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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 ve 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 e ects on

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

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). 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, of death in mining regions (Cordier et al., 1983;

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 (Pfei er et al., 2015).[7]

the impact of duration of exposure. It will also control for the overtime change in illness that are originated from di erent time-varying events. Finally, 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:

$$y_i = \quad + \quad \ln(\text{distance}_i) + \sum_{j=1}^{7} {}_j D_j + X \, {}_i + \, {}_s + \, {}_t + \varepsilon_i; \tag{4}$$

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 activir 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.

3.3. Data

3.3.1. Individual morbidity, socioeconomic and demographic data

We use individual morbidity data from the most recent ve rounds of the Household Socio-Economic Survey (HSES), a nationally representative cross-sectional survey conducted every two years by the National Statistics O ce of Mongolia. The survey uses a strati ed two-stage sample design based on

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

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

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[T3u

(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.

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 con rm that the methods, models, and data used in 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.

References

Adams, P., Hurd, M. D., McFadden, D., Merrill, A., and Ribeiro, T. (2003). Healthy, wealthy, and wise? Tests for direct causal paths between health and socioeconomic status. *Journal of Econometrics*, 112(1):3–56.

Anderson, M. L. (2020). As the wind blows: The effects of long-term exposure to air pollution on mortality. *Journal of the European Economic Association*, 18(4):1886–1927.

Aragon, F. M. and Rud, J. P. (2016). Polluting industries and agricultural productivity: Evidence from mining in Ghana. *Economic Journal*, 126(597):1980–2011.

ATSDR (2007). Arsenic CAS:7440-38-2. Public health statement, Agency for Toxic Substances and Disease Registry, Division of Toxicology and Environmental Medicine, Public Health Service, U.S. Department of Health and Human Services, Atlanta, Georgia, USA. Available from: https://bit.ly/3qR62Ve [Accessed on: 12 August 2020].

Baatarzorig, T., Galindev, R., and Maisonnave, H. (2018). Effects of ups and downs of the Mongolian mining sector. *Environment and Development Economics*, 23(5):527–542.

Banerjee, A. V. and Duflo, E. (2019). *Good Economics for Hard Times*. Public Affairs, New York, USA.

Banzhaf, H. S. and Walsh, R. P. (2008). Do people vote with their feet? An empirical test of Tiebout. *American Economic Review*, 98(3):843–63.

Battogtokh, B., Lee, J. M., and Woo, N. (2014). Contamination of water and soil by the Erdenet copper–molybdenum mine in Mongolia. *Environmental Earth Sciences*, 71(8):3363–3374.

Bazillier, R. and Girard, V. (2020). The gold digger and the machine. Evidence on the distributive effect of the artisanal and industrial gold rushes in Burkina Faso. *Journal of Development Economics*, 143:102411.

Billings, S. B. and Schnepel, K. T. (2017). The value of a healthy home: Lead paint remediation and housing values. *Journal of Public Economics*, 153:69–81.

Bundschuh, J., Schneider, J., Alam, M. A., Niazi, N. K., Herath, I., Parvez, F., Tomaszewska, B., Guilherme, L. R. G., Maity, J. P., Lopez, D. L., et al. (2021). Seven potential sources of arsenic pollution in Latin America and their environmental and health impacts. *Science of the Total Environment*, 780:146274.

Burke, M., Heft-Neal, S., Li, J., Driscoll, A., Baylis, P., Stigler, M., Weill, J., Burney, J., Wen, J., and Childs, M. (2021). Exposures and behavioral responses to wildfire smoke. NBER Working Paper 29380, National Bureau of Economic Research, MA, USA.

Burström, B., Diderichsen, F., and Smedman, L. (1999). Child mortality in Stockholm during 1885–1910: The impact of household size and number of children in the family on the risk of death from measles.

Graff Zivin, J. and Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7):3652–73.

Graff Zivin, J. and Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, 51(3):689–730.

Greenstone, M. and Hanna, R. (2014). Environmental regulations, air and water pollution, and infant mortality in India. *American Economic Review*, 104(10):3038–72.

Greenstone, M. and Jack, B. K. (2015). Envirodevonomics: A research agenda for an emerging field. *Journal of Economic Literature*, 53(1):5–42.

Hanna, R. and Oliva, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics*, 122:68–79.

Harada, M., Nakachi, S., Cheu, T., Hamada, H., Ono, Y., Tsuda, T., Yanagida, K., Kizaki, T., and Ohno, H. (1999). Monitoring of mercury pollution in Tanzania: Relation between head hair mercury and health. *Science of the Total Environment*, 227(2-3):249–256.

Hayashi, F. (2000). *Econometrics*. Princeton University Press, New Jersey, USA.

He, X., Luo, Z., and Zhang, J. (2022). The impact of air pollution on movie theater admissions. *Journal of Environmental Economics and Management*, 112:102626.

Hendryx, M. and Ahern, M. M. (2009). Mortality in Appalachian coal mining regions: The value of statistical life lost. *Public Health Reports*, 124(4):541–550.

Hendryx, M., Islam, M. S., Dong, G.-H., and Paul, G. (2020). Air pollution emissions 2008–2018 from Australian coal mining: Implications for public and occupational health. *International Journal of Environmental Research and Public Health*, 17(5):1570.

Hill, E. L. (2018). Shale gas development and infant health: Evidence from Pennsylvania. *Journal of Health Economics*, 61:134–150.

HRC and SDC (2012). The human rights situation in small-scale mining in Mongolia. Research report, Human Rights Commission (HRC) and Swiss Agency for Development and Cooperation (SDC), Ulaanbaatar, Mongolia. Available from: https://bit.ly/2RsfbGU [Accessed on: 17 May 2021].

Järup, L. (2003). Hazards of heavy metal contamination. *British Medical Bulletin*, 68(1):167–182.

Jolliffe, I. T. and Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A*, 374(2065):20150202.

Khan, K. M., Chakraborty, R., Bundschuh, J., Bhattacharya, P., and Parvez, F. (2020). Health effects of arsenic exposure in Latin America: An overview of the past eight years of research. *Science of the Total Environment*, 710:136071.

Kiel, K. A. and McClain, K. T. (1995). House prices during siting decision stages: The case of an incinerator from rumor through operation. Journal of Environmental Economics and Management, 28(2):241{255.

Komisarow, S. and Pakhtigian, E. L. (2022). Are power plant closures a breath of fresh air? Local air quality and school absences. Journal of Environmental Economics and Management, 112:102569.

Kristensen, A. K. B., Thomsen, J. F., and Mikkelsen, S. (2014). A review of mercury exposure among artisanal small-scale gold miners in developing countries. International Archives of Occupational and Environmental Health, 87(6):579{590.

Landrigan, P. J., Fuller, R., Acosta, N. J., Adeyi, O., Arnold, R., Balde, A. B., Bertollini, R., Bose-O'Reilly, S., Bou ord, J. I., and Breysse, P. N. (2018). The Lancet Commission on pollution and health. Lancet, 391(10119):462{512.

Lavaine, E. (2019). Environmental risk and di erentiated housing values: Evidence from the north of France. Journal of Housing Economics, 44:74{87.

Lee, J.-S., Lee, S.-W., Chon, H.-T., and Kim, K.-W. (2008). Evaluation of human exposure to arsenic due to rice ingestion in the vicinity of abandoned Myungbong Au{Ag mine site, Korea. Journal of Geochemical Exploration, 96(2-3):231{235.

Levasseur, P., Erdlenbruch, K., and Gramaglia, C. (2021). The health and socioeconomic costs of exposure to soil pollution: Evidence from three polluted mining and industrial sites in Europe. Journal of Public Health, pages 1{14.

Li, B. G., Gupta, P., and Yu, J. (2017). From natural resource boom to sustainable economic growth: Lessons from Mongolia. International Economics, 151:7{25.

Li, Z., Ma, Z., van der Kuijp, T. J., Yuan, Z., and Huang, L. (2014). A review of soil heavy metal pollution from mines in China: Pollution and health risk assessment. Science of the Total Environment, 468:843{853.

Lim, H. E., Shim, J. J., Lee, S. Y., Lee, S. H., Kang, S. Y., Jo, J. Y., In, K. H., Kim, H. G., Yoo, S. H., and Kang, K. H. (1998). Mercury inhalation poisoning and acute lung injury. Korean Journal of Internal Medicine, 13(2):127.

Liu, C.-p., Luo, C.-l., Gao, Y., Li, F.-b., Lin, L.-w., Wu, C.-a., and Li, X.-d. (2010). Arsenic contamination and potential health risk implications at an abandoned tungsten mine, southern China. Environmental Pollution, 158(3):820{826.

Marcus, M. (2021). Going beneath the surface: Petroleum pollution, regulation, and health. American Economic Journal: Applied Economics, 13(1):1{37.

MASM (2019). Soil quality. Soil Pollutants Permissible Value MNS 5850:2019. Mongolian National Standard, Mongolian Agency for Standardization and Meteorology (MASM), Ulaanbaatar, Mongolia. Available from: https://bit.ly/37Q9XsZ [Accessed on: 12 August 2020].

National Statistics Office (2016). Mongolian Statistical Yearbook 2016. Report, NSO, National Statistics Office, Ulaanbaatar, Mongolia.

National Statistics Office (2018). Mongolia Household Socio-Economic Survey 2016. Report, NSO, National Statistics Office, Ulaanbaatar, Mongolia.

Neidell, M. J. (2004). Air pollution, health, and socio-economic status: The effect of outdoor air quality on childhood asthma. *Journal of Health Economics*, 23(6):1209–1236.

Offermann, P. V. and Finley, C. J. (1992). Metal fume fever. *Annals of Emergency Medicine*, 21(7):872–875.

Ongley, L. K., Sherman, L., Armienta, A., Concilio, A., and Salinas, C. F. (2007). Arsenic in the soils of Zimapán, Mexico. *Environmental Pollution*, 145(3):793–799.

Palacios, J., Eichholtz, P., Kok, N., and Aydin, E. (2021). The impact of housing conditions on health outcomes. *Real Estate Economics*, 49(4):1172–1200.

Parker, D. P., Foltz, J. D., and Elsea, D. (2016). Unintended consequences of sanctions for human rights: Conflict minerals and infant mortality. *Journal of Law and Economics*, 59(4):731–774.

Pfeiffer, M., Batbayar, G., Hofmann, J., Siegfried, K., Karthe, D., and Hahn-Tomer, S. (2015). Investigating arsenic (As) occurrence and sources in ground, surface, waste and drinking water in northern Mongolia. *Environmental Earth Sciences*, 73(2):649–662.

Pfeiffer, M., Vanya, D., Davison, C., Lkhagvasuren, O., Johnston, L., and Janes, C. R. (2017). Harnessing opportunities for good governance of health impacts of mining projects in Mongolia: Results of a global partnership. *Globalization and Health*, 13(1):1–13.

Power, M. C., Weisskopf, M. G., Alexeeff, S. E., Coull, B. A., Spiro III, A., and Schwartz, J. (2011). Traffic-related air pollution and cognitive function in a cohort of older men. *Environmental Health Perspectives*, 119(5):682–687.

Ragchaa, G., Enkhbat, T., and Lkhamsuren, E. (2018). Arsenic and heavy metals contamination of soils around Oyu-Tolgoi and Tavan-Tolgoi mines, located in the South Gobi desert of Mongolia. *International Journal of Engineering & Technology*, 7(2.23):260–262.

Rau, T., Urzúa, S., and Reyes, L. (2015). Early exposure to hazardous waste and academic achievement: Evidence from a case of environmental negligence. *Journal of the Association of Environmental and Resource Economists*, 2(4):527–563.

Rodrigues, S. M. and Römkens, P. F. (2018). Human health risks and soil pollution. In Duarte, A. C., Cachada, A., and Rocha-Santos, T., editors, *Soil Pollution*, pages 217{250. Academic Press.

Ross, C. E. and Wu, C.-L. (1996). Education, age, and the cumulative advantage in health *Journal of Health and Social Behavior*, 37(1):104{120.

Rowens, B., Guerrero-Betancourt, D., Gottlieb, C. A., Boyes, R. J., and Eichenhorn, M. S. (1991). Respiratory failure and death following acute inhalation of mercury vapor: A clinical and histologic perspective. *Chest*, 99(1):185{190.

SDC (2018). SAM Factsheet 2018. Factsheet, Swiss Agency for Development and Cooperation in Mongolia (SDC), Ulaanbaatar, Mongolia. Available from: https://bit.ly/3rqtlaX [Accessed: 04 Feb, 2022].

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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	7,682
	(0.27)	
Respiratory system illness	0.02	7,682
	(0.15)	
Digestive system illness	0.01	7,682
	(0.09)	
External impact & other illness	0.04	7,682
	(0.19)	
Household medical expenditures	13.51	7,682
	(26.69)	
Panel B: Illness level for suw2M1di76p		

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

Table 3: Proportion of households exposed to di erent 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 e ect 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)

Table 5: IV estimate of the e ect 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 xed e ects	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 xed e ects, individual{speci c controls, including wall and roof type of residence and rural status. Marginal e ects are calculated at the mean values of all other covariates.

Table 6: IV estimate of the e ect 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)

Table 7: IV estimate of the e ect 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 xed e ects	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 xed e ects. Columns 2 adds individual{speci c controls to the speci cation, including rural status of residence. Columns 3 further adds wall and roof type to the model.

Table 8: IV estimate of the e ect of mining pollution on illness for di erent 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 xed e ects	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 xed e ects. Columns 2,4 and 6 add individual{speci c controls to the speci cation, including wall and roof type of residence and rural status. Marginal e ects are calculated at the mean values of all other covariates.

Table 9:

Table 10: IV estimate of the e ect of mining pollution on illness:
e ect 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 xed e ects	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

Table 11: IV estimate of the e ect of mining pollution on illness: e ect 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 xed e ects	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 <

Additional tables

Table A.1: The e ect 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)

Table A.2: IV estimate of the e ect 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 xed e ects	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 xed e ects. Columns 2 and 4 add individual{speci c controls to the speci cation, including wall and roof type of residence and rural status. Marginal e ects are calculated at the mean values of all other covariates.

Table A.3: IV estimate of the e ect 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 xed e ects	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 xed e ects. Columns 2 and 4 add individual{speci c controls to the speci cation, including wall and roof type of residence and rural status. Marginal e ects are calculated at the mean values of all other covariates.

Table A.4: IV estimate of the e ect 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 xed e ects	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 xed e ects. Columns 2 adds individual{speci c controls to the speci cation, including wall and roof type of residence and rural status. Marginal e ects are calculated at the mean values of all other covariates.

Table A.5: The e ect of mining pollution on illness: using mine- xed e ects

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 xed e ects	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:

Table A.6: The e ect of mining pollution on illness: using interaction of province and year xed e ects

Table A.7: The e ect of mining pollution on sickness: using quarter- xed e ects

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

Table A.8: The e ect of mining pollution on sickness: using month- xed e ects

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		

Table A.9: The e ect of mining pollution on illness: using job sector xed e ects & 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 (yis.955 T78510.017								

Table A.10: The e ect 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)		(0.038e325 6.9738 Tf 22.6718 51		

Table A.11: The e ect of mining pollution on illness: using education categories

Table A.12: The e ect 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 xed e ects	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 xed e ects. Columns 2,4,6 and 8 add individual{speci c controls to the speci cation, including wall and roof type of residence and rural status. Marginal e ects 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

Table A.14: The e ect 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 xed e ects	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 xed e ects. Columns 2,4,6 and 8 add individual{speci c controls to the speci cation, including wall and roof type of residence and rural status. Marginal e ects are calculated at the mean values of all other covariates.

Table A.15: The e ect 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 xed e ects	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 xed e ects. Columns 2,4,6 and 8 add individual{speci c controls to the speci cation, including wall and roof type of residence and rural status. Marginal e ects are calculated at the mean values of all other covariates.

Table A.16: The e ect 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