

The Impact of Mining-Induced Earthquakes on Mental Health: Evidence from the Dutch Lifelines Cohort Study and Biobank

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Abstract

A large body of literature demonstrates that exposure to major adverse events such as natural disasters affects physical and mental health. Less is known about health consequences of long-term exposure to smaller, recurring shocks such as mining-induced earthquakes. Leveraging data from the Dutch Lifelines Cohort Study and Biobank and the Royal Netherlands Meteorological Institute, we examine mental health effects of frequent earthquakes generated by the extraction of natural gas, which was a major source of economic revenue for the Netherlands. Long-term exposure is captured by the accumulated peak ground acceleration. We employ individual-level fixed effects models to deal with selective exposure. We find that exposure increases depression and anxiety symptoms. Our results are robust to selective migration and to varying the exposure indicator. The results support a reassessment of the societal costs of the mining of natural gas.

Keywords: Mining-induced earthquakes, Mental health, Gas-extraction

JEL classification: I10, I18, Q33, Q53

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Data Statement: Data may be obtained from a third party and are not publicly available. Researchers can apply to use the Lifelines data used in this study. Information on access to Lifelines data and the conditions of use are available on their website (<https://www.lifelines-biobank.com/researchers/working-with-us>).

1 Introduction

The extraction of natural gas as a source of energy has been a major driver of global economic development since the 1950s. This has brought large economic benefits for gas-producing countries such as the Netherlands, Norway and Qatar (Black et al., 2021; Joskow, 2013). The largest gasfield in Europe to date, which was located in the province of Groningen, the Netherlands, and came into production in 1963, has contributed several percentage points of annual GDP for many years (Van der Voort and Vanclay, 2015). According to CBS (2019), total state revenues from natural gas extraction in the Netherlands in 1965-2019 amount to 417 billion euros in 2018 prices. As recently as 2011, the Groningen gasfield contributed over 10 billion euros to the state budget (Van der Voort and Vanclay, 2015). With the continuous growth in global energy demand and the change in energy consumption structure, natural gas will remain a key player in the energy transition until 2050 (Gas Exporting Countries Forum, 2023). In particular, the recent shale gas revolution has triggered a remarkable surge in gas production (Koster and Van Ommeren, 2015).

Notwithstanding economic benefits, gas extraction goes along with a series of negative externalities and risks to local communities, including air pollution, water contamination, and induced earthquakes (Black et al., 2021; Hill and Ma, 2017; Hill, 2018). Notably, both conventional gas extraction (through a drilled well) and shale gas extraction through fracking can cause earthquakes. As a case in point, the gas extraction in Groningen has given rise to over 1,700 mining-induced earthquakes. These earthquakes have caused substantial societal unrest among the inhabitants (Stroebe et al., 2021b; Van der Voort and Vanclay, 2015).

In light of the above, in this paper, we examine mental health effects of repeated earthquakes induced by gas extraction. It is well known that exposure to catastrophic events, such as major natural (non-induced) earthquakes, affects mental health, as those events instantly endanger property and human life (Dai et al., 2016; Goldmann and Galea, 2014; Neria et al., 2008; Noji, 2000; Ripoll Gallardo et al., 2018). However, much less is known about health consequences of long-term exposure to smaller, recurring shocks such as mining-induced earthquakes. Mining-induced earthquakes differ from natural earthquakes, as they are moderate in magnitude, but they occur at a much higher frequency. Moreover, their shallow depth typically results in higher-intensity shaking. Regarding the potential health effects it is also important to emphasize their human-made nature. McComas et al. (2016) find that people tend to have more negative feelings about induced earthquakes motivated by economic needs than about natural occurring earthquakes. In sum, we may

expect repeated exposure to lead to chronic stress which may in turn develop into mental health conditions such as depression, anxiety, and post-traumatic stress disorder.

The adverse mental health impacts of mining-induced earthquakes may be driven by several factors. First, they increase economic and financial stress. Empirical studies show that earthquakes reduce local housing prices by causing property damage and raising concerns about future risks, thereby burdening homeowners with economic insecurity (Cheung et al., 2018; Durán, 2022; Koster and Van Ommeren, 2015; Stroebe et al., 2022, 2021a). Given the well-established link between financial strain and mental health problems (Ryu and Fan, 2023), such economic stressors may directly contribute to psychological distress. Second, repeated earthquakes elevate feelings of insecurity and the perception of risk. Although typically of moderate magnitude, the repetitive nature of these events intensifies fear and undermines residents' sense of safety (Stroebe et al., 2022; Van der Voort and Vanclay, 2015).

Third, mental health impacts may be amplified by growing distrust in institutions. Slow, inconsistent, and often inadequate responses by the gas extraction company NAM and governmental bodies have fostered frustration and uncertainty, particularly in light of complex and long compensation procedures (Kathmann et al., 2023; Van der Voort and Vanclay, 2015). Fourth, displacement and disruption of social ties may further compound distress. Displacement due to structural damage, prolonged repair timelines, and relocation breaks up community networks and erodes social cohesion, which are factors crucial for resilience in the face of repeated disasters (Kathmann et al., 2023; Stroebe et al., 2021b). Finally, physical injuries and their psychological aftermath might represent a potential link, although reports of physical injuries are rare in the case of the Groningen earthquakes (Van der Voort and Vanclay, 2015). Each of these pathways can provoke negative emotional responses and chronic stress, which, if sufficiently intense, may result in adverse mental health outcomes.

The relevance of the paper extends beyond induced earthquakes. Specifically, our findings on long-term exposure to moderate shocks, where each individual shock is unpredictable but the overall frequency is high, may be relevant for studying the health consequences of shocks with different origins. This includes climate and weather-related disasters such as floods, hurricanes, and typhoons. Although their frequency may not match that of mining-induced earthquakes, these events can recur over extended periods in certain regions. The relevance is likely to be particularly strong when the shocks involve property damage and the resulting financial stress. Our findings

may also be relevant for understanding the impacts of chronic exposures such as high temperatures, air pollution, and background white noise (e.g, wind turbines), even though these stressors may not be unpredictable in the same way.

Our empirical analysis focuses on earthquakes in the Groningen gasfield. To this end, we use the nationwide earthquake dataset of the Royal Netherlands Meteorological Institute (KNMI) with precise information on the timing, geographical coordinates, depth and severity of all earthquakes. Individual mental health outcomes and other relevant characteristics are obtained from Lifelines, which is a longitudinal survey and biobank with extensive health and medical information, of around 167,000 individuals in the three Northern provinces of the Netherlands (of which the province of Groningen is the northernmost). Lifelines data collection started in 2007, so that the period with most earthquakes (2010-2018) is included. Individuals and earthquakes are linked using four-digit postal codes of individual residences.¹

The exposure measures are based on the so-called peak ground acceleration (PGA) of an earthquake. This is the default measure of the strength of shaking during an earthquake, reflecting how much force an individual feels pushing or pulling them, where this of course depends on the distance to the epicenter. Higher PGA means stronger and more intense shaking, which is more likely to cause damage to buildings and infrastructure. We time-aggregate PGA over specified periods to quantify cumulative individual exposure measures.

In our baseline analyses, the individual exposure indicators at time t are based on this cumulative measure (up to t). It seems natural to use a measure that reflects that stress accumulates over time, as the number and severity of experienced earthquakes increases over time. In this context it is important to point out that the first earthquakes were very mild and occurred few and far between, and in that period a relation with gas extraction was not officially recognized, so that the first moment of exposure is not a sensible indicator in the analyses. It is also important to point out that until very recently, a serious reduction of gas mining in Groningen was not in sight. We test the robustness of the results by applying alternative temporal and spatial restrictions to cumulative PGA. We also consider the raw number of past earthquakes experienced, instead of cumulative PGA.

¹The Netherlands has 12 provinces and 4,053 four-digit postal codes (2022). The latter typically cover a village or a small area within a city. This geographical unit is sufficiently small for our purposes, as its diameter is usually negligible as compared to the distance to the earthquake epicenters. The Northern part of the Netherlands is a tectonically inactive region, so buildings were not specifically designed to withstand earthquakes.

We measure mental health outcomes using the Mini International Neuropsychiatric Interview (MINI), a widely recognized, simple, valid, and reliable tool for diagnosing psychiatric disorders. Specifically, we focus on the number of symptoms related to depression and anxiety. Additionally, we assess self-rated health (SRH) as designed in the RAND-36 survey. We employ individual-level fixed-effects panel-data regression models to estimate the effects of interest. The fixed effects enable us to deal with selective exposure across individuals and locations. We pay special attention to out-migration out of the affected areas. Specifically, we quantify such migration patterns, and we repeat the main analyses with a restricted sample of non-movers.

We find significant evidence of negative effects of mining-induced earthquakes on the number of depression and anxiety symptoms. Specifically, a one-unit increase in three-year accumulated PGA results in a 0.0426 increase in depression symptoms and a 0.0547 increase in anxiety symptoms, where one unit of accumulated PGA corresponds to roughly 5 earthquakes with a magnitude of 2.5, a depth of 3 km, and an epicentral distance of 2 km. For depression symptoms, this translates into a 0.79% increase in the probability of experiencing a depressed mood, a 1.15% increase in loss of interest, and a 0.75% increase in difficulty concentrating. For anxiety symptoms, the same increase in PGA leads to a 1.04% rise in restlessness and a 1.51% rise in feelings of tension. Given the population residing in the affected area, the overall mental health burden can be substantial.² Excluding people who migrate out of the region amplifies the observed effects of earthquakes on anxiety symptoms, suggesting a potential bias from exposure misclassification and selection if this is ignored.

Over the past decade, an emerging literature has dealt with the material and health consequences of Groningen earthquakes. Widespread and significant property damage such as visible cracks and damage to walls and beams are reported in e.g. [Kathmann et al. \(2023\)](#); [Koster and Van Ommeren \(2015\)](#); [Trip and Romein \(2019\)](#). Declines in property values and increases in repair costs are documented in [Durán \(2022\)](#); [Koster and Van Ommeren \(2015\)](#). The slowness with which the earthquakes led the government to reduce gas extraction, as well as the lack of adequate compensation policies for property damage, have been documented in e.g. [Kathmann et al. \(2023\)](#). Over time, these negative policy responses have led to a loss of trust in the authorities among affected residents ([Van der Voort and Vanclay, 2015](#)). Thus, what began as a human-made disaster

²Assuming that 10,000 residents are exposed to earthquakes with a cumulative PGA of one, we estimate the following increases in mental health symptom cases: 79 cases of depressed mood, 115 cases of loss of interest, 75 cases of difficulty concentrating, 104 cases of restlessness, and 151 cases of tension.

has evolved into a broader social and political issue, and this may have caused additional distress among affected residents.

The public health literature contains two studies that consider health outcomes of individuals affected by the Groningen earthquakes. [Dückers et al. \(2021\)](#) measures health outcomes by numbers of diagnoses made by general practitioners at the neighborhood level. These data cover a relatively short period (2010-2015), and clinical diagnoses from general practitioners generally reflect severe mental health effects. [Dückers et al. \(2021\)](#) find an almost instantaneous effect of earthquakes on suicides. Longer-term exposure is captured by an indicator for having experienced no, one or more than one earthquake. It is found that effects are mostly medium-run, with a reduction after a few years, which they argue may reflect health adaptation. However, their observation window closes in 2015 and does not deal with individual-level changes and movements over time. [Stroebe et al. \(2021b\)](#) collected longitudinal survey data covering a period of almost two years (2016-2017). Around 2000 respondents participate in all waves. Health indicators are based on self-reported variables. Using a multilevel modeling approach, the authors find a negative association between past exposure and current health (including negative mental health).³

This paper makes several contributions to the literature. First, it integrates comprehensive earthquake data with a large-scale, individual-level cohort study to examine the mental health impacts of mining-induced earthquakes. Second, it advances understanding of the health effects of small, repeated earthquakes caused by human activity, complementing prior research that has primarily focused on the impacts of natural disasters.

2 Gas Extraction and Induced Earthquakes in the Northern Netherlands

The Groningen field, located in the Northern Netherlands, is one of the largest gasfields in the world. It was discovered in 1959, and extensive extraction activities began in 1963. During the global energy crisis of the 1970s, underground drilling activities rapidly increased to meet consumption demands. Approximately 20 years after 1963, mining-induced earthquakes began occurring above

³Our study can also be related to the literature in resource/environmental economics that examines the health impact of energy mining and environmental externalities. This includes effects of shale gas extraction; see e.g. [Hill \(2018, 2024\)](#). Some of these examine the indirect impact on, for example, drinking water quality ([Hill and Ma, 2017](#)), and light pollution ([Boslett et al., 2021](#)). Even more broadly, there is a connection to studies that assess the health impact of infrastructure such as airports ([Passchier et al., 2000](#)), highways ([Anderson, 2020](#)), and onshore wind turbines ([Krekel et al., 2023](#)).

the Groningen gas field. A notable turning point occurred in 1986 when an earthquake near Assen, in the neighboring province of Drenthe, occurred. Although the Northern Netherlands historically experienced virtually no natural earthquakes, the Royal Netherlands Meteorological Institute and Nederlandse Aardolie Maatschappij (NAM) denied that the earthquake was a consequence of gas extraction.⁴ However, in 1993, a scientific study by the Supervisory Committee of Research into Earthquakes (BOA) provided evidence linking earthquakes to gas extraction, prompting KNMI and NAM to acknowledge the connection. Because NAM was legally responsible for damages, the Dutch government wanted to avoid direct involvement in compensation in the early stages of the earthquake events ([Kathmann et al., 2023](#)).

Another turning point occurred in August 2012 when a significant earthquake with a magnitude of 3.6 on the Richter scale happened in the village Huizinge in the province of Groningen. Since then, induced earthquakes have gathered considerable attention from local inhabitants, communities, and the government. Worries increased further after the biggest one happened ([Van der Voort and Vanclay, 2015](#)). Subsequently, the number of damage claims and reinforcement requests increased sharply. However, residents still face challenges in navigating compensation regulations and claim processes, and the number of claims leads to long claim processing times. In response to growing dissatisfaction and complaints in 2018, the government assumed responsibility for claims instead of NAM. By the end of 2022, 267,466 claims had been received regarding earthquake damage ([Kathmann et al., 2023](#)). In February 2021, the House of Representatives established a parliamentary inquiry committee to investigate the natural gas extraction in the Groningen region, earthquakes, damage claims, and the reinforcement of houses. In February 2023, the committee presented its report, titled Groningers Before Gas – Conclusions and Recommendations, to the House of Representatives ([House of Representatives of the Netherlands, 2023](#)). In 2023, production at the Groningen gas field was ceased, and in April 2024 the Dutch Senate passed legislation to permanently close the field as of 1 October 2024. Nevertheless, induced earthquakes are expected to continue for a considerable period even after production has ceased.

⁴NAM, English name Netherlands Petroleum Company, is an exploration and production company in the Netherlands, set up in 1947 by Shell and Esso. It played a major role in the extraction of the Groningen gasfield ([Van der Voort and Vanclay, 2015](#)).

3 Data

3.1 Earthquake Exposure

Our analysis is based on data of by the Royal Netherlands Meteorological Institute, containing comprehensive information on all recorded earthquakes in the Netherlands since 1986. This dataset includes details such as the earthquake’s location (latitude and longitude), precise timing (to the second), date, magnitude (Richter scale), depth (in meters), and type (natural or induced). Figure 1 illustrates the frequency of earthquakes with magnitudes greater than 1 and greater than 2 in the Northern Netherlands.

The impact of earthquakes depends on factors such as magnitude, depth, and distance from the hypocenter. Previous studies have employed various metrics to assess exposure to mining-induced earthquakes. These include the number of noticeable earthquakes (Casey et al., 2019; Dückers et al., 2021), magnitude, frequency of property damage (Stroebe et al., 2021a), and earthquake intensity indicators, such as peak ground velocity (PGV)⁵ (Durán, 2022; Koster and Van Ommeren, 2015) and peak ground acceleration (PGA) (Stroebe et al., 2021a).

To approximate the intensity of each earthquake at a specific location, we calculate the PGA by considering the hypocentral distance between the individual’s location (at the Postal Code-4 level) and the earthquake hypocenter,⁶ as well as the earthquake’s magnitude and depth. We select PGA as our measure for three primary reasons. First, single indicators, such as the count of earthquakes within a defined area and time frame, may fail to fully capture the intensity of seismic events because these measurements do not account for the epicentral and hypocentral distance. Second, humans tend to be more sensitive to PGA than to PGV in the case of small to moderate earthquakes (Wu et al., 2003).⁷ Third, PGA enables the measurement of the accumulation of earthquake exposure within a specific period. To calculate earthquake intensity, we utilize a modified version of the PGA equation adjusted to the context of the Netherlands, as proposed by Dost et al. (2004).⁸

⁵PGV represents the maximum horizontal ground velocity during an earthquake and is particularly useful for assessing structural damage.

⁶The hypocenter is the underground location of the earthquake’s source, while the epicenter is the projection of the earthquake’s source on the surface.

⁷Humans are generally more sensitive to high-frequency ground motion (captured by PGA), whereas PGV reflects lower-frequency motion that more strongly affects structural response. Given that induced earthquakes in Groningen are typically small to moderate in magnitude, PGA better corresponds to what residents perceive.

⁸Dost et al. (2004) provides an adjusted, region-specific equation that better reflects local ground-motion patterns (small and shallow earthquakes) and fits the available Dutch data more accurately. The validation of the local model PGA developed by Dost et al. (2004) has been examined and confirmed in the study of Dost et al. (2013). This validation confirms the reliability of the model’s estimation for PGA, comparable in accuracy to the equation proposed

The intensity of each earthquake j on the location p of individual i is calculated based on the earthquake's magnitude M_j , hypocentral distance s_j , and epicentral distance d_{pj} from the location. Following the model developed by [Dost et al. \(2004\)](#), we determine the intensity of an earthquake j at a specific location using the following equation:

$$\log(PGA_{pj}) = -1.41 + 0.57M_j - 0.00139r_{pj} - 1.33\log(r_{pj}) \quad (1)$$

where PGA_{pj} is PGA in m/s^2 . r_{pj} is the hypocentral distance between location p and hypocenter of earthquake j , which is given by $r_{pj} = \sqrt{d_{pj}^2 + s_j^2}$.

While Eq.(1) calculates the intensity of a single earthquake at a given location, it does not capture the long-term exposure to repeated mining-induced seismicity. Unlike acute disasters, such as singular natural earthquakes or tsunamis, the Northern Netherlands are subject to chronic, repeated exposure to mining-induced earthquakes. This distinction underscores the importance of measuring accumulated exposure rather than focusing solely on individual events.

Accumulated exposure is particularly relevant in understanding the health impacts of mining-induced earthquakes. Repeated exposure to seismic events may lead to chronic stress and adverse psychological effects, such as anxiety, depression, and post-traumatic stress disorder (PTSD), through mechanisms distinct from the immediate effects of acute disasters ([Stroebe et al., 2021a](#)). These mechanisms align with a study on chronic stress, which posits that prolonged exposure to stressors exhausts psychological resilience and disrupts physiological equilibrium, leading to sustained health deterioration ([Aneshensel, 1992](#)). Furthermore, anxiety due to the unpredictability of repeated earthquakes exacerbates these effects.

To measure accumulated exposure, we adopt an approach similar to prior studies ([Durán, 2022](#); [Koster and Van Ommeren, 2015](#); [Stroebe et al., 2021a](#)), calculating accumulated PGA as the sum of all PGA values within a defined time window. Specifically, the k year accumulated earthquake exposure for postal code p at time t is defined as:

$$APGA_{pt}^{ky} = \sum_{t-k < j < t} PGA_{pj}, \quad (2)$$

by [Bommer \(2013\)](#) specifically for small earthquake events. Subsequent studies, such as [Koster and Van Ommeren \(2015\)](#) and [Durán \(2022\)](#), utilize the equation of PGV proposed by [Dost et al. \(2004\)](#) to quantify the intensity of mining-induced earthquakes.

where $APGA_{pt}^{ky}$ represents the accumulated PGA at location p over the time window from $t - k$ to t , and PGA_{pj} indicates the intensity of earthquake j at location p happened between $t - k$ to t . Figures 2 and 3 depict the geographic distribution of accumulated PGA in Groningen and the Northern Netherlands, respectively, for earthquakes occurring between 1986 and 2011 and between 1986 and 2021.

A potential limitation of this approach lies in its assumption that all seismic events within the defined time window contribute equally to health outcomes, regardless of when they occurred. For instance, the psychological and physiological impacts of earthquakes that occurred five years ago may differ from those of more recent events. To address this issue, we limit the $APGA_{pt}^{3y}$ calculation to a three-year window, which balances capturing accumulated exposure with reducing potential biases from outdated events. However, the choice of a three-year window is somewhat arbitrary. To ensure robustness, we perform sensitivity analyses using alternative time windows, such as five years, and examine whether the results remain consistent.

3.2 Health Outcomes

The health data utilized in this study is derived from the Dutch Lifelines cohort study and biobank, which is a multi-disciplinary prospective population-based cohort study examining in a unique three-generation design the health and health-related behaviours of 167,729 persons living in the North of the Netherlands (Scholtens et al., 2015). It employs a broad range of investigative procedures in assessing the biomedical, socio-demographic, behavioural, physical and psychological factors which contribute to the health and disease of the general population, with a special focus on multi-morbidity and complex genetics. These indicators were collected and assessed using structured questionnaires and objective measurements. Lifelines collects data from participants in multiple waves. Wave 1A was conducted between 2007 and 2013, wave 2A between 2014 and 2018, and wave 3A between 2019 and 2023.

Leveraging the Lifelines study enables us to track health variations over the study period and investigate the impact of long-term earthquake exposure on health outcomes. The dataset encompasses individuals from the three northern provinces of the Netherlands, with earthquakes occurring predominantly in Groningen and to a lesser extent in Drenthe and Friesland, ensuring representation of individuals with both low and high levels of earthquake exposure within the study population.

This study focuses on two primary outcomes: the number of depression symptoms and anxiety symptoms, respectively. Typically, the severity of mental health conditions can be assessed through symptom counts, with sum scores serving as a basis for identifying individuals with depressive or anxiety disorders (Fried and Nesse, 2015). We employ the Mini International Neuropsychiatric Interview within the Lifelines dataset to evaluate the mental health status of participants. The MINI is a succinct, valid, and reliable interview designed to diagnose psychiatric disorders in accordance with the international diagnostic criteria of the Diagnostic and Statistical Manual (DSM)-IV and the International Classification of Diseases (ICD)-10 (Sheehan et al., 1997).⁹ Specifically, we utilize eight symptoms based on the criteria of DSM-IV major depressive disorder and six symptoms based on the criteria of DSM-IV generalized anxiety disorder.¹⁰ These symptoms in the Lifelines MINI questionnaire are aligned with DSM-IV. In Lifelines, data on these symptoms, collected during wave 1A, wave 2A, and wave 3A, are recorded as binary responses (1 for yes, 0 for no). The total number of depressive and anxiety symptoms is derived by summing the binary responses for each category. Table A.1 in the appendix A provides a list of depression and anxiety symptoms, including the specific variable names and corresponding questions from the Lifelines, along with their associated symptoms in the DSM-IV.

Self-rated health is derived from the RAND-36 survey conducted as part of the Lifelines study. The RAND-36 assesses health-related quality of life, and its reliability and validity have been established in previous studies (e.g., see Hays and Morales (2001)). SRH is determined based on responses to the question: “How would you rate your health, generally speaking?”, with response options ranging from excellent (1) to poor (5). For our analysis, we recode responses as follows: excellent, very good, and good are grouped into 0 (good self-rated health), while all other responses are assigned to 1 (poor self-rated health). This data is available across wave 1A, wave 2A, and wave 3A of the Lifelines study.

⁹Within Lifelines, MINI versions 1, 2, and 3 were employed in wave 1A, while subsequent follow-ups utilized MINI version 4. It’s noteworthy that MINI version 4 and MINI version 3 are essentially identical. MINI version 3 and MINI version 2 share similar questions but incorporate skips when specific questions are answered with a “no” response. A comprehensive description of these versions can be accessed on the Lifelines Wiki website. Notably, 76,665 participants with MINI version 1 and MINI version 2 in wave 1A were excluded in this paper to maintain consistency in the outcome variable.

¹⁰We remove the depression symptoms of significant unintentional weight or appetite changes, as changes in questions of the questionnaire across waves affect their comparability.

3.3 Linking Individual Health Outcomes to Earthquake Exposure

Previous economics research on earthquakes or other environmental exposures, such as wind turbines (e.g., see [Krekel et al. \(2023\)](#)) and drilling wells (e.g., see [Hill \(2018\)](#)), often utilizes a classical difference-in-differences (DiD) research design to assess the health impacts of a single disaster. In contrast, we take a different design that focus on long-term earthquake exposure for two main reasons.

First, the characteristics of mining-induced earthquakes, importantly their high frequency and moderate magnitude, and how they affect health (usually not through direct or immediate effects but through gradual accumulation over time) necessitate a focus on repeated exposure rather than a single event. This is a significant departure from studies on large-scale earthquakes, such as those in Japan, Indonesia, and Chile. Therefore, our design is driven by the characteristics of these events.

Second, our research design is aligned with studies that investigate the health impacts of long-term exposure. For instance, [Anderson \(2020\)](#) examines the effects of prolonged exposure to air pollution on mortality, measuring long-term exposure by assessing how long the average individual in the sample has lived near a highway. Similarly, we investigate the dose-response relationship between earthquake exposure and health outcomes, enabling us to examine how mental health and SRH respond to increasing levels of accumulated PGA. Unlike the DiD design, we do not specify fixed treatment and control groups.

We link the earthquake exposure indicators and individual health outcomes by postal code (four digit). We obtain individual demographic information, including age, gender, educational attainment, and postal code from Lifelines. The educational attainment is based on the highest education degree in Lifelines, with 'low' (0), 'middle' (1), and 'high' (2). It is available in wave 1A and wave 2A.¹¹ In addition, we obtained the degree of urbanization information at postal code (four digit) level from Statistics Netherlands (Centraal Bureau voor de Statistiek). Based on the description of categorization, the value of urbanization varies from (highly urbanized: area address density is more than 2500 addresses per square kilometer) to 5 (non-urbanized: area address density is less than 500 addresses per square kilometer). We re-coded the urbanization information to 1 (area address density is more than 500 addresses per square kilometer) and 0 (non-urbanized).

¹¹Educational attainment is not available in wave 3A; therefore, we use information reported in wave 2A for individuals observed in wave 3A.

4 Empirical Approach

Our approach to estimating the causal impact of mining-induced earthquakes on health involves assuming that earthquakes occur randomly across time and presumably randomly over space,¹² and individuals cannot decide the number or intensity of earthquakes they experience. Under this assumption, the accumulated PGA serves as a reliable proxy for an individual’s long-term exposure to earthquakes over a specific period. Within this framework, the health impact of mining-induced earthquakes can be assessed by regressing health outcomes on earthquake exposure, using the following equation using pooled OLS:

$$health_{it} = \beta_0 + \beta_1 APGA_{pt}^{3y} + X_{it}\beta + \epsilon_{it}. \quad (3)$$

where $health_{it}$ is the number of depression symptoms, the number of anxiety symptoms, or low self-rated health for individual i living in location p at time t . The variable $APGA_{pt}^{3y}$ indicates the 3-year accumulated PGA at postal code p at time t , calculated using Eq.(2). The vector X_{it} contains individual characteristics: age, age squared, gender, urban, and educational attainment. ϵ_{it} is an error term. We include the estimated results of pooled OLS in our main specification.

While this approach provides a starting point, it oversimplifies the complex relationship by failing to account for unobserved heterogeneity across individuals and locations, as well as time-specific shocks. For example, mining-induced earthquakes tend to decrease local housing prices, particularly in high-risk areas (e.g., see [Koster and Van Ommeren \(2015\)](#), [Cheung et al. \(2018\)](#)). Individuals who prioritize safety or have greater health concerns may choose to relocate to lower-risk areas, while those with lower socioeconomic status may lack the resources to move and remain in earthquake-prone areas. These factors may introduce selection bias, as both groups differ in unobservable ways that may simultaneously affect health outcomes and measured earthquake exposure.

To address the individual unobserved heterogeneity and time-specific shocks, we employ a fixed-effects model. Individual fixed effects control for time-invariant factors, such as risk preferences or baseline health, while time-fixed effects capture health shocks or broader temporal trends, such as health policy change or public health improvements, that might influence health outcomes across

¹²Noticeable earthquakes in Groningen are not statistically significantly concentrated under the condition of the location of weak earthquakes ([Koster and Van Ommeren, 2015](#)).

all individuals.

However, a potential issue arises from the use of time dummy variables as fixed effects. Figure 1 shows that while the frequency of earthquakes with magnitudes greater than 2 remains relatively stable, smaller earthquakes with magnitudes of less than 1 exhibit an upward trend before 2013 and a downward trend afterward, leading to trend-stationarity in the accumulated PGA. Time dummies, which are designed to absorb year-specific shocks, may capture part of the variation in accumulated PGA, thereby absorbing its estimated effect on health outcomes. This issue is also highlighted by Durán (2022), who utilizes time-specific cross-sectional averages to account for business cycle effects instead of using year dummies. To address this, we follow Gösler and Moshgbar (2020) by using smoothing time-fixed effects (trend polynomials). This approach allows us to isolate the effects of accumulated PGA more effectively, without over-controlling for its temporal variation. Therefore, our main equation takes the following form:

$$health_{it} = \beta_0 + \beta_1 APGA_{pt}^{3y} + X_{it}\beta + c_i + \sum_{k=1}^K trend^k \gamma_k + \omega_p + \epsilon_{it} \quad (4)$$

where c_i is time-invariant individual heterogeneity. The $\sum_{k=1}^K trend^k$ are the smoothing year fixed effects used to control for common time-specific shocks and systematic trends over time. In fact, we use second order polynomials for smoothing time fixed effects. The term ω_p is a postal code fixed effect.

A threat to our identification comes from endogenous location sorting if that is not captured by a time-invariant preference for residential moving. For instance, an individual may move out after having accumulated a high PGA. Some studies suggested an association between migration, gas extraction, and mining-induced earthquakes (Hill, 2024; Stroebe et al., 2021a). Indeed, some residents in Groningen actively seek to leave areas affected by mining-induced earthquakes due to property damage, feelings of insecurity, and health concerns (Stroebe et al., 2021b). However, it is important to note that only a tiny fraction of people actually move out of earthquake areas. Therefore, we conduct additional analyses with mobility as an outcome variable, to estimate whether higher earthquake exposure leads to increased migration to investigate the impact of earthquakes on migration. Moreover, we repeat the empirical analysis while excluding individuals who moved away a certain minimum distance.

5 Results

5.1 Estimation Sample and Descriptive Statistics

Our estimation sample includes individuals who participated in the Lifelines study from 2007 to 2021, with at least two participations across waves 1A, 2A, and 3A, and who have no missing data on either health outcomes or covariates. In our adult sample, 151,080 individuals participated in wave 1A, 100,258 in wave 2A, and 26,548 in wave 3A.¹³ A total of 97,792 observations are excluded due to missing data on depression and anxiety outcomes (76,665 from wave 1A, 19,226 from wave 2A, and 1,901 from wave 3A).¹⁴ Additionally, 695 observations are excluded because of missing SRH, 13,229 observations are excluded due to missing covariates, and 36 observations are excluded because of missing earthquake exposure variables.¹⁵ Finally, 4,199 observations are excluded because participants did not reside in one of the three northern provinces (Groningen, Friesland, and Drenthe). After retaining only participants with at least two Lifelines wave participations, the final sample consists of 92,338 observations (wave-person).

Table 1 presents descriptive statistics for both demographic characteristics and health outcomes across three waves of our panel dataset. Across the entire sample, the average age is approximately 49.42 years, with males comprising 40.1% of the participants. Notably, while 61.2% of the individuals reside in urban areas, a significant portion originates from rural areas. Given that most earthquakes occur far from urban centers, our sample is able to examine the dose-response relationship.

Table 1 also outlines variables representing health outcomes, including internalizing symptoms of depression and anxiety, as well as poor SRH. Regarding accumulated PGA, as indicated in the table, there exists a considerable variation in exposure levels between high-exposure and low-exposure areas. This underscores the comprehensive coverage of earthquake exposures within our

¹³Lifelines has been working on the survey execution and data collection of wave 3A since 2019, which explains why wave 3A has a smaller sample size compared to earlier waves.

¹⁴The missing values in depression and anxiety outcomes at wave 1A are primarily due to the changes in the version of MINI used within this wave. In wave 1A, MINI v1, MINI v2, and MINI v3 were administered at different times. To ensure consistency and avoid missing responses to specific questions, we include only those participants who completed the MINI v3 survey. MINI v1 and v2 were used between 08/11/2006 and 16/02/2012, while version 3 was used from 17/02/2011 to 31/12/2013. Consequently, the version of the MINI completed by each participant was determined by their date of participation. As such, the missing MINI data at wave 1A is not expected to introduce sample selection bias.

¹⁵Approximately 3.1% of participants passed away during the study period. Other reasons for withdrawal included the time-intensive participation requirements, loss of interest, relocation outside the research area, or enrollment in a regular health care program (Sijtsma et al., 2022). Unfortunately, the specific reasons for a participant's withdrawal are not observed in the dataset. However, there is no evidence to suggest that missing data are systematically associated with participants being too ill to continue participation.

sample.

Furthermore, Figure 5 and 6 compare health outcomes between the top and bottom deciles of accumulated PGA within a three-year period. The results reveal significant differences across all health outcomes, with individuals in the top 10% of earthquake exposure facing higher health risks, except for observable psychomotor changes. Although these figures do not establish causality, they offer intuitive insights into the potential health impacts of mining-induced earthquakes. Detailed statistical comparisons of health outcomes are presented in Table A.2 in the Appendix A.

5.2 Main Specification

Our estimation strategy is based on the dose-response relationship: individuals residing in areas with high earthquake exposure (high accumulated PGA) are hypothesized to exhibit lower levels of mental and self-rated health. To estimate the effects accurately, we utilize an individual fixed effects model controlling for smoothing time fixed effects to address the individual heterogeneity and health shocks stemming from unobserved factors (see above for details on the identification strategy).

Our analysis focuses on the impact of mining-induced earthquakes on the number of depression symptoms, the number of anxiety symptoms, and poor self-rated health. As shown in Table 2 for pooled OLS and fixed effects estimates, we find evidence of increased depression symptoms and anxiety symptoms. However, we do not find a significant impact on poor SRH after using fixed effects. After accounting for unobserved heterogeneity across individuals and locations, as well as unobserved time-specific shocks and time trends, the coefficients become more pronounced.

Specifically, for each one-unit increase in accumulated PGA within the three years, we observe a rise of 0.0426 in the number of depression symptoms and 0.0547 in the number of anxiety symptoms, statistically significant at the 5% levels.¹⁶ Despite the seemingly modest coefficients, the cumulative effects can be substantial, particularly in heavily affected regions. For instance, the highest accumulated PGA within three years is approximately 6.87. This suggests that, on average, individuals residing in the highest exposure area experience approximately 0.29 and 0.37 more symptoms of depression and anxiety, respectively, than those with little to no exposure to earthquakes.

¹⁶To make the accumulated PGA more understandable, we create a figure illustrating the PGA by distance using an attenuation function (see Figure 4).

Compared to the pooled OLS regressions, the coefficients in the fixed effects models are higher. This suggests that unobserved time-invariant individual characteristics, such as baseline health or risk preferences, may confound the pooled OLS estimates, leading to downward bias. In our analysis, we further control for smoothing time fixed effects, which capture temporal trends and common shocks without over-controlling for the trend-stationary nature of accumulated PGA. Additionally, we include postal code fixed effects to account for time-invariant spatial heterogeneity. While these fixed effects enhance the robustness of our estimates by addressing unobserved heterogeneity, it is important to note that they do not fully account for time-varying factors, such as dynamic migration behavior. To address these potential limitations, we conduct additional robustness checks and sensitivity analyses.

Our results indicate that exposure to mining-induced earthquakes increases the severity of both depression and anxiety. Furthermore, in Table 3 and 4, we present the estimated effects on specific depression and anxiety symptoms using the fixed effects models. As shown, exposure to earthquakes significantly increases the likelihood of experiencing symptoms such as depressed mood, loss of interest, and restlessness. Specifically, a one-unit increase in accumulated PGA causes a 0.79% increase in the probability of experiencing depressed mood, a 1.15% increase in loss of interest, and a 0.75% increase in difficulty concentrating. Regarding anxiety symptoms, a one-unit increase in accumulated PGA leads to a 1.04% increase in restlessness and a 1.51% increase in feeling tense. For other symptoms of depression and anxiety, the estimated coefficients are generally positive, suggesting an increase in symptom prevalence, but are statistically insignificant. These results complement those presented in Table 2, as they account for heterogeneity across depression and anxiety symptoms.

We construct a scenario to estimate the increase in mental health burden. Assuming other factors (e.g., soil type) are the same across space, one unit of accumulated PGA corresponds to approximately five earthquakes with a magnitude of 2.5, a depth of 3 km, and an epicentral distance of 2 km. Based on this assumption, if 10,000 residents are exposed to earthquakes with an accumulated PGA equal to one, we estimate increases in mental health symptoms as follows: 79 cases of depressed mood, 115 cases of loss of interest, 75 cases of difficulty concentrating, 104 cases of restlessness, and 151 cases of tension.

Incorporating population data from Statistics Netherlands into the estimated model, we estimate that, over the three waves, earthquake exposure led to approximately 28,000 additional cases

of depressed mood, 42,000 cases of loss of interest, and 27,000 cases of difficulty concentrating. For anxiety-related symptoms, the model estimates around 37,000 cases of restlessness and 55,000 cases of tension. These figures reflect cumulative effects across the three waves and are based on model estimates. It is important to emphasize that these numbers likely represent a lower bound of the total mental health burden and should be interpreted as rough estimates. Further details on the population data and the estimation approach can be found in [Appendix C](#).

5.3 Sensitivity Analyses

First, we examine the impact of exposure to mining-induced earthquakes on the likelihood of migration and restrict the sample based on moving distance during the study period. Second, we assess the robustness of our baseline results to alternative temporal and spatial definitions of accumulated PGA. Third, we employ the number of noticeable earthquakes as an alternative exposure measure. Finally, we evaluate the sensitivity of our findings to alternative outcome measures by using diagnosed depression and anxiety.

5.2.1 Migration To address the impact of selective migration on our identification strategy, we first examine the impact of exposure to mining-induced earthquakes on migration. Mobility is defined in several ways: individuals who moved at any point during the research period, individuals who moved between wave 1A and wave 2A, and individuals who moved between wave 2A and wave 3A. We determine mobility by comparing postal code information across survey waves. However, due to the limitations of our dataset, we lack information on individuals’ residential locations before the baseline, preventing us from identifying earlier movements. Additionally, we lack details about the exact timing and reasons for migration. As illustrated in [Figure 4](#), PGA is a function of epicentral distance and decreases significantly when the epicentral distance exceeds 10 km. Consequently, moving distance could substantially change accumulated earthquake exposure, especially when individuals relocate from high-exposure areas to low-exposure areas.

In Column 1 of [Table 5](#), we observe a positive but insignificant impact of accumulated PGA on overall migration. Therefore, our results suggest that mobility has a modest impact on our main identification strategy but could still introduce bias into our estimates. Therefore, we conduct a sensitivity analysis restricted to a sample of non-movers. As shown in [Table 6](#), we find a positive but insignificant effect of PGA on depression and anxiety symptoms. This lack of significance may

stem from insufficient statistical power.¹⁷

5.2.2 Temporal restriction in PGA In our main specification, we limit accumulated PGA to three years. However, in Table 7, we extend this restriction to include accumulated PGA over a five-year period and accumulated PGA since the occurrence of the first officially induced earthquake, as proxies for chronic earthquake exposure. The results remain robust to these alternative specifications. We observe a much smaller coefficient in accumulated PGA (total) compared to Table 2. This decline may be attributed to the diminishing impact of earthquakes over time.

5.2.3 Spatial restriction in PGA We further test the sensitivity of our results by adding the distance cut-off used to calculate accumulated PGA. In our main specification, accumulated PGA is calculated without a distance cut-off. In Table 8, we implement cut-offs of 5 km and 10 km to examine their effects on the results. We find significant impacts of APGA with both the 5 km and 10 km cut-offs on depression symptoms. However, no significant adverse effects are observed for anxiety symptoms or SRH. It is important to note that applying the 5 km and 10 km cut-offs substantially reduces the APGA values for most postal codes, as these cut-offs sharply limit the earthquakes included in the calculation. As a result, these measures primarily capture the effects of mining-induced earthquakes that occur very close to individuals' locations. However, we expect that earthquakes occurring in surrounding areas can also contribute to negative health outcomes. Therefore, the 5 km and 10 km cut-offs may not fully capture the long-term exposure of mining-induced earthquakes when trying to interpret the results in Table 8.

5.2.4 The number of earthquakes The literature sometimes uses the raw number of earthquakes when studying earthquake effects. For instance, [Koster and Van Ommeren \(2015\)](#) investigate the impact of mining-induced earthquakes on local housing prices by analyzing the number of noticeable earthquakes based on PGV. Following the guidelines outlined by [Lorant \(2012\)](#), we use the number of earthquakes with a PGA greater than 0.001 m/s^2 to test the robustness of our findings and make it more explainable. Subsequently, we compute the accumulative number of earthquakes

¹⁷We calculate the minimum detectable effect sizes (MDEs) at a 5% significance level and 80% statistical power for the specifications. Since the estimated effects are smaller than the corresponding MDEs, these specifications lack sufficient power to detect effects of this magnitude. This implies that even if the true effects were 0.0291 and 0.0298, the probability of detecting them as statistically significant would be below 80%. Therefore, it remains possible that earthquake exposure has a real effect on depression and anxiety symptoms, but that the analysis is not sufficiently powered to identify it. In addition, Table A.3 in [Appendix A](#) reports the MDEs for both the main specification and the robustness check excluding movers.

using the following equations:

$$Number_{pt} = \sum_{t-3 < j < t} 1, (0.001 m/s^2 < PGA_{pj}) \quad (5)$$

Table 9 presents the results using the accumulated number of earthquakes as explanatory variables. We find a significant adverse effect of earthquakes on the number of depression and anxiety symptoms. Specifically, an increase of one earthquake with a magnitude greater than $0.001 m/s^2$ is associated with an increase of 0.0007 in depression symptoms and 0.0013 in anxiety symptoms. Although these coefficients are small, the cumulative impact can be substantial due to the high frequency of earthquakes. For example, in some regions, the accumulated number of earthquakes with a magnitude greater than $0.001 m/s^2$ exceeds 300, suggesting that even minor individual effects can aggregate into a significant overall impact. These findings are consistent with our baseline results.

5.2.5 Diagnosed depression and anxiety Lastly, we estimate the impact of mining-induced earthquakes on major depression diagnosis (MDD) and generalized anxiety diagnosis (GAD). We find a significant adverse effect on MDD, but no statistically significant effect on GAD. This pattern suggests that earthquake exposure contributes to clinically relevant deterioration in mental health that reaches the diagnostic threshold for depression, while its effect on anxiety remains subclinical. These results also imply that relying solely on diagnostic outcomes may underestimate the broader mental health impacts of earthquake exposure. For further details on the diagnostic variables and full estimation results, see [Appendix B](#).

6 Conclusion

This study examines the effects of mining-induced earthquakes on mental health and self-rated health in the Northern Netherlands, utilizing large-scale panel data from Lifelines and earthquake data from the Royal Netherlands Meteorological Institute. Our results indicate that accumulated exposure to earthquakes significantly increases depression and anxiety symptoms. Notably, even though the impacts of earthquakes appear small, their cumulative effects in high-risk areas are substantial. For example, the highest accumulated exposure corresponds to an average increase of 0.37 anxiety symptoms. Considering the number of people living in the affected area, the total

mental health impact could be significant.

To ensure the robustness of our findings, we conduct additional analyses. First, we address mobility by examining the impact of earthquakes on migration and restricting the sample to non-movers, which revealed stronger effects on anxiety symptoms, suggesting potential bias due to exposure misclassification and selection caused by mobility issues. Second, we test temporal and spatial restrictions of accumulated PGA and confirm that our main findings remain consistent. Finally, we use the number of earthquakes instead of accumulated PGA. Together, these results provide strong evidence for significant and robust mental health risks posed by mining-induced earthquakes.

Despite the Dutch government’s decision to permanently shut down the large Groningen gas field by early 2024, the induced earthquakes are expected to persist in the short to medium term due to the lagging effects of gas extraction. Therefore, our results underscore the potential health benefits of such policy measures, demonstrating the significant gains that could arise from reducing gas extraction activity. Moreover, our study highlights the importance of implementing a policy that addresses these harmful impacts.

Notably, there are significant differences between natural and induced earthquakes in the ways of many characteristics and how they impact public health. Future research should examine the long-term health consequences of induced earthquakes and investigate the mechanisms through which small but high-frequency earthquakes contribute to adverse health outcomes. Additionally, policymakers should prioritize strategies aimed at mitigating the health effects of mining-induced earthquakes.

In conclusion, the negative health externalities caused by natural gas extraction should not be overlooked. Human activities often emphasize the benefits while consciously or unconsciously neglecting their adverse side effects. A well-informed decision should strive for a balance between benefits and adverse impacts.

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Econometrics Workshop, the European Public Health Conference, the Health Economists' Study Group Conference, and the IAAE Annual Conference for valuable insights and feedback. The authors express their gratitude to the Lifelines Cohort Study and Biobank, the research centers providing data to Lifelines, and all the participants of the study. The Lifelines initiative has been made possible by subsidy from the Dutch Ministry of Health, Welfare and Sport, the Dutch Ministry of Economic Affairs, the University Medical Center Groningen (UMCG), Groningen University, and the Provinces in the North of the Netherlands (Drenthe, Friesland, Groningen).

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Figures and Tables

Figures

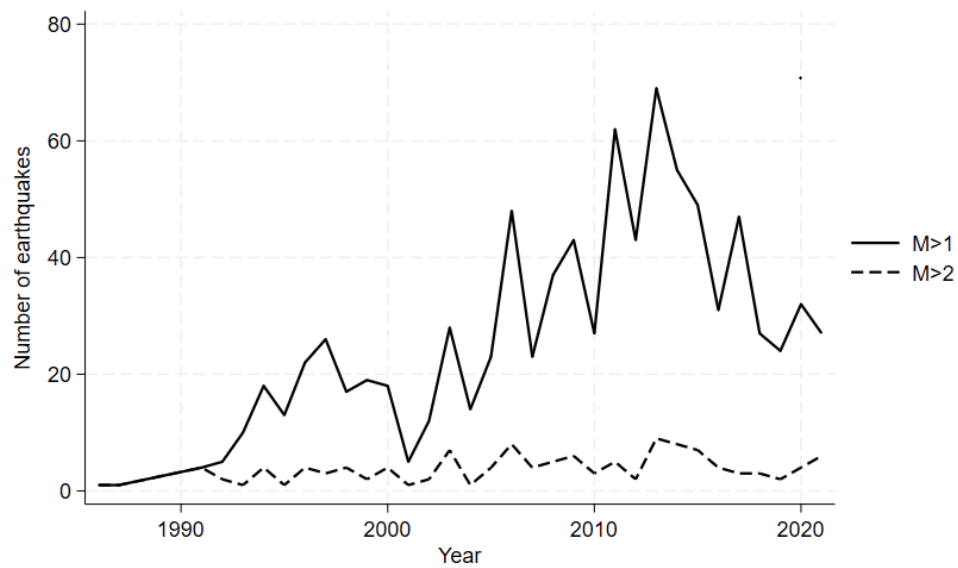


Figure 1: The number of earthquakes in the Northern Netherlands

Notes: This figure summarizes the number of induced earthquakes between 1986 and 2020 in the Northern Netherlands.

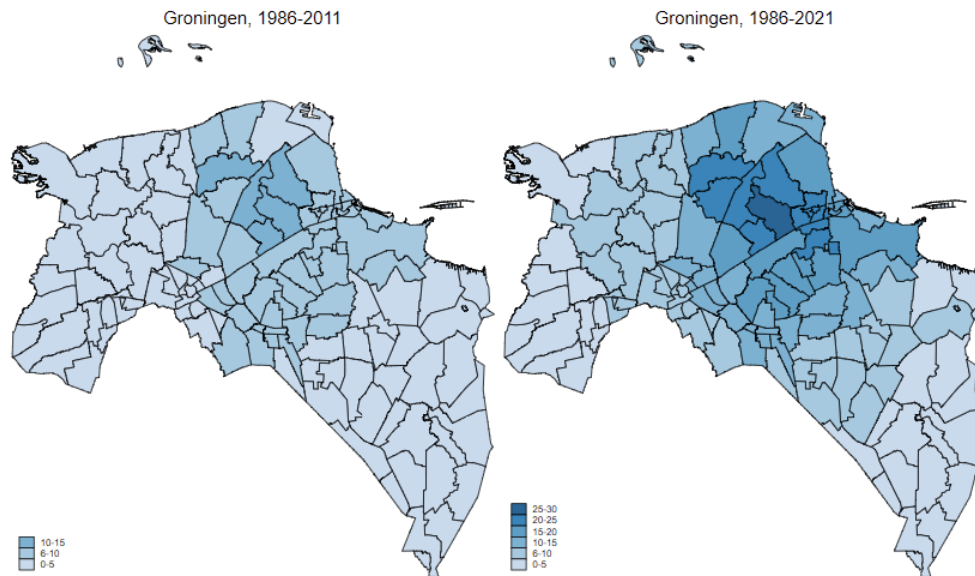


Figure 2: The geographic distribution of accumulated peak ground acceleration in Groningen

Notes: This figure shows the accumulated PGA in Groningen for the periods 1986–2011 (left) and 1986–2021 (right). Darker colors indicate higher levels of earthquake exposure during the respective period.

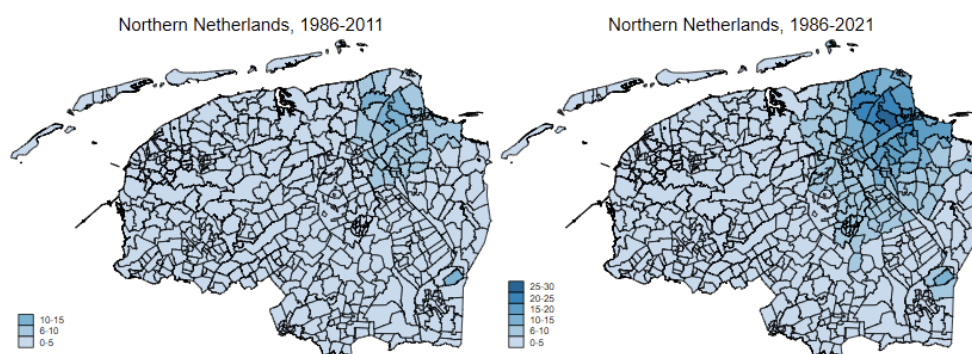


Figure 3: The geographic distribution of accumulated peak ground acceleration in the Northern Netherlands

Notes: This figure shows the accumulated PGA in the Northern Netherlands for the periods 1986–2011 (left) and 1986–2021 (right). Darker colors indicate higher levels of earthquake exposure during the respective period.

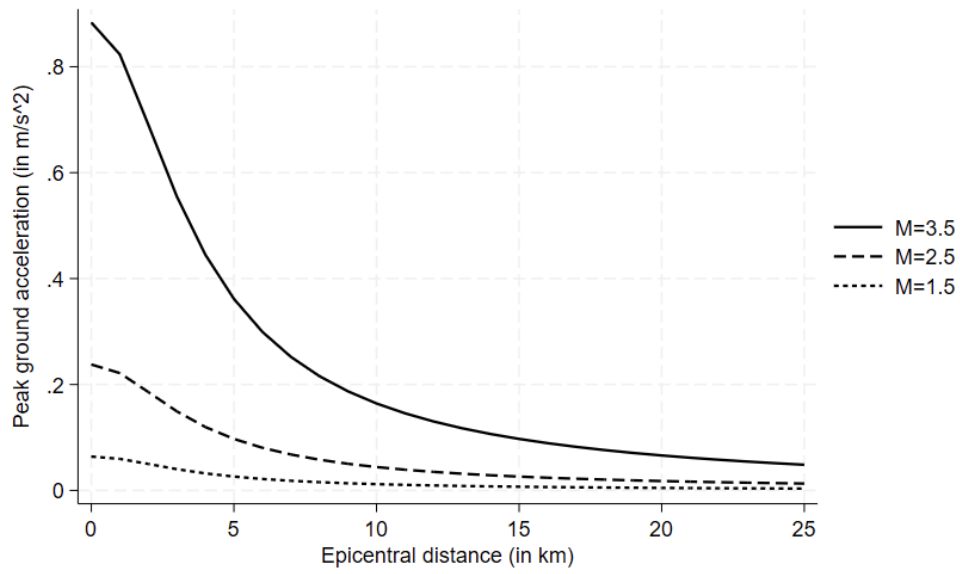


Figure 4: Earthquake's peak ground acceleration by epicentral distance

Notes: We calculate the peak ground acceleration using Eq.(1), where we set the depth of the earthquake to 3 km. Here, we present a hypothetical attenuation curve that illustrates the decrease in earthquake intensity with increasing distance from the epicenter. In reality, earthquake intensity attenuation is influenced by various factors, including soil type, terrain characteristics, and the orientation of seismic zones.

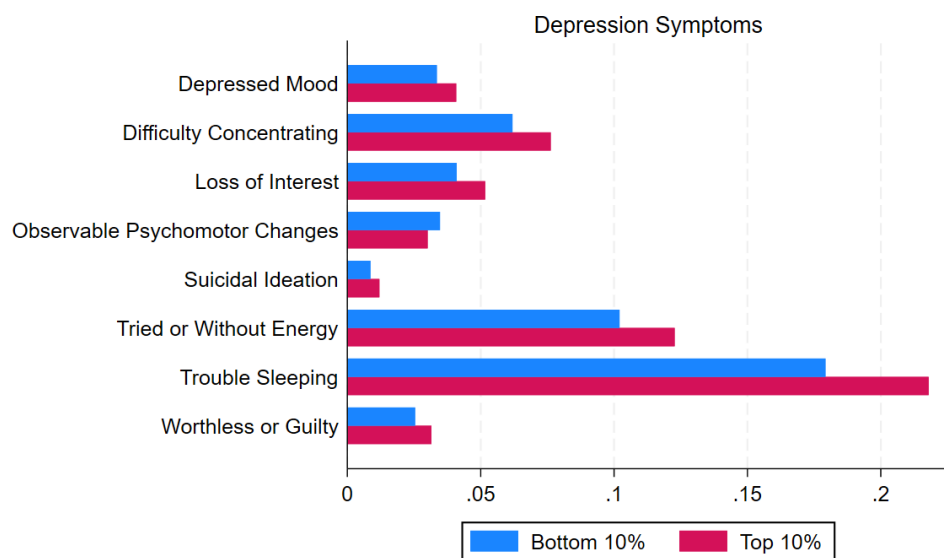


Figure 5: Differences in depression symptoms between the Top and bottom deciles of accumulated PGA over 3 years

Notes: The symptom names in the figure are abbreviated forms of the questions used in the Lifelines MINI interview. The complete questions from the Lifelines MINI and their corresponding symptoms in DSM-IV are provided in Appendix A.1. Additionally, Table A.2 in the Appendix A reports the exact proportions of depression symptoms, as well as the statistical differences between them.

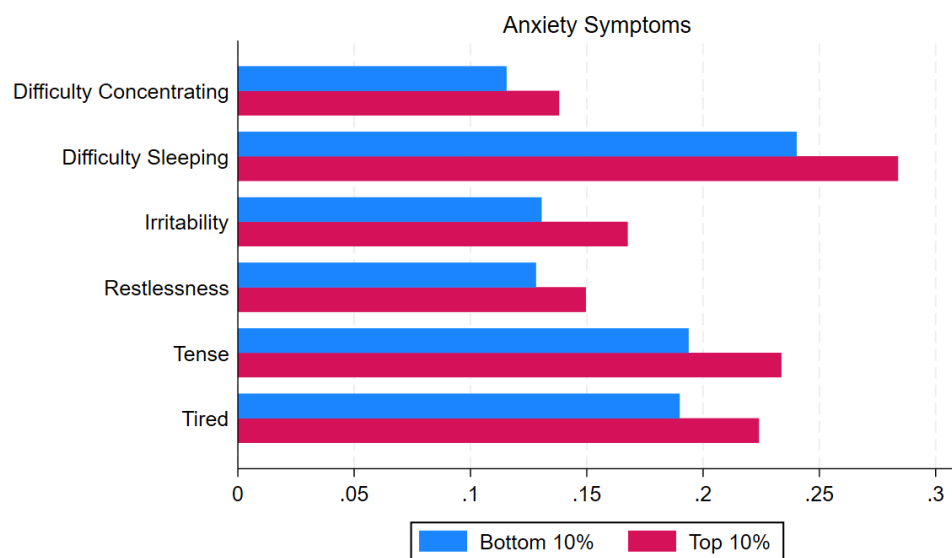


Figure 6: Differences in anxiety symptoms between the top and bottom deciles of accumulated PGA over 3 years

Notes: The symptom names in the figure are abbreviated forms of the questions used in the Lifelines MINI interview. The complete questions from the Lifelines MINI and their corresponding symptoms in DSM-IV are provided in Appendix Table A.1. Additionally, Table A.2 in the Appendix A reports the exact proportions of anxiety symptoms, as well as the statistical differences between them.

Tables

Table 1: Descriptive Statistics

	Wave 1A	Wave 2A	Wave 3A	Total
Age	45.416	49.013	56.875	49.424
Male	0.407	0.401	0.392	0.401
Educational attainment				
Low	0.271	0.256	0.244	0.258
Middle	0.410	0.386	0.371	0.391
High	0.319	0.359	0.385	0.351
Urban	0.595	0.617	0.649	0.616
Number of depression symptoms	0.522	0.565	0.495	0.536
Number of anxiety symptoms	0.901	1.241	1.081	1.093
Poor self-rated health	0.089	0.102	0.104	0.098
APGA (3)	0.596	0.863	0.619	0.723
APGA (5)	0.956	1.335	1.090	1.156
APGA (Total)	2.591	3.616	5.155	3.588
APGA (5 km)	0.054	0.095	0.084	0.079
APGA (10 km)	0.133	0.241	0.196	0.196
Number of earthquakes	120.379	155.733	117.401	135.884
Mobility	-	0.098	0.154	0.076
Sample size	31,151	42,106	19,081	92,338

Notes: APGA (3) and APGA (5) are accumulated peak ground acceleration (PGA) within three years and five years, respectively. APGA (Total) is accumulated PGA since the occurrence of the first officially induced earthquake. APGA (5 km) and APGA (10 km) are the accumulated PGA with 5 km and 10 km distance cut-off respectively.

Table 2: Pooled OLS and fixed effects estimates for the number of depression and anxiety symptoms and poor self-rated health

	Number of depression symptoms		Number of anxiety symptoms		Poor self-rated health	
	(1) POLS	(2) FE	(3) POLS	(4) FE	(5) POLS	(6) FE
APGA(3)	0.0251*** (0.0047)	0.0426** (0.0192)	0.0515*** (0.0069)	0.0547** (0.0263)	0.0023** (0.0012)	0.0003 (0.0047)
Age	0.0135*** (0.0018)	0.0535*** (0.0113)	0.0354*** (0.0025)	0.1188*** (0.0152)	0.0035*** (0.0004)	0.0014 (0.0028)
Age squared	-0.0002*** (0.0000)	-0.0005*** (0.0000)	-0.0005*** (0.0000)	-0.0010*** (0.0001)	-0.0000*** (0.0000)	-0.0000** (0.0000)
Gender	-0.1790*** (0.0075)		-0.4166*** (0.0108)		-0.0181*** (0.0020)	
Urban	0.0917*** (0.0078)		0.1807*** (0.0112)		0.0125*** (0.0020)	
Middle education	-0.1395*** (0.0108)	0.0215 (0.0264)	-0.1522*** (0.0147)	-0.0504 (0.0341)	-0.0363*** (0.0028)	-0.0083 (0.0064)
High education	-0.2508*** (0.0106)	0.0522 (0.0413)	-0.2542*** (0.0147)	0.0539 (0.0548)	-0.0593*** (0.0027)	-0.0088 (0.0100)
Smoothing year FE	No	Yes	No	Yes	No	Yes
Postal code FE	No	Yes	No	Yes	No	Yes
Observations	92,338	92,338	92,338	92,338	92,338	92,338
Numbers of individuals	43,055	43,055	43,055	43,055	43,055	43,055

Notes: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Fixed effects estimates of depression symptoms

	(1) Depressed mood	(2) Loss of interest	(3) Trouble sleeping	(4) Observable psychomotor changes	(5) Tired or without energy	(6) Worthless or guilty	(7) Suicidal ideation	(8) Difficulty concentrating
APGA(3)	0.0079** (0.0037)	0.0115*** (0.0041)	0.0077 (0.0069)	-0.0009 (0.0034)	0.0017 (0.0055)	0.0041 (0.0034)	0.0029 (0.0018)	0.0075* (0.0044)
Smoothing year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Postal code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,338	92,338	92,338	92,338	92,338	92,338	92,338	92,338
Number of individuals	43,055	43,055	43,055	43,055	43,055	43,055	43,055	43,055

Notes: The symptom names in the table are abbreviated forms of the questions used in the Lifelines MINI interview. The complete questions from the Lifelines MINI and their corresponding symptoms in DSM-IV are provided in Appendix A.1. See Table 2 for details about included covariates. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4: Fixed effects estimates of anxiety symptoms

	(1) Restlessness	(2) Tense	(3) Tired	(4) Difficulty concentrating	(5) Irritability	(6) Difficulty sleeping
APGA(3)	0.0104* (0.0059)	0.0151** (0.0069)	0.0084 (0.0066)	0.0080 (0.0060)	0.0051 (0.0063)	0.0078 (0.0075)
Smoothing year FE	Yes	Yes	Yes	Yes	Yes	Yes
Postal code FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,338	92,338	92,338	92,338	92,338	92,338
Number of individuals	43,055	43,055	43,055	43,055	43,055	43,055

Notes: The symptom names in the table are abbreviated forms of the questions used in the Lifelines MINI interview. The complete questions from the Lifelines MINI and their corresponding symptoms in DSM-IV are provided in Appendix A.1. See Table 2 for details about included covariates. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5: Impact of mining-induced earthquakes on migration - fixed effects

	(1) No limit
APGA(3)	0.0083 (0.0066)
Smoothing year FE	Yes
Postal code FE	Yes
Controls	Yes
Observations	36,264
Number of individuals	18,132

Notes: Observations from Wave 1A are excluded, as it is not possible to determine whether respondents moved. Each coefficient is from a different regression. Robust standard errors are in parentheses. See Table 2 for details about included covariates. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: Impact of mining-induced earthquakes on health outcomes excluding movers - fixed effects

	(1) Depression symptoms	(2) Anxiety symptoms	(3) Poor self-rated health
APGA(3)	0.0291 (0.0202)	0.0298 (0.0274)	-0.0016 (0.0050)
Smoothing year FE	Yes	Yes	Yes
Observations	79,515	79,515	79,515
Number of individuals	37,285	37,285	37,285

Notes: Each coefficient is from a different regression. Robust standard errors are in parentheses. See Table 2 for details about included covariates. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7: Robustness to accumulated PGA time window cut-offs - fixed effects

	Depression symptoms		Anxiety symptoms		Poor self-rated health	
	(1)	(2)	(3)	(4)	(5)	(6)
APGA(5)	0.0593*** (0.0144)		0.0565*** (0.0194)		0.0025 (0.0034)	
APGA(Total)		0.0078 (0.0048)		0.0090 (0.0064)		-0.0002 (0.0012)
Smoothing year FE	Yes	Yes	Yes	Yes	Yes	Yes
Postal code FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,338	92,338	92,338	92,338	92,338	92,338
Number of individuals	43,055	43,055	43,055	43,055	43,055	43,055

Notes: Each coefficient is from a different regression. APGA(5) is the 5-year accumulated PGV. APGA(Total) is the accumulated PGA since the first official mining-induced earthquake happened. Robust standard errors are in parentheses. See Table 2 for details about included covariates. *** p<0.01, ** p<0.05, * p<0.10.

Table 8: Robustness to accumulated PGA distance cut-offs - fixed effects

	Depression symptoms		Anxiety symptoms		Poor self-rated health	
	(1)	(2)	(3)	(4)	(5)	(6)
5 km cut-off	0.0755* (0.0396)		0.0610 (0.0545)		0.0062 (0.0103)	
10 km cut-off		0.0549** (0.0251)		0.0496 (0.0347)		0.0053 (0.0063)
Smoothing year FE	Yes	Yes	Yes	Yes	Yes	Yes
Postal code FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,338	92,338	92,338	92,338	92,338	92,338
Number of individuals	43,055	43,055	43,055	43,055	43,055	43,055

Notes: Each coefficient is from a different regression. Robust standard errors are in parentheses. See Table 2 for details about included covariates. *** p<0.01, ** p<0.05, * p<0.10.

Table 9: Impact of the number of earthquakes on health outcomes - fixed effects

	Depression symptoms	Anxiety symptoms	Poor self-rated health
	(1)	(2)	(3)
Number of earthquakes	0.0007*** (0.0002)	0.0013*** (0.0003)	0.0000 (0.0000)
Controls	Yes	Yes	Yes
Observations	92,338	92,338	92,338
Number of individuals	43,055	43,055	43,055

Notes: Here, we sum the number of earthquakes with a magnitude greater than 0.001 m/s^2 within three years. Each coefficient is from a different regression. Robust standard errors are in parentheses. See Table 2 for details about included covariates. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A Appendix: Additional Tables

Table A.1: Depression and anxiety symptoms

Disorder		Symptoms (DSM-IV)	MINI Interview (Lifelines)
Major Depression Disorder	Depression	Depressed mood	Have you been consistently depressed or down, most of the day, nearly every day, for the past two weeks?
		Loss of interest or pleasure	In the past two weeks, have you been much less interested in most things or much less able to enjoy the things you used to enjoy most of the time?
		Sleep disturbance	Did you have trouble sleeping nearly every night (difficulty falling asleep, waking up in the middle of the night, early morning waking or sleeping excessively)?
		Observable psychomotor changes	Did you talk or move more slowly than normal or were you fidgety, restless or having trouble sitting still almost every day?
		Fatigue	Did you feel tired or without energy almost every day?
		Sense of worthlessness or guilt	Did you feel worthless or guilty almost every day?
		Difficulty concentrating	Did you have difficulty concentrating or making decisions almost every day?
		Suicidal ideation	Did you repeatedly consider hurting yourself, feel suicidal, or wish that you were dead?
		Restlessness	When you were anxious in the past 6 months, did you, most of the time, feel restless, keyed up or on edge?
		Muscle tension	When you were anxious in the past 6 months, did you, most of the time, feel tense?
		Fatigue	When you were anxious in the past 6 months, did you, most of the time, feel tired, weak or exhausted easily?
		Difficulty concentrating	When you were anxious in the past 6 months, did you, most of the time, have difficulty concentrating or find your mind going blank?
		Irritability	When you were anxious in the past 6 months, did you, most of the time, feel irritable?
		Sleep disturbance	When you were anxious in the past 6 months, did you, most of the time, have difficulty sleeping?

Notes: The MINI is an independent diagnostic interview, and it is aligned with the international diagnostic criteria outlined in the DSM-IV. Anxiety symptoms are assessed based on the past six months, whereas depression symptoms are primarily evaluated over the preceding two weeks. We list the corresponding DSM-IV symptoms as a reference. In column 2, we use the abbreviated names for symptoms as defined in the DSM-IV. Our analysis is based on participants from the Lifelines who completed MINI versions 3 and 4. We exclude data from MINI version 2, as it is identical to the MINI 5.0.0 manual, which incorporates skip patterns triggered by "no" responses to certain questions. Additionally, one depression symptom, significant unintentional weight or appetite changes, is excluded due to variations in the corresponding questions across different waves of the Lifelines study.

Table A.2: Health differences between the top and bottom deciles of accumulated PGA over 3 years)

	Sample means/proportions of APGA (3)		Statistic of difference
	The bottom 10%	The top 10%	
Number of depression symptoms	0.486	0.583	-5.654***
Depressed mood	0.033	0.041	-2.615***
Loss of interest	0.041	0.051	-3.441***
Trouble sleeping	0.179	0.218	-6.592***
Observable psychomotor changes	0.031	0.030	1.776**
Tried or without energy	0.102	0.123	-4.444***
Worthless or guilty	0.025	0.032	-2.486***
Suicidal ideation	0.008	0.012	-2.260**
Difficulty concentrating	0.062	0.076	-3.844***
Number of anxiety symptoms	0.998	1.196	-7.976***
Restlessness	0.128	0.149	-4.212***
Tense	0.193	0.233	-6.614***
Tired	0.189	0.224	-5.711***
Difficulty concentrating	0.115	0.138	-4.619***
Irritability	0.131	1.167	-7.066***
Difficulty sleeping	0.240	0.284	-6.724***
Self-rated health	0.091	0.101	-2.139***
Sample size	9,239	9,232	

Notes: For the number of depression and anxiety symptoms, we report the t-statistics from two-sample t-tests. For all binary outcomes, we report the z-statistics from two-sample proportion tests. The symptom names in the table are abbreviated forms of the questions used in the Lifelines MINI interview. The complete questions from the Lifelines MINI and their corresponding symptoms in DSM-IV are provided in Appendix A.1.

Table A.3: Minimum Detectable Effect Sizes and Corresponding Estimates Across Specifications

Specification	Corresponding Table/Column	N	APGA(3)	SE	MDE (5%, 80%)
Full sample: depression symptoms	Table 2, Col (2)	92,338	0.0426	0.0192	0.0539
Full sample: anxiety symptoms	Table 2, Col (4)	92,338	0.0547	0.0263	0.0738
Full sample: poor self-rated health	Table 2, Col (6)	92,338	0.0003	0.0047	0.0131
Sub-sample: migration analysis	Table 5, Col (1)	36,264	0.0083	0.0066	0.0184
Excluding movers: depression symptoms	Table 6, Col (1)	79,515	0.0291	0.0202	0.0567
Excluding movers: anxiety symptoms	Table 6, Col (2)	79,515	0.0298	0.0274	0.0768
Excluding movers: poor self-rated health	Table 6, Col (3)	79,515	-0.0016	0.0050	0.0139

Notes: This table reports minimum detectable effect sizes (MDEs) at the 5% significance level and 80% power for each specification.

B Appendix: The Impact of Mining-Induced Earthquakes on Diagnosed Depression and Anxiety

In the main analysis, we use the number of depression and anxiety symptoms as the primary health outcomes. These variables capture the severity of various mental health conditions but do not necessarily reflect formally diagnosed disorders. In this section, we extend the analysis presented in the main text by estimating the health impact of mining-induced earthquakes using clinically diagnosed depression and anxiety as outcomes. We replicate the same estimation specifications used in the main text (Table 2). Our findings indicate a significant negative effect of mining-induced earthquakes on depression diagnoses, but no such effect for anxiety diagnoses.

The following subsections provide an overview of how diagnosed depression and anxiety are measured in the Lifelines dataset, and a discussion of the differences between symptom-based measures and diagnosed mental health conditions. We then present the results using the diagnosed conditions as alternative health outcome variables, followed by a discussion of the findings.

B.1 Diagnosed Depression and Anxiety

We obtained the major depression diagnosis (MDD) and generalized anxiety diagnosis (GAD) variables from the MINI derivatives. These derivatives are based on the MINI questionnaire and were processed by the University Center of Psychiatry in accordance with the manual for MINI version 5.0.0, which is compatible with both DSM-IV and ICD-10 diagnostic criteria. ^{A1}

Compared to the symptom count, the MINI derivatives classify whether an individual meets the diagnostic criteria for depression or anxiety. For instance, a diagnosis of MDD according to the DSM-IV requires at least 5 out of 9 symptoms, including specific mandatory symptoms. Therefore, the severity captured by the diagnosis and symptom count variables differs, with diagnosed variables indicating more severe conditions.

The MDD and GAD variables are available for waves 1a, 2a, and 3a. ^{A2} These data are derived from survey responses within the Lifelines study rather than from diagnoses made by general practitioners. In the main text, we use symptom count because clinical diagnoses may underestimate

^{A1}For further details on the MINI-derived variables, please refer to the Lifelines Wiki and [Van Loo et al. \(2023\)](#).

^{A2}MINI-based diagnoses from wave 3a were not available before March 2025. Additionally, the available sample sizes for these variables in waves 1a and 2a were expanded during this update.

the broader impact on mental health, as they capture only more severe cases. In contrast, symptom counts allow us to capture a wider spectrum of mental health conditions, including subclinical symptoms.

B.2 Results and discussion

We merge the diagnosis data with the sample used in our main analysis, resulting in 84 missing observations in wave 1a, 269 in wave 2a, and 330 in wave 3a.^{A3} We then replicated the estimation strategy from Table 2 of the main text. As shown in Table A.4, the results indicate a statistically significant negative effect of mining-induced earthquakes on depression diagnoses when using an individual-level fixed effects model. Specifically, a one-unit increase in APGA (3) is associated with an approximately 0.81% increase in the probability of being diagnosed with MDD. However, we do not find a statistically significant effect on GAD diagnoses.

These findings suggest that, although exposure to earthquakes is associated with an increase in anxiety symptoms, the effects are not substantial enough to lead to clinical diagnoses. In contrast, for depression, earthquake exposure appears to contribute to more severe mental health deterioration that reaches the clinical threshold for diagnosis. This indicates that relying solely on diagnostic variables may underestimate the broader mental health impact of earthquake exposure, particularly in less severe cases.

^{A3}The attrition is due to differences in the availability of MINI variables and their derivatives across waves. The MINI derivatives were processed by the University Center of Psychiatry instead of Lifelines.

Table A.4: Pooled OLS and fixed effects estimates for the major depression diagnosis and generalized anxiety diagnosis

	Major Depression Diagnosis		Generalized Anxiety Diagnosis	
	(1)	(2)	(3)	(4)
	POLS	FE	POLS	FE
APGA(3)	0.0030*** (0.0008)	0.0081** (0.0034)	0.0046*** (0.0011)	0.0000 (0.0048)
Age	0.0012*** (0.0003)	0.0053** (0.0021)	0.0031*** (0.0004)	0.0099*** (0.0028)
Age squared	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0000*** (0.0000)	-0.0001*** (0.0000)
Gender	-0.0119*** (0.0012)		-0.0327*** (0.0017)	
Urban	0.0077*** (0.0013)		0.0151*** (0.0018)	
Middle education	-0.0175*** (0.0018)	-0.0008 (0.0048)	-0.0182*** (0.0024)	0.0034 (0.0064)
High education	-0.0305*** (0.0018)	0.0118 (0.0076)	-0.0339*** (0.0024)	0.0044 (0.0101)
Smoothing year FE	No	Yes	No	Yes
Postal code FE	No	Yes	No	Yes
Observations	91,655	91,655	91,655	91,655
Numbers of individuals	42,768	42,768	42,768	42,768

Notes: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

C Appendix: Estimating the Total Mental Health Burden of Earthquakes

C.1 CBS Population Data for Each Postal Code

We obtain population data for each 4-digit postal code in the Netherlands from Statistics Netherlands (CBS), which annually publishes key demographic statistics at the postal code level. Specifically, we use data from the 2020 Version 1 release. We then match this population information to our dataset using the 4-digit postal codes. The population for postal code p is denoted as $population2020_p$. It is important to note that the 2020 population data do not necessarily reflect the actual population throughout the full exposure period, which may introduce bias into our estimates.

C.2 Calculating the Total Mental Health Burden

We estimate the average accumulated PGA over a three-year period for each postal code and survey wave by calculating the mean exposure among Lifelines participants residing in the area. Specifically, this is defined as:

$$AverageAPGA_{pw}^{3y} = \frac{\sum_{i=1}^N APGA_{pt}^{3y}}{N} \quad (6)$$

where $AverageAPGA_{pw}^{3y}$ denotes the average accumulated PGA over three years for postal code p at wave w . N is the number of individuals in our sample living in postal code p , and $APGA_{pt}^{3y}$ represents the accumulated PGA at postal code p at time t . For instance, $APGA_{p1}^{3y}$ reflects the mean exposure among sample participants at wave 1A (2007–2013).

We then compute the mental health burden for postal code p at wave w as follows:

$$Burden_{pw} = \beta \cdot APGA_{pw}^{3y} \cdot population2020_p \quad (7)$$

where $Burden_{pw}$ denotes the estimated mental health burden (in terms of depression and anxiety symptoms) for postal code p at wave w , β is the coefficient estimated from Equation (4), and $population2020_p$ is the total population of postal code p in 2020. For a specific symptom, such as

depressed mood, the burden can be estimated as:

$$Burden_{pw}^{DepressedMood} = \beta_{DepressedMood} \cdot APGA_{pw}^{3y} \cdot population2020_p \quad (8)$$

Finally, the total burden of a specific symptom (e.g., depressed mood) across three waves and postal codes is calculated as:

$$TotalBurden^{DepressedMood} = \sum_{w=1}^3 \sum_{p=1}^P Burden_{pw}^{DepressedMood} \quad (9)$$

We repeat this procedure for all health outcomes to estimate the corresponding mental health burdens. However, these estimates should be interpreted as lower-bound and rough approximations of the true burden. This is due to several limitations. First, the use of 2020 population data may introduce bias. Second, the average accumulated PGA values are calculated based on our sample, rather than the full population exposed during the relevant period. Third, our sample does not cover all postal code-4 areas in the affected region.