inspections on facilities, promotes environmental compliance, and imposes sanctions if the entities fail to comply with environmental regulations. Figure 3-1 shows a simplified diagram that represents the SMA's procedure for environmental enforcement in the Chilean context. As shown in Figure 3-1, if a facility violates a regulation and is detected, it has the possibility to submit a compliance program to the SMA to fulfill the environmental regulations during the first stage of the sanctioning procedure. If this program is successful, the facility obtains environmental compliance.[42]

[42] Article 42 of Law Num. 20,417 that regulates the SMA, establishes that once a sanctioning procedure has been initiated, the facility has the option to present a compliance program within a 10-day period. A compliance program is a plan of action and goals to comply with environmental regulations in a period set by the SMA. In case of non-compliance with this program, the sanctioning procedure will continue with a potential fine of up to twice the amount corresponding to the original infraction. If the facility does not accept the sanctioning process, it has the possibility to prosecute claims against the SMA in the Environmental Courts (SMA, 2018).

Figure 3-1. Monitoring and Enforcement Process of Environmental Regulations in Chile



Source: Own elaboration.

According to the existing environmental law, Chilean facilities must typically have to comply with a set of different existing specific environmental regulations. Most of these are related to command-and-control (CAC) instruments such as emission standards, ambient quality standards where facilities are located, prevention and/or decontamination plans; and economic incentives-instruments such as emissions taxes. However, the SMA must also monitor the environmental permits[43], and these represent more than 16,000 different instruments (SMA, 2018).[44]

[43] *Resoluciones de Calificación Ambiental* or just RCA for its acronym in Spanish for environmental permits.
[44] The SMA must monitor compliance of each RCA held by a given facility. Facilities may have more than 1 environmental permit. Among facilities with RCA, 83% have only 1 RCA, 15% have between 2 RCAs and 5 RCAs; and 2% have more than 6 RCAs (SMA, 2018).

The SMA has indicated that its monitoring actions consider the environmental risk, the territory, and the specific characteristics of the facilities and their processes (SMA, 2018). The level of complexity of the facilities is related to the number of environmental instruments that the project faces and to the number of environmental permits that the project has obtained.[45] Non-compliant facilities may be sanctioned at the end of a sanctioning procedure. Available sanctions include three categories. i) written warnings, ii) fines, and iii) temporary or definitive closure. The Law Num. 20,417 that regulates the SMA, establishes that sanctions must be set according to the characteristics of the infractions.[46] Moreover, the Law also indicates that the number of people affected (or potentially affected) by the violation, the compliance history of the facility involved, and the economic impact of the penalty on the violator could also be considered to determine the level of the penalty being imposed.[47]

3.3. Methodology and Data

In this section, we present econometric models to identify drivers of SMA's inspection and facilities' compliance, the determinants of fines, their payment by sanctioned facilities, and the delay of fines payments. We also analyze the intermediate decision of a facility detected in violation that presents a compliance program. At the end of this section, we describe our unique set of data used in this work.

[45] Details about the SMA description about environmental monitoring are available in: https://portal.sma.gob.cl/wp-content/uploads/2018/11/Estrategia-de-Fiscalizacion-Ambiental-2018-2023.pdf
[46] From Law Num. 20,417 that regulates the SMA, the article 36 establishes that infractions are classified into three categories: i) minor; ii) serious; and iii) very serious.
[47] The SMA guidelines establish that the imposition of sanctions by the SMA is proportional to the nature of the infraction. Details in https://portal.sma.gob.cl/index.php/download/bases-metodologicas-para-la-determinacion-de-sanciones-ambientales-2017

3.3.1 Specification for Inspections and Compliance: A Simultaneous Estimation

Our aim is to identify drivers of inspections from the SMA and drivers of individual facility compliance. The problem of asymmetric information between the regulator and the facilities regarding compliance behavior motivates the SMA to conduct inspections. The SMA only knows the compliance status of a facility after it is inspected. We addressed this in our empirical model as a sample selectivity problem. For that, we explore a bivariate probit model with sample selection, which is also called a censored probit or model with partial observability.

Restrictions on observability applied to bivariate probit models are described by Poirier (1980), Meng and Schmidt (1985), and Helland (1998). For our empirical analysis, we estimate, by maximum-likelihood, probit models with sample selection using the heckprobit model from Stata.[48] We analyze jointly both decisions about the inspection (SMA's decision) and the compliance (facility's decision) due to the selectivity problem between monitoring and compliance. Equation 3.1 shows the specification for the inspection carried out by the SMA and equation 3.2 shows the specification for the facility's compliance. We first estimate both equations separately and then simultaneously address the selection problem.

$$INSP_{itr} = \begin{cases} 1, & facility\ is\ inspected\ if\ \ INSP^{*}_{itr} \geq 0 \\ 0, & facility\ is\ not\ inspected\ if\ \ INSP^{*}_{itr} < 0 \end{cases} \tag{3.1}$$

where:

[48] Details on https://www.stata.com/manuals/rheckprobit.pdf

$$INSP_{itr}^{*} = \sum_{j=1}^{6} \alpha_j^1 SECTOR_{ijt} + \sum_{k=1}^{2} \gamma_k^1 SIZE_{ikt} + \sum_{l=1}^{4} \delta_l^1 ZONE_{lit} + \sum_{m=1}^{6} \theta_m^1 YEAR_{imt} + \beta_1^1 AGE_{it}$$

$$+ \beta_2^1 INSP_{it-1} + \beta_3^1 REPORT_{it-1} + \beta_4^1 NON\_COMPL\_3YEAR_{it}$$

$$+ \beta_5^1 FINED\_L3YEAR_{it} + \beta_6^1 COMPL\_PROGM_{it} + \beta_7^1 LOG\_POPULATION_{it}$$

$$+ \beta_8^1 LOG\_POVERTY_{it} + \beta_9^1 PRIOR\_ZONE_{it} + \beta_{10}^1 NUM\_INST_{it}$$

$$+ \beta_{11}^1 \beta LOG\_BUDGET\_SMA_{itr} + \beta_{12}^1 \; LOG\_NUM\_FACILITIES\_REG_{itr} + \varepsilon_{itr}^1$$

$$COMP_{it} = \begin{cases} 1, & facility\ complies\ if\ \ COMP_{it}^{*} \geq 0 \\ 0, & facility\ \ does\ not\ comply\ if\ \ COMP_{it}^{*} < 0 \end{cases} \tag{3.2}$$

where:

$$COMP_{it}^{*} = \sum_{j=1}^{6} \alpha_j^2 SECTOR_{ijt} + \sum_{k=1}^{2} \gamma_k^2 SIZE_{ikt} + \sum_{l=1}^{4} \delta_l^2 ZONE_{lit} + \sum_{t=m}^{6} \theta_m^2 YEAR_{mit} + \beta_1^2 AGE_{it}$$

$$+ \beta_2^2 INSP_{it-1} + \beta_3^2 REPORT_{it-1} + \beta_4^2 NON\_COMPL\_3YEAR_{it}$$

$$+ \beta_5^2 FINED\_L3YEAR_{it} + \beta_6^2 LOG\_POPULATION_{it} + \beta_7^2 LOG\_POVERTY_{it}$$

$$+ \beta_8^2 NUM\_INST_{i} + \beta_9^2 SPILLOVER_{it} + \varepsilon_{it}^2$$

$INSP_{itr}^{*}$ and $COMP_{it}^{*}$ are latent variables related to inspection and compliance, respectively; where *i* denotes the facility, *t* denotes the year and *r* denotes the region where the facility is located $SECTOR_i$ is a set of seven dichotomous indicators according to the following classification: i) Fishing-Aquaculture, as an omitted category; ii) Environmental Sanitation; iii) Housing-Construction; iv) Energy; v) Agroindustry; vi) Mining; and vii) Industrial Factories. $SIZE_i$ indicates the size of the facility according to the information provided by "*Servicio de Impuestos Internos*". It denotes a set of three dichotomous indicators following the categories: i) Small and Micro, ii) Middle, as an omitted category;

and iii) Large. $ZONE_i$ denotes a set of the 5 macrozones in which we have divided the continental territory of Chile: i) Norte Grande (NG); ii) Norte Chico (NCH); iii) Chile Central (CEN); iv) Centro Sur (CES); and iv) Sur (SUR), as omitted category. $YEAR_t$ a set of seven dichotomous indicators following the 7 years of our analysis from 2013 to 2019. The variable AGE_i is a proxy for the age of the facility, calculated from the date that the environmental permit (RCA) was obtained up to the year that this analysis was done. The variable $INSP_{it-1}$ is a dichotomous indicator with $INSP_{it-1} = 1$ to denote if the facility was inspected the period before, and $INSP_{it-1} = 0$ otherwise. The variable $REPORT_{it-1}$ is a dichotomous indicator with $REPORT_{it-1} = 1$ if the facility has self-reported information to the SMA concerning environmental regulation (*Examen de Información*) during the last past period, and $REPORT_{it-1} = 0$ otherwise. The variable $NON\_COMPL\_3YEAR_{it}$ is a dichotomous indicator with $NON\_COMPL\_3YEAR_{it} = 1$ to denote if the facility was found in environmental non-compliance in the last 3 years, and $NON\_COMPL\_3YEAR_{it} = 0$ otherwise. The variable $FINED\_L3YEAR_{it}$ is a dichotomous indicator with $FINED\_L3YEAR_{it} = 1$ to denote if the facility received a fine in the last 3 years, and $FINED\_L3YEAR_{it} = 0$ otherwise. The variable $COMPL\_PROGM_{it}$ is a dichotomous indicator with $COMPL\_PROGM_{it} = 1$ to denote if the facility is operating under a compliance program during the current period, and $COMPL\_PROGM_{it} = 0$. The variable $LOG\_POPULATION_{it}$ is the population (log) of the commune where the facility is located. The variable $LOG\_POVERTY_{it}$ is the percentage of poverty (log) at the commune where the facility is located. The variable $PRIOR\_ZONE_i$ is a dichotomous indicator with $PRIOR\_ZONE_i = 1$ to denote if the facility is located in an area that is prioritized by the SMA. The variable NUM_INST_i indicated the number of environmental instruments that the facility must fulfill. The variable $LOG\_BUDGET\_SMA_{itr}$ is the national budget (log) that the SMA has each year to implement its environmental regional control strategy. The variable $LOG\_NUM\_FACILITIES\_REG_{itr}$ is the number of facilities (log) in each region that the SMA potentially may inspect. The variable $SPILLOVER_{it}$ is a set of three dichotomous indicators denoting the enforcement action of the SMA over related facilities that share firm owners, facilities that belong to the same economic sector, and facilities located nearby.

3.3.2 Sanctioning Procedure and the Alternative to Present a Compliance Program

According to the procedures of the SMA, detected non-compliant facilities have the possibility to present a compliance program to avoid a sanction. We are interested in exploring the drivers of that decision. Because only non-compliant facilities must decide whether to present a compliance program, our sample is not random, and is biased toward noncompliance facilities. A natural alternative to deal with the sample selection is by performing a Heckman-style correction, but this strategy requires that the outcome of interest is a continuous variable.[49] Another alternative is controlling for a variable related to non-compliance, for example, the predicted probability of non-compliance that can be calculated from the output of the previous estimations (equation 3.1 and equation 3.2). We present in this section a generic specification to obtain the determinants of presenting a compliance program, that considers one ad-hoc control variable to deal with this bias. Despite its limitations, we explore the Inverse Mills Ratio (IMR_i) and the probability of non-compliance

[49] Heckman (1979) discusses the bias that results from using nonrandomly selected samples to estimate behavioral relationships as an ordinary specification error or omitted variables bias. Heckman selection models implement firstly, a selection equation that is binary, and secondly, an unbiased estimation for a continuous outcome of interest. In our case, the selection equation (being non-compliance facility) is a binary variable; however, our outcome of interest (presenting a compliance program) also is a binary variable. Alternatively, we may explore as outcome variable the cost of the program, that is a continues variable, but it changes our original question of what determine to present a compliance program.

(equal to $1 - Pr\ (COMP_i = 1)$) as regressors. Equation 3.3 presents the empirical model to explore what determines that a facility presents a compliance program after being found in violation.

$$COMP\_PROG_i = \begin{cases} 1, & facility\ present\ program\ if\ \ COMP\_PROG_i^* \geq 0 \\ 0, & facility\ \ does\ not\ present\ program\ if\ \ COMP\_PROG_i^* < 0 \end{cases} \tag{3.3}$$

where:

$$\begin{aligned} COMP\_PROG_i^* = & \sum_{j=1}^{6} \alpha_j^3 SECTOR_{ij} + \sum_{k=1}^{2} \gamma_k^3 SIZE_{ik} + \sum_{i=1}^{4} \delta_l^3 ZONE_{il} + \sum_{m=1}^{6} \theta_i^3 YEAR_{mi} \\ & + \beta_1^3 AGE_i + \beta_2^3 LOG\_POPULATION_i + \beta_3^3 LOG\_POVERTY_i \\ & + \beta_4^3 NUM\_INFRACTIONS_i + \beta_5^3 LOW\_INFRACTION_i \\ & + \beta_6^3 MIDDLE\_INFRACTIONS_i + \beta_7^3 HIGH\_INFRACTIONS_i + \beta_8^3 RELAPSE_i \\ & + \beta_9^3 COMPLAINT_i + \beta_{10}^3 NUM\_INST_i + \beta_{11}^3 CORRECTION_i + \varepsilon_i^3 \end{aligned}$$

$COMP\_PROG_i^*$ is the latent variable of presenting a compliance program. From this level, we model as cross-section estimates. The variables $SECTOR_i$, $SIZE_i$, $ZONE_i$, $YEAR_t$, AGE_i, $LOG\_POPULATION_i$, $LOG\_POVERTY_i$, and NUM_INST_i come from previous equations. We add four new variables regarding the severity of the impact caused by the violation. The variable $NUM\_INFRACTIONS_i$ denotes the number of infractions established in the sanctioning process.[50] $LOW\_INFRACTIONS_i$ is a dichotomous indicator with $LOW\_INFRACTIONS_i = 1$ to denote that at least one of the infractions is classified as low

[50] During the sanctioning procedure is established with detail the number of infractions incurred by the facility. Each infraction may be classified according to the level of damage or impact on the environment.

impact infraction, and $LOW\_INFRACTIONS_i = 0$ otherwise. $MIDDLE\_INFRACTIONS_i$ is a dichotomous indicator with $MIDDLE\_INFRACTIONS_i = 1$ to denote that at least one of the infractions is classified as middle impact infraction, and $MIDDLE\_INFRACTIONS_i = 0$ otherwise. $HIGH\_INFRACTIONS_i$ is a dichotomous indicator with $HIGH\_INFRACTIONS_i = 1$ to denote that at least one of the infractions is classified as high impact infraction, and $HIGH\_INFRACTIONS_i = 0$ otherwise.[51] We also add the variable $RELAPSE_i$ that is a dichotomous indicator with $RELAPSE_i = 1$ to denote that the facility faced a sanctioning procedure before the submission of the compliance program, and $RELAPSE_i = 0$ otherwise. In this level, we know if the sanction procedure has been related to a complaint from the community near the facility. We include the dichotomous indicator $COMPLAINT_i$ as an explanatory variable to denote if the inspection that uncovered the sanctioned violation was motivated by a community complaint.[52] The variable $CORRECTION_i$ is included to deal with the selection problem.[53]

3.3.3 Imposition of Sanctions: Level of Fines and Payment

According to the procedures of the SMA, non-compliant facilities may be sanctioned at the end of a sanctioning procedure. Our purpose is to analyze what determines the size of the fines defined by the SMA. We focus on fines since, during the study period, more than

[51] We explore a continuous variable to capture environmental damage. Specifically, we construct the variable Impact Index for the environmental damage, which is defined as:
Impact Index = 1(Num. of Low Infractions) + 2*(Num. of Middle Infractions) + 3* (Num. of High Infractions).*
[52] Unfortunately, we do not at the beginning of our analysis if the inspection that uncover the sanctioned violation was motivated by a community complaint. We only know that if the facility has a sanction process.
[53] As mentioned before, to correct for selection bias we use the predicted probability that a facility is non-compliant and also the IMR.

95% of the sanctions imposed on non-compliant facilities correspond to fines.[54] In this part of the sequence, we have first the condition of being detected in violation, and then the imposition of a fine.[55] Equation 3.4 presents our model for the sizes of the fine.

$$FINE_i = \sum_{j=1}^{6} \alpha_j^4 SECTOR_{ij} + \sum_{k=1}^{2} \gamma_k^4 SIZE_{ik} + \sum_{l=1}^{4} \delta_l^4 ZONE_{il} + \sum_{m=1}^{6} \theta_m^4 YEAR_{im} + \beta_1^4 AGE_i \tag{3.4}$$
$$+ \beta_2^4 LOG\_POPULATION_i + \beta_3^4 LOG\_POVERTY_i$$
$$+ \beta_4^4 NUM\_INFRACTIONS_i + \beta_5^4 LOW\_INFRACTION_i$$
$$+ \beta_6^4 MIDDLE\_INFRACTIONS_i + \beta_7^4 HIGH\_INFRACTIONS_i$$
$$+ \beta_8^4 RELAPSE_i + \beta_9^4 COMPLAINT_i + \beta_{10}^4 NUM\_INST_i$$
$$+ \beta_{11}^4 COMP\_PROG_i + \beta_{12}^4 PRIOR\_ZONE_i + \beta_{13}^4 IMR_i + \varepsilon_i^4$$

where:

$$FINE_i \geq 0$$

$FINE_i$ is a left-censored dependent variable indicating the size of the fine imposed on the facility *i* (in thousand USD, starting from 0).[56] The explanatory variables have been previously described. The variable IMR_i is included to deal with the selection problem from the previous stage of inspection. To estimate $FINE_i$ we propose a tobit model to deal with the left censoring. Once the fine is set by the SMA, the facility must pay to continue with their operation (facility's decision). Considering this, we also explore two additional specifications to analyze the probability that the fine is paid and how long it takes for the facility to pay the fine. We estimate equation 3.5 as a probit model and equation 3.6 as a double-censored tobit

[54] The normative framework of the Law Num. 20,417 that regulates SMA, establishes that one fine related to one infraction can range from 0 to 10,000 U.T.A. (7 million USD). However, one facility may have several infractions at the same time in the same sanction procedure.
[55] In this case, the outcome of interest is a continuous variable therefore we use Heckman selection model.
[56] Fines are set in the Annual Tax Unit (UTA by its Spanish acronym) in real terms for each year. In this study we use the conversion that 1 UTA is equal to 705 USD.

model for the amount of the fine and the number of days for the facility to pay the fines, respectively.

$$PAID_i \quad = \begin{cases} 1, & facility\, pays\, the\, fine\, if \;\; PAID_i^* \geq 0 \\ 0, & facility\;\; does\, not\, pay\, the\, fine\, if \;\; PAID_i^* < 0 \end{cases} \tag{3.5}$$

where:

$$PAID_i^* \;= \sum_{j=1}^{6} \alpha_j^5 SECTOR_{ij} + \sum_{k=1}^{2} \gamma_k^5 SIZE_{ik} + \sum_{l=1}^{4} \delta_l^5 ZONE_{il} + \sum_{m=1}^{6} \theta_m^5 YEAR_{im} + \; \beta_1^5 AGE_i$$

$$+ \beta_2^5 RELAPSE_i + \beta_3^5 COMPLAINT_i + \; \beta_4^5 NUM\_INST_i \; + \beta_5^5 PRIOR\_ZONE_i$$

$$+ \beta_6^5 FINE_i + \beta_7^5 IMR_i + \varepsilon_i^5$$

$$PAY\_DELAY_i \;= \sum_{j=1}^{6} \alpha_j^6 SECTOR_{ij} + \sum_{k=1}^{2} \gamma_k^6 SIZE_{ik} + \sum_{i=1}^{4} \delta_l^6 ZONE_{il} + \sum_{m=1}^{6} \theta_m^6 YEAR_{im} \tag{3.6}$$

$$+ \beta_1^6 AGE_i + \beta_2^6 RELAPSE_i + \beta_3^6 COMPLAINT_i + \; \beta_4^6 NUM\_INST_i$$

$$+ \beta_5^6 PRIOR\_ZONE_i + \beta_6^6 FINE_i + \beta_7^6 IMR_i + \varepsilon_i^6$$

where:

$$M > \; PAY\_DELAY_i \; \geq 0$$

The variable $PAID_i^*$ is the latent variable for the payment of the fine. The variable PAY_DELAY_i *i*s a double-censored dependent variable indicating the days taken for the facilities before the payment. We consider two values of M, equal to 365 days and 730 days. The variable IMR_i is included in both equations using the same procedure as before with the same limitations.

3.3.4 Data Set

The main source of our data is the National Environmental Inspection Information System (SNIFA by its Spanish acronym).[57] The SNIFA presents a detailed description in terms of "*Unidad Fiscalizable"* (UF) which is equivalent to facilities in our study. An UF is a "physical unit in which actions and processes are regulated by one or more instruments of SMA competence" (SMA, 2018). We include in our analysis facilities that meet at least one of the following three conditions[58]: i) belong to Agroindustry, Fishing, Aquaculture, Mining Energy, Industrial Factories, Environmental Sanitation, Housing and Construction, ii) have at least one environmental permit for operation[59]; and iii) are subject to compliance with water emissions.[60] Following these criteria, our study considers a total of 6,670 facilities operating during the period 2013-2019.[61]

Figure 3-2 shows the total number of facilities and the distribution by sector of activity through the study period. New facilities enter operation yearly. We consider the first year of a facility's operation as the year in which it obtained the environmental permit. We assume that the facility will continue in operation until the end of our analysis. Moreover, we also assume that, during the studied period, there is no change in individual characteristics such as size, property, or geographic location. At the end of the year 2019, the distribution

[57] The SNIFA is an open-access portal available at https://snifa.sma.gob.cl/

[58] These criteria exclude facilities with significate lower environmental impact as supermarkets, restaurants, schools, or churches that may have been connected with any environmental instrument as the standard for noise or for being inside the zone of an air quality plan.

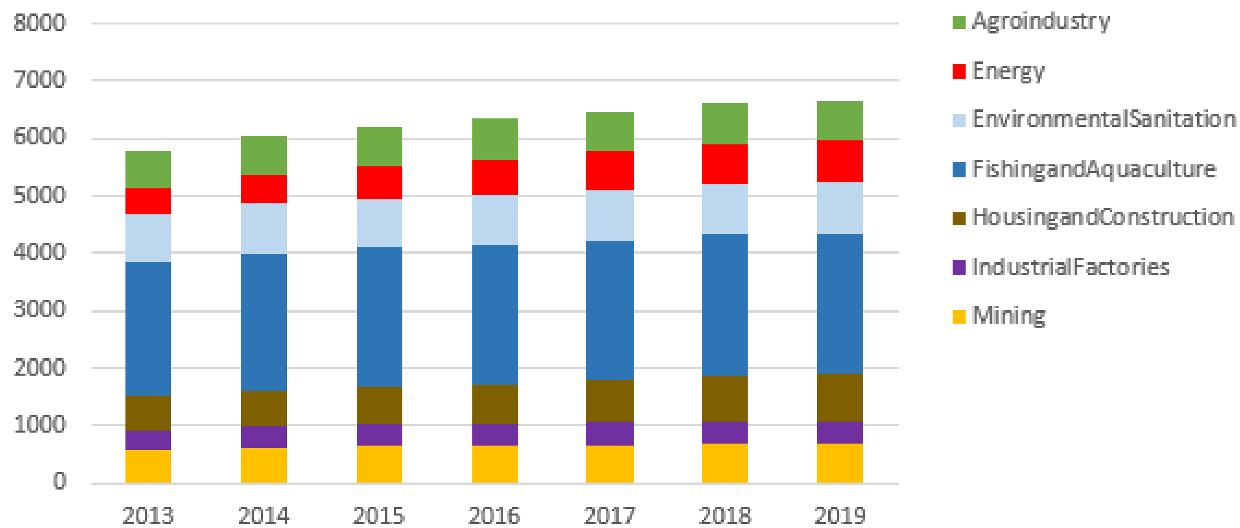
[59] *Resolución de Calificación Ambiental* (RCA). In our data, 97% of the facilities in our sample have at least 1 RCA.

[60] Supreme Decree 460/2002 and Supreme Decree 90/2000 for wastewater discharges.

[61] We built a unique set of data for our study. Even though any part of the information used in this work is public, we obtain the data by web-scraping the SNIFA portal using a suitable software such as MATLAB. Details for scraping data from the web on: https://blogs.mathworks.com/loren/2017/07/10/web-scraping-and-mining-unstructured-data-with-matlab/#0b4dd3c5-8737-47ca-b0b0-0cf5c43ed2da

of facilities in our sample by sector is the following: Fishing and Aquaculture (37%), Environmental and Sanitation (13%), Housing and Construction (12%), Energy (11%), Agroindustry (11%), Mining (10%), and Industrial Factories (6%).

Figure 3-2. Number of Facilities by Sector per Year, from 2013 to 2019



Source: Own elaboration.

Table 3-1 shows the number of facilities in each sector and the subset that has been inspected at least once for each year, during the period 2013 -2019.[62] The total number of facilities inspected each year represents between 2.2% and 2.9% of the total facilities regulated by the SMA during this period, with a minimum of 140 facilities inspected in 2015 up to a maximum of 187 facilities inspected in 2019. In the last year of the period under analysis, the Mining sector had 44 facilities inspected and presents the highest proportion of facilities inspected that year (6.4%). The sector Housing-Construction had only 3 facilities

[62] We do not classify it as an inspection activity such as self-reporting emissions. Nor do we classify as inspection the remote pollutants measurements or the study of satellite images, which we know the SMA has begun to implement in recent years

inspected during 2019, representing the lowest proportion of inspected facilities during that period (0.2%). The sector Fishing-Aquaculture had 31 facilities inspected in 2019, but it is a low proportion (1.3%) considering the total number of facilities that belong to that sector.

Table 3-1. Number of Facilities and Proportion that are Inspected by Sector per Year

Sectors and Years		2013	2014	2015	2016	2017	2018	2019
Agroindustry	Num. Facilities [a]	657	672	683	692	702	712	716
	Inspected Facilities [b]	25	38	21	31	44	24	44
	Proportion [c]	3.8%	5.7%	3.1%	4.5%	6.3%	3.4%	6.1%
Energy	Num. Facilities	446	506	569	612	646	684	706
	Inspected Facilities	21	15	23	22	29	36	23
	Proportion	4.7%	3.0%	4.0%	3.6%	4.5%	5.3%	3.3%
Environmental Sanitation	Num. Facilities	833	846	860	872	880	890	893
	Inspected Facilities	30	24	21	25	22	27	24
	Proportion	3.6%	2.8%	2.4%	2.9%	2.5%	3.0%	2.7%
Fishing-Aquaculture	Num. Facilities	2,322	2,386	2,420	2,439	2,449	2,454	2,459
	Inspected Facilities	37	36	28	16	21	23	31
	Proportion	1.6%	1.5%	1.2%	0.7%	0.9%	0.9%	1.3%
Housing-Construction	Num. Facilities	604	623	646	681	728	781	806
	Inspected Facilities	0	2	1	1	4	6	2
	Proportion	0.0%	0.3%	0.2%	0.1%	0.5%	0.8%	0.2%
Industrial Factories	Num. Facilities	364	384	391	393	399	406	407
	Inspected Facilities	23	18	11	15	20	17	19
	Proportion	6.3%	4.7%	2.8%	3.8%	5.0%	4.2%	4.7%
Mining	Num. Facilities	566	613	640	652	661	679	683
	Inspected Facilities	31	36	35	30	25	40	44
	Proportion	5.5%	5.9%	5.5%	4.6%	3.8%	5.9%	6.4%
Total	Num. Facilities	5,792	6,030	6,209	6,341	6,465	6,606	6,670
	Inspected Facilities	167	169	140	140	165	173	187
	Proportion	2.9%	2.8%	2.3%	2.2%	2.6%	2.6%	2.8%

Source: Own elaboration based on information from SNIFA.
Note:
[a] Num. Facilities shows the number of facilities per sector included in our study for each year.
[b] Inspected Facilities shows the number of different facilities inspected each year. If a facility is inspected more than once during the same year, it is counted only once in that year.
[c] Proportion is the product from *(Inspected Facilities) *100 / (Num. Facilities)*.

Table 3-2 shows the aggregate figures regarding inspected facilities and their outcomes by sector during the period of our study. From the 754 facilities that were inspected during the period 2013-2019, 538 were compliant while the other 216 were found in violation. This suggests that the rate of compliance during the studied period is about 71%, while 29% of the inspected facilities were found in violation during the same period. We notice that the sectors that show higher compliance are Industrial Factories, Energy, and Agroindustry, and sectors with more violations are Housing-Construction, Environmental Sanitation, and Fishing-Aquaculture.

Table 3-2. Inspected Facilities and Compliance Outcomes by Sector During 2013-2019

Sectors	Inspected Facilities [a] (1)	Compliance [b] (2)	Non-Compliance [c] (3)
Agroindustry	156	114 (73%)	42 (27%)
Energy	109	86 (79%)	23 (21%)
Environmental Sanitation	114	74 (65%)	40 (35%)
Fishing-Aquaculture	152	102 (67%)	50 (33%)
Housing-Construction	14	5 (36%)	9 (64%)
Industrial Factories	75	61 (81%)	14 (19%)
Mining	134	96 (72%)	38 (28%)
Total	754	538 (71%)	216 (29%)

Source: Own elaboration based on information from SNIFA.
Note:
[a] Inspected Facilities shows the total number of facilities in each sector inspected at least once during the 2013-2019 period.
[b] Compliance shows the number of facilities found in compliance always.
[c] Non-Compliance shows the number of facilities found in non-compliance at least once. In parentheses are the proportions in each status, with base the column 1. In this table *Inspected Facilities = Compliance + Non-Compliance.*

Table 3-3 shows figures regarding inspected non-compliance facilities, compliance programs, and facilities fined during the period of our study. From the 216 facilities found in violation (Table 10, column 3), 191 facilities presented a compliance program and 68 were fined during the same period. These figures also include the results of sanctioning procedures that were started before 2013 and some that were not finished at the end of our analysis; therefore, we are not able to compare the proportion among columns of this table. Sectors of Fishing-Aquaculture, Agroindustry, and Environmental Sanitation present a higher number of non-compliance facilities and a higher number of compliance programs submitted. Sectors of Mining and Agroindustry show more facilities being fined.

Table 3-3. From Non-Compliance to Facilities Fined During 2013-2019

Sectors	Non-Compliance [a] (1)	Compliance Programs Submitted [b] (2)	Facilities Fined [c] (3)
Agroindustry	42	38	13
Energy	23	19	7
Environmental Sanitation	40	37	12
Fishing-Aquaculture	50	46	7
Housing-Construction	9	6	1
Industrial Factories	14	11	12
Mining	38	34	16
Total	216	191	68

Source: Own elaboration based on information from SNIFA.
Note:
[a] Non-Compliance shows the number of facilities found in non-compliance at least once during the 2013-2019 period. For some facilities of this group, the sanctioning procedure is still ongoing up to the last year of our sample period.
[b] Compliance Programs Submitted shows the number of facilities that had submitted a compliance program after being found in violation in the period of our study. A subset of this group has a compliance program that was still in progress at the end of our study period.
[c] Facilities Fined shows the number of facilities that had been fined in this period. This group includes facilities that had not presented a compliance program and facilities that failed in the implementation of the compliance program. The balance among columns does not hold, since some processes started before 2013 or finished after 2019, outside our period of analysis.
In the table *Non-Compliance ≠ Compliance Program Submitted + Facilities Fined*.

A special characteristic of the observed units in our analysis is that one facility may be controlled by more than one firm and one firm may own more than one facility. In our data, 12% of the units (772 facilities) have multiple firms as their owner. We also identify a total of 4,191 different firms controlling the total sample of facilities. To explore potential spillover effects among these facilities we link facilities that have the same owner firm. Consequently, we create 481 networks joining the facilities that have connections with others (3,561 facilities).[63] In this way, each facility belongs to only one network. We also add facilities without connection with others (3,109) as networks of one unique node, then we obtain in total of 3,590 networks. The construction of these networks has two direct

[63] In Chile, one firm is identified by its Unique Tax Identification number (RUT from its Spanish acronym). It could be the case that a firm has operations with different RUTs. Unfortunately, we are not able to identify these relationships in our sample.

implications in our analysis. First, we can cluster robust standard errors using the network as a cluster, under the assumption that there is correlation in the error of our estimations among facilities that are members of the same network. Second, we can analyze spillover effects among facilities that belong to the same network. In Appendices 3.1 to 3.3 we show more details about our data and what these networks look like. There we present two specific examples in detail for the Mining and Fishing-Aquaculture sectors to give a better understanding of these relationships.

3.4 Results

In this section, we present the main results of our study. First, we show the results of the joint model for inspections and compliance. Second, we present the estimation incorporating the spillover effect in the compliance of facilities with the same owner firm and in facilities that belong to the same sector located in the same location. Third, we show the results regarding drivers of the submission of a compliance program. Fourth, we present the results of our analysis for the size, payment, and delay of payment of imposed fines.

3.4.1 Results for Simultaneous Estimation of Inspections and Compliance

Table 3-4 shows the results for the joint model of inspections and compliance. Column 1 and column 2 present the estimation of the coefficients. Appendix 3.9 presents in detail the marginal effects for each explanatory variable. The results suggest that consistent with the number of inspections previously analyzed, the probabilities of inspection faced by facilities are very low and vary across sectors. Using the sector Fishing-Aquaculture as the base of comparison, 5 sectors present a higher probability of inspection (the increase in probabilities for each sector are: Agroindustry 0.0233, Industrial Factories 0.0164, Mining

0.0161, Energy 0.0155, Environmental Sanitation 0.0151). Regarding the location of the facilities, our results suggest that facilities in the northern part of the country face a higher probability of inspection, with the macrozone south as the base (being located in Norte Grande, increases the probability of inspection by 0.0122). Smaller facilities and larger facilities face a lower probability of inspection than middle-size facilities as a base, but low in magnitude. Analyzing the variables related to history for enforcement and compliance, we find that facilities fined in the past are more likely to face an inspection (increase in a probability of 0.021), and facilities having a compliance program in operation, that also means found in non-compliance in the past, show a higher probability of facing an inspection (increase in a probability of 0.031). Similarly, being located in a prioritized area increases the probability of inspection, but is low in magnitude. The variable related to SMA resources, such as regional budget, or the number of potential facilities to inspect in the region, correlates positively to the facility's probability of facing an inspection, but both have no significant estimates. Finally, the variable age shows that older facilities face a lower probability of being inspected. The social variables related to poverty and density correlate positively with the probability of inspection but are not significant. We also find that the variable number of the instrument correlates positively to inspections but is low in magnitude.

We also estimate the drivers of compliance. Our results suggest that conditioned on the decision of inspection, the expected probability of compliance is low and varies across sectors. Using as the base of comparison the sector Fishing-Aquaculture, 5 sectors present a higher probability of compliance (the increase in probabilities for each sector are: Agroindustry 0.0151, Energy 0.0122, Industrial Factories 0.0116, Mining 0.0106, Environmental Sanitation 0.0067). With respect to the geographical zone, facilities located in the north of Chile present a higher probability of compliance (increase in a probability of 0.014) than facilities in the south. The relation between size and compliance shows no significant effect in our estimates. The variable age shows that older facilities comply with less probability but is very low in magnitude. This result could be explained because older facilities may face higher benefits from violations (for example, higher abatement costs), or different awareness/culture on their environmental responsibility. The social variables related to poverty and density are not significant. We find that enforcement actions of the SMA, such as the imposition of fines and the self-reporting requirement, have a positive effect on compliance (both actions present an increase in the probability of about 0.013). We also find that the variable number of the instruments correlates positively to compliance but is low in magnitude.

Table 3-4 also shows the significance of parameter related to the correlation between the error terms between equation 3.1 (inspections) and equation 3.2 (compliance), therefore our results confirm that the selectivity problem biases the estimation if it is done separately.

Table 3-4. Coefficient Estimates for the Joint Estimation of Inspection and Compliance

VARIABLES	(1) Inspection		(2) Comply
Predicted probability	0.025		0.014
Sectors (base: Fishing-Aquaculture)			
Agroindustry	0.465***		0.449***
	(0.0842)		(0.0952)
Energy	0.347***		0.404***
	(0.0879)		(0.106)
Environmental Sanitation	0.340***		0.242***
	(0.0857)		(0.0864)
Housing-Construction	-0.278**		-0.485***
	(0.119)		(0.155)
Mining	0.357***		0.356***
	(0.0949)		(0.0940)
Industrial Factories	0.363***		0.381***
	(0.0977)		(0.0999)
Age	-0.0149***		-0.0112**
	(0.00418)		(0.00502)
Size (base: Medium): Micro and Small	-0.132**		-0.0882
	(0.0552)		(0.0694)
Large	-0.162***		-0.0843
	(0.0498)		(0.0613)
LogPoverty	0.0664		0.0594
	(0.0444)		(0.0490)
LogDensity	0.00426		0.0219
	(0.0124)		(0.0139)
Inspection_lastyear	0.393***		0.459***
	(0.0744)		(0.0778)
Report_lastyear	0.257***		0.457***
	(0.0614)		(0.0800)
AnyViolation_3y	0.350***		-0.118
	(0.0720)		(0.0782)
Fined_3y	0.438***		0.420**
	(0.163)		(0.176)
Compliance Program	0.634***		
	(0.0666)		
Prioritized Area	0.0780***		
	(0.0298)		
Macrozone (base: SUR)			
NGR	0.223*		0.405***
	(0.123)		(0.100)
NCH	0.138		0.182*
	(0.103)		(0.0937)
CEN	-0.0105		-0.0738
	(0.0852)		(0.105)
CES	0.0353		0.0391
	(0.0746)		(0.0893)
Num. Instruments	0.0698***		0.0460***
	(0.0136)		(0.0101)
LogSMABudgetperFacility	0.0365		
	(0.0655)		
logNumFacilitiesRegion	0.000329		
	(0.0598)		
Constant	-2.196***		-2.563***
	(0.366)		(0.160)
Athrho		3.419***	
		(0.985)	
Controlled per Year	YES		YES
Observations	37,425		37,425

Source: Own elaboration based on information from SNIFA.
Note: Standard errors clustered by networks of facilities with common owners; *** p < 0.01, ** p < 0.05, * p < 0.1

3.4.2 Spillover Effect on Compliance

We estimate again our model for inspection and compliance as in the previous section, adding spillover explanatory variables in the compliance equation.[64] We consider three dichotomous variables to explore the potential effect on a facility's compliance from a fine that was imposed to another connected facility. The first dichotomous variable accounts for facilities with at least one Unique Tax Identification number in common (RUT from its Spanish acronym). The second dichotomous indicator accounts for the network of facilities connected to different RUTS that own one facility (In Appendices 3.1 to 3.3, we show more details about our data and what these networks look like). Finally, we repeat the same procedure, but for facilities that belong to the same sector and same location (commune). In our data, these indicators had the value of one when the SMA imposed a sanction within the last three years to the connected facilities.[65]

Table 3-5 shows the coefficient estimates for the variables related to imposition of fines on individual compliance. Average marginal effects are reported in Appendix 3.10. We keep the variable fined_3y in all the models because it denotes specific deterrence, that is, the improvement in compliance due to a fine imposed at the same facility. Model 1 shows the improvement in compliance due to fines imposed in the same firms (estimates indicates that it is about 0.013).[66] Adding the spillover effect variables, model 2 shows a positive and significant but small effect on compliance due to the imposition of fines on a facility related to the same RUT (the estimated increase in the probability to comply is 0.006). We do not find any spillover effect for facilities in the same network (model 3). Also, we do not detect

[64] We are analyzing potential effects of actions by the SMA on facilities' compliance; therefore, we do not show the estimates for inspections. However, the estimation considers both equations, in the same way as we did in the previous section.
[65] The sanctioning process over facilities demands several months, in most cases more than 1 year. Therefore, we think 3 years behind is a reasonable period to analyze the potential spillover effects.
[66] The model 1 used as reference in Table 3-5 is the same model shown in the last section (Table 3-4 and Appenix 3.9).

an effect for the imposition of fines on facilities in the same location or sector (model 4 and model 5). However, model 6 shows a positive and significant but small effect on compliance due to the imposition of fines on a facility from the same economic sector and location at the same commune (the increase in the probability to comply is estimated to be 0.003). In Appendix 3.11, we show marginal effects for the rest of the variables for both the inspection and compliance equations. The sign and magnitude of these effects do not change with the inclusion of the spillover variables.

In summary, we find that fines have a specific deterrence effect on average greater (twice in magnitude) than the general deterrence effect. Furthermore, sharing the same owner is more relevant than sharing the same economic sector and location regarding the spillover effects on compliance.

Table 3-5. Spillover Variable Coefficient Estimates of Fines on Comply

VARIABLES [a]	(1)	(2)	(3)	(4)	(5)	(6)
Fined_3y	0.0134**	0.0131**	0.0134**	0.0133**	0.0135**	0.0136**
	(0.00551)	(0.00551)	(0.00551)	(0.00553)	(0.00549)	(0.00552)
AnyFine_SameOwner3y		0.00585***				
		(0.00219)				
AnyFine_SameNet3y			-1.05e-05			
			(0.00147)			
AnyFine_Sector3y				0.00223		0.00219
				(0.00208)		(0.00215)
AnyFine_Comune3y					-0.000600	-0.00173
					(0.000854)	(0.00106)
AnyFine_SectorComune3y						0.00335**
						(0.00153)
Other Controls	YES	YES	YES	YES	YES	YES
Observations	37,425	37,425	37,425	37,425	37,425	37,425

Source: Own elaboration based on information from SNIFA.
Note:
Standard errors clustered by networks of facilities with common owners; *** p < 0.01, ** p < 0.05, * p < 0.1
[a] Inspection not presented in this table.

3.4.3 Drivers of Presenting a Compliance Program

Table 3-6 shows the results regarding the decision to present a compliance program once the facility has been found in violation. We present coefficient estimates for six models. Average marginal effects are presented in Appendix 3.12. The first three models differ in how the severity of the violation is measured. The last three models consider all the variables related to the violation. Model 1 and model 4 do not consider bias correction for sample selection. Model 2 and model 5 use the IMR correction, and model 3 and model 6 consider the probability of noncompliance. All the models show the same subset of variables relevant to present a compliance program.

Using the sector Fishing-Aquaculture as the basis, our results show no significance of the variable sector for the decision to present a compliance program. We find that smaller facilities face a lower probability of presenting this program than middle-size facilities as a base (decrease in the probability of -0.335 in model 2 and -0.324 in model 5). Facilities located in central south (CES) show a lower probability (decrease in the probability of -0.217 in model 2 and -0.229 in model 5) to present a compliance program than facilities located in the south, as a base of comparison. The social variable poverty shows a positive effect on the decision of presenting the program (increase in the probability of 0.908 in model 2 and 0.108 in model 5), but with a significance of 10%. Our results show a positive relation between the severity of the violation and the probability to present this program. Facilities with violations that include a serious infraction (category high infraction) are more likely to present the compliance program (increase in the probability of 0.220 in model 5).

Table 3-6. Coefficient Estimates for Probability of submitting a Compliance Program

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Predicted probability	0.7789	0.7791	0.7726	0.7792	0.7804	0.7733
Sectors (base: Fishing-Aqua.)						
Agroindustry	-0.365	0.138	-0.137	-0.370	0.185	-0.103
	(0.393)	(0.461)	(0.413)	(0.390)	(0.473)	(0.414)
Energy	0.502	0.414	0.756	0.486	0.328	0.728
	(0.614)	(0.640)	(0.660)	(0.612)	(0.660)	(0.653)
Environmental Sanitation	0.496	0.535	0.863	0.519	0.497	1.042*
	(0.483)	(0.580)	(0.585)	(0.473)	(0.568)	(0.602)
Mining	-0.334	-0.609	-0.247	-0.280	-0.401	-0.102
	(0.459)	(0.476)	(0.484)	(0.473)	(0.515)	(0.512)
Industrial Factories	-0.464	-0.222	-0.232	-0.414	-0.0753	-0.0794
	(0.444)	(0.504)	(0.455)	(0.441)	(0.526)	(0.460)
Size (base: Medium)						
Micro and Small	-1.293***	-1.329***	-1.249***	-1.234***	-1.343***	-1.198***
	(0.375)	(0.401)	(0.386)	(0.376)	(0.411)	(0.396)
Large	-0.0427	0.316	0.0450	-0.0443	0.324	0.0774
	(0.264)	(0.277)	(0.273)	(0.274)	(0.290)	(0.298)
Macrozone (base: SUR)						
NGR	0.00893	0.786	0.534	-0.108	0.721	0.483
	(0.480)	(0.504)	(0.505)	(0.486)	(0.508)	(0.515)
NCH	0.360	0.807	0.685	0.390	0.764	0.876
	(0.556)	(0.529)	(0.550)	(0.574)	(0.556)	(0.569)
CEN	-0.607	-0.621	-0.581	-0.679	-0.733	-0.643
	(0.524)	(0.560)	(0.534)	(0.539)	(0.595)	(0.568)
CES	-1.198**	-1.028*	-1.106**	-1.260**	-1.146*	-1.274**
	(0.508)	(0.566)	(0.538)	(0.511)	(0.604)	(0.570)
Age	-0.00710	-0.0158	-0.00838	0.000727	-0.0148	-0.000208
	(0.0265)	(0.0304)	(0.0277)	(0.0286)	(0.0326)	(0.0290)
LogPoverty	0.477*	0.515*	0.441	0.532*	0.583*	0.557*
	(0.272)	(0.304)	(0.291)	(0.285)	(0.320)	(0.318)
LogDensity	0.0706	0.129	0.0647	0.0674	0.122	0.0505
	(0.0782)	(0.0836)	(0.0801)	(0.0761)	(0.0839)	(0.0774)
ImpactIndex	0.0112	0.0147	0.0169			
	(0.0210)	(0.0221)	(0.0207)			
Num_Infractions				0.0236	0.0141	0.0207
				(0.0321)	(0.0326)	(0.0301)
LowInfraction				-0.191	0.0755	-0.0222
				(0.456)	(0.500)	(0.507)
MiddleInfraction				-0.215	-0.246	-0.209
				(0.295)	(0.373)	(0.315)
HighInfraction				0.669*	1.187***	1.587***
				(0.401)	(0.448)	(0.553)
Relapse	-1.027***	-0.664*	-0.962***	-1.048***	-0.625*	-1.055***
	(0.315)	(0.368)	(0.328)	(0.311)	(0.375)	(0.335)
Complaint	-0.165	-0.0542	-0.0947	-0.204	-0.0357	-0.141
	(0.271)	(0.293)	(0.279)	(0.281)	(0.311)	(0.299)
Num. Instruments	-0.0275	-0.00619	-0.00528	-0.0291	-0.00647	-0.0139
	(0.0350)	(0.0406)	(0.0427)	(0.0353)	(0.0419)	(0.0441)
IMR		-14.49***			-15.66***	
		(3.063)			(3.261)	
PNONCOMP			-4.575			-5.115*
			(2.891)			(3.047)
Constant	0.400	5.782***	0.377	0.372	6.145***	0.119
	(0.834)	(1.505)	(0.871)	(0.866)	(1.484)	(0.906)
Year Fixed Effect	YES	YES	YES	YES	YES	YES
Observations	193	192	184	193	192	184

Source: Own elaboration based on information from SNIFA.

Note: Standard errors clustered by facilities ownership in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

In our first three models, we do not find a relation using the impact index for the environmental damage. We find that facilities that have a relapse on detected violations have a lower probability to present a compliance program (decrease in the probability of -0.127 in model 2 and -0.116 in model 5), but only with a significance of 10%. Finally, the variables that account for the selection problem are relevant to our analysis according to the significance of IMR and PNONCOMP.

We carried out an alternative analysis using the logarithm of the compliance program cost as dependent variable. Table 3-7 shows the results. We present coefficient estimates for four models. The first two models differ in how the severity of the violation is measured. The last two models consider all the variables related to the violation. Model 1 and model 3 do not consider bias correction for sample selection. Model 2 and model 4 use the IMR correction. All the models show the same subset of variables relevant to present a compliance program.

Using the sector Fishing-Aquaculture as the basis, our results show that the sector of Environmental Sanitation, Energy and Mining present compliance program with higher costs. As before, we find differences in size. Those smaller facilities present programs with lower cost. Our results show a positive relation between the severity of the violation and the cost of the compliance programs though the variable Impact Index for model 1 and 2, and though the variable Number of Infractions for model 3 and 4. Finally, our analysis shows that the compliance program has higher cost when the sanction procedure is motivated by a community complaint.

Table 3-7. Determinants of the Compliance Program Cost (logCost)

VARIABLES	(1) LogCost	(2) LogCost	(3) LogCost	(4) LogCost
Sectors (base: Fishing-Aqua.)				
Agroindustry	0.936	0.984	0.941	0.978
	(0.726)	(0.725)	(0.729)	(0.742)
Energy	1.736**	1.702**	1.612**	1.596**
	(0.670)	(0.680)	(0.650)	(0.659)
Environmental Sanitation	1.924***	1.896***	1.925***	1.905***
	(0.636)	(0.638)	(0.678)	(0.683)
Housing-Construction	0.422	0.363	0.274	0.236
	(0.730)	(0.797)	(0.961)	(0.974)
Mining	1.653**	1.574**	1.544**	1.498**
	(0.653)	(0.681)	(0.680)	(0.702)
Industrial Factories	0.698	0.696	0.660	0.659
	(0.721)	(0.716)	(0.726)	(0.724)
Size (base: Medium)				
Micro and Small	-1.692***	-1.706***	-1.531**	-1.543**
	(0.646)	(0.645)	(0.681)	(0.684)
Large	0.628*	0.610	0.629*	0.620
	(0.362)	(0.370)	(0.374)	(0.378)
Macrozone (base: SUR)				
NGR	-0.546	-0.504	-0.632	-0.601
	(0.632)	(0.658)	(0.645)	(0.676)
NCH	-0.918	-0.896	-0.862	-0.843
	(0.711)	(0.728)	(0.741)	(0.753)
CEN	-0.656	-0.710	-0.749	-0.773
	(0.695)	(0.725)	(0.698)	(0.726)
CES	-0.877	-0.896	-1.006	-1.012
	(0.702)	(0.707)	(0.721)	(0.725)
Age	0.0190	0.0233	0.0340	0.0361
	(0.0374)	(0.0382)	(0.0430)	(0.0433)
LogPoverty	-0.265	-0.255	-0.223	-0.217
	(0.293)	(0.295)	(0.295)	(0.298)
LogDensity	0.0458	0.0582	0.0523	0.0604
	(0.0989)	(0.107)	(0.106)	(0.115)
ImpactIndex	0.0987***	0.0998***		
	(0.0328)	(0.0329)		
Num_Infractions			0.106**	0.106**
			(0.0494)	(0.0490)
LowInfraction			-0.351	-0.323
			(0.712)	(0.723)
MiddleInfraction			0.133	0.147
			(0.362)	(0.374)
HighInfraction			0.770	0.763
			(0.555)	(0.575)
Relapse	-0.0403	0.0164	-0.112	-0.0709
	(0.692)	(0.711)	(0.681)	(0.709)
Complaint	1.218***	1.184***	1.211***	1.192***
	(0.332)	(0.346)	(0.350)	(0.362)
Num. Instruments	0.0673	0.0699	0.0748	0.0769
	(0.0622)	(0.0627)	(0.0629)	(0.0636)
IMR		-1.157		-0.916
		(4.268)		(4.422)
Constant	1.770	2.116	1.725	1.994
	(1.087)	(1.977)	(1.256)	(2.023)
Year Fixed Effect	YES	YES	YES	YES
Observations	170	169	170	169
R-squared	0.378	0.378	0.374	0.373

Source: Own elaboration based on information from SNIFA.
Note: Standard errors clustered by facilities ownership in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

3.4.4 Results for Estimation of Fines

Table 3-8 shows the results for the estimation of drivers for the fine size. We present coefficient estimates for a tobit model that incorporates the IMR variable created from the joint estimation of inspections and compliance. Similar to the previous section, we present two models that differ in how the severity of the violation is considered. The results of our first model suggest, using the sector Fishing-Aquaculture as the basis, that the Mining sector receives fines on average 1,083 thousand USD higher, with a significance of 5%. In our second model, this figure is similar in sign and magnitude but decreases in significance. However, the second model also shows that sector Industrial Factories receive fines on average 908 thousand USD lower than Fishing-Aquaculture, with a significance of 10%. Regarding zone, both models show that Norte Chico presents higher fines on average at around 1,406 (significance of 1%) and 1,122 (significance of 5%) in thousand USD. Both models show that older facilities receive lower fines. That is a decrease of -67.9 thousand USD per year in the first model (significance of 5%) and a decrease of -91.39 thousand USD per year in the second model (significance of 1%). An important result is for both models the severity of the violation correlates positively with the fine. The total number of infractions and having at least one high-level of infraction increases the fine an average of 153,2 and 1,558 thousand USD respectively. Using our index, we find that one additional low-level infraction increases the fine an average of 119,6 thousand USD; increasing 1 middle-level infraction (that counts as 2 low-level infractions) the fine increases an average of 239,2 thousand USD; and increasing 1 high-level infraction (that counts as 3 low-level infractions) the fine increases an average of 358,8 thousand USD. Surprisingly, we also find that complaints from the community decrease the fine by an average of -689,7 and -750.0 thousand USD for model 1 and model 2 respectively. We speculate that the community complains as soon as the environmental violations are perceived, which would prevent further impacts. The variable Number of the Instruments is a proxy of the complexity of the facilities and also, we understand it as the number of dimensions that the facility may potentially do damage to the environment. This variable correlates positively in both models with the fines increasing an average of 60.6 and 58.6 thousand USD respectively. Finally, the variable IMR that accounts for the selection problem is relevant to our analysis.

Table 3-8. Coefficient Estimates for the Size of Fines

VARIABLES		(1) Fines in 1000 USD	(2) Fines in 1000 USD
Sectors	Agroindustry	-610.2	-561.6
(base: Fishing & Aqua.)		(377.7)	(368.0)
	Energy	470.1	504.7
		(550.5)	(561.2)
	Environmental Sanitation	-529.2	-224.9
		(447.2)	(434.3)
	Housing and Construction	-272.0	-2,132
		(1,374)	(1,462)
	Mining	973.5*	1,083**
		(531.5)	(519.9)
	Industrial Factories	-908.0*	-756.5
		(459.7)	(460.0)
Size	Micro and Small	-66.10	129.3
(base: Medium)		(355.0)	(355.0)
	Large	-123.1	28.30
		(294.4)	(293.1)
Macrozone	NGR	575.8	-83.51
(base: SUR)		(501.1)	(531.7)
	NCH	1,122**	1,406***
		(478.6)	(480.8)
	NCH	867.8*	606.3
		(443.6)	(433.1)
	CEN	733.0*	608.6
		(436.3)	(435.8)
Age		-91.39***	-67.90**
		(29.49)	(29.67)
LogPoverty		-486.0*	-288.7
		(286.6)	(292.2)
LogDensity		29.76	15.53
		(62.01)	(61.99)
Compliance Program		7.375	-83.48
		(247.1)	(242.1)
Num_Infractions			153.2***
			(28.31)
LowInfraction			-928.6*
			(475.7)
MiddleInfraction			-471.9
			(338.1)
HighInfraction			1,558***
			(519.3)
ImpactIndex		119.6***	
		(18.15)	
Relapse		-29.88	-163.8
		(263.3)	(257.6)
Complaint		-750.0***	-689.7**
		(254.0)	(269.2)
Num. instruments		58.58*	60.56*
		(32.37)	(31.51)
PrioritizedArea		413.1	316.0
		(303.6)	(292.0)
IMR		6,419**	6,114**
		(2,979)	(3,008)
Constant		-735.2	-483.0
		(1,630)	(1,653)
Year Fixed Effect		YES	YES
Observations		79	79

Source: Own elaboration based on information from SNIFA.
Note: Standard errors clustered by facilities ownership in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.4.5 Results for Drivers of Payment and Delay in Payment

We now turn our attention to the analysis regarding determinants of fine payments and the delay in payment. We present coefficient estimates for three models in Table 3-9. The first model analyzes fines paid in less than one year since the fine was notified to the facility. Model 2 analyzes fines paid in less than two years, and model 3 analyzes fines paid in less than three years. In all models, we incorporate the IMR variable. Marginal effects are presented in Appendix 3.13. Our models do not show differences among sectors regarding the payment of fines. We identify that the category large (as dichotomous indicators for size) increases the probability of payment in comparison with the facilities that are not large. This result is expected since these categories have been defined from the information about sales. Large facilities increase the probability of payment (increase in a probability of 0.307 in model 1, 0.220 in model 2, and 0.248 in model 3). Being located in the central south decreases the probability of the facility's payment (decrease in a probability of -0.283 in model 1, -0.356 in model 2, and -0.316 in model 3). Our results show that an increase of 1 year in the variable age decreases the probability of payment (decrease in a probability of -0.024 in model 1, a significance of 10%). Finally, the variable IMR is not significant may be due to the lower sample of units in this level (n=77).

For the delay in payment in days, Table 3-10 shows results for three estimated models. The first model analyzes delays in payment for fines paid in less than one year since the fine was notified. Model 2 and model 3 consider the delay in payment for fines paid in less than two years and three years respectively. We found that the size of the fine correlates with the delay but in a small magnitude. An additional 100 thousand USD in the level of the fine increases by 1.4 days the delay (significance at 5%) in model 1. We also find a significant correlation in the variable sector. Using the sector Fishing-Aquaculture as the basis, we find that sector Agroindustry delays in addition 83 days more than this base in model 1 and 280 days for model 3; and the sector Energy has an additional 129 days more than the sector Fishing-Aquaculture. Finally, the variable IMR is not significant maybe due to the lower sample of units in this level (n=58).

Table 3-9. Coefficient Estimates and Average Marginal Effects for Payment of Fines

VARIABLES	(1) Fine paid in 1 year or less	(3) Fine paid in 2 year or less	(5) Fine paid in 3 year or less
Predicted probability	0.627	0.652	0.690
Fine_1000USD	-2.22e-06	3.63e-05	0.000138
	(0.000109)	(0.000148)	(0.000234)
Sectors (base: Fishing & Aqu.)			
Agroindustry	-0.167	0.00338	0.626
	(0.576)	(0.612)	(0.665)
Energy	0.354	0.0537	
	(0.908)	(0.964)	
Environmental Sanitation	-0.583	-0.659	-0.877
	(0.630)	(0.666)	(0.691)
Housing and Construction	-	-	-
Mining	-0.235	-0.0485	-0.311
	(0.714)	(0.793)	(0.933)
Industrial Factories	1.161	0.837	0.420
	(0.772)	(0.832)	(0.909)
Large	1.144**	0.832*	1.071*
	(0.456)	(0.505)	(0.625)
Macrozone (base: SUR)			
NGR	-0.747	-1.384	-1.766*
	(0.806)	(0.899)	(1.046)
NCH	-0.143		
	(0.637)		
CEN	-0.176	-0.947	-1.198
	(0.574)	(0.626)	(0.764)
CES	-1.025*	-1.394**	-1.510**
	(0.563)	(0.623)	(0.729)
Age	-0.0904*	-0.0268	0.0253
	(0.0496)	(0.0510)	(0.0517)
Relapse	0.0270	0.281	0.131
	(0.413)	(0.462)	(0.581)
Complaint	0.241	0.372	0.904
	(0.414)	(0.434)	(0.609)
Num. Instruments	0.0420	0.0880	0.197**
	(0.0437)	(0.0583)	(0.0952)
IMR	2.532	-0.357	0.744
	(2.699)	(3.132)	(3.325)
Constant	0.475	0.988	-0.761
	(1.309)	(1.606)	(1.612)
Year Fixed Effect	YES	YES	YES
Observations	77	69	65

Source: Own elaboration based on information from SNIFA.
Note: Standard errors clustered by facilities ownership in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3-10. Coefficient Estimates Payment Delay of Fines

VARIABLES	(1) Payment delay fines paid in 1 year or less	(2) Payment delay fines paid in 2 years or less	(3) Payment delay fines paid in 3 years or less
Fine_1000USD	0.0136**	0.0163	0.0125
	(0.00651)	(0.0154)	(0.0246)
Sectors (base: Fishing & Aqua.)			
Agroindustry	85.78**	119.1	280.4**
	(37.55)	(88.32)	(135.9)
Energy	128.7**	80.92	286.5*
	(49.21)	(114.0)	(163.4)
Environmental Sanitation	-20.57	6.382	33.22
	(42.26)	(86.24)	(140.2)
Housing and Construction	-102.8	-57.68	241.7
	(95.83)	(237.3)	(379.0)
Mining	-46.18	10.55	107.8
	(48.06)	(96.31)	(154.9)
Industrial Factories	-9.219	18.73	-48.87
	(39.40)	(90.91)	(144.6)
Large (dichotomous indicator)	30.60	-53.20	-141.3
	(23.98)	(56.73)	(85.24)
Macrozone (base: SUR)			
NGR	-19.57	-99.88	-310.6
	(53.29)	(126.5)	(200.0)
NCH	-44.83	-103.5	-226.8
	(45.00)	(86.97)	(138.2)
CEN	-28.49	-147.8*	-135.6
	(34.02)	(73.11)	(118.3)
CES	-27.40	-95.39	-75.09
	(33.93)	(80.80)	(125.4)
Age	0.994	5.804	14.88
	(2.942)	(6.738)	(10.32)
Relapse	-31.72	-24.29	-76.02
	(21.86)	(49.96)	(74.47)
Complaint	13.15	25.55	46.72
	(20.79)	(49.57)	(74.38)
Num. Instruments	3.023	6.942	9.521
	(2.948)	(7.055)	(11.22)
Year 2014	-0.690	-76.97	-61.13
	(28.47)	(68.08)	(108.9)
Year 2015	-53.10	-11.94	-39.08
	(33.58)	(75.62)	(122.9)
Year 2016	-30.90	-132.7	152.7
	(34.05)	(79.79)	(104.7)
Year 2017	241.5***	171.6	344.8
	(72.44)	(176.0)	(281.5)
Year 2018	-53.91	57.05	24.97
	(65.51)	(156.9)	(251.7)
Year 2019	98.37	116.5	-41.13
	(74.48)	(180.7)	(291.4)
IMR	-357.9	-1,227**	-175.7
	(251.8)	(560.4)	(862.4)
Constant	161.3	564.9**	-33.64
	(116.3)	(271.4)	(408.8)
Observations	49	54	58

Source: Own elaboration based on information from SNIFA.
Note: Standard errors clustered by facilities ownership in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

3.5 Discussions and Conclusions

This work presents several new results regarding monitoring, enforcement, and environmental compliance in Chile. We find that the monitoring effort from SMA is relatively low and that inspections are driven differently across sectors and are related to some specific characteristics of the facilities. Facilities from sectors of Agroindustry, Energy, and Mining are more likely to be inspected than facilities from sectors of Fishing-Aquaculture and Housing-Construction. Facilities in the north of Chile face inspections with a higher probability than facilities in the south. Small and large facilities are less likely to be inspected than middle-size. Inspections correlate negatively with the age of the facility. The enforcement action of SMA has a positive correlation with conducting a new inspection. Facilities fined in the past and the fact of having a compliance program in operation increase the probability of being inspected. We also find that the focus of the inspections is higher on facilities regulated with a higher number of instruments (as several environmental permits) and located in prioritized areas.

As for compliance behavior, the results indicate that sectors of Agroindustry, Energy, and Industrial Factories have a higher probability of compliance compared with Fishing-Aquaculture and Housing-Construction. Again, facilities located in the north of Chile have higher compliance. We also find that SMA monitoring increases the probability of compliance. Another driver of compliance is having received a fine in the past. That also impacts the compliance of facilities sharing the same firm owner and sharing the same sector and location, as a spillover effect. Our results also find that complex facilities with several environmental instruments have a higher propensity to comply.

Our study also shows that presenting a compliance program is less likely for small-size facilities than for middle and large size facilities. Compliance programs carry several activities such as planning, submission in a limited time, and future internal follow-up of this plan. These may bring relatively high costs for a small facility. On the contrary, for larger facilities, these costs may be relatively low since large facilities may have already the capacity (as administrative personnel, engineers, layers, etc.) and the experience to deal with these programs. We find that facilities located in the south use more of that option than facilities in the central south. This may be due to the possibility that facilities located in south of the country perceive a low probability of being inspected and for them it is cheaper to fulfill the regulation using the compliance program after being caught in non-compliance, instead of doing it from the beginning of its operations. The severity of the violation correlates positively with presenting a compliance program. We do not know in detail the social costs, or the private benefits generated from the violations, but we can speculate that greater environmental damage generates also greater profits, then the facilities could have the incentive of not complying, and then implement a compliance program at a relatively low cost in comparison with the private benefits obtained. We understand that the compliance programs are an opportunity for violators to invest in environmental control and fulfill the regulations, as the SMA also stands. However, we speculate that some facilities could be playing the game "investing only after being caught" and that situation may have a large opportunity cost in terms of the annual SMA budget.

Imposed fines appear to be higher for detected non-compliant facilities in the Mining sector as compared with facilities in Fishing-Aquaculture. Also, imposed fines appear to be higher on facilities located in the north of the country. We also find that the severity of the violation correlates positively with the size of the fine, and the fine payment positively correlates with the size of the facility. Regarding the delay in the payment, we find that the sectors Agroindustry and Energy delayed more days in payment than the sector Fishing-Aquaculture.

The SMA must prioritize what enforcement actions they carry out, given the fact that the number of resources is limited. These resources compete with carrying out new inspections in facilities where there is no information on their compliance (for instance, several facilities in the sector of Fishing-Aquaculture). An alternative to this current strategy may be to impose sanctions immediately once the violations have been found since our findings also show that receiving fines has a positive impact on the compliance of the violators and, we found spillover impacts on related facilities. With the same criteria, we can also speculate that for these fined facilities the investment for environmental compliance was done since we found a higher probability of compliance after the sanction.

Our study contains a description of the monitoring and enforcement actions of the SMA during its first years of operation and links all stages from inspection to payment of fines, adjusting for the selection bias of the inspection. However, we acknowledge that it does not provide causal estimates therefore our results should be interpreted as correlations. Our study may be extended in several ways. First, instead of focusing on sectors, we could extend the comparison of environmental compliance among different environmental instruments, beyond environmental permits. Second, is worth evaluating the deterrence effect of the SMA's monitoring and enforcement actions on the level of emissions (in air or water), instead of the analysis considering only a binary variable for compliance. This type of analysis may provide a better measure of the environmental damage avoided by the actions of the SMA. Finally, another interesting analysis to pursue could focus on a specific sector adding information about the production processes (such as production cycles in aquaculture) or about the abatement costs (such as the investments in filters or in electrostatic precipitators for power plants). By including such detailed information on the analysis of the SMA, the regulator might improve the decision about which facilities to inspect and when that needs to be done. This type of information could be useful for the design of enforcement strategies under limited budget and resources.

V. CONCLUSIONS

The objective of this thesis, as stated in the introduction, is to analyze Chile's path toward sustainable development under the lens of environmental economics. This thesis included empirical research that consider three relevant Chilean economic agents: households, firms, and government. The first two essays focused on households furthest behind in the energy transition (i.e., energy-poverty and families participating in a program to improve their heating technology). Then, in the last essay, this thesis focused on the economic sectors that present difficulties complying with environmental regulations.

This thesis also considered the analysis of externalities and economic inequality. These economic problems call for intervention by the public sector. Therefore, the role of the government in promoting energy transition and clean production is a key transversal element of this research. While conducting this research, I had strong connections and many interactions with local policymakers. We discussed the relevant dimensions of energy poverty with the Ministry of Energy, selected participants for the stove replacement program with the support of the Ministry of Environment, followed their strict COVID protocols and discussed the most important variables related to monitoring, compliance, and sanctions following the advice of the Superintendence of Environment. As a product of this research, I have contributed to improving our understanding of how agents respond to incentives in the context of market failures, poverty and inequality, and weak monitoring and enforcement.

In terms of methods, in this thesis I explored different empirical approaches to perform a rigorous analysis of primary and secondary data. In the first essay, I used the Alkire Foster Multidimensional Poverty method with the data available from the 2017 National Energy Survey carried out by the Ministry of Energy. This method allowed me to build a new Energy Poverty measure, aggregating the deprivations across energy-related dimensions of poverty. In the second essay, I used panel regression models to evaluate the impact of the Chilean stove replacement program over a unique set of data collected by designing and implementing fieldwork. The variables of interest were obtained using electronic devices, paper spreadsheets, and mobile phone surveys from a random sample of households participating in this program during 2019-2020 in the city of Talca. Finally, in the third essay, I analyzed the complete sequence of environmental enforcement by the SMA and facilities' compliance behavior in Chile, including inspections, compliance, submission of compliance programs, size of fines, payment of fines, and delay in payment of these fines. I proposed a simultaneous estimation of inspections and compliance to obtain the key factors determining these outcomes by facilities that belong to several economic sectors. Furthermore, standard regression models were used to analyze other variables of interest. The data was obtained from the SNIFA platform of the SMA through modern methods of web scraping.

I have presented and discussed several new findings. From the first essay I conclude that adopting any definition of energy poverty is a decision that necessarily narrows the resulting set of energy-poor households. For the case of Chile, the use of multiple definitions produces diverging energy poverty rankings across the territory. The proper design of energy policies may benefit by adopting the Perception-based Multidimensional Energy Poverty Index presented in this research since these address supply-side factors not included in other traditional indices which are mainly focused on income or energy costs.

From the second essay of this thesis, I concluded that the energy transition of adopting clean heating technologies has significant private benefits, such as improving indoor air pollution and a more stable temperature of comfort for the users. As lower-income households may receive greater benefits for indoor air pollution by adopting new more-efficient and less-polluting stoves, the replacement of firewood stoves for pellet stoves is progressive in that dimension. However, new and modern heating stoves may have significantly higher operating costs, which are most salient for energy-poor households.

The third essay addresses economic aspects regarding environmental monitoring, enforcement, and compliance in the Chilean context. From this research, I conclude that inspections performed by the regulator are carried out differently across sectors and are related to some specific facilities' characteristics. The enforcement actions have a positive effect on compliance with environmental regulations. These actions, such as the imposition of fines, also have a spillover effect on other facilities' compliance behaviors. The severity of the violation determines the size of the fines, and its payments may be explained by facilities' characteristics such as size.

Achieving sustainable development requires effectively identifying and measuring the impacts of public policies implemented. This thesis demonstrates that Chile's government intends to promote green growth, which can generate positive impacts. Specifically, this research presents evidence that may help to improve the public policy design, particularly in the classification of energy-poor households, the design of sustainable heating subsidies for families, and the planning of monitoring and enforcement to improve compliance with environmental regulations. Of course, the analyses and results of this research do not cover all the dimensions in which Chile should continue to advance in sustainability. However, these results could motivate a research agenda that continues to study the main three problems presented in this thesis.

APPENDICES

Appendices 1

Appendix 1.1. Censored Headcount Ratios (PMEPI) by Macrozones Estimation

Indices	Country	Macrozones					
		NGR	NCH	CEN	CES	SUR	MET
Affordability	0.151	0.111	0.246	0.116	0.159	0.235	0.127
s.e	0.011	0.034	0.058	0.022	0.023	0.043	0.018
Thermal Comfort	0.099	0.051	0.192	0.071	0.096	0.162	0.088
s.e	0.008	0.013	0.052	0.016	0.020	0.030	0.012
Public Lighting	0.056	0.085	0.045	0.044	0.058	0.069	0.054
s.e	0.006	0.024	0.020	0.011	0.014	0.019	0.011
Behavior	0.003	0.011	0.005	0.006	0.001	0.003	0.002
s.e	0.001	0.004	0.004	0.004	0.001	0.003	0.001
Service Quality	0.047	0.033	0.066	0.036	0.052	0.060	0.043
s.e	0.006	0.013	0.025	0.016	0.012	0.015	0.011
Service Reliability	0.042	0.029	0.124	0.019	0.048	0.100	0.019
s.e	0.006	0.017	0.032	0.007	0.016	0.023	0.006
Energy-Saving Information	0.024	0.018	0.039	0.033	0.023	0.024	0.020
s.e	0.004	0.008	0.015	0.011	0.010	0.009	0.005
Information for a Well-informed Consumer	0.080	0.100	0.102	0.088	0.058	0.151	0.064
s.e	0.008	0.027	0.026	0.017	0.017	0.028	0.012
General Knowledge (Energy Education)	0.050	0.024	0.073	0.015	0.077	0.088	0.037
s.e	0.006	0.011	0.019	0.007	0.016	0.020	0.008

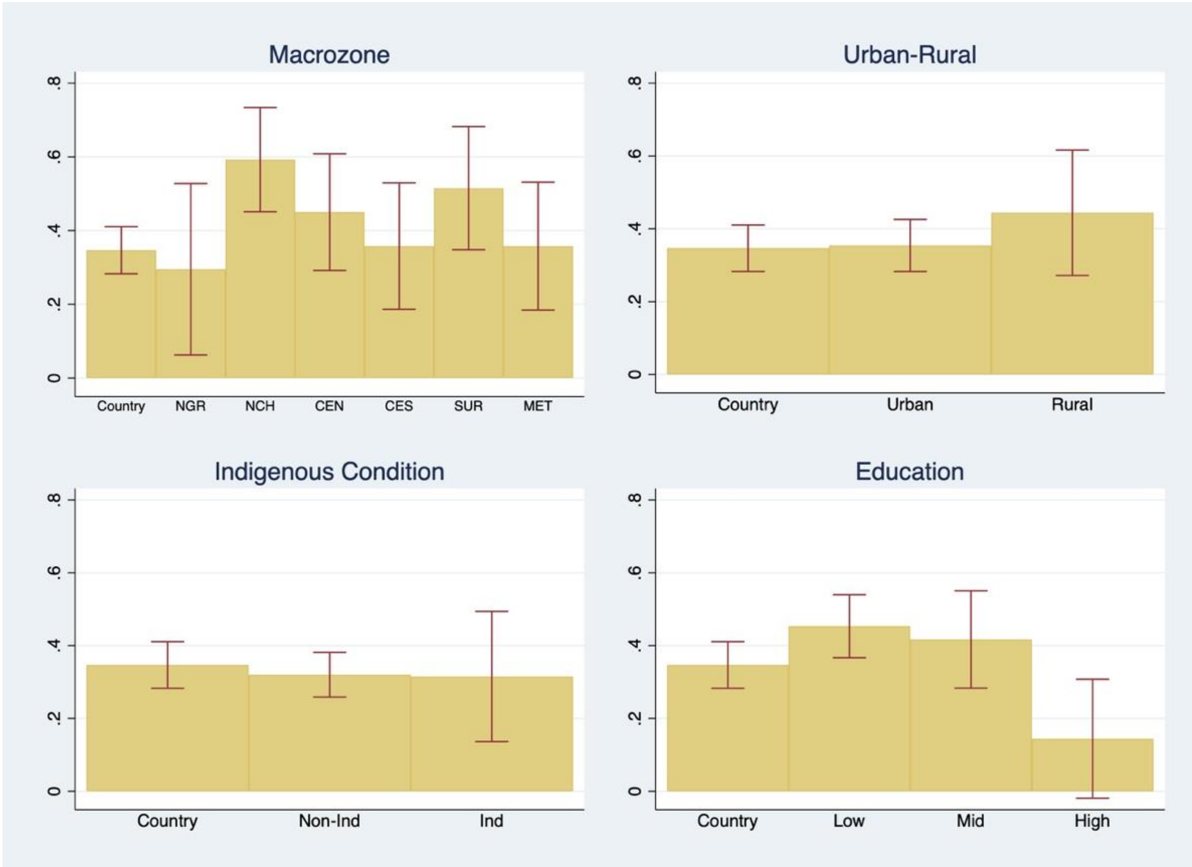
Source: Own elaboration based on ENE2017.

Appendix 1.2. Censored Headcount Ratios (PMEPI) by Population Subgroups

Indices	Socio-Economic level				Ethnic group		Education			Zone	
	ABC1	C2	C3	D+E	Non-Indig.	Indig.	Low	Middle	High	Urban	Rural
Affordability	0.000	0.019	0.103	0.281	0.141	0.248	0.249	0.156	0.044	0.148	0.171
s.e	0.000	0.005	0.011	0.021	0.010	0.038	0.021	0.014	0.011	0.011	0.027
Thermal Comfort	0.001	0.023	0.068	0.179	0.093	0.161	0.160	0.107	0.027	0.096	0.121
s.e	0.001	0.006	0.008	0.018	0.008	0.030	0.018	0.011	0.007	0.008	0.024
Public Lighting	0.001	0.013	0.041	0.100	0.053	0.088	0.098	0.052	0.020	0.059	0.041
s.e	0.001	0.006	0.007	0.013	0.006	0.019	0.015	0.007	0.006	0.007	0.016
Behavior	0.001	0.007	0.006	0.001	0.004	0.000	0.001	0.003	0.006	0.004	0.001
s.e	0.001	0.003	0.002	0.001	0.001	0.000	0.001	0.002	0.002	0.001	0.001
Service Quality	0.000	0.012	0.025	0.090	0.041	0.100	0.066	0.055	0.015	0.047	0.044
s.e	0.000	0.005	0.005	0.013	0.006	0.023	0.012	0.009	0.006	0.006	0.015
Service Reliability	0.001	0.007	0.031	0.075	0.039	0.063	0.062	0.038	0.027	0.038	0.066
s.e	0.001	0.003	0.005	0.014	0.006	0.017	0.013	0.006	0.009	0.006	0.019
Energy-Saving Information	0.001	0.003	0.012	0.049	0.025	0.019	0.038	0.025	0.008	0.023	0.030
s.e	0.001	0.002	0.004	0.008	0.004	0.010	0.008	0.006	0.005	0.004	0.015
Information for a Well-informed Consumer	0.001	0.021	0.066	0.136	0.077	0.114	0.130	0.080	0.030	0.078	0.099
s.e	0.001	0.005	0.009	0.017	0.008	0.025	0.017	0.010	0.009	0.007	0.023
General Knowledge (Energy Education)	0.000	0.007	0.031	0.095	0.046	0.088	0.091	0.051	0.008	0.048	0.067
s.e	0.000	0.003	0.006	0.012	0.006	0.026	0.014	0.008	0.003	0.006	0.020

Source: Own elaboration based on ENE2017.

Appendix 1.3. Redundancy R^0 Measure between PMEPI-H and TPRI, Chile, 2017



Source: Own elaboration based on ENE2017 household survey. 95% confidence intervals.

Appendix 1.4. Survey Probit Estimation for Redundancy Measures

Explanatory Variables	PMEPI-H and TPRI		PMEPI-H and FTG_0	
	Probit Model	Marginal effects (at the mean)	Probit Model	Marginal effects (at the mean)
Basic Education	0.775*	0.169*	1.378*	0.295*
	(0.435)	(0.0921)	(0.757)	(0.169)
Secondary Education	1.063**	0.246**	0.00586	0.00115
	(0.494)	(0.116)	(0.759)	(0.149)
Tertiary Education	0.749	0.181	-0.387	-0.0730
	(1.009)	(0.251)	(0.987)	(0.175)
Indigenous Status	-0.358	-0.0769	-0.523	-0.0921
	(0.438)	(0.0885)	(0.344)	(0.0564)
Household Size	-0.00205	-0.000461	0.110	0.0216
	(0.115)	(0.0260)	(0.0985)	(0.0184)
Rural Area	-0.0494	-0.0111	0.388	0.0810
	(0.431)	(0.0962)	(0.437)	(0.0971)
NCH Macrozone	1.342***	0.323***	0.681**	0.150**
	(0.359)	(0.0813)	(0.325)	(0.0734)
SUR Macrozone	0.993**	0.239**	0.552	0.118
	(0.391)	(0.0943)	(0.393)	(0.0894)
Constant	-1.664***	-	-1.817**	-
	(0.587)	-	(0.882)	-
Number of observations	3,500		3,500	
Population size	12,754,999		12,754,999	
Subpopulation	260		394	
Subpopulation size	1,761,242		1,981,181	
F	2.33		4.96	
Prob > F	0.0242		0.0000	

Source: Own elaboration based on ENE2017 and EPF 2017 household surveys.
Note: The probit models rely on the subpopulations to estimate coefficients. However, given the complex survey design, they rely on the full sample to estimate unbiased standard errors. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

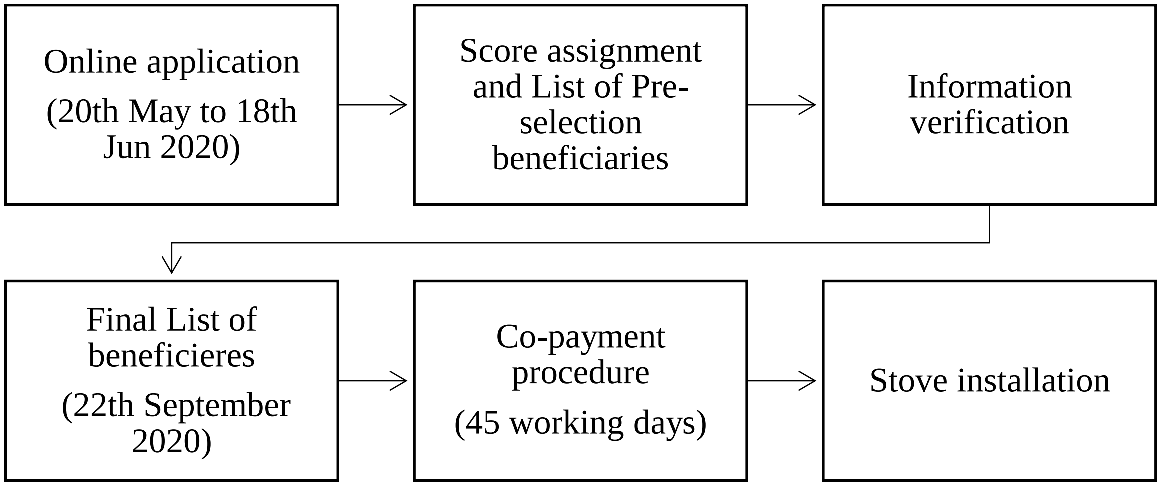
Appendices 2

Appendix 2.1. Number of Stove Replacements Carried Out in Chile, 2011-2019

Stove Installed/Fuel	2011	2012	2013	2014	2015	2016	2017	2018	2019
Electricity								35	46
Gas				1		188	45	80	15
Kerosene				122	193	1,508	2,204	1,042	2,064
Firewood	438	1,652	2,528	1,742	1,132	1,884	452	473	236
Pellets			421	380	737	1,904	5,375	2,855	10,674
Total	438	1,652	2,949	2,245	2,062	5,484	8,076	4,485	13,035

Source: Own elaboration based on official records. Information was retrieved from https://www.portaltransparencia.cl/

Appendix 2.2. Schematic of the Stove Replacement Program Year 2020



Source: Own elaboration.

Note: Own elaboration based on interviews with the Regional Secretary of the Ministry of Environment. This figure depicts the application process of the replacement program for year 2020 in Talca.

Appendix 2.3. Pellet Stove Offered and Salamander Stove

Source: Own elaboration MMA

Note: Pellet stove offered by the program (left) and salamander stove (right)

Appendix 2.4. Firewood Stove Before the Replacement and Pellet Stove Obtained

Source: with the consent of an anonymous beneficiary.

Source: with the consent of an anonymous beneficiary.

Appendix 2.5. House Chosen for Stove Replacement Program in Talca

Source: with the consent of an anonymous beneficiary.

Appendix 2.6. Selection criteria and points by criterion for 2019 and 2020

A. Evaluation Criteria used by the Ministry of Environment to select beneficiaries for the stove replacement program in Talca during 2019

Dimension	**Sub-dimension**	**Detail**	**Scores**		**Max. score**
Family	Risk of illness	Num. people older than 60 OR younger than 5.	3 or more 1 or 2 none	15 pts. 10 pts. 0 pts.	15 pts.
	Num. Persons	Num. people per household	4 or more 2 or 3 1	15 pts. 10 pts. 0 pts.	15 pts.
Type of stove	Type of stove	Higher score for less efficient technology	1 Homemade and salamander stove 2 Cookstove 3 Single chamber 4 Double chamber	40 pts. 30 pts. 20 pts. 10 pts.	40 pts.
Housing	Housing construction	Year of construction	After 2007 Between 2000 and 2007 Before 2000	10 pts. 5 pts. 0 pts.	10 pts
	Thermal insulation	Household obtained the subsidy from MINVU	Beneficiary Not Beneficiary	20 pts. 0 pts.	20 pts.

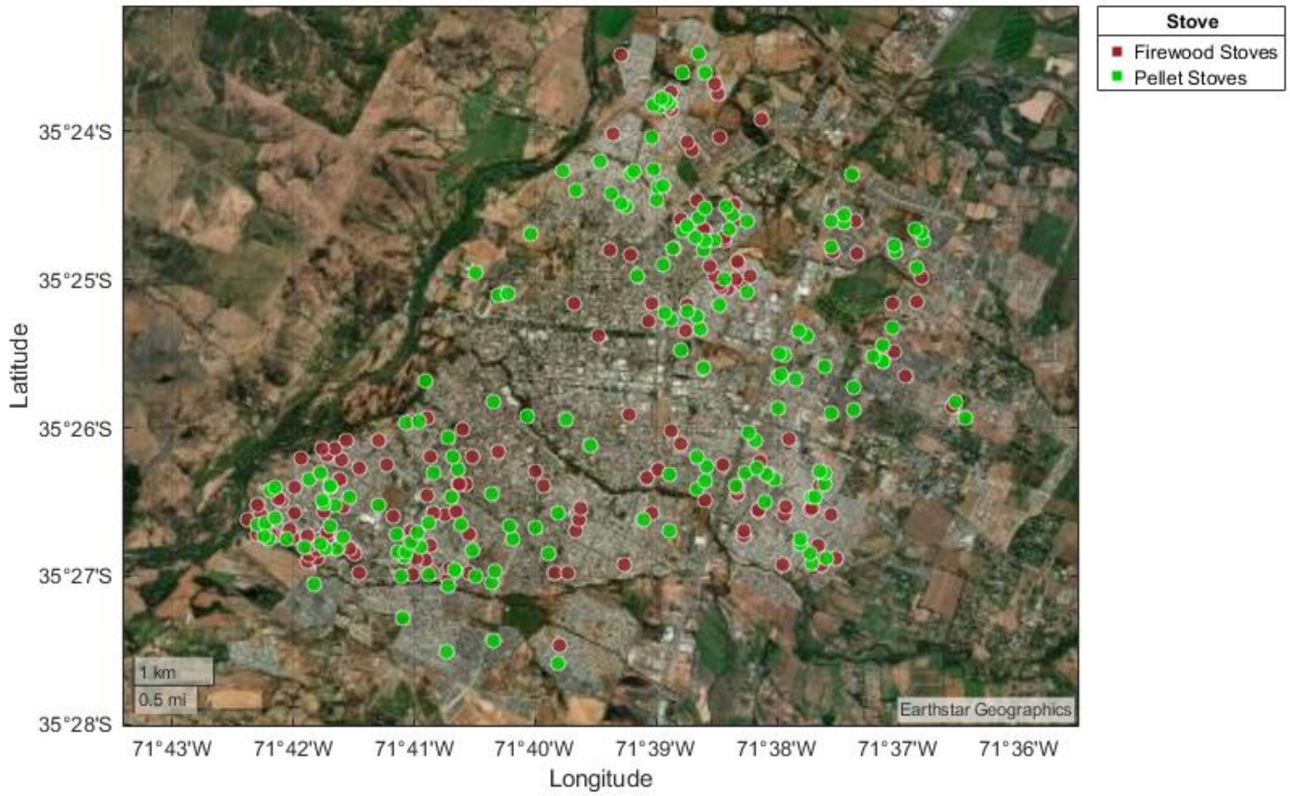
Source: Own elaboration based on information from Ministry of Environment https://calefactores.mma.gob.cl/region/9.

B. Evaluation Criteria used by the Ministry of Environment to select beneficiaries for the stove replacement program in Talca during 2020

Dimension	Sub-dimension	Detail	Scores		Max. score
Family	Risk of illness	Num. people older than 60 OR younger than 5.	3 or more 1 or 2 none	7 pts. 4 pts. 0 pts.	7 pts.
	Num. Persons	Num. people per household	5 or more 3 or 4 2	8 pts. 4 pts. 1 pts.	8 pts.
Type of stove	Type of stove	Higher scores for less efficient technology	1 Single chamber 2 Double chamber	40 pts. 10 pts.	40 pts.
Territory	Location	Higher score for zones more contaminated	Zone 1 Zone 2 Zone 3 and 4	10 pts. 5 pts. 2 pts.	10 pts
Housing	Housing construction	Year of construction	After 2007 Between 2000 and 2007 Before 2000	35 pts. 10 pts. 5 pts.	35 pts
	Thermal insulation	Household obtained the subsidy from MINVU	Beneficiary Not Beneficiary	25 pts. 0 pts.	

Source: Own elaboration based on information from Ministry of Environment https://calefactores.mma.gob.cl/region/9.

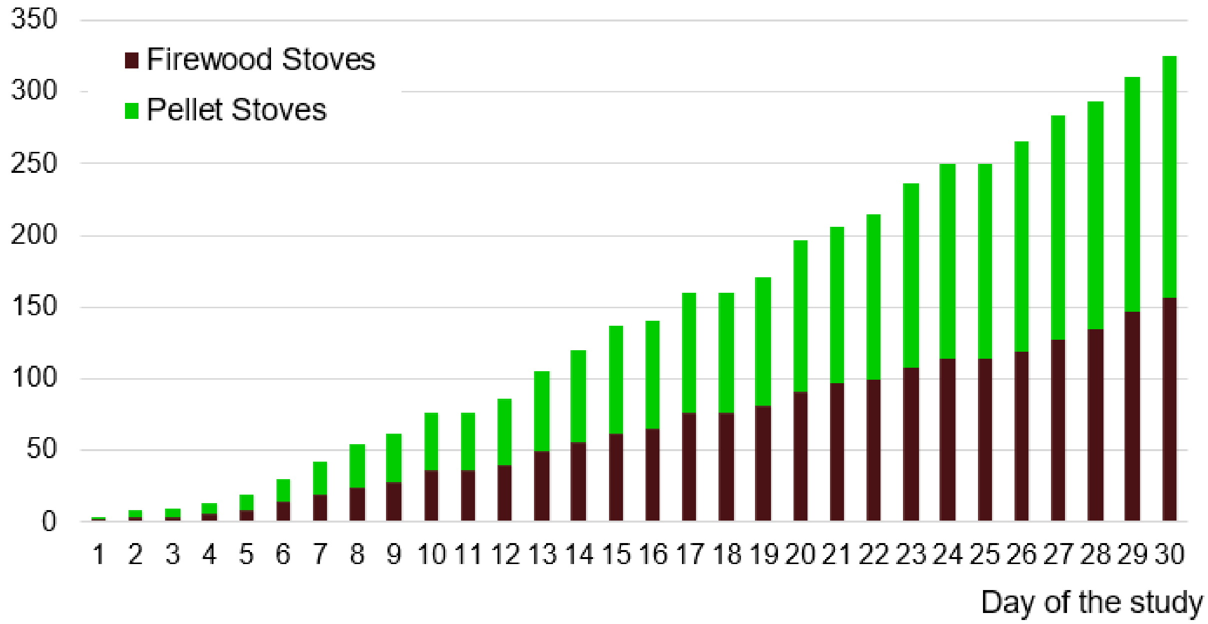
Appendix 2.7. Participants in the Study Distributed Across Talca



Source: Own elaboration.

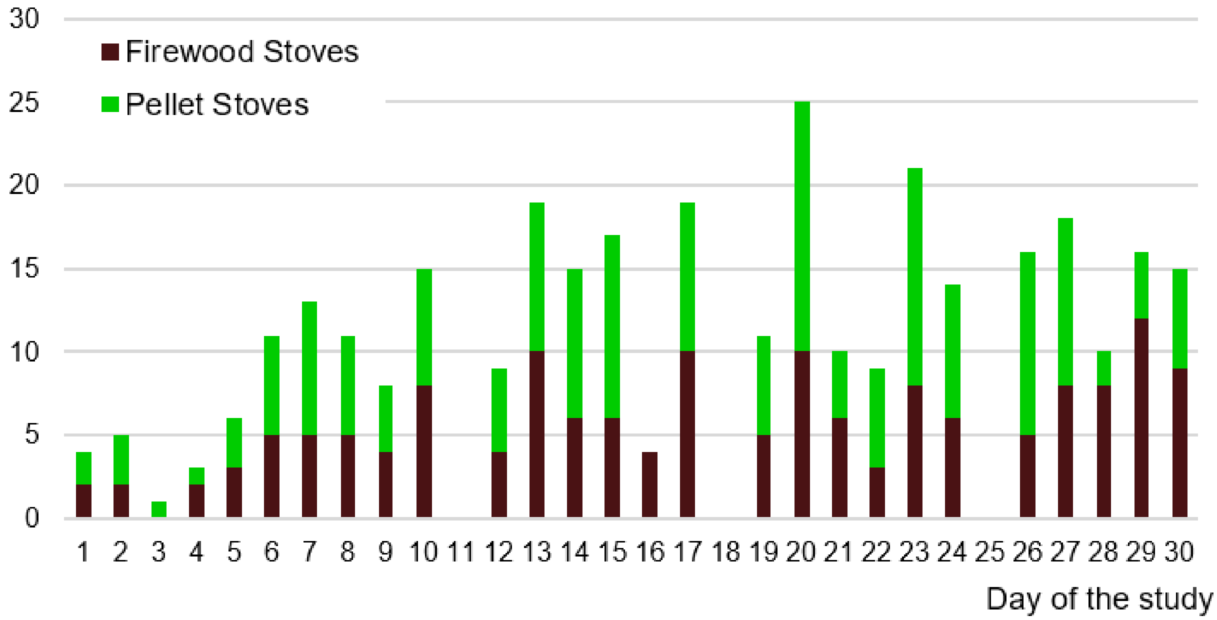
Note: In brown color households with firewood stoves (control) and in green color households with pellet stoves (treatment)

Appendix 2.8. Cumulative Number Households Visited During the Fieldwork



Source: Own elaboration.

Appendix 2.9. Number Households Visited per Day During the Fieldwork



Source: Own elaboration.

Appendix 2.10. Prototype of Air Quality Sensors Assembled for this Study

Source: Own elaboration.

Appendix 2.11. Comparison Between SDS11 PM2.5 Sensor and Reference Station

Source: Own elaboration.

Appendix 2.12. Stoves Use Monitors

Source: Own elaboration.

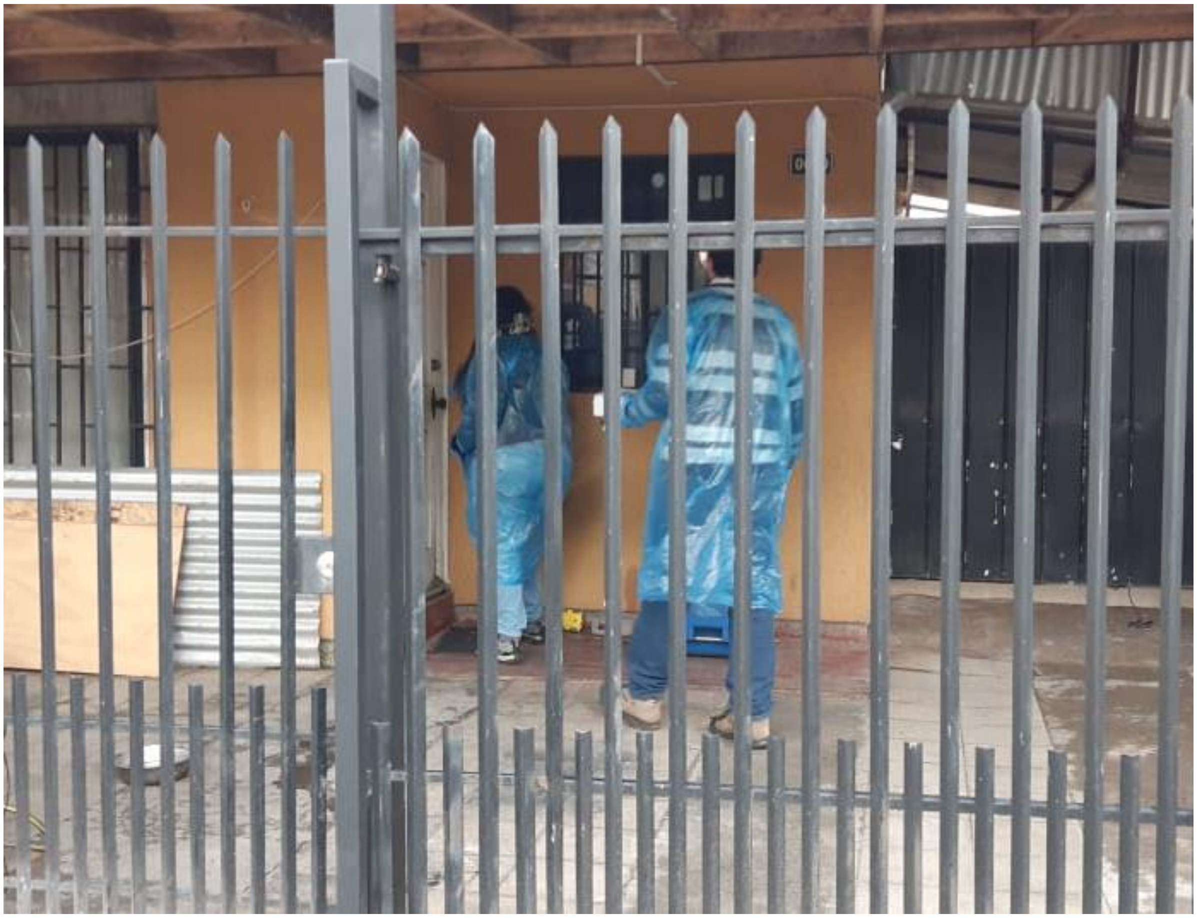
Appendix 2.13. Electronic Devices Used in Fieldwork.

Source: Own elaboration.

Appendix 2.14. Collecting Information from Electronic Devices

Source: Own elaboration.

Appendix 2.15. Visiting Households Using Personal Protection Again Covid-19



Source: Own elaboration.

Appendix 2.16. Fixed-Effects Model Control Variable Definitions and Expected Signs

	Expected sign and motivation	
Variable	Indoor air pollution	Indoor temperature
ON: Dummy variable to indicate the use of a pellet stove or firewood stove on each measurement period.	(+) The emissions are generated when the stoves are used.	(+) The purpose for using stoves is to increase indoor the temperature.
PELLET*ON: Dummy variable to indicate that pellet stove is used during the measurement period.	(-) Installing a pellet stove and using it should reduce indoor air pollution.	(+) Users can control the heat from pellet stoves; however, it may involve a higher cost.
SECONDSTOVEON: Dummy variable to indicate that another stove is used during the measurement period.	Effect is likely to depend on the technology used as second stove.	(+) The use of any stove increases the indoor temperature.
LOG_PM_OUT: Log of concentration of PM2.5 measured outside the dwelling.	(+) Pollution in the outdoor ambient air infiltrates to inside the dwellings with lack of proper thermal insulation.	
LOG_TEMP_OUT: Log of temperature measured outside the dwelling.		Lower outdoor temperature motivates to increase indoor temperature only if stove is used.

Source: Own elaboration.

Appendix 2.17. Cross Section Model Control Variable Definitions and Expected Signs

	Expected sign and motivation	
Variable	Variance of indoor temperature	Cost of fuel
PELLET: Dummy variable indicating a pellet stove.	(-) Pellet stoves control the combustion, releasing heat evenly.	(+) Pellet is a high efficiency fuel. Its production is more complex than firewood.
HOURSON_MEASURED: Number of hours per day that stove was used over 48-hour measurement period.	(null) There is no prior reason for an association.	(+) Any extra hour of use increases the expenditure in fuel.
HOURSON_REPORTED: Number of hours per day that stove is used according to the survey.		(+) Any extra hour of use increases the expenditure in fuel.
SECONDSTOVE_MEASURED: Dummy variable to indicate another stove is used at least in one hour of measurements.	It depends on the type of technology used as second stove.	(-) Decrease the use of the main stove (firewood or pellet).
SECONDSTOVE_REPORTED: Dummy variable to indicate that household reported in survey that uses another stove.		(-) Decrease the use of the main stove (firewood or pellet).
INSULATION: Dummy to indicate that the dwelling has thermal insulation.[67]	(-) The insulation decreases the heat losses from the dwelling.	(-) The insulation decreases the heating demand.
NFAMILY: Number of family members	(null) There is no prior reason for an association.	(+) Bigger families may demand heating services for more time

Source: Own elaboration.

The baseline survey collected information on socioeconomic and dwelling characteristics, which were expected to be crucial for identifying the effects of the stove replacement program on the outcomes of interest. We perform tests of differences in means of the covariates across treatment and control groups (i.e., balance tests) to evaluate whether the sampling approximated a randomized process. Table C.3 presents the results of this analysis. For 13 of the 12 variables examined, we do not find evidence at the 5% significance level that treatment and control groups exhibit differences in means. The only exception is household size, which we include as a control in our models.

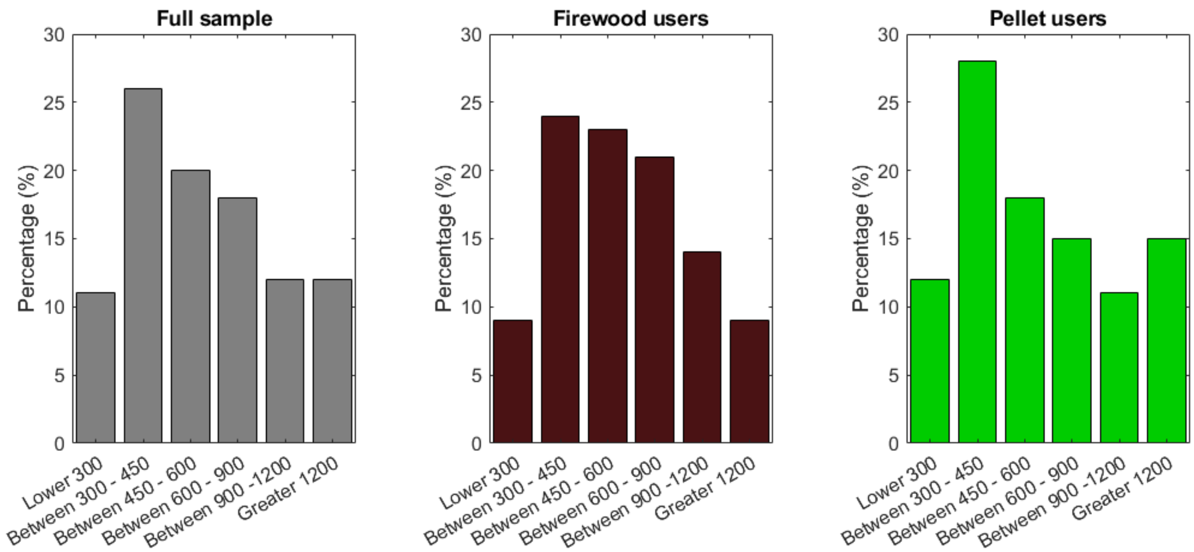
[67] In this study we consider that a dwelling has thermal insulation if the household reported it directly in the survey, or if the households reported having the subsidy for thermal insulation from the Ministry of Housing and Urban Planning (MINVU), or if a dwelling built after 2007 was compliant with energy efficiency standards.

Appendix 2.18. Balance and Statistics for Households and Dwelling Characteristics

Variable	N	(1) Control Mean/SE	N	(2) Treatment Mean/SE	t-test Difference (1)-(2)
Household characteristics:					
Number of family members (persons)	156	3.846	169	4.219	-0.373**
		(0.121)		(0.108)	
Age of household head (years)	155	49.665	165	51.830	-2.166
		(1.004)		(1.046)	
Formal schooling of household head (years)	155	12.665	165	13.170	-0.505
		(0.300)		(0.269)	
Any person younger than 5 years old (1 if yes, 0 if no)	156	0.410	169	0.527	-0.116
		(0.051)		(0.063)	
Any person older than 60 years old (1 if yes, 0 if no)	156	0.583	169	0.704	-0.121
		(0.065)		(0.063)	
Any person facing respiratory issues (1 if yes, 0 if no)	155	0.406	166	0.380	0.027
		(0.058)		(0.049)	
Income lower than Ch$ 300.000 (1 if yes, 0 if no)	156	0.346	169	0.385	-0.038
		(0.038)		(0.038)	
Dwelling characteristics:					
Dwelling size (Area in m^2)	156	73.776	169	80.734	-6.958*
		(2.227)		(2.828)	
Dwelling type (1 if Single dwelling, 0 Otherwise)	155	0.168	165	0.248	-0.081*
		(0.030)		(0.034)	
Construction Before 2000 (1 if yes, 0 if no)	156	0.583	169	0.533	0.051
		(0.040)		(0.038)	
Construction Between 2000 and 2007 (1 if yes, 0 if no)	156	0.205	169	0.266	-0.061
		(0.032)		(0.034)	
Construction after 2007 (1 if yes, 0 if no)	156	0.192	169	0.189	0.003
		(0.032)		(0.030)	
High insulation by subsidy, private investment or construction after 2007 (1 if yes, 0 if no)	156	0.327	169	0.320	0.007
		(0.038)		(0.036)	

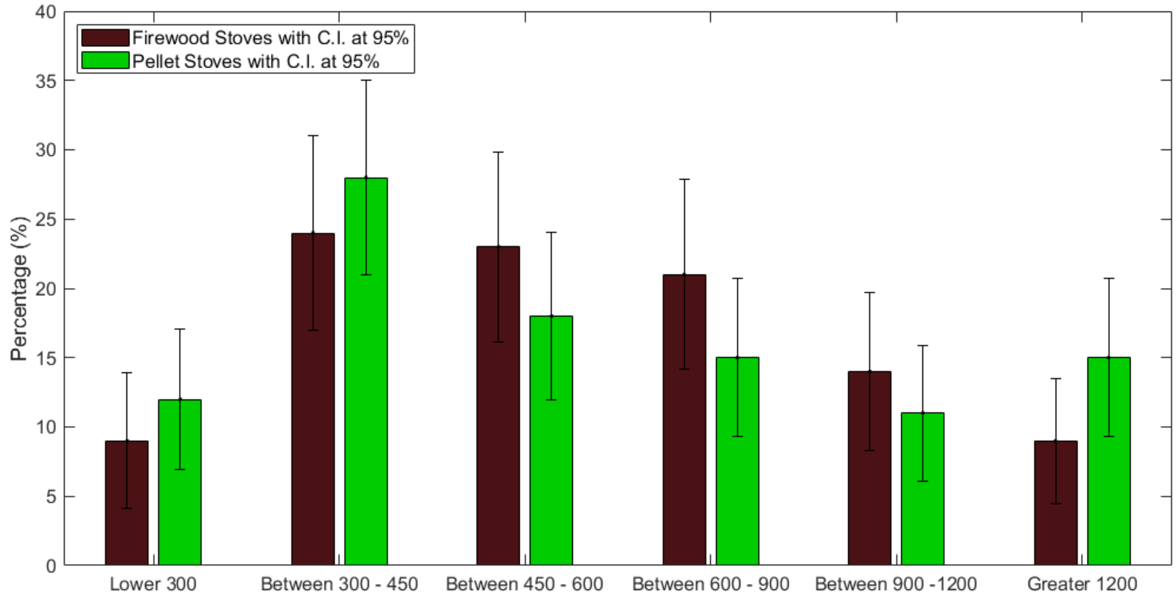
Note: Value displayed for t-tests are the differences in the means across the groups. * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$.

Appendix 2.19. Income Distribution for Sample and Subsamples



Source: Own elaboration

Appendix 2.20. Comparison of Income Distribution Subsamples



Source: Own elaboration

Appendix 2.21. Energy Poverty Analysis

Assumptions

1. Ten Percent Rule of Income (TPR) calculations

- We took the upper limit from each level of income. For instance, level 0-300K, 300K was selected as income since is closer to the minimum wage in Chile.
- Then we consider expenditure in heating reported in our survey for the month of July 2020 (firewood or pellet) + Electricity bill + LPG bill.
- For the electricity bill, we take an average of 34,392.1 CLP per month. This value comes from National Energy Commission. In n city of Talca during July 2019 was 17,789,577 kWh and the total amount of billing regulated customers Residential BT1 Tariff in Talca: 94584 clients. Data for July 2020 is not available yet[68]. Then we divide 17,789,577 kWh (total amount of electricity distributed) over 94,584 clients, obtaining 188.08 kWh per client during July 2019 in average. From our survey, we know that households spent more time at home during 2020 than in 2019. We found they use 3.6 hours more the stove than last year (3.6/24 = 15% more). But specifically, for electricity, recent report found than on winter 2020 the residential sector spent 15-20% more than 2019[69]. We take 17% as the increase in electricity bill due to the pandemic. Then: 188.08 * 1.17 = 220.1 kWh /client, in average, for July 2020. We consider the price of electricity according the BT1 Tariff for Talca from CGE[70]. For July 2020, the tariff is divided on 1046.9 CLP for management, 20.8 CLP/kWh for distribution and 130.7 CLP/kWh for consumption. P = 1046.9 + 151.5 Q (Q in kWh). For a household consuming 220.1 kWh, the bill is equivalent to: 1,046.9+151.5 *(220.1) = 34,392.1 CLP / month for electricity bill.
- We consider the average annual demand of LGP equivalent to 1,812 kWh per household, that is the sum for cooking and warm water for shower and cleaning in the report (CDT, 2019). We take only 1 month; we assume 151 kWh per month for year 2018. From our survey, we know that the households report than they spend more time at home and more people is doing home office or home school at home than before. In average, household report that 1.3 persons in average are doing home office. The families have in average 4 persons. Seems reasonable to think that other energy consumptions also increase. We take the same percentage of 17% used for electricity. Therefore, we consider 151 kWh *1.17 = 176.7 kWh per July 2020 for GLP consumption in average. For price, we take 18,132 CLP per 15 kg for July 2020[71] and a calorific value of 12,8 kWh per Kg[72] We obtain a monthly average demand

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[68] Data from National Energy Commission http://datos.energiaabierta.cl/dataviews/257030/facturacion-clientes-regulados/

[69] Reports that support this idea are: Revista EI https://www.revistaei.cl/2020/07/29/las-tres-causas-del-alza-de-las-tarifas-electricas-segun-la-asociacion-de-empresas-del-sector/; Documentos OLADE http://biblioteca.olade.org/opac-tmpl/Documentos/old0452.pdf ;Revista Ingeniería de Sistemas http://www.dii.uchile.cl/~ris/RIS2020/p5_impactos_covid19_consumo_electrico.pdf

[70] Reports from CGE https://www.cge.cl/wp-content/uploads/2020/07/Tarifas-de-Suministro-CGE-Julio-2020.pdf

[71] Price for LPG http://datos.energiaabierta.cl/dataviews/242618/precios-nacionales-de-gas-licuado-petroleo/

[72] Calorific value considered from: https://energia.gob.cl/sites/default/files/documentos/informe_final_caracterizacion_residencial_2018.pdf

of GAS with a cost of: (176.7 kWh) / (12.8 kWh / Kg)*(18,132 CLP/15 kg) = 16,687.1 CLP per month.

2. Minimum Income Standard (MIS) calculations

According with Moore (2012), "*households are deemed to be in fuel poverty if, after deducting their actual housing costs, they have insufficient residual net income to meet their total required fuel costs after all other minimum living costs (as defined by the MIS) have been met*". "*a household is in MIS based fuel poverty if: Fuel costs > Net household income – housing costs – minimum living costs (MIS).*" We rewrite this equation as:
Net household income – Fuel costs – housing costs – minimum living costs (MIS) < 0."

- Net household income: we took the upper limit from each level of income. For instance, level 0-300K, 300K was selected as income since is closer to the minimum wage in Chile.
- Fuel Cost: as before, we consider expenditure in heating reported in our survey for the month of July 2020 (firewood or pellet) + Electricity bill + LPG bill.
- For housing costs: We took for each quantile, the amount of expenditure reported in by INE[73]
- Minimum living costs: We consider the Minimum wage in Chile of 326,500 CLP.

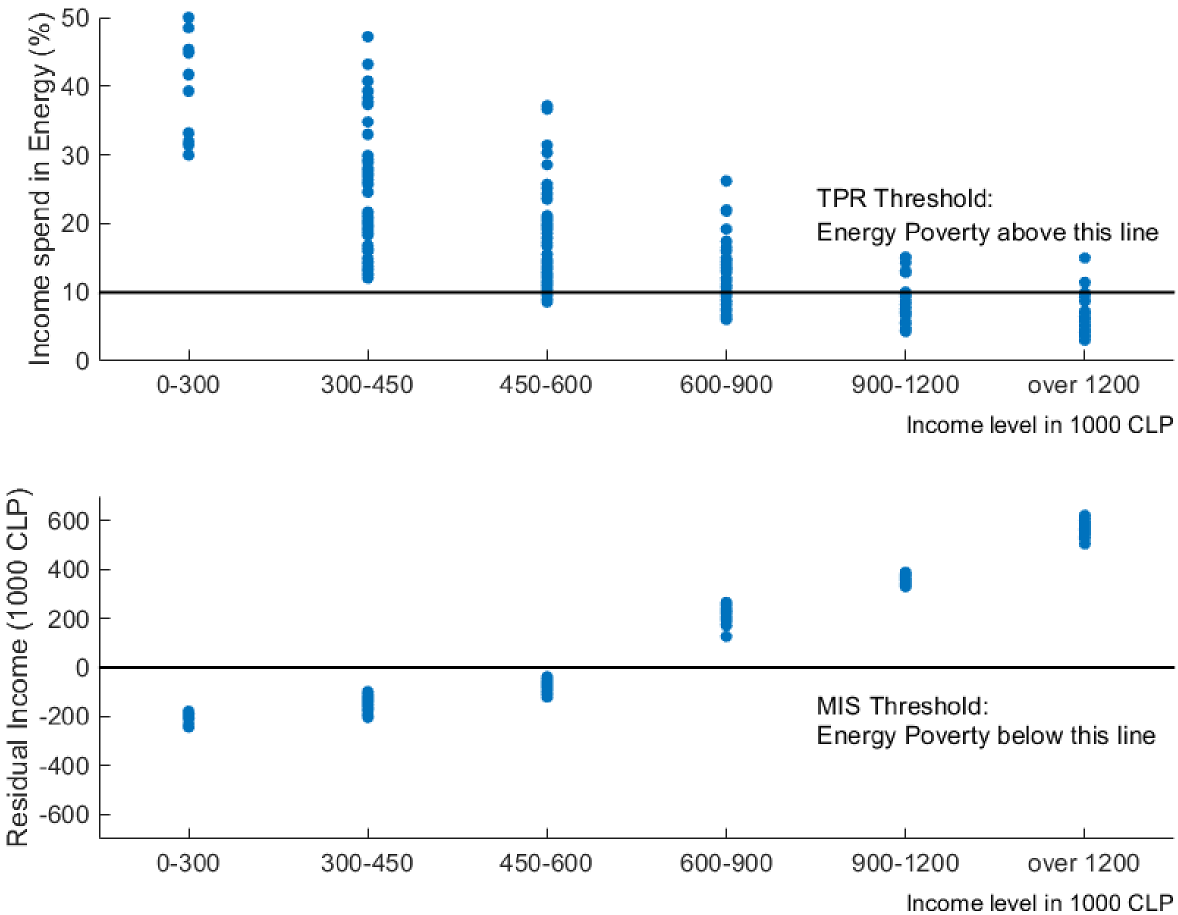
Energy poverty analysis

Our computed measure of energy poverty based on the TPR index is displayed on the upper side of Figure D1. Under this index we show the percentage of income spent in energy services for different income levels for all the households in our sample. We find that the lower the income level, the higher the TPR index. However, we also identify households facing higher energy costs (more than 10%) at the upper side of the income distribution for income levels over 900,000 CLP (US$ 1,154) per month. According to the TPR index, we find that 68% of the total sample is classified as energy poor and these households are located above the red line of TPR threshold in this figure.

We also extend our analysis based on the MSI index. It is displayed on the bottom of Figure D1. This figure suggests that energy poverty is correlated with income distribution. Under this index we identify as energy poor households only at income levels lower than 600,000 CLP (US$ 769) per month. According to the MSI index, we find that 58% of the total sample is classified as energy poor and these households are located below the zero-red line MSI threshold in this figure.

[73] According to INE reports https://www.ine.cl/docs/default-source/encuesta-de-presupuestos-familiares/publicaciones-y-anuarios/viii-epf---(julio-2016---junio-2017)/informe-de-principales-resultados-viii-epf.pdf?sfvrsn=d5bd824f_2

Appendix 2.22. Households Experiencing Energy Poverty



Note: In the upper panel, energy poverty is measured using the TPR method, represented by dots above the red 10% threshold line. In the lower panel, energy poverty measured using the MIS method is represented by the dots below the zero line.

Source: Own elaboration.

Appendix 2.23. Income Category as Proxy for the Baseline Stove Type

Model 1 (binary logit model)

$StoveType_i = \beta_1 * Income_i + \beta_o + \varepsilon_i$

The dummy variable $StoveType_i$ takes the value of 1 if the household has a high firewood technology (wood burning stove with 1 chamber or 2 chambers). It takes the value of 0 if the household has lower firewood technology such as a salamander stove, cooking stove, or homemade stove. $Income_i$ is a proxy for the income of the household, considering the lower level of the income group for household i in the control group (i =1,…,156).

Model 2 (binary logit model)

$StoveType_i = \beta_1 * MiddleIncome_i + \beta_2 * HighIncome_i + \beta_o + \varepsilon_i$

Same as Model 1, but in this case $LowIncome_i$, $MiddleIncome_i$, and $HighIncome_i$ are dummy variables indicating the income level of each household i in the control group (i =1,…,156). (*LowIncome* is the base category).

Estimates for the Baseline Stove Type

VARIABLES	(1) *StoveType*	(2) *StoveType*
Income	0.00212*** (0.000640)	
MiddleIncome		1.061*** (0.383)
HighIncome		2.020*** (0.600)
Constant	-0.540 (0.394)	-0.0741 (0.272)
Observations	156	156

Note: Own elaboration. Standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1
Source: Own elaboration.

The results indicate that higher-income increases the probability of a household owning a better firewood technology. In other words, having a high firewood technology is positively correlated with having higher income.

Appendix 2.24. Mundlak's Estimates Indoor Air Pollution and Indoor Temperature

VARIABLES	(1) log_PM2.5Indoor	(2) log_TIndoor
ON	0.0861**	0.125***
	(0.0346)	(0.00867)
PELLET*ON	-0.126***	-0.00264
	(0.0458)	(0.0121)
SECONDSTOVEON	0.0530*	0.0349***
	(0.0312)	(0.0114)
LOG_PM_OUT	0.641***	0.00816***
	(0.0193)	(0.00253)
LOG_TEMP_OUT	0.202***	0.0744***
	(0.0288)	(0.00860)
NFAMILY	0.00408	-0.00280
	(0.0131)	(0.00420)
Mean_ON	-0.0245	0.124***
	(0.0839)	(0.0264)
Mean_PELLET*ON	-0.155*	0.00725
	(0.0849)	(0.0309)
Mean_SECONDSTOVEON	0.193	0.0312
	(0.128)	(0.0738)
Mean_LOG_PM_OUT	-0.0410	-0.00789
	(0.0632)	(0.0160)
Mean_LOG_TEMP_OUT	-0.242	0.0853
	(0.204)	(0.0552)
Constant	0.800*	2.452***
	(0.456)	(0.130)
Observations	14,484	14,713
Number of ID	302	307
Household FE	YES	YES
Period FE	YES	YES

Source: Own elaboration
Note: Own elaboration. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 2.25. OLS Estimates for Indoor Air Pollution and Indoor Temperature

VARIABLES	(1) logPM2.5i	(2) logTi
PELLET	-0.141***	-0.00295
	(0.0386)	(0.0147)
log_PMo	0.663***	
	(0.0178)	
log_To		0.0910***
		(0.0132)
Constant	0.655***	2.630***
	(0.0760)	(0.0677)
Observations	14,484	15,711
R-squared	0.501	0.242
Day FE	YES	YES
Period FE	YES	YES

Source: Own elaboration
Note: Own elaboration. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 2.26. Mundlak's Estimates for Households Facing Energy Poverty

VARIABLES	(1) log_PMi	(2) log_PMi	(3) log_Ti	(4) log_Ti
ON	0.0861**	0.0861**	0.125***	0.125***
	(0.0346)	(0.0346)	(0.00867)	(0.00867)
PELLET*ON	-0.126***	-0.126***	-0.00264	-0.00264
	(0.0458)	(0.0458)	(0.0121)	(0.0121)
SECONDSTOVEON	0.0528*	0.0528*	0.0350***	0.0350***
	(0.0313)	(0.0313)	(0.0114)	(0.0114)
LOG_PM_OUT	0.641***	0.641***	0.00815***	0.00815***
	(0.0193)	(0.0193)	(0.00253)	(0.00253)
LOG_TEMP_OUT:	0.202***	0.202***	0.0745***	0.0745***
	(0.0288)	(0.0288)	(0.00860)	(0.00859)
EnergyPoverty_TPR	0.0991**		-0.0142	
	(0.0436)		(0.0137)	
EnergyPoverty_MIS		0.0982**		-0.0164
		(0.0410)		(0.0135)
Mean_ON	-0.0324	-0.0335	0.125***	0.126***
	(0.0819)	(0.0817)	(0.0264)	(0.0262)
Mean_PELLET*ON	-0.151*	-0.140*	0.00596	0.00413
	(0.0847)	(0.0845)	(0.0305)	(0.0307)
Mean_SECONDSTOVEON	0.188	0.205*	0.0324	0.0300
	(0.128)	(0.125)	(0.0729)	(0.0726)
Mean_LOG_PM_OUT	-0.0514	-0.0531	-0.00621	-0.00543
	(0.0610)	(0.0618)	(0.0157)	(0.0156)
Mean_LOG_TEMP_OUT:	-0.222	-0.230	0.0800	0.0816
	(0.202)	(0.202)	(0.0543)	(0.0541)
Constant	0.758*	0.796*	2.454***	2.447***
	(0.453)	(0.453)	(0.130)	(0.130)
Observations	14,484	14,484	14,713	14,713
Number of ID	302	302	307	307
Household FE	YES	YES	YES	YES
Period FE	YES	YES	YES	YES

Source: Own elaboration
Note: Own elaboration. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 2.27. Mundlak's Estimates by Income Distribution

VARIABLES	(1) log_PM2.5Indoor	(2) log_TIndoor	(3) log_PM2.5Indoor	(4) log_TIndoor
ON	0.0861**	0.125***	0.0861**	0.125***
	(0.0346)	(0.00867)	(0.0346)	(0.00866)
PELLET*ON	-0.126***	-0.00263	-0.126***	-0.00263
	(0.0458)	(0.0121)	(0.0458)	(0.0121)
SECONDSTOVEON	0.0529*	0.0349***	0.0529*	0.0350***
	(0.0312)	(0.0114)	(0.0313)	(0.0114)
LOG_PM_OUT	0.641***	0.00817***	0.641***	0.00815***
	(0.0193)	(0.00253)	(0.0193)	(0.00253)
LOG_TEMP_OUT:	0.202***	0.0745***	0.202***	0.0744***
	(0.0288)	(0.00860)		
Income = Low	0.112**	-0.0352**		
	(0.0557)	(0.0174)		
Income = Middle	0.0928*	-0.00119		
	(0.0541)	(0.0176)		
Income = High	-	-		
IncomePerCap = Low			0.123**	-0.0420***
			(0.0532)	(0.0157)
IncomePerCap = Middle			0.0363	-0.0349**
			(0.0466)	(0.0154)
IncomePerCap = High			-	-
mean_ON	-0.0254	0.122***	-0.0180	0.122***
	(0.0819)	(0.0264)	(0.0827)	(0.0260)
mean_PELLETON	-0.136	0.00358	-0.166*	0.00812
	(0.0847)	(0.0306)	(0.0860)	(0.0302)
mean_OtherStoveON	0.154	0.0305	0.217*	0.0293
	(0.129)	(0.0719)	(0.125)	(0.0725)
mean_log_PMo	-0.0472	-0.00543	-0.0483	-0.00468
	(0.0614)	(0.0153)	(0.0614)	(0.0156)
mean_log_To	-0.225	0.0840	-0.247	0.0840
	(0.201)	(0.0538)	(0.201)	(0.0534)
Constant	0.745	2.446***	0.825*	2.455***
	(0.453)	(0.128)	(0.454)	(0.126)
Observations	14,484	14,713	14,484	14,713
Number of ID	302	307	302	307
Household FE	YES	YES	YES	YES
Period FE	YES	YES	YES	YES

Source: Own elaboration
Note: Own elaboration. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 2.28. Variance of Indoor Temperature by Income Distribution

VARIABLES	(1) Variance Temp. Lower Income	(2) Variance Temp. Middle Income	(3) Variance Temp. High Income
PELLET	-0.259	-0.911	-1.755*
	(0.598)	(0.857)	(1.047)
NFAMILY	0.468	-0.472	-0.272
	(0.357)	(0.320)	(0.205)
INSULATION	-0.117	0.349	0.140
	(0.804)	(0.952)	(0.666)
HOURSON_MEASURED	0.0753**	0.0168	0.0551*
	(0.0342)	(0.0283)	(0.0279)
SECONDSTOVE_MEASURED	-0.0757	0.301	-1.055
	(0.897)	(1.088)	(1.289)
Constant	-0.146	6.494***	4.041**
	(1.188)	(2.282)	(1.907)
Observations	106	110	70
R-squared	0.194	0.083	0.211
Week FE	YES	YES	YES

Source: Own elaboration.
Note: Own elaboration. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Lower Income: income lower than Ch$ 450,000 (about US$ 577) per month; Middle Income: income between Ch$ 450,001 and Ch$ 900,000 (US$ 577 – US$ $1,154) per month; High Income: income over Ch$ 900,000 (>US$ 1,154) per month.

Appendix 2.29. Fixed Effects Estimation for Households Facing Energy Poverty

VARIABLES	(1) logPM2.5i TPR = 1	(2) logPM2.5i TPR = 0	(3) logTi TPR = 1	(4) logTi TPR = 0
ON	0.130***	0.0276	0.133***	0.0961***
	(0.0420)	(0.0603)	(0.0105)	(0.0120)
PELLET ON	-0.150***	-0.135	0.00182	-0.00425
	(0.0547)	(0.0845)	(0.0152)	(0.0174)
OtherStoveON	0.0875*	0.0704	0.0207	0.0486***
	(0.0446)	(0.0439)	(0.0132)	(0.0182)
log_PMo	0.685***	0.597***		
	(0.0189)	(0.0233)		
log_To			0.0762***	0.0616***
			(0.0128)	(0.0119)
Constant	0.422*	0.245	2.792***	2.801***
	(0.225)	(0.340)	(0.0885)	(0.0955)
Observations	10,061	4,423	11,068	4,643
R-squared	0.522	0.483	0.488	0.469
Number of ID	211	91	225	94
Household FE	YES	YES	YES	YES
Day FE	YES	YES	YES	YES
Period FE	YES	YES	YES	YES

Source: Own elaboration.
Note: Own elaboration. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Model 1 considers the subsample of households facing energy poverty according to TPR index (TPR=1) for PM2.5 and Model 2 considers the rest of households (TPR=0) for PM2.5. Model 3 considers the subsample of households facing energy poverty according to TPR index (TPR=1) for indoor Temperature, and Model 4 considers the rest of households (TPR=0) for indoor Temperature.

Appendix 2.30. Variance Indoor Temperature for Households Facing Energy Poverty

VARIABLES	(1) VarTi ON TPR=1	(2) VarTi ON TPR=0
PELLET	-0.613	-1.257*
	(0.537)	(0.689)
NFAMILY	0.213	-0.254
	(0.270)	(0.170)
INSULATION	0.191	-0.102
	(0.597)	(0.679)
HOURSON_MEASURED	0.0569**	0.0352
	(0.0229)	(0.0237)
SECONDSTOVE_MEASURED	0.169	-0.280
	(0.800)	(0.849)
2.Week	0.960	-0.727
	(1.309)	(0.825)
3.Week	-0.882	-1.298*
	(0.708)	(0.731)
4.Week	-1.628***	-0.617
	(0.581)	(0.956)
5.Week	-0.339	-1.519
	(0.810)	(1.128)
Constant	1.834	4.400***
	(1.238)	(1.252)
Observations	192	94
R-squared	0.082	0.144

Source: Own elaboration.
Note: Own elaboration. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 2.31. Cost of Fuel for Households Facing Energy Poverty

PANEL A	*Energy Poverty by TPR*	
	(1) TPR = 1	(2) TPR = 0
VARIABLES	Cost48h	Cost48h
PELLET	1,906***	2,828***
	(279.3)	(332.7)
NFAMILY	18.75	104.2
	(102.9)	(134.9)
INSULATION	482.1	174.0
	(310.0)	(349.8)
HOURSON_MEASURED	75.56***	50.63***
	(14.06)	(13.97)
SECONDSTOVE_MEASURED	575.1	170.8
	(492.1)	(484.0)
Constant	382.0	-265.2
	(525.6)	(727.9)
Observations	211	114
R-squared	0.331	0.514
Week FE	YES	YES
PANEL B	*Energy Poverty by TPR*	
	(1) TPR = 1	(2) TPR = 0
VARIABLES	Cost 1 month	Cost 1 month
PELLET	12,016***	15,462***
	(2,992)	(4,109)
NFAMILY	871.9	1,220
	(1,099)	(1,123)
INSULATION	-4,986*	621.5
	(2,787)	(3,994)
HOURSON_REPORTED	1,592***	1,524***
	(358.5)	(510.8)
SECONDSTOVE_REPORTED	3,565	-1,787
	(3,396)	(3,957)
Constant	10,180*	5,565
	(5,358)	(9,754)
Observations	204	109
R-squared	0.166	0.172
PANEL C	*Energy Poverty by TPR*	
	(1) TPR = 1	(2) TPR = 0
VARIABLES	Cost 1 year	Cost Cost 1 year
PELLET	24,768**	21,143
	(10,061)	(18,701)
NFAMILY	6,079	9,343
	(3,740)	(6,092)
INSULATION	-20,028**	10,654
	(9,682)	(18,242)
HOURSON_REPORTED	5,265***	3,037
	(1,323)	(2,658)
SECONDSTOVE_REPORTED	6,738	30,321
	(11,881)	(21,896)
Constant	67,794***	83,076*
	(18,744)	(48,005)
Observations	205	109
R-squared	0.133	0.066

Source: Own elaboration.
Note: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

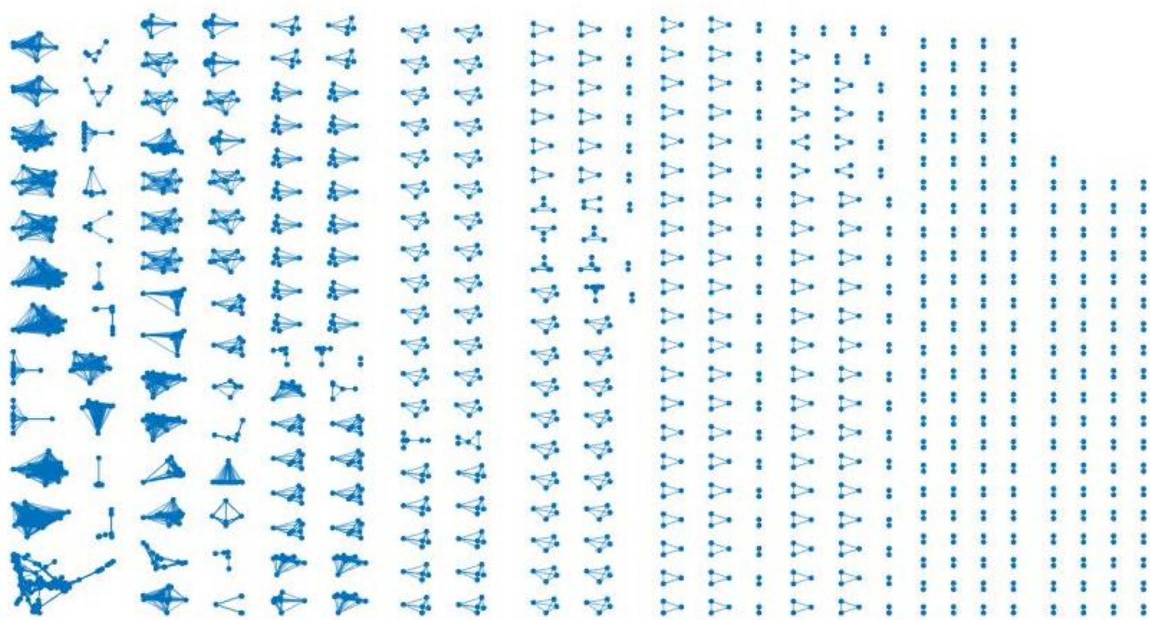
Appendix 2.32. Estimates for Selected Households by Propensity Score Matching

VARIABLES	(1) logPM2.5i	(2) logTi
ON	0.102**	0.115***
	(0.0416)	(0.00890)
PELLETON	-0.167***	-0.00985
	(0.0543)	(0.0133)
OtherStoveON	0.130***	0.0346**
	(0.0426)	(0.0154)
log_PMo	0.664***	
	(0.0183)	
log_To		0.0626***
		(0.00782)
Constant	0.259	2.738***
	(0.298)	(0.0699)
Observations	8,996	9,726
R-squared	0.529	0.548
Number of ID	187	196
Household FE	YES	YES
Day FE	YES	YES
Period FE	YES	YES

Source: Own elaboration.
Note: Own elaboration. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

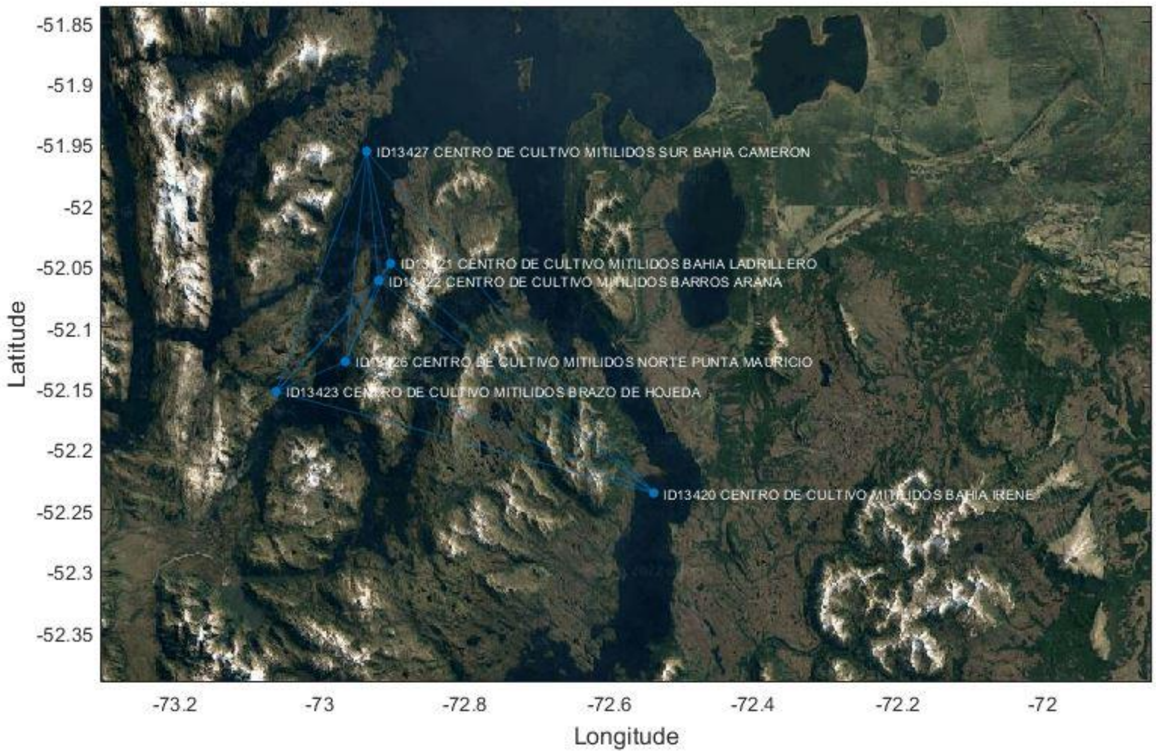
Appendices 3

Appendix 3.1. Different Networks Connecting Facilities with Same Owner



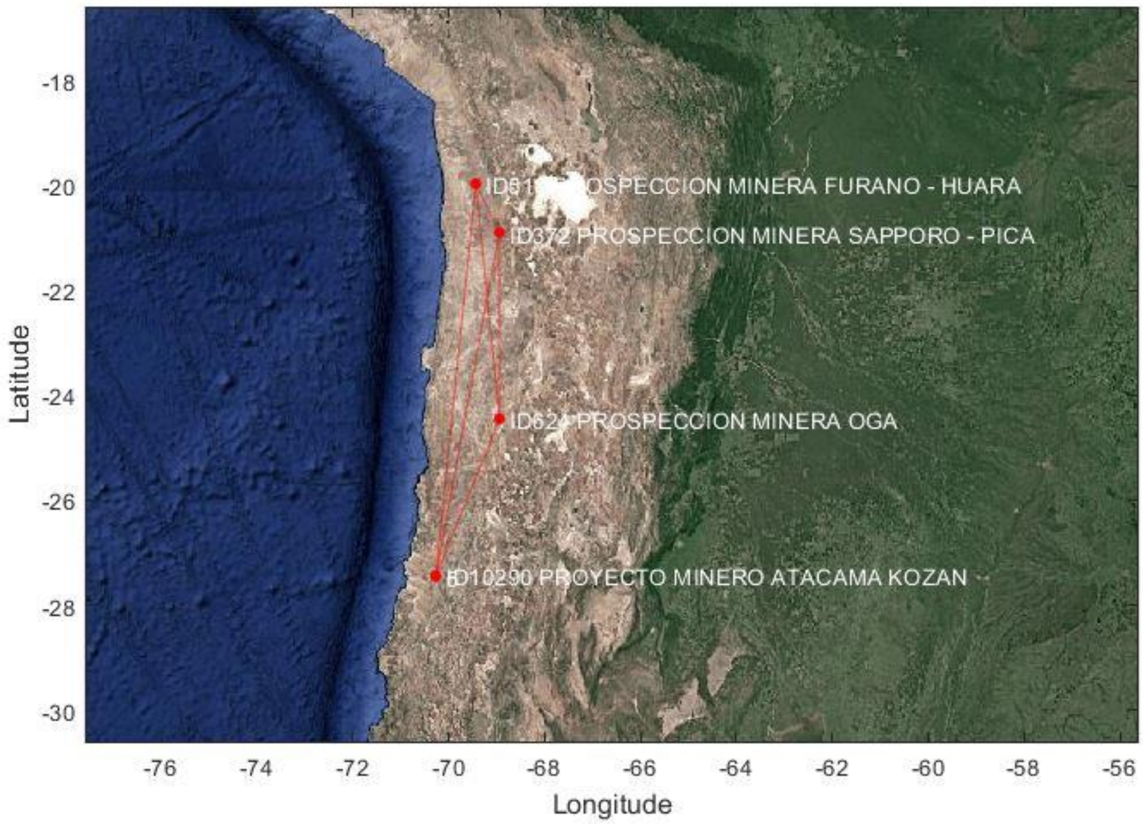
Source: Own elaboration based on information from SNIFA.

Appendix 3.2. Cluster (N465) Belonging to Fishing-Aquaculture Sector



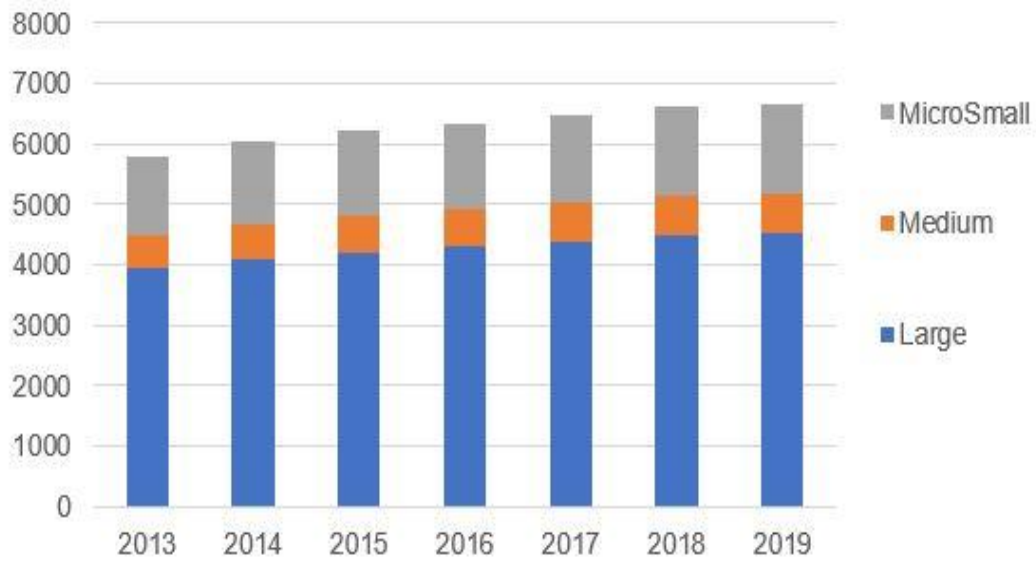
Source: Own elaboration based on information from SNIFA.

Appendix 3.3. Cluster (N56) Belonging to Mining Sector



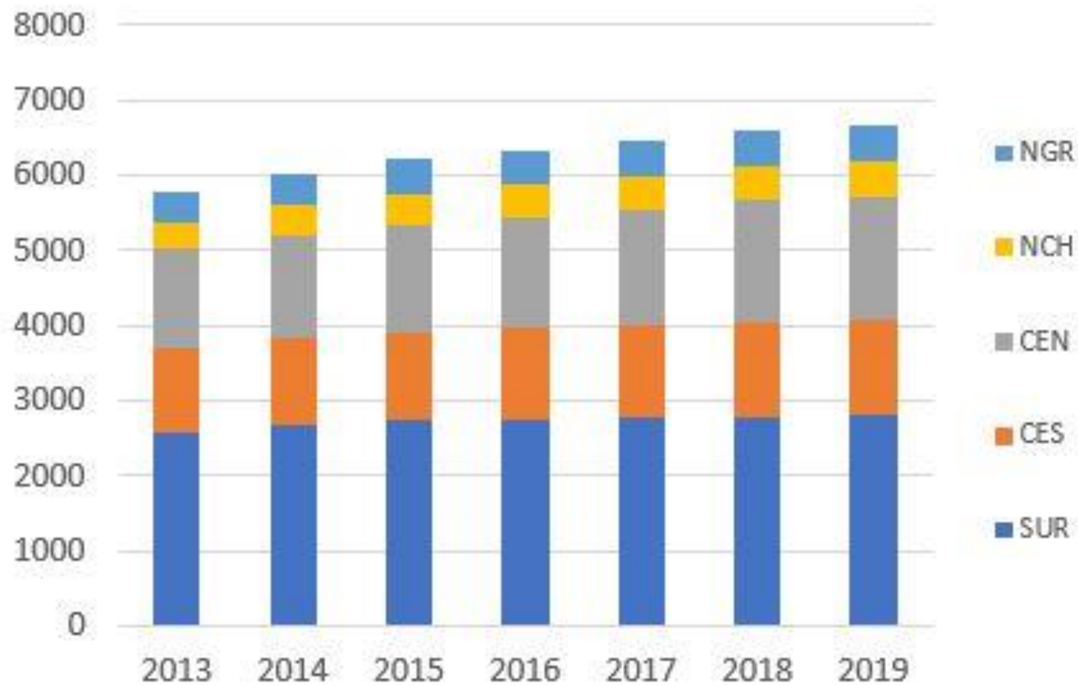
Source: Own elaboration based on information from SNIFA.

Appendix 3.4. Number of Facilities by Size from 2013 to 2019



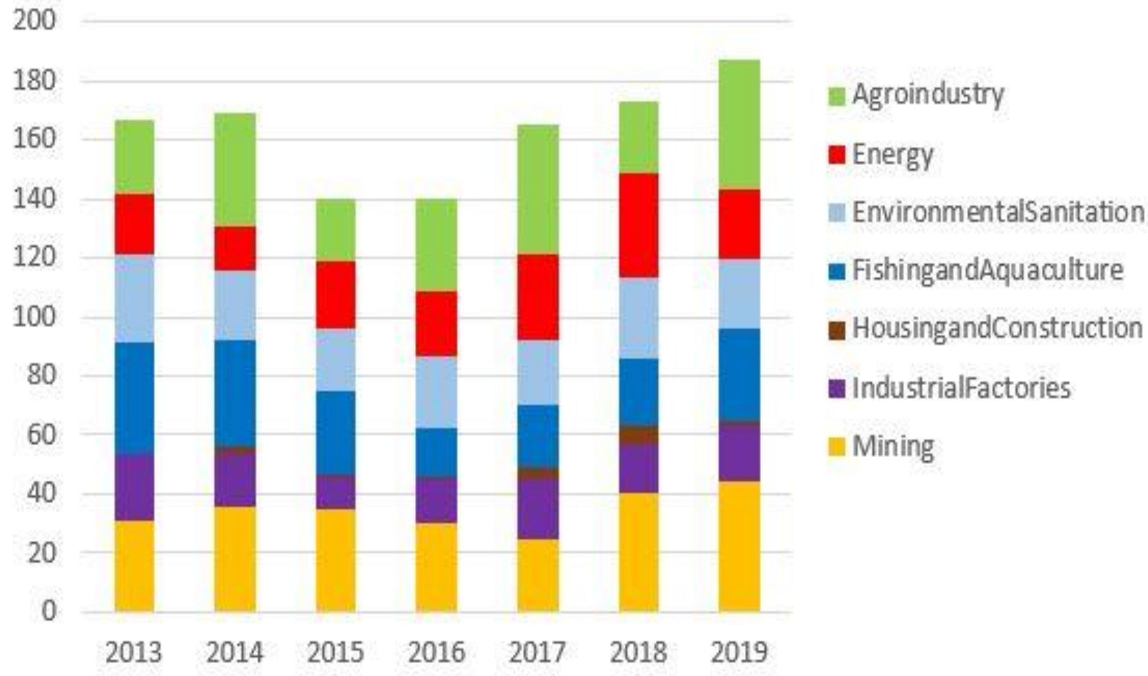
Source: Own elaboration based on information from SNIFA.

Appendix 3.5. Number of Facilities by Macrozone from 2013 to 2019



Source: Own elaboration based on information from SNIFA.

Appendix 3.6. Number of Facilities Inspected per Year

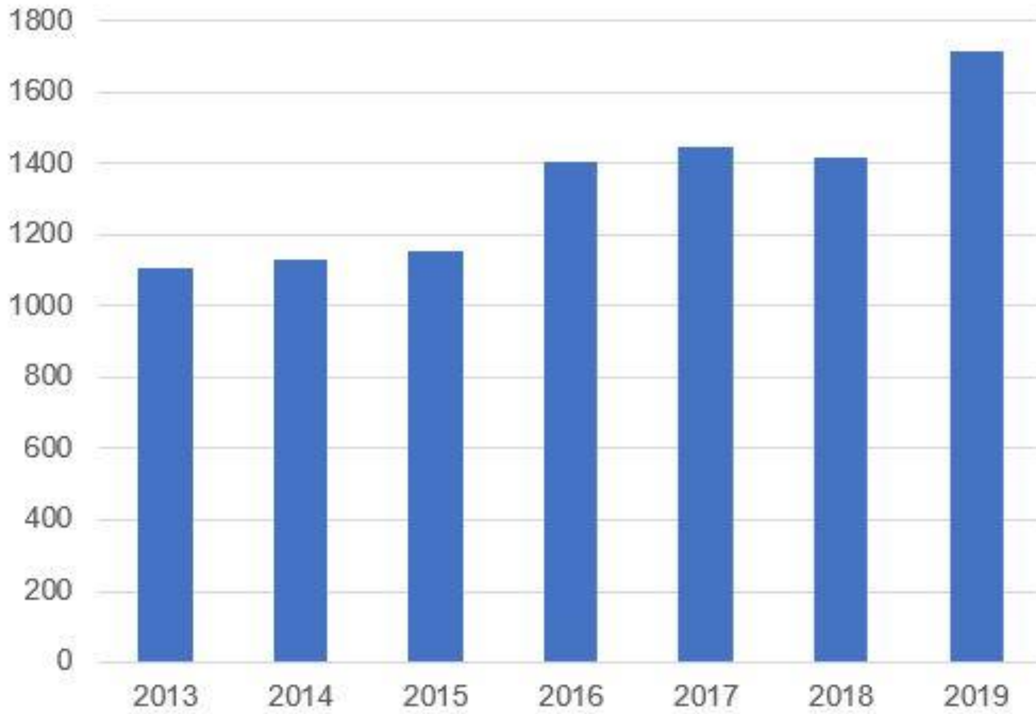


Source: Own elaboration based on information from SNIFA.
Note: We count the number of facilities that faced at least 1 inspection by sector in time from 2013 to 2019

Appendix 3.7. Number of Inspectors and Workers at SMA from 2013 to 2019

Source: Own elaboration based on information from SNIFA.

Appendix 3.8. Budget SMA in Millions of Nominal Pesos (Ch$)



Source: Own elaboration based on information from SNIFA.

Appendix 3.9. Average Marginal Effects for Inspection and Comply

VARIABLES	Average Marginal Effects. Pr(Insp.=1)	Average Marginal Effects. Pr(Comp.=1, Insp.=1)
Sectors (base: Fishing-Aqu.)		
Agroindustry	0.0233***	0.0151***
	(0.00469)	(0.00365)
Energy	0.0155***	0.0122***
	(0.00442)	(0.00364)
Environmental Sanitation	0.0151***	0.00667***
	(0.00416)	(0.00242)
Housing-Construction	-0.00677***	-0.00561***
	(0.00262)	(0.00141)
Mining	0.0161***	0.0106***
	(0.00476)	(0.00318)
Industrial Factories	0.0164***	0.0116***
	(0.00505)	(0.00353)
Age	-0.00072***	-0.000374**
	(0.000199)	(0.000151)
Size (base: Medium)		
Micro and Small	-0.00717**	-0.00316
	(0.00312)	(0.00231)
Large	-0.00861***	-0.00321
	(0.00290)	(0.00214)
LogPoverty	0.00320	0.00192
	(0.00211)	(0.00148)
LogDensity	0.000205	0.000599
	(0.000595)	(0.000412)
Inspection_lastyear	0.0189***	0.0142***
	(0.00361)	(0.00248)
Report_lastyear	0.0124***	0.0134***
	(0.00297)	(0.00223)
AnyViolation_last3years	0.0168***	-0.00128
	(0.00348)	(0.00241)
Fined_last3years	0.0211***	0.0134**
	(0.00795)	(0.00551)
Compliance Program	0.0305***	0.00333
	(0.00332)	(0.00206)
Prioritized Area	0.00375***	0.000410
	(0.00145)	(0.000344)
Macrozone (base: SUR)		
NGR	0.0122*	0.0141***
	(0.00722)	(0.00498)
NCH	0.00698	0.00593*
	(0.00533)	(0.00329)
CEN	-0.000466	-0.00177
	(0.00378)	(0.00262)
CES	0.00163	0.00114
	(0.00344)	(0.00252)
Num. Instruments	0.00336***	0.00158***
	(0.000657)	(0.000342)
logSMABudgetperFacility	0.00176	0.000192
	(0.00316)	(0.000406)
logNumFacilitiesRegion	1.59e-05	1.73e-06
	(0.00288)	(0.000314)

Standard errors clustered by networks of facilities with common owners; *** p < 0.01, ** p < 0.05, * p < 0.1

Appendix 3.10. Spillover Average Marginal Effect on Compliance

	Spillover RUT		Spillover Network		Spillover Sector		Spillover Comunne		Spillover SectorComunne	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Comp	Insp	Comp	Insp	Comp	Insp	Comp	Insp	Comp	Insp
Agroindustry	0.455***	0.466***	0.449***	0.465***	0.448***	0.464***	0.451***	0.465***	0.453***	0.465***
	(0.0950)	(0.0839)	(0.0975)	(0.0839)	(0.0954)	(0.0845)	(0.0953)	(0.0838)	(0.0968)	(0.0835)
Energy	0.403***	0.347***	0.404***	0.347***	0.406***	0.346***	0.404***	0.346***	0.415***	0.345***
	(0.106)	(0.0875)	(0.107)	(0.0877)	(0.107)	(0.0882)	(0.105)	(0.0876)	(0.108)	(0.0871)
Env.Sanitation	0.246***	0.341***	0.242***	0.340***	0.242***	0.339***	0.242***	0.340***	0.256***	0.338***
	(0.0862)	(0.0855)	(0.0887)	(0.0855)	(0.0867)	(0.0860)	(0.0865)	(0.0855)	(0.0870)	(0.0851)
Housing-Construction	-0.478***	-0.277**	-0.485***	-0.278**	-0.401**	-0.279**	-0.484***	-0.279**	-0.391**	-0.279**
	(0.155)	(0.119)	(0.156)	(0.119)	(0.173)	(0.119)	(0.155)	(0.119)	(0.175)	(0.118)
Mining	0.354***	0.358***	0.356***	0.357***	0.367***	0.356***	0.358***	0.356***	0.380***	0.355***
	(0.0940)	(0.0947)	(0.0969)	(0.0945)	(0.0951)	(0.0953)	(0.0933)	(0.0947)	(0.0933)	(0.0941)
Industrial Factories	0.380***	0.363***	0.381***	0.363***	0.378***	0.362***	0.381***	0.362***	0.393***	0.361***
	(0.100)	(0.0975)	(0.101)	(0.0973)	(0.100)	(0.0977)	(0.100)	(0.0976)	(0.101)	(0.0971)
Age	-0.0111**	-0.0149***	-0.0112**	-0.0149***	-0.0113**	-0.0149***	-0.0112**	-0.0149***	-0.0118**	-0.0149***
	(0.00502)	(0.00418)	(0.00502)	(0.00418)	(0.00505)	(0.00418)	(0.00501)	(0.00417)	(0.00503)	(0.00417)
Micro and Small	-0.0844	-0.132**	-0.0882	-0.132**	-0.0875	-0.132**	-0.0898	-0.132**	-0.0827	-0.133**
	(0.0716)	(0.0551)	(0.0694)	(0.0552)	(0.0696)	(0.0552)	(0.0695)	(0.0552)	(0.0685)	(0.0553)
Large	-0.0775	-0.162***	-0.0843	-0.162***	-0.0848	-0.162***	-0.0861	-0.162***	-0.0807	-0.164***
	(0.0618)	(0.0497)	(0.0611)	(0.0499)	(0.0614)	(0.0499)	(0.0615)	(0.0498)	(0.0619)	(0.0497)
logPercentagePovertyCity	0.0582	0.0667	0.0594	0.0664	0.0574	0.0666	0.0595	0.0664	0.0557	0.0670
	(0.0490)	(0.0445)	(0.0485)	(0.0442)	(0.0515)	(0.0442)	(0.0482)	(0.0444)	(0.0490)	(0.0443)
LogDensity	0.0218	0.00416	0.0219	0.00426	0.0221	0.00451	0.0217	0.00427	0.0211	0.00435
	(0.0138)	(0.0124)	(0.0139)	(0.0124)	(0.0143)	(0.0124)	(0.0138)	(0.0124)	(0.0144)	(0.0125)
Inspection_lastyear	0.458***	0.393***	0.459***	0.393***	0.464***	0.392***	0.459***	0.393***	0.456***	0.394***
	(0.0780)	(0.0743)	(0.0772)	(0.0745)	(0.0791)	(0.0745)	(0.0776)	(0.0744)	(0.0801)	(0.0742)
Report_lastyear	0.455***	0.258***	0.457***	0.257***	0.454***	0.257***	0.458***	0.256***	0.461***	0.254***
	(0.0792)	(0.0613)	(0.0801)	(0.0615)	(0.0825)	(0.0615)	(0.0779)	(0.0614)	(0.0762)	(0.0613)
AnyViolation_last3years	-0.123	0.351***	-0.118	0.350***	-0.122	0.350***	-0.118	0.350***	-0.118	0.351***
	(0.0787)	(0.0718)	(0.0784)	(0.0720)	(0.0802)	(0.0721)	(0.0772)	(0.0720)	(0.0765)	(0.0719)
Fined_3y	0.408**	0.434***	0.420**	0.438***	0.417**	0.437***	0.425**	0.437***	0.429**	0.433***
	(0.176)	(0.162)	(0.177)	(0.163)	(0.178)	(0.164)	(0.175)	(0.163)	(0.176)	(0.163)
PDCactiv		0.633***		0.634***		0.634***		0.633***		0.632***
		(0.0664)		(0.0666)		(0.0667)		(0.0666)		(0.0665)
PrioritizedArea		0.0750**		0.0780***		0.0784**		0.0762***		0.0799***
		(0.0300)		(0.0303)		(0.0307)		(0.0291)		(0.0286)
logSMABudgetperFacilityRE		0.0343		0.0365		0.0424		0.0390		0.0582
		(0.0640)		(0.0667)		(0.0687)		(0.0648)		(0.0620)
logNumFacilitiesRegion		0.000639		0.000381		0.00359		0.00366		0.0214
		(0.0595)		(0.0604)		(0.0602)		(0.0595)		(0.0609)
o.logBudgetRE		-		-		-		-		-
Nins	0.0454***	0.0698***	0.0460***	0.0698***	0.0463***	0.0697***	0.0458***	0.0699***	0.0459***	0.0699***
	(0.0101)	(0.0136)	(0.0102)	(0.0136)	(0.0102)	(0.0136)	(0.0101)	(0.0136)	(0.0101)	(0.0136)
AnyFine_SameOwner3y	0.222**									
	(0.0896)									
AnyFine_SameNet3y			-0.000400							
			(0.0559)							
AnyFine_Sector3y					0.0855				0.0834	
					(0.0813)				(0.0816)	
AnyFine_Comune3y							-0.0226		-0.0658	
							(0.0326)		(0.0410)	
AnyFine_SectorCom3y									0.128**	
									(0.0559)	
Constant	-2.565***	-2.203***	-2.563***	-2.196***	-2.632***	-2.203***	-2.558***	-2.211***	-2.618***	-2.282***
	(0.160)	(0.364)	(0.162)	(0.358)	(0.178)	(0.364)	(0.160)	(0.360)	(0.180)	(0.369)
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Macrozone Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	37,425	37,425	37,425	37,425	37,425	37,425	37,425	37,425	37,425	37,425

Note: Standard errors clustered by Networks of facilities with common owners. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 3.11. Comparison Among Coefficient Estimates with Spillover Effects

	Original model		Model with RUT spillover		Model with Network spillover	
VARIABLES	(1) Inspection	(2) Comply	(3) Inspection	(4) Comply	(5) Inspection	(6) Comply
Agroindustry	0.465***	0.449***	0.467***	0.454***	0.466***	0.447***
	(0.0842)	(0.0952)	(0.0850)	(0.0938)	(0.0857)	(0.0967)
Energy	0.347***	0.404***	0.348***	0.402***	0.348***	0.398***
	(0.0879)	(0.106)	(0.0881)	(0.106)	(0.0888)	(0.109)
Env. Sanitation	0.340***	0.242***	0.342***	0.243***	0.341***	0.237***
	(0.0857)	(0.0864)	(0.0861)	(0.0862)	(0.0865)	(0.0885)
Housing-Construction	-0.278**	-0.485***	-0.277**	-0.477***	-0.277**	-0.481***
	(0.119)	(0.155)	(0.119)	(0.157)	(0.119)	(0.161)
Mining	0.357***	0.356***	0.359***	0.351***	0.359***	0.350***
	(0.0949)	(0.0940)	(0.0958)	(0.0938)	(0.0958)	(0.0988)
Industrial Factories	0.363***	0.381***	0.364***	0.378***	0.363***	0.379***
	(0.0977)	(0.0999)	(0.0978)	(0.100)	(0.0975)	(0.101)
Age	-0.0149***	-0.0112**	-0.0149***	-0.0109**	-0.0149***	-0.0111**
	(0.00418)	(0.00502)	(0.00419)	(0.00498)	(0.00419)	(0.00505)
Micro and Small	-0.132**	-0.0882	-0.131**	-0.0862	-0.131**	-0.0922
	(0.0552)	(0.0694)	(0.0549)	(0.0759)	(0.0551)	(0.0748)
Large	-0.162***	-0.0843	-0.162***	-0.0774	-0.162***	-0.0858
	(0.0498)	(0.0613)	(0.0497)	(0.0627)	(0.0499)	(0.0619)
LogPoverty	0.0664	0.0594	0.0666	0.0602	0.0661	0.0633
	(0.0444)	(0.0490)	(0.0442)	(0.0537)	(0.0442)	(0.0547)
LogDensity	0.00426	0.0219	0.00387	0.0215	0.00395	0.0211
	(0.0124)	(0.0139)	(0.0124)	(0.0137)	(0.0124)	(0.0143)
Inspection_lastyear	0.393***	0.459***	0.392***	0.459***	0.393***	0.458***
	(0.0744)	(0.0778)	(0.0745)	(0.0769)	(0.0745)	(0.0767)
Report_lastyear	0.257***	0.457***	0.259***	0.454***	0.258***	0.453***
	(0.0614)	(0.0800)	(0.0615)	(0.0823)	(0.0618)	(0.0856)
AnyViolation_last3years	0.350***	-0.118	0.351***	-0.122	0.350***	-0.116
	(0.0720)	(0.0782)	(0.0718)	(0.0800)	(0.0720)	(0.0789)
Fined_last3years	0.438***	0.420**	0.433***	0.404**	0.440***	0.413**
	(0.163)	(0.176)	(0.162)	(0.174)	(0.164)	(0.177)
Compliance Program	0.634***		0.634***		0.634***	
	(0.0666)		(0.0664)		(0.0666)	
Prioritized Area	0.0780***		0.0759**		0.0778**	
	(0.0298)		(0.0318)		(0.0331)	
NGR	0.223*	0.405***	0.230*	0.398***	0.227*	0.400***
	(0.123)	(0.100)	(0.126)	(0.100)	(0.130)	(0.102)
NCH	0.138	0.182*	0.143	0.183*	0.141	0.184*
	(0.103)	(0.0937)	(0.105)	(0.0950)	(0.108)	(0.0965)
CEN	-0.0105	-0.0738	-0.00965	-0.0751	-0.00880	-0.0690
	(0.0852)	(0.105)	(0.0850)	(0.107)	(0.0854)	(0.111)
CES	0.0353	0.0391	0.0374	0.0388	0.0374	0.0417
	(0.0746)	(0.0893)	(0.0753)	(0.0900)	(0.0762)	(0.0937)
logSMABudgetperFacility	0.0365		0.0357		0.0352	
	(0.0655)		(0.0647)		(0.0670)	
logNumFacilitiesRegion	0.000329		0.00398		0.00225	
	(0.0598)		(0.0598)		(0.0627)	
Num. Instruments	0.0698***	0.0460***	0.0698***	0.0454***	0.0698***	0.0461***
	(0.0136)	(0.0101)	(0.0136)	(0.0101)	(0.0136)	(0.0103)
athrho	3.419***	3.419***	3.569**	3.569**	3.569*	3.569*
	(0.985)	(0.985)	(1.447)	(1.447)	(1.838)	(1.838)
Inspection_l3years_S_RUT				0.0210		
				(0.0459)		
AnyViolation_l3years_S_RUT				-0.0356		
				(0.0449)		
Fined_l3years_RUT				0.232**		
				(0.101)		
Inspection_l3years_S_Network						0.0319
						(0.0549)
AnyViolation_l3years_S_Network						-0.0390
						(0.0561)
Fined_l3years_S_Network						0.00523
						(0.0582)
Constant	-2.196***	-2.563***	-2.221***	-2.572***	-2.211***	-2.568***
	(0.366)	(0.160)	(0.377)	(0.168)	(0.391)	(0.174)
Observations	37,425	37,425	37,425	37,425	37,425	37,425

Standard errors clustered by Networks of facilities with common owners. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 3.12. Average Marginal Effects for Compliance Program

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Sectors (base: Fishing-Aqua.)						
Agroindustry	-0.0876	0.0255	-0.0335	-0.0883	0.0339	-0.0249
	(0.0921)	(0.0857)	(0.100)	(0.0916)	(0.0869)	(0.0991)
Energy	0.0857	0.0710	0.133	0.0841	0.0580	0.133
	(0.0931)	(0.105)	(0.101)	(0.0938)	(0.112)	(0.104)
Environmental Sanitation	0.0848	0.0886	0.146	0.0886	0.0840	0.169**
	(0.0790)	(0.0902)	(0.0911)	(0.0759)	(0.0909)	(0.0860)
Mining	-0.0794	-0.134	-0.0627	-0.0650	-0.0839	-0.0246
	(0.111)	(0.106)	(0.124)	(0.113)	(0.110)	(0.124)
Industrial Factories	-0.115	-0.0451	-0.0586	-0.100	-0.0147	-0.0190
	(0.112)	(0.103)	(0.115)	(0.109)	(0.103)	(0.110)
Size (base: Medium)						
Micro and Small	-0.372***	-0.335***	-0.357***	-0.346***	-0.324***	-0.322***
	(0.112)	(0.101)	(0.113)	(0.112)	(0.0986)	(0.110)
Large	-0.00908	0.0577	0.00962	-0.00934	0.0569	0.0160
	(0.0560)	(0.0518)	(0.0585)	(0.0577)	(0.0519)	(0.0618)
Macrozone (base: SUR)						
NGR	0.00140	0.0923	0.0734	-0.0171	0.0810	0.0640
	(0.0754)	(0.0612)	(0.0679)	(0.0781)	(0.0582)	(0.0677)
NCH	0.0483	0.0941	0.0881	0.0494	0.0845	0.0979
	(0.0707)	(0.0627)	(0.0676)	(0.0677)	(0.0609)	(0.0605)
CEN	-0.122	-0.118	-0.124	-0.134	-0.133	-0.131
	(0.104)	(0.103)	(0.111)	(0.104)	(0.102)	(0.110)
CES	-0.289***	-0.217**	-0.274**	-0.295***	-0.229**	-0.301***
	(0.109)	(0.110)	(0.119)	(0.106)	(0.110)	(0.116)
Age	-0.00161	-0.00301	-0.00190	0.000163	-0.00275	-4.54e-05
	(0.00601)	(0.00579)	(0.00625)	(0.00641)	(0.00605)	(0.00632)
LogPoverty	0.109*	0.0984*	0.100	0.119*	0.108*	0.121*
	(0.0595)	(0.0565)	(0.0638)	(0.0614)	(0.0571)	(0.0668)
LogDensity	0.0161	0.0247	0.0147	0.0151	0.0225	0.0110
	(0.0177)	(0.0159)	(0.0181)	(0.0170)	(0.0154)	(0.0169)
ImpactIndex	0.00255	0.00281	0.00383			
	(0.00479)	(0.00422)	(0.00472)			
Num_Infractions				0.00529	0.00260	0.00451
				(0.00715)	(0.00605)	(0.00655)
LowInfraction				-0.0428	0.0140	-0.00483
				(0.101)	(0.0927)	(0.110)
MiddleInfraction				-0.0482	-0.0456	-0.0455
				(0.0648)	(0.0684)	(0.0675)
HighInfraction				0.150*	0.220***	0.346***
				(0.0897)	(0.0797)	(0.121)
Relapse	-0.233***	-0.127*	-0.218***	-0.235***	-0.116*	-0.230***
	(0.0686)	(0.0688)	(0.0717)	(0.0661)	(0.0677)	(0.0696)
Complaint	-0.0376	-0.0104	-0.0215	-0.0457	-0.00662	-0.0307
	(0.0618)	(0.0560)	(0.0636)	(0.0633)	(0.0577)	(0.0654)
Num. instruments	-0.00627	-0.00118	-0.00120	-0.00651	-0.00120	-0.00303
	(0.00796)	(0.00777)	(0.00968)	(0.00791)	(0.00777)	(0.00963)
IMR		-2.769***			-2.902***	
		(0.533)			(0.537)	
PNONCOMP			-1.038			-1.114*
			(0.649)			(0.655)
Observations	193	192	184	193	192	184

Source: Own elaboration based on information from SNIFA.
Note: Standard errors clustered by facilities ownership in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Appendix 3.13. Estimates and Average Marginal Effects for Payment of Fines

VARIABLES	(1) Fine paid in 1 year or less	(2) Average marginal effect	(3) Fine paid in 2 year or less	(4) Average marginal effect	(5) Fine paid in 3 year or less	(6) Average marginal effect
Fine_1000USD	-2.22e-06	-5.96e-07	3.63e-05	9.58e-06	0.000138	3.21e-05
	(0.000109)	(2.91e-05)	(0.000148)	(3.92e-05)	(0.000234)	(5.38e-05)
Sectors (base: Fishing & Aqu.)						
Agroindustry	-0.167	-0.0507	0.00338	0.000947	0.626	0.138
	(0.576)	(0.174)	(0.612)	(0.171)	(0.665)	(0.147)
Energy	0.354	0.0995	0.0537	0.0149		
	(0.908)	(0.247)	(0.964)	(0.267)		
Environmental Sanitation	-0.583	-0.180	-0.659	-0.193	-0.877	-0.206
	(0.630)	(0.191)	(0.666)	(0.193)	(0.691)	(0.160)
Housing and Construction	-	-	-	-	-	-
Mining	-0.235	-0.0717	-0.0485	-0.0137	-0.311	-0.0745
	(0.714)	(0.214)	(0.793)	(0.223)	(0.933)	(0.220)
Industrial Factories	1.161	0.265	0.837	0.198	0.420	0.0956
	(0.772)	(0.171)	(0.832)	(0.191)	(0.909)	(0.205)
Large	1.144**	0.307***	0.832*	0.220*	1.071*	0.248*
	(0.456)	(0.102)	(0.505)	(0.120)	(0.625)	(0.127)
Macrozone (base: SUR)						
NGR	-0.747	-0.203	-1.384	-0.354	-1.766*	-0.381
	(0.806)	(0.226)	(0.899)	(0.248)	(1.046)	(0.233)
NCH	-0.143	-0.0359				
	(0.637)	(0.160)				
CEN	-0.176	-0.0445	-0.947	-0.226*	-1.198	-0.237*
	(0.574)	(0.142)	(0.626)	(0.131)	(0.764)	(0.123)
CES	-1.025*	-0.283**	-1.394**	-0.356***	-1.510**	-0.316***
	(0.563)	(0.135)	(0.623)	(0.127)	(0.729)	(0.113)
Age	-0.0904*	-0.0243*	-0.0268	-0.00707	0.0253	0.00586
	(0.0496)	(0.0126)	(0.0510)	(0.0133)	(0.0517)	(0.0120)
Relapse	0.0270	0.00725	0.281	0.0742	0.131	0.0303
	(0.413)	(0.111)	(0.462)	(0.122)	(0.581)	(0.135)
Complaint	0.241	0.0646	0.372	0.0982	0.904	0.210
	(0.414)	(0.110)	(0.434)	(0.112)	(0.609)	(0.129)
Num. Instruments	0.0420	0.0113	0.0880	0.0232	0.197**	0.0458**
	(0.0437)	(0.0117)	(0.0583)	(0.0156)	(0.0952)	(0.0219)
IMR	2.532	0.680	-0.357	-0.0942	0.744	0.172
	(2.699)	(0.725)	(3.132)	(0.826)	(3.325)	(0.775)
Constant	0.475		0.988		-0.761	
	(1.309)		(1.606)		(1.612)	
Observations	77	77	69	69	65	65

Standard errors clustered by facilities ownership in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

BIBLIOGRAPHY

Alkire, S., Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, *95*(7–8), 476–487. https://doi.org/10.1016/J.JPUBECO.2010.11.006

Allen, M., Dube, O. P., Solecki, W., Aragón-Durand, F., Cramer, W., Humphreys, S., Kainuma, M., Kala, J., Mahowald, N., Yacob, M., Perez, R., Wairiu, M., Zickfield, K. (2018). Global Warming of 1.5°C. Chapter 1: Framing and Context. In *Intergovernmental Panel on Climate Change* (Vol. 4, Issue 1).

Bazilian, M., Nussbaumer, P., Cabraal, A. il, Centurelli, R., Detchon, R., Gielen, D., Howells, M., McMahon, H., Modi, V., O'Gallachoir, B., Radka, M., Rijal, K., Takada, M. (2010). Measuring Energy Access Supporting a Global Target. *United Nations Industrial Development Organization*, 1–22.

Bensch, G., Peters, J. (2015). The intensive margin of technology adoption - Experimental evidence on improved cooking stoves in rural Senegal. *Journal of Health Economics*, *42*, 44–63.

Bersisa, M. (2019). Multidimensional measure of household energy poverty and its determinants in Ethiopia. *Economic Transformation for Poverty Reduction in Africa: A Multidimensional Approach*, 59–84. https://doi.org/10.4324/9780429268939

Besagni, G., Borgarello, M. (2019). Measuring fuel poverty in Italy: A comparison between different indicators. *Sustainability (Switzerland)*, *11*(10). https://doi.org/10.3390/su11102732

Birol, F. (2018). Energy Economics : A Place for Energy Poverty in the Agenda ? Published by : International Association for Energy Economics Stable URL : https://www.jstor.org/stable/41323106 Energy Economics : A Place for Energy Poverty in the A. *The Energy Journal*, *28*(3), 1–6.

Blackman, A. (2010). Alternative Pollution Control Policies in Developing Countries. *Review of Environmental Economics and Policy* 4(2): 234–53.

Blackman, A., Zhengyan L., Antung A. L. (2018). Efficacy of Command-and-Control and Market-Based Environmental Regulation in Developing Countries. *Annual Review of Resource Economics* 10: 381–404.

Boardman, B. (1991). *Fuel Poverty: From Cold Homes to Affordable Warmth (Bellhaven, London)*.

Bond, T. C., S. J. Doherty, D. W. Fahey, P. M. Forster, T. Berntsen, B. J. DeAngelo, M. G. Flanner, et al. 2013. Bounding the Role of Black Carbon in the Climate System: A Scientific Assessment. *Journal of Geophysical Research: Atmospheres* 118 (11): 5380–5552.

Boso, À., Oltra, C., Hofflinger, Á. (2019). Participation in a programme for assisted replacement of wood-burning stoves in Chile: The role of sociodemographic factors, evaluation of air quality and risk perception. *Energy Policy*, *129*, 1220–1226.

Bouzarovski, S., Herrero, S. T., Petrova, S., Ürge-Vorsatz, D. (2016). Unpacking the spaces and politics of energy poverty: path-dependencies, deprivation and fuel switching in post-communist Hungary. *Local Environment*, *21*(9), 1151–1170. https://doi.org/10.1080/13549839.2015.1075480

Bouzarovski, S., Petrova, S., Sarlamanov, R. (2012). Energy poverty policies in the EU: A critical perspective. *Energy Policy*, *49*, 76–82. https://doi.org/10.1016/J.ENPOL.2012.01.033

Bouzarovski, S., Herrero, S. T., Petrova, S., Ürge-Vorsatz, D. (2016). Unpacking the spaces and politics of energy poverty: path-dependencies, deprivation and fuel switching in post-communist Hungary. *Local Environment*, *21*(9), 1151–1170. https://doi.org/10.1080/13549839.2015.1075480

Bouzarovski, S.,Petrova, S. (2015). A global perspective on domestic energy deprivation: Overcoming the energy poverty–fuel poverty binary. *Energy Research Social Science*, *10*, 31–40. https://doi.org/10.1016/J.ERSS.2015.06.007

Briceño, S., Chávez C. (2010). Determinantes de Cumplimiento En El Programa de Tasas Retributivas En Colombia: Elcaso de Corpochivor. *Trimestre Economico* 77(308): 1007–36.

Buso, T., Dell'Anna, F., Becchio, C., Bottero, M. C., Corgnati, S. P. (2017). Of comfort and cost: Examining indoor comfort conditions and guests' valuations in Italian hotel rooms. *Energy Research and Social Science*, *32*.

Caffera, M. (2004). Effectiveness of the Enforcement of Industrial Emission Standards in Montevideo, Uruguay. *Revista de Ciencias Empresariales y Economía* (3): 79–116.

Carpenter, K.A., Jampolsky, J.A., (2015). Indigenous peoples: from energy poverty to energy empowerment. In: International Energy and Poverty: the Emerging Contours. *Taylor and Francis Inc.*, pp. 39–52.

Castaño-Rosa, R., Solís-Guzmán, J., Rubio-Bellido, C., Marrero, M. (2019). Towards a multiple-indicator approach to energy poverty in the European Union: A review. *Energy and Buildings*, *193*, 36–48. https://doi.org/10.1016/j.enbuild.2019.03.039

Cerda, R., González, L. (2017). Pobreza Energética e Impuestos a las Emisiones de Co2 en Chile. *Documento de Trabajo N°30*. Retrieved from http://www.clapesuc.cl/assets/uploads/2017/06/27-06-17-cerda-y-gonzales-2017-vf.pdf

Celis, J. E., Flocchini, R. G., Carvacho, O. F., Morales, J. R., Zaror, C. A., Inzunza, J. C., Pineda, M. J. (2006). Analysis of Aerosol Particles and Coarse Particulate Matter Concentrations in Chillán, Chile, 2001–2003. *Journal of the Air and Waste Management Association*.

Celis, J. E., Morales, J. R., Zaror, C. A., Inzunza, J. C. (2004). A study of the particulate matter PM10 composition in the atmosphere of Chillán, Chile. *Chemosphere*, *54*(4), 541–550.

Crentsil, A. O., Asuman, D., Fenny, A. P. (2019). Assessing the determinants and drivers of multidimensional energy poverty in Ghana. *Energy Policy*, *133*(July), 110884. https://doi.org/10.1016/j.enpol.2019.110884

Chakraborti, L. (2022). Environmental deterrence in developing countries: evidence from enforcement actions and fines under the toxics monitoring program of Mexico. *Environment and Development Economics*, 1-22.

Charlier, D., Legendre, B. (2019). A multidimensional approach to measuring fuel poverty. *Energy Journal*. https://doi.org/10.5547/01956574.40.2.bleg

Chávez, C. A., Stranlund, J. K., Gómez, W. (2011). Controlling urban air pollution caused by households: Uncertainty, prices, and income. *Journal of Environmental Management*.

Cohen MA. (1987). Optimal Enforcement Strategy to Prevent Oil Spills: An Application of a Principal-Agent Model with Moral Hazard. *J. Law Econ*. 30:23–51

Dasgupta S, Laplante B, Mamingi N, Wang H. (2001). Inspections, Pollution Prices, and Environmental Performance: Evidence from China. Ecol. Econ. 36:487–98

Deller, D. (2018). Energy affordability in the EU: The risks of metric driven policies. *Energy Policy*, *119*(August 2017), 168–182. https://doi.org/10.1016/j.enpol.2018.03.033

Delugas, E., Brau, R. (2018). *Subjective Well-Being and Energy Poverty : new insights from the combination of objective and subjective*. 1–32.

Dirección de Presupuesto del Ministerio de Hacienda (DIPRES) (2019). Evaluación Programa de Recambio de Calefactores a Leña del Ministerio del Medio Ambiente. Informe final, Centro de Servicios Públicos, Universidad de Chile. Retrieved from: https://www.dipres.gob.cl/597/articles-187242_informe_final.pdf

Dreze Jean, A. Sen. (1995). India: Economic Development and Social Opportunity. *Indian Economic Review*, *31*(1), 127–130. Retrieved from http://www.jstor.org/stable/29793737

Earnhart D. (2004). Regulatory Factors Shaping Environmental Performance at Publicly-owned Treatment Plants. *J. Environ. Econ. Manag*. 48:655–81

Earnhart, D. (2009). The Influence of Facility Characteristics and Permit Conditions on the Effectiveness of Environmental Regulatory Deterrence. *Journal of Regulatory Economics* 36(3): 247–73.

Eckert H, Eckert A. (2010). The Geographic Distribution of Environmental Inspections. *J. Regul. Econ*. 37:1–22

Escobar, N. Chávez C. (2013). Monitoring, Firms' Compliance and Imposition of Fines: Evidence from the Federal Industrial Inspection Program in Mexico City. *Environment and Development Economics* 18(6): 723–48.

Fang, X., Bianchi, M. V, Christensen, C. (2012). Monetization of Thermal Comfort in Residential Buildings Comfort Model Description. *National Renewable Energy Laboratory*.

Foster, J., Greer, J., Thorbecke, E. (1984). A Class of Decomposable Poverty Measures. *Econometrica*. https://doi.org/10.2307/1913475

Gebreegziabher, Z., Beyene, A., Bluffstone, R., Martinsson, P., Mekonnen, A., and Toman, M. (2018). Fuel Savings, Cooking Time and User Satisfaction with Improved Biomass Cookstoves: Evidence from Controlled Cooking Tests in Ethiopia. *Resource and Energy Economics* 52: 173-185.

Giannini Pereira, M., Vasconcelos Freitas, M. A., da Silva, N. F. (2011). The challenge of energy poverty: Brazilian case study. *Energy Policy*, *39*(1), 167–175. https://doi.org/10.1016/j.enpol.2010.09.025

Gómez, W., Salgado, H., Vásquez, F., Chávez, C. (2014). Using stated preference methods to design cost-effective subsidy programs to induce technology adoption: An application to a stove program in southern Chile. *Journal of Environmental Management*.

González-Eguino, M. (2015). Energy poverty: An overview. *Renewable and Sustainable Energy Reviews*, *47*, 377–385. https://doi.org/10.1016/j.rser.2015.03.013

Gouveia, J. P., Palma, P., Simoes, S. G. (2019). Energy poverty vulnerability index: A multidimensional tool to identify hotspots for local action. *Energy Reports*. https://doi.org/10.1016/j.egyr.2018.12.004

Grennfelt, P., Engleryd, A., Forsius, M., Hov, Ø., Rodhe, H., Cowling, E. (2020). Acid rain and air pollution: 50 years of progress in environmental science and policy. In *Ambio* (Vol. 49, Issue 4).

Gray, W. B., Shimshack J.P. (2011). The Effectiveness of Environmental Monitoring and Enforcement: A Review of the Empirical Evidence. *Review of Environmental Economics and Policy* 5(1): 3–24.

Healy, J. D., Clinch, P. J. (2002). Fuel poverty, thermal comfort and occupancy: Results of a national household - survey in Ireland. *Applied Energy*, *73*(3–4), 329–343. https://doi.org/10.1016/S0306-2619(02)00115-0

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153-161.

Heindl, P., Schuessler, R. (2015). Dynamic properties of energy affordability measures. *Energy Policy*, *86*. https://doi.org/10.1016/j.enpol.2015.06.044

Helland, E. (1998). The Enforcement of Pollution Control Laws: Inspections, Violations, and Self-Reporting. *Review of Economics and Statistics* 80(1).

Helland E. (1998b). The Revealed Preferences of State EPAs: Stringency, Enforcement, and Substitution. *J. Environ. Econ. Manag.* 35:242–61

Herrero, S. T. (2017). Energy poverty indicators: A critical review of methods. *Indoor and Built Environment*, *26*(7), 1018–1031. https://doi.org/10.1177/1420326X17718054

Hills, J. (2012). Getting the measure of fuel poverty: Final Report of the Fuel Poverty Review. CASEreport (72). *London School of Economics and Political Science. London.*

Howden-Chapman, P., Viggers, H., Chapman, R., O'Dea, D., Free, S., and O'Sullivan, K. (2009). Warm Homes: Drivers of the Demand for Heating in the Residential Sector in New Zealand. *Energy Policy* 37 (9): 3387–99.

IEA 2020. *World Energy Outlook 2020*. International Energy Agency. Paris: IEA.

Imbens, G., Wooldridge, J. (2007). *What's new in econometrics? Lecture Notes 2, National Bureau of Economics Research Summer 2007 Workshop*.

Imbert, I., Nogues, P., Sevenet, M. (2016). Same but different: On the applicability of fuel poverty indicators across countries - Insights from France. *Energy Research and Social Science*. https://doi.org/10.1016/j.erss.2016.03.002

Ito, K. and Zhang. S. (2020). Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China. *Journal of Political Economy* 128 (5): 1626 - 1672.

IQAir. (2021). *2020 World Air Quality Report PM2.5 Ranking*. 22. https://www.iqair.com/world-air-quality-report

Jaime, M. M., Chávez, C., Gómez, W. (2020). Fuel choices and fuelwood use for residential heating and cooking in urban areas of central-southern Chile: The role of prices, income, and the availability of energy sources and technology. *Resource and Energy Economics*, *60.*

Jeuland, M. A., Pattanayak, S. K. (2012). Benefits and costs of improved cookstoves: Assessing the implications of variability in health, forest and climate impacts. *PLoS ONE*, *7*(2).

Jeuland, M., Fetter, T. R., Li, Y., Pattanayak, S. K., Usmani, F., Bluffstone, R. A., Chávez, C., Girardeau, H., Hassen, S., Jagger, P., Jaime, M. M., Karumba, M., Köhlin, G., Lenz, L., Litzow, E. L., Masatsugu, L., Naranjo, M. A., Peters, J., Qin, P., … Toman, M. (2021). Is energy the golden thread? A systematic review of the impacts of modern and traditional energy use in low- and middle-income countries. In *Renewable and Sustainable Energy Reviews* (Vol. 135, p. 110406). Elsevier Ltd.

Johansson, L. S., Tullina C., Leckner B., Sjövall. P. (2003). Particle Emissions from Biomass Combustion in Small Combustors. *Biomass and Bioenergy* 25 (4): 435-446

Kelly, J. A., Clinch, J. P., Kelleher, L., Shahab, S. (2020). Enabling a just transition: A composite indicator for assessing home-heating energy-poverty risk and the impact of environmental policy measures. *Energy Policy*, *146*, 111791.

Kish, L. (1949). A Procedure for Objective Respondent Selection within the Household. *Journal of the American Statistical Association*, *44*(247). https://doi.org/10.1080/01621459.1949.10483314

Klasen, S., Villalobos, C., (2020). Diverging identification of the poor: a non-random process. Chile 1992–2017. *World Dev*. 130 https://doi.org/10.1016/j.worlddev.2020.104944.Kuzemko, C., Keating, M. F., Goldthau, A. (2017). Energy, Climate Change and the Environment. In *The Global Energy Challenge*. https://doi.org/10.1057/978-1-137-41008-5_6

Laplante, B., Rilstone P. (1996). Environmental Inspections and Emissions of the Pulp and Paper Industry in Quebec. *Journal of Environmental Economics and Management* 31(1): 19–36.

LaFave, D., Beyene, A. D., Bluffstone, R., Dissanayake, S. T. M., Gebreegziabher, Z., Mekonnen, A., Toman, M. (2021). Impacts of improved biomass cookstoves on child and adult health: Experimental evidence from rural Ethiopia. *World Development*, *140*, 105332.

Legendre, B., Ricci, O. (2015). Measuring fuel poverty in France: Which households are the most fuel vulnerable? *Energy Economics*. https://doi.org/10.1016/j.eneco.2015.01.022

Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*, *525*(7569).

Li, P., Parkinson, T., Schiavon, S., Froese, T. M., de Dear, R., Rysanek, A., Staub-French, S. (2020). Improved long-term thermal comfort indices for continuous monitoring. *Energy and Buildings*, *224*, 110270.

Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., Amann, M., Anderson, H. R., Andrews, K. G., Aryee, M., Atkinson, C., Bacchus, L. J., Bahalim, A. N., Balakrishnan, K., Balmes, J., Barker-Collo, S., Baxter, A., Bell, M. L., Blore, J. D., … Ezzati, M. (2012). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: A systematic analysis for the Global Burden of Disease Study 2010. *The Lancet*, *380*(9859), 2224–2260.

Ludwinski, D., Moriarty, K., Wydick, B. (2011). Environmental and health impacts from the introduction of improved wood stoves: Evidence from a field experiment in Guatemala. *Environment, Development and Sustainability*, *13*(4).

Malla, S. (2013). Household energy consumption patterns and its environmental implications: Assessment of energy access and poverty in Nepal. *Energy Policy*, *61*, 990–1002. https://doi.org/10.1016/j.enpol.2013.06.023

Mardones, C. (2021). "Ex-post evaluation and cost-benefit analysis of a heater replacement program implemented in southern Chile." *Energy,* 227, July, 120484.

Meng, C., Schmidt P. (1985). On the Cost of Partial Observability in the Bivariate Probit Model. *International Economic Review* 26(1).

Mbewe, S. (2018). *Investigating household energy poverty in South Africa by using unidimensional and multidimensional measures*. https://doi.org/10.1148/radiol.2403050937

Mendoza, C. B., Cayonte, D. D. D., Leabres, M. S., Manaligod, L. R. A. (2019). Understanding multidimensional energy poverty in the Philippines. *Energy Policy*, *133*(October 2018), 110886. https://doi.org/10.1016/j.enpol.2019.110886

Míguez, J. L., Morán J.C., Granada E., Porteiro J. (2012). Review of Technology in Small-Scale Biomass Combustion Systems in the European Market. *Renewable and Sustainable Energy Reviews*. 16 (6): 3867-3875

Milne, G., Boardman, B. (2000). Making cold homes warmer: The effect of energy efficiency improvements in low-income homes. *Energy Policy*, *28*(6–7).

Miniaci, R., Scarpa, C., Valbonesi, P. (2014). Fuel Poverty and the Energy Benefits System: The Italian Case. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2433441

Ministry of Environment Government of Chile-MMA. (2020). "Portal Transparencia." Ministerio de Medio Ambiente. 2020. https://www.portaltransparencia.cl/PortalPdT/directorio-de-organismos-regulados/?org=AW002.

Ministry of Environment Government of Chile-MMA. (2019). *Quinto Reporte del Estado del Medio Ambiente*.

Ministry of Environment Government of Chile-MMA. (2014). *Planes de Descontaminación Atmosférica- Estrategia 2014 - 2018*.

Mobarak, A. M., Dwivedi, P., Bailis, R., Hildemann, L., Miller, G. (2012). Low demand for nontraditional cookstove technologies. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(27).

Moore, R. (2012). Definitions of fuel poverty: Implications for policy. *Energy Policy*, *49*, 19–26.

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica*, *46*(1).

Noonan, C. W., Navidi, W., Sheppard, L., Palmer, C. P., Bergauff, M., Hooper, K., and Ward, T. J. (2012). Residential Indoor PM 2.5 in Wood Stove Homes: Follow-up of the Libby Changeout Program. *Indoor Air* 22 (6): 492–500.

Nadeau, L. W. (1997). EPA Effectiveness at Reducing the Duration of Plant-Level Noncompliance. *Journal of Environmental Economics and Management* 34(1): 54–78.

Nussbaumer, P., Bazilian, M., Modi, V. (2012). Measuring energy poverty: Focusing on what matters. *Renewable and Sustainable Energy Reviews*, Vol. 16, pp. 231–243. https://doi.org/10.1016/j.rser.2011.07.150

Nussbaumer, P., Nerini, F. F., Onyeji, I., Howells, M. (2013). Global insights based on the multidimensional energy poverty index (MEPI). *Sustainability (Switzerland)*. https://doi.org/10.3390/su5052060

Okushima, S. (2017). Gauging energy poverty: A multidimensional approach. *Energy*, *137*, 1159–1166. https://doi.org/10.1016/J.ENERGY.2017.05.137

Olang, T. A., Esteban, M., Gasparatos, A. (2018). Lighting and cooking fuel choices of households in Kisumu City, Kenya: A multidimensional energy poverty perspective. *Energy for Sustainable Development*. https://doi.org/10.1016/j.esd.2017.09.006

Olawumi Israel-Akinbo, S., Snowball, J., Fraser, G. (2018). An Investigation of Multidimensional Energy Poverty among South African Low-income Households. *South African Journal of Economics*. https://doi.org/10.1111/saje.12207

Ogwumike, F. O., Ozughalu, U. M. (2015). Analysis of energy poverty and its implications for sustainable development in Nigeria. *Environment and Development Economics*, *21*(3), 273–290. https://doi.org/10.1017/S1355770X15000236

Ozughalu, U. M., Ogwumike, F. O. (2019). Extreme Energy Poverty Incidence and Determinants in Nigeria: A Multidimensional Approach. *Social Indicators Research*. https://doi.org/10.1007/s11205-018-1954-8

Papada, L., Kaliampakos, D. (2016). Measuring energy poverty in Greece. *Energy Policy*, *94*, 157–165. https://doi.org/10.1016/j.enpol.2016.04.004

Poirier, D. J. (1980). Partial Observability in Bivariate Probit Models. *Journal of Econometrics* 12(2).

Porras-Salazar, J. A., Contreras-Espinoza, S., Cartes, I., Piggot-Navarrete, J., Pérez-Fargallo, A. (2020). Energy poverty analyzed considering the adaptive comfort of people living in social housing in the central-south of Chile. *Energy and Buildings*, *223*.

Reyes, R., Nelson, H., Navarro, F., Retes, C. (2015). The firewood dilemma: Human health in a broader context of well-being in Chile. *Energy for Sustainable Development*, *28*, 75–87. https://doi.org/10.1016/j.esd.2015.07.005

Reyes, R., Schueftan, A., Ruiz, C. (2018). Control de la contaminación atmosférica en un contexto de pobreza de energía en el sur de Chile: los efectos no deseados de la política de descontaminación. *Bosques, Energía y Sociedad*.

Reyes, R., Schueftan, A., Ruiz, C., González, A. D. (2019). Controlling air pollution in a context of high energy poverty levels in southern Chile: Clean air but colder houses? *Energy Policy*, *124*(April 2018), 301–311.

Robinson, C., Bouzarovski, S., Lindley, S. (2018). 'Getting the measure of fuel poverty': The geography of fuel poverty indicators in England. *Energy Research and Social Science*. https://doi.org/10.1016/j.erss.2017.09.035

Rockefeller Foundation. https://www.rockefellerfoundation.org/

Romero, J. C., Linares, P., López, X. (2018). The policy implications of energy poverty indicators. *Energy Policy*. https://doi.org/10.1016/j.enpol.2017.12.054

Rousseau, S. (2009). Empirical Analysis of Sanctions for Environmental Offenses. *International Review of Environmental and Resource Economics*.

Ruiz-Tagle, J. C., Schueftan, A. (2021). Nudging for cleaner air: Experimental evidence from an RCT on wood stove usage. *Environmental and Resource Economics* 79: 713-743.

Sadath, A. C., Acharya, R. H. (2017). Assessing the extent and intensity of energy poverty using Multidimensional Energy Poverty Index: Empirical evidence from households in India. *Energy Policy, 102,* 540–550. https://doi.org/10.1016/j.enpol.2016.12.056

Sanusi, Y. A., Owoyele, G. S. (2016). Energy Poverty and its Spatial Differences in Nigeria: Reversing the Trend. *Energy Procedia*, *93*, 53–60. https://doi.org/10.1016/j.egypro.2016.07.149

Shimshack, J. P. (2014). The Economics of Environmental Monitoring and Enforcement. *Annual Review of Resource Economics* 6(1): 339–60.

Shimshack, J. P., Ward M.B. (2005). Regulator Reputation, Enforcement, and Environmental Compliance. *Journal of Environmental Economics and Management*.

Schueftan, A, Sommerhoff J., González A. D. (2016). Firewood demand and energy policy in south-central Chile. *Energy for Sustainable Development*, 33: 26-35.

Sen, A. (1985). *Commodities and Capabilities*.Retrieved from http://www.amazon.com/Commodities-Capabilities-Amartya-Sen/dp/0195650387/ref=sr_1_1?s=booksie=UTF8qid=1310679705sr=1-1

Sher, F., Ullah, R. A., Abbas, A. (2013). An investigation of multidimensional energy poverty in Pakistan: A province level analysis. *International Journal of Energy Economics and Policy*, *4*(1), 65–75.

Sen, A. (1999). Development as Freedom. In *Development*. https://doi.org/10.2307/40203469

SMA. (2018). Superintendencia del Medio Ambiente Chile *Memoria de Gestion 2014-2018 Superintendencia Del Medio Ambiente Chile*.

Smith, D. B. (2018). The Grand Transition. *Calgary's Grand Story*, 199–224. https://doi.org/10.2307/j.ctv6cfqsc.15

Stranlund, J. K. (2013). Enforcement. In *Encyclopedia of Energy, Natural Resource, and Environmental Economics*, Elsevier Inc., 150–54.

Tang, X., Liao, H. (2014). Energy poverty and solid fuels use in rural China: Analysis based on national population census. *Energy for Sustainable Development*, *23*, 122–129. https://doi.org/10.1016/j.esd.2014.08.006

Thomson, H., Bouzarovski, S., Snell, C. (2017). Rethinking the measurement of energy poverty in Europe: A critical analysis of indicators and data. *Indoor and Built Environment*, *26*(7), 879–901. https://doi.org/10.1177/1420326X17699260

Thomson, H., Snell, C., Liddell, C. (2016). Fuel poverty in the European Union: a concept in need of definition? *People Place and Policy Online*, *10*(1), 5–24. https://doi.org/10.3351/ppp.0010.0001.0002

Tirado Herrero, S., Ürge-Vorsatz, D. (2012). Trapped in the heat: A post-communist type of fuel poverty. *Energy Policy*, *49*, 60–68. https://doi.org/10.1016/j.enpol.2011.08.067

UN. (2015). *Transforming our world: the 2030 Agenda for Sustainable Development*. https://wedocs.unep.org/20.500.11822/9814

UN. (2018). Pobreza energética : análisis de experiencias internacionales y aprendizajes para Chile. In *Santiago de Chile, Programa de las Naciones Unidas para el Desarrollo*.

UNDP. (2018). Sustainable Development Goals Report 2018. *United Nations Department of Economic and Social Affairs*, (December), 64.

Urquiza, A., Amigo, C., Billi, M., Calvo, R., Labraña, J., Oyarzún, T., Valencia, F. (2019). Quality as a hidden dimension of energy poverty in middle-development countries. Literature review and case study from Chile. *Energy and Buildings*, *204*.

US Agency Environmental Protection. (2020). *Superfund Compliance and Penalties*. https://www.epa.gov/enforcement/superfund-compliance-and-penalties

Villalobos, C., Chávez, C., Uribe, A. (2021). Energy poverty measures and the identification of the energy poor: A comparison between the utilitarian and capability-based approaches in Chile. *Energy Policy*, *152*.

Ward, T., Noonan, C. (2008). Results of a Residential Indoor PM2.5 Sampling Program before and after a Woodstove Changeout. *Indoor Air* 18 (5): 408–15.

Wassie, Y. Adaramola, M. (2021). Analysis of Potential Fuel Savings, Economic and Environmental Effects of Improved Biomass Cookstoves in Rural Ethiopia. *Journal of Cleaner Production* 280.

WHO. (1987). *Health impact of low indoor temperatures : report on a WHO meeting : Copenhagen, 11-14 November 1985.* Copenhagen: World Health Organization, Regional Office for Europe.

Wyss, A., Ciesielski, A., Bølling, A., Kissling, G., Chartier, R., Jørgen, H., Rodes, Ch. et al. (2016). Particulate Matter 2.5 Exposure and Self-Reported Use of Wood Stoves and Other Indoor Combustion Sources in Urban Nonsmoking Homes in Norway. *PLoS ONE* 11 (11).

Zhang, D., Li, J., Han, P. (2019). A multidimensional measure of energy poverty in China and its impacts on health: An empirical study based on the China family panel studies. *Energy Policy*, *131*, 72–81. https://doi.org/10.1016/j.enpol.2019.04.037