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No pain, no gain? Mining pollution and morbidity*

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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.

Keywords: Mining pollution, Health, Development, Mongolia

JEL-Classification: I15, O13, Q53, Q56

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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, 2016; 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.[1] 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.

[1] 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).

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. Finally, consistent with Aragón and Rud (2016) 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 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 describes the empirical strategy and the data employed in the paper. The results from our analysis, including a bunch of robustness checks we conducted, are presented in Section 4. Section 5 discusses the findings, including their policy implications. Section 6 concludes.

2. Background

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).[2]

[2]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).

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).[3] In addition, chronic mercury exposure through dietary intake can cause Minamata disease, renal, 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

[3] 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 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).

of death in mining regions (Cordier et al., 1983; Hendryx and Ahern, 2009).[4] 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).

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.[5] 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.[6] 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).

[4]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).

[5]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).

[6]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).

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).[7] 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 location-specific soil pollution data linked with nationally representative household-level survey data.

3. Methodology

3.1. Model specification

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:

$$y_i = \alpha + \beta\, ln(distance_i) + \boldsymbol{\gamma} \boldsymbol{X}_i + \lambda_s + \eta_t + \varepsilon_i, \tag{1}$$

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 λ indicates 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 η, to capture

[7] 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 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).

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, ε 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.[8]

Our dataset contains information about seven different types of heavy metals at the mining sites. Therefore, a natural extension of Equation (1) is to modify the model to capture the impact of seven different contaminants (heavy metals), as given below:

$$y_i = \alpha + \beta_j \sum_{j=1}^{7} ln(distance_{j,i}) + \boldsymbol{\gamma} \boldsymbol{X}_i + \lambda_s + \eta_t + \varepsilon_i, \tag{2}$$

where everything is the same as Equation (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 (2) separately for every single pollutant.[9]

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):

$$\begin{aligned} y_i &= \alpha + \sum_{j=1}^{7} ln(distance_{ji}^{\beta_j} \times level_{ji}^{\delta_j}) + \boldsymbol{\gamma} \boldsymbol{X}_i + \lambda_s + \eta_t + \varepsilon_i \\ &= \alpha + \sum_{j=1}^{7} \beta_j \, ln(distance_{ji}) + \sum_{j=1}^{7} \delta_j \, ln(level_{ji}) + \boldsymbol{\gamma} \boldsymbol{X}_i + \lambda_s + \eta_t + \varepsilon_i \\ &= \alpha + \beta \, ln(distance_i) + \sum_{j=1}^{7} \delta_j \, ln(level_{ji}) + \boldsymbol{\gamma} \boldsymbol{X}_i + \lambda_s + \eta_t + \varepsilon_i, \end{aligned} \tag{3}$$

[8]There is no consensus in the literature on the exact distance buffer. For example, Aragón and Rud (2016); 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.

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

where, the last step follows Equation (1) and include only distance from the nearest mine to avoid multicollinearity. As evident, compared to Equation (1), Equation (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. Thus, following Currie et al. (2009), we include dummy variables for the heavy metals that are above the permissible levels as given below:

$$y_i = \alpha + \beta \, ln(distance_i) + \sum_{j=1}^{7} \delta_j D_j + \boldsymbol{\gamma} \boldsymbol{X}_i + \lambda_s + \eta_t + \varepsilon_i, \tag{4}$$

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.

3.2. 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).[10] 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).

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

[10] 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.

specification.[11] 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 4.7 for more discussions on this issue.

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. 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).

[11]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.

3.3. Data

3.3.1. Individual morbidity, socioeconomic and demographic data

We use individual morbidity data from the most recent five rounds of the 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 (National Statistics Office, 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.

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.[12] 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 cardio-vascular disease, damage, or intoxication by external impact. The survey also provides information

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

about individuals' expenditure on medication, transportation, hospitalization, and other medical services in the prior 12 months. Table 1 Panel A 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.

[Table 1]

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.

Table 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 2]

To address the endogeneity issues in the primary model discussed in Subsection 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).

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.[13] Their mean values and standard deviations in Table 2 indicate that the control variables are reasonably stable.

3.3.2. 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.[14] 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.[15] 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.[16] 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.

[13] 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.

[14] 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).

[15] 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).

[16] 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).

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.[17] 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 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.

[Figure 1]

Table 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]

[17] 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.

4. Results

4.1. Main results

We estimate Equation (1) to examine whether the distance to the nearest mine affects the likelihood of reporting illness (Table 4). We estimate the model initially with OLS, i.e., employ a linear probability model (LPM). First, we estimate Model (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 (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.[18]

[Table 4]

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).

To address the issue of endogeneity in Model (1), that we have discussed in detail in Subsection 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 F-statistics far exceeds the threshold level 10, the selection criteria for strong instruments, as suggested in Stock et al. (2002). The Durbin-Wu-Hausman test of endogeneity 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

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

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, 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% 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 (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.[19] Table 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.

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

[Table 5]

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 3.3.2 and estimate Model (3). As we have seen in Table 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).

The results in Table 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.

[Table 6]

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. To examine whether addressing the case changes our findings, we use the threshold values reported in MASM (2019) and follow Currie et al. (2009) 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 (4). Results in Table 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.

The results from Tables 4-6 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 (2016) 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 4.7, 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.

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 (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.[20] The estimated model outputs are presented in Table 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.

[Table 7]

4.3. Effect of mining pollution on different age groups

Understanding that Equation (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

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

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 is smaller than adults, and their exposure to pollution may have more severe effects (Currie et al., 2014; Rau et al., 2015; Komisarow and Pakhtigian, 2022).

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 (1) separately with each age group-specific sub-sample. Results in Table 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.

[Table 8]

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).

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 (1) but now the dependent variables are the illnesses related to different types of body systems (Table 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 9]

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.[21]

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.[22] 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.

[21] 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).

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

The results from our analysis that estimates Equation (1) for two sub-samples – official license holders and small scale mines – are presented in Table 10. The baseline model without 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.

[Table 10]

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 (1) separately.

The results from the analysis are reported in Table 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 11]

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 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.[23]

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 4 by using distance in km and arrive at a similar conclusion (Table 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.

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 1 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 2 km of mines provide similar results (Table 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

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

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 A.3).

Fifth, we use the principal component analysis (PCA) technique to capture the effect of various heavy metals in Model (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 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 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 A.6). Adding quarter fixed effects, to control for seasonality and quarterly factors and events, provide comparable results (Table A.7). Controlling for the seasonality in illness, by adding month fixed effects, also generate similar results (Table A.8).

Eighth, we redo the analysis with job sector fixed effects and mine numbers in Model (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 A.9).

Finally, we employ different forms of control variables. This includes categorical controls for age (Table A.10) and education (Table 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 A.12–A.15). We also repeat the analysis by excluding some missing values that we currently include in the analysis sample (Table 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.

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.[24] 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 (2016) 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 policies and regulations to reduce pollution and therefore the health risks in resource-rich developing countries.

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.

[24]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.

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 bear the burden of environmental pollution on their health most significantly. Living nearby artisanal and small-scale mining operations and gold mines increases the likelihood of becoming unwell more significantly.

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 and mitigating the pollution generated by the mining activities. Policies that curb environmental pollution and mitigate their adverse impact will significantly lower the health risks to the local population and enhance the social and economic benefits of the extractive industry, especially in the long run.

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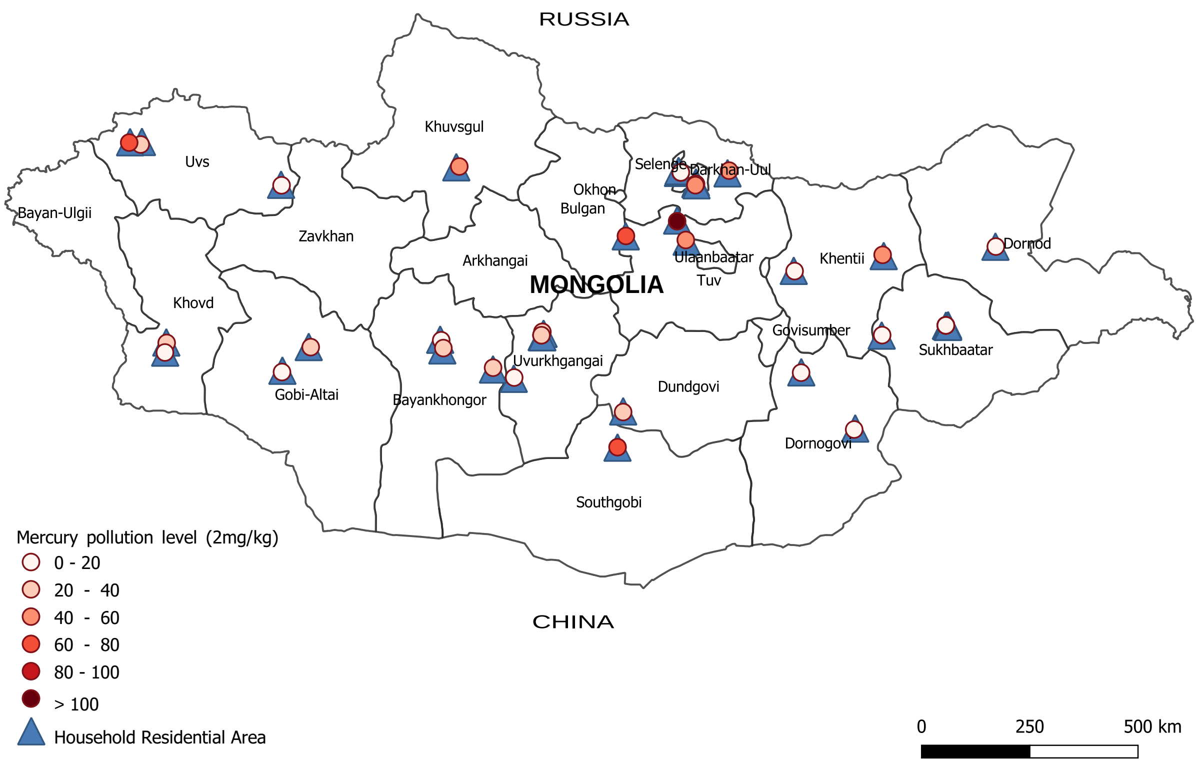
Figures



Source: Authors' compilation

Figure 1: Geographic distribution of household residential areas and mercury contamination at mining sites

Tables

Table 1: **Summary statistics of outcome variables**

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

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.

Table 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.

Table 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.

Table 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.

Table 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 6: **IV estimate of the effect of mining pollution on illness: including the level of pollution in the model**

	Pollution level		Non-linear 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.

Table 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.

Table 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.

Table 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.

Table 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.

Table 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.

Additional tables

Table A.1: **The effect of mining pollution on illness: Using 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 A.2: **IV estimate of the effect of mining pollution on sickness: using 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 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 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 A.5: **The effect of mining pollution on illness: using 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 A.6: **The effect of mining pollution on illness: using 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 A.7: **The effect of mining pollution on sickness: using 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 A.8: **The effect of mining pollution on sickness: using 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 A.9: **The effect of mining pollution on illness: using 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 A.10: **The effect of mining pollution on illness: using 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 A.11: **The effect of mining pollution on illness: using 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 A.12: **The effect of mining pollution on illness: using 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 A.13: **The effect of mining pollution on illness: using 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 A.14: **The effect of mining pollution on illness: using 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 A.15: **The effect of mining pollution on illness: using 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 A.16: **The effect of mining pollution on illness: sample with 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.