# Essays on Natural Resources, Energy, and Development

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Odmaa Narantungalag

School of Economics and Finance
Massey University
Palmerston North, New Zealand

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To

my mom and dad, Altantuya and Narantungalag, for their love and belief in me,

my husband, Enkhbold, for his love and continuous support,

my children, Chinbadral and Khantushig, for giving me the reasons to be a better person.

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# Abstract

This thesis examines the local economic and health impacts of natural resource extraction on communities and the effectiveness of large energy subsidies using microdata from Mongolia for 2008–2018. The results are presented in three stand-alone empirical chapters.

Chapter 2 examines the economic impacts of the mining industry's indirect linkages on household expenditure patterns in a quasi-experiment setting. Households benefit from mining activities by increasing their expenditures on food, health care, and electricity by reducing their expenditures on education, non-food goods, and services. However, increased mining activities do not adversely affect health and educational outcomes because of improved access to health and education services.

Chapter 3 investigates the impact of mining-induced pollution on individuals' likelihood of reporting illnesses, employing a novel instrumental variable. Individuals who reside within five kilometers of mining activities are more likely to report illness. This is true for all age groups, although the effect is most severe for younger children. Small-scale mines and gold mines cause greater health risks than larger and other types of mines.

Chapter 4 evaluates the effectiveness of large electricity subsidies on reducing fossil fuel use, such as coal, and improving ambient air quality. The subsidy program achieves its intended goal of reducing illness, but it affects household electricity consumption behavior, which might further help the transition from coal to electricity and reduce air pollution.

The results reported in this thesis generate findings important for policymaking in resource-rich developing countries. First, household disaggregated expenditure analysis can provide useful information about household consumption decisions, which can be used for policy formulation to increase the benefits of mining activities to local communities. Second, pollution control and mitigation are essential in resource-producing regions to reduce the population's health risks from mining activities and enhance welfare. Third, large energy subsidies may be useful for changing consumer behavior, further contributing to subsidy effectiveness.

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# Chapter 1 Introduction

## 1.1 Motivation

Natural resource abundance has served as the engine of growth and industrialization for many countries, while for others, it has done little for economic development and advancement. The stark differences between resource-rich industrialized nations such as Norway, Canada, and Australia, and resource-rich developing countries such as Mongolia, Ghana, and Venezuela, spark many questions about the impacts of natural resources on development outcomes (van der Ploeg, 2011; Venables, 2016). Issues such as the 'resource curse' have received widespread attention in the economics literature identifying factors that influence whether or not resource abundance leads to growth and development, which benefits a nation's citizens. These factors include institutional quality, market volatility, political regime, and the macroeconomic environment governing the manners in which natural resources are exploited (Robinson et al., 2006; Gylfason and Zoega, 2006). Empirical findings on the effects of natural resource extraction on local communities in the resource-producing regions highlight that extractive industries affect local economies through direct and indirect linkages (Cust and Poelhekke, 2015; van der Ploeg and Poelhekke, 2017).

The discovery and development of non-renewable natural resources such as minerals, gas, and oil will impact national, regional, and local economies. Extractive industries have the potential to create backward (direct) links to the economy by creating jobs and purchasing locally produced goods and services (Aragón and Rud, 2015; Badeeb et al., 2017; Allcott and Keniston, 2017). Mining can also supply raw materials for the production of goods and services in other industries through its forward (direct) linkages (Sachs and Warner, 1999; De Haas and Poelhekke, 2019). Furthermore, mining activities have fiscal (indirect) linkages via the resources sector's tax revenues to a national government. The government is then responsible for redistribution and investment decisions about the use of those revenues (van der Ploeg and Venables, 2013; Orihuela and Gamarra-Echenique, 2020). Despite the benefits that extractive industries can bring to a country, it can also mean that a nation becomes highly dependent on one industry, making it vulnerable to commodity price fluctuations and business cycles (van der Ploeg and Poelhekke, 2009; Marchand, 2012). Mining is also one of the most polluting industries, one that can adversely affect the population living nearby to mining activities (Aragón and Rud, 2015; von der Goltz and Barnwal, 2019).

Such intricate complexities of natural resource exploitation motivate the research questions tackled in this thesis. The thesis aims to answer the following three questions. First, it examines whether natural resource extraction benefits the communities in the resource-producing region. Second, it investigates how negative externalities such as mining pollution affect individuals' health outcomes near mining activities. Third, it explores if subsidies aiming to improve ambient air quality effectively reduce households' dependence on coal for heating and the incidence of reporting air pollution-related illnesses. The thesis analyses the research questions in three separate empirical papers.

The empirical analyses of these questions will help us understand the economic and social impacts of non-renewable natural resource extraction and processing so that appropriate policy settings can be established to ensure that resource exploitation brings real and positive benefits to the populace. The research papers reported in this thesis aim to provide empirical evidence on the indirect linkages and impacts of extractive industries on residents and the effectiveness of large electricity subsidies in enhancing household welfare.

## 1.2 Data

The thesis uses data from six rounds of the Mongolia Household Socio-Economic Survey (HSES) over 2008-2018, a nationally representative household survey conducted by the National Statistics Office of Mongolia (NSO) every two years (NSO, 2019). HSES reports detailed information about household income sources and different household expenditure categories. The survey also collects information about each household member's age, education, employment status, and whether the person was ill in the month prior to the survey. In addition, the survey contains information about household-level variables such as residential property type, access to water, electricity, heating sources, floor, roof, wall materials of the residential property, and household urban/rural status.

The three empirical papers presented in this thesis use several rounds of the survey, where the relevant chapter drops some survey rounds due to the nature of the analysis. The papers reported in this thesis also use regional-level macroeconomic data, pollution indicators, and health statistics to support the empirical analyses and findings. The chapter on the impacts of mining-induced pollution also uses geo-referenced soil pollution data from mining sites in Mongolia, accessed from the Geo-Database on Ecological Health (GDEH), the Ministry of Environment, and Green Development (GDEH, 2012).

## 1.3 The effects of natural resource extraction on household expenditure patterns: Evidence from Mongolia

Extractive industries can play a crucial role in advancing the development of resource-rich, low-income countries. These industries may contribute substantially to a national economy's revenue base, yet their effects on local residents in resource-producing regions are not well understood. Previous studies examining the local effects of mining activities mainly investigated the resource sector's direct linkages (Aragón and Rud, 2015; Orihuela and Gamarra-Echenique, 2020; Kotsadam and Tolonen, 2016; Tolonen, 2019) and relied on aggregate outcome variables such as district-level income, consumption, and the poverty index (Arellano-Yanguas, 2011; Caselli and Michaels, 2013; Cust and Rusli, 2014; Loayza and Rigolini, 2016; Hilmawan and Clark, 2021). However, a detailed analysis of household expenditure categories provides more accurate understanding of the mining sector's impacts on household living standards (Deaton, 1997; Deaton and Zaidi, 2002; Cust and Poelhekke, 2015).

The impacts of the Oyu Tolgoi mine on local household expenditures are investigated and reported in Chapter 2. Relying on a quasi-experiment setting and employing household-level data from Mongolia, the study established a causal link between mining activities and various categories of household expenditure. The findings indicate that households in a resource-producing region change their expenditure patterns more than those in other regions. The individuals in the mining region do not report a higher incidence of illness, but increase their spending on health care. Schooling years are significantly higher in the mining area, even though households reduced their education expenditures. These can be due to increased local government and mining company investment on the education sector. The results highlight that the impacts of the mining sector are better understood than they are with conventional income and consumption measures of welfare.

## 1.4 No pain, no gain? Mining pollution and morbidity

Local communities directly exposed to the extraction and processing of minerals bear the greatest burden of any resulting pollution. Pollution from mining activities creates negative externalities that affect both people working in the mines and those environmentally exposed to mining (Graff Zivin and Neidell, 2013; Aragón and Rud, 2015; Hendryx et al., 2020; Levasseur et al., 2021). Previous studies provide evidence that mining activities reduce the welfare of local communities if effective pollution mitigation and control are not in place. For example, in examining the case of large-scale gold mines in Ghana, Aragón and Rud (2015) find that pollution reduces agricultural productivity and increases poverty. Similarly, lead pollution from mining increases anemia among women and stunting in children in resource-rich developing countries (von der Goltz and Barnwal, 2019). These studies mainly examined the impacts of mining-induced air and water pollution, or the distance from mines, on health outcomes. However, location-specific pollution data is likely to better capture the impacts of mining activities on local communities.

Chapter 3 examines the effects of mining-induced pollution on the likelihood of reporting the incidence of illness by employing a novel instrument in the analysis: the perceived lease value of a residential property. The study findings indicate that pollution from mining activities adversely affects the local populace living within five kilometers of mines, with younger children the most affected. Individuals living closer to mines spend more on their health care than those residing further away. In addition, small-scale mines and gold mines appear to increase the probability of reporting illness more than other types of mines. The investigation contributes to the existing literature by establishing a causal link between mining-induced pollution and health outcomes through using a novel instrument, and highlights the importance of regulations to control mining pollution in resource-rich developing countries.

## 1.5 The intended and unintended consequences of electricity subsidies: Evidence from Mongolia

Many countries worldwide provide fuel and energy subsidies to increase residential access to cleaner energy, such as electricity. Energy subsidies accounted for 6.5 percent of the global gross domestic product in 2015 (Coady et al., 2017). Subsidies, however, increase global carbon emissions and air pollution-related deaths because consumers tend to increase their electricity demand when faced with lower prices (Clements et al., 2014; Coady et al., 2017; Burke and Kurniawati, 2018; Hahn and Metcalfe, 2021). The empirical literature examining the impacts of electricity subsidies is mainly focused on energy demand (Burke and Kurniawati, 2018; Durmaz et al., 2020), welfare (Giuliano et al., 2020; Hahn and Metcalfe, 2021; Alvarez and Tol, 2021), energy conservation (Allcott and Rogers, 2014; Ito, 2015; Boccard and Gautier, 2021), and lost opportunities (Davis, 2014; Coady et al., 2019). However, no study examines the effects of electricity subsidies on health and household preferences for electricity consumption.

Chapter 4 investigates the effects of a large electricity subsidy in Mongolia, aiming to improve ambient air quality by providing 50-100 percent price reductions for night-time electricity use. The subsidy makes electricity affordable to households that burn coal to heat their homes in the winter months in the most polluting regions of the capital city, Ulaanbaatar. Those living in apartments connected to central heating are not eligible for the subsidy. Such a distinction between eligible and ineligible households creates an ideal quasi-experimental setting for a study to examine the policy's effectiveness. The study results provide evidence that subsidies reduce the probability of reporting overall illness and respiratory illnesses in the winter months. In addition, eligible households increase their electricity consumption in both winter and non-winter seasons, indicating that they change their electricity consumption preferences. The findings may provide guidance about the factors to be considered when a government considers the implementation of an energy subsidy, with the costs weighed against both intended and unintended benefits of the subsidy.

## 1.6 Thesis structure and writing style

This dissertation follows a publications style rather than a Monograph style. It comprises five chapters, including an introduction, three independent empirical papers, and a conclusion. The empirical chapters each examine a particular development issue, with the analyses employing data from the HSES. Therefore, each empirical chapter contains its own abstract, while there is some repetitive descriptive information about the data.

It seems relevant to clarify a particular writing style followed in this thesis. The thesis uses 'I' and 'we' in the relevant chapters. Chapter 2 uses 'I' as a sole-authored empirical research paper. Chapters 3 and 4 use 'we' as they are co-authored with my Ph.D. supervisors.

# Chapter 2 The effects of natural resource extraction on household expenditure patterns: Evidence from Mongolia[1]


## Abstract

This paper investigates the economic impacts of the mining sector on household expenditures. Employing the difference-in-differences model and the Mongolia Household Socio-Economic Survey data from 2008 to 2016, I find that the mining activities benefited local residents. Specifically, mining activities increase household expenditures on food, health, and electricity, respectively, while households reduce their expenditures on education and other non-food items. Interestingly, illness did not increase in the resource-producing region, while educational attainment improved. The findings highlight that the positive impacts of the mining sector are likely to be higher than what is determined by traditional welfare measurements of income and consumption. I provide some anecdotal evidence that the changes in household expenditure patterns can be due to increased availability of health care services and educational facilities in the mining region.



**JEL-Classification:** L72, O12, O13, Q32, R11

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## 2.1 Introduction

Countries endowed with abundant subsoil resources, such as minerals, oil, and gas, may follow divergent growth and development paths. Evidence on how natural resource exploitation affects economic growth shows that there are many mechanisms through which natural resources can influence a country's development trajectory (Sachs and Warner, 2001; van der Ploeg, 2011; Al-Ubaydli, 2012; Venables, 2016). There is, for example, clear evidence that the mining sector has backward, forward, and fiscal linkages to both national and local economies (Cust and Poelhekke, 2015; van der Ploeg and Poelhekke, 2017). However, empirical evidence on the within-country effects of mining on household consumption patterns in a developing country remains limited and inconclusive. Using a large-scale copper-gold mine's taxes and fees as a proxy for mining activities, I investigate the local impacts of the extractive industry on household expenditures. I provide robust evidence on the positive effects of mining on household expenditures on food, health, and electricity and show how these outcomes link to a large-scale mine's development and operation.

I focus on a large-scale copper-gold mine, Oyu Tolgoi, in Mongolia for two main reasons. First, Mongolia is a lower-middle-income country heavily reliant on export commodities such as coal and copper. For example, in 2015, copper exports accounted for 49 percent of export earnings (NSO, 2019). This means, however, that the economy and the welfare of the populace are susceptible to movements in international demand and commodity prices.[2] It is therefore important to understand the outcomes of changes in economic activity, particularly at the local level, so that appropriate policy setting can be established. Oyu Tolgoi is by far the most significant mining investment in Mongolia as it attracted the largest amount of foreign direct investment (FDI) to the country just after the global financial crisis (GFC) in 2010, creating an ideal quasi-experimental setting for analyzing its local impacts.

Second, I examine the indirect impacts of mining activities on local, nearby communities. Large-scale resource extraction is capital and infrastructure intensive, so questions arise as to the direct impacts and benefits in the local economy through avenues such as job creation and demand for local goods and services. In Mongolia, the mining companies pay local fees for using land and water resources, which accrues to the subnational (provincial) government. In addition,

[2] This is one reason that several countries have established sovereign wealth funds, which serve to smooth out the impacts of demand and price movements, along with ensuring that resource exploitation results in sustainable benefits for the community.

mining companies pay local real estate and automobile taxes. These fees and taxes, separate from the resource windfalls accrued by the central government, comprise an indirect linkage to the local economy. Such a distinction between the revenue sharing mechanisms enables me to identify the effects of the mining sector's economic impacts on local communities, a matter which has received limited attention in the literature on the local impacts of natural resource extraction (van der Ploeg, 2011; Cust and Poelhekke, 2015; Cust and Viale, 2016).

I explore the local effects of mining activities on various household consumption categories using Mongolia's nationally representative household-level socio-economic survey data. Previous studies examining the impacts of local linkages on living standards in developing countries relied on outcome variables at the district aggregate level, such as the annual conflict incidence index (Arellano-Yanguas, 2011), crime rates (Andrews and Deza, 2018), corruption (Cappelen et al., 2021), GDP per capita (Caselli and Michaels, 2013; Cust and Rusli, 2014), average per capita consumption, the poverty index (Loayza and Rigolini, 2016), gross regional domestic product (Hilmawan and Clark, 2021), and household aggregate income and consumption (Aragón and Rud, 2013). The detailed analysis of household food, non-food, medical, education, and electricity expenditures allows me to examine the natural resource sector's indirect impacts on household expenditure patterns.

The current study findings highlight that large-scale mining activity positively affects household expenditure patterns in a resource-producing region. While studies on the local impacts of mining activities mainly examine the backward and forward linkages, such as local purchases and procurement in Peru (Aragón and Rud, 2013; Orihuela and Gamarra-Echenique, 2020), job creation in Africa (Kotsadam and Tolonen, 2016; Tolonen, 2018), and spillovers and agglomeration in Australia and the United States (Black et al., 2005; Michaels, 2011; Fleming and Measham, 2015; Allcott and Keniston, 2017), institutional reforms in Colombia (Gallego et al., 2020), only a couple of studies examine the indirect links in developing countries using household-level data (Aragón and Rud, 2013; Orihuela and Gamarra-Echenique, 2020). As applied in my analysis, local taxes and fees resulting from the large-scale mine's operation and output provide a more accurate measure of the indirect linkage.

The main challenge in estimating the causal effects of natural resource extraction is the endogeneity issue arising from confounding factors, the appropriate definition of resource dependence and abundance, and political distortions at the macroeconomic level (van der Ploeg, 2011; James and Aadland, 2011). However, subnational level studies employing within-country data sets mitigate some of the endogeneity issues as these studies suffer less from variations in the cultural norm, institutional quality, laws, and regulations within a country (Cust and Poelhekke, 2015; van der Ploeg and Poelhekke, 2017). In order to overcome the endogeneity issues, I exploit the empirical quasi-experimental strategy following (Aragón and Rud, 2013; Fleming and Measham, 2015). I use the difference-in-differences (DiD) model with four rounds of the Mongolia Household Socio-Economic Survey to draw a causal inference about the impacts of mining activities on household consumption. I consider three crucial characteristics of the resource-producing region for the quasi-experiment. First, the existence of large-scale mineral deposits, like Oyu Tolgoi, mainly depends on geology, making their occurrence random (Bonfatti and Poelhekke, 2017). Second, world mineral prices and demand for commodities drive the investment and development of the mine (De Haas and Poelhekke, 2019). Third, the mine has been developed and managed by non-local entities, such as foreign investors and the central government (Fleming and Measham, 2015).

This article shows that the large-scale mine's operations benefit the mining region households and influence their expenditure patterns. A 10 percent increase in collecting local taxes and fees results in a one percent increase in household per capita food expenditures. Furthermore, the same increase in mining activities leads to a 0.8 and 2.6 percent increase in household expenses on medical care and electricity, respectively. Conversely, a 10 percent increase in local taxes and fees collection reduces household non-food and education expenses by 0.9 and 2.1 percent compared to the households in the neighboring provinces. Therefore, the households in the resource-producing region increase their expenditures on basic needs such as food, medical care, and electricity by reducing their spending on other non-food items.

I consequently investigate whether increased medical and reduced education expenditures in the mining region are associated with respective health and educational outcomes. My examination confirms that individuals living in the large-scale mining region do not report illness significantly more than the control groups in neighboring regions. Furthermore, the educational attainment of individuals is significantly higher than those of the control individuals. Overall, the findings indicate that the mining activities impact local households beyond the traditional income channel but through other channels such as local taxes and fees. The results are robust to alternative models, explanatory variables, and data that I employ.

This study suggests that the application of appropriate local revenue-generating mechanisms, such as taxes and fees for the utilization of land and water by the extractive industry, is beneficial for households in the resource-producing region. Resource-rich remote regions in developing countries often lack skilled labor and market capacity that support backward and forward linkages to the mining sector (Cust and Viale, 2016). However, my investigation documents a positive impact of an alternative local linkage on household expenditure patterns, providing new empirical evidence on the local impacts of natural resource extraction. My findings lend additional support to Cust and Rusli (2014) and Hilmawan and Clark (2021) who argue that local government spending resulting from resource windfalls increases local GDP at the subnational level in Indonesia. My work also closely relates to two papers that find weak effects of fiscal linkages on local welfare. For example, Aragón and Rud (2013) find a negligible effect of revenue windfall on real incomes when examining the case of a large-scale gold mine in Peru. Similarly, Caselli and Michaels (2013) find that household incomes do not increase despite the increased oil-related revenues, but spending on schools increases in oil-rich Brazilian municipalities.

The rest of the paper proceeds as follows. Section 2.2 provides the background to the study, focusing on the Mongolian economy and Oyu Tolgoi mine. Section 2.3 discusses the empirical strategy and data. Section 2.4 presents the main results, robustness checks and Section 2.5 discusses the associated policy implications. Section 2.6 concludes the paper.

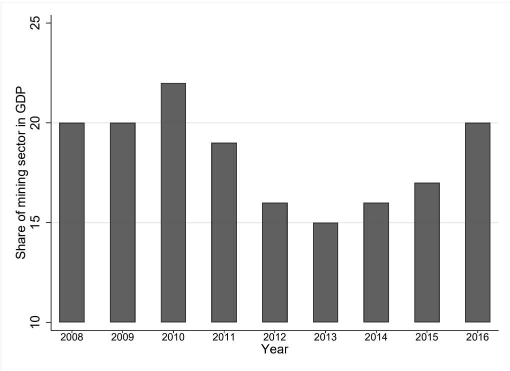
## 2.2 Background

### 2.2.1 Mongolia's dependence on minerals

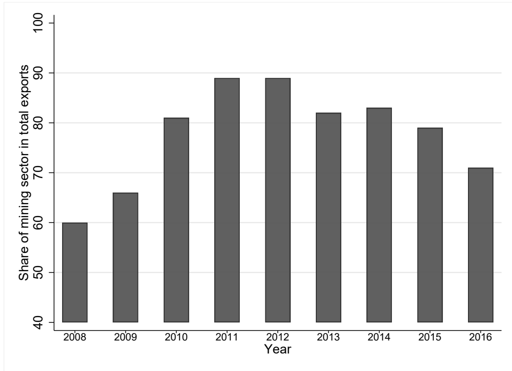
Mongolia is a fast-growing lower-middle-income country with a small, open economy, which relies on minerals, including coal, copper, gold, iron ore, and zinc. The country is a mineral dependent nation, with mining contributing around 20 percent of gross domestic product (GDP) and over 75 percent of total exports in the period 2008-2016, as shown in Panels A and B in Figure 2.1 (NSO, 2019).[3] Economic growth in Mongolia topped 17 percent in 2011 as FDI poured in with the expectation of substantial returns from mineral development. The mining sector received more than 75 percent of FDI in the period 2011-2016 (Panel C in Figure 2.1) (NSO, 2019). Economic growth averaged 7.5 percent per annum since 2000 until the Global Financial Crisis (GFC) hit the economy with a contraction of 1.3 percent in 2009. However, China's increased de-

[3] Haglund (2011) defines a country as mineral-dependent if it generates at least 25 percent of export earnings from minerals. Based on this definition, the number of mineral-dependent low and middle-income countries, including Mongolia, stood at 61 in 2010. There are, however, other definitions of mineral dependency. For example, Auty (1993) defines a nation as mineral-dependent if it generates at least eight percent of Gross Domestic Product (GDP) and 40 percent of export earnings from minerals.

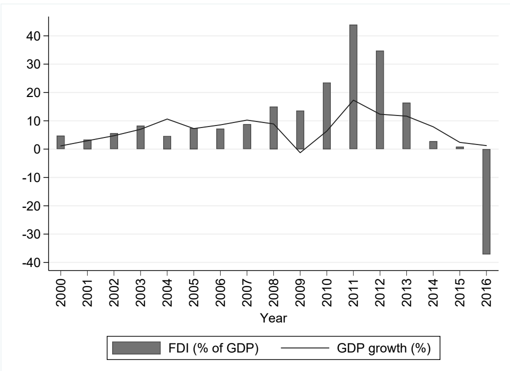
mand for minerals, which underpinned a rapid increase in FDI and high commodity prices, led to a mining boom and substantial structural changes in the economy between 2010 and 2013 (Baatarzorig et al., 2018; Doojav and Luvsannyam, 2019).



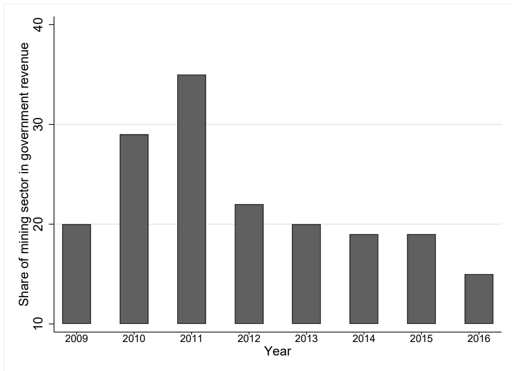

**Panel A: Mining and quarrying sector share in GDP (%)**




**Panel B: Share of mineral exports in total exports (%)**




**Panel C: FDI and GDP growth**




**Panel D: The share of mining sector to budget revenue (%)**

**Figure 2.1: The mining sector in the Mongolian economy**
Source: NSO (2019)

The mining sector contributed over 20 percent of central government budget revenues (Panel D in Figure 2.1) and accounted for four percent of total employment in 2009-2016 (NSO, 2019).[4] Several mineral deposits of economic and strategic significance comprise the majority of fiscal revenues from the mining sector. The central government invests parts of the revenues in public funds and allocates some parts to provincial governments.[5] However, whether the provinces endowed with the major mineral deposits benefit from their mineral extraction despite their sig-

[4]Mining license holders in Mongolia need to pay a standard royalty based on the total sales value of the minerals, ranging from 2.5 percent for coal to 5.0 percent for commonly exported minerals. Additional tax categories include personal income tax, corporate income tax, value-added tax, real estate tax, water consumption tariff, land use fee, import duty, customs duty, excise tax, and taxes for foreign specialists' employment (Mineral Resources and Petroleum Authority, 2016). Either the provincial or central government collects these taxes.

[5]The government projected that in 2019 it would source 27 percent of Mongolia's consolidated total budget revenue from mining revenues, of which 10 and 36 percent would be transferred to the Stabilization Fund (SF) and the Future Heritage Fund (FHF), respectively (Vanchin, 2018). The SF and FHF, established in 2010 and 2016, respectively, act as counter-cyclical policy tools and create sustainable funds by saving parts of resource revenues (Parliament of Mongolia, 2010, 2016). The SF contributes to intra-generational equity, while the FHF underwrites inter-generational equity.

nificant contribution to the national economy is uncertain. Answering this question sheds some light on our understanding of the mining sector's impact on the provincial economies and motivates this paper to further examine the sector's microeconomic effects.

### 2.2.2 Oyu Tolgoi mine

The high global demand for minerals in the early 2000s made Mongolia an exciting destination for FDI and led to the discovery of the country's largest copper-gold deposit, Oyu Tolgoi, in 2001. Oyu Tolgoi, located in the Gobi desert of Southgobi province, has 31.3m tonnes of copper reserves and 3.3b tonnes of mineable copper ore reserves and is believed to be one of the top five copper-gold deposits in the world when fully operational (Oyu Tolgoi, 2018).[6] The commencement of Oyu Tolgoi's commercial production in 2013 increased Mongolia's copper concentrate exports volume to 1.4m tonnes in 2014 (Figure 2.2), accounting for seven percent of copper concentrates traded globally and making Mongolia the sixth-largest exporter of the mineral (WITS, 2014). The mine's annual production is projected at 0.43m tonnes of copper and 0.42m ounces of gold over the next 20 years (Rio Tinto, 2019). The Government of Mongolia established a joint venture with international investors Rio Tinto and Turquoise Hill Resources in 2009, commencing the country's largest foreign-invested resource development project under Oyu Tolgoi LLC (OT). OT is the entity at the center of my analysis.[7]

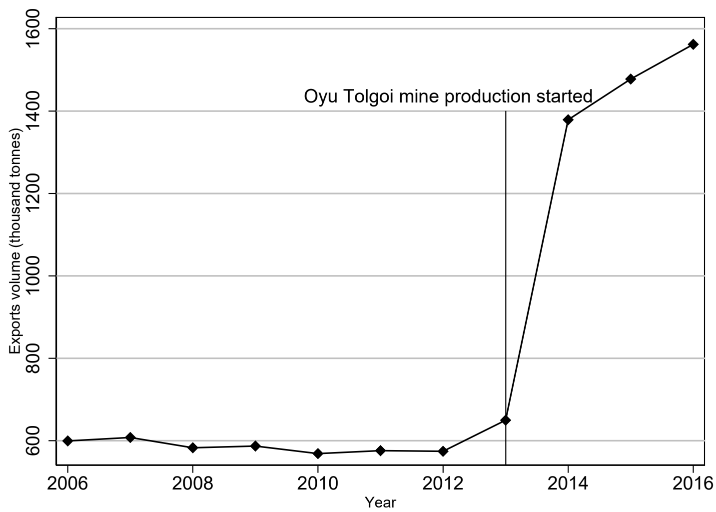



**Figure 2.2: Exports volume of copper concentrate, 2006-2016**
Source: NSO (2019)

[6] In this paper, m refers to million and b refers to billion.

[7] Oyu Tolgoi attracted $6.2b (50 percent of GDP) in FDI in 2010; the second stage of underground mine development, underway since 2016, required a further $5.3b of FDI (Rio Tinto, 2019; Li et al., 2017). The Government of Mongolia owns 34 percent, and Turquoise Hill Resources owns 66 percent.

As Mongolia's largest foreign-invested mining project, OT is believed to significantly impact the national economy and regional development. Taxes paid by OT to the central government constituted 7–13 percent of total tax revenues for 2012-2020 (Mongolian Economy, 2021). While the project's macroeconomic impacts are apparent, its local effects are not well understood. Around 20 percent of total employees come from Southgobi province (Oyu Tolgoi, 2018), while the rest of workforce are fly-in-fly-out (FIFO) employees who travel to the remote mining site when rostered for work and return to their home location when not working (Storey, 2001; McKenzie, 2010). In addition, the majority of equipment and construction materials are not purchased locally due to the limited capacity of the local market. Therefore, the company's employment, procurement, and production have limited effects on the provincial economy because of skill shortages, limited supply of goods and materials, and absorptive capacity constraints (Cust and Poelhekke, 2015).

The mining and quarrying sector requires a substantial amount of resources such as water and land, large-scale infrastructure to operate (De Haas and Poelhekke, 2019). For a large-scale mine like OT, the amount of land and water required is substantial. The provincial governments in Mongolia apply various taxes for the use of land and water, along with additional imposts, including real estate tax, automobile taxes, and royalty fees for mineral resources. Therefore, local fees and taxes paid by mining companies can comprise a significant share of revenue base of the provincial government. The taxes and fees paid by OT were US$0.3m and accounted for around two percent of provincial government revenue in 2008. They increased substantially in the subsequent years and accounted for 18 and 23 percent of provincial government revenues in 2014 and 2016, respectively, after the mine commenced copper production in 2013 (Oyu Tolgoi, 2019; NSO, 2019). I exploit these exogenous changes in local taxes and fees created by the development of the large-scale copper-gold mine to examine the local economic impacts of the mine on household expenditure patterns.

## 2.3 Methodology and data

### 2.3.1 Empirical model

I examine whether a large-scale mine's taxes and fees to the local economy has a discernible impact on the consumption of goods and services by residents in the resource-producing region using a quasi-experimental setting. Employing ordinary least squares (OLS) can produce biased or inconsistent estimates in the presence of endogeneity that may arise due to the omission of relevant variables in the model (Wooldridge, 2015). The difference-in-differences (DiD) model can be employed to overcome (Parmeter and Pope, 2013) and is, therefore, used in the analysis. The empirical specification closely follows the DiD model used by Aragón and Rud (2013) and takes the following form:

$$y_i = \delta + \beta(M_t \times D_s) + \eta_t + \alpha_s + X_i\mathbf{\Theta} + \varepsilon_{ist}, \tag{2.1}$$

where, depending on the analysis, $y_i$ is the (natural logarithm of) monthly per capita income or expenditure (or specific categories of expenditure in separate analyses) of household $i$ ($i = 1, \ldots n$); $X_i$ is a set of household/individual-level control variables (described in Subsection 4.3.1), $\eta_t$ is the year fixed effects and $\alpha_s$ is the province fixed effects. I consider 2008 as the control period as local fees and taxes in the large-scale mining region were similar to those of the neighboring provinces (EITIM, 2020). The analysis excludes 2010 as it is the year when the investment agreement between the international investor and the government came into effect: I do not expect any immediate impact in 2010. The DiD estimate ($\beta$) captures the economic impact of mining activities on household expenditures in Southgobi province. The exposure variable $M_t$, a continuous variable, is the (natural logarithm of) annual local taxes and fees collected by the provincial government for the use of land, water and real estate, and automobile taxes. In the model, I expect local taxes and fees to impact the households in Southgobi positively. Note that some of the effects may occur due to the wages paid to employees, local purchases made from the market, and the company's social investment in the local economy.[8] Households in the neighboring regions might benefit from the mine's various spillover effects, but not directly from local taxes, which are used to support the health and education sectors and infrastructure development.

My analysis, therefore, focuses on the Southgobi province (gray shaded area in Figure 2.3) and considers Southgobi households as the treatment group. Households from the four neighboring provinces, Bayankhongor, Uvurkhangai, Dundgobi, and Dornogobi, are the control households (diagonal line shaded area in Figure 2.3).[9] The neighboring provinces are similar to Southgobi and also possess a wealth of mineral resources such as gold, coal, iron, and wolfram. However,

[8] Southgobi province transfers more than half of the resource revenues to the central government. Local taxes from the mining sector, including real estate, water, land use, and automobile taxes, are paid to the provincial government every year, in addition to royalties and donations. These taxes rose substantially from $0.3m in 2008 to $7.9m in 2016, following the commencement of OT's open-pit mine operation in mid-2013 (Oyu Tolgoi, 2019).

[9] Comparing the expenditures of households in Southgobi against those in neighboring provinces is a more reliable measure than the distance from the mine. The reason is that local tax revenues do not have to be spent in the vicinity of the mine.

they do not have mines comparable to Oyu Tolgoi. Thus $D_s$ in the model is an indicator variable taking the value of one for households living in Southgobi and zero for those in the neighboring provinces.[10]


**Figure 2.3: Map of Mongolia**

The identifying assumption for the DiD model is that the difference in the outcome variable between the treatment and control households would have remained the same in the absence of Oyu Tolgoi's investment agreement, which came into effect in 2010, following exogenous shocks in the global demand for minerals in the early 2000s. While I cannot test the assumption directly, I validate it by graphically showing overtime income and expenditure patterns for both the treatment and control groups as discussed in Subsection 2.4.4.

### 2.3.2 Data

I use data from four rounds of the Mongolia Household Socio-Economic Survey (HSES), a nationally representative cross-sectional survey conducted by the National Statistics Office (NSO) every two years. The survey uses a stratified two-stage sample design based on population figures obtained from the administrative records of local governments. The first stage stratifies the

[10] It is essential to note that mining licenses are issued across Mongolia and mining operations take place in the neighboring provinces. However, the amount of mineral resources, the scale of operation, and the FDIs these mines attracted are not comparable to the Oyu Tolgoi mine, which significantly impact the national economy and central government revenue collection. For example, the total value of mineral extracted and sold were similar across the provinces in 2008 with just above MNT100.0b in all provinces. While the value in Southgobi province increased to MNT6,885.6b in 2016, the value in the neighboring provinces ranged from MNT110.0b to MNT612.0b in the same year (EITIM, 2020).

capital city, Ulaanbaatar, and the 21 provinces. The second stage divides the 21 provinces into two substrata: urban – provincial capitals, and rural – small towns and the countryside (NSO, 2019).[11]

The four HSES rounds that I employ in my study – 2008, 2012, 2014, and 2016 – comprised of an initial sample of 56,608 households with 138,584 individuals. I retained a total of 10,400 households located in Southgobi and its neighboring provinces – Bayankhongor, Uvurkhangai, Dundgobi, and Dornogobi, and omitted 47 households that did not report any monetary income. Consequently, the final sample consists of 36,704 individuals in 10,353 households, of which 1,901 belong to 2008, 2,131 belong to 2012, 3,115 belong to 2014, and 3,206 belong to the 2016 survey. I considered 611 individuals without any formal schooling as these individuals had missing data for education. In addition, I considered 1,438 individuals as not being ill as they did not report their illness status. The missing data could be due to errors in collecting and reporting the data and individuals not being comfortable reporting their education or illness.

The survey collects detailed data on various sources of income and all household consumption/expenditure categories. In my estimation, I employ various household expenditure categories to analyze the large-scale mine's local impacts. Following previous studies such as those of Banks et al. (1997), Blundell et al. (2007) and Hasan (2016), I categorize household expenditures to food, non-food, health, education, electricity, and other non-food expenditures and use them as the dependent variables to estimate Equation 2.1.[12]

Table 2.1 reports the summary statistics for the dependent variables for treatment and control households in each survey round. Panel A reports the variables used for the household-level analysis. The monthly household income was higher for the treatment households in the base year 2008, while both groups increased their incomes steadily in all years, except for the treatment group in 2016. The decline in incomes in 2016 is attributable to a sudden decrease in FDI in 2014, a sharp drop in commodity prices in 2015, and risks and uncertainties that affected the mining sector at that time (Doojav and Luvsannyam, 2019).[13] In contrast, the treatment households' food consumption was similar to that of the control group in 2008. Although both groups increased their food consumption over time, the treatment households' food expenditure was higher in 2012-2016, indicating that they positively benefited from increased mining activities.

[11] The HSES questionnaires and the primary datasets are publicly available from the NSO Census and Survey data catalog and can be obtained using the following link: http://web.nso.mn/nada.

[12] In constructing the variable consumption, I exclude some of the lumpy non-consumption items, such as spending on weddings and religious activities, from household expenditure. However, throughout the analysis, I use consumption and expenditure interchangeably.

[13] At the same time, the national poverty rate increased to 29.6 percent in 2016 from its lowest level of 21.6 percent in 2014 (NSO, 2019).

**Table 2.1: Summary statistics of dependent variables**

| | 2008 | | 2012 | | 2014 | | 2016 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Treatment | Control | Treatment | Control | Treatment | Control | Treatment | Control |
| *Panel A: Household-level variables* | | | | | | | | |
| Per capita income | 130 | 94 | 223 | 164 | 292 | 191 | 274 | 222 |
| | (129) | (91) | (172) | (143) | (262) | (150) | (179) | (159) |
| Per capita food expenditures | 44 | 45 | 70 | 59 | 87 | 65 | 71 | 53 |
| | (33) | (27) | (53) | (41) | (52) | (38) | (42) | (33) |
| Per capita non-food expenditures | 106 | 61 | 157 | 87 | 187 | 122 | 146 | 121 |
| | (131) | (76) | (179) | (95) | (188) | (112) | (116) | (105) |
| Per capita medical expenditures | 2 | 1 | 3 | 3 | 11 | 3 | 6 | 5 |
| | (3) | (4) | (7) | (7) | (101) | (8) | (14) | (16) |
| Per capita education expenditures | 7 | 6 | 6 | 5 | 4 | 6 | 4 | 6 |
| | (16) | (12) | (15) | (12) | (13) | (13) | (11) | (17) |
| Per capita electricity expenditures | 1 | 1 | 2 | 2 | 2 | 2 | 4 | 3 |
| | (2) | (2) | (2) | (3) | (3) | (3) | (4) | (3) |
| Per capita other non-food expenditures | 96 | 52 | 145 | 77 | 169 | 110 | 132 | 107 |
| | (126) | (72) | (177) | (91) | (149) | (109) | (110) | (97) |
| Number of households | 304 | 1,597 | 312 | 1,819 | 622 | 2,493 | 624 | 2,582 |
| *Panel B: Individual-level variables* | | | | | | | | |
| Ill in the past month | 0.08 | 0.05 | 0.09 | 0.05 | 0.08 | 0.06 | 0.06 | 0.05 |
| | (0.3) | (0.2) | (0.3) | (0.2) | (0.3) | (0.2) | (0.2) | (0.2) |
| Number of individuals | 1,201 | 6,407 | 985 | 6,527 | 1,961 | 8,917 | 1,894 | 8,812 |
| Individual's education (years) | 7.68 | 7.39 | 8.72 | 8.42 | 8.66 | 8.50 | 9.48 | 8.56 |
| | (4.6) | (4.7) | (5.1) | (5.2) | (5.6) | (5.3) | (5.3) | (5.1) |
| Number of individuals | 1,102 | 5,864 | 887 | 5,820 | 1,716 | 7,847 | 1,616 | 7,700 |

*Note:* Panel A reports the dependent variables for the analyses conducted at household level. All values are on per capita monthly basis. Means are reported in thousand Tugrik (MNT) and adjusted for 2010 price level. The exchange rate was US$1 $\approx$ 1,257 MNT at the end of 2010. Panel B reports the illness rate for all individuals whereas individual's education is years of schooling for only those aged 6 and above from the HSES. Standard deviations are reported in the parentheses.

While non-food expenditures were higher for the treatment group in 2008, they changed over time in a pattern similar to income. Other non-food expenditures, including transportation, services, communication, clothing, and others, were higher for the treatment households in 2008 and grew similarly to income and non-food expenditure. On the other hand, both groups' expenditures on medical services and electricity increased over time, except that medical expenditures declined for the treatment group in 2016. Interestingly, treatment households' expenditure on education declined over time, whereas the control group had relatively stable expenditure on education.

Panel B in Table 2.1 presents the summary statistics for the dependent variables, the incidence of illness, and education years, which are used for the individual-level analysis. Eight percent of the treatment individuals reported that they were ill in 2008, compared to the five percent of control group individuals. Their illness rate increased in 2012 and declined in 2014-2016. On the other hand, the illness rate of control individuals did not change in all years, except 2014. I also use schooling years for individuals aged six and above as a dependent variable in my analysis. The treatment individuals had slightly higher years of education than the control group in 2008. The educational attainments of both groups increased in subsequent years, except that it was lower for the treatment individuals in 2014 than in 2012.

Before estimating the empirical model, I conducted t-tests to check the significance of the differences in (the natural logarithms of) income, various categories of expenditures, illness rate, and educational attainment between the treatment and control groups (Table 2.2). Panel A presents the differences in dependent variables between treatment and control households over the years. Income, expenditures on non-food consumption, health, and other non-food items were significantly higher for the treatment households in 2008, as indicated by the significance from the t-test. The differences in these items, except medical expenditures, declined over time, indicating that the treatment households increased them less than the control group.

The expenditures on food, education, and electricity also provide interesting patterns. For example, treatment households' food expenditure was significantly lower than the control group's in 2008. It increased substantially in subsequent years, and the difference in food expenditure was significantly higher in 2012-2016. On the other hand, the treatment group's education expenditure was slightly higher than that of the control group in 2008, although the difference was insignificant. Over time, however, the pattern of expenditures changed, with treatment households spending less on education. Expenditure on electricity was higher for treatment households in the base year without a significant difference between both groups in the initial period. Treatment households increased their electricity expenditure over time, except in 2012, and the difference was significant in 2016.

**Table 2.2: Differences in income and expenditures between treatment and control groups**

| Variable name | 2008 | 2012 | 2014 | 2016 |
|---|---|---|---|---|
| *Panel A: Household-level variables* | | | | |
| Ln(per capita income) | 0.304*** | 0.349*** | 0.398*** | 0.235*** |
| | (0.050) | (0.041) | (0.028) | (0.029) |
| Ln(per capita food expenditures) | -0.075** | 0.129*** | 0.287*** | 0.291*** |
| | (0.032) | (0.034) | (0.023) | (0.023) |
| Ln(per capita non-food expenditures) | 0.548*** | 0.588*** | 0.391*** | 0.195*** |
| | (0.051) | (0.045) | (0.031) | (0.031) |
| Ln(per capita medical expenditures) | 0.242*** | 0.277*** | 0.466*** | 0.252*** |
| | (0.092) | (0.085) | (0.060) | (0.062) |
| Ln(per capita education expenditures) | 0.156 | -0.761*** | -0.794*** | -0.385** |
| | (0.239) | (0.229) | (0.175) | (0.177) |
| Ln(per capita electricity expenditures) | 0.022 | -0.970*** | 0.109 | 0.439*** |
| | (0.229) | (0.213) | (0.164) | (0.156) |
| ln(per capita other non-food expenditures) | 0.592*** | 0.631*** | 0.419*** | 0.214*** |
| | (0.052) | (0.046) | (0.033) | (0.031) |
| Number of households | 1,901 | 2,131 | 3,115 | 3,206 |
| *Panel B: Individual-level variables* | | | | |
| Ill in the past month | 0.026*** | 0.045*** | 0.024*** | 0.015*** |
| | (0.007) | (0.008) | (0.006) | (0.006) |
| Number of individuals | 7,608 | 7,512 | 10,878 | 10,706 |
| Individual's education (years) | 0.135 | 0.194 | -0.025 | 0.678*** |
| | (0.154) | (0.188) | (0.144) | (0.141) |
| Number of individuals | 6,966 | 6,707 | 9,563 | 9,316 |

*Note:* Mean of differences between households/individuals in treatment and control regions are reported for each year. Panel A reports the dependent variables for the analyses conducted at household level. All values are in their natural logarithm. Panel B reports the illness rate for all individuals whereas individual's education is years of schooling for only those aged 6 and above from the HSES. Standards errors are recorded in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I also examine the difference in individual-level dependent variables, which are shown in Panel B of Table 2.2. The treatment individuals reported a significantly higher incidence of illness than their control counterparts in 2008. The difference in reporting illness increased in 2012 but declined afterward. On the other hand, educational attainment for the treatment individuals was higher in the base year, with the difference increasing in 2012 and significantly so in 2016. Overall, the t-test results indicate that treatment households adjusted their food and non-food expenditures, while the increased mining activities in Southgobi province did not negatively impact their health and educational outcomes.

The HSES also collects information on each household member's age, gender, education, employment status, whether a person was ill in the month before the survey, and residential property type and urban/rural status (NSO, 2019). Since these characteristics can affect income and consumption at the household level, I control these factors in the model when estimating the impacts of large-scale mining activities. Specifically, the household-specific control variables are the household head's age, gender, marital status, years of education, and household size. The household's urban/rural status and dwelling type are also included in the model to account for differences in living conditions.

Table 2.3 presents the summary statistics for the independent variables. Panel A presents the main variable of interest: taxes paid by the mine to the provincial government, including fees for land and water use, real estate, and automobile taxes. I use local taxes and fees to proxy mining activities for the local economy. The taxes and fees paid were US$0.3m and accounted for around two percent of provincial government revenue in 2008 and they increased substantially in the subsequent years, accounting for over 15 percent of revenues in 2014-2016 (Oyu Tolgoi, 2019; NSO, 2019). The taxes and fees are nil for the control households as the mine does not pay any local taxes or fees to the neighboring provinces. However, it pays taxes to the central government, which then manages and redistributes mining revenues across the country.[14]

Panel B presents the household-level control variables. The age of household heads declined for the treatment households, while it increased for the control households. The shift in age may happen due to the migration of younger people into the mining regions, which may offer them better job opportunities.[15] For both groups, the proportion of male-headed households decreased. Although treatment household heads had slightly lower years of schooling in 2008, their education was higher than that of the control group in 2014 and 2016. The proportion of households living in apartments and houses increased for the treatment group over time, except in 2014, whereas there is no clear pattern for the control households. The share of treatment households living in rural areas remained stable while it declined for the control households. Internal migration from rural areas to urban areas, including the capital city, rose in the 2010-2016 period due to people's search for better economic opportunities and access to markets and services.

[14] Mining operations take place on five percent of country's territory (EITIM, 2020). Therefore, most provinces collect local mining taxes and fees from the mining companies. But they are not as high as that of OT's because of the scale of the mining activities.

[15] Traditionally in Mongolia, following a divorce or the death of a husband, the oldest son becomes household head. The number of divorces in Southgobi during 2008-2016 increased by 285 percent, compared to 110 percent for the entire country (NSO, 2019). The relatively higher divorce rates in Southgobi may partly explain the younger age of households as the proportion of married couples decreased for both the control and treatment groups.

**Table 2.3: Summary statistics of independent variables**

| | 2008 | | 2012 | | 2014 | | 2016 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Treatment | Control | Treatment | Control | Treatment | Control | Treatment | Control |
| *Panel A: Regional-level variable* | | | | | | | | |
| Local taxes from mining (million US$) | 0.31 | 0 | 1.36 | 0 | 10.15 | 0 | 12.96 | 0 |
| *Panel B: Household-level variables* | | | | | | | | |
| Household head's age (years) | 46.50 | 44.51 | 46.30 | 44.98 | 44.78 | 45.80 | 43.35 | 46.26 |
| | (15.06) | (14.39) | (15.57) | (14.51) | (15.00) | (14.26) | (14.63) | (15.05) |
| Household head is married | 0.63 | 0.69 | 0.47 | 0.67 | 0.51 | 0.63 | 0.47 | 0.59 |
| | (0.48) | (0.46) | (0.50) | (0.47) | (0.50) | (0.48) | (0.50) | (0.49) |
| Household head is male | 0.74 | 0.82 | 0.71 | 0.80 | 0.73 | 0.77 | 0.71 | 0.75 |
| | (0.44) | (0.39) | (0.45) | (0.40) | (0.44) | (0.42) | (0.45) | (0.43) |
| Household head's education (years) | 8.79 | 8.82 | 9.52 | 9.57 | 10.34 | 10.12 | 12.10 | 10.30 |
| | (4.22) | (4.15) | (4.30) | (4.35) | (4.91) | (4.50) | (4.40) | (4.79) |
| Ln(per capita income) | 11.45 | 11.15 | 12.11 | 11.77 | 12.35 | 11.95 | 12.34 | 12.10 |
| | (0.79) | (0.79) | (0.62) | (0.68) | (0.67) | (0.63) | (0.61) | (0.65) |
| Lives in apartment/house | 0.07 | 0.11 | 0.08 | 0.07 | 0.06 | 0.10 | 0.10 | 0.11 |
| | (0.26) | (0.31) | (0.27) | (0.26) | (0.24) | (0.29) | (0.30) | (0.32) |
| Lives in rural area | 0.61 | 0.70 | 0.62 | 0.74 | 0.61 | 0.61 | 0.62 | 0.63 |
| | (0.49) | (0.46) | (0.49) | (0.44) | (0.49) | (0.49) | (0.49) | (0.48) |
| Number of households | 304 | 1,597 | 312 | 1,819 | 622 | 2,493 | 624 | 2,582 |
| *Panel C: Individual-level variables* | | | | | | | | |
| Individual's age (years) | 28.16 | 27.33 | 30.10 | 28.55 | 28.51 | 28.60 | 27.82 | 28.99 |
| | (19.11) | (18.15) | (19.99) | (18.95) | (19.30) | (19.31) | (19.35) | (19.98) |
| Individual is male | 0.48 | 0.49 | 0.47 | 0.49 | 0.48 | 0.49 | 0.50 | 0.49 |
| | (0.50) | (0.50) | (0.50) | (0.50) | (0.50) | (0.50) | (0.50) | (0.50) |
| Individual's education (years) | 6.90 | 6.76 | 7.76 | 7.51 | 7.42 | 7.48 | 7.89 | 7.48 |
| | (4.93) | (4.92) | (5.49) | (5.59) | (5.98) | (5.72) | (5.97) | (5.55) |
| Ln(per capita wage income) | 5.16 | 4.37 | 5.80 | 5.49 | 6.28 | 5.92 | 7.50 | 6.25 |
| | (5.42) | (5.32) | (5.77) | (5.65) | (5.90) | (5.69) | (5.67) | (5.65) |
| Lives in apartment/house | 0.08 | 0.10 | 0.07 | 0.07 | 0.06 | 0.09 | 0.10 | 0.11 |
| | (0.27) | (0.31) | (0.25) | (0.25) | (0.23) | (0.29) | (0.30) | (0.32) |
| Lives in rural area | 0.59 | 0.69 | 0.62 | 0.75 | 0.62 | 0.63 | 0.62 | 0.62 |
| | (0.49) | (0.46) | (0.49) | (0.44) | (0.49) | (0.48) | (0.48) | (0.48) |
| Number of individuals | 1,201 | 6,407 | 985 | 6,527 | 1,961 | 8,917 | 1,894 | 8,812 |

*Note:* Panel A reports local taxes and fees paid by the mining company. The control group does not receive any fees from the large-scale mining company. Panel B and C reports the independent variables for the household- and individual-level analysis, respectively. Dummy variables indicating male, married, living in apartment/house and rural areas show their sample proportions. Standard deviations are reported in the parentheses.

Southgobi is the only province with more people settling in than those emigrating (IAM, 2018). However, these factors are believed to be minor to affect my analysis setting[16].

Finally, Panel C provides individual-specific control variables. Individuals' age, the proportion of males in the community, and education in years are similar and stable over time for both groups. The log of wage income remains higher for the treatment individuals. There is no clear pattern in the share of households living in apartments/houses and rural areas for both groups. The independent variables indicate that the treatment and control households/individuals are not systematically different.

## 2.4 Results

I start this section with a brief descriptive macroeconomic analysis. Before estimating the primary model in Subsection 2.3.1, I examine the mining sector's impact on provincial macroeconomic indicators to understand whether the extractive industry has an overall effect on the local economy. I estimate an unrestricted three-variable vector autoregressive (VAR) model, employing Mongolia's provincial data, and use the Cholesky decomposition to estimate impulse response functions, thereby analyzing the mining sector's impact ($\Delta$M) on provincial GDP ($\Delta$Y) and government revenue ($\Delta$G).[17]

The results of the VAR model and impulse response functions shown in Figure 2.4 suggest that provinces with significant mineral resources are those that most benefit from mining activities, reinforcing my preference to study the large-scale mine's impact at the household level. I find that a shock to mining sector production has, in the short run, a significantly positive effect on provincial GDP and a positive though insignificant effect on government revenue in those provinces with large mineral deposits (Panel (a) in Figure 2.4). The effect is not significant in provinces without considerable mineral deposits (Panel (b) in Figure 2.4) (see Appendix 2.A for the entire model).

In investigating the causal effect of the mining activity on household expenditures, I estimate the DiD model in three stages. In the baseline model, I regress the dependent variables on the exposure variable (i.e., $M_t \times D_s$) with survey year and province fixed effects. I then add the household-specific control variables to the model. I include (log of) household per capita income

[16]The number of households in Southgobi in the HSES sample changes proportionally with other provinces, indicating the faster growth in number of households in Southgobi compared to the control provinces is not unique to Southgobi province.

[17]The Cholesky decomposition constrains the VAR system such that the shock from the least exogenous series has no direct contemporaneous effect on the most exogenous series (Sims, 1980; Enders, 2010). In the exercise, I rank the variables in terms of their contemporaneous exogeneity as mining production, GDP, and government revenue per capita.

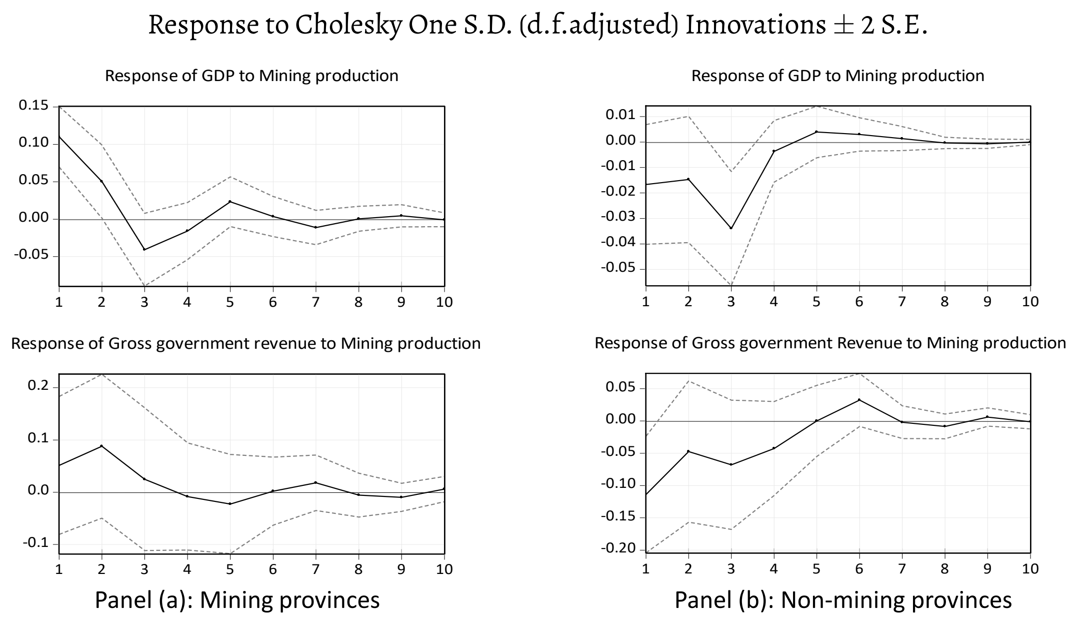



**Figure 2.4: Impulse response functions for provinces**

in the final stage to estimate the preferred model. Sample weights are used, and robust standard errors are clustered at the HSES survey cluster-level to account for differences in the model within households.[18] All tests are conducted at the conventional five percent significance level.[19]

### 2.4.1 Effect on income, food and non-food expenditures

Table 2.4 reports the estimates of Model 2.1. The DiD estimate on household per capita income is statistically insignificant in column 1, indicating no difference in income between the treatment and control groups. The year fixed effects show the significant growth in the incomes of control households during 2012-2016. The addition of household-specific control variables does not affect the results, as shown in column 2. Therefore, I do not find evidence that local taxes and fees from the large-scale mine significantly increase household incomes. However, income is a more volatile and sensitive measure than consumption/expenditure because accurate income measurement requires survey respondents to understand their assets, returns, profits, and income (Deaton, 1997). In addition, income does not provide us with detailed information about how households make consumption choices as local economic activity increases.

[18] For individual level analysis, robust standard errors are clustered at the household level.
[19] Results that are not presented here are available from the author upon request.

**Table 2.4: DiD results of the mining impact on income, food and non-food expenditures**

| | ln(income) | | ln(food) | | | ln(non-food) | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Ln(local taxes) × mining | 0.005 | 0.002 | 0.105*** | 0.105*** | 0.104*** | -0.074*** | -0.087*** | -0.088*** |
| | (0.020) | (0.018) | (0.017) | (0.016) | (0.014) | (0.021) | (0.019) | (0.014) |
| 2012 | 0.627*** | 0.609*** | 0.245*** | 0.241*** | 0.000 | 0.510*** | 0.488*** | 0.068** |
| | (0.034) | (0.033) | (0.027) | (0.027) | (0.023) | (0.043) | (0.039) | (0.033) |
| 2014 | 0.799*** | 0.768*** | 0.341*** | 0.334*** | 0.031 | 0.804*** | 0.769*** | 0.240*** |
| | (0.034) | (0.032) | (0.025) | (0.024) | (0.022) | (0.040) | (0.036) | (0.032) |
| 2016 | 0.923*** | 0.856*** | 0.117*** | 0.095*** | -0.244*** | 0.787*** | 0.718*** | 0.128*** |
| | (0.034) | (0.032) | (0.027) | (0.027) | (0.023) | (0.040) | (0.036) | (0.031) |
| Household head's age (years) | | 0.011*** | | 0.006*** | 0.001*** | | 0.006*** | -0.002*** |
| | | (0.001) | | (0.000) | (0.000) | | (0.001) | (0.000) |
| Household head is male | | 0.186*** | | 0.157*** | 0.083*** | | 0.140*** | 0.011 |
| | | (0.022) | | (0.019) | (0.016) | | (0.023) | (0.018) |
| Household head's education (years) | | 0.027*** | | 0.003* | -0.008*** | | 0.038*** | 0.019*** |
| | | (0.002) | | (0.001) | (0.001) | | (0.002) | (0.002) |
| Household head is married | | -0.209*** | | -0.297*** | -0.214*** | | -0.070*** | 0.074*** |
| | | (0.021) | | (0.017) | (0.014) | | (0.022) | (0.017) |
| Ln(per capita income) | | | | | 0.395*** | | | 0.689*** |
| | | | | | (0.011) | | | (0.016) |
| Lives in apartment/house | | 0.362*** | | 0.095*** | -0.048** | | 0.341*** | 0.091*** |
| | | (0.034) | | (0.022) | (0.021) | | (0.034) | (0.024) |
| Lives in rural area | | 0.012 | | 0.146*** | 0.141*** | | -0.087*** | -0.096*** |
| | | (0.021) | | (0.019) | (0.016) | | (0.026) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.24 | 0.33 | 0.13 | 0.20 | 0.41 | 0.20 | 0.28 | 0.58 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 6 run the basic models with province and year fixed effects. Columns 2, 4 and 7 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 5 and 8 add log of household per capita income in the model.

Consequently, I focus on household expenditures, which is considered a better and more reliable indicator of living standards at the household level (Deaton and Zaidi, 2002).[20]

The DiD estimate in the baseline model in column 3 for household per capita food expenditure is positive and significant, providing evidence that a 10 percent increase in local taxes from the large-scale mine increases food expenditure by the treatment households by one percent in Southgobi. The control households increased their food consumption significantly over time, as indicated by the year fixed effects.

Household food expenditure is combination of food price and quantity. Therefore, the positive effect on food expenditure can result from increases in either prices or quantity of food purchased. I examine the monthly overall consumer price index (CPI) across the country over the period between 2011 and 2015 in Figure 2.5. The monthly CPI for Southgobi province and the neighboring provinces are similar. Furthermore, the CPI for Southgobi is lower in 2014 and 2015 than those of the control provinces, indicating that price increases do not drive the empirical results for household food expenditure.

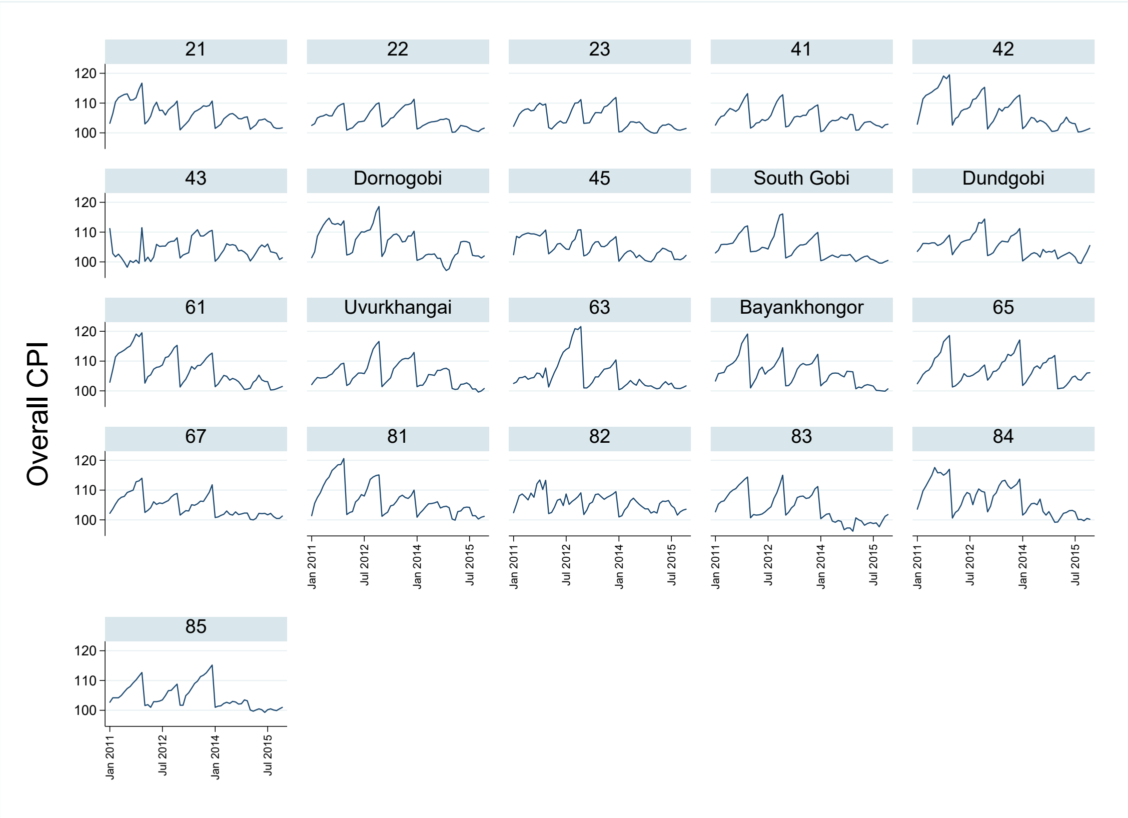



**Figure 2.5: Provincial monthly CPI, 2011-2015**

[20]Consumption has smaller seasonal fluctuations than income, especially in developing countries where households finance their consumption from their assets or credits to smooth their consumption even when there is little or no income (Deaton and Zaidi, 2002).

The results remain similar when I add the household-specific control variables in column 4. The coefficients of the control variables reported in column 4 are mostly meaningful. As expected, households with male, older, and more educated heads living in apartments/houses spend significantly more food than younger, female, and single-headed households living in traditional gers.[21] In addition, rural households spend significantly more on food in comparison to their urban counterparts because of higher food prices, which are attributable to mainly transportation costs (Li, 2021). On the other hand, households with married heads spend significantly less on food per person than those households with a single head, possibly because they can take advantage of economies of scale, cook more at home, and spend less on food outside the home (Gerrior et al., 1995; Roos et al., 1998). Educational attainment, along with the marital and socio-economic status of household heads, therefore, affect food choices and expenditures (Fraser et al., 2000; Venn et al., 2018).

I include income to estimate the preferred model and report the results in column 5. Although income significantly affects food expenditures, it does not alter the main finding. The positive and significant DiD estimate in column 5 indicates that mining activities may positively affect food consumption beyond the conventional income channel. Including income in the model reverses the household head's education and residential property signs; i.e., the coefficients become negative. These variables are highly correlated with income, and without the income variable, they have the expected signs, indicating that I could be over-controlling. Notably, the DiD estimate remains similar to columns 3 and 4. The adjusted–$R^2$ of 0.41 in the preferred model in column 5 explains the variations in household food consumption reasonably well.

I next examine the impact of mining activities on household non-food expenditure as I have no *a prior* expectations about households' preferences for non-food items when local economic activities increase. The results presented in Columns 6, 7, and 8 of Table 2.4, indicate that mining taxes lead to a reduction in non-food expenditure. Specifically, a 10 percent increase in the collection of local taxes results in around a one percent reduction in non-food expenditure (Column 8). Although we previously observed that the absolute value of household non-food expenditure increased over time for the treatment households, it increased to a lesser extent than that of the control counterparts. While the elasticity of non-food expenditure is usually higher than that for food, the opposite may occur in low-income countries where the budget share for food may in-

[21] A ger is a traditional Mongolian house that is built by assembling a wooden framework and covering it with traditional felt. It is the most portable and suitable dwelling for nomads. People live in gers in both rural and urban areas in Mongolia. In 2016, 40 percent of the total Mongolian population lived in gers, 36 percent in detached houses, and 24 percent in apartments (NSO, 2019).

crease as income rises (Almås, 2012). My results indicate that the treatment households spend more on food and less on non-food items. For example, Bhalotra and Attfield (1998) report that low-income households in rural Pakistan spent nearly all of their additional income on food, indicating a higher elasticity for food expenditure than for non-food spending. Similarly, Hasan (2016) find that households in Bangladesh, a low-income country, initially increased their budget share for food when their incomes rose.

The results reported in this study provide additional evidence on the economic benefits realized by local communities when large-scale mining occurs. Overall, the results in Table 2.4 highlight that the treatment households modify their consumption patterns when local economic activities increase as large-scale mining development commences. The findings align with other studies that examine the effect of mining on welfare. For example, mining appears to have a positive impact on household consumption around a large-scale gold mine and to reduce poverty in mining districts in Peru (Aragón and Rud, 2013; Loayza and Rigolini, 2016). Bazillier and Girard (2020) also find that a 1.2 percent increase in household consumption near artisanal and small-scale gold mines in Burkina Faso is associated with a 10 percent increase in gold prices. Similarly, in developed country context, a coal seam gas discovery increased median household incomes in Southern Queensland, Australia, and oil and gas endowments resulted in real wage increases in U.S counties (Fleming and Measham, 2015; Allcott and Keniston, 2017).

### 2.4.2 Effect on health and educational outcomes

The health and education outcomes of the local population are primary pillars of sustainable economic growth and development in mining regions in developing countries. Public and private investments resulting from mining activities can improve local health and education outcomes, which benefit the population in the long run (Stijns, 2006; Mousavi and Clark, 2021). Therefore, I examine whether large-scale mining activities affect household health and educational outcomes and report the analysis of household medical expenditure in Table 2.5. The DiD estimate in column 1 is positive but statistically insignificant. However, as soon as I include the household-specific control variables in column 2, the results are significant at the conventional level, indicating that a 10 percent rise in local taxes increases medical expenditure by 0.8 percent. The result remains similar with the inclusion of household income in the model.

**Table 2.5: DiD results of the mining impact on medical expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(local taxes) × mining | 0.053 | 0.080** | 0.079** |
| | (0.036) | (0.033) | (0.031) |
| 2012 | 0.585*** | 0.546*** | 0.217*** |
| | (0.070) | (0.068) | (0.070) |
| 2014 | 0.900*** | 0.835*** | 0.420*** |
| | (0.065) | (0.065) | (0.069) |
| 2016 | 1.236*** | 1.110*** | 0.648*** |
| | (0.064) | (0.063) | (0.067) |
| Household head's age (years) | | 0.032*** | 0.026*** |
| | | (0.001) | (0.001) |
| Household head is male | | 0.092** | -0.008 |
| | | (0.045) | (0.043) |
| Household head's education (years) | | 0.023*** | 0.008** |
| | | (0.003) | (0.003) |
| Household head is married | | -0.252*** | -0.139*** |
| | | (0.040) | (0.038) |
| Ln(per capita income) | | | 0.540*** |
| | | | (0.024) |
| Lives in apartment/house | | 0.361*** | 0.166*** |
| | | (0.058) | (0.056) |
| Lives in rural area | | -0.232*** | -0.239*** |
| | | (0.046) | (0.045) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.15 | 0.27 | 0.33 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

The results in Table 2.5 provide evidence that the treatment households increase their medical expenditure, which could result from two possibilities. First, increased health care expenses could mean that local people living nearby the mine experience more frequent or severe illnesses than their counterparts. Studies in other countries sometimes reported such an outcome. For example, the incidence of anemia among women and stunting in children in 44 resource-rich developing countries were higher for those who live in the proximity of mines that release lead contamination than those who live further away (von der Goltz and Barnwal, 2019). Similarly, pollution from gold mines appears to reduce productivity in rural areas in Ghana (Aragón and Rud, 2013) and individuals living within five kilometers of a mine have a higher likelihood of reporting illness in Mongolia (Narantungalag et al., 2021).

Therefore, I examine whether the likelihood of reporting illness increases with mining activities in Southgobi. I estimate Equation 2.1 for individuals using the linear probability, probit and logit models. In this setting, the dependent variable is a dummy variable taking the value of one for individuals who were ill in the month prior to the survey and zero otherwise. I include individual-specific control variables in the preferred specification and report the results in Table 2.6. The results from all three models without and with the control variables indicate that the probability of reporting illness does not increase significantly in Southgobi province. Since the results provide no evidence that mining is causing adverse health impacts on residents in Southgobi, I associate the positive health expenditure elasticity with higher income and access to health care services created by the mining industry.

The other reason for the increased medical expenditure of households in Southgobi is the availability of improved health care services and facilities. The provincial government capital investment in the health sector in Southgobi increased from less than one percent of total provincial government expenditures in 2009. However, it increased to four and five percent in 2011 and 2014, respectively, marking the highest level of capital investment during 2008-2016 (NSO, 2019; SHD, 2020).[22] Such an increase in the health sector investment in Southgobi also reflects the overall impact of the mining industry in 2010-2014, when the country experienced its highest economic growth rates. In addition, OT provided training and scholarships for doctors and nurses on medical waste management, first aid and supplied hospital equipment to various towns within the province between 2012-2013 (Oyu Tolgoi, 2018). Hence, the increased public investment in the health sector and the additional support from the mining company can strengthen the capacity, quality, and accessibility of health care services in Southgobi. Such improvements allow people to spend more on their health care by relaxing the supply constraints on medical services.[23]

The findings on medical expenditure and health outcomes in Southgobi province align with the population health statistics. For example, the monthly under-five mortality rate per 1,000 live births was below the national median, dropping to 16 in 2016 from 23 in 2009. In contrast, other provinces made slower progress. Although the new cases of cancer reported per 10,000 population rose by 4-9 percent annually on average across the provinces in the study, the growth in mortality rate from cancer per 10,000 population remained similar across Southgobi and two of the control provinces, Dundgovi and Uvurkhangai (NSO, 2019). The increased number of new cases of cancers can also be linked to better health services as people are more likely to be diagnosed with such illnesses when health services are improved. Therefore, my results point out that local

[22]At the same time the percentage of health expenditure to total central government budget expenditures dropped to seven percent in 2016 from nine percent in 2008 (NSO, 2019).

[23]Note that such programs proved to be useful for health promotion. For example, infant mortality declined in African localities. Large-scale gold-mining spurred local economic growth and improved access to health care information, contributing to the effective treatment of child diarrhea (Tolonen, 2018).

communities increase their medical expenditure because of improved and more accessible health care services.

**Table 2.6: DiD results of the mining impact on the likelihood of reporting illness**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Ln(local taxes) × mining | -0.004 | -0.003 | -0.003 | -0.001 | -0.003 | -0.001 |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| 2012 | | -0.006 | | -0.007 | | -0.006 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2014 | | 0.003 | | 0.002 | | 0.002 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2016 | | -0.007* | | -0.008* | | -0.007* |
| | | (0.004) | | (0.004) | | (0.004) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Individual is male | | -0.015*** | | -0.013*** | | -0.013*** |
| | | (0.002) | | (0.002) | | (0.002) |
| Individual's education (years) | | -0.002*** | | -0.001*** | | -0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Ln(per capita wage income) | | -0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Lives in apartment/house | | 0.015** | | 0.013*** | | 0.011** |
| | | (0.006) | | (0.005) | | (0.004) |
| Lives in rural area | | -0.031*** | | -0.027*** | | -0.025*** |
| | | (0.004) | | (0.003) | | (0.003) |
| Model | LPM | LPM | Probit | Probit | Logit | Logit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$/Psedu $R^2$ | 0.00 | 0.02 | 0.01 | 0.05 | 0.01 | 0.05 |
| Number of individuals | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1, 3 and 5 run the basic models with province and year fixed effects. Columns 2, 4 and 6 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

I now investigate the effects of mining activities on household education expenditure in Table 2.7. The DiD estimate in the baseline model is negative and only marginally significant at the 10 percent level. However, the results with additional control variables in columns 2 and 3 are negative and significant, indicating that a 10 percent rise in the collection of mining taxes leads to a decline of 2.1 percent in per capita education expenditure (column 3). Furthermore, an increase in income reduces education expenses, as indicated by the model's log of per capita income variable. This shows that households in Southgobi do not increase their education expenditure even if their incomes rise.

I associate this pattern of education expenditure with two potential mechanisms: young people seeking higher incomes in the mining sector and improved access to schools, vocational education, and scholarships provided by OT at no cost. First, the lower expenditure on education could mean that younger people may substitute their additional years of education for higher incomes when the mining sector is booming. Some previous studies find that natural resource extraction negatively affects educational attainment, and reduces test scores and college enrolment levels (e.g., Douglas and Walker, 2017; Santos, 2018; Ahlerup et al., 2020; Mejía, 2020). Conversely, oil windfall revenues led to an increase in the number of teachers and classrooms in Brazilian municipalities (Caselli and Michaels, 2013). Hence, I examine whether mining activities affect educational outcomes negatively in Southgobi.

**Table 2.7: DiD results of the mining impact on education expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(local taxes) × mining | -0.133* | -0.213*** | -0.210*** |
| | (0.077) | (0.067) | (0.069) |
| 2012 | -0.394*** | -0.326*** | 0.541*** |
| | (0.141) | (0.125) | (0.132) |
| 2014 | -0.428*** | -0.340*** | 0.752*** |
| | (0.140) | (0.128) | (0.139) |
| 2016 | -0.757*** | -0.524*** | 0.693*** |
| | (0.136) | (0.125) | (0.140) |
| Household head's age (years) | | -0.085*** | -0.069*** |
| | | (0.003) | (0.003) |
| Household head is male | | -1.796*** | -1.530*** |
| | | (0.136) | (0.127) |
| Household head's education (years) | | 0.054*** | 0.093*** |
| | | (0.009) | (0.009) |
| Household head is married | | 3.097*** | 2.800*** |
| | | (0.113) | (0.106) |
| Ln(per capita income) | | | -1.422*** |
| | | | (0.062) |
| Lives in apartment/house | | -0.393*** | 0.122 |
| | | (0.139) | (0.137) |
| Lives in rural area | | -0.413*** | -0.396*** |
| | | (0.087) | (0.088) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.01 | 0.23 | 0.28 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

I estimate Equation 2.1 for individuals using the OLS and ordered logit models. The outcome variable is each household member's years of schooling above six, and I add individual-specific control variables in the preferred specifications. The results in Table 2.8 from both models are positive and significant. It implies that the increase in educational attainment in Southgobi is significantly higher than those of the control group over the period. Thus, I reject the hypothesis that school enrollment is low and conclude that mining activities positively impact educational outcomes for Southgobi residents while allowing them to spend less on education services than their control counterparts.[24] The reduction in education expenditure may be attributable to the availability of new schools, kindergartens, vocational education centers, and tertiary scholarships provided by OT through its corporate social responsibility investments (Oyu Tolgoi, 2018). This allows households to spend less on education while achieving better educational outcomes.

**Table 2.8: DiD results of the mining impact on educational attainment**

| | OLS | | Ordered-logit | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Ln(local taxes) × mining | 0.122** | 0.147*** | 0.067*** | 0.070*** |
| | (0.058) | (0.054) | (0.021) | (0.020) |
| 2012 | 0.882*** | 0.164 | 0.194*** | -0.077** |
| | (0.108) | (0.104) | (0.037) | (0.039) |
| 2014 | 0.864*** | 0.065 | 0.171*** | -0.105*** |
| | (0.097) | (0.102) | (0.033) | (0.037) |
| 2016 | 1.094*** | 0.051 | 0.334*** | -0.041 |
| | (0.095) | (0.100) | (0.033) | (0.037) |
| Individual's age (years) | | 0.079*** | | 0.030*** |
| | | (0.002) | | (0.001) |
| Individual is male | | -0.711*** | | -0.283*** |
| | | (0.050) | | (0.018) |
| Ln(per capita income) | | 0.822*** | | 0.313*** |
| | | (0.052) | | (0.020) |
| Lives in apartment/house | | 1.482*** | | 0.674*** |
| | | (0.113) | | (0.046) |
| Lives in rural area | | -1.019*** | | -0.418*** |
| | | (0.069) | | (0.026) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.02 | 0.15 | | |
| Pseudo $R^2$ | | | 0.00 | 0.03 |
| Number of individuals | 32,552 | 32,552 | 32,552 | 32,552 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1 and 3 run the basic models with province and year fixed effects. Columns 2 and 4 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

The results from Tables 2.5–2.8 confirm that the residents in Southgobi are better off with the large-scale copper-gold mine development in their localities. I observe that the treatment households increase their medical expenditure, but they do not report illness more than their control counterparts. Although they reduce their educational expenses, their educational attainments are significantly higher than those in the neighboring provinces. Together these findings highlight that examining household expenditure patterns at a disaggregated level provides useful information about the potential social benefits of large-scale mining activities, complementing the findings of previous studies such as Douglas and Walker (2017); Tolonen (2018) and Mejía (2020).

[24] For example, the number of full-time students enrolled in the general education schools in Southgobi remained at 10.5 thousand during 2009-2011, and declined slightly to 10.4 thousand in 2012-2013 and then increased to 11.4 thousand in 2016. On the other hand, the number of students in the three other neighboring provinces was in decline, while it increased slightly in one of the control provinces in the same period (NSO, 2019).

### 2.4.3 Effect on electricity and other non-food expenditures

My final investigation looks at whether the large-scale mining activities have a discernible impact on expenditures on electricity and other non-food items, including clothing, transportation, and communication services. Resource extraction and utilization require large-scale infrastructure development such as power plants, roads, and rail networks for operating mines and transporting commodities (Michaels, 2011; Collier and Laroche, 2015; Bonfatti and Poelhekke, 2017; De Haas and Poelhekke, 2019). I investigate whether the OT mining region households benefit from such infrastructure development.

The results from the analysis of expenditure on electricity and other non-food items are presented in Table 2.9. The DiD estimate in column 3 shows that electricity expenditure increases by 2.6 percent when there is a 10 percent increase in the collection of mining taxes and fees. The higher expenditures relate to the increased generation and supply of electricity in the mining region, with the central government and the mining company jointly supporting the development of power supply infrastructure. The central government built a power transmission line and substation connected to the central grid system in 2013 in Southgobi, which ensured permanent access to electricity for households in Southgobi (Ministry of Energy, 2013). In addition, OT connected two Southgobi towns, which had intermittent electricity supply, to the central electric grid (Oyu Tolgoi, 2018). Therefore, households have a permanent electricity supply due to increased public and private investment, raising household consumption and expenditure on power.

The final outcome variable I examine is household expenditures on other non-food items. The DiD estimates for all models in columns 4-6 in Table 2.9 are negative and significant. The results from the preferred model indicate that a 10 percent increase in the collection of local mining taxes and fees reduces expenditures on other non-food items by 0.8 percent (column 6). As expected, these results are similar to the findings in Table 2.4 and confirm that the treatment households increased their expenditures on non-food items, excluding medical services and electricity, to a lesser extent than the control households in the neighboring provinces. The observed changes in non-food consumption expenditures may come about for the following reasons. First, it appears that households are increasing their food consumption by significantly reducing their expenditures on non-food items. Second, the treatment households may have more varieties of non-food goods offered at more competitive prices in the local markets than the control households.

**Table 2.9: DiD results of the mining impact on electricity and other non-food expenditures**

| | ln(electricity) | | | ln(other non-food) | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(local taxes) × mining | 0.322* | 0.259** | 0.258** | -0.081*** | -0.095*** | -0.096*** |
| | (0.186) | (0.122) | (0.121) | (0.022) | (0.020) | (0.015) |
| 2012 | 1.049*** | 0.723*** | 0.588*** | 0.564*** | 0.545*** | 0.101*** |
| | (0.276) | (0.191) | (0.193) | (0.043) | (0.040) | (0.033) |
| 2014 | 0.665** | 0.283 | 0.114 | 0.868*** | 0.838*** | 0.279*** |
| | (0.319) | (0.204) | (0.209) | (0.041) | (0.037) | (0.032) |
| 2016 | 1.658*** | 1.002*** | 0.813*** | 0.833*** | 0.771*** | 0.149*** |
| | (0.301) | (0.199) | (0.200) | (0.040) | (0.037) | (0.032) |
| Household head's age (years) | | 0.021*** | 0.018*** | | 0.005*** | -0.004*** |
| | | (0.003) | (0.003) | | (0.001) | (0.000) |
| Household head is male | | -0.592*** | -0.633*** | | 0.162*** | 0.027 |
| | | (0.100) | (0.101) | | (0.025) | (0.019) |
| Household head's education (years) | | 0.243*** | 0.237*** | | 0.035*** | 0.015*** |
| | | (0.008) | (0.009) | | (0.002) | (0.002) |
| Household head is married | | -0.220** | -0.174* | | -0.087*** | 0.065*** |
| | | (0.091) | (0.092) | | (0.023) | (0.017) |
| Ln(per capita income) | | | 0.221*** | | | 0.728*** |
| | | | (0.062) | | | (0.016) |
| Lives in apartment/house | | 0.583*** | 0.503*** | | 0.345*** | 0.081*** |
| | | (0.126) | (0.132) | | (0.036) | (0.025) |
| Lives in rural area | | -3.063*** | -3.066*** | | -0.067** | -0.076*** |
| | | (0.116) | (0.116) | | (0.027) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.08 | 0.39 | 0.39 | 0.21 | 0.27 | 0.58 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1, 3 and 5 run the basic models with province and year fixed effects. Columns 2, 4 and 6 add household-specific controls to the specification. The reference groups is female, never married, separated or widowed, living in traditional gers and urban areas.

For example, De Haas and Poelhekke (2019) find that mining activities have a positive impact on firms in non-tradable sectors within the immediate vicinity of the mines and positive overall spending effects on firms further away. The findings also highlight that large-scale capital-intensive mining activities do not directly result in local price increases as the demand for labor is less intensive than smaller scale labor-intensive mines, putting less pressure on local prices (Pelzl and Poelhekke, 2021). Therefore, households may face more competitive prices and consumption opportunities because more goods and services become locally available following increased economic activities resulting from mining activity (Papageorgiou and Thisse, 1985).

### 2.4.4 Common trend

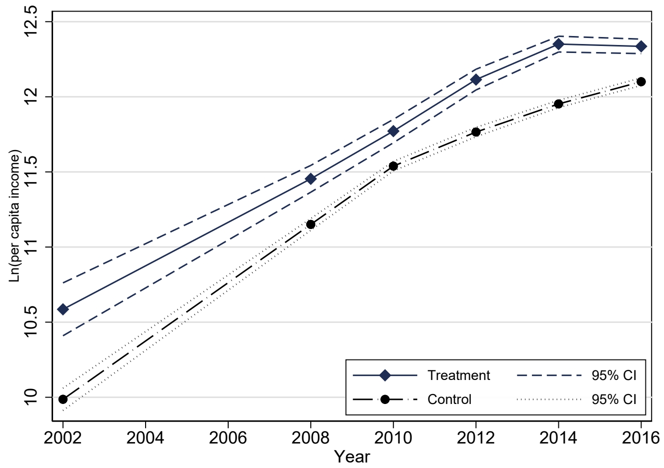
The validity of DiD model relies on the common trend assumption as discussed previously. The earliest HSES round that I have available to examine the common trend is the 2002 round, the first HSES Mongolia conducted using the internationally applied methodology for the household survey. However, the 2002 round lacks data for the critical control variables used in my empirical specifications. Therefore, I examine the common trend assumption visually, using the key dependent variables such as income, food, and non-food expenditures in Figure 2.6.

Panel A plots the log of monthly per capita real income and shows that the incomes of treatment and control households had similar patterns until 2010. Although there was a slight increase in the incomes of the treatment households over the period 2012-2016, an apparent divergence between both groups did not occur, suggesting that the impact of mining activities on income is negligible. Panel B shows that although the treatment households had higher food expenditures in 2002, both groups had similar food expenses, which grew in parallel in 2008-2010. After 2012, the difference in food expenditure between the treatment and control households increased, with the treatment households increasing their food expenditure at a higher rate than the control households. The common trend observed in food expenditure confirms the validity of the DiD model. The picture is less clear for the non-food expenditures in Panel C as the expenditures of both groups seem to follow similar patterns. The reason is that the non-food expenditures comprise expenses for many different types of goods and services consumed by households. However, the disaggregated expenditures on health, education, and electricity items analyzed empirically show significant differences between the two groups. Overall, the common trend assumption is likely to be valid.

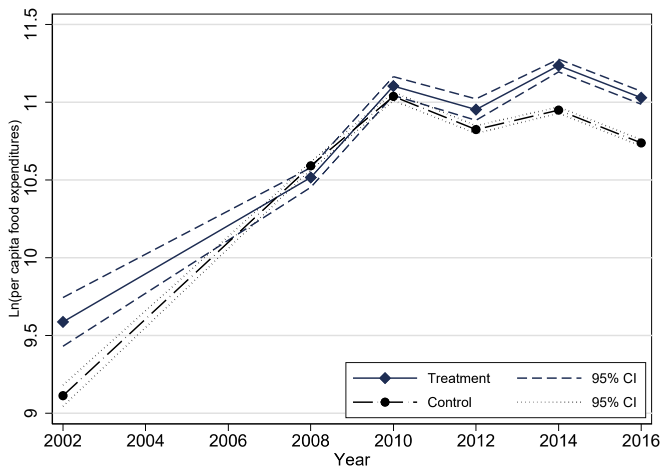
### 2.4.5 Robustness checks

I perform additional robustness checks to confirm that the main results are consistent with data, model, and methods modifications. First, I employ a traditional DiD model that uses dummy variables to show that the choice of my independent variable, local mining taxes and fees, does not drive the results. In this model, the base year is 2008, and *After* is an indicator variable taking the value of one for the years after 2012.[25] The interaction term between Southgobi and *After* is the DiD estimate–the variable of interest. I estimate the DiD models with the household-specific controls on all outcome variables from Tables 2.4, 2.5, 2.7 and 2.9. The DiD estimates presented in Table 2.B.1 are in line with my main findings, providing evidence that large-scale mining activities have a significant impact on household expenditures. Although the effects on household medical and electricity expenditures are statistically insignificant, the coefficient estimates are high and economically significant.

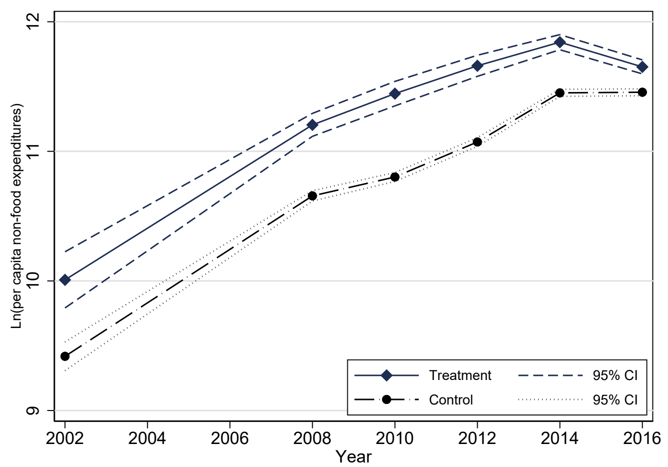
[25] I estimate the following conventional DD model: $y_i = \delta + \gamma D_s + \beta_t(\eta_t \times D_s) + \eta_t + \alpha_s + X_i\Theta + \varepsilon_i$, where, in addition to the previous notations, $\eta_t$ is a dummy taking the value of one for the years after 2012, and zero otherwise. The results also remain robust when I use a flexible DiD model with the interaction of Southgobi with each year, instead of $After$.




**Panel A: Household income**




**Panel B: Household food expenditure**




**Panel C: Household non-food expenditure**

**Figure 2.6: Monthly income, food and non-food consumption, 2002-2016**

Source: NSO (2019)

In the main analysis, I used local taxes and fees paid to the provincial government to measure mining activities. Mining taxes and fees are preferred because they indirectly link to the local economy when the backward and forward linkages are limited because of local market constraints. The subnational government spends these mining-related revenues to provide public services and invest in infrastructure and health and education sectors. However, there are other direct and indirect linkages to the local economy, which can affect household expenditures.

Thus, I next examine two competing variables that can capture the impact of mining activities on household expenditures. They are wages paid to employees (proxied by taxes paid for employee social security and medical insurance) and corporate social responsibility (CSR) investment made by the mining company. In modeling household expenditures, health, and education outcome variables, I use wages paid by the company to its employees as a proxy for mining activities and repeat Tables 2.4–2.9. The results indicate that mining wages also have a significant impact on household consumption and health and educational outcomes in the mining region (Tables 2.C.1 – 2.C.6). Note that the coefficient magnitudes are likely to be underestimated because the wages in the neighboring regions can also increase due to the high economic growth experienced in the country during the period of my analysis, leading to a smaller effect of mining wages on the components of household expenditures.

Third, I use CSR investment as a proxy for mining activities, and the results also indicate that there are similar significant effects on household expenditures (Tables 2.C.7 – 2.C.12). I observe that the effects of both mining wages and CSR investment on medical and electricity expenditures are positive but statistically insignificant. These outcomes could result because local taxes and fees already capture some of their effects.

Fourth, I undertake the analyses on a household rather than per capita basis. In this case, I employ household-level outcome variables and include household size in all models. Again, the DiD estimates with the household-level variables support the main findings (Tables 2.D.1 – 2.D.6). Although the estimates for educational expenditures are only marginally significant at the 10 percent level, they are consistent with the main results.

Finally, I examine whether variables in per capita terms affect my results. I explore this because there are economies of scale in household consumption, while demographic factors may also affect consumption levels. Income and consumption analyses widely utilize equivalence scales to address those issues (Bishop et al., 2014). Two well-known equivalence scales – the square root of family size (SRFS) and OECD equivalence scale are used (Schwarze, 2003; Breunig et al., 2019).

The former takes the square root of the number of family members to adjust the household size. The latter assigns one to the first adult and adds 0.5 for an additional adult and 0.3 for an extra child in the household. The models using the equivalized variables, the SRFS (Tables 2.E.1 – 2.E.6) and OECD scale (Tables 2.F.1 – 2.F.6), produce qualitatively similar results, supporting my main findings.

The overall results of this study highlight that large-scale mining activities significantly affect household consumption patterns in nearby communities. The treatment households increase their food consumption more than those who are not directly affected by large-scale mining activities. They also display a greater increase in their medical and electricity expenditures than their counterparts, although their educational expenditures are lower. While increased mining activities do not adversely affect the health of residents, educational outcomes improve in the mining region. Hence, my findings indicate that large-scale mining activities positively affect local residents' living standards.

## 2.5 Discussion and policy implications

This study documents some local economic benefits of early-stage large-scale mining activities on household expenditure patterns. I associate the significant changes in household food and non-food expenditures with increased local economic activities resulting from the investment in and development of a large-scale copper-gold mine. In particular, I use local taxes and fees paid by the large-scale mining company as a proxy for mining activities to arrive at three main findings.

First, the households living in the mining region increase their food expenditure relative to those living in the neighboring provinces. This positive outcome in food consumption highlights that households living in remote rural regions in developing countries have unmet food demands. Increased spending by the local government, financed by mining tax revenues, and lower transportation costs enabled by mining-related infrastructure development can increase the supply and variety of food and local produce in the market. Previous studies such as Aragón and Rud (2013), Lippert (2014) and Loayza and Rigolini (2016) find that real incomes and consumption increased in mining areas. My study establishes the causal link between mining activities and household food consumption.

Second, I observe that households also increase their expenditure on health care and services more than those not affected by large-scale mining. Consequently, I examine whether the higher medical expenditure is due to either increased illness or the availability of health care services. I find that individuals in the large-scale mining province do not report illness significantly more than their control counterparts. Thus, I associate higher spending on medical services with the increased availability of health care enabled by provincial government capital investment in the health sector. This finding to some extent, aligns with Tolonen (2018) who report that local industrial shocks such as mining activities spurred economic growth and created jobs, which reduced infant mortality. However, my results contrast with Aragón and Rud (2015) and von der Goltz and Barnwal (2019) who find that pollution from mining activities increases morbidity in resource-rich developing countries.

Third, the educational expenditures of the households in the mining region decline despite their increased incomes. My subsequent investigation of mining activities' effect on educational outcomes confirms that individuals' years of schooling increased significantly more than in the control group in the neighboring provinces. Earlier studies on the effects of natural resource extraction on human capital find that school drop-outs increase, and test scores and college enrolments decline in the presence of mining activities (Douglas and Walker, 2017; Zuo et al., 2019; Mejía, 2020; Ahlerup et al., 2020). However, I argue that the positive impact on educational outcomes is driven by CSR, which supports increased availability of schools, training centers, and additional financial support for tertiary education, as argued in other studies such as Stijns (2006, 2009) and Mousavi and Clark (2021).

I also find that households increase their electricity expenditure in the mining region as a result of increased investment in the energy sector and improved availability of electricity. Households reduce their expenditures on other non-food goods and services by increasing their expenses on food, medical care, and electricity. The increased spending on food and health care will benefit residents over time in the province with the large-scale mine. A higher level of nutrition and better access to health care will improve people's quality of life and increase their life-expectancy. In addition, higher educational outcomes, coupled with better health, will raise productivity, which is essential to sustainable growth and development of the mining region, including when mining operations cease in the future (Cust and Poelhekke, 2015; Venables, 2016).

The results of this study highlight that the mining sector's indirect channels such as local taxes for real estate and automobile use, along with fees on the use of land and water paid by mining companies, positively affect household consumption patterns. My investigation of disaggregated expenditures points out that households make their spending decisions based on their unmet food demands and increased availability of health and education services. These findings show that households prioritize the consumption of essential items such as food and expenditures that positively impact their future well-being, such as those on health and electricity, over other non-food goods and services. Importantly, reducing expenditure on education without reducing their service intake was possible due to the support of the mining company and local governments on that sector. The same is likely to be true for expenditure on other non-food items. Therefore, in addition to managing windfall revenues from the mining sector, resource-rich developing countries should ensure that some taxes and fees accrue to the local governments, which have a better understanding of local development needs. My findings also indicate that using household aggregate income or consumption may not indicate the magnitude of the positive impact when people enjoy a higher share of public benefit.

It is important to note two potential issues with this study. First, I investigated the impacts of a foreign-invested mega-mining project, Oyu Tolgoi, which has significantly higher capacity, scale, and resource use needs than mines smaller in size. While the results reported in this study are important, there remain some unresolved issues related to the investment agreement for Oyu Tolgoi, which may affect the positive outcomes in the local community in the future. Second, the study only focused on the short-run gains from mining as I only examined the effects occurring in the mine's early development and operational periods. Although I can infer that the short-run improvement in health, education, and food availability will provide long-run benefits, future research should examine the *ex-post* gains, focusing on the intermediate/outcome welfare indicators.

## 2.6 Conclusion

The current study finds that large-scale extractive industries can positively affect residents in developing countries by employing the difference-in-differences models with several rounds of recent household survey data from Mongolia. I provide robust evidence that increases in mining-related local taxes and fees result in increased household spending on food, health care, and electricity in the mining region. At the same time, households reduce their expenditures on education and other non-food items. These outcomes result from a large-scale mine's investment and development in the resource-producing region.

Three findings of the study are of particular importance. First, households in the mining region increase their food consumption relative to those in neighboring provinces. Second, household expenditure on health care in the mining area increases, but individuals in the area do not report illness more than their control counterparts. Third, households spend less on education, but their schooling years are significantly higher than the control group. Thus, my study highlights that households in the mining region prioritize their spending decisions based on unmet demands for basic needs such as food, electricity, and health care by reducing their expenses on education and other non-food items. Importantly, local government and mining companies support on education allowed people to reduce expenditure on that category without reducing their educational attainment. The increased food consumption and positive health and educational outcomes will assist in sustainable growth and development in the mining region now and in the future.

My investigation extends the literature on the effect of the mining sector's indirect linkages on the local economy by providing a detailed analysis of household expenditure patterns. Specifically, this study emphasizes that using household aggregate income or consumption may not indicate the extent of the positive impact of mining activities, as shown in this paper. The findings emphasize the importance of appropriate policy settings where local governments collect taxes for the use of local resources such as land and water by the extractive industries and use the proceeds for the benefit of local communities who might otherwise be negatively affected.

## 2.A Impact of mining: sub-national differences

Both large and small-scale mining activities take place across Mongolia. The mining sector's production comprises at least 40 percent of the provincial GDP in provinces where large-scale mining occurs. In contrast, mining activities make up less than five percent of provincial GDP in other provinces without large-scale mines (NSO, 2019). Therefore, examining the mining sector's impact at the sub-national level is useful to analyze and understand outcomes at the micro-level subsequently. Following the definition of Auty (1993) for a resource-rich country, I categorize nine provinces as resource-rich, mining provinces as at least eight percent of their annual provincial GDP comes from the mining sector for the period 2010-2018.[26] The remaining 12 are non-mining provinces. Table 4.A.1 presents the list of provinces with the categorization.

I examine sub-national effects, reflecting the importance of mining to provincial economies, through VAR analyses of macroeconomic variables. I investigate the following three-variable autoregressive process, separately for mining and non-mining provinces:

$$Y_{i,t} = A + B \times Y_{i,t-1} + e_{it} \tag{2.2}$$

where,

$$Y_{i,t} = \begin{bmatrix} Y^1_{i,t} \\ Y^2_{i,t} \\ Y^3_{i,t} \end{bmatrix}, \quad A = \begin{bmatrix} a_{10} \\ a_{20} \\ a_{30} \end{bmatrix}, \quad B = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, \quad e_{it} = \begin{bmatrix} \varepsilon^1_{i,t} \\ \varepsilon^2_{i,t} \\ \varepsilon^3_{i,t} \end{bmatrix},$$

and $Y^1_{i,t}, Y^2_{i,t}, Y^3_{i,t}, a_{m0}, a_{mn}$, and $\varepsilon^m$ indicates the natural logarithm of mining sector's production, GDP and government revenue, intercepts, coefficients, and error terms, respectively. All three macroeconomic variables are on per capita basis. I use provincial level macroeconomic panel data available for the period 2010-2018.

I use the Cholesky decomposition to create the impulse response functions from the VAR system to analyze the impact of the mining sector on the provincial economy. The Cholesky decomposition constrains the VAR system such that the shock ($\epsilon^3_{i,t}$) from the least exogenous series ($Y^3_{i,t}$) has no direct effect on the most exogenous series ($Y^1_{i,t}$), while forcing a significant asymmetry on the system (Sims, 1980; Enders, 2010). Changes in provincial GDP per capita are likely to influence

[26] I excluded the capital city Ulaanbaatar from the analysis because it is a separate urban area that is different from all provinces in terms of market size, population, and economic structure.

the government revenue collection due to tax implications. However, it is unlikely that changes in revenue collected by the provincial government have an instantaneous effect on the GDP per capita. All series are in their natural logarithms and first differenced to satisfy the stationary condition.[27] I divided the panel into mining and non-mining provinces based on the criteria mentioned above.

Figure 2.4 shows the impulse response functions for mining sector production, GDP, and government revenue, to a one standard deviation shock in the mining sector production. Panel (a) relates to the mining provinces. The top graph shows the response of the mining sector production to its one standard deviation shock. The mining sector production increases by 0.45 percent in the same year, then declines up to year four, increases up to year six, and reaches long-term stability after year eight. GDP increases by a little more than 0.1 percent in year one to a one standard deviation shock in the mining sector production in the following graph. GDP grows in the second year, and then the response is insignificant. Although the mining sector production shock increases the provincial government revenue up to year four, the effect is not significantly different from zero. Overall, a shock in mining sector production has positive effects on GDP and government revenue in the mining provinces in the short-run.

[Figure 2.4]

Panel (b) in Figure 2.4 shows the impulse response functions for non-mining provinces. A one standard deviation shock in the mining sector production causes itself to increase by 0.8 percent in the same year in the top graph. The non-mining provinces' response is higher than that of mining provinces because of the mining sector's volatility in non-mining provinces. After year two, the mining sector production response remains negative until year four and becomes insignificant after that. However, provincial GDP and government revenue drop by less than 0.02 percent and more than 0.1 percent, respectively, in year one and stay around zero. Overall, the impulse response functions for non-mining provinces reveal that mining sector production does not significantly affect GDP and government revenue in these provinces. The results of VAR model indicate that the mining provinces predominantly realize the benefits of mining activities.

[27] I performed panel unit root tests for serial correlation. The Johansen test results, available from the author upon request, confirm that the three variables are not cointegrated and meet the VAR model requirement.

**Table 2.A.1: Categorization of mining and non-mining provinces in Mongolia**

| Province | Mining production | Government revenue | GDP | % of Mining in GDP | Mining |
|---|---|---|---|---|---|
| Arkhangai | 13.40 | 489.25 | 3,513.74 | 0.31 | Non-mining |
| Bayankhongor | 316.01 | 542.09 | 3,451.97 | 7.50 | Non-mining |
| Bayan-Ulgii | 59.13 | 491.55 | 2,666.06 | 2.07 | Non-mining |
| Bulgan | 56.06 | 632.71 | 4,232.63 | 1.23 | Non-mining |
| Darkhan-Uul | 354.25 | 395.50 | 3,291.44 | 10.57 | Mining |
| Dornod | 3,741.44 | 509.94 | 6,674.69 | 51.42 | Mining |
| Dornogovi | 515.53 | 578.41 | 4,019.90 | 13.49 | Mining |
| Dundgovi | 34.04 | 653.75 | 4,448.71 | 0.73 | Non-mining |
| Govi-Altai | 242.63 | 680.51 | 3,458.76 | 5.40 | Non-mining |
| Govisumber | 1,039.53 | 715.17 | 4,062.97 | 25.98 | Mining |
| Khentii | 18.95 | 560.50 | 3,942.83 | 0.51 | Non-mining |
| Khovd | 84.66 | 521.77 | 3,144.19 | 2.29 | Non-mining |
| Khuvsgul | 273.52 | 485.65 | 3,242.44 | 6.93 | Non-mining |
| Orkhon | 9,714.98 | 782.80 | 13,251.47 | 75.53 | Mining |
| Selenge | 1,279.24 | 483.35 | 5,042.28 | 27.11 | Mining |
| Southgobi | 2,682.00 | 1,783.80 | 6,671.04 | 40.00 | Mining |
| Sukhbaatar | 1,734.61 | 624.14 | 5,343.96 | 32.83 | Mining |
| Tuv | 456.65 | 547.02 | 4,557.51 | 8.08 | Mining |
| Uvs | 223.98 | 556.64 | 3,278.32 | 5.66 | Non-mining |
| Uvurkhangai | 103.92 | 461.30 | 2,951.84 | 3.12 | Non-mining |
| Zavkhan | 62.39 | 605.09 | 3,656.78 | 1.48 | Non-mining |

*Note:* All variables are in thousand Mongolian Tugrik (MNT) and on per capita basis. The figures are an average of annual data for the period 2010-2018. Provinces are defined as mining provinces if at least 8 percent of the provincial GDP comes from the mining sector, following Auty (1993).

## 2.B Alternative DiD approach

**Table 2.B.1: The effect of mining on household income and expenditures: an alternative DiD approach**

| Variable | ln(income) (1) | ln(food) (2) | ln(non-food) (3) | ln(medical) (4) | ln(education) (5) | ln(electricity) (6) | ln(other non-food) (7) |
|---|---|---|---|---|---|---|---|
| Southgobi | 0.228*** | -0.318*** | 0.351*** | -0.134 | 0.339 | -1.257*** | 0.407*** |
| | (0.072) | (0.050) | (0.050) | (0.123) | (0.267) | (0.411) | (0.052) |
| 2012 | 0.605*** | -0.025 | 0.084** | 0.205*** | 0.606*** | 0.591*** | 0.119*** |
| | (0.036) | (0.023) | (0.035) | (0.075) | (0.139) | (0.204) | (0.035) |
| 2014 | 0.764*** | 0.042** | 0.225*** | 0.436*** | 0.744*** | 0.207 | 0.264*** |
| | (0.033) | (0.021) | (0.033) | (0.070) | (0.141) | (0.209) | (0.033) |
| 2016 | 0.852*** | -0.227*** | 0.109*** | 0.667*** | 0.674*** | 0.918*** | 0.129*** |
| | (0.032) | (0.022) | (0.032) | (0.068) | (0.140) | (0.197) | (0.033) |
| Southgobi × After | 0.032 | 0.296*** | -0.213*** | 0.175 | -0.693*** | 0.290 | -0.239*** |
| | (0.070) | (0.052) | (0.053) | (0.126) | (0.267) | (0.400) | (0.055) |
| Household head's age (years) | 0.012*** | 0.001*** | -0.002*** | 0.026*** | -0.069*** | 0.018*** | -0.004*** |
| | (0.001) | (0.000) | (0.000) | (0.001) | (0.003) | (0.003) | (0.000) |
| Household head is male | 0.186*** | 0.084*** | 0.011 | -0.007 | -1.530*** | -0.627*** | 0.026 |
| | (0.022) | (0.016) | (0.018) | (0.043) | (0.127) | (0.101) | (0.019) |
| Household head's education (years) | 0.027*** | -0.007*** | 0.019*** | 0.009** | 0.092*** | 0.239*** | 0.015*** |
| | (0.002) | (0.001) | (0.002) | (0.003) | (0.009) | (0.009) | (0.002) |
| Household head is married | -0.208*** | -0.214*** | 0.074*** | -0.140*** | 2.797*** | -0.181* | 0.065*** |
| | (0.021) | (0.014) | (0.017) | (0.038) | (0.106) | (0.092) | (0.017) |
| Ln(per capita income) | | 0.395*** | 0.689*** | 0.540*** | -1.421*** | 0.221*** | 0.728*** |
| | | (0.011) | (0.016) | (0.024) | (0.062) | (0.062) | (0.017) |
| Lives in apartment/house | 0.362*** | -0.050** | 0.093*** | 0.164*** | 0.127 | 0.498*** | 0.083*** |
| | (0.034) | (0.022) | (0.025) | (0.057) | (0.137) | (0.131) | (0.025) |
| Lives in rural area | 0.012 | 0.142*** | -0.097*** | -0.238*** | -0.397*** | -3.061*** | -0.076*** |
| | (0.021) | (0.016) | (0.020) | (0.045) | (0.088) | (0.117) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.33 | 0.41 | 0.57 | 0.33 | 0.28 | 0.39 | 0.58 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns run the preferred models with province and year fixed effects and household-specific controls. The reference groups is female, never married, separated or widowed, living in traditional gers and urban areas.

## 2.C The impact of mining wages and CSR investment on household expenditures

**Table 2.C.1: DiD results of mining wages on income, food and non-food expenditures**

| | ln(income) | | ln(food) | | | ln(non-food) | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Ln(mine wages) × mining | 0.002 | 0.001 | 0.014$^{***}$ | 0.013$^{***}$ | 0.012$^{***}$ | -0.007$^{*}$ | -0.008$^{***}$ | -0.009$^{***}$ |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.002) | (0.004) | (0.003) | (0.002) |
| 2012 | 0.620$^{***}$ | 0.605$^{***}$ | 0.215$^{***}$ | 0.214$^{***}$ | -0.025 | 0.520$^{***}$ | 0.501$^{***}$ | 0.084$^{**}$ |
| | (0.037) | (0.036) | (0.027) | (0.028) | (0.023) | (0.046) | (0.042) | (0.035) |
| 2014 | 0.793$^{***}$ | 0.764$^{***}$ | 0.349$^{***}$ | 0.344$^{***}$ | 0.042$^{**}$ | 0.787$^{***}$ | 0.751$^{***}$ | 0.225$^{***}$ |
| | (0.034) | (0.033) | (0.024) | (0.023) | (0.021) | (0.041) | (0.036) | (0.033) |
| 2016 | 0.918$^{***}$ | 0.852$^{***}$ | 0.129$^{***}$ | 0.109$^{***}$ | -0.227$^{***}$ | 0.767$^{***}$ | 0.696$^{***}$ | 0.109$^{***}$ |
| | (0.034) | (0.032) | (0.026) | (0.026) | (0.022) | (0.040) | (0.037) | (0.032) |
| Household head's age (years) | | 0.012$^{***}$ | | 0.006$^{***}$ | 0.001$^{***}$ | | 0.006$^{***}$ | -0.002$^{***}$ |
| | | (0.001) | | (0.000) | (0.000) | | (0.001) | (0.000) |
| Household head is male | | 0.186$^{***}$ | | 0.157$^{***}$ | 0.084$^{***}$ | | 0.139$^{***}$ | 0.011 |
| | | (0.022) | | (0.019) | (0.016) | | (0.023) | (0.018) |
| Household head's education (years) | | 0.027$^{***}$ | | 0.003$^{**}$ | -0.007$^{***}$ | | 0.038$^{***}$ | 0.019$^{***}$ |
| | | (0.002) | | (0.001) | (0.001) | | (0.002) | (0.002) |
| Household head is married | | -0.208$^{***}$ | | -0.296$^{***}$ | -0.214$^{***}$ | | -0.069$^{***}$ | 0.074$^{***}$ |
| | | (0.021) | | (0.017) | (0.014) | | (0.022) | (0.017) |
| Ln(per capita income) | | | | | 0.395$^{***}$ | | | 0.689$^{***}$ |
| | | | | | (0.011) | | | (0.016) |
| Lives in apartment/house | | 0.362$^{***}$ | | 0.093$^{***}$ | -0.050$^{**}$ | | 0.342$^{***}$ | 0.093$^{***}$ |
| | | (0.034) | | (0.022) | (0.022) | | (0.035) | (0.025) |
| Lives in rural area | | 0.012 | | 0.147$^{***}$ | 0.142$^{***}$ | | -0.088$^{***}$ | -0.097$^{***}$ |
| | | (0.021) | | (0.019) | (0.016) | | (0.026) | (0.020) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.24 | 0.33 | 0.12 | 0.20 | 0.41 | 0.19 | 0.28 | 0.57 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 6 run the basic models with province and year fixed effects. Columns 2, 4 and 7 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 5 and 8 add log of household per capita income in the model.

**Table 2.C.2: DiD results of mining wages on medical expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(mine wages) × mining | 0.006 | 0.008 | 0.007 |
| | (0.006) | (0.006) | (0.005) |
| 2012 | 0.573*** | 0.532*** | 0.205*** |
| | (0.075) | (0.073) | (0.075) |
| 2014 | 0.907*** | 0.849*** | 0.436*** |
| | (0.066) | (0.066) | (0.070) |
| 2016 | 1.245*** | 1.128*** | 0.668*** |
| | (0.064) | (0.064) | (0.068) |
| Household head's age (years) | | 0.032*** | 0.026*** |
| | | (0.001) | (0.001) |
| Household head is male | | 0.093** | -0.007 |
| | | (0.045) | (0.043) |
| Household head's education (years) | | 0.023*** | 0.009** |
| | | (0.003) | (0.003) |
| Household head is married | | -0.252*** | -0.140*** |
| | | (0.040) | (0.038) |
| Ln(per capita income) | | | 0.540*** |
| | | | (0.024) |
| Lives in apartment/house | | 0.360*** | 0.164*** |
| | | (0.058) | (0.057) |
| Lives in rural area | | -0.231*** | -0.238*** |
| | | (0.046) | (0.045) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.15 | 0.27 | 0.33 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.C.3: DiD results of mining on the likelihood of reporting illness**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Ln(mine wages) × mining | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| 2012 | | -0.007* | | -0.008* | | -0.007* |
| | | (0.004) | | (0.004) | | (0.004) |
| 2014 | | 0.001 | | 0.000 | | 0.000 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2016 | | -0.009** | | -0.010** | | -0.009** |
| | | (0.004) | | (0.004) | | (0.004) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Individual is male | | -0.015*** | | -0.013*** | | -0.013*** |
| | | (0.002) | | (0.002) | | (0.002) |
| Individual's education (years) | | -0.002*** | | -0.002*** | | -0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Ln(per capita wage income) | | -0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Lives in apartment/house | | 0.015** | | 0.013*** | | 0.011** |
| | | (0.006) | | (0.005) | | (0.004) |
| Lives in rural area | | -0.032*** | | -0.027*** | | -0.025*** |
| | | (0.004) | | (0.003) | | (0.003) |
| Model | LPM | LPM | Probit | Probit | Logit | Logit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$/Psedu $R^2$ | 0.00 | 0.02 | 0.01 | 0.05 | 0.01 | 0.05 |
| Number of individuals | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 5 run the basic models with province and year fixed effects. Columns 2, 4 and 6 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.C.4: DiD results of mining wages on education expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(mine wages) × mining | -0.031*** | -0.031*** | -0.029*** |
| | (0.012) | (0.011) | (0.011) |
| 2012 | -0.307** | -0.254* | 0.606*** |
| | (0.149) | (0.131) | (0.140) |
| 2014 | -0.389*** | -0.343*** | 0.743*** |
| | (0.142) | (0.130) | (0.141) |
| 2016 | -0.723*** | -0.538*** | 0.674*** |
| | (0.136) | (0.125) | (0.140) |
| Household head's age (years) | | -0.085*** | -0.069*** |
| | | (0.003) | (0.003) |
| Household head is male | | -1.794*** | -1.530*** |
| | | (0.136) | (0.127) |
| Household head's education (years) | | 0.054*** | 0.092*** |
| | | (0.009) | (0.009) |
| Household head is married | | 3.094*** | 2.797*** |
| | | (0.113) | (0.106) |
| Ln(per capita income) | | | -1.421*** |
| | | | (0.062) |
| Lives in apartment/house | | -0.388*** | 0.127 |
| | | (0.139) | (0.137) |
| Lives in rural area | | -0.414*** | -0.397*** |
| | | (0.087) | (0.088) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.01 | 0.23 | 0.28 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.C.5: DiD results of mining wages on educational attainment**

| | OLS | | Ordered-logit | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Ln(mine wages) × mining | 0.015* | 0.016* | 0.008** | 0.008** |
| | (0.009) | (0.008) | (0.003) | (0.003) |
| 2012 | 0.853*** | 0.139 | 0.181*** | -0.090** |
| | (0.112) | (0.108) | (0.039) | (0.040) |
| 2014 | 0.875*** | 0.087 | 0.179*** | -0.095*** |
| | (0.098) | (0.102) | (0.033) | (0.037) |
| 2016 | 1.110*** | 0.079 | 0.345*** | -0.029 |
| | (0.094) | (0.100) | (0.033) | (0.036) |
| Individual's age (years) | | 0.079*** | | 0.030*** |
| | | (0.002) | | (0.001) |
| Individual is male | | -0.711*** | | -0.283*** |
| | | (0.050) | | (0.018) |
| Ln(per capita income) | | 0.822*** | | 0.313*** |
| | | (0.052) | | (0.020) |
| Lives in apartment/house | | 1.482*** | | 0.673*** |
| | | (0.113) | | (0.046) |
| Lives in rural area | | -1.019*** | | -0.418*** |
| | | (0.069) | | (0.026) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.02 | 0.15 | | |
| Pseudo $R^2$ | | | 0.00 | 0.03 |
| Number of households | 32,552 | 32,552 | 32,552 | 32,552 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1 and 3 run the basic models with province and year fixed effects. Columns 2 and 4 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.C.6: DiD results of mining wages on electricity and other non-food expenditures**

| | ln(electricity) | | | ln(other non-food | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(mine wages) × mining | 0.018 | 0.012 | 0.012 | -0.007** | -0.009*** | -0.010*** |
| | (0.027) | (0.017) | (0.017) | (0.004) | (0.003) | (0.002) |
| 2012 | 1.043*** | 0.725*** | 0.592*** | 0.576*** | 0.560*** | 0.119*** |
| | (0.281) | (0.203) | (0.204) | (0.046) | (0.043) | (0.035) |
| 2014 | 0.773** | 0.376* | 0.208 | 0.851*** | 0.820*** | 0.264*** |
| | (0.307) | (0.204) | (0.209) | (0.041) | (0.037) | (0.033) |
| 2016 | 1.782*** | 1.107*** | 0.919*** | 0.812*** | 0.749*** | 0.129*** |
| | (0.282) | (0.196) | (0.197) | (0.040) | (0.038) | (0.033) |
| Household head's age (years) | | 0.021*** | 0.018*** | | 0.005*** | -0.004*** |
| | | (0.003) | (0.003) | | (0.001) | (0.000) |
| Household head is male | | -0.586*** | -0.627*** | | 0.161*** | 0.026 |
| | | (0.100) | (0.101) | | (0.025) | (0.019) |
| Household head's education (years) | | 0.245*** | 0.239*** | | 0.035*** | 0.015*** |
| | | (0.008) | (0.009) | | (0.002) | (0.002) |
| Household head is married | | -0.227** | -0.181* | | -0.087*** | 0.065*** |
| | | (0.091) | (0.092) | | (0.023) | (0.017) |
| Ln(per capita income) | | | 0.221*** | | | 0.728*** |
| | | | (0.062) | | | (0.017) |
| Lives in apartment/house | | 0.578*** | 0.498*** | | 0.347*** | 0.083*** |
| | | (0.126) | (0.131) | | (0.037) | (0.025) |
| Lives in rural area | | -3.059*** | -3.061*** | | -0.068** | -0.076*** |
| | | (0.117) | (0.117) | | (0.027) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.08 | 0.39 | 0.39 | 0.20 | 0.27 | 0.58 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1 and 4 run the basic models with province and year fixed effects. Columns 2 and 5 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 3 and 6 add log of household per capita income in the model.

**Table 2.C.7: DiD results of mining CSR investment on income, food and non-food expenditures**

| | ln(income) | | ln(food) | | | ln(non-food) | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Ln(mining CSR) × mining | -0.003 | -0.013 | 0.086*** | 0.080*** | 0.085*** | -0.059** | -0.075*** | -0.066*** |
| | (0.024) | (0.021) | (0.021) | (0.019) | (0.017) | (0.026) | (0.023) | (0.017) |
| 2012 | 0.630*** | 0.616*** | 0.223*** | 0.221*** | -0.023 | 0.526*** | 0.508*** | 0.084** |
| | (0.037) | (0.036) | (0.027) | (0.028) | (0.023) | (0.046) | (0.042) | (0.035) |
| 2014 | 0.802*** | 0.773*** | 0.371*** | 0.365*** | 0.059*** | 0.782*** | 0.746*** | 0.214*** |
| | (0.033) | (0.031) | (0.024) | (0.023) | (0.021) | (0.039) | (0.035) | (0.031) |
| 2016 | 0.928*** | 0.864*** | 0.133*** | 0.113*** | -0.229*** | 0.775*** | 0.706*** | 0.112*** |
| | (0.034) | (0.032) | (0.027) | (0.027) | (0.023) | (0.041) | (0.037) | (0.032) |
| Household head's age (years) | | 0.011*** | | 0.006*** | 0.001*** | | 0.006*** | -0.002*** |
| | | (0.001) | | (0.000) | (0.000) | | (0.001) | (0.000) |
| Household head is male | | 0.187*** | | 0.158*** | 0.084*** | | 0.139*** | 0.011 |
| | | (0.022) | | (0.019) | (0.016) | | (0.023) | (0.018) |
| Household head's education (years) | | 0.027*** | | 0.003** | -0.008*** | | 0.038*** | 0.019*** |
| | | (0.002) | | (0.001) | (0.001) | | (0.002) | (0.002) |
| Household head is married | | -0.210*** | | -0.297*** | -0.214*** | | -0.070*** | 0.074*** |
| | | (0.021) | | (0.017) | (0.014) | | (0.022) | (0.017) |
| Ln(per capita income) | | | | | 0.396*** | | | 0.688*** |
| | | | | | (0.011) | | | (0.016) |
| Lives in apartment/house | | 0.362*** | | 0.092*** | -0.051** | | 0.343*** | 0.094*** |
| | | (0.034) | | (0.022) | (0.022) | | (0.034) | (0.024) |
| Lives in rural area | | 0.013 | | 0.147*** | 0.142*** | | -0.088*** | -0.097*** |
| | | (0.021) | | (0.019) | (0.016) | | (0.026) | (0.020) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.24 | 0.33 | 0.12 | 0.20 | 0.41 | 0.20 | 0.28 | 0.57 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 6 run the basic models with province and year fixed effects. Columns 2, 4 and 7 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 5 and 8 add log of household per capita income in the model.

**Table 2.C.8: DiD results of mining CSR investment on medical expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(mining CSR) × mining | 0.002 | 0.016 | 0.023 |
| | (0.045) | (0.041) | (0.038) |
| 2012 | 0.593*** | 0.552*** | 0.219*** |
| | (0.075) | (0.073) | (0.075) |
| 2014 | 0.928*** | 0.872*** | 0.454*** |
| | (0.064) | (0.063) | (0.067) |
| 2016 | 1.266*** | 1.148*** | 0.681*** |
| | (0.064) | (0.065) | (0.069) |
| Household head's age (years) | | 0.032*** | 0.026*** |
| | | (0.001) | (0.001) |
| Household head is male | | 0.095** | -0.006 |
| | | (0.045) | (0.043) |
| Household head's education (years) | | 0.024*** | 0.009** |
| | | (0.003) | (0.003) |
| Household head is married | | -0.255*** | -0.142*** |
| | | (0.040) | (0.038) |
| Ln(per capita income) | | | 0.540*** |
| | | | (0.024) |
| Lives in apartment/house | | 0.360*** | 0.164*** |
| | | (0.058) | (0.057) |
| Lives in rural area | | -0.231*** | -0.238*** |
| | | (0.046) | (0.045) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.15 | 0.27 | 0.33 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.C.9: DiD results of mining CSR investment on the likelihood of reporting illness**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Ln(mining CSR) × mining | 0.001 | 0.001 | 0.001 | 0.002 | 0.001 | 0.002 |
| | (0.004) | (0.004) | (0.003) | (0.003) | (0.003) | (0.002) |
| 2012 | | -0.008* | | -0.008* | | -0.008* |
| | | (0.004) | | (0.004) | | (0.004) |
| 2014 | | 0.001 | | 0.000 | | 0.000 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2016 | | -0.010** | | -0.010** | | -0.010** |
| | | (0.004) | | (0.004) | | (0.004) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Individual is male | | -0.015*** | | -0.013*** | | -0.013*** |
| | | (0.002) | | (0.002) | | (0.002) |
| Individual's education (years) | | -0.002*** | | -0.002*** | | -0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Ln(per capita wage income) | | -0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Lives in apartment/house | | 0.015** | | 0.013*** | | 0.011** |
| | | (0.006) | | (0.005) | | (0.004) |
| Lives in rural area | | -0.032*** | | -0.027*** | | -0.025*** |
| | | (0.004) | | (0.003) | | (0.003) |
| Model | LPM | LPM | Probit | Probit | Logit | Logit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$/Psedu $R^2$ | 0.00 | 0.02 | 0.01 | 0.05 | 0.01 | 0.05 |
| Number of individuals | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 5 run the basic models with province and year fixed effects. Columns 2, 4 and 6 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.C.10: DiD results of mining CSR investment on education expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(mining CSR) × mining | -0.161* | -0.174** | -0.193** |
| | (0.087) | (0.080) | (0.083) |
| 2012 | -0.340** | -0.280** | 0.598*** |
| | (0.149) | (0.131) | (0.139) |
| 2014 | -0.450*** | -0.399*** | 0.701*** |
| | (0.137) | (0.124) | (0.136) |
| 2016 | -0.750*** | -0.556*** | 0.674*** |
| | (0.137) | (0.126) | (0.141) |
| Household head's age (years) | | -0.085*** | -0.069*** |
| | | (0.003) | (0.003) |
| Household head is male | | -1.797*** | -1.531*** |
| | | (0.136) | (0.127) |
| Household head's education (years) | | 0.054*** | 0.093*** |
| | | (0.009) | (0.009) |
| Household head is married | | 3.097*** | 2.798*** |
| | | (0.113) | (0.106) |
| Ln(per capita income) | | | -1.424*** |
| | | | (0.062) |
| Lives in apartment/house | | -0.388*** | 0.128 |
| | | (0.139) | (0.137) |
| Lives in rural area | | -0.415*** | -0.397*** |
| | | (0.088) | (0.088) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.01 | 0.23 | 0.28 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.C.11: DiD results of mining CSR investment on educational attainment**

| | OLS | | Ordered-logit | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Ln(mining CSR) × mining | 0.159** | 0.176*** | 0.076*** | 0.083*** |
| | (0.067) | (0.064) | (0.024) | (0.024) |
| 2012 | 0.830*** | 0.109 | 0.171*** | -0.103** |
| | (0.112) | (0.108) | (0.039) | (0.040) |
| 2014 | 0.878*** | 0.085 | 0.180*** | -0.096*** |
| | (0.095) | (0.100) | (0.032) | (0.036) |
| 2016 | 1.082*** | 0.042 | 0.333*** | -0.045 |
| | (0.095) | (0.101) | (0.033) | (0.037) |
| Individual's age (years) | | 0.079*** | | 0.030*** |
| | | (0.002) | | (0.001) |
| Individual is male | | -0.711*** | | -0.283*** |
| | | (0.050) | | (0.018) |
| Ln(per capita income) | | 0.823*** | | 0.314*** |
| | | (0.052) | | (0.020) |
| Lives in apartment/house | | 1.480*** | | 0.672*** |
| | | (0.113) | | (0.046) |
| Lives in rural area | | -1.019*** | | -0.419*** |
| | | (0.069) | | (0.026) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.02 | 0.15 | | |
| Pseudo $R^2$ | | | 0.00 | 0.03 |
| Number of households | 32,552 | 32,552 | 32,552 | 32,552 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1 and 3 run the basic models with province and year fixed effects. Columns 2 and 4 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.C.12: DiD results of mining CSR investment on electricity and other non-food expenditures**

| | ln(electricity) | | | ln(other non-food) | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(mining CSR) × mining | 0.090 | 0.013 | 0.016 | -0.066** | -0.082*** | -0.073*** |
| | (0.190) | (0.125) | (0.124) | (0.027) | (0.024) | (0.017) |
| 2012 | 1.064*** | 0.762*** | 0.626*** | 0.582*** | 0.567*** | 0.120*** |
| | (0.277) | (0.202) | (0.204) | (0.046) | (0.043) | (0.035) |
| 2014 | 0.810*** | 0.415** | 0.245 | 0.845*** | 0.813*** | 0.251*** |
| | (0.295) | (0.196) | (0.201) | (0.039) | (0.036) | (0.032) |
| 2016 | 1.799*** | 1.143*** | 0.952*** | 0.820*** | 0.760*** | 0.132*** |
| | (0.279) | (0.198) | (0.199) | (0.041) | (0.038) | (0.033) |
| Household head's age (years) | | 0.021*** | 0.018*** | | 0.005*** | -0.004*** |
| | | (0.003) | (0.003) | | (0.001) | (0.000) |
| Household head is male | | -0.582*** | -0.624*** | | 0.162*** | 0.026 |
| | | (0.101) | (0.102) | | (0.025) | (0.019) |
| Household head's education (years) | | 0.245*** | 0.239*** | | 0.035*** | 0.015*** |
| | | (0.008) | (0.009) | | (0.002) | (0.002) |
| Household head is married | | -0.232** | -0.185** | | -0.087*** | 0.065*** |
| | | (0.091) | (0.093) | | (0.023) | (0.017) |
| Ln(per capita income) | | | 0.221*** | | | 0.727*** |
| | | | (0.062) | | | (0.016) |
| Lives in apartment/house | | 0.579*** | 0.499*** | | 0.347*** | 0.084*** |
| | | (0.126) | (0.132) | | (0.037) | (0.025) |
| Lives in rural area | | -3.057*** | -3.060*** | | -0.067** | -0.076*** |
| | | (0.117) | (0.117) | | (0.027) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.08 | 0.39 | 0.39 | 0.20 | 0.27 | 0.58 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1 and 4 run the basic models with province and year fixed effects. Columns 2 and 5 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 3 and 6 add log of household per capita income in the model.

## 2.D Household level analysis

**Table 2.D.1: DiD results of the mining impact on income, food and non-food expenditures**

| | ln(income) | | ln(food) | | | ln(non-food) | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Ln(local taxes) × mining | -0.022 | -0.019 | 0.077*** | 0.084*** | 0.089*** | -0.102*** | -0.106*** | -0.093*** |
| | (0.019) | (0.017) | (0.016) | (0.015) | (0.013) | (0.021) | (0.018) | (0.014) |
| 2012 | 0.483*** | 0.536*** | 0.101*** | 0.168*** | 0.027 | 0.367*** | 0.425*** | 0.068** |
| | (0.036) | (0.033) | (0.027) | (0.026) | (0.023) | (0.047) | (0.039) | (0.033) |
| 2014 | 0.674*** | 0.702*** | 0.217*** | 0.268*** | 0.083*** | 0.680*** | 0.711*** | 0.243*** |
| | (0.034) | (0.032) | (0.024) | (0.022) | (0.021) | (0.043) | (0.036) | (0.032) |
| 2016 | 0.731*** | 0.770*** | -0.075*** | 0.009 | -0.194*** | 0.595*** | 0.643*** | 0.129*** |
| | (0.033) | (0.031) | (0.025) | (0.025) | (0.022) | (0.042) | (0.036) | (0.031) |
| Household head's age (years) | | 0.006*** | | 0.000 | -0.001*** | | 0.001 | -0.003*** |
| | | (0.000) | | (0.000) | (0.000) | | (0.001) | (0.000) |
| Household head is male | | 0.073*** | | 0.044*** | 0.025* | | 0.034 | -0.015 |
| | | (0.021) | | (0.015) | (0.013) | | (0.024) | (0.019) |
| Household head's education (years) | | 0.029*** | | 0.004*** | -0.003*** | | 0.039*** | 0.020*** |
| | | (0.002) | | (0.001) | (0.001) | | (0.002) | (0.002) |
| Household head is married | | 0.258*** | | 0.169*** | 0.101*** | | 0.354*** | 0.181*** |
| | | (0.020) | | (0.014) | (0.012) | | (0.023) | (0.018) |
| Household size | | 0.109*** | | 0.110*** | 0.081*** | | 0.136*** | 0.063*** |
| | | (0.004) | | (0.004) | (0.003) | | (0.005) | (0.005) |
| Ln(household income) | | | | | 0.263*** | | | 0.667*** |
| | | | | | (0.011) | | | (0.018) |
| Lives in apartment/house | | 0.319*** | | 0.052** | -0.032 | | 0.305*** | 0.092*** |
| | | (0.032) | | (0.020) | (0.020) | | (0.033) | (0.024) |
| Lives in rural area | | -0.009 | | 0.125*** | 0.127*** | | -0.107*** | -0.101*** |
| | | (0.020) | | (0.017) | (0.015) | | (0.026) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.17 | 0.37 | 0.10 | 0.34 | 0.43 | 0.12 | 0.38 | 0.60 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 6 run the basic models with province and year fixed effects. Columns 2, 4 and 7 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 5 and 8 add log of household per capita income in the model.

**Table 2.D.2: DiD results of the mining impact on medical expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(local taxes) × mining | 0.025 | 0.056* | 0.064** |
| | (0.036) | (0.033) | (0.031) |
| 2012 | 0.442*** | 0.461*** | 0.227*** |
| | (0.071) | (0.067) | (0.070) |
| 2014 | 0.776*** | 0.761*** | 0.454*** |
| | (0.064) | (0.063) | (0.068) |
| 2016 | 1.045*** | 1.013*** | 0.677*** |
| | (0.064) | (0.063) | (0.067) |
| Household head's age (years) | | 0.026*** | 0.024*** |
| | | (0.001) | (0.001) |
| Household head is male | | -0.030 | -0.062 |
| | | (0.045) | (0.043) |
| Household head's education (years) | | 0.024*** | 0.012*** |
| | | (0.003) | (0.003) |
| Household head is married | | 0.265*** | 0.152*** |
| | | (0.043) | (0.042) |
| Household size | | 0.079*** | 0.031*** |
| | | (0.011) | (0.011) |
| Ln(household income) | | | 0.437*** |
| | | | (0.027) |
| Lives in apartment/house | | 0.311*** | 0.172*** |
| | | (0.058) | (0.057) |
| Lives in rural area | | -0.256*** | -0.252*** |
| | | (0.045) | (0.044) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.13 | 0.23 | 0.26 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.D.3: DiD results of the mining impact on the likelihood of reporting illness**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Ln(local taxes) × mining | -0.004 | -0.003 | -0.003 | -0.002 | -0.003 | -0.002 |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| 2012 | | -0.008* | | -0.008** | | -0.008** |
| | | (0.004) | | (0.004) | | (0.004) |
| 2014 | | 0.002 | | 0.001 | | 0.001 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2016 | | -0.009** | | -0.009** | | -0.009** |
| | | (0.004) | | (0.004) | | (0.004) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Individual is male | | -0.015*** | | -0.013*** | | -0.013*** |
| | | (0.002) | | (0.002) | | (0.002) |
| Individual's education (years) | | -0.002*** | | -0.001*** | | -0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Household size | | -0.004*** | | -0.003*** | | -0.003*** |
| | | (0.001) | | (0.001) | | (0.001) |
| Ln(household wage income) | | -0.000 | | 0.000 | | 0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Lives in apartment/house | | 0.014** | | 0.012** | | 0.010** |
| | | (0.006) | | (0.005) | | (0.004) |
| Lives in rural area | | -0.031*** | | -0.027*** | | -0.025*** |
| | | (0.004) | | (0.003) | | (0.003) |
| Model | LPM | LPM | Probit | Probit | Logit | Logit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$/Psedu $R^2$ | 0.00 | 0.02 | 0.01 | 0.05 | 0.01 | 0.05 |
| Number of individuals | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 5 run the basic models with province and year fixed effects. Columns 2, 4 and 6 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.D.4: DiD results of the mining impact on education expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(local taxes) × mining | -0.154* | -0.100* | -0.096* |
| | (0.090) | (0.057) | (0.056) |
| 2012 | -0.489*** | 0.326*** | 0.201* |
| | (0.164) | (0.120) | (0.121) |
| 2014 | -0.508*** | 0.138 | -0.026 |
| | (0.163) | (0.123) | (0.130) |
| 2016 | -0.916*** | 0.094 | -0.086 |
| | (0.157) | (0.123) | (0.131) |
| Household head's age (years) | | -0.071*** | -0.072*** |
| | | (0.003) | (0.003) |
| Household head is male | | -1.544*** | -1.561*** |
| | | (0.106) | (0.106) |
| Household head's education (years) | | 0.055*** | 0.048*** |
| | | (0.008) | (0.008) |
| Household head is married | | 0.910*** | 0.850*** |
| | | (0.105) | (0.107) |
| Household size | | 1.733*** | 1.707*** |
| | | (0.032) | (0.033) |
| Ln(household income) | | | 0.233*** |
| | | | (0.059) |
| Lives in apartment/house | | -0.049 | -0.124 |
| | | (0.134) | (0.135) |
| Lives in rural area | | -0.348*** | -0.346*** |
| | | (0.085) | (0.085) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.01 | 0.53 | 0.54 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.D.5: DiD results of the mining impact on educational attainment**

| | OLS | | Ordered-logit | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Ln(local taxes) × mining | 0.122** | 0.164*** | 0.067*** | 0.076*** |
| | (0.058) | (0.055) | (0.021) | (0.021) |
| 2012 | 0.882*** | 0.059 | 0.194*** | -0.112*** |
| | (0.108) | (0.104) | (0.037) | (0.039) |
| 2014 | 0.864*** | -0.102 | 0.171*** | -0.163*** |
| | (0.097) | (0.101) | (0.033) | (0.037) |
| 2016 | 1.094*** | -0.102 | 0.334*** | -0.094** |
| | (0.095) | (0.100) | (0.033) | (0.037) |
| Individual's age (years) | | 0.084*** | | 0.032*** |
| | | (0.002) | | (0.001) |
| Individual is male | | -0.705*** | | -0.281*** |
| | | (0.050) | | (0.018) |
| Household size | | -0.092*** | | -0.038*** |
| | | (0.023) | | (0.009) |
| Ln(household income) | | 1.106*** | | 0.413*** |
| | | (0.055) | | (0.021) |
| Lives in apartment/house | | 1.394*** | | 0.647*** |
| | | (0.114) | | (0.047) |
| Lives in rural area | | -0.997*** | | -0.413*** |
| | | (0.069) | | (0.026) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.15 | 0.27 | 0.33 | |
| Number of households | 10,353 | 10,353 | 10,353 | |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1 and 3 run the basic models with province and year fixed effects. Columns 2 and 4 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.D.6: DiD results of the mining impact on electricity and other non-food expenditures**

| | ln(electricity) | | | ln(other non-food) | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(local taxes) × mining | 0.346 | 0.277** | 0.281** | -0.109*** | -0.115*** | -0.102*** |
| | (0.213) | (0.140) | (0.140) | (0.021) | (0.019) | (0.015) |
| 2012 | 1.073*** | 0.752*** | 0.649*** | 0.421*** | 0.472*** | 0.105*** |
| | (0.319) | (0.226) | (0.226) | (0.046) | (0.040) | (0.033) |
| 2014 | 0.626* | 0.235 | 0.100 | 0.743*** | 0.773*** | 0.292*** |
| | (0.370) | (0.240) | (0.245) | (0.043) | (0.037) | (0.033) |
| 2016 | 1.699*** | 1.031*** | 0.882*** | 0.640*** | 0.687*** | 0.159*** |
| | (0.349) | (0.231) | (0.234) | (0.041) | (0.037) | (0.032) |
| Household head's age (years) | | 0.019*** | 0.018*** | | -0.001* | -0.005*** |
| | | (0.003) | (0.003) | | (0.001) | (0.000) |
| Household head is male | | -0.683*** | -0.697*** | | 0.050** | -0.000 |
| | | (0.111) | (0.111) | | (0.024) | (0.019) |
| Household head's education (years) | | 0.276*** | 0.270*** | | 0.036*** | 0.017*** |
| | | (0.010) | (0.010) | | (0.002) | (0.002) |
| Household head is married | | 0.006 | -0.044 | | 0.375*** | 0.198*** |
| | | (0.108) | (0.110) | | (0.023) | (0.018) |
| Household size | | 0.084*** | 0.063** | | 0.112*** | 0.037*** |
| | | (0.027) | (0.028) | | (0.005) | (0.004) |
| Ln(household income) | | | 0.193** | | | 0.686*** |
| | | | (0.081) | | | (0.018) |
| Lives in apartment/house | | 0.587*** | 0.525*** | | 0.303*** | 0.084*** |
| | | (0.146) | (0.153) | | (0.034) | (0.024) |
| Lives in rural area | | -3.532*** | -3.530*** | | -0.087*** | -0.081*** |
| | | (0.134) | (0.134) | | (0.027) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.07 | 0.38 | 0.38 | 0.13 | 0.36 | 0.59 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1 and 4 run the basic models with province and year fixed effects. Columns 2 and 5 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 3 and 6 add log of household per capita income in the model.

## 2.E Square root of household size

**Table 2.E.1: DiD results of the mining impact on income, food and non-food expenditures**

| | ln(income) | | ln(food) | | | ln(non-food) | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Ln(local taxes) × mining | -0.008 | -0.016 | 0.091*** | 0.090*** | 0.093*** | -0.088*** | -0.102*** | -0.094*** |
| | (0.019) | (0.017) | (0.015) | (0.015) | (0.013) | (0.021) | (0.018) | (0.014) |
| 2012 | 0.555*** | 0.534*** | 0.173*** | 0.182*** | 0.038* | 0.439*** | 0.428*** | 0.070** |
| | (0.034) | (0.033) | (0.025) | (0.026) | (0.023) | (0.044) | (0.039) | (0.033) |
| 2014 | 0.736*** | 0.707*** | 0.279*** | 0.284*** | 0.097*** | 0.742*** | 0.719*** | 0.251*** |
| | (0.033) | (0.031) | (0.023) | (0.022) | (0.021) | (0.041) | (0.036) | (0.032) |
| 2016 | 0.827*** | 0.775*** | 0.021 | 0.029 | -0.177*** | 0.691*** | 0.652*** | 0.137*** |
| | (0.032) | (0.031) | (0.025) | (0.025) | (0.022) | (0.040) | (0.036) | (0.031) |
| Household head's age (years) | | 0.007*** | | 0.002*** | 0.000 | | 0.002*** | -0.003*** |
| | | (0.000) | | (0.000) | (0.000) | | (0.001) | (0.000) |
| Household head is male | | 0.104*** | | 0.085*** | 0.055*** | | 0.068*** | -0.007 |
| | | (0.020) | | (0.014) | (0.013) | | (0.023) | (0.019) |
| Household head's education (years) | | 0.028*** | | 0.004*** | -0.004*** | | 0.039*** | 0.020*** |
| | | (0.002) | | (0.001) | (0.001) | | (0.002) | (0.002) |
| Household head is married | | 0.176*** | | 0.026** | -0.004 | | 0.253*** | 0.179*** |
| | | (0.020) | | (0.013) | (0.011) | | (0.021) | (0.017) |
| Ln(adjusted income) | | | | | 0.260*** | | | 0.652*** |
| | | | | | (0.011) | | | (0.018) |
| Lives in apartment/house | | 0.316*** | | 0.059*** | -0.026 | | 0.305*** | 0.092*** |
| | | (0.032) | | (0.020) | (0.020) | | (0.033) | (0.024) |
| Lives in rural area | | -0.004 | | 0.132*** | 0.132*** | | -0.102*** | -0.101*** |
| | | (0.020) | | (0.017) | (0.016) | | (0.025) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.24 | 0.33 | 0.15 | 0.18 | 0.29 | 0.17 | 0.30 | 0.54 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1, 3 and 6 run the basic models with province and year fixed effects. Columns 2, 4 and 7 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 5 and 8 add log of household per capita income in the model.

**Table 2.E.2: DiD results of the mining impact on medical expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(local taxes) × mining | 0.039 | 0.065** | 0.070** |
| | (0.036) | (0.032) | (0.031) |
| 2012 | 0.514*** | 0.487*** | 0.253*** |
| | (0.070) | (0.067) | (0.070) |
| 2014 | 0.838*** | 0.786*** | 0.480*** |
| | (0.064) | (0.064) | (0.068) |
| 2016 | 1.140*** | 1.046*** | 0.709*** |
| | (0.063) | (0.063) | (0.067) |
| Household head's age (years) | | 0.029*** | 0.025*** |
| | | (0.001) | (0.001) |
| Household head is male | | 0.020 | -0.028 |
| | | (0.044) | (0.043) |
| Household head's education (years) | | 0.024*** | 0.012*** |
| | | (0.003) | (0.003) |
| Household head is married | | 0.071* | 0.022 |
| | | (0.040) | (0.039) |
| Ln(adjusted income) | | | 0.426*** |
| | | | (0.027) |
| Lives in apartment/house | | 0.326*** | 0.187*** |
| | | (0.057) | (0.056) |
| Lives in rural area | | -0.247*** | -0.246*** |
| | | (0.045) | (0.044) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.14 | 0.24 | 0.28 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.E.3: DiD results of the mining impact on the likelihood of reporting illness**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Ln(local taxes) × mining | -0.004 | -0.003 | -0.003 | -0.001 | -0.003 | -0.001 |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| 2012 | | -0.006 | | -0.007 | | -0.006 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2014 | | 0.003 | | 0.002 | | 0.002 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2016 | | -0.007* | | -0.008* | | -0.007* |
| | | (0.004) | | (0.004) | | (0.004) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Individual is male | | -0.015*** | | -0.013*** | | -0.013*** |
| | | (0.002) | | (0.002) | | (0.002) |
| Individual's education (years) | | -0.002*** | | -0.001*** | | -0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Ln(adjusted wage income) | | -0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Lives in apartment/house | | 0.015** | | 0.013*** | | 0.011** |
| | | (0.006) | | (0.005) | | (0.004) |
| Lives in rural area | | -0.031*** | | -0.027*** | | -0.025*** |
| | | (0.004) | | (0.003) | | (0.003) |
| Model | LPM | LPM | Probit | Probit | Logit | Logit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$/Psedu $R^2$ | 0.00 | 0.02 | 0.01 | 0.05 | 0.01 | 0.05 |
| Number of individuals | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1, 3 and 5 run the basic models with province and year fixed effects. Columns 2, 4 and 6 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.E.4: DiD results of the mining impact on education expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(local taxes) × mining | -0.143* | -0.229*** | -0.233*** |
| | (0.083) | (0.073) | (0.074) |
| 2012 | -0.441*** | -0.362*** | -0.177 |
| | (0.152) | (0.135) | (0.138) |
| 2014 | -0.468*** | -0.366*** | -0.124 |
| | (0.151) | (0.137) | (0.147) |
| 2016 | -0.837*** | -0.570*** | -0.304** |
| | (0.146) | (0.135) | (0.148) |
| Household head's age (years) | | -0.093*** | -0.090*** |
| | | (0.003) | (0.003) |
| Household head is male | | -1.910*** | -1.871*** |
| | | (0.147) | (0.147) |
| Household head's education (years) | | 0.055*** | 0.064*** |
| | | (0.010) | (0.010) |
| Household head is married | | 3.418*** | 3.456*** |
| | | (0.123) | (0.123) |
| Ln(adjusted income) | | | -0.336*** |
| | | | (0.070) |
| Lives in apartment/house | | -0.449*** | -0.339** |
| | | (0.149) | (0.149) |
| Lives in rural area | | -0.440*** | -0.440*** |
| | | (0.094) | (0.094) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.01 | 0.23 | 0.23 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.E.5: DiD results of the mining impact on educational attainment**

| | OLS | | Ordered-logit | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Ln(local taxes) × mining | 0.122** | 0.158*** | 0.067*** | 0.074*** |
| | (0.058) | (0.055) | (0.021) | (0.021) |
| 2012 | 0.882*** | 0.082 | 0.194*** | -0.103*** |
| | (0.108) | (0.103) | (0.037) | (0.039) |
| 2014 | 0.864*** | -0.065 | 0.171*** | -0.149*** |
| | (0.097) | (0.101) | (0.033) | (0.037) |
| 2016 | 1.094*** | -0.071 | 0.334*** | -0.082** |
| | (0.095) | (0.100) | (0.033) | (0.037) |
| Individual's age (years) | | 0.082*** | | 0.031*** |
| | | (0.002) | | (0.001) |
| Individual is male | | -0.708*** | | -0.282*** |
| | | (0.050) | | (0.018) |
| Ln(adjusted income) | | 1.039*** | | 0.389*** |
| | | (0.056) | | (0.021) |
| Lives in apartment/house | | 1.418*** | | 0.655*** |
| | | (0.114) | | (0.046) |
| Lives in rural area | | -1.003*** | | -0.414*** |
| | | (0.069) | | (0.026) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.02 | 0.15 | | |
| Pseudo $R^2$ | | | 0.00 | 0.03 |
| Number of households | 32,552 | 32,552 | 32,552 | 32,552 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Columns 1 and 3 run the basic models with province and year fixed effects. Columns 2 and 4 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.E.6: DiD results of the mining impact on electricity and other non-food expenditures**

| | ln(electricity) | | | ln(other non-food) | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(local taxes) × mining | 0.334* | 0.264** | 0.266** | -0.095*** | -0.110*** | -0.101*** |
| | (0.200) | (0.131) | (0.130) | (0.021) | (0.019) | (0.015) |
| 2012 | 1.061*** | 0.720*** | 0.633*** | 0.492*** | 0.485*** | 0.113*** |
| | (0.297) | (0.208) | (0.209) | (0.044) | (0.040) | (0.033) |
| 2014 | 0.645* | 0.246 | 0.132 | 0.805*** | 0.788*** | 0.302*** |
| | (0.345) | (0.222) | (0.227) | (0.041) | (0.036) | (0.033) |
| 2016 | 1.679*** | 0.999*** | 0.874*** | 0.737*** | 0.706*** | 0.171*** |
| | (0.325) | (0.215) | (0.217) | (0.040) | (0.037) | (0.032) |
| Household head's age (years) | | 0.019*** | 0.018*** | | 0.001 | -0.004*** |
| | | (0.003) | (0.003) | | (0.001) | (0.000) |
| Household head is male | | -0.649*** | -0.667*** | | 0.090*** | 0.013 |
| | | (0.105) | (0.105) | | (0.023) | (0.019) |
| Household head's education (years) | | 0.259*** | 0.255*** | | 0.036*** | 0.017*** |
| | | (0.009) | (0.009) | | (0.002) | (0.002) |
| Household head is married | | -0.038 | -0.056 | | 0.236*** | 0.158*** |
| | | (0.096) | (0.096) | | (0.021) | (0.017) |
| Ln(adjusted income) | | | 0.158** | | | 0.677*** |
| | | | (0.075) | | | (0.018) |
| Lives in apartment/house | | 0.574*** | 0.522*** | | 0.309*** | 0.088*** |
| | | (0.136) | (0.142) | | (0.034) | (0.025) |
| Lives in rural area | | -3.300*** | -3.300*** | | -0.081*** | -0.080*** |
| | | (0.125) | (0.125) | | (0.026) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.08 | 0.38 | 0.39 | 0.19 | 0.29 | 0.54 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1 and 4 run the basic models with province and year fixed effects. Columns 2 and 5 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 3 and 6 add log of household per capita income in the model.

## 2.F OECD equivalence scale

**Table 2.F.1: DiD results of the mining impact on income, food and non-food expenditures**

| | ln(income) | | ln(food) | | | ln(non-food) | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Ln(local taxes) × mining | -0.003 | -0.016 | 0.096*** | 0.087*** | 0.097*** | -0.083*** | -0.103*** | -0.092*** |
| | (0.019) | (0.017) | (0.016) | (0.015) | (0.013) | (0.020) | (0.018) | (0.014) |
| 2012 | 0.573*** | 0.533*** | 0.191*** | 0.165*** | 0.037 | 0.457*** | 0.422*** | 0.077** |
| | (0.033) | (0.032) | (0.025) | (0.026) | (0.023) | (0.043) | (0.038) | (0.033) |
| 2014 | 0.750*** | 0.707*** | 0.293*** | 0.274*** | 0.090*** | 0.755*** | 0.717*** | 0.258*** |
| | (0.032) | (0.031) | (0.023) | (0.022) | (0.021) | (0.040) | (0.035) | (0.032) |
| 2016 | 0.851*** | 0.779*** | 0.045* | 0.018 | -0.180*** | 0.715*** | 0.652*** | 0.147*** |
| | (0.032) | (0.031) | (0.025) | (0.024) | (0.023) | (0.039) | (0.036) | (0.031) |
| Household head's age (years) | | 0.005*** | | -0.001** | -0.001*** | | -0.000 | -0.003*** |
| | | (0.000) | | (0.000) | (0.000) | | (0.001) | (0.000) |
| Household head is male | | 0.064*** | | 0.035** | 0.032** | | 0.025 | -0.016 |
| | | (0.019) | | (0.014) | (0.014) | | (0.023) | (0.018) |
| Household head's education (years) | | 0.027*** | | 0.002* | -0.005*** | | 0.037*** | 0.020*** |
| | | (0.002) | | (0.001) | (0.001) | | (0.002) | (0.002) |
| Household head is married | | 0.188*** | | 0.099*** | -0.047*** | | 0.283*** | 0.159*** |
| | | (0.019) | | (0.013) | (0.012) | | (0.022) | (0.017) |
| Ln(adjusted income) | | | | | 0.284*** | | | 0.649*** |
| | | | | | (0.011) | | | (0.018) |
| Lives in apartment/house | | 0.315*** | | 0.048** | -0.026 | | 0.301*** | 0.097*** |
| | | (0.032) | | (0.021) | (0.020) | | (0.033) | (0.024) |
| Lives in rural area | | -0.004 | | 0.129*** | 0.134*** | | -0.102*** | -0.099*** |
| | | (0.020) | | (0.017) | (0.016) | | (0.025) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.25 | 0.34 | 0.15 | 0.23 | 0.29 | 0.18 | 0.30 | 0.54 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 6 run the basic models with province and year fixed effects. Columns 2, 4 and 7 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 5 and 8 add log of household per capita income in the model.

**Table 2.F.2: DiD results of the mining impact on medical expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(local taxes) × mining | 0.044 | 0.059* | 0.072** |
| | (0.036) | (0.032) | (0.031) |
| 2012 | 0.532*** | 0.458*** | 0.253*** |
| | (0.070) | (0.067) | (0.070) |
| 2014 | 0.852*** | 0.766*** | 0.475*** |
| | (0.064) | (0.063) | (0.068) |
| 2016 | 1.165*** | 1.023*** | 0.707*** |
| | (0.063) | (0.062) | (0.067) |
| Household head's age (years) | | 0.025*** | 0.024*** |
| | | (0.001) | (0.001) |
| Household head is male | | -0.039 | -0.047 |
| | | (0.044) | (0.043) |
| Household head's education (years) | | 0.022*** | 0.010*** |
| | | (0.003) | (0.003) |
| Household head is married | | 0.194*** | -0.011 |
| | | (0.042) | (0.038) |
| Ln(adjusted income) | | | 0.444*** |
| | | | (0.027) |
| Lives in apartment/house | | 0.307*** | 0.187*** |
| | | (0.058) | (0.056) |
| Lives in rural area | | -0.251*** | -0.244*** |
| | | (0.045) | (0.044) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.15 | 0.25 | 0.27 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.F.3: DiD results of the mining impact on the likelihood of reporting illness**

| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Ln(local taxes) × mining | -0.004 | -0.003 | -0.003 | -0.001 | -0.003 | -0.001 |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| 2012 | | -0.006 | | -0.007 | | -0.006 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2014 | | 0.003 | | 0.002 | | 0.002 |
| | | (0.004) | | (0.004) | | (0.004) |
| 2016 | | -0.007* | | -0.008* | | -0.007* |
| | | (0.004) | | (0.004) | | (0.004) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Individual is male | | -0.015*** | | -0.013*** | | -0.013*** |
| | | (0.002) | | (0.002) | | (0.002) |
| Individual's education (years) | | -0.002*** | | -0.002*** | | -0.001*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Ln(adjusted wage income) | | -0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Lives in apartment/house | | 0.015** | | 0.013*** | | 0.011** |
| | | (0.006) | | (0.005) | | (0.004) |
| Lives in rural area | | -0.031*** | | -0.027*** | | -0.025*** |
| | | (0.004) | | (0.003) | | (0.003) |
| Model | LPM | LPM | Probit | Probit | Logit | Logit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$/Psedu $R^2$ | 0.00 | 0.02 | 0.01 | 0.05 | 0.01 | 0.05 |
| Number of individuals | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 | 36,704 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1, 3 and 5 run the basic models with province and year fixed effects. Columns 2, 4 and 6 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.F.4: DiD results of the mining impact on education expenditure**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(local taxes) × mining | -0.140* | -0.100* | -0.231*** |
| | (0.082) | (0.054) | (0.073) |
| 2012 | -0.423*** | 0.288** | -0.025 |
| | (0.150) | (0.113) | (0.138) |
| 2014 | -0.453*** | 0.111 | 0.062 |
| | (0.150) | (0.116) | (0.147) |
| 2016 | -0.810*** | 0.073 | -0.089 |
| | (0.145) | (0.116) | (0.147) |
| Household head's age (years) | | -0.068*** | -0.090*** |
| | | (0.002) | (0.003) |
| Household head is male | | -1.509*** | -1.880*** |
| | | (0.101) | (0.144) |
| Household head's education (years) | | 0.053*** | 0.069*** |
| | | (0.007) | (0.010) |
| Household head is married | | 0.893*** | 3.394*** |
| | | (0.100) | (0.120) |
| Ln(adjusted income) | | | -0.564*** |
| | | | (0.070) |
| Lives in apartment/house | | -0.037 | -0.246* |
| | | (0.127) | (0.147) |
| Lives in rural area | | -0.331*** | -0.434*** |
| | | (0.080) | (0.093) |
| Province fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.01 | 0.50 | 0.24 |
| Number of households | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita basis. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column 1 runs the basic model with province and year fixed effects. Column 2 adds household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Column 3 adds log of household per capita income in the model.

**Table 2.F.5: DiD results of the mining impact on educational attainment**

| | OLS | | Ordered-logit | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Ln(local taxes) × mining | 0.122** | 0.153*** | 0.067*** | 0.072*** |
| | (0.058) | (0.055) | (0.021) | (0.021) |
| 2012 | 0.882*** | 0.066 | 0.194*** | -0.109*** |
| | (0.108) | (0.104) | (0.037) | (0.039) |
| 2014 | 0.864*** | -0.072 | 0.171*** | -0.154*** |
| | (0.097) | (0.102) | (0.033) | (0.037) |
| 2016 | 1.094*** | -0.090 | 0.334*** | -0.090** |
| | (0.095) | (0.101) | (0.033) | (0.037) |
| Individual's age (years) | | 0.082*** | | 0.032*** |
| | | (0.002) | | (0.001) |
| Individual is male | | -0.703*** | | -0.281*** |
| | | (0.050) | | (0.018) |
| Ln(adjusted income) | | 1.025*** | | 0.386*** |
| | | (0.055) | | (0.021) |
| Lives in apartment/house | | 1.412*** | | 0.652*** |
| | | (0.113) | | (0.046) |
| Lives in rural area | | -1.010*** | | -0.416*** |
| | | (0.069) | | (0.026) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.02 | 0.15 | | |
| Pseudo $R^2$ | | | 0.00 | 0.03 |
| Number of households | 32,552 | 32,552 | 32,552 | 32,552 |

*Note:* Robust standard errors, clustered at the household level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1 and 3 run the basic models with province and year fixed effects. Columns 2 and 4 add individual-specific controls to the specification. The reference groups is female, living in traditional gers and urban areas.

**Table 2.F.6: DiD results of the mining impact on electricity and other non-food expenditures**

| | ln(electricity) | | | ln(other non-food) | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(local taxes) × mining | 0.336* | 0.262** | 0.268** | -0.089*** | -0.112*** | -0.100*** |
| | (0.197) | (0.130) | (0.129) | (0.021) | (0.019) | (0.015) |
| 2012 | 1.065*** | 0.708*** | 0.623*** | 0.511*** | 0.470*** | 0.115*** |
| | (0.294) | (0.206) | (0.207) | (0.043) | (0.039) | (0.033) |
| 2014 | 0.653* | 0.244 | 0.125 | 0.819*** | 0.778*** | 0.302*** |
| | (0.340) | (0.219) | (0.224) | (0.040) | (0.036) | (0.033) |
| 2016 | 1.683*** | 0.991*** | 0.861*** | 0.760*** | 0.696*** | 0.173*** |
| | (0.321) | (0.213) | (0.215) | (0.039) | (0.036) | (0.032) |
| Household head's age (years) | | 0.017*** | 0.017*** | | -0.002*** | -0.005*** |
| | | (0.003) | (0.003) | | (0.001) | (0.000) |
| Household head is male | | -0.683*** | -0.687*** | | 0.041* | 0.003 |
| | | (0.105) | (0.105) | | (0.023) | (0.019) |
| Household head's education (years) | | 0.256*** | 0.252*** | | 0.034*** | 0.016*** |
| | | (0.009) | (0.009) | | (0.002) | (0.002) |
| Household head is married | | -0.003 | -0.082 | | 0.304*** | 0.139*** |
| | | (0.101) | (0.095) | | (0.022) | (0.017) |
| Ln(adjusted income) | | | 0.181** | | | 0.683*** |
| | | | (0.073) | | | (0.018) |
| Lives in apartment/house | | 0.567*** | 0.517*** | | 0.299*** | 0.089*** |
| | | (0.135) | (0.141) | | (0.034) | (0.025) |
| Lives in rural area | | -3.265*** | -3.262*** | | -0.083*** | -0.079*** |
| | | (0.124) | (0.123) | | (0.026) | (0.021) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.08 | 0.39 | 0.39 | 0.19 | 0.31 | 0.54 |
| Number of households | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 | 10,353 |

*Note:* All dependent variables are in per capita level. Robust standard errors, clustered at the HSES cluster level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Columns 1 and 4 run the basic models with province and year fixed effects. Columns 2 and 5 add household-specific controls to the specification. The reference group is female, never married, separated or widowed, living in traditional gers and urban areas. Columns 3 and 6 add log of household per capita income in the model.

# Chapter 3 No pain, no gain? Mining pollution and morbidity[1]


## Abstract

We investigate the impact of mining pollution on the likelihood of reporting illness by linking geocoded soil pollution information with five rounds of Mongolian Household Socio-Economic Survey data. Using perceived property rent as an instrument, our probit regression results indicate that doubling the distance between a person's residence and nearest mine reduces their probability of feeling unwell by around 7.4 percentage points on average. Individuals also increase their medical expenditure as a result of increased illness. We observe mining pollution to disproportionately hurt younger children. Artisanal and small-scale mines have stronger effects on human health than medium and large-scale mines. Gold mines were observed to be worst, compared to the mines extracting other types of minerals. Our findings suggest that environmental regulations to control/mitigate mining pollution can reduce short- to long-term health risks of the people living near mines.



**JEL-Classification:** I15, O13, Q53, Q56

**Keywords:** Mining pollution, Health, Development, Mongolia



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## 3.1 Introduction

Mining and processing of minerals release toxic substances that affect not only the people working in mines but also those living nearby (Graff Zivin and Neidell, 2013; von der Goltz and Barnwal, 2019). A significant number of studies have been undertaken on the health impacts of mining that primarily rely on the mining-induced air and water pollution or distance from mines (e.g., Cardoso, 2015; Aragón and Rud, 2015; Hendryx et al., 2020; Levasseur et al., 2021). However, empirical evidence on the impacts of mining activity employing precise soil pollution location data remains limited. Using location-specific soil pollution information, we investigate the impact of mining activities on the likelihood of reporting illnesses at the individual level. In particular, using the case of mines in Mongolia, we document that individuals close to a polluted mining site experience a higher probability of feeling ill. It, therefore, increases their health expenditures. We subsequently investigate how types and level of heavy metal soil pollution affect reported illness, and conclude that distance from the nearest mine is the salient determining factor of mining activity on reporting illness.

We focus on mines located in Mongolia for three reasons. First, as a developing country with a large mining industry (Li et al., 2017; Baatarzorig et al., 2018; Doojav and Luvsannyam, 2019) and a limited regulatory environment (Greenstone and Hanna, 2014), Mongolia presents an ideal place to study adverse effects of mining pollution on health outcomes. At the same time, people living near mines typically benefit from the increased economic activity created by mining (Tolonen, 2019). Thus, analyzing Mongolia's situation can provide potential costs and benefits of mining on health: relevant to low-income resource-rich countries. Second, mining activities in small, medium, and large-scale mines are geographically very common, covering jointly around 5 percent of Mongolia's territory. Of that, more than 60,000 miners and their dependents rely on artisanal and small-scale mines (ASMs) for their livelihood in Mongolia (SDC, 2018). This widespread use of mining provides for a large dataset that will limit the effects outliers have on studies of smaller samples of mines. It simultaneously allows us to compare the effects of ASMs and large-scale mines (similar to Bazillier and Girard (2020) in Burkina Faso). Third, the availability and accessibility of precise soil pollution location data for mines in Mongolia strengthens our empirical analysis.

The use of precise mining-related soil pollution data allows us to estimate precisely the effect of soil pollution on human health - our key contribution. While the effects of distance from mines on general health have been studied previously (e.g., Rau et al., 2015; Currie et al., 2015; von der Goltz and Barnwal, 2019), ours is the first study to capture the precise distance of an individual household from the polluting mine site. Many previous studies on the impact of mines rely on air and water pollution from mining, with a few studying the effects of toxic emissions and heavy metal pollution (e.g., Currie et al., 2015; von der Goltz and Barnwal, 2019). The lack of precise information limits the current economic literature, despite biological evidence linking soil pollution to the deterioration in human health (Rodrigues and Römkens, 2018; Cachada et al., 2018).

Graff Zivin and Neidell (2013) note that the distance from a polluted site is a critical factor that influence health outcomes from pollution. However, a key problem - including in our estimation - is that distance (hence the level of pollution that residents are exposed to) can be endogenous due to well-documented avoidance or residential sorting behaviour.[2] Another source of endogeneity in the model of pollution on illness is residential sorting, as some households choose to relocate to a cleaner area to avoid pollution exposure (Currie, 2011; Graff Zivin and Neidell, 2013; von der Goltz and Barnwal, 2019; Marcus, 2021). On the other hand, city-level amenities attract highly skilled individuals who make extra investments in their health to address the impacts of potential pollution in the city. To control for the endogeneity and estimate the average biological effect of pollution, our instrumental variable approach uses households' perceived property rent as an instrument for distance to the nearest mine.

In our IV-probit model, distance to the pollution source significantly increases the likelihood of reporting illness. Our estimated "local average treatment effect" (LATE) of mines implies that the reported illness incidence declines by 7.4 percentage points when an individual doubles the distance of their residence from the nearest mine, on average. The finding is robust to the choice of methods, models and employed data. We corroborate this key result with an auxiliary regression which establishes that private medical expenditures on health decline significantly with the distance from the mine sites.

We next study the adverse effects of soil pollution on health outcomes by age and type of illness. Although the estimated effect of pollution is high for older people, the probability of illness increases most significantly for younger children. There are no significant differences across a variety of reported illnesses (respiratory, cardiovascular, digestive, and other body systems). Consistent with some previous literature (Tolonen, 2019; Greenstone and Jack, 2015), we find that small-scale mines increase the likelihood of illness more than medium- and large-scale mines.

[2] See e.g., Neidell (2004); Graff Zivin and Neidell (2012); Burke et al. (2021); Currie (2011); Graff Zivin and Neidell (2013); von der Goltz and Barnwal (2019); Marcus (2021).

Finally, consistent with Aragón and Rud (2015) and von der Goltz and Barnwal (2019), we find that gold mines have a higher impact on the probability of feeling ill compared to the mines extracting other minerals. With our findings, we contribute to the literature by providing a more general and precise impact of mining pollution on illness that complements to the previous studies like von der Goltz and Barnwal (2019) who find negative impact of mining on the women and children health.

The rest of the paper proceeds as follows. Section 3.2 presents the effects of heavy metal pollution on human health and briefly discusses relevant studies along with the background information on Mongolia. Section 3.3 describes the empirical strategy and the data employed in the paper. The results from our analysis, including a bunch of robusness checks we conducted, are presented in Section 3.4. Section 3.5 discusses the findings, including their policy implications. Section 3.6 concludes.

## 3.2 Background

### 3.2.1 Pollution and human health

The mining industry can raise income and consumption and positively affect health outcomes. At the same time, it can exert significant negative externalities on the local communities (Tolonen, 2019). In particular, mining can substantially increase the health risk of the local population by contaminating soil, water, and air. Mining and processing of minerals release numerous types of harmful pollutants to the environment, including lead, cadmium, mercury, and nickel (Facchinelli et al., 2001; Li et al., 2014).[3]

Mercury is a dangerous neurotoxin that is harmful to people, especially developing fetuses and young children. Mercury increases the risks of damaging brain and nervous system development and function (Landrigan et al., 2018). Symptoms such as swollen gingiva, fever, dry cough, shortness of breath, dyspnoea, abdominal pain, nausea, vomiting, and diarrhea occur after acute exposure to mercury vapor (Solis et al., 2000). The inhalation of mercury vapor can affect the body in three phases, with different symptoms occurring in each phase (Lim et al., 1998).[4] In addition, chronic mercury exposure through dietary intake can cause Minamata disease, renal,

[3]For example, each kilogram of gold extraction releases around 1.3 kilograms of mercury into the environment (Harada et al., 1999). Around 40 percent of the mercury goes to tailings, soils, stream sediments, lakes, and rivers during the initial stage of gold and mercury amalgamation. The remaining 60 percent of the lost mercury enters into the atmosphere during the amalgam burning process used to extract gold (Van Straaten, 2000).

[4]Initially, flu-like symptoms occur in 1-3 days after exposure. Later, the patient can develop chronic bronchiolitis similar to symptoms of metal fume fever (Offermann and Finley, 1992). In the intermediate stage, diseases related to

pulmonary, reproductive, and cardiovascular toxicity and have neurotoxic effects (Żukowska and Biziuk, 2008).

Arsenic is another toxic heavy metal that poses significant health risks to people exposed for a long time. Mining and smelting are the primary sources of arsenic pollution in air, water and soil (Duker et al., 2005; Ongley et al., 2007; Lee et al., 2008). Breathing air with high arsenic levels can cause shortness of breath, chest pain, and cough. Arsenic intake can also affect several organs such as skin, gastrointestinal, peptic, neurological, and respiratory systems (ATSDR, 2007). Arsenic is a known toxin related to mining activities in developing countries in particular. For example, in Latin American countries where mining operations are prevalent, exposure to anthropogenic sources of arsenic have been found to be associated with increased risks of cancer, cardio-respiratory diseases, reproductive outcome, and cognitive effects in adults and children (Khan et al., 2020; Bundschuh et al., 2021). The weathering processes of untreated tailing from an abandoned tungsten mine in China has posed public health threats to the local population through food consumption and environmental exposure caused by arsenic pollution in water and soil (Liu et al., 2010).

Acute exposure to the different heavy metal vapor and intoxication may have similar symptoms. For example, acute exposure to other heavy metals such as nickel and lead also results in nausea, vomiting, and diarrhea (Järup, 2003; WHO, 2018). However, chronic exposure to arsenic, cadmium, and nickel can cause cancer, and long-term exposure to mercury and lead can damage the neurological systems, affecting human motor function, IQ level, and short-term memory (Järup, 2003). The danger of the heavy metals remains over the long run as they do not decompose over time (Facchinelli et al., 2001). Over time, chronic illnesses and cancer can develop as leading causes of death in mining regions (Cordier et al., 1983; Hendryx and Ahern, 2009).[5] However, despite the known harmful effects of heavy metals, the monitoring of mining pollution to protect human health is inadequate in developing countries (Greenstone and Hanna, 2014; Greenstone and Jack, 2015).

pulmonary infections and complications develop due to severe pulmonary toxicity (Rowens et al., 1991). The late phase of toxicity causes insomnia, short-term memory loss, anxiety, and depression (Solis et al., 2000).

[5]Chronic conditions such as cancer from exposure to heavy metals are not diagnosed as quickly as acute symptoms because chronic illnesses take longer to develop. Although determining the presence of heavy metals in the body uses human tissue samples (e.g., hair, blood, and urine), it does not assist in the diagnoses of the symptoms of chronic conditions without proper clinical examinations (Solis et al., 2000).

### 3.2.2 Mining and health in Mongolia

Mongolia is a lower-middle-income country heavily reliant on the mining of minerals such as coal, copper, gold, and iron ore.[6] It is one of the 45 countries where mercury is the dominant pollutant at ASM sites (Caravanos et al., 2013). Illegal mercury use is common among the artisanal placer gold miners as it is cheaper to use than the alternative gravitational methods (Dore et al., 2006). Among others, Mongolia's largest copper-molybdenum mine Erdenet releases chemicals like copper, molybdenum, and mercury during the processing and tailing of materials. The contamination in soil spread outside the mining area through wind-driven dust (Battogtokh et al., 2014).

The large, medium, and small-scale mining operations in Mongolia have already caused water quality deterioration, air pollution, increased waste-rock piles and tailing repositories, and threats to natural habitat and biodiversity (Dore et al., 2006). Some mining operations have permanently altered landscapes and landforms, reducing pasture availability for traditional livestock herding and, in some cases, leading to the cessation of farming and herding activities (Cane et al., 2015).

Yet, precise empirical evidence on the impacts of mining pollution on human health is scarce in Mongolia.[7] Only a few field studies from small-scale mining activities report the adverse health impacts of mining operations on a sub-sample of resident population. For example, an environmental epidemiological study examining 200 human urine, blood, and hair samples finds high mercury body burden among gold miners and elevated levels of mercury among the residents around small-scale gold mines in Mongolia (Steckling et al., 2011). In addition, adults face higher risks of suffering from asthma and tuberculosis, and children have an increased prevalence of respiratory illness around ASMs in Mongolia (HRC and SDC, 2012).

High concentrations of arsenic in surface, ground, drinking water, and soils are commonly found in Mongolia. The elevated level of arsenic in these media is attributable to gold mining activities (Pfeiffer et al., 2015).[8] However, there is no comprehensive soil pollution analysis related to the mining sector. We bridge a number of the aforementioned gaps in our study by utilizing

[6] The country received a substantial amount of foreign direct investment (FDI) into the extractive industries at the onset of the commodity price boom in the early 2000s, accounting for more than 75 percent of FDI during 2011-2016 (National Statistics Office, 2016).

[7] Health impact assessments of Mongolian mines have not been carried out widely as it is not part of the mandatory environmental impact assessments (Pfeiffer et al., 2017).

[8] Specifically, the gold mines at the Zaamar site were estimated to increase the arsenic load of the major river Tuul by 30 tons a year. Another gold mine, Gatsuurt, had arsenic levels reaching 121 $\mu g/L$ in its artificial ponds (Thorslund et al., 2012; Gandoljin et al., 2013). Drinking water and river samples also contain arsenic levels above the Word Health Organization (WHO) maximum permissible limit of 10 $\mu g/L$ (Pfeiffer et al., 2015). Similarly, the average concentration

location-specific soil pollution data linked with nationally representative household-level survey data.

## 3.3 Methodology and data

### 3.3.1 Empirical model

We model an individual's likelihood of reporting illness on the shortest distance of the individual's residence from a mine. The choice of distance is motivated by the fact that it can capture the impact of all types of pollution –air, water, and land and have been used in many earlier studies (e.g., Rau et al., 2015; Currie et al., 2015). We primarily employ the following specification:

$$y_i = \alpha + \beta \, ln(distance_i) + \boldsymbol{X}_i\gamma + \lambda_s + \eta_t + \varepsilon_i, \tag{3.1}$$

where, for each individual $i$, the outcome variable $y$ takes the value of one if the individual has been ill in the past month and zero otherwise. The primary variable of interest, $distance$, measures the distance from an individual's residential area to the nearest mine and is a proxy to exposure to mining pollution. Note that the heavy metal contaminants originated from the same mine are highly correlated, and therefore distance will capture the combined impact of all the heavy metals on illness. Furthermore, mines pollute soil, water, and air simultaneously, so our measure of pollution exposure will also tap the impact of all types of pollution.

The vector $X$ includes a person's age, gender, education, household size, (household) consumption, and housing characteristics, to control for the factors affecting illness. The term $\lambda$ indicates (s) province fixed effects to account for possible omitted location variables and the time-invariant differences in provinces that could affect illness. We also include survey year fixed effects $\eta$, to capture the impact of duration of exposure. It will also control for the overtime change in illness that are originated from different time-varying events. Finally, $\varepsilon$ is the independently and identically distributed error term. We restrict our focus on mines within five km of individuals' residences. The choice of our distance cutoff follows von der Goltz and Barnwal (2019), who uses a five km cutoff to determine the effect of lead contamination on health outcomes.[9]

of arsenic is 1.4 times higher than the maximum permissible level around the largest coal mine, Tavan Tolgoi, and copper-gold mine, Oyu Tolgoi, in Southgobi province, Mongolia (Ragchaa et al., 2018).

[9]There is no consensus in the literature on the exact distance buffer. For example, Aragón and Rud (2015); Parker et al. (2016); De Haas and Poelhekke (2019) use 20 km distance for Ghana, Democratic Republic of Congo, Colombia and several resource-rich countries, respectively, to examine the health and economic impacts of mining. On the other hand, Tolonen (2019); Bazillier and Girard (2020) use 10 km buffer in African countries.

Our dataset contains information about seven different types of heavy metals at the mining sites. Therefore, a natural extension of Equation (3.1) is to modify the model to capture the impact of seven different contaminants (heavy metals), as given below:

$$y_i = \alpha + \beta_j \sum_{j=1}^{7} ln(distance_{j,i}) + \boldsymbol{X}_i\boldsymbol{\gamma} + \lambda_s + \eta_t + \varepsilon_i, \tag{3.2}$$

where everything is the same as Equation (3.1), but $distance_j$ now captures the distance from an individual's residence to the sample point where the highest level of heavy metal $j$ is recorded. Since most heavy metals originate from the same source, including all seven distances in a single model creates multicollinearity. Therefore, to compare the estimated coefficients for each heavy metal, we estimate Equation (3.2) separately for every single pollutant.[10]

We further extend our model to account for the level of each heavy metal pollution in the model. The model below controls for the impact of heavy metal contamination level that are above the permissible level set by the Mongolian Agency for Standardization and Meteorology (MASM, 2019):

$$\begin{aligned} y_i &= \alpha + \sum_{j=1}^{7} ln(distance_{ji}^{\beta_j} \times level_{ji}^{\delta_j}) + \boldsymbol{X}_i\boldsymbol{\gamma} + \lambda_s + \eta_t + \varepsilon_i \\ &= \alpha + \sum_{j=1}^{7} \beta_j \, ln(distance_{ji}) + \sum_{j=1}^{7} \delta_j \, ln(level_{ji}) + \boldsymbol{X}_i\boldsymbol{\gamma} + \lambda_s + \eta_t + \varepsilon_i \\ &= \alpha + \beta \, ln(distance_i) + \sum_{j=1}^{7} \delta_j \, ln(level_{ji}) + \boldsymbol{X}_i\boldsymbol{\gamma} + \lambda_s + \eta_t + \varepsilon_i, \end{aligned} \tag{3.3}$$

where, the last step follows Equation (3.1) and include only distance from the nearest mine to avoid multicollinearity. As evident, compared to Equation (3.1), Equation (3.3) additionally includes the (logarithm of) heavy metal level at the nearest sites. Since the contamination level for only arsenic and mercury exceed the value, we drop heavy metal levels for the other contaminants from our regressions.

A final specification considers that the causal link between pollution and illness can be non-linear in the log distance. Thus, following Currie et al. (2009a), we include dummy variables for the heavy metals that are above the permissible levels as given below:

[10] For some heavy metals, the highest level of pollution within five km is below permissible levels.

$$y_i = \alpha + \beta \, ln(distance_i) + \sum_{j=1}^{7} \delta_j D_j + \boldsymbol{X}_i \gamma + \lambda_s + \eta_t + \varepsilon_i, \quad (3.4)$$

where, in addition to the notations defined earlier, $D_j$ takes the value of one for individuals exposed to heavy metal pollution $j$ (in the nearest mine) if its level is above the critical value and zero otherwise. For the reason stated earlier, we include the dummies for arsenic and mercury only.

### 3.3.2 Endogeneity issues

The problem with the above models is that distance may suffer from endogeneity for several reasons. First, pollution is endogenous due to the avoidance behavior of residents (Neidell, 2004; Graff Zivin and Neidell, 2012, 2013; Burke et al., 2021). Public announcements on outdoor air quality and the visibility of the pollution allow people assess the level of pollution and take steps to avoid it. For example, people reduce their outdoor activities and use air filters in their residence when exposed to air pollution. Such actions may limit their exposure to pollution (Neidell, 2004; He et al., 2022).

People affected by pollution might not be aware of the potential hazards if they cannot observe the pollution, or local authorities do not inform them (Graff Zivin and Neidell, 2013). For example, mercury vapor is odorless and colorless, making it difficult to see and smell during the mercury and gold amalgamation process until the human body reacts adversely to the vapor evaporation (Solis et al., 2000). Similarly, most inorganic arsenic compounds are white or colorless powders with no smell or taste (ATSDR, 2007).[11] Therefore, deliberate avoidance behavior is limited when public information about pollution is unavailable, or when the heavy metals in soil are not readily observable (Graff Zivin and Neidell, 2013).

Nevertheless, residents usually have some understanding of local pollution, if not directly from the public offices, then indirectly from social interaction or by observing increased incidence of illness among the people living nearby. They may, therefore, attempt to avoid pollution. The avoidance behavior is an ex-post decision, and excluding this action from the empirical model would give us a lower-bound of the average biological effect of pollution. Since the variable of interest in our study is the biological effect of pollution, it will be underestimated by the extent to which avoidance behavior can mitigate the adverse health effects (Currie et al., 2014).

[11] Inorganic arsenic is found in minerals and ores that contain copper or lead. During the smelting of these minerals, most arsenic enters into the atmosphere as fine colorless, tasteless, and odorless dust.

The second source of endogeneity in our model may arise from residential sorting. Households choose to relocate to a cleaner area to permanently avoid their exposure to pollution (Graff Zivin and Neidell, 2013; von der Goltz and Barnwal, 2019). Educated people, informed about the adverse impacts of pollution, are the primary drivers of residential sorting (Currie, 2011; Marcus, 2021). These higher-income earners are most likely to relocate away from polluted areas than the financially more constrained households. Greater employment opportunities in cities attract high skilled workers. These individuals may make extra investments in their health to address the potential health impacts of pollution in the city (Graff Zivin and Neidell, 2013). Residential sorting, therefore, may make health outcomes endogenous to socio-economic status and skill level (Graff Zivin and Neidell, 2013; Currie et al., 2014).

In developing countries, residential sorting is further limited by labor market frictions and mismatch between skills and jobs (Banerjee and Duflo, 2019). Attachment to the community, economic and job opportunities provided by polluting industries affect households' decision to emigrate from or immigrate into polluted areas (Banzhaf and Walsh, 2008), further limit residential sorting. Nevertheless, even with indirect and circumstantial information about local pollution and illness, residential sorting presents a potential challenge to our empirical identification and specification.[12] Omitting the residential sorting in our empirical model would yield an average effect of pollution that under-estimates the direct biological effect.

Several other omitted variables complicate our causal inference. For example, prevailing winds, water flows, differences in altitude, changes in seasonal temperatures, and other allergens in the environment may affect illness and can correlate with pollution (Graff Zivin and Neidell, 2013; Anderson, 2020). The inclusion of location fixed effects in the models are likely to account for a significant part of the time-invariant permanent differences among the provinces, such as altitude and water flows. They will also account for unobserved spatial amenities such as public goods that can affect households' decisions to stay or move away (Banzhaf and Walsh, 2008). We also control for survey-year effects to account for time-varying characteristics of households that may affect a person's likelihood of feeling unwell. To account for the seasonality of illness, we have added survey quarter (or month) fixed effects. See Subsection 4.4.3 for more discussions on this issue.

[12] Interestingly, in our estimation sample, the educational attainment of the residents above 15 years remained stable during the period 2008-2018. Education level rose slightly to above 11 years in the last two survey waves 2016-2018. Educational attainment of the population above 15 years who live further away than five km increased over the same period. However, the average educational attainment is 10 years, slightly lower than the population living closer to the mining sites.

To address endogeneity concerns due to avoidance behavior and residential sorting, we follow an instrumental variable approach. We employ perceived property rent of a household-owned residential property as the instrument for distance to the nearest mine, the endogenous variable capturing exposure to pollution in our analysis.[13] Pollution significantly affects property prices (e.g., Currie et al., 2015; Lavaine, 2019) and thus rents. On the other hand, property value can also affect the location of disamenities like an incinerator (Kiel and McClain, 1995). The same can also be true for mines, especially when they are small in scale. Therefore, perceived property rents should be highly correlated with the endogenous proxy for pollution, making our instrument relevant.

The instrument satisfies the exclusion restriction as it is likely to be correlated with illness solely through its correlation with distance. In other words, the instrument is uncorrelated with the error in the outcome equation. This is particularly true as we have controlled for consumption and housing characteristics in the model. Otherwise, perceived property rent could be correlated with the error term in the outcome model, through its correction with income and socio-economic status and the direct effect of housing condition on illness, as found in some earlier studies (Adams et al., 2003; Billings and Schnepel, 2017; Palacios et al., 2021).

### 3.3.3 Individual morbidity, socioeconomic and demographic data

We use individual morbidity data from the most recent five rounds of the Mongolia Household Socio-Economic Survey (HSES), a nationally representative cross-sectional survey conducted every two years by the National Statistics Office of Mongolia. The survey uses a stratified two-stage sample design based on population figures obtained from local governments' administrative records. The first stage stratifies the capital city, Ulaanbaatar, and the 21 provinces. The second stage divides the 21 provinces into two substrata: urban, comprising the provincial capitals, and rural, consisting of small towns and the countryside (NSO, 2018). Our analysis includes 2008, 2010, 2014, 2016, and 2018 rounds and exclude the 2012 round of the HSES, as it has missing geographic coordinates of the households. The data on households' geographic coordinates are crucial as we construct the exposure variable - distance to the nearest mine - based on the information.

[13]The HSES asks participants the following questions about a household's residential property "1. Do you own the property you are currently living in? 2. If not, do you rent the property? 3. If you rent, how much do you pay for a month? 4. If you own the property, how much would you expect to be paid if you were to rent it to someone?" We use the information from the HSES and use the property rent as the instrumental variable.

The five rounds of survey data employed in this study included 265,049 individuals in 71,449 households. We drop 32,657 households who live in sub-provinces with no mines, leaving us with 38,792 households with 140,773 individuals. Then we drop 133,091 individuals who live further than five km away from any mine –the cutoff we selected based on earlier literature. Thus, our final analysis sample size is 7,682 individuals, with 739 in 2008, 1,042 in 2010, 2,028 in 2014, 2,060 in 2016, and 1,813 in the 2018 survey rounds. In the final sample, we replace the income of three individuals with their consumption as they report zero income. Also, 250 individuals did not report their health status, which is likely due to the confusion between missing and zero values during data entry. As a result, we treat them as not being ill in the past month. Finally, a total of 155 individuals also did not report their education. Assuming that people in the lower education group are not comfortable reporting their education, we treat their years of schooling as zero.

The HSES asks participants what type of health problem they had in the last month before the survey interview.[14] The illnesses reported by individuals fall into the following categories of body systems: (i) respiratory, (ii) digestive, and (iii) external impact and other illnesses, including cardiovascular disease, damage, or intoxication by external impact. The survey also provides information about individuals' expenditure on medication, transportation, hospitalization, and other medical services in the prior 12 months. Panel A in Table 3.1 presents the summary statistics of the outcome variables. About eight percent of the analysis sample reported illness in the previous month. When disaggregated by illness type, we find that about one percent of all individuals experience digestive illnesses, two percent have respiratory illnesses, and four percent suffer from other types of illnesses. The monthly average medical expense per person is MNT13,510 in the 2010 price level.

Panel B in the table reports the illness levels for three age groups and individuals' exposure to different mines, their sizes, and the mineral types. While 17 percent of the people above the age of 50 have been ill in the past one month, the rate is much lower for other groups – about seven percent of younger children and six percent of the economically active population have been ill in the same period. Individuals exposed to small-scale mines are more likely to be ill than those exposed to larger mines that mining license holders usually operate. Finally, nine percent of individuals living near gold mining sites felt unwell in the previous month compared to the six percent of individuals living near mines extracting other minerals. The summary statistics indicate that the scale of mining activities and mineral types may affect illnesses disproportionately.

[14]The HSES questionnaires and the primary datasets are publicly available from the NSO Census and Survey data catalog: http://web.nso.mn/nada.

Table 3.2 reports the summary statistics for the pollution exposure variable, the instrument and other control variables. The primary variable of interest that captures the exposure to mining pollution is the distance from an individual's residence to the nearest mine. The average distance to the nearest mining site is about 2.5 km. The distances are roughly similar when compared to the mines that release specific heavy metals beyond some threshold level.

**Table 3.1: Summary statistics of outcome variables**

| Variable name | Mean | N |
|---|---|---|
| *Panel A: Overall illness* | | |
| Sick in the past month | 0.08 | 7,682 |
| | (0.27) | |
| Respiratory system illness | 0.02 | 7,682 |
| | (0.15) | |
| Digestive system illness | 0.01 | 7,682 |
| | (0.09) | |
| External impact & other illness | 0.04 | 7,682 |
| | (0.19) | |
| Household medical expenditures | 13.51 | 7,682 |
| | (26.69) | |
| *Panel B: Illness level for sub-samples* | | |
| Age group: 0–14 years | 0.07 | 2,148 |
| | (0.25) | |
| Age group: 15–50 years | 0.06 | 4,354 |
| | (0.23) | |
| Age group: 50+ years | 0.17 | 1,180 |
| | (0.37) | |
| Individuals exposed to license holders | 0.07 | 4,022 |
| | (0.25) | |
| Individuals exposed to small-scale mines | 0.09 | 3,660 |
| | (0.29) | |
| Individuals exposed to gold mines | 0.09 | 3,944 |
| | (0.29) | |
| Individuals exposed to coal & spar mines | 0.06 | 1,387 |
| | (0.24) | |
| Individuals exposed to other minerals | 0.06 | 2,351 |
| | (0.24) | |

*Notes:* Standard deviations are reported in the parentheses. The mean of monthly medical expenses are reported in thousand Tugrik (MNT) and adjusted for 2010 price level. The exchange rate was US$1≈MNT1,257 at the end of 2010.

To address the endogeneity issues in the primary model discussed in Subsection 3.3.2, we employ an instrumental variable approach using household-level information. The survey asks households how much they would charge for a month if they leased their dwelling to someone. We use this perceived rental rate as the instrument for the endogenous distance variables. In the HSES data, the mean perceived rent is around MNT60,000 in the 2010 price level. As we expect, the perceived property rent usually increases with the proximity to the mining sites (data not presented).

**Table 3.2: Summary statistics of independent variables**

| Variable name | Mean | SD |
|---|---|---|
| Distance to the nearest mine (km) | 2.50 | 1.47 |
| Distance to the nearest mine emitting mercury | 2.70 | 1.56 |
| Distance to the nearest mine emitting arsenic | 2.69 | 1.55 |
| Distance to the nearest mine emitting lead | 2.94 | 1.43 |
| Distance to the nearest mine emitting zinc | 3.13 | 1.40 |
| Distance to the nearest mine emitting cadmium | 2.89 | 1.44 |
| Distance to the nearest mine emitting copper | 3.15 | 1.42 |
| Distance to the nearest mine emitting nickel | 3.07 | 1.45 |
| Perceived monthly rent rate | 60.07 | 60.78 |
| Individual is female | 0.51 | 0.50 |
| Individual's age (years) | 28.79 | 19.33 |
| Individual's education (years) | 7.76 | 5.54 |
| Number of household members | 4.32 | 1.58 |
| Ln(household consumption) | 13.10 | 0.26 |
| Brick/wood wall | 0.42 | 0.49 |
| Asphalt/metal roof | 0.41 | 0.49 |
| Household lives in rural area | 0.56 | 0.50 |
| Number of observations | 7,682 | |

*Notes:* The mean of household monthly income is reported in thousand Tugrik (MNT) and adjusted for 2010 price level. The exchange rate was US$1≈MNT1,257 at the end of 2010.

The individual-specific control variables in our data include residents' gender, age, and years of schooling. The household-related control variables are family size, logarithm of household-level monthly consumption, type of wall and roof materials of residential property (house/flat/yurt), and household urban/rural status.[15] Their mean values and standard deviations in Table 3.2 indicate that the control variables are reasonably stable.

[15] Household income and expenditure can be endogenous in our models as sickness can affect them. As a result, we predicted household expenditure using all the control variables along with the share of working age members and employed the predicted value in our models. Our conclusions remain unaffected with their exclusion from the models.

### 3.3.4 Contamination data

We use geo-referenced soil pollution data from mining sites in Mongolia, accessed from the Geo-Database on Ecological Health (GDEH), the Ministry of Environment and Green Development. The database records a total of 1,315 soil samples from 262 mining sites in 95 sub-provinces across 17 provinces for the period 2002-2019.[16] As we limit the mines examined in the study to those located within five km of a residential area, our final sample consists of 33 mining sites in 32 sub-provinces across 13 provinces. The level of heavy metal pollution at these mining sites was examined during 2011-2012.[17] We exclude the samples taken before 2011 or after 2012 as only a few site samples were taken during the period. Moreover, the morbidity data from the household survey does not exist for the years prior to 2008.

The database records the presence of heavy metals across mines extracting different minerals such as gold, coal, limestone, and wolfram. The level of mercury, arsenic, lead, zinc, cadmium, copper and nickel contamination in soil samples is recorded at each mine site sample point. Each mine has around four sample points where soil samples are taken. To assess the heavy metal pollution level, we consider the following three values set by MASM (2019): precaution, trigger, and action.[18] Our analysis only considers the levels of mercury and arsenic as, in our data, only their levels sometimes exceed the action and precaution values, respectively.

We use each soil sample point's longitude and latitude, along with a household's residential area coordinates, to calculate the distance from a household residential area to the sample point. We calculate the great-circle distance from the interior centroid of the location (i.e., residential area) to the closest interior centroid of a soil sample point using the Haversine formula employed in Gradstein and Klemp (2020). As a mining site has several sampling points for heavy metals, we calculate the distance from a household residential area to each sample point and then use the shortest distance in the analysis. The residential area in this context is a subdistrict, which is the second smallest administrative unit in Mongolia. Each subdistrict has its zip code assigned.[19]

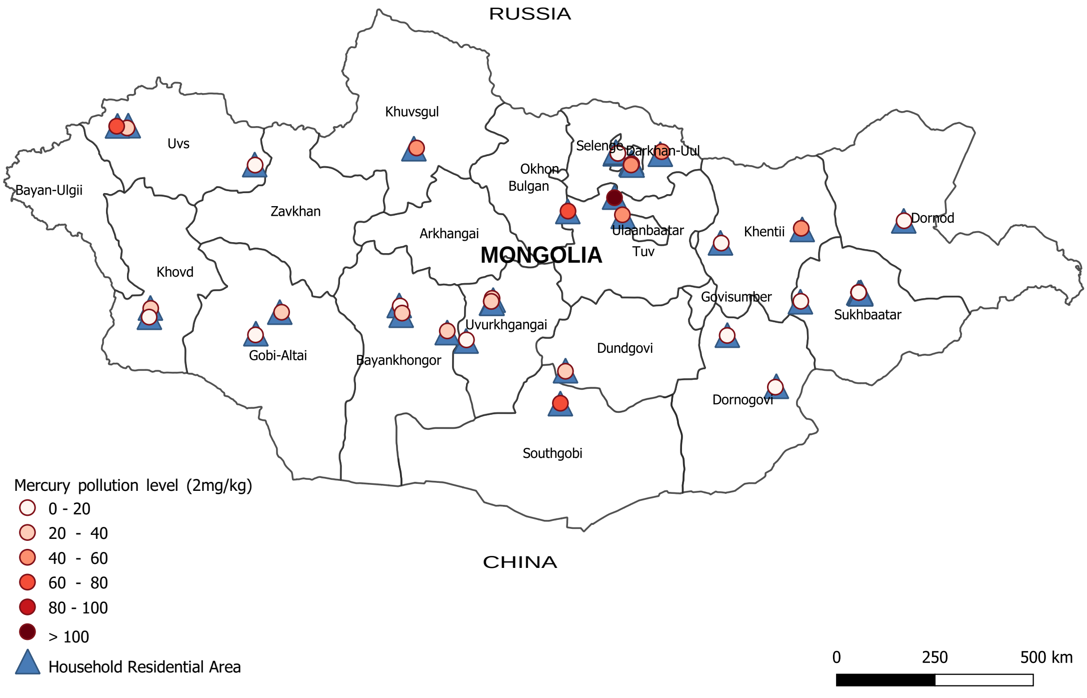
[16] There were 3,222 mining and exploration licenses issued to 2,063 mining companies in Mongolia between 1995 and 2019. The total area covered by mining licenses comprises 4.75 percent of the country's territory (EITIM, 2020).

[17] The Geo-ecological Institute, the Central Geological Laboratory, and the Laboratory of National Agency for Meteorology and Environmental Monitoring examine soil samples in Mongolia using the atomic absorption spectrometry method (GDEH, 2012). The method detects heavy metals in solid samples by applying characteristic wavelengths of electromagnetic radiation from a light source. Individual metals absorb wavelengths differently, and this absorbance is measured against the standards set to analyze the level of heavy metals (Thermo Fisher Scientific, 2021).

[18] A value above the precaution value indicates heavy metal soil pollution. A value exceeding the trigger value implies the pollution level causes harm to the living organisms and water body. A value over the action value requires immediate action to neutralize the soil, stop current land uses, and relocate the affected population MASM (2019).

[19] We use the residential area geographic coordinates data from the National Statistics Office. However, when there are missing geographic coordinates, we use the zip code coordinates from the Communication Regulatory Commission https://bit.ly/3Iz5aN3.

Following Neidell (2004) and Currie and Neidell (2005) who assign air pollution to each individual from their zip code centroid to the air pollution monitoring stations within 20 miles of a zip code radius, we assign pollution from the soil sample point to each individual's residential area. As an example, Figure 3.1 below shows the geographic distribution of household residential areas and mercury contamination at mining sites. It appears that the mining sites and the households are distributed throughout the country.




Source: Authors' compilation

**Figure 3.1: Geographic distribution of household residential areas and mercury contamination at mining sites**

Table 3.3 reports the extent of soil heavy metal contamination and individual exposure to the pollution. Almost all individuals are exposed to mercury pollution, significantly affecting living organisms (columns 4 and 5). More importantly, about 49 percent of them are exposed to mercury pollution that exceeds the action value requiring soil cleansing and relocating the inhabitants (column 6). On the other hand, around 35 percent of individuals are exposed to arsenic pollution. In our data, only very few people are exposed to lead, zinc, and cadmium pollution. The other heavy metals, such as copper, and nickel, do not pollute the soil as they are within the permissible level.

**Table 3.3: Proportion of households exposed to different contamination level**

| | Lower limit for | | | Percentage of individuals living within 5 km of a mine with pollution level > | | |
|---|---|---|---|---|---|---|
| | Precaution value | Trigger value | Action value | Precaution value | Trigger value | Action value |
| Heavy metal | (1) | (2) | (3) | (4) | (5) | (6) |
| Mercury (Hg) | 2 | 10 | 20 | 0.96 | 0.90 | 0.49 |
| Arsenic (As) | 20 | 50 | 100 | 0.35 | 0.11 | 0.03 |
| Lead (Pb) | 100 | 500 | 1,200 | 0.02 | 0.01 | 0.01 |
| Zinc (Zn) | 300 | 500 | 1,000 | 0.02 | 0.01 | 0.00 |
| Cadmium (Cd) | 3 | 10 | 20 | 0.02 | 0.00 | 0.00 |
| Copper (Cu) | 100 | 500 | 1,000 | 0.01 | 0.00 | 0.00 |
| Nickel (Ni) | 150 | 600 | 1,000 | 0.00 | 0.00 | 0.00 |
| N | | | | 7,682 | 7,682 | 7,682 |

*Notes:* All values for the precaution, trigger and action levels are in mg/kg unit. The sample consists of households living within 5 km of a mining site. They are distributed among 33 mining sites.

## 3.4 Results

### 3.4.1 Main results

We estimate Equation (3.1) to examine whether the distance to the nearest mine affects the likelihood of reporting illness (Table 3.4). We estimate the model initially with OLS, i.e., employ a linear probability model (LPM). First, we estimate Model (3.1) excluding the individual and household-specific controls. The results in Column 1 indicate an expected protective effect of distance that is significant at the 10 percent level, indicating that proximity to mines increases the level of reported illness. Next, we add the control variables and survey-year fixed effects in the model to estimate the full Model (3.1). We again find a similar effect that is significant at the 5 percent level (Column 2); our results indicate that moving away from mines in a way that will double the distance from the nearest mine reduces reported illness by 1.5 percentage points. Standard errors are clustered at the household-level and reported in the parentheses.[20]

Due to the issue of constant marginal effects and implausible predicted probability values associated with the LPM, we employ a probit model and estimate the marginal effects (MEs). Estimated MEs from the model without individual and household level controls indicate a slightly lower impact than the comparable LPM (Column 3). Next, we add the control variables to the probit model. MEs evaluated at the mean values of other covariates reveal a slightly lower but similar impact as the comparable LPM (Column 4).

[20]We follow the same analysis pattern, clustering, and significance level throughout the study.

**Table 3.4: The effect of mining pollution on illness**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.009* | -0.015** | -0.008* | -0.013*** | -0.071** | -0.074** | -0.066** | -0.074** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.028) | (0.029) | (0.028) | (0.031) |
| Individual is female | | 0.019*** | | 0.018*** | | 0.019*** | | 0.018*** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.006) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.001 | | 0.001 | | 0.002 | | 0.001 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Number of household members | | 0.023*** | | 0.014** | | 0.025*** | | 0.016** |
| | | (0.008) | | (0.006) | | (0.008) | | (0.007) |
| Ln(household consumption) | | -0.306*** | | -0.202*** | | -0.320*** | | -0.225*** |
| | | (0.076) | | (0.057) | | (0.079) | | (0.066) |
| Brick/wood wall | | 0.003 | | 0.003 | | 0.007 | | 0.007 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | 0.002 | | 0.003 | | -0.010 | | -0.009 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.010) |
| Household lives in rural area | | 0.022** | | 0.018* | | 0.008 | | 0.005 |
| | | (0.011) | | (0.010) | | (0.014) | | (0.013) |
| 2010 | | 0.156*** | | 0.110*** | | 0.167*** | | 0.125*** |
| | | (0.035) | | (0.027) | | (0.037) | | (0.032) |
| 2014 | | 0.159*** | | 0.101*** | | 0.160*** | | 0.104*** |
| | | (0.047) | | (0.036) | | (0.048) | | (0.040) |
| 2016 | | 0.097*** | | 0.054** | | 0.094*** | | 0.052* |
| | | (0.035) | | (0.027) | | (0.036) | | (0.030) |
| 2018 | | 0.156*** | | 0.106*** | | 0.154*** | | 0.108*** |
| | | (0.039) | | (0.030) | | (0.040) | | (0.033) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.07 | 61.16 | 50.08 | 61.16 | 50.08 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.03) | (0.02) | (0.03) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

To address the issue of endogeneity in Model (3.1), that we have discussed in detail in Subsection 3.3.2, we estimate the model using perceived property rent as an instrument for distance to the nearest mine. Results from the models without individual and household level controls indicate the relevance of the instrument (Column 5); the first-stage F-statistics far exceeds the threshold level 10, the selection criteria for strong instruments, as suggested in Stock et al. (2002).[21] The Durbin-Wu-Hausman test of exogeneity rejects the null hypothesis at a 5 percent significance level, indicating that the distance variable is endogenous (Hayashi, 2000). As we guessed, the impact of distance is now much higher - moving away from mines by doubling the distance reduces reported illness by 7.1 percentage points. We observe similar results when we include individual and household level controls in the model (Column 6).

Finally, we employ an instrumental variable approach with the probit model (IV-Probit). Marginal effects from the basic IV-Probit model, presented in Column 7, are similar to the comparable IV model results. The effects also remain comparable when we add individual, and household level controls to the specification (Column 8). In this preferred specification, 'distance to the nearest mine' has a statistically significant impact on the reported illness of surveyed individuals. The ME indicates that if an individual moves in a way that doubles the distance between her/his residence and nearest mine, the reported illness will reduce by 7.4 percentage points. The Wald test of the exogeneity of the instrumented variable shows that we reject the null hypothesis of no endogeneity at the 5 percent significance level.

Our finding is similar to some previous studies. For example, von der Goltz and Barnwal (2019) find that heavy metal toxicity increases anemia among women and stunting in young children by ten and five percentage points, respectively. Similarly, Levasseur et al. (2021) also report that living in polluted mining and industrial areas increases the likelihood of suffering from any chronic disease by 7.7 percentage points for working-age adults.

The estimated impact of distance indicates that the coefficients would be biased and underestimated without adequately addressing the endogeneity of pollution in our model. However, the coefficient appears to be a little high, particularly for individuals closer to mines. Let us consider the case of the people living within one kilometre of the mines who have a reported illness level of 11.36 percent. Our estimate implies that moving one km further from the mines will reduce their reported illness level to 3.96 percent. This, however, does not provide a comparable number as,

[21] Since we have only one endogenous regressor in the model, the Sanderson-Windmeijer (SW) statistics reported is identical to the Kleibergen-Paap rk Wald statistics.

in our data, the reported illness is 9.17 percent for people living between 1–2 km away from gold mines.

The finding of a higher than expected impact is a known problem of the instrumental variable estimation. For example, estimates of returns to schooling in studies using institutional changes in the education system as instruments are 20–40 percent higher than the corresponding OLS estimates. The higher impact is partly because the marginal returns to schooling for specific subgroups are higher than the average returns in the population as a whole, and IV captures the effect only for the population whose education has been affected by the instrument (Card, 1999). In other words, the higher estimate with the IV approach is because it identifies the "local average treatment effect" (LATE) rather than the "average treatment effect" (ATE).

The instrument in our analysis, the perceived property rent, is more closely associated with properties near the mines where pollution impact is significant. Our instrument thus identifies the LATE of pollution that is higher than its ATE. This means that the true average marginal impact, a more policy-relevant quantity, lies somewhere between the ME estimated by probit and the IV-Probit models. Therefore, for the rest of the analysis, we focus less on the coefficient size and more on the impact's direction.

The marginal effect of other covariates in this preferred model also appears to be sensible and in line with the findings of some earlier studies. Higher level of reported illness is associated with gender (Gove, 1984), age (Ross and Wu, 1996) and education (Winkleby et al., 1992). Household size significantly increases illness possibly due to the crowding of family members, which increases the probability and risks of infections within a household (Burström et al., 1999). Household consumption has a significant protective effect on illness as found studies such as Winkleby et al. (1992). While previous literature finds housing type and characteristics (Palacios et al., 2021) important for illness, their marginal effects (at the mean values of other covariates) are not statistically significant in our model. The coefficients of year fixed effects are mostly significant, indicating that illness can be affected by many other factors associated with time but not explicitly controlled for in the model.

Next, we examine whether distance to the nearest mines releasing different types of heavy metals significantly affects illness as given by Model (3.2). This model uses the distance to the mining site with the highest heavy metal contamination level instead of the shortest distance to a mine. As discussed earlier, the seven heavy metals coexist at most locations resulting in high multicollinearity in our model. Therefore, we estimate the model, each time including only one distance in the model.[22] Table 3.5 presents the results from each model. The coefficient estimates are negative and statistically significant at the 5 percent level. The coefficients are also sometimes a little different, which can be due to the change in the sample. However, all of the model results indicate that, even if we consider only a single heavy metal for our analysis, proximity to mines is dangerous for people's health.

In the previous analysis, we have not considered the effect of heavy metal released into the soil that can adversely affect the nearby residents. We now examine the issue by including the level of pollution based on the three threshold values discussed in Subsection 3.3.4 and estimate Model (3.3). As we have seen in Table 3.3, more than 40 percent of individuals reside in areas with high levels of mercury pollution that require actions, such as cleansing the soil and relocating exposed households. Also, nearly 40 percent of the sample population is exposed to mild arsenic pollution. As a result, we include arsenic and mercury contamination levels (in logarithm) in Model (3.3).

The results in Table 3.6, both when we exclude individual level controls (Column 1) or not (Column 2), indicate that mercury pollution level does not have a statistically significant effect on reported illness, but arsenic pollution has a significant effect. This can be due to strong association in mercury and arsenic pollution in our data and the assumption of constant ME of the (logarithm of) pollution level in the model. Importantly, the coefficient of our primary variable of interest - distance to the nearest mine - remains similar to the earlier estimates.

Up to this point of our analysis, we assumed that the (log of) pollution level has a linear effect on illness while the true impact can be non-linear in the log of distance. To examine whether addressing the case changes our findings, we use the threshold values reported in MASM (2019) and follow Currie et al. (2009a) to construct indicator variables for heavy metals that exceed the action value. In our setting, it implies including a dummy variable controlling for individuals exposed to mercruy level above the action value and estimate Model (3.4).

Results in Table 3.6 indicate that the pollution threshold indicator do not significantly affect reported illness, regardless of including individual and household level controls (Column 3 and 4). Again, the impact of distance, which is an essential indicator of exposure to pollution, remains qualitatively similar to our earlier estimates.

[22] Since not all sites report each the heavy metals, the number of observations differs in each analysis.

**Table 3.5: IV estimate of the effect of mining pollution on illness: using distance from the nearest mine with particular types of heavy metal contamination**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Ln(distance to highest Mercury level) | -0.058** | | | | | | |
| | (0.026) | | | | | | |
| Ln(distance to highest Arsenic level) | | -0.058** | | | | | |
| | | (0.026) | | | | | |
| Ln(distance to highest Lead level) | | | -0.135** | | | | |
| | | | (0.062) | | | | |
| Ln(distance to highest Zinc level) | | | | -0.136** | | | |
| | | | | (0.067) | | | |
| Ln(distance to highest Cadmium level) | | | | | -0.084** | | |
| | | | | | (0.037) | | |
| Ln(distance to highest Copper level) | | | | | | -0.094** | |
| | | | | | | (0.042) | |
| Ln(distance to highest Nickel level) | | | | | | | -0.117** |
| | | | | | | | (0.058) |
| Individual is female | 0.012* | 0.013** | 0.024*** | 0.024*** | 0.020*** | 0.022*** | 0.026*** |
| | (0.006) | (0.006) | (0.008) | (0.009) | (0.008) | (0.008) | (0.008) |
| Individual's age (years) | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Individual's education (years) | 0.002* | 0.002 | 0.003 | 0.002 | 0.003* | 0.003 | 0.002 |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) |
| Number of household members | 0.024*** | 0.023*** | 0.028*** | 0.024** | 0.029*** | 0.027*** | 0.022** |
| | (0.007) | (0.008) | (0.011) | (0.010) | (0.009) | (0.010) | (0.010) |
| Ln(household consumption) | -0.307*** | -0.296*** | -0.368*** | -0.324*** | -0.370*** | -0.343*** | -0.308*** |
| | (0.069) | (0.071) | (0.103) | (0.099) | (0.087) | (0.093) | (0.094) |
| Brick/wood wall | 0.008 | 0.007 | 0.004 | -0.012 | 0.008 | 0.009 | -0.008 |
| | (0.009) | (0.009) | (0.012) | (0.015) | (0.011) | (0.011) | (0.014) |
| Asphalt/metal roof | -0.007 | -0.007 | -0.031* | -0.023 | -0.018 | -0.025* | -0.020 |
| | (0.010) | (0.010) | (0.016) | (0.014) | (0.012) | (0.014) | (0.013) |
| Household lives in rural area | 0.003 | 0.003 | -0.022 | -0.026 | 0.009 | 0.032* | 0.001 |
| | (0.018) | (0.018) | (0.034) | (0.039) | (0.025) | (0.018) | (0.022) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| First-stage F-stat | 64.40 | 64.13 | 25.46 | 23.71 | 48.82 | 41.94 | 27.53 |
| Wald test of exogeneity | (0.06) | (0.06) | (0.02) | (0.03) | (0.04) | (0.04) | (0.05) |
| N | 6,346 | 6,109 | 4,864 | 4,590 | 4,967 | 4,611 | 4,691 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. All columns run the the preferred models with province and survey year fixed effects, individual–specific controls, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.6: IV estimate of the effect of mining pollution on illness: including the level of pollution in the model**

| | Pollution level | | Binary form | |
|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) |
| Ln(distance to the nearest mine) | -0.067** | -0.074** | -0.089** | -0.089** |
| | (0.029) | (0.031) | (0.043) | (0.040) |
| Ln(Mercury pollution level) | 0.002 | 0.000 | | |
| | (0.005) | (0.005) | | |
| Ln(Arsenic pollution level) | -0.021** | -0.024** | | |
| | (0.009) | (0.012) | | |
| Mercury above action value | | | -0.059 | -0.062 |
| | | | (0.037) | (0.038) |
| Individual is female | | 0.018*** | | 0.018*** |
| | | (0.006) | | (0.006) |
| Individual's age (years) | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.001 | | 0.001 |
| | | (0.001) | | (0.001) |
| Number of household members | | 0.016** | | 0.015** |
| | | (0.007) | | (0.007) |
| Ln(household consumption) | | -0.222*** | | -0.226*** |
| | | (0.065) | | (0.067) |
| Brick/wood wall | | 0.006 | | 0.011 |
| | | (0.009) | | (0.010) |
| Asphalt/metal roof | | -0.008 | | -0.007 |
| | | (0.010) | | (0.010) |
| Household lives in rural area | | 0.035** | | 0.033* |
| | | (0.016) | | (0.017) |
| 2010 | | 0.125*** | | 0.129*** |
| | | (0.031) | | (0.033) |
| 2014 | | 0.107*** | | 0.103** |
| | | (0.040) | | (0.041) |
| 2016 | | 0.057* | | 0.053* |
| | | (0.030) | | (0.031) |
| 2018 | | 0.108*** | | 0.107*** |
| | | (0.033) | | (0.034) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| First-stage F-stat | 65.25 | 54.48 | 50.31 | 52.63 |
| Wald test of exogeneity | (0.03) | (0.03) | (0.02) | (0.02) |
| N | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1 and 3 run the basic models with province and survey year fixed effects. Columns 2 and 4 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

The results from Tables 3.4-3.6 confirm that being close to mines that release environmental pollution increases a person's likelihood of reporting illnesses. The results are in line with Hill (2018) and Marcus (2021) who find adverse effects of shale gas well and petroleum leakage, respectively, on infant health. The findings also support Aragón and Rud (2015) and von der Goltz and Barnwal (2019), who report that mining activities deteriorate health outcomes of communities exposed to mining pollution. Our individual-level survey data, that only records self-reported illnesses rather than clinical records, do not allow us to examine long-term chronic illnesses and cancer. Nevertheless, our thorough analysis, along with extensive robustness checks discussed in Subsection 4.4.3, indicate that the community near mining activities is susceptible to environmental pollution, and their likelihood of reporting illness increases as they live closer to mines.

### 3.4.2 Medical expenses

Since living closer to mines increases the level of reported illness, it is also likely to increase the out-of-pocket medical expenses of those individuals unless they report illnesses for other reasons. We, therefore, examine the issue by estimating Model (3.1) but now use (logarithm of) medical expenditure as the dependent variable. As the medical expenditure is a continuous variable, we now use the linear IV model as our preferred approach.[23] The estimated model outputs are presented in Table 3.7. The results in the baseline model (Column 1) indicate a significant negative effect of proximity on medical expenditure. When we add other individual and household level controls in the model (Columns 2 and 3), the statistical significance of distance drops significantly, particularly when we add controls for housing construction materials (Column 3). However, the coefficient of distance in the preferred specification is still large, indicating that medical expenses decline by 31 percent as a person doubles the distance to the nearest mine. Overall, the analysis with medical expenses further supports our argument that mining has negative externalities that can affect the nearby residents' health.

### 3.4.3 Effect of mining pollution on different age groups

Understanding that Equation (3.1) is sufficient to capture the effect of exposure to pollution, we next investigate whether pollution from mining affects different age groups disproportionately. Children and older people are more vulnerable and susceptible to experiencing adverse health impacts because of their sensitive immune systems (Landrigan et al., 2018). In particular, children below the age of 14 undergo significant development changes that can have lasting effects on their well-being throughout their adulthood. Also, children are more vulnerable because their body size

[23]We again use the same instrument to address the endogeneity of the endogenous variable, distance.

**Table 3.7: IV estimate of the effect of mining pollution on monthly individual medical expenses**

| | ln(medical expenses) | | |
|---|---|---|---|
| Variable names | (1) | (2) | (3) |
| Ln(distance to the nearest mine) | -0.832*** | -0.610** | -0.307 |
| | (0.263) | (0.259) | (0.270) |
| Individual is female | | 0.036 | 0.037 |
| | | (0.023) | (0.023) |
| Individual's age (years) | | 0.011*** | 0.011*** |
| | | (0.002) | (0.002) |
| Individual's education (years) | | -0.009 | -0.011 |
| | | (0.009) | (0.009) |
| Number of household members | | 0.014 | 0.011 |
| | | (0.069) | (0.066) |
| Ln(household consumption) | | 0.628 | 0.664 |
| | | (0.597) | (0.576) |
| Household lives in rural area | | -0.342*** | -0.248* |
| | | (0.126) | (0.128) |
| 2010 | | 0.439 | 0.396 |
| | | (0.281) | (0.272) |
| 2014 | | 0.465 | 0.470 |
| | | (0.374) | (0.361) |
| 2016 | | 0.954*** | 0.982*** |
| | | (0.293) | (0.282) |
| 2018 | | 1.262*** | 1.277*** |
| | | (0.317) | (0.306) |
| Brick/wood wall | | | 0.114 |
| | | | (0.082) |
| Asphalt/metal roof | | | 0.132 |
| | | | (0.093) |
| Province fixed effects | Yes | Yes | Yes |
| First-stage F-stat | 61.16 | 58.69 | 50.08 |
| Hausman test of exogeneity | (0.00) | (0.02) | (0.33) |
| N | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Column 1 runs the basic model with province and survey year fixed effects. Columns 2 adds individual–specific controls to the specification, including rural status of residence. Columns 3 further adds wall and roof type to the model.

is smaller than adults, and their exposure to pollution may have more severe effects (Currie et al., 2014; Rau et al., 2015).

On the other hand, older people are likely to experience a more substantial impact, compared to their working-age counterparts, as they may have been exposed to pollution for a long time or because of their age-related vulnerability (Power et al., 2011; Chen et al., 2017). Finally, the working-age population runs the risk of occupational exposure to heavy metal pollution (Goldenberg et al., 2010; Graff Zivin and Neidell, 2013). They range from miners to smelters, gold refiners, and people working in the auxiliary sectors such as trade, services, and transportation. Therefore, examining the effect of mining pollution separately by age groups can provide interesting perspectives.

Using our preferred approach (IV-Probit), we now estimate Equation (3.1) separately with each age group-specific sub-sample. Results in Table 3.8 indicate a negative effect of distance on reported illness for all age groups. As expected, the impact is most pronounced for younger children. The coefficient estimates for age groups 0-14-year-old (columns 1 and 2) are relatively higher than what we found in the analysis that combines all age groups.

Compared to younger children, pollution affects the working-age population to a lesser extent, and the estimated impacts are not statistically significant (columns 3 and 4). The effect of pollution for people above 50 years is also very high in our models (columns 5 and 6). Unfortunately, the number of older people in the data set is low, which is likely to be responsible for the statistical insignificance of the distance coefficient. Thus, our analysis provides support to the hypothesis that mining pollution exerts a significant negative externality that affects the health of the young children as observed in Currie et al. (2014) and Rau et al. (2015).

### 3.4.4 Response of different body systems to mining pollution

Next, we test whether exposure to mining pollution affects various body systems. Using our preferred approach, we estimate Equation (3.1) but now the dependent variables are the illnesses related to different types of body systems (Table 3.9). Column 1 results indicate that exposure to pollution increases the likelihood of reporting respiratory system illness. This is in line with the findings that mining activities produce a substantial amount of dust in the air (Li et al., 2014). Some field surveys on artisanal and small-scale mining in Mongolia also find higher risks of suffering from asthma and tuberculosis among adults and increased prevalence of respiratory illnesses among children (HRC and SDC, 2012). The effect, however, is not significant at the conventional level. We also observe negative but insignificant effects of pollution on digestive illness (Column 2). However, there is a larger negative impact of exposure to pollution on other illnesses that also includes cardiovascular diseases and external impact (Column 3). Such an outcome can be due to injuries and accidents related to mining activities, but the effect is only marginally significant at the 10 percent level. Thus our overall analysis with different body systems provides limited support to the hypothesis that mining can affect body systems differently.

**Table 3.8: IV estimate of the effect of mining pollution on illness for different age groups**

| | Age: 0-14 years | | Age: 15-50 years | | Age: 50+ years | |
|---|---|---|---|---|---|---|
| Variable names | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(distance to the nearest mine) | -0.168*** | -0.151** | -0.032 | -0.020 | -0.046 | -0.103 |
| | (0.063) | (0.067) | (0.024) | (0.024) | (0.112) | (0.135) |
| Individual is female | | 0.009 | | 0.013** | | 0.019 |
| | | (0.012) | | (0.006) | | (0.020) |
| Individual's education (years) | | -0.009*** | | 0.006*** | | 0.003 |
| | | (0.003) | | (0.001) | | (0.004) |
| Number of household members | | -0.012 | | 0.022*** | | 0.031* |
| | | (0.023) | | (0.007) | | (0.019) |
| Ln(household consumption) | | 0.029 | | -0.268*** | | -0.381** |
| | | (0.213) | | (0.067) | | (0.149) |
| Brick/wood wall | | -0.000 | | -0.000 | | 0.035 |
| | | (0.018) | | (0.008) | | (0.034) |
| Asphalt/metal roof | | -0.013 | | 0.004 | | -0.056 |
| | | (0.021) | | (0.010) | | (0.037) |
| Household lives in rural area | | -0.018 | | 0.022* | | 0.012 |
| | | (0.027) | | (0.012) | | (0.041) |
| 2010 | | 0.148 | | 0.112*** | | 0.182** |
| | | (0.106) | | (0.030) | | (0.081) |
| 2014 | | 0.065 | | 0.110*** | | 0.172* |
| | | (0.138) | | (0.042) | | (0.102) |
| 2016 | | 0.048 | | 0.060* | | 0.054 |
| | | (0.107) | | (0.032) | | (0.081) |
| 2018 | | 0.086 | | 0.108*** | | 0.165* |
| | | (0.115) | | (0.034) | | (0.086) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| First-stage F-stat | 33.87 | 30.48 | 66.74 | 54.77 | 13.18 | 9.94 |
| Wald test of exogeneity | (0.00) | (0.00) | (0.34) | (0.77) | (0.66) | (0.48) |
| N | 2,148 | 2,148 | 4,354 | 4,354 | 1,180 | 1,180 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3 and 5 run the basic models with province and survey year fixed effects. Columns 2,4 and 6 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

### 3.4.5 Effect of mine scale on morbidity

For many reasons, the impact of large and medium-scale mines on human health can be different from those of ASMs. The small-scale miners are either unlicensed individuals or a group of individuals partnered under one mining license to extract minerals from the same land (HRC and SDC, 2012). They usually operate on public land, and many miners mine at the same time resulting in an outcome similar to the 'tragedy of the commons' (Bazillier and Girard, 2020). They also suffer from financial and technical constraints. Thus, the incentive to care for the environmental footprints may be weaker for small-scale miners.[24]

[24] ASM is the single largest buyer of mercury in the world, consuming around 1,400 tonnes in 2011 and releasing 17 percent of annual mercury emissions to the atmosphere (Telmer and Stapper, 2012).

**Table 3.9: IV estimate of the effect of mining pollution on different types of illness**

| Variable name | Respiratory (1) | Digestive (2) | Other illnesses (3) |
|---|---|---|---|
| Ln(distance to the nearest mine) | -0.011 | -0.010 | -0.035* |
| | (0.009) | (0.014) | (0.020) |
| Individual is female | 0.004** | 0.002 | 0.005 |
| | (0.002) | (0.002) | (0.004) |
| Individual's age (years) | -0.000*** | 0.000 | 0.001*** |
| | (0.000) | (0.000) | (0.000) |
| Individual's education (years) | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.001) |
| Number of household members | 0.004 | 0.001 | 0.003 |
| | (0.003) | (0.001) | (0.004) |
| Ln(household consumption) | -0.061*** | -0.013 | -0.054 |
| | (0.022) | (0.009) | (0.039) |
| Brick/wood wall | 0.003 | 0.002 | -0.001 |
| | (0.003) | (0.003) | (0.006) |
| Asphalt/metal roof | -0.002 | -0.002 | -0.001 |
| | (0.004) | (0.003) | (0.006) |
| Household lives in rural area | 0.005 | -0.001 | -0.003 |
| | (0.004) | (0.005) | (0.007) |
| 2010 | 0.042*** | 0.007 | 0.027 |
| | (0.008) | (0.006) | (0.018) |
| 2014 | 0.036** | -0.001 | 0.026 |
| | (0.015) | (0.008) | (0.023) |
| 2016 | 0.026** | -0.003 | 0.003 |
| | (0.011) | (0.007) | (0.018) |
| 2018 | 0.036*** | 0.002 | 0.032 |
| | (0.011) | (0.006) | (0.020) |
| Province fixed effects | Yes | Yes | Yes |
| First-stage F-stat | 50.83 | 45.19 | 57.76 |
| Wald test of exogeneity | (0.44) | (0.28) | (0.05) |
| N | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. All columns run the the preferred models with province and survey year fixed effects, individual–specific controls, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

On the other hand, medium- and large-scale mining takes place with official mining licenses that designate private land to extract minerals. These official license-holding mining entities are likely to enforce safety standards for their workers and adhere to environmental regulations.[25] Thus, it appears likely that the severity of the negative impact of mining on health is higher for ASM, compared to the license holding mines. At this point, we examine whether it is the case.

The results from our analysis that estimates Equation (3.1) for two sub-samples – official license holders and small scale mines – are presented in Table 3.10. The baseline model without

[25] Although, the extent they pollute the environment can be considerable due to the scale of operation.

individual and household level controls indicates a significant negative impact of official license holding mines on reported illness (Column 1). However, when we add other controls, the size of the impact becomes smaller and statistically insignificant (Column 2). In contrast, the estimated impacts for small-scale mines appear slightly smaller than license holders in the baseline model (Column 3). However, as soon as we add other controls, the coefficient becomes much larger and statistically significant at the conventional level (Column 4). Together, these results support our hypothesis that the severity of the negative impact of mining on health is higher for small-scale mines than their licensed counterpart.

### 3.4.6 The impact of different types of minerals mined on illness

The final investigation looks at the impacts of different minerals mined. The motivation for this investigation is that previous studies examined the impact of pollution on human health by the types of minerals mined. For example, the investigation of Tolonen (2019) focused only on the gold mines while Datt et al. (2020) focused only on the coal mines. The magnitudes of the impacts in those two studies are not comparable. Gold, spar, and coal are the primary minerals within five km of the household residence in our analysis sample. In particular, gold mines are the most frequent mines in our data, and many previous studies focused on them. As a result, for our analysis, we divide the mines in our sample into three categories – gold, coal and spar, and other types of mines and then estimate Equation (3.1) separately.

The results from the analysis are reported in Table 3.11. The baseline model for the gold mines, without individual level controls, indicates a significant negative impact of those mines on reported illness (Column 1). The negative impact remains similar when other controls are added (Column 2). Coal and spar mines also negatively impact illness significantly but the effect is much lower than that of gold mines (Columns 3 and 4). On the other hand, the estimated impacts for the mines extracting minerals other than gold, coal, and spar are large but statistically insignificant in the baseline model (Column 5). The results remain the same with other controls added to the model (Column 6). Together these results show that gold, coal, and spar mines drive the severity of the negative impact of mining on health.

**Table 3.10: IV estimate of the effect of mining pollution on illness: effect by mining-scale**

| | Mining license holders | | Small-scale miners | |
|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) |
| Ln(distance to the nearest mine) | -0.087* | -0.062 | -0.061* | -0.144** |
| | (0.046) | (0.040) | (0.036) | (0.060) |
| Individual is female | | 0.009 | | 0.030*** |
| | | (0.007) | | (0.010) |
| Individual's age (years) | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.001 | | 0.001 |
| | | (0.001) | | (0.002) |
| Number of household members | | 0.016* | | 0.016 |
| | | (0.008) | | (0.013) |
| Ln(household consumption) | | -0.212*** | | -0.251** |
| | | (0.079) | | (0.120) |
| Brick/wood wall | | 0.015 | | -0.023 |
| | | (0.012) | | (0.018) |
| Asphalt/metal roof | | -0.004 | | -0.014 |
| | | (0.011) | | (0.020) |
| Household lives in rural area | | 0.017 | | -0.050 |
| | | (0.019) | | (0.038) |
| 2010 | | 0.144*** | | 0.109** |
| | | (0.041) | | (0.054) |
| 2014 | | 0.134*** | | 0.095 |
| | | (0.051) | | (0.073) |
| 2016 | | 0.077** | | 0.042 |
| | | (0.039) | | (0.056) |
| 2018 | | 0.129*** | | 0.094 |
| | | (0.043) | | (0.060) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| First-stage F-stat | 27.41 | 31.32 | 41.48 | 20.74 |
| Wald test of exogeneity | (0.04) | (0.13) | (0.13) | (0.01) |
| N | 4,022 | 4,022 | 3,660 | 3,660 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1 and 3 run the basic models with province and survey year fixed effects. Columns 2 and 4 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

### 3.4.7 Robustness checks

We undertake additional robustness checks to confirm that the methods, models, and data used in the analysis do not drive the results. First, to check whether the method matters for our conclusions, we repeat the entire analysis using OLS (LPM), probit, logit, and IV-LPM approaches. As we have seen in Table 3.4, OLS and probit approaches provide much smaller but highly significant results than the IV-Probit estimates. On the other hand, coefficients from the IV-LPM approach are largely comparable to the IV-Probit estimates that we have employed throughout the study. Although the magnitude of pollution impact differs, depending on whether we use the IV approach or not, our overall conclusions remain similar in all the cases.[26]

**Table 3.11: IV estimate of the effect of mining pollution on illness: effect by mine types on illness**

| | Gold | | Coal & spar | | Other minerals | |
|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) |
| Ln(distance to the nearest mine) | -0.055** | -0.054** | -0.086** | -0.038** | -0.297 | -0.297 |
| | (0.024) | (0.024) | (0.096) | (0.077) | (0.301) | (0.313) |
| Individual is female | | 0.013 | | 0.037 | | 0.015 |
| | | (0.009) | | (0.011) | | (0.010) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001** |
| | | (0.000) | | (0.000) | | (0.001) |
| Individual's education (years) | | 0.001 | | -0.001 | | 0.001 |
| | | (0.002) | | (0.002) | | (0.002) |
| Number of household members | | 0.020** | | 0.013** | | -0.002 |
| | | (0.010) | | (0.012) | | (0.014) |
| Ln(household consumption) | | -0.274*** | | -0.175*** | | -0.042 |
| | | (0.091) | | (0.119) | | (0.131) |
| Brick/wood wall | | 0.009 | | -0.003 | | -0.017 |
| | | (0.012) | | (0.019) | | (0.020) |
| Asphalt/metal roof | | -0.006 | | 0.002 | | 0.003 |
| | | (0.012) | | (0.020) | | (0.017) |
| Household lives in rural area | | -0.104** | | 0.038** | | -0.458*** |
| | | (0.048) | | (0.062) | | (0.108) |
| 2010 | | 0.105** | | 0.110** | | 0.088* |
| | | (0.042) | | (0.060) | | (0.050) |
| 2014 | | 0.134** | | 0.111** | | -0.017 |
| | | (0.056) | | (0.079) | | (0.094) |
| 2016 | | 0.071* | | 0.035* | | -0.001 |
| | | (0.043) | | (0.064) | | (0.059) |
| 2018 | | 0.151*** | | 0.079*** | | 0.005 |
| | | (0.047) | | (0.071) | | (0.068) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| First-stage F-stat | 77.21 | 66.42 | 7.81 | 17.07 | 12.29 | 9.69 |
| Wald test of exogeneity | (0.04) | (0.06) | (0.28) | (0.35) | (0.13) | (0.12) |
| N | 3,944 | 3,944 | 1,387 | 1,387 | 2,351 | 2,351 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3 and 5 run the basic models with province and survey year fixed effects. Columns 2,4 and 6 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

Second, to capture the exposure to pollution, we have relied on the logarithm of distance from the nearest mine as the exposure variable. We repeat Table 3.4 by using distance in km and arrive at a similar conclusion (Table 3.A.1). However, we only present the results from our semi-elasticity models as they can more realistically reflect the pattern of changes in property prices, the employed instrument in our analysis.

[26] All robustness check results are available from the authors unless provided here or in the online appendix.

Third, to examine the case of the very localized impact of mines, we compare the illness of people living between 1–5 km distance from mines (as the reference group) against the group living within one km of mines. We find that living closer significantly increases the probability of reporting illness. Additional exercise of comparing the illness of people residing within 2–5 km of mines to those living within twos km of mines provide similar results (Table 3.A.2).

Fourth, as an alternative strategy to find a causal effect of proximity to mines, we conduct a propensity score (PS) matched analysis. Such analysis addresses the concern that individuals living closer to mines are systematically different from those living away. Our investigation repeats the previous analysis with distance dummies, but now only with PS-matched individuals. We match both groups of individuals based on individual-specific control variables. In all cases, the final matched sample consists of a lower number of treatment and control properties with no statistically significant difference in their age, gender, household size, and consumption. Our PS matched analysis again provides a conclusion that is similar to the main analysis (Table 3.A.3).

Fifth, we use the principal component analysis (PCA) technique to capture the effect of various heavy metals in Model (3.3). The advantage of using PCA in our analysis is to reduce the number of heavy metals when we include their levels in the model. The method does so by creating new uncorrelated variables principal components with the highest variance from a large dataset (Jolliffe and Cadima, 2016). We reduce the levels of seven types of heavy metals into three components, each component grouping specific heavy metals together. An analysis with a principal component containing mercury and arsenic provides similar results to the primary analysis (Table 3.A.4).

Sixth, we repeat the main analysis with mine fixed effects added to the model. The exercise is to address the concern that some mines can have stronger effects for some location-specific factors that may drive our results. The results reveal that our findings are robust to the inclusion of mine fixed effects (Table 3.A.5).

Seventh, we repeat our analysis adding the interaction of province and year fixed effects in the model. The approach addresses the concern that some provinces may experience time-varying effects that can affect the results. Despite the inclusion of province and year fixed effects, the effects remain large and statistically significant in all the specifications employed in our earlier investigations (Table 3.A.6). Adding quarter fixed effects, to control for seasonality and quarterly factors and events, provide comparable results (Table 3.A.7). Controlling for the seasonality in illness, by adding month fixed effects, also generate similar results (Table 3.A.8).

Eighth, we redo the analysis with job sector fixed effects and mine numbers in Model (3.1). Job fixed effects address the concern that the negative effect of distance on illness can come exclusively through the mining workers who are disproportionately exposed to the mining pollution due to their job nature. On the other hand, adding mine numbers to the model relaxes the assumption that mines located further away from people's place of living, other than the nearest mine, do not affect illness. Our analysis indicates that, while both job types and the number of mining in the vicinity can have some effect on illness, they only affect our estimates marginally (Table 3.A.9).

Finally, we employ different forms of control variables. This includes categorical controls for age (Table 3.A.10) and education (Table 3.A.11), and the use of equivalized consumption (with OECD scale or Square Root of Family Size scale) or household income or their logarithm in the models (Tables 3.A.12–3.A.15). We also repeat the analysis by excluding some missing values that we currently include in the analysis sample (Table 3.A.16). Our results appear to be robust in all the cases.

Thus our overall analysis indicates that pollution from mining activities adversely and significantly affects the health of nearby communities. As a result of the increased illness, people increase their expenditure on health. Younger children living within five km of a mine site are seemingly more prone to illness. However, our analysis provides limited support to the hypothesis that the respiratory system is more affected by mining pollution than the other types of illness. We observe that ASMs have a larger negative impact on health than medium and larger mines. We also find that gold mines have a higher and more significant impact on the reported illness than the mines extracting other minerals. The results in this analysis are robust to applying different methods, models, and data.

## 3.5 Discussion and policy implications

We document extractive industry's negative health externalities stemming from the soil pollution caused by mining, refining, and processing of minerals. We find that the exposure to pollution, measured by the distance to the nearest mine, significantly increases the likelihood of illness. Second, although the effect of pollution is large for above the age of 50, the probability of illness increases most significantly for younger children aged 0–14 years.

This higher negative impact on children is concerning because early life exposure to neurotoxins such as mercury and arsenic has been shown to lower their cognitive abilities, disrupt concentration and behavior, and lead to lifetime earnings loss (Landrigan et al., 2018; von der Goltz and Barnwal, 2019). These damages are irreversible and cause inter-generational loss of well-being of residents exposed to mining pollution, as well as lower future productivity and earnings. Higher sickness levels of the affected people lead to higher health expenditures, indicating significant direct costs of pollution exposure.

We also find that smaller-scale mining activities have more significant negative health effects than medium- and large-scale mines. This is likely caused by medium- and large-scale mines' typical operation on private lands, as well as the better management needed to manage larger mines, and possibly stronger shareholder scrutiny of negative externalities in general.[27] Small-scale mines suffer from the tragedy of commons problems, as they operate on public lands and exist for shorter periods, complicating the enforcement of the environmental protection and rehabilitation responsibilities (HRC and SDC, 2012; Bazillier and Girard, 2020).

Of all the mines we study, gold mines have the worst impact on the probability of feeling ill. This is because gold is extracted using mercury and cyanide, which are known to have acute and long-term toxic effects on the respiratory system, on children's cognitive abilities, and on motor functions among those occupationally exposed to mercury (Kristensen et al., 2014). This finding is in line with Aragón and Rud (2015) who report that pollution from gold mining reduces productivity and contributes to the increased poverty in rural areas in Ghana.

The adverse personal and societal effects of ill health have been well documented in the literature. Illness deteriorates human physical and emotional well-being, lowering labor supply and productivity (Graff Zivin and Neidell, 2013; Hanna and Oliva, 2015; Wang et al., 2022). It leads to school absences and lower performance in the short-term for young children, and a loss in lifetime earnings in the long-term (Neidell, 2004; Rau et al., 2015; Chen et al., 2018; Komisarow and Pakhtigian, 2022). Pollution-related illnesses and diseases disrupt family stability due to loss in years of life (Landrigan et al., 2018). These costs, while difficult to measure in aggregate, have a potential to significantly outstrip the economic benefits of mining activities. Our findings highlight the need for the regulation of mining to achieve more favourable societal health outcomes.

Our findings that exposure reduction to pollution by moving further away from mines substantially benefits the resident population has obvious policy implications. Significant additional health, social and economic benefits can be realized by implementing appropriate environmental

[27] On the other hand, medium- and large-scale mining companies release larger absolute amounts of toxins and waste into the environment due to the scale of their operations.

policies and regulations to reduce pollution and therefore the health risks in resource-rich developing countries.

## 3.6 Conclusion

We examined the impact of mining pollution on the residents' likelihood of reporting illness by linking five rounds of Mongolian household socio-economic survey data to the soil pollution data. Using distance to the nearest mine as the proxy to pollution exposure, we find that exposure to mining pollution significantly increases a person's probability of feeling unwell. The closer a person lives from a mine, the higher the chances of being ill and the corresponding increase in health expenditures. Although the adverse impact of pollution is also high for older people, children significantly bear the burden of environmental pollution on their health. Living nearby artisanal and small-scale mining operations and gold mines more significantly increase the likelihood of becoming unwell.

The study is the first to use detailed soil pollution information and a novel instrument to provide new empirical evidence on the negative externalities of the extractive industry, which may offset the economic gains they can bring to the local communities. Our results indicate the importance of controlling/internalizing/mitigating the pollution generated by the mining activities. Formulation and implementation of policies to curb environmental pollution and mitigate their adverse impact may substantially lower the health risks to the local population and enhance the social and economic benefits of the extractive industry, especially in the long run.

## 3.A Robustness check tables

**Table 3.A.1: The effect of mining pollution on illness: distance levels (km)**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Distance to the nearest mine (km) | -0.005 | -0.007** | -0.004 | -0.006** | -0.050** | -0.058** | -0.049** | -0.062** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.021) | (0.024) | (0.022) | (0.029) |
| Individual is female | | 0.020*** | | 0.018*** | | 0.019*** | | 0.020*** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.006) |
| Individual's education (years) | | 0.002 | | 0.001 | | 0.002 | | 0.001 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Number of household members | | 0.023*** | | 0.013** | | 0.026*** | | 0.018** |
| | | (0.008) | | (0.006) | | (0.009) | | (0.008) |
| Ln(household consumption) | | -0.307*** | | -0.203*** | | -0.340*** | | -0.260*** |
| | | (0.076) | | (0.057) | | (0.084) | | (0.081) |
| Brick/wood wall | | 0.003 | | 0.003 | | 0.011 | | 0.011 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.011) |
| Asphalt/metal roof | | 0.002 | | 0.002 | | -0.019 | | -0.020 |
| | | (0.010) | | (0.008) | | (0.014) | | (0.015) |
| Household lives in rural area | | 0.021* | | 0.017* | | -0.013 | | -0.017 |
| | | (0.011) | | (0.010) | | (0.020) | | (0.021) |
| 2010 | | 0.156*** | | 0.109*** | | 0.173*** | | 0.139*** |
| | | (0.035) | | (0.027) | | (0.039) | | (0.039) |
| 2014 | | 0.160*** | | 0.102*** | | 0.170*** | | 0.121** |
| | | (0.047) | | (0.036) | | (0.051) | | (0.048) |
| 2016 | | 0.098*** | | 0.055** | | 0.100*** | | 0.062* |
| | | (0.035) | | (0.028) | | (0.038) | | (0.035) |
| 2018 | | 0.157*** | | 0.107*** | | 0.161*** | | 0.122*** |
| | | (0.039) | | (0.030) | | (0.042) | | (0.040) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.07 | 31.98 | 22.43 | 31.98 | 22.43 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.02) | (0.02) | (0.02) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.2: IV estimate of the effect of mining pollution on sickness: binary distance**

| | Reference: 1-5 km | | Reference: 2-5 km | |
|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) |
| Distance to a mine (0-1 km) | 0.112** | 0.113** | | |
| | (0.044) | (0.044) | | |
| Distance to a mine (0-2 km) | | | 0.166** | 0.164** |
| | | | (0.068) | (0.067) |
| Individual is female | | 0.019*** | | 0.020*** |
| | | (0.006) | | (0.006) |
| Individual's age (years) | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.001 | | 0.002 |
| | | (0.001) | | (0.001) |
| Number of household members | | 0.022*** | | 0.027*** |
| | | (0.008) | | (0.009) |
| Ln(household consumption) | | -0.296*** | | -0.330*** |
| | | (0.078) | | (0.082) |
| Brick/wood wall | | -0.002 | | 0.017 |
| | | (0.010) | | (0.012) |
| Asphalt/metal roof | | -0.000 | | -0.017 |
| | | (0.010) | | (0.013) |
| Household lives in rural area | | 0.036*** | | 0.011 |
| | | (0.012) | | (0.014) |
| 2010 | | 0.154*** | | 0.174*** |
| | | (0.035) | | (0.038) |
| 2014 | | 0.146*** | | 0.165*** |
| | | (0.047) | | (0.050) |
| 2016 | | 0.083** | | 0.098*** |
| | | (0.035) | | (0.037) |
| 2018 | | 0.143*** | | 0.168*** |
| | | (0.040) | | (0.043) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| First-stage F-stat | 91.96 | 81.37 | 33.97 | 30.46 |
| Hausman test of exogeneity | (0.02) | (0.04) | (0.01) | (0.02) |
| N | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1 and 3 run the basic models with province and survey year fixed effects. Columns 2 and 4 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.3: IV estimate of the effect of mining pollution on sickness: propensity-score matched analysis**

| | Matched to: 1-5 km | | Matched to: 2-5 km | |
|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) |
| Distance to a mine (0-1 km) | 0.132** | 0.137*** | | |
| | (0.058) | (0.052) | | |
| Distance to a mine (0-2 km) | | | 0.251* | 0.196** |
| | | | (0.130) | (0.085) |
| Individual is female | | 0.016 | | 0.028*** |
| | | (0.012) | | (0.010) |
| Individual's age (years) | | 0.001** | | 0.001* |
| | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.002 | | 0.002 |
| | | (0.002) | | (0.002) |
| Number of household members | | 0.030** | | 0.017 |
| | | (0.015) | | (0.013) |
| Ln(household consumption) | | -0.372** | | -0.304** |
| | | (0.148) | | (0.127) |
| Brick/wood wall | | 0.016 | | -0.008 |
| | | (0.016) | | (0.015) |
| Asphalt/metal roof | | -0.012 | | 0.010 |
| | | (0.016) | | (0.016) |
| Household lives in rural area | | 0.046** | | 0.045** |
| | | (0.020) | | (0.020) |
| 2010 | | 0.227*** | | 0.176*** |
| | | (0.072) | | (0.060) |
| 2014 | | 0.201** | | 0.176** |
| | | (0.091) | | (0.080) |
| 2016 | | 0.110 | | 0.089 |
| | | (0.068) | | (0.060) |
| 2018 | | 0.182** | | 0.199*** |
| | | (0.075) | | (0.068) |
| Province fixed effects | Yes | Yes | Yes | Yes |
| First-stage F-stat | 57.29 | 69.59 | 10.57 | 19.47 |
| Hausman test of exogeneity | (0.05) | (0.03) | (0.03) | (0.02) |
| N | 2,526 | 2,526 | 3,302 | 3,302 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1 and 3 run the basic models with province and survey year fixed effects. Columns 2 and 4 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.4: IV estimate of the effect of mining pollution on illness: principal component analysis**

| Variable name | (1) | (2) |
|---|---|---|
| Ln(distance to the nearest mine) | -0.065** | -0.074** |
| | (0.028) | (0.031) |
| Principal component: Mercury & Arsenic | 0.006 | 0.005 |
| | (0.005) | (0.005) |
| Individual is female | | 0.018*** |
| | | (0.006) |
| Individual's age (years) | | 0.001*** |
| | | (0.000) |
| Individual's education (years) | | 0.001 |
| | | (0.001) |
| Number of household members | | 0.016** |
| | | (0.007) |
| Ln(household consumption) | | -0.223*** |
| | | (0.066) |
| Brick/wood wall | | 0.006 |
| | | (0.009) |
| Asphalt/metal roof | | -0.009 |
| | | (0.010) |
| Household lives in rural area | | 0.004 |
| | | (0.013) |
| 2010 | | 0.124*** |
| | | (0.032) |
| 2014 | | 0.104*** |
| | | (0.040) |
| 2016 | | 0.052* |
| | | (0.030) |
| 2018 | | 0.108*** |
| | | (0.034) |
| Province fixed effects | Yes | Yes |
| First-stage F-stat | 62.62 | 50.40 |
| Wald test of exogeneity | (0.02) | (0.03) |
| N | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1 runs the basic models with province and survey year fixed effects. Columns 2 adds individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.5: The effect of mining pollution on illness: mine-fixed effects**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.012$^{*}$ | -0.017$^{**}$ | -0.008$^{*}$ | -0.012$^{***}$ | -0.065$^{**}$ | -0.063$^{**}$ | -0.052$^{**}$ | -0.052$^{**}$ |
| | (0.007) | (0.007) | (0.005) | (0.004) | (0.028) | (0.026) | (0.025) | (0.022) |
| Individual is female | | 0.019$^{***}$ | | 0.015$^{***}$ | | 0.019$^{***}$ | | 0.015$^{***}$ |
| | | (0.006) | | (0.005) | | (0.006) | | (0.005) |
| Individual's age (years) | | 0.001$^{***}$ | | 0.001$^{***}$ | | 0.001$^{***}$ | | 0.001$^{***}$ |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.002 | | 0.001 | | 0.001 | | 0.001 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Number of household members | | 0.024$^{***}$ | | 0.013$^{**}$ | | 0.024$^{***}$ | | 0.013$^{**}$ |
| | | (0.008) | | (0.005) | | (0.008) | | (0.005) |
| Ln(household consumption) | | -0.319$^{***}$ | | -0.186$^{***}$ | | -0.312$^{***}$ | | -0.186$^{***}$ |
| | | (0.076) | | (0.047) | | (0.077) | | (0.048) |
| Brick/wood wall | | 0.002 | | 0.002 | | 0.001 | | 0.002 |
| | | (0.010) | | (0.007) | | (0.010) | | (0.007) |
| Asphalt/metal roof | | -0.002 | | -0.001 | | -0.005 | | -0.004 |
| | | (0.010) | | (0.007) | | (0.010) | | (0.007) |
| Household lives in rural area | | 0.058 | | 0.045 | | 0.139$^{**}$ | | 0.117$^{**}$ |
| | | (0.038) | | (0.031) | | (0.056) | | (0.048) |
| 2010 | | 0.165$^{***}$ | | 0.103$^{***}$ | | 0.162$^{***}$ | | 0.103$^{***}$ |
| | | (0.036) | | (0.022) | | (0.036) | | (0.022) |
| 2014 | | 0.171$^{***}$ | | 0.097$^{***}$ | | 0.164$^{***}$ | | 0.094$^{***}$ |
| | | (0.047) | | (0.030) | | (0.047) | | (0.031) |
| 2016 | | 0.103$^{***}$ | | 0.052$^{**}$ | | 0.097$^{***}$ | | 0.047$^{**}$ |
| | | (0.035) | | (0.023) | | (0.035) | | (0.024) |
| 2018 | | 0.162$^{***}$ | | 0.096$^{***}$ | | 0.156$^{***}$ | | 0.093$^{***}$ |
| | | (0.039) | | (0.025) | | (0.039) | | (0.025) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Mine fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.05 | 0.03 | 0.08 | 71.08 | 83.02 | 71.08 | 83.02 |
| Hausman/Wald test of exogeneity | | | | | (0.05) | (0.07) | (0.05) | (0.05) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with mine and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.6: The effect of mining pollution on illness: interaction of province and year fixed effects**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.005 | -0.008 | -0.003 | -0.006 | -0.086*** | -0.111*** | -0.092*** | -0.120*** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.025) | (0.026) | (0.028) | (0.031) |
| Individual is female | | 0.022*** | | 0.020*** | | 0.021*** | | 0.021*** |
| | | (0.006) | | (0.006) | | (0.006) | | (0.006) |
| Individual's age (years) | | 0.002*** | | 0.001*** | | 0.002*** | | 0.002*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Individual's education (years) | | -0.002*** | | -0.002** | | -0.002** | | -0.002** |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Number of household members | | -0.003 | | -0.004 | | -0.000 | | -0.002 |
| | | (0.004) | | (0.003) | | (0.004) | | (0.004) |
| Ln(household consumption) | | -0.055* | | -0.041* | | -0.066* | | -0.056* |
| | | (0.031) | | (0.022) | | (0.034) | | (0.030) |
| Brick/wood wall | | -0.003 | | -0.003 | | -0.001 | | -0.002 |
| | | (0.010) | | (0.009) | | (0.011) | | (0.010) |
| Asphalt/metal roof | | 0.005 | | 0.006 | | -0.010 | | -0.011 |
| | | (0.010) | | (0.009) | | (0.011) | | (0.011) |
| Household lives in rural area | | -0.009 | | -0.015* | | -0.053*** | | -0.071*** |
| | | (0.010) | | (0.009) | | (0.016) | | (0.019) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province x Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.06 | 82.27 | 79.08 | 80.73 | 81.68 |
| Hausman/Wald test of exogeneity | | | | | (0.00) | (0.00) | (0.00) | (0.00) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with the interaction of province and survey fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.7: The effect of mining pollution on sickness: quarter-fixed effects**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.008 | -0.013** | -0.006 | -0.011** | -0.072*** | -0.072** | -0.069** | -0.074** |
| | (0.006) | (0.006) | (0.005) | (0.004) | (0.028) | (0.029) | (0.028) | (0.031) |
| Individual is female | | 0.019*** | | 0.017*** | | 0.019*** | | 0.017*** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.006) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.002 | | 0.001 | | 0.002 | | 0.001 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Number of household members | | 0.024*** | | 0.013** | | 0.025*** | | 0.015** |
| | | (0.008) | | (0.006) | | (0.008) | | (0.007) |
| Ln(household consumption) | | -0.318*** | | -0.202*** | | -0.330*** | | -0.225*** |
| | | (0.076) | | (0.055) | | (0.079) | | (0.065) |
| Brick/wood wall | | 0.003 | | 0.003 | | 0.007 | | 0.007 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | 0.003 | | 0.003 | | -0.009 | | -0.009 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.010) |
| Household lives in rural area | | 0.023** | | 0.017* | | 0.008 | | 0.004 |
| | | (0.011) | | (0.009) | | (0.013) | | (0.012) |
| 2010 | | 0.162*** | | 0.109*** | | 0.172*** | | 0.124*** |
| | | (0.035) | | (0.026) | | (0.036) | | (0.031) |
| 2014 | | 0.169*** | | 0.103*** | | 0.169*** | | 0.107*** |
| | | (0.047) | | (0.035) | | (0.048) | | (0.039) |
| 2016 | | 0.105*** | | 0.057** | | 0.101*** | | 0.055* |
| | | (0.035) | | (0.026) | | (0.036) | | (0.030) |
| 2018 | | 0.169*** | | 0.112*** | | 0.166*** | | 0.114*** |
| | | (0.039) | | (0.029) | | (0.040) | | (0.033) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.05 | 0.03 | 0.08 | 62.47 | 50.33 | 62.47 | 50.33 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.03) | (0.01) | (0.02) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province, quarter and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.8: The effect of mining pollution on sickness: month-fixed effects**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.008 | -0.012** | -0.005 | -0.010** | -0.081** | -0.082** | -0.076** | -0.084** |
| | (0.006) | (0.006) | (0.005) | (0.004) | (0.032) | (0.035) | (0.033) | (0.038) |
| Individual is female | | 0.019*** | | 0.017*** | | 0.018*** | | 0.017*** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.006) |
| Individual's age (years) | | 0.001*** | | 0.001*** | | 0.001*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.002 | | 0.001 | | 0.002 | | 0.001 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Number of household members | | 0.024*** | | 0.013** | | 0.026*** | | 0.015** |
| | | (0.008) | | (0.006) | | (0.008) | | (0.007) |
| Ln(household consumption) | | -0.319*** | | -0.200*** | | -0.336*** | | -0.230*** |
| | | (0.076) | | (0.055) | | (0.080) | | (0.067) |
| Brick/wood wall | | 0.002 | | 0.002 | | 0.006 | | 0.007 |
| | | (0.009) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | 0.005 | | 0.004 | | -0.009 | | -0.010 |
| | | (0.010) | | (0.008) | | (0.012) | | (0.011) |
| Household lives in rural area | | 0.028*** | | 0.021** | | 0.011 | | 0.005 |
| | | (0.011) | | (0.009) | | (0.015) | | (0.013) |
| 2010 | | 0.162*** | | 0.108*** | | 0.175*** | | 0.127*** |
| | | (0.034) | | (0.025) | | (0.037) | | (0.033) |
| 2014 | | 0.168*** | | 0.102*** | | 0.172*** | | 0.110*** |
| | | (0.046) | | (0.034) | | (0.049) | | (0.041) |
| 2016 | | 0.105*** | | 0.057** | | 0.104*** | | 0.058* |
| | | (0.035) | | (0.026) | | (0.036) | | (0.031) |
| 2018 | | 0.170*** | | 0.112*** | | 0.170*** | | 0.118*** |
| | | (0.039) | | (0.029) | | (0.040) | | (0.034) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.02 | 0.05 | 0.03 | 0.08 | 47.62 | 36.70 | 47.62 | 36.70 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.03) | (0.02) | (0.02) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province, month and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.9: The effect of mining pollution on illness: job sector fixed effects & mine numbers**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.011* | -0.017*** | -0.009** | -0.016*** | -0.065** | -0.073** | -0.058** | -0.068** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.027) | (0.029) | (0.026) | (0.030) |
| Individual is female | | 0.018*** | | 0.017*** | | 0.018*** | | 0.018*** |
| | | (0.006) | | (0.006) | | (0.006) | | (0.006) |
| Individual's age (years) | | 0.002*** | | 0.001*** | | 0.002*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Individual's education (years) | | 0.001 | | 0.001 | | 0.001 | | 0.001 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Number of household members | | 0.013 | | 0.006 | | 0.013 | | 0.007 |
| | | (0.008) | | (0.007) | | (0.008) | | (0.007) |
| Ln(household consumption) | | -0.196** | | -0.125** | | -0.199** | | -0.132* |
| | | (0.078) | | (0.062) | | (0.080) | | (0.068) |
| Brick/wood wall | | 0.004 | | 0.004 | | 0.008 | | 0.008 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | -0.002 | | -0.001 | | -0.014 | | -0.012 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.010) |
| Household lives in rural area | | 0.006 | | -0.002 | | -0.020 | | -0.025 |
| | | (0.013) | | (0.012) | | (0.020) | | (0.019) |
| 2010 | | 0.112*** | | 0.077*** | | 0.118*** | | 0.085*** |
| | | (0.035) | | (0.028) | | (0.036) | | (0.031) |
| 2014 | | 0.093* | | 0.054 | | 0.088* | | 0.050 |
| | | (0.048) | | (0.038) | | (0.049) | | (0.041) |
| 2016 | | 0.049 | | 0.019 | | 0.042 | | 0.012 |
| | | (0.036) | | (0.029) | | (0.036) | | (0.032) |
| 2018 | | 0.102** | | 0.067** | | 0.096** | | 0.063* |
| | | (0.040) | | (0.032) | | (0.041) | | (0.034) |
| Number of mines within 5 km | | -0.014** | | -0.021** | | -0.025*** | | -0.031*** |
| | | (0.006) | | (0.008) | | (0.008) | | (0.010) |
| Number of samples within 5 km | | -0.006** | | -0.008** | | -0.011*** | | -0.012*** |
| | | (0.003) | | (0.003) | | (0.004) | | (0.005) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Job sector fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.05 | 0.02 | 0.08 | 65.21 | 51.02 | 65.21 | 51.02 |
| Hausman/Wald test of exogeneity | | | | | (0.04) | (0.05) | (0.04) | (0.05) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province, job sector and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.10: The effect of mining pollution on illness: age group dummies**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.009* | -0.015*** | -0.008* | -0.013*** | -0.071** | -0.071** | -0.066** | -0.068** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.028) | (0.029) | (0.028) | (0.030) |
| Individual is female | | 0.018*** | | 0.017*** | | 0.017*** | | 0.017*** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.006) |
| Individual's education (years) | | 0.004*** | | 0.004*** | | 0.005*** | | 0.004*** |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Age group: 15-49 years | | -0.017** | | -0.022*** | | -0.017** | | -0.022** |
| | | (0.008) | | (0.008) | | (0.008) | | (0.009) |
| Age group: 50+ years | | 0.064*** | | 0.036*** | | 0.067*** | | 0.042*** |
| | | (0.014) | | (0.010) | | (0.014) | | (0.012) |
| Number of household members | | 0.027*** | | 0.018*** | | 0.029*** | | 0.021*** |
| | | (0.008) | | (0.006) | | (0.008) | | (0.007) |
| Ln(household consumption) | | -0.337*** | | -0.238*** | | -0.351*** | | -0.262*** |
| | | (0.073) | | (0.051) | | (0.076) | | (0.059) |
| Brick/wood wall | | 0.002 | | 0.002 | | 0.006 | | 0.005 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | 0.000 | | 0.001 | | -0.011 | | -0.010 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.010) |
| Household lives in rural area | | 0.027** | | 0.023** | | 0.013 | | 0.011 |
| | | (0.011) | | (0.010) | | (0.013) | | (0.012) |
| 2010 | | 0.168*** | | 0.122*** | | 0.178*** | | 0.137*** |
| | | (0.034) | | (0.025) | | (0.035) | | (0.029) |
| 2014 | | 0.175*** | | 0.118*** | | 0.177*** | | 0.123*** |
| | | (0.045) | | (0.033) | | (0.046) | | (0.036) |
| 2016 | | 0.106*** | | 0.064** | | 0.104*** | | 0.064** |
| | | (0.034) | | (0.025) | | (0.034) | | (0.028) |
| 2018 | | 0.167*** | | 0.118*** | | 0.166*** | | 0.121*** |
| | | (0.038) | | (0.027) | | (0.038) | | (0.030) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.07 | 61.16 | 50.30 | 61.16 | 50.30 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.05) | (0.02) | (0.04) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, under 15 years of age, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.11: The effect of mining pollution on illness: education categories**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.009* | -0.014** | -0.008* | -0.013*** | -0.071** | -0.071** | -0.066** | -0.071** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.028) | (0.030) | (0.028) | (0.031) |
| Individual is female | | 0.019*** | | 0.017*** | | 0.019*** | | 0.018*** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.006) |
| Primary school | | 0.003 | | -0.001 | | 0.006 | | 0.002 |
| | | (0.014) | | (0.011) | | (0.015) | | (0.012) |
| Secondary school | | -0.022** | | -0.018* | | -0.016 | | -0.014 |
| | | (0.010) | | (0.010) | | (0.011) | | (0.011) |
| High school | | -0.013 | | -0.010 | | -0.014 | | -0.012 |
| | | (0.010) | | (0.009) | | (0.010) | | (0.010) |
| Vocational degree | | 0.011 | | 0.009 | | 0.010 | | 0.008 |
| | | (0.021) | | (0.014) | | (0.021) | | (0.015) |
| Bachelor | | 0.013 | | 0.012 | | 0.013 | | 0.011 |
| | | (0.016) | | (0.014) | | (0.016) | | (0.014) |
| Master | | 0.017 | | 0.012 | | 0.008 | | 0.002 |
| | | (0.026) | | (0.023) | | (0.027) | | (0.025) |
| PhD | | 0.073 | | 0.059 | | 0.065 | | 0.053 |
| | | (0.121) | | (0.077) | | (0.123) | | (0.083) |
| Individual's age (years) | | 0.002*** | | 0.001*** | | 0.002*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Number of household members | | 0.017*** | | 0.011** | | 0.017*** | | 0.011** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.005) |
| Ln(household consumption) | | -0.243*** | | -0.170*** | | -0.245*** | | -0.180*** |
| | | (0.054) | | (0.041) | | (0.055) | | (0.046) |
| Brick/wood wall | | 0.003 | | 0.003 | | 0.007 | | 0.007 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | 0.000 | | 0.001 | | -0.010 | | -0.010 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.010) |
| Household lives in rural area | | 0.021* | | 0.018* | | 0.006 | | 0.004 |
| | | (0.011) | | (0.010) | | (0.014) | | (0.013) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.07 | 61.16 | 48.84 | 61.16 | 48.84 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.05) | (0.02) | (0.03) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, have no education, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.12: The effect of mining pollution on illness: OECD equivalence scale adjusted consumption**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.009* | -0.015** | -0.008* | -0.014*** | -0.071** | -0.079*** | -0.066** | -0.082** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.028) | (0.029) | (0.028) | (0.032) |
| Individual is female | | 0.016*** | | 0.016*** | | 0.015** | | 0.016*** |
| | | (0.006) | | (0.006) | | (0.006) | | (0.006) |
| Individual's education (years) | | 0.008*** | | 0.006** | | 0.009*** | | 0.006** |
| | | (0.003) | | (0.002) | | (0.003) | | (0.003) |
| Individual's age (years) | | 0.002*** | | 0.001*** | | 0.002*** | | 0.002*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Ln(adjusted consumption) | | -0.800*** | | -0.553*** | | -0.845*** | | -0.627*** |
| | | (0.219) | | (0.171) | | (0.231) | | (0.200) |
| Brick/wood wall | | 0.004 | | 0.003 | | 0.008 | | 0.007 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | 0.002 | | 0.002 | | -0.011 | | -0.011 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.011) |
| Household lives in rural area | | 0.045*** | | 0.035*** | | 0.031* | | 0.022 |
| | | (0.015) | | (0.013) | | (0.016) | | (0.015) |
| 2010 | | 0.363*** | | 0.257*** | | 0.387*** | | 0.294*** |
| | | (0.090) | | (0.071) | | (0.096) | | (0.084) |
| 2014 | | 0.482*** | | 0.330*** | | 0.503*** | | 0.366*** |
| | | (0.138) | | (0.108) | | (0.144) | | (0.125) |
| 2016 | | 0.349*** | | 0.232*** | | 0.361*** | | 0.254*** |
| | | (0.105) | | (0.082) | | (0.110) | | (0.095) |
| 2018 | | 0.429*** | | 0.299*** | | 0.444*** | | 0.328*** |
| | | (0.115) | | (0.090) | | (0.121) | | (0.104) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.06 | 61.16 | 50.56 | 61.16 | 50.56 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.02) | (0.02) | (0.01) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.13: The effect of mining pollution on illness: square root of family size adjusted consumption**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.009* | -0.015** | -0.008* | -0.014*** | -0.071** | -0.079*** | -0.066** | -0.082** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.028) | (0.029) | (0.028) | (0.032) |
| Individual is female | | 0.020*** | | 0.018*** | | 0.019*** | | 0.019*** |
| | | (0.006) | | (0.006) | | (0.006) | | (0.006) |
| Individual's education (years) | | 0.000 | | 0.000 | | 0.000 | | 0.000 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Individual's age (years) | | 0.002*** | | 0.002*** | | 0.002*** | | 0.002*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Ln(adjusted consumption)) | | -0.258*** | | -0.178*** | | -0.273*** | | -0.202*** |
| | | (0.071) | | (0.055) | | (0.075) | | (0.065) |
| Brick/wood wall | | 0.004 | | 0.003 | | 0.008 | | 0.007 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | 0.002 | | 0.002 | | -0.011 | | -0.011 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.011) |
| Household lives in rural area | | 0.020* | | 0.017* | | 0.004 | | 0.002 |
| | | (0.011) | | (0.010) | | (0.013) | | (0.013) |
| 2010 | | 0.142*** | | 0.104*** | | 0.153*** | | 0.121*** |
| | | (0.033) | | (0.026) | | (0.035) | | (0.031) |
| 2014 | | 0.136*** | | 0.091*** | | 0.137*** | | 0.094** |
| | | (0.044) | | (0.035) | | (0.046) | | (0.040) |
| 2016 | | 0.084** | | 0.049* | | 0.080** | | 0.046 |
| | | (0.034) | | (0.027) | | (0.035) | | (0.031) |
| 2018 | | 0.139*** | | 0.099*** | | 0.137*** | | 0.101*** |
| | | (0.037) | | (0.029) | | (0.039) | | (0.034) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.06 | 61.16 | 50.56 | 61.16 | 50.56 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.02) | (0.02) | (0.01) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.14: The effect of mining pollution on illness: the level of household income**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.009* | -0.013** | -0.008* | -0.012** | -0.071** | -0.070** | -0.066** | -0.071** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.028) | (0.031) | (0.028) | (0.033) |
| Individual is female | | 0.023*** | | 0.020*** | | 0.023*** | | 0.021*** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.006) |
| Individual's education (years) | | -0.003*** | | -0.002*** | | -0.003*** | | -0.003*** |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Individual's age (years) | | 0.002*** | | 0.001*** | | 0.002*** | | 0.002*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Number of household members | | -0.009*** | | -0.008*** | | -0.008*** | | -0.007*** |
| | | (0.002) | | (0.002) | | (0.002) | | (0.002) |
| Household income | | 0.000* | | 0.000** | | 0.000 | | 0.000 |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Brick/wood wall | | 0.002 | | 0.002 | | 0.006 | | 0.006 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | -0.002 | | 0.000 | | -0.011 | | -0.010 |
| | | (0.010) | | (0.008) | | (0.011) | | (0.010) |
| Household lives in rural area | | 0.008 | | 0.009 | | -0.006 | | -0.005 |
| | | (0.010) | | (0.009) | | (0.014) | | (0.013) |
| 2010 | | 0.032* | | 0.027* | | 0.038** | | 0.034** |
| | | (0.018) | | (0.014) | | (0.018) | | (0.016) |
| 2014 | | -0.030** | | -0.026** | | -0.035** | | -0.032** |
| | | (0.013) | | (0.012) | | (0.014) | | (0.013) |
| 2016 | | -0.042*** | | -0.039*** | | -0.048*** | | -0.048*** |
| | | (0.013) | | (0.012) | | (0.013) | | (0.014) |
| 2018 | | 0.001 | | 0.002 | | -0.003 | | -0.003 |
| | | (0.014) | | (0.012) | | (0.014) | | (0.013) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.07 | 61.16 | 44.94 | 61.16 | 44.94 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.06) | (0.02) | (0.04) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.15: The effect of mining pollution on illness: the logarithm of household income**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.009* | -0.014** | -0.008* | -0.012** | -0.071** | -0.071** | -0.066** | -0.071** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.028) | (0.030) | (0.028) | (0.032) |
| Individual is female | | 0.023*** | | 0.021*** | | 0.023*** | | 0.021*** |
| | | (0.006) | | (0.005) | | (0.006) | | (0.006) |
| Individual's education (years) | | -0.003*** | | -0.002*** | | -0.003*** | | -0.003*** |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Individual's age (years) | | 0.002*** | | 0.001*** | | 0.002*** | | 0.002*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Number of household members | | -0.009*** | | -0.008*** | | -0.008*** | | -0.008*** |
| | | (0.002) | | (0.002) | | (0.002) | | (0.002) |
| Ln(household income) | | 0.010* | | 0.009* | | 0.006 | | 0.005 |
| | | (0.005) | | (0.005) | | (0.005) | | (0.006) |
| Brick/wood wall | | 0.002 | | 0.002 | | 0.006 | | 0.006 |
| | | (0.010) | | (0.008) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | -0.001 | | 0.000 | | -0.011 | | -0.010 |
| | | (0.010) | | (0.009) | | (0.011) | | (0.010) |
| Household lives in rural area | | 0.008 | | 0.009 | | -0.006 | | -0.005 |
| | | (0.010) | | (0.009) | | (0.013) | | (0.013) |
| 2010 | | 0.028 | | 0.023 | | 0.036* | | 0.032* |
| | | (0.018) | | (0.014) | | (0.019) | | (0.016) |
| 2014 | | -0.033** | | -0.030** | | -0.037*** | | -0.035** |
| | | (0.014) | | (0.013) | | (0.014) | | (0.014) |
| 2016 | | -0.046*** | | -0.044*** | | -0.051*** | | -0.051*** |
| | | (0.013) | | (0.013) | | (0.014) | | (0.014) |
| 2018 | | -0.002 | | -0.002 | | -0.005 | | -0.006 |
| | | (0.014) | | (0.012) | | (0.014) | | (0.013) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.07 | 61.16 | 47.42 | 61.16 | 47.42 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.05) | (0.02) | (0.04) |
| N | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 | 7,682 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

**Table 3.A.16: The effect of mining pollution on illness: missing illness values dropped**

| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ln(distance to the nearest mine) | -0.010* | -0.015** | -0.008* | -0.014*** | -0.071** | -0.077*** | -0.067** | -0.077** |
| | (0.006) | (0.006) | (0.005) | (0.005) | (0.028) | (0.029) | (0.028) | (0.032) |
| Individual is female | | 0.020*** | | 0.019*** | | 0.020*** | | 0.019*** |
| | | (0.006) | | (0.006) | | (0.006) | | (0.006) |
| Individual's education (years) | | 0.000 | | -0.000 | | 0.000 | | -0.000 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.001) |
| Individual's age (years) | | 0.002*** | | 0.001*** | | 0.002*** | | 0.001*** |
| | | (0.000) | | (0.000) | | (0.000) | | (0.000) |
| Number of household members | | 0.019** | | 0.010 | | 0.020** | | 0.012 |
| | | (0.008) | | (0.006) | | (0.008) | | (0.007) |
| Ln(household consumption) | | -0.263*** | | -0.168*** | | -0.274*** | | -0.185*** |
| | | (0.079) | | (0.060) | | (0.082) | | (0.068) |
| Brick/wood wall | | 0.004 | | 0.003 | | 0.007 | | 0.007 |
| | | (0.010) | | (0.009) | | (0.010) | | (0.009) |
| Asphalt/metal roof | | 0.002 | | 0.003 | | -0.009 | | -0.009 |
| | | (0.010) | | (0.009) | | (0.011) | | (0.011) |
| Household lives in rural area | | 0.020* | | 0.016 | | 0.004 | | 0.001 |
| | | (0.011) | | (0.010) | | (0.014) | | (0.013) |
| 2010 | | 0.139*** | | 0.097*** | | 0.149*** | | 0.110*** |
| | | (0.036) | | (0.028) | | (0.038) | | (0.032) |
| 2014 | | 0.134*** | | 0.081** | | 0.133*** | | 0.081** |
| | | (0.048) | | (0.037) | | (0.050) | | (0.041) |
| 2016 | | 0.079** | | 0.039 | | 0.074** | | 0.035 |
| | | (0.036) | | (0.028) | | (0.037) | | (0.031) |
| 2018 | | 0.137*** | | 0.091*** | | 0.134*** | | 0.091*** |
| | | (0.040) | | (0.031) | | (0.041) | | (0.034) |
| Model | LPM | LPM | Probit | Probit | IVreg | IVreg | IVprobit | IVprobit |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$/Pseudo $R^2$/First-stage F-stat | 0.01 | 0.04 | 0.02 | 0.07 | 62.74 | 52.13 | 62.74 | 52.13 |
| Hausman/Wald test of exogeneity | | | | | (0.02) | (0.03) | (0.02) | (0.02) |
| N | 7,432 | 7,432 | 7,432 | 7,432 | 7,432 | 7,432 | 7,432 | 7,432 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is male individuals, living in houses with cement, stone and other wall, and tile and other roof, and living in urban areas. Columns 1,3,5 and 7 run the basic models with province and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including wall and roof type of residence and rural status. Marginal effects are calculated at the mean values of all other covariates.

# Chapter 4 The intended and unintended consequences of electricity subsidies: Evidence from Mongolia[1]

## Abstract

We investigate the effectiveness of large electricity subsidies to reduce the consumption of dirty energy and improve ambient air quality. We exploit a policy change in Mongolia that provides 50–100 percent subsidy to households in some regions, allowing us to use difference-in-differences models. Using five rounds of the Mongolia Household Socio-Economic Survey, we find that the subsidy reduces the likelihood of reporting illness. We further find that households receiving the electricity subsidy increase their (total of subsidised and un-subsidised) electricity expenditure by at least 17 percent more than those who have not received any such benefit. This is an important positive outcome, indicating that households changed their behavior of daytime and non-winter season electricity consumption, when they do not receive any subsidy. Policy-makers, therefore, need to internalize the unintended benefit of the subsidy when comparing with the cost of the programme.

**JEL-Classification:** D12, O13, Q41, Q53, Q56, L94

**Keywords:** Electricity demand, Inequality of electricity access, Health, Development, Mongolia

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## 4.1 Introduction

Reducing greenhouse gas emissions and supporting a net-zero future requires access to affordable, reliable, sustainable, and modern energy for all (United Nations, 2021). Therefore, countries around the world subsidize electricity resulting in many desirable but also undesirable outcomes (Lay et al., 2013; Shahbaz et al., 2017; Balarama et al., 2020; Imelda, 2020). While many studies focused on the consequences of subsidizing electricity, little research has focused on how it affects health and changes the preference for electricity consumption. In this article, we discuss this issue by providing evidence that subsidizing electricity not only helps reduce pollution and thus improve health outcomes but also changes household preferences for electricity. Using the case of electricity subsidy in Ulaanbaatar, Mongolia, we document that the provision of electricity subsidy is associated with significant changes in electricity expenditure even when it is not subsidized. We subsequently explore potential mechanisms and conclude that change in preference is the most plausible explanation.

We study the case of electricity subsidy in Ulaanbaatar, as it presents three valuable features for our purposes. First, the winter in Mongolia is very cold, with the temperature falling up to $-30^{o}$C at night. Such low nighttime temperature implies that people can be severely unwell if they cannot heat their homes. This is particularly problematic for the people living in traditional "ger" (a form of a tent), which is known to be energy-inefficient (MEEI, 2020). Second, as a developing country, Mongolia has many low-income households living below or close to the poverty line (NSO, 2020). Extreme cold forces them to use dirty energy like coal to warm their home during winters. Harmful chemicals and particulate matter from the use of coal cause indoor pollution, which is so severe that it also causes severe outdoor pollution at the regional level (Markandya and Wilkinson, 2007; Haines et al., 2007). Both indoor and outdoor pollution results in poor health of the members of the affected households.

Third, the subsidy rate on electricity consumption for eligible households in Ulaanbaatar is huge, ranging from 50–100 percent during cold winter months from October to April. With the aim to reduce fine particulate matters and other airborne toxins that result from the residential use of coal for cooking and heating during cold winter months, the subsidy has been in place since 2011. Thus the subsidy is expected to bring significant health benefits to the eligible residents who suffer substantially from respiratory and other related illnesses. The subsidy is expected to benefit the ineligible population as they are also exposed to reduced outdoor pollution caused by the eligible households. The significant price subsidy can also alter the recipient households' preference and thus electricity consumption pattern in the short and long run.

The results of this article highlight how a subsidy to less polluting energy like electricity can achieve the intended health outcomes and change the preference for energy in a context where people burn dirty fuels like coal and wood for heating homes and cooking. These channels have not been extensively investigated, despite the existing evidence linking air pollution to morbidity and mortality (Neidell, 2004; Currie et al., 2009a,b) and product use to habit formation and behavioral change (Jessoe and Rapson, 2014; Meriggi et al., 2021). Instead, it has mostly focused on the effect of electricity subsidy on welfare (Giuliano et al., 2020; Hahn and Metcalfe, 2021; Alvarez and Tol, 2021), energy demand (Burke and Kurniawati, 2018; Durmaz et al., 2020), energy conservation (Allcott and Rogers, 2014; Ito, 2015; Boccard and Gautier, 2021) and lost opportunities (Davis, 2014; Plante, 2014; Coady et al., 2019). Identifying and quantifying the intended and unintended consequences is important to inform the debate on energy policies and to compare the net benefits with the cost of the subsidy.

To empirically identify the effect of the subsidy on the probability of reporting illness and the expenditure on electricity, we employ Mongolian microdata. The five rounds of nationally representative Mongolia Household Socio-Economic Survey (HSES) data allow us to model individual illness and electricity expenditure on the eligibility of the subsidy. The detailed information in the survey enables us to control for many socioeconomic, locational, and demographic factors and improve the precision of the estimated impacts.

The main challenge in identifying the impact is that households eligible for subsidy are systematically different from those not eligible. To overcome this concern, we use a difference-in-differences (DiD) approach exploiting two sources of variation: the eligibility of the subsidy and changes in the provision of subsidy over the years, particularly between 2010 and 2012. Since the subsidy has been given to households living in houses and 'gers' in specific regions for particular years, it provides us with a perfect quasi-natural experimental situation. The setup allows us to employ a DiD technique and produce credible estimates of the impact of subsidy. The main identification assumption is that the change in electricity expenditure over time for both types of households would be similar in the absence of the subsidy.

We believe that, conditional on satisfying the common trend assumption, the difference-in-differences method is the best approach to evaluate a large electricity subsidy with a sufficiently large sample size. A randomized control trial (RCT) research design for investigating the impact of electricity subsidy is rare due to the huge cost involvement and ethical issues. Moreover, RCTs in such situations are likely to perform poorly due to the possibility of bias in selecting the sites (Allcott, 2015).

We find that electricity subsidy effectively reduces illness, including respiratory diseases. Our estimates suggest that the electricity subsidy reduces the reported illness by 5-6 percentage points (pp) except for 2016 when the subsidy-eligible households badly suffer from the spread of infectious diseases. The reduction is about 3-5 pp when we consider only respiratory illness. While the lack of appropriate data does not allow us to compare the pollution level between the subsidy-eligible and ineligible regions with a credible econometric method and directly verify the effectiveness of the subsidy, our results provide indirect evidence in favor of the policy effectiveness.

Since in our analysis electricity subsidy is associated with a reduction in pollution-induced illness, we investigate the change in the expenditure pattern on electricity.[2] We find that eligible households increase their electricity expenditure both in winter and non-winter seasons. In particular, the subsidy increases electricity expenditure by 17–24 percent in winter months and 16–23 percent in non-winter months. The results are robust to the sample restrictions, alternative estimation methods, and model specifications. We also find evidence of the presence of common trends in all cases. It is important to note that our results refer to the total expenditure on electricity, which includes the heavily discounted expenditure (a 50-100% discount, depending on the month and year)[3].

Increasing access to clean fuel and reducing energy poverty through subsidies have significant public health benefits. The transition from fossil fuel to electricity significantly improves indoor and outdoor air quality. Air pollution is the leading cause of morbidity for infants and children (Neidell, 2004; Currie et al., 2009a,b; Chen et al., 2013). Furthermore, being unable to afford the electricity to heat homes at a comfortable level has adverse impacts on mental well-being and self-assessed health conditions (Churchill et al., 2020; Llorca et al., 2020), infant health (Cesur et al., 2017; Palma et al., 2022) and mortality during winter months (Neidell et al., 2021). Changes in preference to switch to cleaner energy are thus an added benefit of the subsidy program, which can have a protective impact on human health and the environment. Thus, the electricity sub-

[2]Consumption is a more important policy variable than expenditure. Since we do not have data on consumption, we analyze expenditure on electricity. However, when it is not apparent, we explained the implication of our findings on electricity consumption. Using available information, we also provide a back-of-the-envelope calculation of overtime consumption of people eligible for subsidy against those who are not.

[3]For example, in periods when the discount is 100% in winter months (October-April), households would need to *more than double* their consumption of electricity (in $kWh$) for their observed nominal electricity expenditure to increase.

sidy can be an essential policy intervention in developing countries where people rely heavily on biomass and fossil fuel for heating and cooking, which have adverse health impacts.

Our study adds to the growing literature on the impact of an electricity subsidy on improving health outcomes in developing countries and the literature on habit formation for cleaner energy use. A limited number of studies investigates the impact of a large electricity subsidy in a developing country context (e.g., Burke and Kurniawati, 2018; Khalid and Salman, 2020). Using a quasi-experiment setting with rich microdata, we provide credible estimates of the effect of the subsidy on illness and electricity expenditure. Our findings of increased electricity use resulting from a large electricity subsidy are particularly novel that can shape public policies related to poverty, energy, and the environment.

The rest of the paper proceeds as follows. Section 4.2 presents some background of Mongolia and the context of the policy that we examine in this study. Methodology and data employed for our investigation are discussed in Section 4.3. Section 4.4 presents the results and discusses the validity of the identifying assumption and the robustness of the results. Section 4.5 also discusses the policy implications of our study. Section 4.6 concludes the paper.

## 4.2 Background

### 4.2.1 Coal use and public health concerns in Mongolia

Ulaanbaatar, the capital city of Mongolia, is one of the coldest capitals, with temperatures fallng significantly during the winter. Such low temperature requires enormous energy demand in the winter for keeping the place of living warm. While around 98 percent of the population in Mongolia has access to electricity, the country's electricity consumption has been 2.3 MWh/capita in 2018, up from 1.05 MWh/capita in 2000 (Ministry of Energy, 2018). It is below the average level (2.8 MWh/capita) in the Asia-Pacific region and is short of meeting the residential demand for heating.[4] Therefore, some of the city's residential energy demand for heating during winter is met by heavy use of coal, creating a deadly level of indoor and outdoor air pollution.

The use of coal by residents for heating in the winter months is the major source of air pollution in Ulaanbaatar. More than 60 percent of households in the city live in traditional Mongolian gers and basic houses with no water, sanitation, and heating infrastructure in the "ger districts."[5]

[4] MWh represents megawatt-hours of electricity. Six laptop computers can operate in one kWh during a standard workday. $tCO_2$ here indicates greenhouse gas emissions equivalent to tons of $CO_2$.

[5] A ger or yurt is a traditional Mongolian house that is built by assembling a wooden framework and covering it with traditional felt. It is the most portable and suitable dwelling for nomads. However, a significant proportion of people

These households burn raw brown coal for cooking and heating during cold winter months from October through April, despite their metered electricity connections (Allen et al., 2013). About 200,000 households living in ger districts burn around 200,000 tons of raw coal and 160,000 cubic meters of firewood annually to heat their homes (World Bank, 2019). Although ger district households accounted for around 16 percent of total electricity consumption during 2014–2018, their residential heating is met by burning of coal in winter.[6]

Mongolia also heavily depends on coal-based power plants for generating electricity. The country produced 79 percent of its electricity from thermal power plants in 2018 (Ministry of Energy, 2018). Coal-based electricity generation is the largest emitter of carbon dioxide ($CO_2$) in the country, with $CO_2$ emissions standing at 6.7 t$CO_2$ per capita in 2018, which is higher than the average 3.92 t$CO_2$ per capita in the Asia–Pacific region (IEA, 2018). Both electricity generation and residential use of coal result in high levels of air pollution in all major cities in Mongolia, including Ulaanbaatar.

The burning of fossil fuels releases many toxic substances in the air, ranging from fine particulate matter and nitrogen dioxide ($NO_2$) to sulfur dioxide ($SO_2$). Among these pollutants, the most dangerous fine particulate matter of 2.5 microns or less in diameter ($PM_{2.5}$) was 12 times higher than the WHO guideline of 10 $\mu g/m^3$ in 2011 in Ulaanbaatar (Guttikunda et al., 2013). The daily mean $PM_{2.5}$ declined to 86 $\mu g/m^3$ in 2014, reached 164 $\mu g/m^3$ in 2016 and 138 $\mu g/m^3$ in 2018, with the maximum 280 $\mu g/m^3$ in the last year (Ganbat et al., 2020). The $PM_{2.5}$ level has remained consistently higher than the safe level set by the WHO and the national standard of 50 $\mu g/m^3$ (IQ Air, 2020). The high level of pollution made Ulaanbaatar the fourth most polluted city in the world in 2020.

Air pollution is the sixth riskiest factor that drives death and disability in Mongolia. The death rate from air pollution was 82 deaths per 100,000 in 2017, which was higher than 79 in the Central Asian region (IHME, 2018). Diseases of the respiratory system were the leading cause of morbidity among children and adolescents in 2018, with 4,755 cases per 10,000 population for the age group 1–4. Pneumonia was the most frequently occurring disease among infants and children under-five and accounted for 28 percent of morbidity in 2018 (NCHD, 2018). Outdoor air pollution contributed to 29 percent of cardiopulmonary deaths and 40 percent of lung cancer deaths in the capital city, all of which accounted for 10 percent of total mortality (Allen et al., 2013). All

still live in gers in both rural and urban areas in Mongolia. In 2016, 40 percent of the total Mongolian population lived in gers, 36 percent in detached houses, and 24 percent in apartments (National Statistics Office, 2017).

[6]Households in apartments and public and private entities consumed 11 and 73 percent of total electricity during the same period, respectively.

of these indicate that Mongolia faces significant challenges to meet its current and future need of clean energy and mitigate the negative health impacts of coal-based power generation and the burning of coal for residential heating, especially in its capital city.

### 4.2.2 Mongolian Government's policies to curb pollution

Although air pollution reduction in the capital city has been among the top priorities of the Government of Mongolia (GoM), the desired outcomes of the policies implemented have not materialised. The Parliament passed the Law on Air Pollution Reduction in 2011, and the GoM has put relevant policies in place to implement the law. The first significant project implemented to reduce air pollution was the Ulaanbaatar Clean Air Project (UBCAP), implemented by the GoM and the World Bank in 2012–2019, with total financing of US$27m. The project distributed around 40,000 clean stoves to ger district households in the initial stage, 2013–2015. Between 2010 and 2015, the project distributed a total of 175,000 clean stoves to ger district households with subsidies from the Ministry of Energy, the City of Ulaanbaatar, the Millennium Challenge Corporation, and UBCAP (World Bank, 2019). However, the initiative of the project has been inadequate to address air pollution effectively in the country.

Although there are three coal-fired thermal power plants located adjacent to the city, the primary pollution source is the combustion of coal by residents to heat their homes in winter (ERC, 2020). Thus, the extent of air pollution reduction depends mainly on making households switch from coal-based heating to alternative energy sources such as electricity. The GoM has been providing subsidies through discounts for nighttime use of electricity for ger district households at various discount rates since 2011. The Ministry of Environment and Green Development (MoEGD) and the Ulaanbaatar City Mayor's Office jointly identify the air pollution reduction zones where households burn raw coal in winter. The households in these zones are eligible for the nighttime use electricity discounts that the Energy Regulatory Commission sets.

The timelines of subsidy provisions and zoning details are provided in Table 4.1. Panel A lists the evolution of the subsidy chronologically. The first discount was a 50 percent reduction for nighttime use of electricity during the winter months from October until May, effective from November 2011 to December 2016.[7]

[7]We have not been able to acquire aggregate data on the amount of subsidy provided and the number of participants households prior to 2017.

**Table 4.1: Overview of electricity subsidy programs and zoning policies**

| Date | Policy name | Duration | Actions |
|---|---|---|---|
| **Panel A: Electricity subsidy programs** | | | |
| 10 Feb 2011 | Parliament Resolution No.11 to implement the Law on Air Pollution Reduction | 1 October–1 May | Specified electricity subsidy program for air polluting zones. |
| 2 Nov 2011 | Government Resolution No.309 on air pollution reduction and electricity tariff discount | 1 October–1 May | 50% discount for the evening and night rates for households in the air pollution reduction zones. |
| 17 Jul 2014 | Joint Resolution No.263/A-616 of Minister of Environment and Green Development and Ulaanbaatar City Mayor | 1 Oct 2014–1 May 2015 | 50% discount for the evening and night rates for households in the air pollution reduction zones. |
| 28 Dec 2016 | Government Resolution No.214 on air pollution reduction and electricity tariff discount | 28 Dec 2016–1 May 2017 | 100% discount for households in the air pollution reduction zones in the capital city. Zones 1, 3 and 4 remain. |
| 4 Jul 2017 | Government Resolution No.199 on air pollution reduction and electricity tariff discount | 1 Oct 2017–1 May 2018 | 100% discount for households from 9 pm to 6 am in the air pollution reduction zones in the capital city. Zones 1, 2, 3 and 4 remain. |
| 25 Oct 2018 | Energy Regulatory Commission Resolution on discount for night tariff rates | 1 Nov 2018–1 Apr 2019 | 100% for 700kWh for 220V capacity; 100% for 1500 kWh for 380V capacity; 50% discount on the excess from 9 pm to 6 am. Zones 1, 2, 3 and 4 remain. |
| **Panel B: Policies on zoning** | | | |
| 23 Dec 2015 | Joint Resolution No.A989 of Minister of Environment and Green Development and Ulaanbaatar City Mayor | 23 Dec 2015–10 Jan 2017 | Zones 1, 2 and 3 are identified and the 50% discount applies from the 2014 Government Resolution No.263/A-616. |
| 10 Jan 2017 | Joint Resolution No.A014/-A/19 of Minister of Environment and Green Development and Ulaanbaatar City Mayor | 10 Jan 2017–6 Jul 2018 | Zones are modified. Zones 1, 2, 3 and 4 are identified and the 100% discount applies from the 2016 Government Resolution No.214. and 2017 Government Resolution No.199. |
| 6 Jul 2018 | Joint Resolution No.A/226-A/619 of Minister of Environment and Green Development and Ulaanbaatar City Mayor | 1 Nov 2018–1 Apr 2019 | Zones 1, 2, 3 and 4 are modified slightly and the 100% discount applies from the 2018 Energy Regulatory Commission Regulation. |

Source: Unified Legal Information System (2021)

Then the subsidy was increased to 100 percent discount for nighttime use in 2016, and a time limit was set from 9 pm–6 am in 2017.[8] The GoM put a cap on the discount for nighttime elec-

[8]There are two types of tariffs for residential electricity consumption. A kWh of electricity is priced at US$0.041 for the first 150 kWh, and US$0.049 for over 150 kWh per month for simple meters. A double meter tariff is also applied separately for daytime and nighttime use. The daytime tariff (6 am–9 pm) is US$0.043 per kWh, while the nighttime tariff (9 pm–6 am) is US$0.032 per kWh. The monthly base tariff is US$0.828 per kWh (Ministry of Energy, 2018).

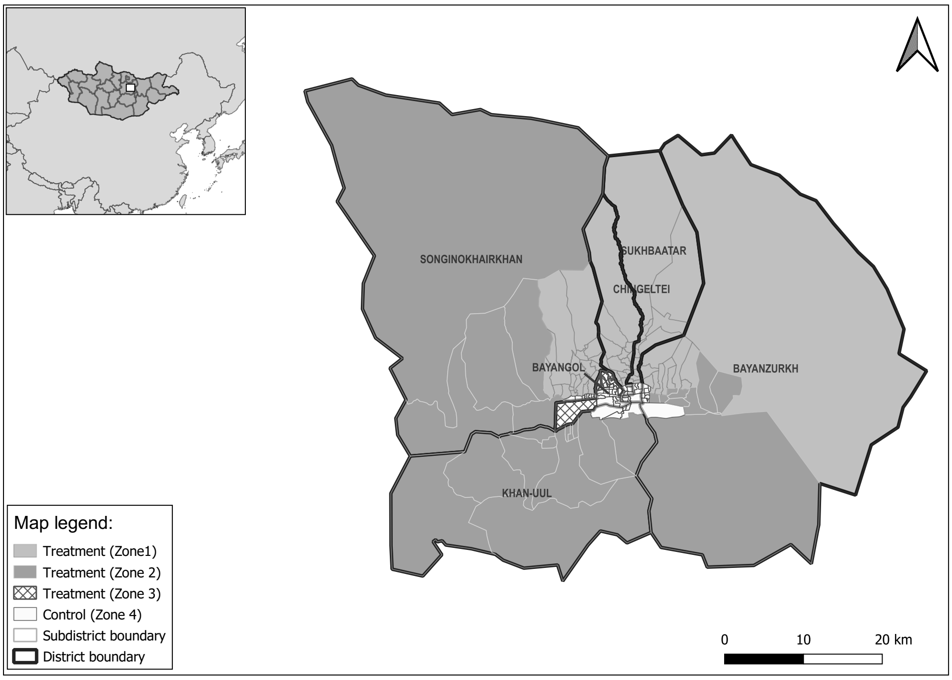
tricity use in October 2018, limiting it to 700kWh and 1,500 kWh for 220V and 380V capacity, respectively. The GoM extended the subsidy to the national level in 2019 with the provision of 50 percent discount for the nighttime rate to ger district households in province centers and settlements with a population above 10,000 (ERC, 2019).

The subsidy applies to only households living in the ger districts classified into specific zones. Panel B of Table 4.1 lists the changes in the details of the zones. The earliest data on the zoning is reported in 2015. Although the zoning changes every year, we believe that it has not changed significantly. Initially, there were two polluting zones and one affected zone, with total three zones identified in 2015. In 2017, one of the polluting zones was divided into two, resulting in three polluting zones and one affected zone (MoEGD, 2015, 2017).

Zones vary by population, type of residence and pollution level. Zone 1 is the primary source of air pollution, shown in light grey in the districts of Songinokhairkhan, Chingeltei, Sukhbaatar, and Bayanzurkh in Figure 4.1, where 130,076 households live and $PM_{2.5}$ concentration was 10–30 times higher than the national standard of 50 $\mu g/m^3$ in 2017. Zone 2, shown in dark grey in the districts of Songinokhairkhan, Khan-Uul, and Bayanzurkh in Figure 4.1, where 51,910 households live and $PM_{2.5}$ concentration was 3–8 times higher than the national standard. Zone 3, shown in hashed pattern in Figure 4.1, where 12,446 households live and $PM_{2.5}$ concentration was 2–5 times higher than the standard. Both zones 2 and 3 are affected by the air pollution from Zone 1. Lastly, Zone 4, in white in Figure 4.1, is affected by air pollution from zones 1, 2, and 3, and all households in Zone 4 live in modern apartments connected to a central heating system. The $PM_{2.5}$ concentration in Zone 4 was 2–3 times higher than the national standard (NSO, 2021).

The eligibility criteria for households to receive the subsidy are straightforward. A household must reside in zones 1, 2, and 3 and have one of the heating solutions such as electric and gas heaters, renewable energy-based heating, or clean stoves that use only coking or processed clean coal as described in the Law on Air Pollution Reduction (PoM, 2011). In addition, a household must have no outstanding electricity bills, have both day and nighttime use meters, and ensure the safe installation of electric wires, switches, and plugs (MoEGD, 2015).

The subsidy program had a wide coverage rate and benefited a significant proportion of people. There were 365,000 residential electricity consumers in Ulaanbaatar in 2018, and 152,000 of those households live in the ger districts eligible for the subsidy. Eighty-five percent of ger district households had both daytime and nighttime meters for electricity consumption, making them eligible for the subsidy (Bold, 2018). The total subsidy amount was US$2.5m in 2017 and US$3.6m




Source: Compiled by authors

**Figure 4.1: Ulaanbaatar city district zoning map for air pollution reduction**

in 2018. The households were estimated to reach 116,000 with the subsidy amount of US$7.4m in 2019, including those households in provinces (ERC, 2019). The average electricity consumption for ger district households was 458kWh in 2019, with eligible households receiving subsidies ranging from US$15–30 per month during the winter months (Tsetseg, 2020).

Theoretically, the electricity subsidy will have both income and substitution effects for the participating households. We illustrate the mechanisms through which households would adjust their consumption behaviour in Figure 4.2. The horizontal axis denotes electricity consumption ($x_1$) and the vertical axis denotes the consumption of non-electricity goods ($x_2$). A participating household's budget constraint and indifference curves are $B_1$ and $I_1$, respectively, with the equilibrium consumption bundle of $x_2^1$ units of non-electricity goods and $x_1^1$ units of electricity.

With the electricity subsidy, households consume up to 700kWh of free electricity at night and 50 percent discount thereafter, shifting the budget constraint to $B_2$. With indifference curve $I_2$ the new equilibrium occurs at point b with consumption bundle ($x_1^2$, $x_2^2$). To isolate the income and substitution effect, we draw the budget line $B_3$ that is parallel to $B_2$ and tangent to the original indifference curve $I_1$. Movement from point a to c indicates the substitution effect that raises electricity consumption by $x_1^1 x_1^3$. On the other hand, movement from point c to b indicates the income effect that raises electricity consumption by $x_1^3 x_1^2$. The figure demonstrates that a large subsidy results in a significant increase in the electricity consumption by the beneficiary

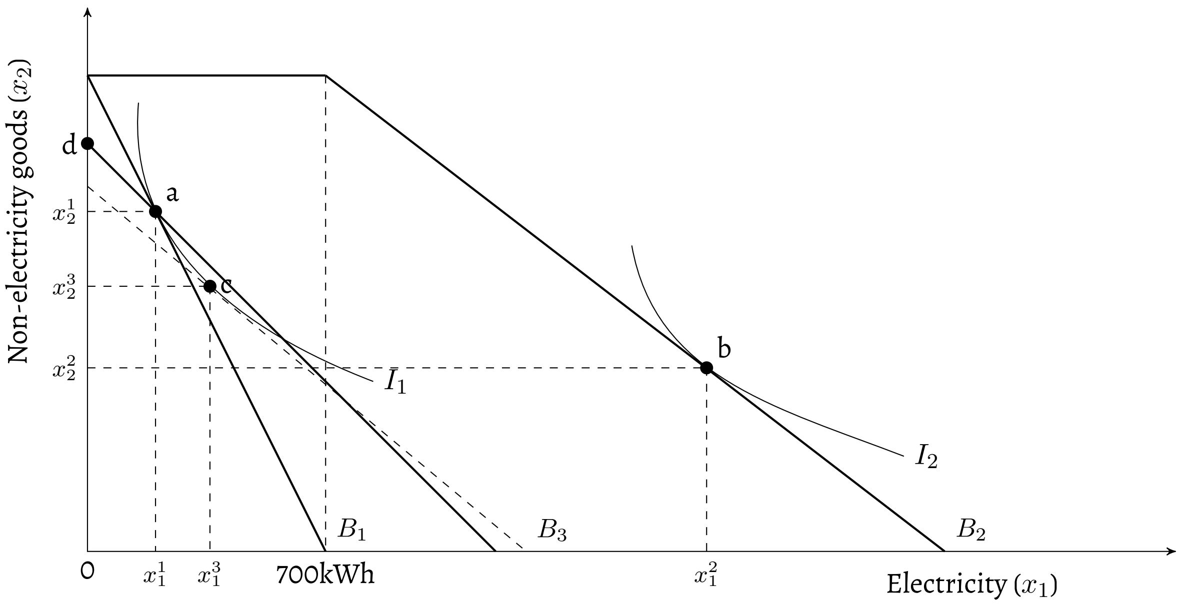



**Figure 4.2: Impact of an electricity subsidy**

households. With an average consumption (of subsidised and un-subsidised households) below 700kWh implies that households may experience a corner solution, at the kink at the end of the horizontal part of $B_2$, rather than the optimum shown in the figure[9].

The figure indicates that it is theoretically obvious that we should expect an increase in electricity consumption by treated households. What is less clear is the effect of the subsidy on the *nominal* electricity expenditure, as this depends on both the elasticity of the demand for electricity, and on any change in behaviour in the summer months when heating is not needed. Given the significant decline in the effective average annual price of the electricity for the treatment households (in the range of 50-100% in the winter months), and the fact that households do not need to use heating to any meaningful degree in the summer months, our finding that the nominal expenditure on electricity increases significantly indicates a long-term change in household behaviour as they purchase electric appliances.

[9]The electricity price subsidy reduces the average price for the participating households during the winter months. Since the subsidy evolved and became more generous, households adjusted their consumption behaviour. For example, the average nighttime electricity consumption being much lower than 700kWh indicates that households, on average, do not pay for nighttime electricity consumption. Therefore, any expenditure on electricity for the treatment households comes from their daytime electricity consumption.

## 4.3 Data and methodology

### 4.3.1 Household survey data

We use the data from the most recent five rounds of the Mongolia Household Socio-Economic Survey (HSES), a nationally representative cross-sectional household survey undertaken by the National Statistics Office of Mongolia every two years. The survey uses a stratified two-stage sample design based on population figures obtained from local governments' administrative records. The first stage stratifies the capital city, Ulaanbaatar, and the 21 provinces. The second stage divides the 21 provinces into two substrata: urban, comprising the provincial capitals, and rural, consisting of small towns and the countryside (NSO, 2018).[10] We focused our analysis on households in the capital city Ulaanbaatar, where the electricity subsidy program initially commenced in late 2011. The program has been extended to other provinces in 2019, after that no HSES data are available till now.

The five rounds of the HSES - 2010, 2012, 2014, 2016, and 2018 - include 73,088 households. We shelved 55,211 households in the provinces and 960 households in the districts that did not participate in the subsidy program. We then dropped 2,584 households belonging to neither the control nor the treatment groups, as described in Subsection 4.3.2 below. We eliminated a further 467 households that do not meet the requirements to receive the subsidy, such as student dormitories, public houses for employees, non-living quarters, and other types of properties. Finally, we omitted 125 households as they did not report any expenditures on food or electricity. This gives us an analysis sample of 13,741 households in Ulaanbaatar consisting of 51,798 individuals. Of them, 21,985 individuals in 5,766 households have been surveyed in winter months while information of the rest 29,813 persons in 7,975 households have been collected during the non-winter months.

The HSES records whether, in the last month before the survey, a person's has been ill and, if yes, whether the illness is related to the respiratory system. Panel A of Table 4.2 presents the overall illness rates in winter months, separately for the treatment and control individuals.[11] The general illness level is higher for the treatment individuals than their control counterparts in 2010. However, the control group's illness level increases over time at a higher rate than the treatment group. A similar pattern is observed for respiratory system illness.

[10]The HSES questionnaires and the primary datasets are publicly available from the NSO Census and Survey data catalog http://web.nso.mn/nada.

[11]We recorded 1,012 individuals with missing illness data as not being ill since coding zeros as missing is common in survey data.

**Table 4.2: Summary statistics of dependent variables**

| | 2010 | | 2012 | | 2014 | | 2016 | | 2018 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Treatment | Control | Treatment | Control | Treatment | Control | Treatment | Control | Treatment | Control |
| *Panel A: Individual illness in winter months* | | | | | | | | | | |
| Sick in the past month | 0.09 | 0.06 | 0.07 | 0.10 | 0.07 | 0.10 | 0.11 | 0.08 | 0.11 | 0.13 |
| | (0.28) | (0.24) | (0.26) | (0.30) | (0.26) | (0.30) | (0.31) | (0.27) | (0.31) | (0.34) |
| Respiratory illness | 0.04 | 0.02 | 0.04 | 0.04 | 0.04 | 0.06 | 0.07 | 0.04 | 0.04 | 0.07 |
| | (0.19) | (0.15) | (0.19) | (0.20) | (0.19) | (0.24) | (0.25) | (0.20) | (0.21) | (0.25) |
| Number of individuals | 2,203 | 1,306 | 3,266 | 1,508 | 2,996 | 1,305 | 3,117 | 1,474 | 3,069 | 1,741 |
| *Panel B: Individual illness in non-winter months* | | | | | | | | | | |
| Sick in the past month | 0.05 | 0.05 | 0.06 | 0.07 | 0.07 | 0.05 | 0.07 | 0.06 | 0.10 | 0.07 |
| | (0.23) | (0.22) | (0.24) | (0.25) | (0.25) | (0.21) | (0.25) | (0.24) | (0.30) | (0.25) |
| Respiratory illness | 0.02 | 0.01 | 0.02 | 0.03 | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.01 |
| | (0.12) | (0.11) | (0.14) | (0.17) | (0.14) | (0.14) | (0.15) | (0.16) | (0.17) | (0.12) |
| Number of individuals | 2,979 | 1,949 | 4,133 | 2,456 | 4,369 | 1,948 | 4,227 | 1,687 | 4,352 | 1,713 |
| *Panel C: Household energy expenditures in winter months* | | | | | | | | | | |
| Electricity expenses | 12.47 | 15.85 | 14.14 | 15.62 | 13.56 | 13.88 | 15.31 | 16.41 | 15.64 | 15.10 |
| | (7.53) | (6.65) | (9.68) | (8.55) | (10.99) | (6.17) | (10.78) | (6.36) | (12.18) | (5.52) |
| Share of electricity expenses (%) | 2.99 | 2.69 | 2.78 | 2.19 | 2.66 | 1.90 | 3.39 | 2.73 | 3.40 | 2.38 |
| | (1.62) | (1.32) | (1.76) | (1.43) | (1.85) | (1.16) | (2.11) | (1.36) | (2.44) | (1.37) |
| Other energy expenses | 29.25 | 0.07 | 50.02 | 0.16 | 34.87 | 0.07 | 28.28 | 0.02 | 27.04 | 0.03 |
| | (31.81) | (1.18) | (55.90) | (2.04) | (35.19) | (1.00) | (29.88) | (0.37) | (25.74) | (0.51) |
| Share of other energy expenses (%) | 7.05 | 0.00 | 10.12 | 0.03 | 7.63 | 0.01 | 6.63 | 0.00 | 6.35 | 0.00 |
| | (7.65) | (0.03) | (12.23) | (0.34) | (9.16) | (0.10) | (7.69) | (0.06) | (7.24) | (0.04) |
| Number of households | 528 | 353 | 797 | 424 | 798 | 387 | 802 | 424 | 758 | 495 |
| *Panel D: Household energy expenditures in non-winter months* | | | | | | | | | | |
| Electricity expenses | 13.91 | 15.96 | 14.74 | 15.91 | 13.70 | 13.69 | 15.28 | 15.71 | 16.96 | 14.70 |
| | (9.32) | (6.10) | (8.31) | (6.74) | (11.65) | (5.36) | (9.18) | (5.64) | (12.82) | (4.71) |
| Share of electricity expenses (%) | 3.18 | 2.90 | 2.94 | 2.18 | 2.60 | 1.85 | 3.56 | 2.78 | 3.49 | 2.35 |
| | (1.83) | (1.71) | (2.17) | (1.53) | (1.78) | (0.97) | (1.91) | (2.16) | (2.33) | (1.30) |
| Other energy expenses | 15.69 | 0.07 | 19.75 | 0.13 | 11.11 | 0.12 | 16.04 | 0.02 | 11.73 | 0.04 |
| | (35.44) | (1.05) | (39.14) | (1.43) | (27.93) | (1.53) | (32.95) | (0.36) | (22.52) | (0.90) |
| Share of other energy expenses (%) | 3.92 | 0.01 | 3.86 | 0.02 | 2.25 | 0.01 | 3.87 | 0.00 | 2.62 | 0.01 |
| | (9.12) | (0.22) | (8.10) | (0.24) | (6.47) | (0.17) | (8.00) | (0.04) | (5.97) | (0.13) |
| Number of households | 718 | 544 | 1,048 | 711 | 1,155 | 587 | 1,133 | 505 | 1,089 | 485 |

*Notes:* Treatment households are those living in gers and basic houses in zones 1, 2 and 3. The control households are those living in apartments in zone 4. Means are reported in thousand Tugrik (MNT). The exchange rate for the end of survey period (December) ranged from US\$1 ≈ 1,257.0 MNT in 2010 to US\$1≈ 2,647.0 MNT in 2018. All values are on per capita monthly basis and adjusted for inflation. Standard deviations are reported in the parentheses.

Panel B of the table reports the illness rates in non-winter months. Unlike the winter months, treatment individuals report a slightly higher level of illness than the control individuals in 2014-2018. In contrast, the respiratory illness rates are a bit higher for the treatment group in 2010 and 2018. Overall, the treatment individuals report a higher level of illness in non-winter months, whereas the control group reports more in winter.

The survey also records expenditure on energy and electricity that we also investigate to examine the impact of the subsidy. Panel C in Table 4.2 presents the summary statistics for the outcome variables in winter months.[12] The monthly household electricity expenditure was lower for the treatment households than their control counterparts in the base year, 2010. The treatment group increased its electricity expenditures in 2012, decreased them in 2014, and increased them later. Conversely, the control households' electricity expenditures remained stable over the years, except in 2014 when both groups had lower expenditures than in the previous year. In the table, we have also presented the share of electricity expenditures in household total expenditures. The expenditure share of electricity was three percent for the treatment households in 2010, whereas it was slightly lower for the control counterparts. The share declined for the treatment households in 2012-2014 and increased in 2016-2018. In contrast, the control households had a more stable share of electricity expenditures in all years, except in 2014 when it was much lower than the other years.

The non-electricity energy expenditure displays a downward trend for the treatment households as they are burning less coal and wood at night due to the subsidy. Since the control households have central heating, their other energy expenditures are minimal compared to the treatment group. The treatment households' share of non-electricity energy expenditures in household total expenses is seven percent in 2010, and it increases to above ten percent in 2012 and declines after that. Overall, the share of energy expenditures in total household expenses declines slightly for the treatment households. However, we observe that the treatment households increase their electricity expenditures more than the control group during the analysis period.

Panel D of Table 4.2 shows the energy expenditures in non-winter months. Both electricity and other energy expenditures follow similar patterns as in the winter months. However, the share of electricity expenditures in total expenditures is higher for the treatment households in non-winter months than in winter as there is no subsidy in the former period. In contrast, their

[12] In our analysis sample, we replaced the missing monthly electricity expenditures of 32 households with their annual electricity expenditures averaged over 12 months.

share of non-electricity energy expenditures is lower in that season as they burn wood and coal mainly for cooking and less for heating purposes in non-winter months.

One advantage of using HSES for our investigation is that it collects some additional information on the socio-demographic characteristics of the participants that are important to control for in the analysis. Employed household member-specific information includes age, gender, education, marital status, employment, income and type of residence. On the other hand, collected household-specific information includes the household's residential property type, income and expenditure. In both types of models, we also include the type of heating devices used in residence to control for the channel that public distribution of heating devices can affect household consumption of electricity and thus their members' illness level.

Panel A in Table 4.3 reports the summary statistics of the control variables for the individual-level analysis. The treatment individuals appear to be younger, have lower years of education, and have a larger family. For both groups, about half of the sample is female, and around 40 percent of them live in traditional gers. There is no difference in the consumption expenditure between the two groups. The share of treatment individuals who use private boiler heaters increases over time while there is no clear pattern in electric heaters. Finally, the percentage of treatment individuals using traditional stoves reduces over time. This indicates that the treatment households switch from coal-based heating to cleaner solutions such as private boilers. Panel B in the table reports the summary statistics of the control variables for our household-level analysis. It shows that the age, gender, and marital status of household heads are similar for both groups, and they remain similar throughout the periods. Treatment household heads have slightly lower education and income and have larger families than the control group.

### 4.3.2 Empirical model

Our data will allow us to employ a flexible difference-in-differences (DiD) model to evaluate the impact of the subsidy program on household electricity expenditures. The specific model is outlined below:

$$y_i = \alpha + \beta d_z + \sum_{t=2012}^{2018} (\gamma_t d_t + \delta_t d_z \times d_t) + \mathbf{X_{it}}\boldsymbol{\theta} + \phi_z + \varepsilon_i \tag{4.1}$$

**Table 4.3: Summary statistics of control variables for winter month sample**

| | 2010 | | 2012 | | 2014 | | 2016 | | 2018 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Treatment | Control | Treatment | Control | Treatment | Control | Treatment | Control | Treatment | Control |
| *Panel A: Individual level controls* | | | | | | | | | | |
| Individual's age (years) | 28.2 | 31.6 | 28.4 | 30.5 | 29.0 | 30.3 | 28.7 | 29.1 | 28.0 | 30.6 |
| | (18.5) | (19.9) | (18.8) | (19.8) | (19.3) | (19.5) | (19.6) | (20.0) | (20.1) | (21.6) |
| Individual is female | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) |
| Individual's education (years) | 9.0 | 10.2 | 8.9 | 10.7 | 8.8 | 10.3 | 8.7 | 9.9 | 8.6 | 10.2 |
| | (5.4) | (5.9) | (5.9) | (7.0) | (5.6) | (6.4) | (5.8) | (6.5) | (5.9) | (6.7) |
| Household size | 5.0 | 4.3 | 4.9 | 4.2 | 4.4 | 3.9 | 4.6 | 4.1 | 4.9 | 4.3 |
| | (2.4) | (1.6) | (2.2) | (1.6) | (1.6) | (1.3) | (1.7) | (1.4) | (2.0) | (1.6) |
| Ln(consumption) | 13.1 | 13.2 | 13.4 | 13.5 | 13.4 | 13.5 | 13.2 | 13.3 | 13.3 | 13.4 |
| | (0.2) | (0.2) | (0.2) | (0.2) | (0.2) | (0.2) | (0.2) | (0.2) | (0.2) | (0.2) |
| Lives in ger | 0.4 | 0.0 | 0.4 | 0.0 | 0.4 | 0.0 | 0.4 | 0.0 | 0.4 | 0.0 |
| | (0.5) | (0.0) | (0.5) | (0.0) | (0.5) | (0.0) | (0.5) | (0.0) | (0.5) | (0.0) |
| Private boiler | 0.02 | 0.00 | 0.09 | 0.00 | 0.11 | 0.00 | 0.11 | 0.00 | 0.13 | 0.00 |
| | (0.1) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) |
| Electric heater | 0.00 | 0.00 | 0.01 | 0.00 | 0.03 | 0.00 | 0.01 | 0.00 | 0.03 | 0.00 |
| | (0.0) | (0.0) | (0.1) | (0.0) | (0.2) | (0.0) | (0.1) | (0.0) | (0.2) | (0.0) |
| Traditional stove | 0.96 | 0.00 | 0.89 | 0.00 | 0.88 | 0.00 | 0.89 | 0.00 | 0.87 | 0.00 |
| | (0.2) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) |
| Number of individuals | 2,203 | 1,306 | 3,266 | 1,508 | 2,996 | 1,305 | 3,117 | 1,474 | 3,069 | 1,741 |
| *Panel B: Household level controls* | | | | | | | | | | |
| Household head's age (years) | 45.8 | 47.7 | 44.9 | 45.9 | 46.2 | 44.7 | 46.5 | 43.9 | 47.6 | 47.5 |
| | (13.9) | (14.9) | (14.2) | (15.4) | (14.0) | (14.6) | (13.4) | (14.6) | (13.7) | (15.5) |
| Household head is female | 0.3 | 0.3 | 0.2 | 0.3 | 0.3 | 0.2 | 0.3 | 0.3 | 0.3 | 0.3 |
| | (0.4) | (0.5) | (0.4) | (0.4) | (0.4) | (0.4) | (0.4) | (0.5) | (0.5) | (0.4) |
| Household head's education (years) | 12.0 | 13.8 | 12.1 | 15.3 | 12.7 | 15.9 | 12.5 | 14.4 | 12.5 | 14.7 |
| | (2.5) | (2.4) | (3.4) | (3.3) | (2.9) | (3.0) | (2.5) | (2.1) | (2.5) | (2.3) |
| Household head is married | 0.7 | 0.6 | 0.6 | 0.6 | 0.6 | 0.6 | 0.6 | 0.6 | 0.6 | 0.6 |
| | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) | (0.5) |
| Share of working members | 0.3 | 0.3 | 0.3 | 0.4 | 0.3 | 0.4 | 0.3 | 0.4 | 0.3 | 0.4 |
| | (0.2) | (0.3) | (0.2) | (0.3) | (0.3) | (0.3) | (0.3) | (0.3) | (0.2) | (0.3) |
| Household size | 4.2 | 3.7 | 4.1 | 3.6 | 3.8 | 3.4 | 3.9 | 3.5 | 4.0 | 3.5 |
| | (1.9) | (1.6) | (1.8) | (1.5) | (1.6) | (1.4) | (1.6) | (1.5) | (1.8) | (1.6) |
| Ln(income) | 12.3 | 12.4 | 13.0 | 13.5 | 13.2 | 13.7 | 13.3 | 13.6 | 13.2 | 13.7 |
| | (1.2) | (1.5) | (0.7) | (0.8) | (0.6) | (0.6) | (0.5) | (0.6) | (0.6) | (0.6) |
| Lives in ger | 0.4 | 0.0 | 0.4 | 0.0 | 0.4 | 0.0 | 0.4 | 0.0 | 0.4 | 0.0 |
| | (0.5) | (0.0) | (0.5) | (0.0) | (0.5) | (0.0) | (0.5) | (0.0) | (0.5) | (0.0) |
| Private boiler | 0.01 | 0.00 | 0.07 | 0.00 | 0.10 | 0.00 | 0.11 | 0.00 | 0.12 | 0.00 |
| | (0.1) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) |
| Electric heater | 0.00 | 0.00 | 0.01 | 0.00 | 0.03 | 0.00 | 0.02 | 0.00 | 0.03 | 0.00 |
| | (0.0) | (0.0) | (0.1) | (0.0) | (0.2) | (0.0) | (0.1) | (0.0) | (0.2) | (0.0) |
| Traditional stove | 0.97 | 0.00 | 0.90 | 0.00 | 0.89 | 0.00 | 0.89 | 0.00 | 0.88 | 0.00 |
| | (0.2) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) | (0.3) | (0.0) |
| Number of households | 528 | 353 | 797 | 424 | 798 | 387 | 802 | 424 | 758 | 495 |

*Notes:* Treatment households are those living in gers and basic houses in zones 1, 2 and 3. The control households are those living in apartments in zone 4. Means are reported in thousand Tugrik (MNT). The exchange rate for the end of survey period (December) was US$1 ≈ MNT1,257.0 in 2010. All values are on monthly basis and adjusted for 2010 price level. Standard deviations are reported in the parentheses.

where, for each individual (or household in other models) $i$, y represents the likelihood of reporting illness (or the natural logarithm of household monthly electricity expenditure in other models), $d_z$ is a dummy variable taking the value of one for the treatment group who live in the air pollution reduction zones 1, 2 and 3 (the light and dark grey, and hashed patterns areas in Figure 4.1) where the electricity subsidy is provided during winter, and zero for the control households who live in zone 4 (white areas in Figure 4.1), $d_t$ is a dummy taking the value of one for the year $t$ and zero for other years (2010 is the reference period), $\mathbf{X}$ is a set of control variables and $\varepsilon$ accounts for unobservable effects. Please note that we do not have the zoning information for 2012, and so we use the property types and heating source as the main criteria to identify the treatment households.

For individual-level analysis, $\mathbf{X}$ includes individual-specific controls listed in panel A of Table 4.3 while for the analysis of electricity expenditure, $\mathbf{X}$ includes household-specific variables listed in panel B of the same table. We also control for districts, survey years, and months fixed effects to account for district-level and time-specific variations in electricity expenditures. We cluster the standard errors at the household level for the individual-level analysis, and at the district level for the household-level analysis.

The coefficients $\delta_t$ in Model (4.1) are the difference-in-differences (DiD) estimates, indicating the impact of the subsidy on the likelihood of reporting illness (or household electricity expenditures). For several reasons, the DiD estimates provide the lower bound of the effect of the subsidy on household electricity expenditure. The first reason is spillover, in which the subsidy also results in reduced pollution for the control individuals. With the increased use of electricity to heat homes, the indoor pollution resulting from burning coal and wood would reduce substantially for the treatment households. This will also result in lower outdoor pollution for the control households, likely reducing their illness level. Second, the use of only a few years of data will ignore the long-run health impact of pollution and thus report lower level of illness.

On the other hand, the electricity expenditures for 2010 include both daytime and nighttime electricity consumption expenditures for the treatment households. However, for the subsidy period 2012-2018, the treatment group's electricity expenditures are more likely to be for daytime usage as the nighttime electricity was effectively free. Thus, the DiD estimates provide the lower bound of the effect of the subsidy on household electricity consumption.

The DiD model compares the difference in the probability of reporting illness (or electricity expenditures) between treatment households (i.e., those receiving the subsidy living in gers and basic houses in the polluting zones) and the control households (i.e., those not eligible for the subsidy living in apartments in zone 4) before and after the policy change. Since households living in apartments in zone 4 are not eligible for the electricity price discount, we have an ideal and clean control group to estimate the program's causal effect.

The identifying assumption for the DiD model is that the difference in the probability of reporting illness and electricity expenditures between the treatment and control households would have remained the same in the absence of the policy. We cannot test the identifying assumption directly. However, we validate the 'common trends' assumption by evaluating the historical trends in electricity expenditures and undertake several placebo tests to examine the impact of the subsidy program (Subsection 4.4.2).

## 4.4 Results

### 4.4.1 Main results

To investigate whether an electricity subsidy program reduces illness and affect household electricity expenditures, we estimate Equation (4.1) with different sets of independent variables and present those results. In modelling individual illness (or respiratory illness), the first sets of results are derived from a model (basic model) that regresses the dependent variable on treatment and the interaction of treatment and (survey) year dummies, together with district, month, and survey year fixed effects. On the other hand, the final sets of results rely on a model (preferred model) that adds individual-specific controls to the specification, including the heating sources in residence.

In modelling household expenditure on electricity, the first sets of results are derived from a model (basic model) that regresses electricity expenditure on treatment and the interaction of treatment and (survey) year dummies, together with district, month, and survey year fixed effects. The next sets of results rely on a model that adds household-specific controls to the specification. The final sets of results rely on a model (preferred model) that further adds heating sources in residence. This way of analysis is to ensure that the estimated effects of the subsidy are not driven by any strong association of the treatment variable with any control variable.

The results for the probability of feeling ill in winter seasons are given in Table 4.4.

**Table 4.4: DiD results of the probability of illness in winter months**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.030*** | 0.017 | 0.050* | -0.017 | 0.030*** | 0.033 | 0.018 | 0.066 |
| | (0.012) | (0.022) | (0.026) | (0.032) | (0.011) | (0.022) | (0.052) | (0.109) |
| 2012 | 0.043*** | 0.082*** | 0.064** | -0.000 | 0.041*** | 0.094*** | 0.008 | 0.121** |
| | (0.012) | (0.017) | (0.028) | (0.045) | (0.012) | (0.015) | (0.048) | (0.057) |
| 2014 | 0.044*** | 0.078*** | 0.102*** | 0.031 | 0.035*** | 0.085*** | -0.042 | 0.059 |
| | (0.013) | (0.017) | (0.030) | (0.045) | (0.013) | (0.015) | (0.051) | (0.057) |
| 2016 | 0.011 | 0.022* | 0.054** | 0.027 | -0.003 | 0.011 | 0.013 | 0.039 |
| | (0.011) | (0.012) | (0.026) | (0.027) | (0.010) | (0.010) | (0.055) | (0.055) |
| 2018 | 0.071*** | 0.090*** | 0.105*** | 0.066** | 0.053*** | 0.079*** | 0.069 | 0.130** |
| | (0.013) | (0.014) | (0.027) | (0.032) | (0.013) | (0.013) | (0.051) | (0.053) |
| Treatment × 2012 | -0.060*** | -0.067*** | -0.098*** | -0.109*** | -0.053*** | -0.054*** | 0.002 | -0.014 |
| | (0.015) | (0.015) | (0.034) | (0.034) | (0.015) | (0.015) | (0.066) | (0.066) |
| Treatment × 2014 | -0.058*** | -0.066*** | -0.117*** | -0.117*** | -0.050*** | -0.053*** | 0.026 | 0.017 |
| | (0.016) | (0.016) | (0.037) | (0.037) | (0.016) | (0.016) | (0.067) | (0.068) |
| Treatment × 2016 | 0.008 | -0.000 | -0.003 | -0.009 | 0.005 | 0.002 | 0.002 | 0.012 |
| | (0.015) | (0.015) | (0.034) | (0.034) | (0.014) | (0.014) | (0.072) | (0.071) |
| Treatment × 2018 | -0.048*** | -0.055*** | -0.109*** | -0.110*** | -0.026 | -0.028* | -0.013 | -0.020 |
| | (0.016) | (0.016) | (0.034) | (0.034) | (0.017) | (0.017) | (0.069) | (0.069) |
| Individual's age (years) | | 0.001*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.017*** | | -0.001 | | 0.022*** | | 0.027 |
| | | (0.004) | | (0.008) | | (0.004) | | (0.018) |
| Individual's education (years) | | -0.005*** | | -0.015*** | | 0.003*** | | 0.001 |
| | | (0.001) | | (0.002) | | (0.001) | | (0.004) |
| Household size | | 0.006* | | -0.024** | | 0.011*** | | 0.031*** |
| | | (0.004) | | (0.011) | | (0.003) | | (0.011) |
| Ln(consumption) | | -0.135*** | | 0.249* | | -0.211*** | | -0.386*** |
| | | (0.049) | | (0.137) | | (0.037) | | (0.125) |
| Lives in ger | | 0.004 | | 0.028** | | 0.000 | | -0.035 |
| | | (0.006) | | (0.012) | | (0.006) | | (0.028) |
| Private boiler | | 0.030 | | 0.093*** | | 0.015 | | -0.079 |
| | | (0.023) | | (0.032) | | (0.023) | | (0.115) |
| Electric heater | | -0.017 | | -0.097*** | | 0.003 | | 0.178 |
| | | (0.023) | | (0.031) | | (0.030) | | (0.120) |
| Traditional stove | | 0.013 | | 0.064*** | | -0.001 | | -0.040 |
| | | (0.020) | | (0.024) | | (0.020) | | (0.104) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.03 | 0.02 | 0.03 | 0.01 | 0.02 | 0.04 | 0.05 |
| N | 21,985 | 21,985 | 6,160 | 6,160 | 14,233 | 14,233 | 1,592 | 1,592 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

Column 1 shows the basic model estimates for all ages and indicates that treatment individuals have a three percentage points higher probability of reporting illness in the reference year, 2010. The survey-year fixed effects indicate that the likelihood of feeling unwell increases over time for the control individuals. The likelihood of reporting illness of the treatment individuals, compared to the control individuals, declines by 6.0 and 5.8 percentage points in 2012 and 2014, respectively.

The probability of illness changes similarly between the treatment and control individuals in 2016. The insignificant impact of the subsidy in 2016 can be attributable to the outbreak of highly infectious diseases in Ulaanbaatar around that time.[13] The treatment households are likely to have higher risks of contracting infectious diseases because of their housing characteristics and poor hygiene practices which is likely to offset the potential health benefit from the subsidy.

The relative probability of being ill again declines for the treatment individuals in 2018, this time by about 4.8 percentage points. These outcomes are expected as the provision of subsidy allows the treatment households to use electricity for heating and thus benefit directly from the reduced indoor air pollution, although the resulting lower outdoor air pollution will positively affect the health of both the treatment and control individuals.

Results from estimating the preferred model, presented in column 2 of Table 4.4, shows a similar finding to that of the basic model, but the magnitudes of the DiD coefficients are now slightly higher. We observe that females and older people are more likely to report illness while education and household consumption reduce the likelihood of illness as found previously (Gove, 1984; Winkleby et al., 1992; Ross and Wu, 1996). Housing conditions and heating devices at the residence have no significant effect on illness in our data. Our overall finding is consistent with the previous studies that find a negative effect of pollution on the exposed population (e.g., Janke et al., 2009).

Since distinct age groups may respond differently when they are exposed to pollution, we investigate the impact of the subsidy on the illness level for different age groups. Specifically, we investigate the case for children (under 14 years), working-age adults (15-60 years) and older adults (over 60 years). The DiD estimates for the children, presented in columns 3–4 of Table 4.4 suggest that the younger benefits significantly from the subsidy. The likelihood of reporting illness for the treatment children, compared to the control children, decline by 10.9 pp in 2012 and 11.7 pp in 2014. Again, it does not decline (relative to the control households) significantly in 2016 but by 11 pp in 2018. The results highlight that air pollution severely affects children, the most vulner-

[13]The outbreak of young children's hand, foot, and mouth diseases was higher than the national average. It had been in its highest record in 2016 since 2010. At the same time, Ulaanbaatar recorded the highest level of measles outbreak in 2016, which was first diagnosed in 2015 after acquiring a measles elimination certificate from the WHO in 2014. (NCHD, 2016, 2018; Orsoo et al., 2019). Hence, the the spread of the infectious disease could have offset the positive health benefits of the electricity subsidy for the treatment households.

able group and that the electricity subsidy positively impacts their health. This finding is in line with other studies which find that air pollution increases infant morbidity and mortality, school absences, and hospital admissions (Neidell, 2004; Currie et al., 2009a; Cesur et al., 2017; Palma et al., 2022).

The results for the working-age population are similar to the analysis for all age groups. Their likelihoods of reporting illness are significantly lower for all years except for 2016. However, the impacts are lower in magnitude for all the years, and it is less significant for 2018. Interestingly, the treatment individuals above the age of 60 do not report significantly higher illness levels than those reported by the control individuals. The pattern is in contrast to Anderson (2020), who find pollution to increase mortality among adults over 75 years of age. The findings for older people in our case may reflect that they have already taken adequate measures for their protection, so the change in air pollution might not immediately impact them.

Air pollution has a direct impact on the respiratory system. Therefore, we investigate next whether the subsidy reduces respiratory illnesses among the population in the winter season. We report the results for all ages, children, the economically active group, and older people in Table 4.5. The effects are similar to our previous findings with overall illness, but the magnitudes are lower, as expected. For example, compared to their control counterpart, the likelihood of reporting respiratory illness for the treatment individuals has reduced by 3.1, 4.6, and 4.0 percentage points in 2012, 2014, and 2018, respectively (column 2). Again, no significant difference in the changes (in reporting respiratory illness) is observed for all groups for 2016. The results remain similar for children, the working-age population and older adults (columns 4, 6 and 8). This finding is in line with studies that find that air pollution increases respiratory symptoms such as asthma (Chay and Greenstone, 2003; Neidell, 2004).

Overall, the results in Tables 4.4–4.5 indicate that the electricity subsidy program significantly reduces the likelihood of reporting illness for all ages, especially the younger children. These short-term gains in health are likely to have significant long-term benefits for the population as healthier residents are generally more productive and will enjoy a higher living standard in the longer run.

**Table 4.5: DiD results of the probability of having respiratory illness in winter months**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.020** | -0.010 | 0.042* | -0.019 | 0.014** | -0.003 | -0.019 | -0.035 |
| | (0.008) | (0.009) | (0.024) | (0.032) | (0.007) | (0.006) | (0.029) | (0.027) |
| 2012 | 0.023*** | 0.055*** | 0.046* | 0.075* | 0.017*** | 0.009 | -0.009 | 0.022 |
| | (0.008) | (0.012) | (0.025) | (0.043) | (0.006) | (0.009) | (0.028) | (0.030) |
| 2014 | 0.040*** | 0.069*** | 0.102*** | 0.126*** | 0.021*** | 0.013 | -0.007 | 0.024 |
| | (0.010) | (0.012) | (0.029) | (0.045) | (0.008) | (0.009) | (0.029) | (0.031) |
| 2016 | 0.016** | 0.021*** | 0.048** | 0.047* | 0.002 | -0.001 | -0.011 | -0.004 |
| | (0.008) | (0.008) | (0.024) | (0.026) | (0.005) | (0.005) | (0.029) | (0.029) |
| 2018 | 0.043*** | 0.058*** | 0.091*** | 0.094*** | 0.024*** | 0.019** | -0.015 | 0.001 |
| | (0.009) | (0.010) | (0.025) | (0.030) | (0.008) | (0.008) | (0.026) | (0.026) |
| Treatment × 2012 | -0.029*** | -0.031*** | -0.072** | -0.074** | -0.018** | -0.018** | 0.022 | 0.025 |
| | (0.011) | (0.011) | (0.032) | (0.031) | (0.009) | (0.009) | (0.035) | (0.034) |
| Treatment × 2014 | -0.045*** | -0.046*** | -0.106*** | -0.101*** | -0.027*** | -0.028*** | -0.011 | -0.010 |
| | (0.012) | (0.012) | (0.035) | (0.035) | (0.010) | (0.010) | (0.035) | (0.035) |
| Treatment × 2016 | 0.009 | 0.010 | 0.012 | 0.012 | 0.005 | 0.004 | 0.036 | 0.040 |
| | (0.011) | (0.011) | (0.032) | (0.032) | (0.008) | (0.008) | (0.037) | (0.038) |
| Treatment × 2018 | -0.038*** | -0.040*** | -0.093*** | -0.081*** | -0.024** | -0.025** | 0.017 | 0.019 |
| | (0.012) | (0.012) | (0.032) | (0.031) | (0.010) | (0.010) | (0.033) | (0.033) |
| Individual's age (years) | | -0.001*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.004 | | -0.003 | | 0.007*** | | 0.009 |
| | | (0.003) | | (0.008) | | (0.002) | | (0.009) |
| Individual's education (years) | | -0.002*** | | 0.006** | | -0.000 | | 0.003* |
| | | (0.001) | | (0.003) | | (0.000) | | (0.002) |
| Household size | | 0.007*** | | 0.005 | | -0.003 | | 0.008 |
| | | (0.002) | | (0.011) | | (0.002) | | (0.005) |
| Ln(consumption) | | -0.123*** | | -0.130 | | 0.030 | | -0.125** |
| | | (0.033) | | (0.140) | | (0.022) | | (0.061) |
| Lives in ger | | 0.003 | | 0.019 | | 0.001 | | -0.010 |
| | | (0.005) | | (0.012) | | (0.004) | | (0.013) |
| Private boiler | | 0.031*** | | 0.063** | | 0.026*** | | -0.015 |
| | | (0.011) | | (0.031) | | (0.008) | | (0.013) |
| Electric heater | | -0.021 | | -0.079*** | | -0.001 | | 0.065 |
| | | (0.017) | | (0.028) | | (0.021) | | (0.060) |
| Traditional stove | | 0.023*** | | 0.057** | | 0.018*** | | 0.024** |
| | | (0.006) | | (0.025) | | (0.003) | | (0.012) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.04 | 0.02 | 0.05 | 0.01 | 0.01 | 0.01 | 0.01 |
| N | 21,985 | 21,985 | 6,160 | 6,160 | 14,233 | 14,233 | 1,592 | 1,592 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

Next, we investigate the effect of the subsidy on electricity expenditures, another outcome variable in our study. Again, we conduct separate analyses for expenditures made on winter and non-winter months, and the results are reported in Table 4.6. The basic model results in column 1

**Table 4.6: DiD results of the impact of subsidy on household monthly electricity expenditures**

| | Winter months | | | Non-winter months | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | -0.296** | -0.208** | -0.339** | -0.177*** | -0.116*** | 0.004 |
| | (0.075) | (0.067) | (0.099) | (0.024) | (0.021) | (0.039) |
| 2012 | -0.045 | -0.125** | -0.113** | -0.034 | -0.117** | -0.106** |
| | (0.038) | (0.032) | (0.032) | (0.033) | (0.035) | (0.035) |
| 2014 | -0.133*** | -0.225*** | -0.209*** | -0.161*** | -0.246*** | -0.232*** |
| | (0.032) | (0.029) | (0.028) | (0.006) | (0.021) | (0.018) |
| 2016 | 0.043 | -0.024 | -0.013 | -0.006 | -0.072 | -0.064 |
| | (0.040) | (0.019) | (0.020) | (0.052) | (0.039) | (0.040) |
| 2018 | -0.040 | -0.127*** | -0.115*** | -0.073 | -0.148*** | -0.139*** |
| | (0.030) | (0.014) | (0.012) | (0.037) | (0.017) | (0.017) |
| Treatment × 2012 | 0.156*** | 0.208*** | 0.185*** | 0.116 | 0.180** | 0.156* |
| | (0.034) | (0.047) | (0.041) | (0.060) | (0.058) | (0.066) |
| Treatment × 2014 | 0.190** | 0.253*** | 0.193** | 0.137** | 0.197*** | 0.161*** |
| | (0.062) | (0.059) | (0.057) | (0.036) | (0.035) | (0.035) |
| Treatment × 2016 | 0.186* | 0.211** | 0.173* | 0.132*** | 0.187*** | 0.165*** |
| | (0.078) | (0.069) | (0.070) | (0.033) | (0.029) | (0.026) |
| Treatment × 2018 | 0.261*** | 0.298*** | 0.237*** | 0.255*** | 0.294*** | 0.232*** |
| | (0.058) | (0.057) | (0.048) | (0.031) | (0.030) | (0.032) |
| Household head's age (years) | | 0.003** | 0.003** | | 0.002*** | 0.002*** |
| | | (0.001) | (0.001) | | (0.000) | (0.000) |
| Household head is female | | -0.001 | -0.002 | | -0.006 | -0.008 |
| | | (0.017) | (0.019) | | (0.014) | (0.015) |
| Household head's education (years) | | 0.012*** | 0.009*** | | 0.012*** | 0.011*** |
| | | (0.001) | (0.002) | | (0.001) | (0.001) |
| Household head is married | | 0.083*** | 0.082** | | 0.078*** | 0.063*** |
| | | (0.019) | (0.024) | | (0.011) | (0.013) |
| Share of working members | | 0.043** | 0.037** | | 0.021 | 0.020 |
| | | (0.012) | (0.011) | | (0.033) | (0.033) |
| Household size | | 0.057*** | 0.060*** | | 0.056*** | 0.059*** |
| | | (0.005) | (0.005) | | (0.006) | (0.005) |
| Ln(income) | | 0.071*** | 0.063*** | | 0.069*** | 0.062*** |
| | | (0.013) | (0.012) | | (0.012) | (0.011) |
| Lives in ger | | -0.228*** | -0.181*** | | -0.197*** | -0.146*** |
| | | (0.015) | (0.009) | | (0.015) | (0.010) |
| Private boiler | | | 0.200** | | | -0.016 |
| | | | (0.070) | | | (0.026) |
| Electric heater | | | 1.504*** | | | 1.005*** |
| | | | (0.104) | | | (0.101) |
| Traditional stove | | | 0.109 | | | -0.160** |
| | | | (0.066) | | | (0.041) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.04 | 0.17 | 0.26 | 0.03 | 0.17 | 0.27 |
| Number of households | 5,766 | 5,766 | 5,766 | 7,975 | 7,975 | 7,975 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 and 4 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 5 add household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 and 6 further add heating sources in the residence to the specification.

indicate that the electricity expenditure of the treatment households in the winter season are around 34 percent lower in 2010 than those in the control group. The survey year fixed effects indicate that the control households reduced their electricity expenditures in all years, except for 2016. This can be due to the use of energy-saving electric appliances as a result of governmental and non-governmental initiatives for reducing electricity consumption and previous research find that normative social influence can produce change in behaviour (Nolan et al., 2008; Allcott and Rogers, 2014).

The DiD estimates for each survey year are positive and significant, indicating that the treatment households significantly increase their expenditure on electricity relative to their control counterpart. Following the intervention, the difference in electricity expenditures between the two groups declined. Specifically, compared to the control group, the treatment households increased their electricity expenditures by 17, 21, 20 and 30 percent more in 2012, 2014, 2016 and 2018. These estimated effects are particularly large, especially when we consider that they are the lower bound of the estimates, as discussed earlier.

We add household-specific control variables into the model and report the results in column 2 of Table 4.6. The results are roughly similar except that the estimates of the DiD coefficients are slightly higher than those in the base model. The coefficients of the household-specific control variables, reported in column 2, are intuitive. For example, the household head's age, education, marital status, family size, and household income significantly increase electricity expenditures. Such impacts are expected as they all are likely to affect electricity demand positively.

On the other hand, households with female heads have lower electricity expenditures than those with male heads. Households living in traditional gers have significantly lower electricity expenditures than those living in other residential property types. Households in gers have limited space to heat or use large electrical appliances such as washing machines, refrigerators, and electric cooking stoves compared to houses. This pattern of expenditure has been observed in the previous empirical analysis of electricity demand (Hasan and Mozumder, 2017; Thomas et al., 2020).

Our preferred specification adds heating appliances to the model. The results in column 3 of Table 4.6 provide DiD estimates that are slightly lower than those in columns 1–2. Specifically, the treatment households increase their electricity expenditures by 20, 21, 19 and 27 percent respectively in 2012, 2014, 2016 and 2018, compared to their control counterparts. The additional control variables show that households with different heating appliances have varying electricity usage. For example, compared to the control group (living in apartments with central heating systems), households living in basic houses with private boilers and electric heaters have significantly higher electricity expenditures. On the other hand, households that use traditional stoves also have higher but statistically insignificant electricity expenditures. The preferred model in column 3 has an adjusted $R^2$ of 0.26, implying that our model explains the variations in electricity expenditures reasonably well.

The significance of the DiD estimates after controlling for the heating appliances used in residence is particularly informative about increased electricity expenditure. These results indicate that increased electricity expenditure is likely to be associated with the change in preference for energy rather than the availability of heating appliances. The convenience and health benefit makes it difficult to ignore electricity. Given the incentive (subsidy) to transition from the traditional energy sources during high demand periods, people make a permanent switch to electric appliances more generally, thus increasing their electricity expenditure significantly in the months without the subsidy. The policy therefore results in ancillary benefits of transition to cleaner energy.

The results from the analysis with electricity expenditures in non-winter months, during which treatment households do not receive any subsidy, is shown in columns 4–6 of Table 4.6. The coefficients of the DiD estimates are positive and significant, although slightly lower than those for the winter. Without any subsidy during the non-winter seasons, a positive DiD estimate indicates a positive effect on their electricity consumption. The finding may appear counter-intuitive in the first instance as, without any subsidy, treatment households are unlikely to change their electricity consumption differently than the control group. However, the change in their electricity consumption behaviour can be due to the change in treatment households' demand and preference for electricity. Since the treatment households do not pay for their nighttime electricity use in the winter season, they are likely to change their habit and continue to use electrical appliances for cooking and other purposes. This may allow them to switch from coal to electricity even in the non-winter months. Also, being used to electricity may make the treatment households understand its value, making them unlikely to switch to non-electric fuels such as wood and coal in the non-winter months.

The findings in Table 4.6 show that treatment households increase their daytime electricity use significantly since they face free or lower-priced nighttime consumption. Such outcomes are comparable to the findings of other studies (Burke and Kurniawati, 2018; Boccard and Gautier, 2021; Xie et al., 2022). For example, Xie et al. (2022) find rural households in China experiencing sharp increases in heating expenditure after being enrolled in the clean heating program, even with the subsidized electricity prices. Households in Belgium increase their electricity consumption significantly when they face a lower price (Boccard and Gautier, 2021). A reduction in energy subsidy lowers the electricity demand in Indonesia (Burke and Kurniawati, 2018). However, our findings are in contrast to some previous studies like Bagnoli and Bertoméu-Sánchez (2022) who find subsidies to decrease expenditure on electricity. Showing that subsidy on electricity price in the winter season increases expenditure in winter and non-winter seasons, our findings provide additional insights into how consumers react when facing a subsidized energy price.

### 4.4.2 Placebo test and common trend

The validity of our estimates in Table 4.4 (Table 4.5) rely on the assumption that the difference in illness (respiratory illness) of the treatment and control households would have remained the same in the absence of the subsidy. To do so, we now investigate the same with the individuals for which the data has been collected in the non-winter months. This will serve as a placebo test since we would not expect any impact in the absence of the subsidy. In line with our expectation, we generally do not observe any significantly negative DiD estimates for the entire population or younger children, working-age population, and older people (Table 4.7).

We then repeat the analysis with the respiratory system illness using the non-winter sample. We again observe no significant negative effect except for small effects in 2012 (Table 4.8). Thus these two two placebo test results validate the common trend assumption for our models of illness and respiratory system illness.

Similarly, for household electricity expenditure model, DiD estimates' validity relies on the assumption that the difference in the electricity expenditure between the treatment and control households would have remained the same in the absence of the subsidy. We validate this assumption in two ways. First, we examine the common trend graphically by plotting the (natural logarithm of) electricity expenditures (Figure 4.3).

The figure shows that the control households had higher electricity expenditures in 2008 and 2010 before the onset of the subsidy. The electricity expenditures grew at a similar rate from 2008 to 2010. However, in 2012 the treatment households increased their electricity expenditures while the control group slightly reduced their spending. Although both groups reduced their electricity expenditures in 2014 from the previous year, the difference in their electricity expenditures decreased. The electricity expenditures for both groups increased in 2016 and declined in 2018, but the difference was even smaller in 2018. The common trend graph confirms that the DiD estimates are valid for evaluating the effectiveness of the subsidy.

**Table 4.7: Placebo test results of the probability of reporting illness**

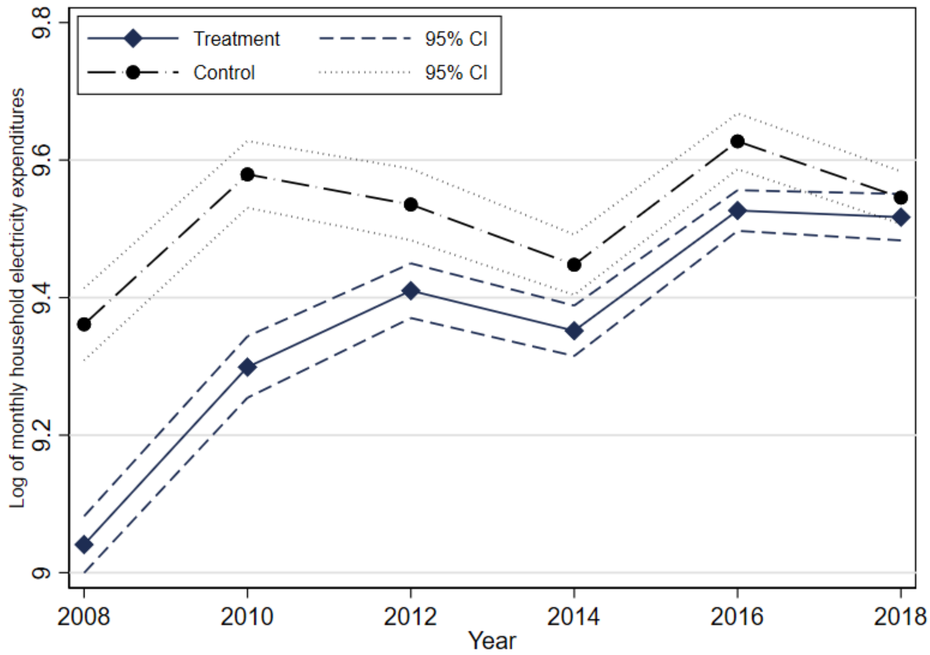
| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.004 | 0.007 | 0.011 | 0.018 | 0.006 | 0.009 | -0.007 | -0.009 |
| | (0.008) | (0.015) | (0.012) | (0.025) | (0.008) | (0.015) | (0.051) | (0.101) |
| 2012 | 0.016* | 0.065*** | 0.052*** | 0.020 | 0.006 | 0.084*** | -0.031 | 0.071 |
| | (0.009) | (0.013) | (0.017) | (0.028) | (0.009) | (0.012) | (0.043) | (0.050) |
| 2014 | -0.006 | 0.038*** | 0.028* | -0.004 | -0.008 | 0.066*** | -0.094** | 0.004 |
| | (0.008) | (0.012) | (0.016) | (0.026) | (0.008) | (0.011) | (0.042) | (0.049) |
| 2016 | 0.011 | 0.022** | 0.048*** | 0.037** | -0.009 | 0.008 | 0.023 | 0.053 |
| | (0.009) | (0.009) | (0.017) | (0.018) | (0.008) | (0.008) | (0.048) | (0.048) |
| 2018 | 0.018** | 0.039*** | 0.002 | -0.015 | 0.027** | 0.064*** | 0.005 | 0.056 |
| | (0.009) | (0.010) | (0.013) | (0.017) | (0.011) | (0.012) | (0.046) | (0.048) |
| Treatment × 2012 | -0.006 | -0.012 | -0.029 | -0.031 | -0.009 | -0.008 | 0.111* | 0.093 |
| | (0.011) | (0.011) | (0.020) | (0.020) | (0.011) | (0.011) | (0.062) | (0.062) |
| Treatment × 2014 | 0.021** | 0.016 | -0.021 | -0.023 | 0.019* | 0.019* | 0.146** | 0.134** |
| | (0.010) | (0.010) | (0.019) | (0.019) | (0.011) | (0.011) | (0.060) | (0.060) |
| Treatment × 2016 | 0.004 | -0.002 | -0.026 | -0.031 | 0.014 | 0.013 | 0.028 | 0.028 |
| | (0.011) | (0.011) | (0.020) | (0.020) | (0.011) | (0.011) | (0.065) | (0.065) |
| Treatment × 2018 | 0.030** | 0.030*** | 0.037** | 0.031* | 0.021 | 0.024* | 0.070 | 0.081 |
| | (0.012) | (0.012) | (0.017) | (0.017) | (0.014) | (0.014) | (0.063) | (0.064) |
| Individual's age (years) | | 0.002*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.012*** | | 0.002 | | 0.012*** | | 0.028* |
| | | (0.003) | | (0.005) | | (0.003) | | (0.017) |
| Individual's education (years) | | -0.002*** | | -0.007*** | | 0.004*** | | -0.001 |
| | | (0.001) | | (0.001) | | (0.001) | | (0.003) |
| Household size | | 0.008*** | | -0.013** | | 0.017*** | | 0.026** |
| | | (0.003) | | (0.007) | | (0.002) | | (0.010) |
| Ln(consumption) | | -0.182*** | | 0.117 | | -0.321*** | | -0.360*** |
| | | (0.039) | | (0.084) | | (0.030) | | (0.109) |
| Lives in ger | | 0.003 | | -0.001 | | 0.009** | | -0.003 |
| | | (0.004) | | (0.007) | | (0.005) | | (0.028) |
| Private boiler | | 0.009 | | 0.029 | | 0.005 | | -0.020 |
| | | (0.015) | | (0.026) | | (0.015) | | (0.100) |
| Electric heater | | -0.021 | | -0.005 | | -0.025 | | -0.097 |
| | | (0.017) | | (0.036) | | (0.015) | | (0.077) |
| Traditional stove | | -0.003 | | -0.002 | | -0.004 | | -0.000 |
| | | (0.014) | | (0.022) | | (0.014) | | (0.094) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.04 | 0.02 | 0.02 | 0.01 | 0.02 | 0.03 | 0.05 |
| N | 29,813 | 29,813 | 8,379 | 8,379 | 19,325 | 19,325 | 2,109 | 2,109 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.8: Placebo test results of the probability of having respiratory illness**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.004 | -0.005 | 0.008 | 0.008 | 0.001 | -0.005* | 0.002 | -0.018 |
| | (0.005) | (0.006) | (0.011) | (0.020) | (0.004) | (0.003) | (0.016) | (0.014) |
| 2012 | 0.017*** | 0.043*** | 0.038** | 0.005 | 0.008* | 0.018*** | 0.024 | 0.036* |
| | (0.006) | (0.008) | (0.015) | (0.026) | (0.004) | (0.006) | (0.014) | (0.019) |
| 2014 | 0.005 | 0.028*** | 0.019 | -0.015 | -0.003 | 0.007 | 0.016 | 0.027 |
| | (0.005) | (0.007) | (0.015) | (0.024) | (0.004) | (0.005) | (0.015) | (0.019) |
| 2016 | 0.013** | 0.017*** | 0.036** | 0.024 | -0.003 | -0.001 | 0.030 | 0.032 |
| | (0.006) | (0.006) | (0.015) | (0.016) | (0.004) | (0.004) | (0.019) | (0.020) |
| 2018 | 0.000 | 0.011** | -0.001 | -0.019 | -0.005 | 0.000 | 0.015 | 0.021 |
| | (0.005) | (0.005) | (0.012) | (0.015) | (0.003) | (0.004) | (0.014) | (0.016) |
| Treatment × 2012 | -0.015** | -0.017** | -0.025 | -0.027 | -0.012** | -0.012** | -0.007 | -0.010 |
| | (0.007) | (0.007) | (0.018) | (0.018) | (0.005) | (0.005) | (0.023) | (0.023) |
| Treatment × 2014 | -0.002 | -0.003 | -0.015 | -0.017 | 0.002 | 0.002 | -0.003 | -0.006 |
| | (0.006) | (0.006) | (0.018) | (0.018) | (0.005) | (0.005) | (0.022) | (0.022) |
| Treatment × 2016 | -0.006 | -0.007 | -0.022 | -0.026 | 0.003 | 0.002 | -0.008 | -0.009 |
| | (0.007) | (0.007) | (0.018) | (0.018) | (0.005) | (0.005) | (0.026) | (0.026) |
| Treatment × 2018 | 0.011* | 0.012* | 0.023 | 0.016 | 0.009* | 0.009* | -0.008 | -0.008 |
| | (0.006) | (0.006) | (0.015) | (0.015) | (0.005) | (0.005) | (0.020) | (0.020) |
| Individual's age (years) | | -0.000*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.001 | | 0.001 | | 0.002 | | 0.008 |
| | | (0.002) | | (0.005) | | (0.001) | | (0.007) |
| Individual's education (years) | | -0.001 | | -0.008*** | | 0.001*** | | 0.000 |
| | | (0.000) | | (0.001) | | (0.000) | | (0.001) |
| Household size | | 0.005*** | | -0.013** | | 0.001 | | 0.001 |
| | | (0.002) | | (0.006) | | (0.001) | | (0.004) |
| Ln(consumption) | | -0.101*** | | 0.120 | | -0.044*** | | -0.044 |
| | | (0.021) | | (0.076) | | (0.014) | | (0.044) |
| Lives in ger | | -0.002 | | -0.003 | | 0.002 | | -0.002 |
| | | (0.003) | | (0.006) | | (0.002) | | (0.010) |
| Private boiler | | 0.016** | | 0.031 | | 0.009*** | | 0.028 |
| | | (0.006) | | (0.021) | | (0.003) | | (0.017) |
| Electric heater | | 0.001 | | 0.003 | | 0.001 | | -0.034** |
| | | (0.013) | | (0.034) | | (0.008) | | (0.017) |
| Traditional stove | | 0.007 | | 0.005 | | 0.007*** | | 0.023* |
| | | (0.005) | | (0.017) | | (0.002) | | (0.012) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.02 | 0.02 | 0.03 | 0.00 | 0.00 | 0.01 | 0.01 |
| N | 29,813 | 29,813 | 8,379 | 8,379 | 19,325 | 19,325 | 2,109 | 2,109 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.




Source: HSES, 2008-2018

**Figure 4.3: Household monthly electricity expenditures in winter months, 2008-2018**

Second, we check the policy's effectiveness by performing a placebo test with a false treatment. In that test, we estimate Equation (4.1) using the same control group, but households living in *apartments* (rather than gers) located in zones 1, 2, and 3 (the polluting zones) are considered as treatment households. These treatment households do not rely on coal as they have a central heating system and should not be affected by the policy intervention.[14] Note that we exclude 2012 survey round data from this placebo test as they do not have subdistrict level location information for the households to precisely define the zones.

We present the placebo test results in Table 4.9, again separately for households surveyed in winter and non-winter seasons. The results in column 1 for the winter sample indicate that, compared to the control group, the alternative treatment households had around 12 percent higher electricity expenditures in 2010. The survey year-fixed effects indicate that the control group reduces their electricity expenditures over time, although the coefficients are not always statistically significant. The DiD estimates show the difference in changes in electricity expenditures between the two groups but are not statistically significant at any conventional level of significance. Adding household-specific control variables in column 2 does not affect the results. The DiD estimates in

[14]Note that, as a consequence of selecting households living in apartments, for both for the treatment and the control groups, control variables like property type and heating appliances are dropped from the model.

columns 3–4 for the non-winter months are also statistically insignificant. Overall, the results validate the DiD estimates in Table 4.6.

**Table 4.9: Placebo test results of the effect of electricity subsidy on household monthly electricity expenditures**

| | Winter months | | Non-winter months | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Treatment | 0.112 | 0.061 | -0.167 | -0.218* |
| | (0.083) | (0.045) | (0.089) | (0.085) |
| 2014 | -0.197*** | -0.203*** | -0.159*** | -0.181*** |
| | (0.032) | (0.022) | (0.017) | (0.018) |
| 2016 | -0.021 | -0.023 | -0.029 | -0.028 |
| | (0.047) | (0.030) | (0.062) | (0.058) |
| 2018 | -0.074 | -0.093** | -0.106* | -0.123*** |
| | (0.058) | (0.031) | (0.046) | (0.028) |
| Treatment × 2014 | -0.029 | -0.023 | 0.065 | 0.066 |
| | (0.142) | (0.111) | (0.077) | (0.069) |
| Treatment × 2016 | 0.074 | 0.088 | 0.030 | 0.006 |
| | (0.087) | (0.055) | (0.135) | (0.130) |
| Treatment × 2018 | -0.078 | -0.092 | 0.105 | 0.064 |
| | (0.079) | (0.050) | (0.073) | (0.065) |
| Household head's age (years) | | 0.005*** | | 0.004*** |
| | | (0.001) | | (0.000) |
| Household head is female | | -0.047 | | 0.007 |
| | | (0.029) | | (0.015) |
| Household head's education (years) | | 0.009** | | 0.010** |
| | | (0.003) | | (0.004) |
| Household head is married | | 0.026 | | 0.069** |
| | | (0.027) | | (0.027) |
| Share of working members | | 0.022 | | 0.034 |
| | | (0.034) | | (0.059) |
| Household size | | 0.089*** | | 0.081*** |
| | | (0.007) | | (0.006) |
| Ln(income) | | 0.043*** | | 0.032** |
| | | (0.005) | | (0.010) |
| Subdistrict fixed effects | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.06 | 0.23 | 0.06 | 0.20 |
| Number of households | 2,184 | 2,184 | 2,851 | 2,851 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is households with male & unmarried household head and the reference year is 2010. Columns 1 and 3 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 4 add household–specific controls to the specification. Residence type and heating source in the residence are not included in the model as all households live in apartments connected to central heating.

### 4.4.3 Robustness checks

We undertake several robustness checks to ensure that our choice of data, estimation technique and model and data do not drive the results. First, dropping observations for which we have corrected for missing illness values (assuming no illness) do not affect our conclusions (Tables 4.A.1–4.A.2). Second, as the preferred technique, we used the linear probability model (LPM) to estimate illness models. Now we estimate those models with probit and logit techniques to see whether the results are sensitive to different estimation techniques (Tables 4.A.3–4.A.6). In both cases, we arrive at a similar conclusion.

Next, we examine whether covariate selection significantly modifies our results. In our result tables for the illness models, we present two sets of results – one without covariates and the other with them. The similar results in both cases indicate that our results do not depend heavily on the included covariates. Furthermore, using education as categories (instead of continuous) (Tables 4.A.7–4.A.8) and/or age in quadratic form (Table 4.A.9) does not affect our results. Thus, all the robustness check results support our finding that individuals benefit from the support program as their likelihood of reporting illness and respiratory illness reduces with the introduction of the subsidy.[15]

We also investigate the sensitivity of the estimated impact of the subsidy with different models and data. First, when we use the level value of electricity expenditure, we arrive at a similar conclusion (Table 4.A.10). Second, our results do not change qualitatively when we use per capita electricity expenditures and per capita income in the model (Table 4.A.11). A similar result is also observed when using equivalized income with either the OECD scale (Table 4.A.12) or the square root of the family size scale (Table 4.A.13). Using education as a categorical (rather than a continuous) variable and/or age in quadratic form in the model provide similar results (Tables 4.A.14–4.A.15).

We also examine the consequence of using a pooled dataset or a subsample. In that, rather than conducting analysis separately for winter and non-winter samples, we analyze electricity expenditures with the entire sample of 13,741 households. Again, we observe results that are similar to our main findings (Table 4.A.16). Repeating the analysis with only 2010 and 2012 data, since it can be argued that the introduction of subsidy is really a shock in 2012 but not afterwards, provides a similar coefficient for the later period (Table 4.A.17). Again, all of our robustness checks validate our finding that the subsidy on nighttime electricity consumption increases the electricity expenditure of the affected households.

## 4.5 Discussion and policy implications

We find that a subsidy on nighttime electricity consumption reduces the recipient households' reported sicknesses. While we have not directly investigated whether the program achieves its intended consequence of reducing pollution, a reduced sickness for the treated households in-

[15] All the mentioned results are available from the corresponding author upon request.

dicates its likely success. The estimated health benefit occurs even when (by design) the benefit spills over to the control households in the form of reducing pollution.

Therefore, our findings are important for Mongolia and other countries that provide substantial energy subsidies. Country-level studies find energy subsidy to improve household health and welfare, including Argentina (Giuliano et al., 2020), China (Teng et al., 2019; Liu et al., 2020), Indonesia (Burke and Kurniawati, 2018), Pakistan (Khalid and Salman, 2020), Turkey (Cesur et al., 2017) and the United States (Hahn and Metcalfe, 2021). These short-term health gains will have substantial long-term socio-economic benefits as healthier children will have better education outcomes and be more productive members of society. On the other hand, improved health outcomes will reduce morbidity costs of air pollution, such as health care expenditures and utilization (Liu and Ao, 2021).

We also find an unintended positive consequence of the subsidy. The preference of the beneficiary households changes in a way that increases their daytime electricity expenditure in winter months, when they do not receive any subsidy on their electricity consumption. They even increase their electricity expenditure in the non-winter season, when there is no provision of subsidy on daytime or nightime expenditure on electricity.

Our finding aligns with previous studies that describe habit formation as a crucial channel to stimulate future use of products and services. For example, Meriggi et al. (2021) study how a short-term subsidy for a new product affects its future demand and find that short-term subsidies increase future willingness-to-pay. Dupas (2014) find short-run subsidies for new health products to impact its' long-run adoption by raising knowledge about the usefulness of the product. Along that line, Hussam et al. (2022) find that monitoring and incentives persistently raise handwashing in rural India, providing evidence for rational habit formation.[16]

In case of energy, Boccard and Gautier (2021) find that subsidies to encourage renewable energy use result in a higher than expected increase in electricity consumption, which is counter to the original policy's intended outcome. High-frequency information has been found to affect residential electricity usage beyond the short and medium run, providing evidence of habit formation (Jessoe and Rapson, 2014). Thus, our findings indicate an important channel that can induce increased electricity use (and decreased dirty energy use), further raising the health benefit.

[16] Persistence in behavior can result from changes in the production function, knowledge acquisition (explicit or tacit) of the costs and benefit of actions, influence of social interactions, or the changes in consumption stock (Hussam et al., 2021, 2022). We have not distinguished among those channels as existing literature typically defines long-run persistence of temporary interventions as habit formation.

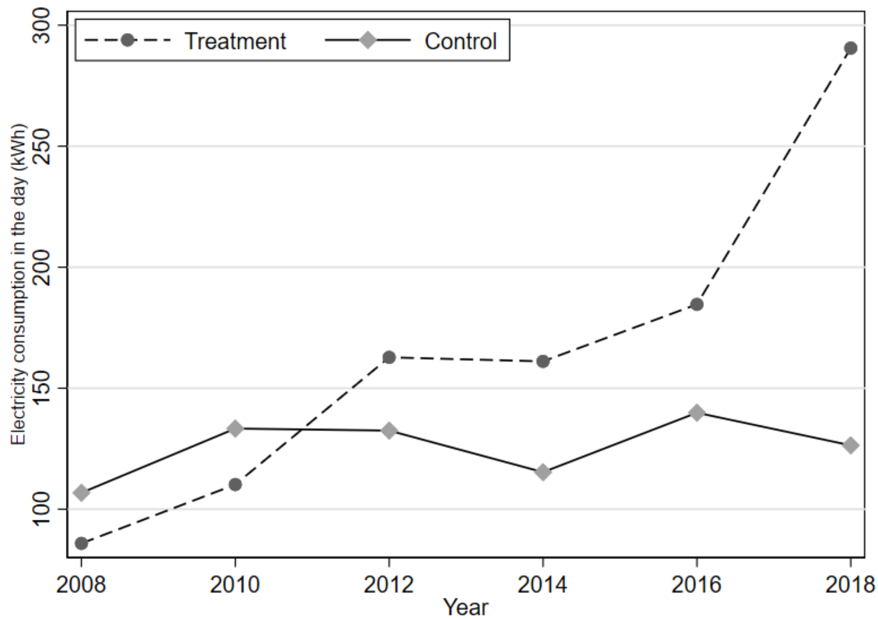
Due to the lack of electricity usage data in the household survey, our analysis focuses on electricity expenditures instead of actual consumption. To get a more precise idea about the program, we would ideally like to know the change in electricity usage, a more policy-relevant variable. Therefore, using the available data, we have made a back-of-the-envelope calculation of overtime electricity consumption for treatment and control households.[17]

Based on the calculations, Figure 4.4 shows the electricity usage before the onset of the intervention in 2010 and the subsequent years. The treatment households consume around 86 kWh and 110 kWh of electricity a day in 2008 and 2010, respectively, against the control group's usage of 107 kWh and 133 kWh at the same time. After the subsidy commencement in 2012, the treatment households increase their electricity consumption to 162 kWh, while the control households use 132 kWh. The treatment households' electricity usage are 162 kWh in 2014, 185 kWh in 2016, and 290 kWh in 2018. The control households have a relatively stable electricity usage in the same period, fluctuating between 107 kWh and 140 kWh. The pattern reassures us that the treatment households adjust their electricity consumption behaviour as a result of the subsidy program.

It is also important to note that coal-based power plants generate electricity in Ulaanbaatar. Therefore, the subsidized electricity used for heating in winter can still pollute the environment and negatively affect the local population's health. However, the advantage of subsidizing electricity is that the government can monitor and manage the pollution generated at the thermal power plant level more easily than at the household level. Power plants are also likely to be more efficient in using energy than individual heating units. Another benefit is that power plants generate out-

[17] We obtained some data about the received subsidy from the Ministry of Energy through personal communication. We have the number of households (treatment households) who received the subsidy, the total electricity consumed in kWh during the subsidy months, and the total monetary amount of subsidy provided for 2017 and 2018. Relying on these aggregate figures, we calculated the average electricity consumption per household per month by dividing total electricity consumption (in kWh) by the number of households. The average electricity consumption per household gives us an approximate electricity usage at nighttime during the subsidy months from November until April. However, the average electricity consumption was below the cap of 700kWh of free electricity at night, indicating that households did not pay for nighttime use in November and December 2018. Note that the aggregate data did not have information about the household appliance capacity, such as 220V versus 380V.

Since we know that nighttime electricity is free from the above calculation, we estimated the electricity usage in the daytime for the treatment households using the tariffs. The daytime tariff (6 am–9 pm) is US$0.043 per kWh, while the nighttime tariff (9 pm–6 am) is US$0.032 per kWh. The monthly base tariff is US$0.828 per month. First, we subtracted the base tariff from household monthly electricity expenditures to estimate the daytime consumption expenditures. Then we divided the daytime expenditures by daytime tariff to calculate daytime electricity consumption. We added daytime usage to the nighttime usage calculated from the aggregate figures above to get the total electricity consumption per household. Since there was an increase of 15-20 percent in the average nighttime electricity consumption per household from 2017 to 2018, we reduced the nighttime electricity consumption by 10 percent from the 2017 usage to calculate 2016 usage. The same procedure is applied to get the electricity consumption for all previous years. However, we used the discount for nighttime usage for a 50 percent discount subsidy in 2012-2016. Instead of the flat usage rate for the control households, we averaged nighttime and daytime rates to estimate the price per kWh. Then we subtracted the base rate from the electricity expenditures and divided the difference by average price to arrive at total electricity consumption.

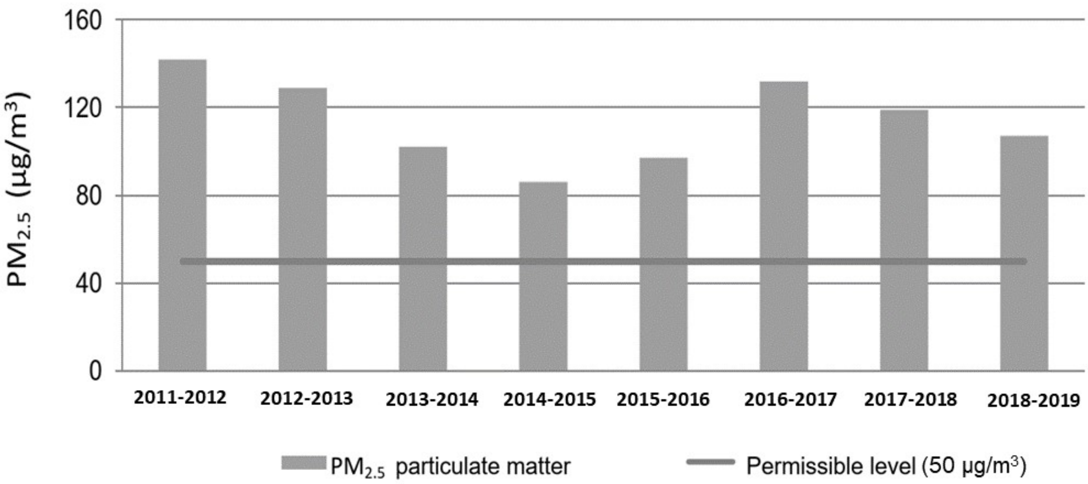



Source: HSES, 2008-2018

**Figure 4.4: Back of the envelope analysis of household electricity consumption (kWh), 2008-2018**

door pollution, which is likely to be less severe than the indoor pollution generated by individual coal-based heating and cooking units.

It is important to note that the huge electricity subsidy imposes a huge fiscal burden, and the benefit needs to be weighed against the opportunity cost of the subsidy on welfare (Coady et al., 2017). For example, in Mongolia, it is uncertain how long the subsidy will be available and whether it is fiscally feasible for a prolonged period (World Bank, 2019). In this context, we argue that, while comparing to costs of a subsidy, benefit from the intended as well as unintended consequences should be considered. This is particularly because the overtime pollution level remains very high in Mongolia. The distribution of $PM_{2.5}$ levels in Ulaanbaatar during cold winter months from October to April in 2011-2019 in Figure 4.5 demonstrates so as an example. The situation is similar in many other countries around the world (Currie et al., 2014; Graff Zivin and Neidell, 2013; Arceo et al., 2016).




Source: NAMEM (2019)

**Figure 4.5: $PM_{2.5}$ level during winter months (October-April) in Ulaanbaatar, 2011-2019**

## 4.6 Conclusion

We investigate the impact of an electricity subsidy program on the likelihood of reporting illness and household electricity expenditures in Ulaanbaatar, Mongolia. For our investigation, we use five rounds of household survey data covering 2010-2018 and difference-in-differences models employing individuals and households eligible for the subsidy as treatment vs those ineligible as the control group. The results suggest a positive effect of the policy that reduces the likelihood of individuals' reporting illnesses, especially for children and working-age people. Our analysis also indicates that households receiving the subsidy increase their electricity expenditures significantly than the control households during the cold winter months and non-winter months. These findings are robust to alternative specifications.

Our investigation adds to the existing literature on the effectiveness of government intervention to increase access to electricity and reduce air pollution. The study shows that electricity subsidy effectively reduces the prevalence of respiratory illnesses among the general population and can even induce households to permanently increase their non-subsidised electricity usage. The short-term gains from reduced air pollution and improved health benefits further improve productivity and raise living standards in the long run. On the other hand, electricity subsidy changes the habit of the recipient households who increase their expenditure on (and thereby consumption of) electricity when the subsidy is not provided. This will allow the subsidy to indirectly contribute in improving health of the affected population. Therefore, in determining the usefulness of the electricity subsidy program, its fiscal cost needs to be compared with the benefit it generates, including the unintended benefit of increased electricity usage in winter and non-winter seasons.

## 4.A Robustness check tables

**Table 4.A.1: DiD results of the probability of illness: dropped missing illness values**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.029** | 0.015 | 0.050* | -0.018 | 0.029** | 0.032 | 0.014 | 0.061 |
| | (0.012) | (0.022) | (0.026) | (0.033) | (0.012) | (0.023) | (0.052) | (0.109) |
| 2012 | 0.047*** | 0.073*** | 0.069** | 0.004 | 0.046*** | 0.108*** | 0.004 | 0.116** |
| | (0.013) | (0.018) | (0.028) | (0.045) | (0.013) | (0.016) | (0.049) | (0.057) |
| 2014 | 0.044*** | 0.062*** | 0.101*** | 0.030 | 0.035*** | 0.091*** | -0.046 | 0.053 |
| | (0.013) | (0.017) | (0.030) | (0.046) | (0.013) | (0.015) | (0.051) | (0.057) |
| 2016 | 0.011 | 0.015 | 0.054** | 0.027 | -0.004 | 0.012 | 0.010 | 0.037 |
| | (0.012) | (0.012) | (0.026) | (0.027) | (0.010) | (0.011) | (0.056) | (0.056) |
| 2018 | 0.071*** | 0.080*** | 0.105*** | 0.065** | 0.053*** | 0.084*** | 0.067 | 0.128** |
| | (0.013) | (0.015) | (0.027) | (0.032) | (0.013) | (0.014) | (0.052) | (0.054) |
| Treatment × 2012 | -0.064*** | -0.075*** | -0.104*** | -0.115*** | -0.058*** | -0.062*** | 0.007 | -0.011 |
| | (0.016) | (0.016) | (0.035) | (0.035) | (0.016) | (0.016) | (0.066) | (0.066) |
| Treatment × 2014 | -0.058*** | -0.066*** | -0.117*** | -0.117*** | -0.051*** | -0.056*** | 0.031 | 0.021 |
| | (0.016) | (0.016) | (0.037) | (0.037) | (0.016) | (0.017) | (0.068) | (0.069) |
| Treatment × 2016 | 0.009 | 0.002 | -0.003 | -0.010 | 0.007 | 0.002 | 0.004 | 0.014 |
| | (0.015) | (0.015) | (0.034) | (0.034) | (0.015) | (0.014) | (0.072) | (0.072) |
| Treatment × 2018 | -0.048*** | -0.055*** | -0.110*** | -0.110*** | -0.026 | -0.030* | -0.010 | -0.017 |
| | (0.017) | (0.017) | (0.034) | (0.034) | (0.017) | (0.017) | (0.070) | (0.070) |
| Individual's age (years) | | 0.002*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.018*** | | -0.002 | | 0.024*** | | 0.025 |
| | | (0.004) | | (0.008) | | (0.004) | | (0.019) |
| Individual's education (years) | | -0.008*** | | -0.015*** | | 0.000 | | -0.001 |
| | | (0.001) | | (0.002) | | (0.001) | | (0.004) |
| Household size | | 0.002 | | -0.024** | | 0.012*** | | 0.030*** |
| | | (0.004) | | (0.011) | | (0.003) | | (0.012) |
| Ln(consumption) | | -0.070 | | 0.251* | | -0.228*** | | -0.378*** |
| | | (0.050) | | (0.139) | | (0.038) | | (0.126) |
| Lives in ger | | 0.004 | | 0.028** | | -0.001 | | -0.037 |
| | | (0.006) | | (0.013) | | (0.006) | | (0.028) |
| Private boiler | | 0.030 | | 0.095*** | | 0.015 | | -0.077 |
| | | (0.023) | | (0.032) | | (0.024) | | (0.115) |
| Electric heater | | -0.016 | | -0.098*** | | 0.004 | | 0.207* |
| | | (0.023) | | (0.031) | | (0.030) | | (0.124) |
| Traditional stove | | 0.010 | | 0.064*** | | -0.004 | | -0.041 |
| | | (0.020) | | (0.024) | | (0.020) | | (0.104) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.03 | 0.02 | 0.03 | 0.01 | 0.02 | 0.04 | 0.05 |
| N | 21,579 | 21,579 | 6,114 | 6,114 | 13,882 | 13,882 | 1,583 | 1,583 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.2: DiD results of the probability of having respiratory illness: dropped missing illness values**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.020** | -0.011 | 0.042* | -0.014 | 0.014** | -0.003 | -0.020 | -0.036 |
| | (0.008) | (0.009) | (0.025) | (0.032) | (0.007) | (0.006) | (0.029) | (0.027) |
| 2012 | 0.025*** | 0.051*** | 0.050* | -0.011 | 0.019*** | 0.012 | -0.010 | 0.022 |
| | (0.009) | (0.012) | (0.026) | (0.042) | (0.007) | (0.009) | (0.028) | (0.030) |
| 2014 | 0.041*** | 0.061*** | 0.102*** | 0.034 | 0.022*** | 0.015* | -0.008 | 0.023 |
| | (0.010) | (0.012) | (0.029) | (0.043) | (0.008) | (0.009) | (0.030) | (0.031) |
| 2016 | 0.016** | 0.018** | 0.048** | 0.023 | 0.002 | -0.000 | -0.011 | -0.005 |
| | (0.008) | (0.008) | (0.025) | (0.026) | (0.005) | (0.005) | (0.030) | (0.029) |
| 2018 | 0.043*** | 0.053*** | 0.091*** | 0.053* | 0.024*** | 0.021** | -0.016 | 0.001 |
| | (0.009) | (0.010) | (0.025) | (0.030) | (0.008) | (0.008) | (0.027) | (0.026) |
| Treatment × 2012 | -0.031*** | -0.035*** | -0.076** | -0.087*** | -0.019** | -0.020** | 0.023 | 0.025 |
| | (0.011) | (0.011) | (0.032) | (0.032) | (0.009) | (0.009) | (0.035) | (0.035) |
| Treatment × 2014 | -0.046*** | -0.047*** | -0.106*** | -0.105*** | -0.028*** | -0.029*** | -0.009 | -0.009 |
| | (0.012) | (0.012) | (0.035) | (0.035) | (0.010) | (0.010) | (0.035) | (0.035) |
| Treatment × 2016 | 0.010 | 0.010 | 0.011 | 0.007 | 0.005 | 0.004 | 0.037 | 0.040 |
| | (0.012) | (0.011) | (0.032) | (0.032) | (0.008) | (0.008) | (0.038) | (0.038) |
| Treatment × 2018 | -0.039*** | -0.041*** | -0.093*** | -0.092*** | -0.024** | -0.025** | 0.018 | 0.019 |
| | (0.012) | (0.012) | (0.032) | (0.032) | (0.010) | (0.010) | (0.034) | (0.034) |
| Individual's age (years) | | -0.001*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.005* | | 0.001 | | 0.008*** | | 0.008 |
| | | (0.003) | | (0.008) | | (0.002) | | (0.009) |
| Individual's education (years) | | -0.004*** | | -0.015*** | | -0.001 | | 0.003 |
| | | (0.001) | | (0.002) | | (0.001) | | (0.002) |
| Household size | | 0.004* | | -0.022** | | -0.003 | | 0.008 |
| | | (0.003) | | (0.011) | | (0.002) | | (0.005) |
| Ln(consumption) | | -0.089*** | | 0.237* | | 0.028 | | -0.124** |
| | | (0.033) | | (0.131) | | (0.022) | | (0.061) |
| Lives in ger | | 0.003 | | 0.024** | | 0.001 | | -0.010 |
| | | (0.005) | | (0.012) | | (0.004) | | (0.013) |
| Private boiler | | 0.031*** | | 0.066** | | 0.026*** | | -0.016 |
| | | (0.011) | | (0.031) | | (0.009) | | (0.013) |
| Electric heater | | -0.021 | | -0.080*** | | -0.001 | | 0.070 |
| | | (0.017) | | (0.027) | | (0.022) | | (0.064) |
| Traditional stove | | 0.022*** | | 0.054** | | 0.017*** | | 0.024** |
| | | (0.006) | | (0.024) | | (0.003) | | (0.012) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.04 | 0.02 | 0.03 | 0.01 | 0.01 | 0.01 | 0.01 |
| N | 21,579 | 21,579 | 6,114 | 6,114 | 13,882 | 13,882 | 1,583 | 1,583 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.3: DiD results of the probability of illness: probit model**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.034** | 0.018 | 0.062* | -0.074 | 0.034** | 0.036 | 0.017 | 0.054 |
| | (0.014) | (0.028) | (0.033) | (0.081) | (0.013) | (0.025) | (0.053) | (0.121) |
| 2012 | 0.047*** | 0.079*** | 0.076** | 0.016 | 0.044*** | 0.098*** | 0.010 | 0.129** |
| | (0.013) | (0.017) | (0.033) | (0.047) | (0.013) | (0.016) | (0.051) | (0.059) |
| 2014 | 0.047*** | 0.075*** | 0.108*** | 0.041 | 0.038*** | 0.088*** | -0.050 | 0.060 |
| | (0.014) | (0.017) | (0.032) | (0.046) | (0.014) | (0.016) | (0.059) | (0.064) |
| 2016 | 0.016 | 0.026* | 0.066** | 0.040 | -0.002 | 0.012 | 0.015 | 0.044 |
| | (0.014) | (0.014) | (0.032) | (0.032) | (0.014) | (0.014) | (0.057) | (0.056) |
| 2018 | 0.070*** | 0.085*** | 0.111*** | 0.072** | 0.053*** | 0.079*** | 0.069 | 0.134*** |
| | (0.013) | (0.014) | (0.030) | (0.034) | (0.013) | (0.013) | (0.049) | (0.051) |
| Treatment × 2012 | -0.066*** | -0.075*** | -0.115*** | -0.126*** | -0.057*** | -0.057*** | -0.001 | -0.017 |
| | (0.017) | (0.016) | (0.040) | (0.039) | (0.016) | (0.016) | (0.068) | (0.068) |
| Treatment × 2014 | -0.062*** | -0.072*** | -0.124*** | -0.123*** | -0.054*** | -0.057*** | 0.035 | 0.019 |
| | (0.017) | (0.017) | (0.040) | (0.039) | (0.017) | (0.017) | (0.075) | (0.075) |
| Treatment × 2016 | 0.002 | -0.008 | -0.021 | -0.028 | 0.005 | 0.000 | -0.002 | 0.003 |
| | (0.017) | (0.016) | (0.038) | (0.037) | (0.017) | (0.017) | (0.073) | (0.072) |
| Treatment × 2018 | -0.049*** | -0.056*** | -0.114*** | -0.114*** | -0.030* | -0.032** | -0.014 | -0.020 |
| | (0.016) | (0.016) | (0.037) | (0.037) | (0.016) | (0.016) | (0.067) | (0.066) |
| Individual's age (years) | | 0.001*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.017*** | | -0.001 | | 0.021*** | | 0.030 |
| | | (0.004) | | (0.008) | | (0.004) | | (0.019) |
| Individual's education (years) | | -0.005*** | | -0.016*** | | 0.003*** | | 0.001 |
| | | (0.001) | | (0.003) | | (0.001) | | (0.004) |
| Household size | | 0.004 | | -0.022** | | 0.012*** | | 0.033*** |
| | | (0.003) | | (0.011) | | (0.003) | | (0.012) |
| Ln(consumption) | | -0.104** | | 0.226* | | -0.213*** | | -0.406*** |
| | | (0.042) | | (0.135) | | (0.036) | | (0.128) |
| Lives in ger | | 0.004 | | 0.027** | | 0.001 | | -0.035 |
| | | (0.006) | | (0.012) | | (0.006) | | (0.029) |
| Private boiler | | 0.034 | | 0.158** | | 0.015 | | -0.070 |
| | | (0.028) | | (0.078) | | (0.024) | | (0.125) |
| Electric heater | | -0.015 | | -0.130** | | -0.000 | | 0.153 |
| | | (0.022) | | (0.055) | | (0.023) | | (0.097) |
| Traditional stove | | 0.018 | | 0.133* | | -0.000 | | -0.028 |
| | | (0.026) | | (0.076) | | (0.022) | | (0.114) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pseudo-$R^2$ | 0.02 | 0.05 | 0.03 | 0.04 | 0.02 | 0.03 | 0.04 | 0.05 |
| N | 21,985 | 21,985 | 6,160 | 6,160 | 14,233 | 14,233 | 1,592 | 1,592 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.4: DiD results of the probability of having respiratory illness: probit model**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.026** | -0.039 | 0.053* | -0.053 | 0.019** | -0.121*** | -0.017 | -0.191*** |
| | (0.011) | (0.026) | (0.032) | (0.073) | (0.009) | (0.012) | (0.023) | (0.034) |
| 2012 | 0.029*** | 0.050*** | 0.058* | 0.005 | 0.021*** | 0.013 | -0.007 | 0.015 |
| | (0.011) | (0.012) | (0.032) | (0.044) | (0.008) | (0.009) | (0.021) | (0.017) |
| 2014 | 0.044*** | 0.060*** | 0.107*** | 0.046 | 0.024*** | 0.016* | -0.005 | 0.017 |
| | (0.010) | (0.011) | (0.031) | (0.043) | (0.008) | (0.009) | (0.022) | (0.017) |
| 2016 | 0.023** | 0.022** | 0.061** | 0.037 | 0.005 | 0.003 | -0.008 | -0.001 |
| | (0.010) | (0.009) | (0.031) | (0.031) | (0.009) | (0.008) | (0.022) | (0.015) |
| 2018 | 0.046*** | 0.050*** | 0.098*** | 0.062* | 0.026*** | 0.020** | -0.011 | 0.003 |
| | (0.010) | (0.009) | (0.030) | (0.033) | (0.008) | (0.008) | (0.020) | (0.014) |
| Treatment × 2012 | -0.036*** | -0.032*** | -0.088** | -0.098*** | -0.022** | -0.021** | 0.018 | 0.016 |
| | (0.013) | (0.011) | (0.039) | (0.038) | (0.010) | (0.009) | (0.029) | (0.020) |
| Treatment × 2014 | -0.049*** | -0.043*** | -0.110*** | -0.107*** | -0.030*** | -0.028*** | -0.025 | -0.020 |
| | (0.013) | (0.011) | (0.038) | (0.037) | (0.011) | (0.010) | (0.033) | (0.022) |
| Treatment × 2016 | -0.001 | -0.000 | -0.009 | -0.014 | 0.000 | -0.001 | 0.029 | 0.023 |
| | (0.013) | (0.011) | (0.037) | (0.036) | (0.011) | (0.010) | (0.030) | (0.021) |
| Treatment × 2018 | -0.041*** | -0.036*** | -0.099*** | -0.096*** | -0.025** | -0.024** | 0.012 | 0.010 |
| | (0.013) | (0.011) | (0.036) | (0.035) | (0.010) | (0.010) | (0.029) | (0.020) |
| Individual's age (years) | | -0.001*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.005* | | 0.002 | | 0.007*** | | 0.007 |
| | | (0.002) | | (0.007) | | (0.002) | | (0.006) |
| Individual's education (years) | | -0.002*** | | -0.018*** | | 0.000 | | 0.002* |
| | | (0.001) | | (0.003) | | (0.000) | | (0.001) |
| Household size | | 0.005** | | -0.018* | | -0.002 | | 0.005 |
| | | (0.002) | | (0.010) | | (0.001) | | (0.004) |
| Ln(consumption) | | -0.101*** | | 0.196 | | 0.025 | | -0.081** |
| | | (0.031) | | (0.126) | | (0.019) | | (0.037) |
| Lives in ger | | 0.003 | | 0.023** | | 0.001 | | -0.008 |
| | | (0.004) | | (0.012) | | (0.003) | | (0.009) |
| Private boiler | | 0.063** | | 0.112 | | 0.145*** | | -0.013 |
| | | (0.026) | | (0.070) | | (0.012) | | (0.012) |
| Electric heater | | -0.019 | | -0.121** | | -0.002 | | 0.213*** |
| | | (0.019) | | (0.054) | | (0.014) | | (0.041) |
| Traditional stove | | 0.059** | | 0.104 | | 0.139*** | | 0.184*** |
| | | (0.025) | | (0.067) | | (0.011) | | (0.031) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pseudo-$R^2$ | 0.02 | 0.10 | 0.03 | 0.05 | 0.03 | 0.03 | 0.02 | 0.05 |
| N | 21,985 | 21,985 | 6,160 | 6,160 | 14,233 | 14,233 | 1,592 | 1,592 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.5: DiD results of the probability of illness: logit model**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.035** | 0.015 | 0.061* | -0.084 | 0.034** | 0.037 | 0.018 | 0.058 |
| | (0.014) | (0.030) | (0.034) | (0.098) | (0.014) | (0.025) | (0.053) | (0.118) |
| 2012 | 0.047*** | 0.074*** | 0.075** | 0.012 | 0.044*** | 0.094*** | 0.009 | 0.125** |
| | (0.014) | (0.016) | (0.034) | (0.046) | (0.013) | (0.015) | (0.051) | (0.058) |
| 2014 | 0.048*** | 0.073*** | 0.106*** | 0.038 | 0.039*** | 0.085*** | -0.050 | 0.055 |
| | (0.014) | (0.016) | (0.033) | (0.045) | (0.014) | (0.015) | (0.061) | (0.065) |
| 2016 | 0.017 | 0.026* | 0.066** | 0.039 | -0.002 | 0.012 | 0.014 | 0.042 |
| | (0.014) | (0.014) | (0.033) | (0.033) | (0.015) | (0.015) | (0.057) | (0.055) |
| 2018 | 0.068*** | 0.081*** | 0.107*** | 0.067* | 0.052*** | 0.075*** | 0.066 | 0.129*** |
| | (0.013) | (0.013) | (0.032) | (0.034) | (0.013) | (0.013) | (0.048) | (0.050) |
| Treatment × 2012 | -0.065*** | -0.069*** | -0.112*** | -0.118*** | -0.056*** | -0.055*** | 0.002 | -0.011 |
| | (0.017) | (0.016) | (0.041) | (0.039) | (0.016) | (0.016) | (0.067) | (0.067) |
| Treatment × 2014 | -0.063*** | -0.068*** | -0.122*** | -0.117*** | -0.056*** | -0.056*** | 0.033 | 0.025 |
| | (0.017) | (0.016) | (0.040) | (0.039) | (0.017) | (0.017) | (0.077) | (0.077) |
| Treatment × 2016 | 0.001 | -0.008 | -0.021 | -0.026 | 0.004 | 0.001 | 0.000 | 0.011 |
| | (0.017) | (0.016) | (0.039) | (0.037) | (0.018) | (0.017) | (0.073) | (0.072) |
| Treatment × 2018 | -0.047*** | -0.052*** | -0.111*** | -0.106*** | -0.030* | -0.031** | -0.013 | -0.015 |
| | (0.016) | (0.015) | (0.038) | (0.037) | (0.016) | (0.016) | (0.066) | (0.065) |
| Individual's age (years) | | 0.001*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.015*** | | -0.001 | | 0.021*** | | 0.027 |
| | | (0.004) | | (0.008) | | (0.004) | | (0.019) |
| Individual's education (years) | | -0.005*** | | -0.017*** | | 0.003*** | | 0.001 |
| | | (0.001) | | (0.003) | | (0.001) | | (0.003) |
| Household size | | 0.004 | | -0.022** | | 0.011*** | | 0.033*** |
| | | (0.003) | | (0.010) | | (0.003) | | (0.012) |
| Ln(consumption) | | -0.104*** | | 0.223* | | -0.202*** | | -0.407*** |
| | | (0.039) | | (0.128) | | (0.035) | | (0.128) |
| Lives in ger | | 0.004 | | 0.026** | | 0.001 | | -0.034 |
| | | (0.006) | | (0.012) | | (0.006) | | (0.029) |
| Private boiler | | 0.034 | | 0.165* | | 0.012 | | -0.075 |
| | | (0.029) | | (0.095) | | (0.023) | | (0.122) |
| Electric heater | | -0.014 | | -0.136** | | 0.002 | | 0.147* |
| | | (0.021) | | (0.061) | | (0.021) | | (0.088) |
| Traditional stove | | 0.019 | | 0.139 | | -0.001 | | -0.035 |
| | | (0.027) | | (0.093) | | (0.022) | | (0.111) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pseudo-$R^2$ | 0.02 | 0.05 | 0.03 | 0.05 | 0.02 | 0.03 | 0.04 | 0.05 |
| N | 21,985 | 21,985 | 6,160 | 6,160 | 14,233 | 14,233 | 1,592 | 1,592 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.6: DiD results of the probability of having respiratory illness: logit model**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.027** | -0.038 | 0.053 | -0.059 | 0.019** | -0.204*** | -0.016 | -0.224*** |
| | (0.012) | (0.030) | (0.034) | (0.085) | (0.009) | (0.034) | (0.023) | (0.014) |
| 2012 | 0.029*** | 0.044*** | 0.058* | 0.000 | 0.021** | 0.012 | -0.006 | 0.011 |
| | (0.011) | (0.011) | (0.034) | (0.043) | (0.008) | (0.009) | (0.020) | (0.012) |
| 2014 | 0.044*** | 0.054*** | 0.104*** | 0.040 | 0.024*** | 0.015* | -0.005 | 0.012 |
| | (0.011) | (0.010) | (0.032) | (0.042) | (0.009) | (0.009) | (0.021) | (0.012) |
| 2016 | 0.024** | 0.020** | 0.061* | 0.035 | 0.006 | 0.003 | -0.008 | -0.001 |
| | (0.011) | (0.008) | (0.033) | (0.031) | (0.010) | (0.008) | (0.022) | (0.012) |
| 2018 | 0.045*** | 0.044*** | 0.095*** | 0.056* | 0.025*** | 0.018** | -0.012 | 0.001 |
| | (0.010) | (0.008) | (0.031) | (0.033) | (0.008) | (0.008) | (0.020) | (0.011) |
| Treatment × 2012 | -0.035*** | -0.028*** | -0.087** | -0.090** | -0.021** | -0.019** | 0.018 | 0.012 |
| | (0.014) | (0.011) | (0.041) | (0.039) | (0.010) | (0.009) | (0.028) | (0.015) |
| Treatment × 2014 | -0.049*** | -0.038*** | -0.108*** | -0.100*** | -0.030*** | -0.027*** | -0.027 | -0.015 |
| | (0.013) | (0.010) | (0.039) | (0.037) | (0.011) | (0.010) | (0.034) | (0.018) |
| Treatment × 2016 | -0.002 | -0.000 | -0.010 | -0.012 | -0.001 | -0.001 | 0.028 | 0.017 |
| | (0.013) | (0.010) | (0.038) | (0.036) | (0.011) | (0.010) | (0.029) | (0.016) |
| Treatment × 2018 | -0.040*** | -0.032*** | -0.096** | -0.089** | -0.025** | -0.022** | 0.013 | 0.008 |
| | (0.013) | (0.010) | (0.038) | (0.036) | (0.010) | (0.010) | (0.029) | (0.015) |
| Individual's age (years) | | -0.001*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.003 | | 0.001 | | 0.006*** | | 0.005 |
| | | (0.002) | | (0.007) | | (0.002) | | (0.005) |
| Individual's education (years) | | -0.001** | | -0.018*** | | -0.000 | | 0.001* |
| | | (0.001) | | (0.003) | | (0.000) | | (0.001) |
| Household size | | 0.005** | | -0.019** | | -0.002 | | 0.004 |
| | | (0.002) | | (0.009) | | (0.001) | | (0.003) |
| Ln(consumption) | | -0.092*** | | 0.201* | | 0.023 | | -0.061** |
| | | (0.028) | | (0.117) | | (0.017) | | (0.026) |
| Lives in ger | | 0.003 | | 0.022* | | 0.001 | | -0.005 |
| | | (0.003) | | (0.011) | | (0.003) | | (0.007) |
| Private boiler | | 0.059** | | 0.116 | | 0.227*** | | -0.008 |
| | | (0.029) | | (0.081) | | (0.039) | | (0.012) |
| Electric heater | | -0.019 | | -0.126** | | -0.000 | | 0.236*** |
| | | (0.018) | | (0.062) | | (0.012) | | (0.012) |
| Traditional stove | | 0.055* | | 0.106 | | 0.221*** | | 0.219 |
| | | (0.029) | | (0.080) | | (0.037) | | (0.000) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pseudo-$R^2$ | 0.02 | 0.10 | 0.03 | 0.05 | 0.03 | 0.03 | 0.03 | 0.05 |
| N | 21,985 | 21,985 | 6,160 | 6,160 | 14,233 | 14,233 | 1,592 | 1,592 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.7: DiD results of the probability of illness: categorical education**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.030*** | 0.018 | 0.050* | -0.021 | 0.030*** | 0.031 | 0.018 | 0.083 |
| | (0.012) | (0.022) | (0.026) | (0.033) | (0.011) | (0.022) | (0.052) | (0.107) |
| 2012 | 0.043*** | 0.070*** | 0.064** | 0.002 | 0.041*** | 0.096*** | 0.008 | 0.129** |
| | (0.012) | (0.017) | (0.028) | (0.045) | (0.012) | (0.015) | (0.048) | (0.060) |
| 2014 | 0.044*** | 0.073*** | 0.102*** | 0.033 | 0.035*** | 0.088*** | -0.042 | 0.064 |
| | (0.013) | (0.017) | (0.030) | (0.045) | (0.013) | (0.015) | (0.051) | (0.057) |
| 2016 | 0.011 | 0.020* | 0.054** | 0.028 | -0.003 | 0.013 | 0.013 | 0.043 |
| | (0.011) | (0.012) | (0.026) | (0.027) | (0.010) | (0.010) | (0.055) | (0.056) |
| 2018 | 0.071*** | 0.086*** | 0.105*** | 0.066** | 0.053*** | 0.085*** | 0.069 | 0.137** |
| | (0.013) | (0.014) | (0.027) | (0.032) | (0.013) | (0.014) | (0.051) | (0.054) |
| Treatment × 2012 | -0.060*** | -0.062*** | -0.098*** | -0.108*** | -0.053*** | -0.055*** | 0.002 | -0.021 |
| | (0.015) | (0.015) | (0.034) | (0.034) | (0.015) | (0.015) | (0.066) | (0.068) |
| Treatment × 2014 | -0.058*** | -0.065*** | -0.117*** | -0.116*** | -0.050*** | -0.054*** | 0.026 | 0.009 |
| | (0.016) | (0.016) | (0.037) | (0.037) | (0.016) | (0.016) | (0.067) | (0.069) |
| Treatment × 2016 | 0.008 | -0.001 | -0.003 | -0.008 | 0.005 | 0.000 | 0.002 | 0.009 |
| | (0.015) | (0.015) | (0.034) | (0.034) | (0.014) | (0.014) | (0.072) | (0.072) |
| Treatment × 2018 | -0.048*** | -0.054*** | -0.109*** | -0.108*** | -0.026 | -0.032* | -0.013 | -0.027 |
| | (0.016) | (0.017) | (0.034) | (0.034) | (0.017) | (0.017) | (0.069) | (0.070) |
| Individual's age (years) | | 0.002*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.017*** | | -0.002 | | 0.023*** | | 0.025 |
| | | (0.004) | | (0.008) | | (0.004) | | (0.019) |
| Primary school | | -0.053*** | | -0.083*** | | 0.091*** | | 0.193*** |
| | | (0.009) | | (0.012) | | (0.018) | | (0.067) |
| Secondary school | | -0.068*** | | -0.080*** | | 0.079*** | | 0.160** |
| | | (0.012) | | (0.029) | | (0.011) | | (0.067) |
| High school | | -0.081*** | | -0.156*** | | 0.081*** | | 0.153** |
| | | (0.012) | | (0.030) | | (0.010) | | (0.064) |
| Vocational degree | | -0.081*** | | -0.209*** | | 0.091*** | | 0.162** |
| | | (0.014) | | (0.035) | | (0.011) | | (0.066) |
| Bachelor | | -0.099*** | | 0.000 | | 0.070*** | | 0.139* |
| | | (0.015) | | (0.000) | | (0.012) | | (0.074) |
| Master | | -0.074*** | | 0.000 | | 0.098*** | | 0.092 |
| | | (0.019) | | (0.000) | | (0.016) | | (0.091) |
| PhD | | -0.058* | | -0.288*** | | 0.130*** | | 0.182* |
| | | (0.034) | | (0.053) | | (0.035) | | (0.104) |
| Household size | | 0.005 | | -0.023** | | 0.012*** | | 0.030*** |
| | | (0.004) | | (0.011) | | (0.003) | | (0.011) |
| Ln(consumption) | | -0.119** | | 0.235* | | -0.216*** | | -0.379*** |
| | | (0.049) | | (0.137) | | (0.038) | | (0.125) |
| Lives in ger | | 0.004 | | 0.027** | | -0.001 | | -0.040 |
| | | (0.006) | | (0.012) | | (0.006) | | (0.028) |
| Private boiler | | 0.030 | | 0.096*** | | 0.015 | | -0.093 |
| | | (0.023) | | (0.032) | | (0.023) | | (0.112) |
| Electric heater | | -0.017 | | -0.096*** | | 0.005 | | 0.186 |
| | | (0.023) | | (0.031) | | (0.030) | | (0.118) |
| Traditional stove | | 0.014 | | 0.067*** | | -0.003 | | -0.055 |
| | | (0.020) | | (0.024) | | (0.020) | | (0.103) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.03 | 0.02 | 0.03 | 0.01 | 0.02 | 0.04 | 0.06 |
| N | 21,985 | 21,985 | 6,160 | 6,160 | 14,233 | 14,233 | 1,592 | 1,592 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.8: DiD results of the probability of having respiratory illness: categorical education**

| | All age groups combined | | Children (under 14 years) | | Working age adults (15-60 years) | | Older adults (over 60 years) | |
|---|---|---|---|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment | 0.020** | -0.008 | 0.042* | -0.015 | 0.014** | -0.003 | -0.019 | -0.027 |
| | (0.008) | (0.009) | (0.024) | (0.032) | (0.007) | (0.006) | (0.029) | (0.027) |
| 2012 | 0.023*** | 0.043*** | 0.046* | -0.014 | 0.017*** | 0.010 | -0.009 | 0.035 |
| | (0.008) | (0.012) | (0.025) | (0.041) | (0.006) | (0.009) | (0.028) | (0.031) |
| 2014 | 0.040*** | 0.061*** | 0.102*** | 0.036 | 0.021*** | 0.016* | -0.007 | 0.027 |
| | (0.010) | (0.012) | (0.029) | (0.043) | (0.008) | (0.009) | (0.029) | (0.031) |
| 2016 | 0.016** | 0.018** | 0.048** | 0.023 | 0.002 | 0.000 | -0.011 | 0.001 |
| | (0.008) | (0.008) | (0.024) | (0.025) | (0.005) | (0.005) | (0.029) | (0.029) |
| 2018 | 0.043*** | 0.052*** | 0.091*** | 0.054* | 0.024*** | 0.021*** | -0.015 | 0.005 |
| | (0.009) | (0.010) | (0.025) | (0.029) | (0.008) | (0.008) | (0.026) | (0.026) |
| Treatment × 2012 | -0.029*** | -0.027** | -0.072** | -0.082*** | -0.018** | -0.017* | 0.022 | 0.014 |
| | (0.011) | (0.011) | (0.032) | (0.032) | (0.009) | (0.009) | (0.035) | (0.035) |
| Treatment × 2014 | -0.045*** | -0.045*** | -0.106*** | -0.104*** | -0.027*** | -0.028*** | -0.011 | -0.015 |
| | (0.012) | (0.012) | (0.035) | (0.035) | (0.010) | (0.010) | (0.035) | (0.035) |
| Treatment × 2016 | 0.009 | 0.009 | 0.012 | 0.008 | 0.005 | 0.004 | 0.036 | 0.033 |
| | (0.011) | (0.011) | (0.032) | (0.032) | (0.008) | (0.008) | (0.037) | (0.038) |
| Treatment × 2018 | -0.038*** | -0.039*** | -0.093*** | -0.091*** | -0.024** | -0.024** | 0.017 | 0.015 |
| | (0.012) | (0.012) | (0.032) | (0.032) | (0.010) | (0.010) | (0.033) | (0.033) |
| Individual's age (years) | | -0.001*** | | | | | | |
| | | (0.000) | | | | | | |
| Individual is female | | 0.004 | | 0.001 | | 0.008*** | | 0.009 |
| | | (0.003) | | (0.008) | | (0.002) | | (0.009) |
| Primary school | | -0.047*** | | -0.077*** | | 0.031*** | | 0.049*** |
| | | (0.007) | | (0.011) | | (0.011) | | (0.017) |
| Secondary school | | -0.055*** | | -0.118*** | | 0.019*** | | 0.056*** |
| | | (0.007) | | (0.019) | | (0.006) | | (0.017) |
| High school | | -0.053*** | | -0.128*** | | 0.015*** | | 0.058*** |
| | | (0.008) | | (0.028) | | (0.005) | | (0.018) |
| Vocational degree | | -0.047*** | | -0.175*** | | 0.011** | | 0.081*** |
| | | (0.009) | | (0.034) | | (0.005) | | (0.020) |
| Bachelor | | -0.053*** | | 0.000 | | 0.012* | | 0.055** |
| | | (0.010) | | (0.000) | | (0.007) | | (0.024) |
| Master | | -0.040*** | | 0.000 | | 0.016* | | 0.038 |
| | | (0.012) | | (0.000) | | (0.010) | | (0.023) |
| PhD | | -0.003 | | -0.251*** | | 0.044* | | 0.109* |
| | | (0.025) | | (0.049) | | (0.026) | | (0.065) |
| Household size | | 0.005** | | -0.021** | | -0.002 | | 0.008 |
| | | (0.002) | | (0.010) | | (0.002) | | (0.005) |
| Ln(consumption) | | -0.100*** | | 0.230* | | 0.021 | | -0.122** |
| | | (0.032) | | (0.130) | | (0.022) | | (0.061) |
| Lives in ger | | 0.004 | | 0.023* | | 0.000 | | -0.011 |
| | | (0.005) | | (0.012) | | (0.004) | | (0.013) |
| Private boiler | | 0.031*** | | 0.065** | | 0.025*** | | -0.021 |
| | | (0.011) | | (0.031) | | (0.008) | | (0.015) |
| Electric heater | | -0.022 | | -0.079*** | | -0.001 | | 0.066 |
| | | (0.017) | | (0.027) | | (0.021) | | (0.063) |
| Traditional stove | | 0.025*** | | 0.054** | | 0.017*** | | 0.019 |
| | | (0.007) | | (0.024) | | (0.003) | | (0.014) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.04 | 0.02 | 0.03 | 0.01 | 0.01 | 0.01 | 0.02 |
| N | 21,985 | 21,985 | 6,160 | 6,160 | 14,233 | 14,233 | 1,592 | 1,592 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1,3,5 and 7 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2,4,6 and 8 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.9: DiD results of the probability of having overall and respiratory illness: age in quadratic form**

| | Overall illness | | Respiratory illness | |
|---|---|---|---|---|
| Variable name | (1) | (2) | (3) | (4) |
| Treatment | 0.030*** | 0.016 | 0.020** | -0.011 |
| | (0.012) | (0.022) | (0.008) | (0.009) |
| 2012 | 0.043*** | 0.040** | 0.023*** | 0.024** |
| | (0.012) | (0.017) | (0.008) | (0.012) |
| 2014 | 0.044*** | 0.038** | 0.040*** | 0.039*** |
| | (0.013) | (0.017) | (0.010) | (0.012) |
| 2016 | 0.011 | 0.011 | 0.016** | 0.014* |
| | (0.011) | (0.012) | (0.008) | (0.008) |
| 2018 | 0.071*** | 0.067*** | 0.043*** | 0.043*** |
| | (0.013) | (0.014) | (0.009) | (0.010) |
| Treatment × 2012 | -0.060*** | -0.068*** | -0.029*** | -0.033*** |
| | (0.015) | (0.015) | (0.011) | (0.011) |
| Treatment × 2014 | -0.058*** | -0.067*** | -0.045*** | -0.048*** |
| | (0.016) | (0.016) | (0.012) | (0.012) |
| Treatment × 2016 | 0.008 | -0.001 | 0.009 | 0.008 |
| | (0.015) | (0.015) | (0.011) | (0.011) |
| Treatment × 2018 | -0.048*** | -0.055*** | -0.038*** | -0.042*** |
| | (0.016) | (0.016) | (0.012) | (0.012) |
| Individual's age ($age^2$) | | 0.000*** | | -0.000 |
| | | (0.000) | | (0.000) |
| Individual is female | | 0.018*** | | 0.006** |
| | | (0.004) | | (0.003) |
| Individual's education (years) | | -0.007*** | | -0.006*** |
| | | (0.001) | | (0.001) |
| Household size | | -0.005 | | -0.002 |
| | | (0.004) | | (0.002) |
| Ln(consumption) | | 0.030 | | 0.000 |
| | | (0.048) | | (0.032) |
| Lives in ger | | 0.005 | | 0.004 |
| | | (0.006) | | (0.005) |
| Private boiler | | 0.032 | | 0.033*** |
| | | (0.023) | | (0.011) |
| Electric heater | | -0.016 | | -0.020 |
| | | (0.023) | | (0.017) |
| Traditional stove | | 0.015 | | 0.024*** |
| | | (0.019) | | (0.006) |
| District fixed effects | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes |
| Adjusted-$R^2$ | 0.01 | 0.03 | 0.01 | 0.04 |
| N | 21,985 | 21,985 | 21,985 | 21,985 |

*Notes:* Standard errors, clustered at the household level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is individuals living in house, male and using regular heater for residential heating; the reference year is 2010. Columns 1 and 3 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 4 add individual–specific controls to the specification, including the type of the residence and heating sources in residence.

**Table 4.A.10: The subsidy impact on the level value of electricity expenses**

| | Winter months | | | Non-winter months | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | -3.615** | -1.841* | -3.503*** | -1.789** | -0.541 | 3.965* |
| | (0.984) | (0.848) | (0.709) | (0.510) | (0.556) | (1.641) |
| 2012 | -0.309 | -1.758** | -1.372* | -0.192 | -1.576* | -1.216 |
| | (0.776) | (0.548) | (0.566) | (0.622) | (0.673) | (0.632) |
| 2014 | -1.981*** | -3.705*** | -3.186*** | -2.482*** | -3.914*** | -3.465*** |
| | (0.313) | (0.437) | (0.326) | (0.195) | (0.436) | (0.329) |
| 2016 | 0.517 | -0.680 | -0.297 | -0.401 | -1.549** | -1.281* |
| | (0.603) | (0.420) | (0.398) | (0.619) | (0.534) | (0.563) |
| 2018 | -0.824 | -2.358*** | -1.976*** | -1.499** | -2.748*** | -2.452*** |
| | (0.415) | (0.322) | (0.213) | (0.473) | (0.126) | (0.136) |
| Treatment × 2012 | 1.947* | 2.922** | 2.151** | 0.999 | 2.036* | 1.349 |
| | (0.945) | (0.949) | (0.779) | (1.012) | (0.938) | (1.200) |
| Treatment × 2014 | 3.091** | 4.191*** | 2.207* | 2.148** | 3.118** | 2.054** |
| | (1.037) | (1.037) | (0.993) | (0.767) | (0.818) | (0.710) |
| Treatment × 2016 | 2.331** | 2.720** | 1.526 | 1.602*** | 2.502*** | 1.933*** |
| | (0.853) | (0.823) | (0.864) | (0.277) | (0.257) | (0.342) |
| Treatment × 2018 | 4.013*** | 4.646*** | 2.666*** | 4.383*** | 5.019*** | 3.048*** |
| | (0.799) | (0.868) | (0.600) | (0.573) | (0.447) | (0.434) |
| Household head's age (years) | | 0.044** | 0.049*** | | 0.030*** | 0.037*** |
| | | (0.011) | (0.011) | | (0.004) | (0.005) |
| Household head is female | | -0.402 | -0.437* | | -0.063 | -0.122 |
| | | (0.272) | (0.204) | | (0.129) | (0.169) |
| Household head's education (years) | | 0.268*** | 0.175*** | | 0.190*** | 0.145*** |
| | | (0.024) | (0.026) | | (0.015) | (0.022) |
| Household head is married | | 0.893*** | 0.845** | | 1.107*** | 0.627** |
| | | (0.163) | (0.253) | | (0.173) | (0.194) |
| Share of working members | | 0.794** | 0.592** | | 0.176 | 0.152 |
| | | (0.293) | (0.204) | | (0.483) | (0.490) |
| Household size | | 0.727*** | 0.809*** | | 0.710*** | 0.803*** |
| | | (0.110) | (0.093) | | (0.121) | (0.106) |
| Ln(income) | | 1.144*** | 0.901*** | | 1.133*** | 0.895*** |
| | | (0.234) | (0.182) | | (0.233) | (0.174) |
| Lives in ger | | -3.982*** | -2.387*** | | -3.677*** | -2.076*** |
| | | (0.353) | (0.191) | | (0.328) | (0.066) |
| Private boiler | | | 3.467*** | | | -2.491* |
| | | | (0.774) | | | (1.005) |
| Electric heater | | | 48.831*** | | | 34.538*** |
| | | | (5.045) | | | (5.088) |
| Traditional stove | | | 0.843 | | | -5.794*** |
| | | | (0.519) | | | (1.416) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.01 | 0.10 | 0.40 | 0.02 | 0.10 | 0.38 |
| Number of households | 5,766 | 5,766 | 5,766 | 7,975 | 7,975 | 7,975 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 and 4 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 5 add household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 and 6 further add heating sources in the residence to the specification.

**Table 4.A.11: The subsidy impact on per capita electricity expenses**

| | Winter months | | | Non-winter months | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | -0.422*** | -0.267** | -0.331** | -0.326*** | -0.212*** | -0.093 |
| | (0.061) | (0.086) | (0.100) | (0.019) | (0.028) | (0.080) |
| 2012 | -0.006 | -0.228** | -0.217** | 0.008 | -0.219*** | -0.206*** |
| | (0.053) | (0.073) | (0.070) | (0.048) | (0.046) | (0.045) |
| 2014 | -0.045 | -0.309*** | -0.293*** | -0.073** | -0.332*** | -0.316*** |
| | (0.042) | (0.056) | (0.053) | (0.022) | (0.051) | (0.048) |
| 2016 | 0.118** | -0.110* | -0.098 | 0.090** | -0.149** | -0.139** |
| | (0.031) | (0.054) | (0.050) | (0.030) | (0.046) | (0.045) |
| 2018 | 0.036 | -0.234** | -0.222** | -0.042** | -0.278*** | -0.266*** |
| | (0.034) | (0.062) | (0.059) | (0.012) | (0.044) | (0.042) |
| Treatment × 2012 | 0.131 | 0.237* | 0.217* | 0.129 | 0.232** | 0.208** |
| | (0.080) | (0.098) | (0.092) | (0.073) | (0.067) | (0.078) |
| Treatment × 2014 | 0.214** | 0.278** | 0.221** | 0.155*** | 0.250*** | 0.214*** |
| | (0.064) | (0.074) | (0.073) | (0.019) | (0.047) | (0.046) |
| Treatment × 2016 | 0.183** | 0.219** | 0.187* | 0.164*** | 0.233*** | 0.213*** |
| | (0.053) | (0.083) | (0.082) | (0.023) | (0.033) | (0.035) |
| Treatment × 2018 | 0.229*** | 0.300** | 0.244** | 0.281*** | 0.348*** | 0.284*** |
| | (0.039) | (0.080) | (0.073) | (0.034) | (0.053) | (0.057) |
| Household head's age (years) | | 0.006*** | 0.006*** | | 0.005*** | 0.006*** |
| | | (0.001) | (0.001) | | (0.000) | (0.000) |
| Household head is female | | 0.009 | 0.008 | | -0.004 | -0.005 |
| | | (0.029) | (0.034) | | (0.027) | (0.028) |
| Household head's education (years) | | 0.011*** | 0.009** | | 0.012*** | 0.010*** |
| | | (0.002) | (0.002) | | (0.001) | (0.002) |
| Household head is married | | -0.196*** | -0.197*** | | -0.221*** | -0.235*** |
| | | (0.023) | (0.027) | | (0.029) | (0.031) |
| Share of working members | | 0.207*** | 0.201*** | | 0.152*** | 0.152*** |
| | | (0.020) | (0.021) | | (0.037) | (0.036) |
| Ln(income) | | 0.185*** | 0.177*** | | 0.184*** | 0.174*** |
| | | (0.013) | (0.013) | | (0.024) | (0.022) |
| Lives in ger | | -0.195*** | -0.153*** | | -0.164*** | -0.114*** |
| | | (0.015) | (0.012) | | (0.012) | (0.007) |
| Private boiler | | | 0.070 | | | -0.043 |
| | | | (0.071) | | | (0.062) |
| Electric heater | | | 1.480*** | | | 1.069*** |
| | | | (0.115) | | | (0.120) |
| Traditional stove | | | 0.043 | | | -0.158* |
| | | | (0.054) | | | (0.073) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.06 | 0.21 | 0.27 | 0.05 | 0.20 | 0.26 |
| Number of households | 5,766 | 5,766 | 5,766 | 7,975 | 7,975 | 7,975 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 and 4 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 5 add household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 and 6 further add heating sources in the residence to the specification.

**Table 4.A.12: The subsidy impact on electricity expenses: OECD equivalence scale adjusted**

| | Winter months | | | Non-winter months | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | -0.368*** | -0.240** | -0.340** | -0.265*** | -0.161*** | -0.029 |
| | (0.058) | (0.066) | (0.088) | (0.015) | (0.023) | (0.062) |
| 2012 | -0.014 | -0.124** | -0.111** | 0.000 | -0.107** | -0.094* |
| | (0.036) | (0.046) | (0.043) | (0.042) | (0.040) | (0.040) |
| 2014 | -0.063 | -0.200*** | -0.183*** | -0.091*** | -0.214*** | -0.199*** |
| | (0.036) | (0.038) | (0.035) | (0.016) | (0.032) | (0.029) |
| 2016 | 0.108*** | 0.003 | 0.015 | 0.072 | -0.030 | -0.020 |
| | (0.027) | (0.026) | (0.023) | (0.036) | (0.037) | (0.037) |
| 2018 | 0.021 | -0.104** | -0.091** | -0.033** | -0.133*** | -0.121*** |
| | (0.023) | (0.030) | (0.027) | (0.011) | (0.021) | (0.019) |
| Treatment × 2012 | 0.133* | 0.201** | 0.178** | 0.122 | 0.183** | 0.159* |
| | (0.056) | (0.068) | (0.062) | (0.067) | (0.063) | (0.073) |
| Treatment × 2014 | 0.199** | 0.250*** | 0.191** | 0.141*** | 0.196*** | 0.160*** |
| | (0.055) | (0.058) | (0.056) | (0.024) | (0.038) | (0.038) |
| Treatment × 2016 | 0.175** | 0.198** | 0.163* | 0.148*** | 0.188*** | 0.166*** |
| | (0.056) | (0.065) | (0.066) | (0.022) | (0.024) | (0.025) |
| Treatment × 2018 | 0.240*** | 0.278*** | 0.219*** | 0.262*** | 0.292*** | 0.229*** |
| | (0.032) | (0.051) | (0.044) | (0.025) | (0.036) | (0.041) |
| Household head's age (years) | | 0.003** | 0.003** | | 0.002*** | 0.002*** |
| | | (0.001) | (0.001) | | (0.000) | (0.000) |
| Household head is female | | 0.020 | 0.019 | | 0.008 | 0.007 |
| | | (0.022) | (0.026) | | (0.020) | (0.021) |
| Household head's education (years) | | 0.014*** | 0.012*** | | 0.014*** | 0.012*** |
| | | (0.002) | (0.002) | | (0.002) | (0.002) |
| Household head is married | | -0.065** | -0.065* | | -0.084*** | -0.098*** |
| | | (0.020) | (0.026) | | (0.019) | (0.022) |
| Share of working members | | 0.115*** | 0.107*** | | 0.077* | 0.075* |
| | | (0.012) | (0.013) | | (0.034) | (0.034) |
| Ln(income) | | 0.083*** | 0.074*** | | 0.075*** | 0.066*** |
| | | (0.012) | (0.012) | | (0.016) | (0.015) |
| Lives in ger | | -0.211*** | -0.166*** | | -0.183*** | -0.131*** |
| | | (0.014) | (0.011) | | (0.012) | (0.007) |
| Private boiler | | | 0.138 | | | -0.038 |
| | | | (0.070) | | | (0.049) |
| Electric heater | | | 1.520*** | | | 1.042*** |
| | | | (0.111) | | | (0.108) |
| Traditional stove | | | 0.079 | | | -0.171** |
| | | | (0.057) | | | (0.061) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.06 | 0.13 | 0.21 | 0.05 | 0.12 | 0.21 |
| Number of households | 5,766 | 5,766 | 5,766 | 7,975 | 7,975 | 7,975 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 and 4 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 5 add household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 and 6 further add heating sources in the residence to the specification.

**Table 4.A.13: The subsidy impact on electricity expenses: square root of family size scale adjusted**

| | Winter months | | | Non-winter months | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | -0.359*** | -0.228** | -0.330** | -0.252*** | -0.142*** | -0.013 |
| | (0.060) | (0.064) | (0.084) | (0.016) | (0.023) | (0.047) |
| 2012 | -0.026 | -0.105** | -0.094* | -0.013 | -0.091* | -0.078* |
| | (0.032) | (0.039) | (0.037) | (0.040) | (0.038) | (0.038) |
| 2014 | -0.089** | -0.189*** | -0.174*** | -0.117*** | -0.207*** | -0.192*** |
| | (0.033) | (0.034) | (0.033) | (0.013) | (0.028) | (0.025) |
| 2016 | 0.081** | 0.014 | 0.026 | 0.042 | -0.025 | -0.016 |
| | (0.026) | (0.022) | (0.020) | (0.039) | (0.036) | (0.036) |
| 2018 | -0.002 | -0.093*** | -0.081*** | -0.058** | -0.123*** | -0.112*** |
| | (0.018) | (0.021) | (0.018) | (0.017) | (0.014) | (0.012) |
| Treatment × 2012 | 0.144** | 0.199** | 0.175** | 0.123 | 0.172** | 0.148* |
| | (0.047) | (0.058) | (0.052) | (0.066) | (0.063) | (0.073) |
| Treatment × 2014 | 0.202** | 0.242*** | 0.182** | 0.146*** | 0.188*** | 0.151** |
| | (0.060) | (0.059) | (0.057) | (0.025) | (0.037) | (0.039) |
| Treatment × 2016 | 0.185** | 0.195** | 0.158* | 0.148*** | 0.176*** | 0.154*** |
| | (0.059) | (0.064) | (0.066) | (0.024) | (0.024) | (0.024) |
| Treatment × 2018 | 0.245*** | 0.273*** | 0.213*** | 0.268*** | 0.285*** | 0.221*** |
| | (0.038) | (0.049) | (0.041) | (0.023) | (0.031) | (0.035) |
| Household head's age (years) | | 0.005*** | 0.005*** | | 0.004*** | 0.004*** |
| | | (0.001) | (0.001) | | (0.000) | (0.000) |
| Household head is female | | -0.006 | -0.007 | | -0.009 | -0.010 |
| | | (0.018) | (0.023) | | (0.018) | (0.019) |
| Household head's education (years) | | 0.014*** | 0.011*** | | 0.014*** | 0.012*** |
| | | (0.001) | (0.002) | | (0.001) | (0.001) |
| Household head is married | | -0.032 | -0.032 | | -0.042* | -0.055** |
| | | (0.020) | (0.025) | | (0.018) | (0.020) |
| Share of working members | | 0.137*** | 0.129*** | | 0.108** | 0.105** |
| | | (0.014) | (0.014) | | (0.032) | (0.032) |
| Ln(income) | | 0.059*** | 0.052*** | | 0.050** | 0.042** |
| | | (0.011) | (0.011) | | (0.013) | (0.012) |
| Lives in ger | | -0.222*** | -0.176*** | | -0.195*** | -0.142*** |
| | | (0.012) | (0.009) | | (0.013) | (0.007) |
| Private boiler | | | 0.157* | | | -0.028 |
| | | | (0.072) | | | (0.037) |
| Electric heater | | | 1.507*** | | | 1.037*** |
| | | | (0.110) | | | (0.098) |
| Traditional stove | | | 0.080 | | | -0.170** |
| | | | (0.059) | | | (0.048) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.06 | 0.13 | 0.23 | 0.05 | 0.12 | 0.22 |
| Number of households | 5,766 | 5,766 | 5,766 | 7,975 | 7,975 | 7,975 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 and 4 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 5 add household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 and 6 further add heating sources in the residence to the specification.

**Table 4.A.14: The subsidy impact on electricity expenses: with categorical education**

| | Winter months | | | Non-winter months | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | -0.296** | -0.208** | -0.338** | -0.177*** | -0.112*** | 0.002 |
| | (0.075) | (0.069) | (0.100) | (0.024) | (0.023) | (0.042) |
| 2012 | -0.045 | -0.119** | -0.105** | -0.034 | -0.113** | -0.101** |
| | (0.038) | (0.031) | (0.031) | (0.033) | (0.033) | (0.032) |
| 2014 | -0.133*** | -0.219*** | -0.200*** | -0.161*** | -0.242*** | -0.227*** |
| | (0.032) | (0.028) | (0.028) | (0.006) | (0.020) | (0.016) |
| 2016 | 0.043 | -0.025 | -0.013 | -0.006 | -0.077 | -0.068 |
| | (0.040) | (0.021) | (0.021) | (0.052) | (0.039) | (0.040) |
| 2018 | -0.040 | -0.126*** | -0.113*** | -0.073 | -0.153*** | -0.143*** |
| | (0.030) | (0.015) | (0.013) | (0.037) | (0.018) | (0.018) |
| Treatment × 2012 | 0.156*** | 0.204*** | 0.179*** | 0.116 | 0.175** | 0.151* |
| | (0.034) | (0.044) | (0.038) | (0.060) | (0.057) | (0.065) |
| Treatment × 2014 | 0.190** | 0.248*** | 0.184** | 0.137** | 0.192*** | 0.157*** |
| | (0.062) | (0.059) | (0.056) | (0.036) | (0.037) | (0.036) |
| Treatment × 2016 | 0.186* | 0.210** | 0.170* | 0.132*** | 0.190*** | 0.168*** |
| | (0.078) | (0.069) | (0.070) | (0.033) | (0.029) | (0.026) |
| Treatment × 2018 | 0.261*** | 0.296*** | 0.234*** | 0.255*** | 0.297*** | 0.235*** |
| | (0.058) | (0.056) | (0.047) | (0.031) | (0.031) | (0.035) |
| Household head's age (years) | | 0.003** | 0.003** | | 0.002*** | 0.002*** |
| | | (0.001) | (0.001) | | (0.000) | (0.000) |
| Household head is female | | -0.000 | -0.001 | | -0.006 | -0.007 |
| | | (0.016) | (0.019) | | (0.013) | (0.014) |
| Primary school | | 0.089 | 0.082 | | -0.078 | -0.055 |
| | | (0.069) | (0.071) | | (0.046) | (0.038) |
| Secondary school | | 0.157 | 0.157 | | 0.013 | 0.038 |
| | | (0.109) | (0.111) | | (0.046) | (0.033) |
| High school | | 0.188* | 0.182 | | 0.052 | 0.072** |
| | | (0.090) | (0.093) | | (0.038) | (0.027) |
| Vocational degree | | 0.215* | 0.205* | | 0.075 | 0.087** |
| | | (0.091) | (0.093) | | (0.038) | (0.027) |
| Bachelor | | 0.234* | 0.207 | | 0.132** | 0.134*** |
| | | (0.103) | (0.105) | | (0.043) | (0.027) |
| Master | | 0.236* | 0.201 | | 0.106* | 0.112** |
| | | (0.093) | (0.101) | | (0.046) | (0.040) |
| PhD | | 0.334** | 0.299** | | 0.143** | 0.152** |
| | | (0.090) | (0.099) | | (0.045) | (0.044) |
| Household head is married | | 0.083*** | 0.082** | | 0.078*** | 0.063*** |
| | | (0.019) | (0.024) | | (0.010) | (0.013) |
| Share of working members | | 0.044** | 0.038** | | 0.023 | 0.022 |
| | | (0.012) | (0.011) | | (0.031) | (0.032) |
| Household size | | 0.057*** | 0.059*** | | 0.056*** | 0.059*** |
| | | (0.006) | (0.005) | | (0.006) | (0.006) |
| Ln(income) | | 0.071*** | 0.064*** | | 0.069*** | 0.062*** |
| | | (0.012) | (0.012) | | (0.012) | (0.011) |
| Lives in ger | | -0.228*** | -0.181*** | | -0.196*** | -0.144*** |
| | | (0.015) | (0.009) | | (0.015) | (0.010) |
| Private boiler | | | 0.197** | | | -0.011 |
| | | | (0.071) | | | (0.027) |
| Electric heater | | | 1.506*** | | | 1.008*** |
| | | | (0.104) | | | (0.103) |
| Traditional stove | | | 0.106 | | | -0.156** |
| | | | (0.067) | | | (0.040) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.04 | 0.17 | 0.26 | 0.03 | 0.17 | 0.27 |
| Number of households | 5,766 | 5,766 | 5,766 | 7,975 | 7,975 | 7,975 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 and 4 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 5 add household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 and 6 further add heating sources in the residence to the specification.

**Table 4.A.15: The subsidy impact on electricity expenses: age in quadratic form**

| | Winter months | | | Non-winter months | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | -0.296** | -0.208** | -0.339** | -0.177*** | -0.117*** | 0.004 |
| | (0.075) | (0.067) | (0.099) | (0.024) | (0.021) | (0.039) |
| 2012 | -0.045 | -0.125** | -0.114** | -0.034 | -0.119** | -0.107** |
| | (0.038) | (0.032) | (0.031) | (0.033) | (0.035) | (0.035) |
| 2014 | -0.133*** | -0.226*** | -0.210*** | -0.161*** | -0.247*** | -0.233*** |
| | (0.032) | (0.029) | (0.028) | (0.006) | (0.020) | (0.017) |
| 2016 | 0.043 | -0.026 | -0.014 | -0.006 | -0.074 | -0.066 |
| | (0.040) | (0.019) | (0.020) | (0.052) | (0.039) | (0.040) |
| 2018 | -0.040 | -0.127*** | -0.116*** | -0.073 | -0.150*** | -0.140*** |
| | (0.030) | (0.013) | (0.012) | (0.037) | (0.017) | (0.017) |
| Treatment × 2012 | 0.156*** | 0.209*** | 0.185*** | 0.116 | 0.180** | 0.156* |
| | (0.034) | (0.046) | (0.040) | (0.060) | (0.058) | (0.066) |
| Treatment × 2014 | 0.190** | 0.254*** | 0.194** | 0.137** | 0.198*** | 0.162*** |
| | (0.062) | (0.059) | (0.057) | (0.036) | (0.034) | (0.034) |
| Treatment × 2016 | 0.186* | 0.213** | 0.176* | 0.132*** | 0.188*** | 0.167*** |
| | (0.078) | (0.068) | (0.070) | (0.033) | (0.029) | (0.026) |
| Treatment × 2018 | 0.261*** | 0.299*** | 0.239*** | 0.255*** | 0.296*** | 0.234*** |
| | (0.058) | (0.056) | (0.048) | (0.031) | (0.030) | (0.032) |
| Household head's age ($age^2$) | | 0.000** | 0.000** | | 0.000*** | 0.000*** |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Household head is female | | 0.004 | 0.003 | | -0.003 | -0.004 |
| | | (0.016) | (0.019) | | (0.014) | (0.015) |
| Household head's education (years) | | 0.012*** | 0.009*** | | 0.012*** | 0.010*** |
| | | (0.001) | (0.002) | | (0.001) | (0.001) |
| Household head is married | | 0.086*** | 0.085** | | 0.080*** | 0.065*** |
| | | (0.019) | (0.024) | | (0.011) | (0.013) |
| Share of working members | | 0.044** | 0.038** | | 0.021 | 0.020 |
| | | (0.012) | (0.011) | | (0.032) | (0.033) |
| Household size | | 0.058*** | 0.060*** | | 0.056*** | 0.059*** |
| | | (0.006) | (0.005) | | (0.006) | (0.006) |
| Ln(income) | | 0.071*** | 0.064*** | | 0.070*** | 0.062*** |
| | | (0.013) | (0.012) | | (0.012) | (0.011) |
| Lives in ger | | -0.230*** | -0.183*** | | -0.199*** | -0.147*** |
| | | (0.015) | (0.009) | | (0.015) | (0.009) |
| Private boiler | | | 0.201** | | | -0.016 |
| | | | (0.070) | | | (0.026) |
| Electric heater | | | 1.504*** | | | 1.003*** |
| | | | (0.104) | | | (0.101) |
| Traditional stove | | | 0.109 | | | -0.161** |
| | | | (0.066) | | | (0.041) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.04 | 0.17 | 0.26 | 0.03 | 0.17 | 0.27 |
| Number of households | 5,766 | 5,766 | 5,766 | 7,975 | 7,975 | 7,975 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 and 4 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 5 add household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 and 6 further add heating sources in the residence to the specification.

**Table 4.A.16: The subsidy impact on electricity expenses: year-round**

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Treatment | -0.224*** | -0.152*** | -0.127** |
| | (0.043) | (0.033) | (0.043) |
| 2012 | -0.038 | -0.121*** | -0.109*** |
| | (0.026) | (0.024) | (0.023) |
| 2014 | -0.149*** | -0.237*** | -0.223*** |
| | (0.013) | (0.018) | (0.015) |
| 2016 | 0.017 | -0.051 | -0.041 |
| | (0.043) | (0.027) | (0.028) |
| 2018 | -0.053 | -0.135*** | -0.124*** |
| | (0.033) | (0.010) | (0.011) |
| Treatment × 2012 | 0.131** | 0.190** | 0.165** |
| | (0.046) | (0.051) | (0.055) |
| Treatment × 2014 | 0.158** | 0.218*** | 0.172*** |
| | (0.044) | (0.038) | (0.039) |
| Treatment × 2016 | 0.153** | 0.196*** | 0.167*** |
| | (0.041) | (0.030) | (0.033) |
| Treatment × 2018 | 0.253*** | 0.293*** | 0.230*** |
| | (0.040) | (0.030) | (0.027) |
| Household head's age (years) | | 0.002*** | 0.003*** |
| | | (0.000) | (0.000) |
| Household head is female | | -0.005 | -0.006 |
| | | (0.010) | (0.009) |
| Household head's education (years) | | 0.012*** | 0.010*** |
| | | (0.001) | (0.001) |
| Household head is married | | 0.080*** | 0.071*** |
| | | (0.008) | (0.009) |
| Share of working members | | 0.029 | 0.026 |
| | | (0.020) | (0.020) |
| Household size | | 0.057*** | 0.059*** |
| | | (0.006) | (0.005) |
| Ln(income) | | 0.070*** | 0.063*** |
| | | (0.011) | (0.010) |
| Lives in ger | | -0.211*** | -0.161*** |
| | | (0.011) | (0.008) |
| Private boiler | | | 0.064 |
| | | | (0.041) |
| Electric heater | | | 1.194*** |
| | | | (0.104) |
| Traditional stove | | | -0.057 |
| | | | (0.038) |
| District fixed effects | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.03 | 0.17 | 0.26 |
| Number of households | 13,741 | 13,741 | 13,741 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 runs the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 adds household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 further adds heating sources in the residence to the specification.

**Table 4.A.17: The subsidy impact on electricity expenses: 2012 as the treatment year**

| | Winter months | | | Non-winter months | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | -0.282** | -0.190* | -0.402** | -0.163*** | -0.102*** | 0.089 |
| | (0.087) | (0.078) | (0.112) | (0.023) | (0.017) | (0.071) |
| 2012 | -0.028 | -0.063* | -0.067** | -0.022 | -0.064* | -0.062* |
| | (0.040) | (0.027) | (0.026) | (0.033) | (0.030) | (0.031) |
| Treatment × 2012 | 0.144*** | 0.184*** | 0.184*** | 0.106 | 0.150** | 0.146* |
| | (0.034) | (0.041) | (0.032) | (0.058) | (0.056) | (0.064) |
| Household head's age (years) | | 0.002** | 0.002** | | 0.002* | 0.002* |
| | | (0.001) | (0.001) | | (0.001) | (0.001) |
| Household head is female | | 0.021 | 0.025 | | -0.032 | -0.032 |
| | | (0.040) | (0.039) | | (0.030) | (0.028) |
| Household head's education (years) | | 0.012** | 0.012** | | 0.014*** | 0.012*** |
| | | (0.005) | (0.004) | | (0.002) | (0.002) |
| Household head is married | | 0.083* | 0.081 | | 0.043 | 0.042 |
| | | (0.037) | (0.041) | | (0.023) | (0.024) |
| Share of working members | | 0.113** | 0.106** | | 0.010 | 0.012 |
| | | (0.032) | (0.034) | | (0.019) | (0.019) |
| Household size | | 0.058*** | 0.059*** | | 0.066*** | 0.065*** |
| | | (0.007) | (0.007) | | (0.009) | (0.009) |
| Ln(income) | | 0.026** | 0.027* | | 0.027* | 0.027* |
| | | (0.010) | (0.011) | | (0.012) | (0.012) |
| Lives in ger | | -0.249*** | -0.255*** | | -0.198*** | -0.181*** |
| | | (0.034) | (0.016) | | (0.009) | (0.013) |
| Private boiler | | | 0.065 | | | -0.159** |
| | | | (0.178) | | | (0.058) |
| Electric heater | | | 1.855*** | | | 0.267 |
| | | | (0.293) | | | (0.206) |
| Traditional stove | | | 0.225* | | | -0.212** |
| | | | (0.094) | | | (0.065) |
| District fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Month fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.04 | 0.14 | 0.16 | 0.03 | 0.14 | 0.15 |
| Number of households | 2,102 | 2,102 | 2,102 | 3,021 | 3,021 | 3,021 |

*Notes:* Robust standard errors, clustered at the district level, are presented in the parentheses. * p <0.10, ** p <0.05, *** p <0.01. The reference group is households living in house, have male & unmarried household head and using regular heater for residential heating; the reference year is 2010. Columns 1 and 4 run the basic difference-in-differences model with district, month, and survey year fixed effects. Columns 2 and 5 add household–specific controls to the specification, including the type of residence. The preferred model results in Columns 3 and 6 further add heating sources in the residence to the specification.

# Chapter 5 Conclusion

## 5.1 Main findings

The impacts of natural resource extraction on local communities and the effectiveness of a large electricity subsidy program in reducing illness were examined, using household survey data from Mongolia. The analyses generated several findings consistent with previous literature and provided new insights relevant to policymaking in resource-rich developing countries. The analyses also comprised the first comprehensive empirical work exploring the microeconomic effects of natural resource exploitation and energy subsidies on local communities in Mongolia.

The thesis has three main findings within the development economics literature relating to natural resources and energy. First, mining activities are of benefit to local residents because of their indirect linkages. Households are able to increase expenditures on food, health care, and electricity, and to reduce expenditures on education and non-food consumption. Second, pollution from mining activities increases the likelihood that residents will report illness. Third, large electricity subsidies, designed to reduce the use of coal for heating, significantly reduce the probability of reporting illness for all age groups and affect household preferences for electricity consumption. The contributions and policy recommendations are summarized below for each empirical chapter.

## 5.2 The effects of natural resource extraction on household expenditure patterns: Evidence from Mongolia

Chapter 2 investigates the local impacts of mining activities on household living standards in a resource-producing region. Specifically, the study examines the effects of the mining sector's indirect linkage on various household expenditure categories, including food, health care, electricity, education, and other non-food items. In addition, individual-level analyses were carried out to understand the potential causes of changes in health care and education expenditures. The findings show that households benefit from mining activities and prioritize their expenditure based on basic needs such as food and welfare-enhancing services such as health care. These changes in expenditure patterns, coupled with higher educational attainments, will be vital for the sustainable development of the mining region. The results indicate that the analysis of disaggregated household expenditures provides better estimates of the local impacts of mining activities than traditional welfare measures of household aggregate income and consumption. The findings also emphasize that resource-rich developing countries should ensure that indirect linkages are established in resource-producing regions to increase the benefits of mining activities to local communities, which have limited market capacity.

## 5.3 No pain, no gain? Mining pollution and morbidity

Chapter 3 studies the impacts of mining-induced pollution on the health outcomes of local communities exposed to mining activities. In particular, relying on location-specific pollution data and employing a novel instrumental variable, perceived property rent, the study documents the adverse impacts of pollution from mining on all age groups within five kilometers of mines. Additional analyses on specific age groups, different scales of mining, and mineral types show that younger children suffer the most from mining-induced pollution, while small-scale mines and gold mines generate stronger adverse effects than other mine types. The results highlight that environmental policies and regulations to mitigate/control pollution from mining activities will reduce the health risks to local communities, which may otherwise offset the economic gains realized from mining.

## 5.4 The intended and unintended consequences of electricity subsidies: Evidence from Mongolia

Chapter 4 evaluates the effectiveness of a large electricity subsidy program in increasing access to electricity and improving ambient air quality in a quasi-experiment setting. The analytical results indicate that the policy effectively reduces the likelihood of reporting respiratory illnesses for all ages in the winter season, with the most significant positive effect on younger children. The short-term gains in the general population's health will increase productivity and raise living standards in the future. The eligible households increase their electricity consumption at daytime in winter months and in non-winter months when subsidies are unavailable. The results also highlight that the eligible households change their habit and indicate that the subsidy allows households to switch from dirty energy to clean energy. This change in habit will positively affect the population who bear the costs of air pollution from household coal use. Countries that provide large energy subsidies should consider the unintended benefits of subsidies when weighing benefits against costs.

## 5.5 Future work

As with most research, certain caveats apply to the analytical work undertaken, with those caveats suggesting that further research in related fields is warranted. First, despite the consistent empirical results with previous literature, the three empirical chapters relied on data from Mongolia. While the direction of the impact may hold for other similar countries, there is a need to analyze the local impacts of mining activities using data sets from other regions. Second, the negative externalities of mining activities could be analyzed more widely to include environmental impacts such as the loss of forest land or arable land for herders to assess the impacts on the livelihoods of local populations. Lastly, analyzing the distributional effects of large electricity subsidy will help improve the effectiveness of subsidies on low-income households in Mongolia.

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