The Impact of Internal Migration on Health

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Abstract

Despite large and persistent spatial differences in productivity, wages, and standards of living, internal migration in developing countries remains low. Could this puzzle be explained by compensating amenity differentials that affect health? This study attempts to infer the role of compensating amenities as a deterrent for internal migration by comparing the health of migrants before and after migration using data from five waves of the Indonesia Family Life Survey (IFLS). To account for selection into migration, we employ a sequential variation of the difference-in-differences design and an instrumental variable approach. We find no evidence of deterioration in migrants' health. Our findings cast doubt on the compensating differential as an explanation for low rates of migration.

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1 Introduction

Recent research has documented large spatial variation in wages, consumption, and general standards of living in developing countries (Ferré et al., 2012; Herrendorf and Schoellman, 2018; Bryan and Morten, 2019; Gollin et al., 2021). And yet, internal migration in these countries remains low and a severely under-utilized adaptation strategy (Gollin et al., 2014; Bryan et al., 2014; Munshi and Rosenzweig, 2016). The literature has advanced two explanations for this low-migration puzzle: (i) sorting and (ii) compensating amenity differentials or movement costs.[1]

The sorting hypothesis and the amenities hypothesis offer different perspectives on why people choose to migrate. According to the sorting hypothesis, individuals sort themselves into locations based on their skills and preferences, with high-skilled workers often gravitating towards areas with good amenities. While there is strong evidence that people with different skills and abilities sort into various regions and sectors, the sorting hypothesis is unable to fully explain the persistence of low migration (Gollin et al., 2014; Munshi and Rosenzweig, 2016; Bryan and Morten, 2019; Hamory et al., 2021).

The other non-monetary explanation proposed in the literature relates to high wage premiums paid as compensation for relatively poor amenities in urban areas Glaeser and Gottlieb (2009). Amenity differentials (or movement costs) are often considered as a residual explanation - areas with lower wages and consumption must have better amenities to counterbalance the pull factor of higher wages.[2] The evidence in its favor is mixed. Bryan et al. (2014) find that rural households in Bangladesh are more likely to send out a migrant during the lean season when they receive a monetary incentive to cover the risk of failing to find satisfactory employment at the destination. However, less than a quarter of the incentivized households in their experiment send out a migrant. Even among those, fewer repeat it in later lean seasons. In the context of India, Munshi and Rosenzweig (2016) argue that the risk of losing caste-based rural insurance networks inhibit migration. But the argument does not explain low levels of urban-to-urban migration in India or internal migration elsewhere, where such informal insurance networks are scarce or absent. Using high-resolution information on three categories of non-pecuniary amenities - pub-

[1] The agricultural productivity gap puzzle or the rural-urban wage puzzle are alternative labels for this phenomenon of low migration rates in the face of large disparities in opportunities.

[2] Following most studies in this space, we do not distinguish between amenities differential and movement costs. One recent exception is Bryan and Morten (2019) who estimate amenities differential as the variation in the compensating wage differential across destinations for migrants from the same origin adjusting for distance and movement costs as the part of wage differential that varies with distance from origin.

lic goods (electricity, piper water, sewage systems, paved roads, schools, police stations, health facilities), crime, and air pollution - from 20 Sub-Saharan African countries, Gollin et al. (2021) find that in almost all countries the quality and availability of these amenities in urban areas was at least as good as in rural areas. The implication is that amenities differentials should reinforce the direction of migration implied by the rural-urban wage differential, and not counteract it.

However, the role of amenity differentials has been difficult to measure. Defined as a residual, amenities can include everything from public infrastructure (e.g. hospitals and schools) to living conditions (disease environment, pollution, crime, and housing) to the pecuniary and non-pecuniary benefits of maintaining proximity to networks (e.g. informal insurance networks or emotional support from family and friends).[3]

Our paper proposes a simple solution to analyse the impact of amenities on (the low levels of) internal migration. The setting for our analysis is Indonesia. We compare well-being measures right before and after migration. As per revealed preference, people who willingly choose to migrate are likely to be better off at the destination than they would have been had they stayed at the origin. To the extent that objective and subjective health measures are good proxies of well-being, movers should enjoy overall better well-being at the destination. Amenities, by definition, are facilities that make life more pleasant or comfortable. Declines in the well-being of migrants after the move, especially after taking into account the role of income, could potentially be indicative of poor amenities at the destination.[4]

Against this backdrop, our analysis offers three main contributions to the existing literature. Firstly, it uses five waves of the Indonesia Family Life Survey (IFLS), a rich panel dataset which account for 16,931 households interviewed in the last waves in 2014 (Strauss et al., 2016). This allows us to analyse changes in five measures of migrant well-being before and after migration. Specifically, we use five key individual well-being measures: lung capacity, haemoglobin count, overweight status, Assisted Daily Living (ADL) score, and self-rated health. Of these measures, the first three are objective measures of

[3]Another complication arises from the generally observed correlation between economic opportunities and level of amenities. Cities with better opportunities tend to have better infrastructural amenities, making it difficult to distinguish in-migration in response to amenities from in-migration in response to better earnings.

[4]For example, if migrants in India lose their informal caste-based insurance networks when they move, it would show up as higher fluctuations in consumption and, therefore, worse physical or mental well-being. Disease environment, pollution, crime, and housing conditions, all have well-being implications.

health that are directly measured by trained IFLS enumerators, and the last two are self-reported indicators. Previous studies on internal migration from Indonesia using the IFLS focus on other aspect, which include Pardede et al. (2020) that examine the roles of individual and household characteristics in internal migration, Marta et al. (2020) which focuses on the impact of migration motives on household welfare, and Parhah et al. (2025) who examines the earnings differential between users and non-users of networks of Indonesian internal migrants.

We begin by investigating the trends in these measures before and after the migration event to understand the gradual determinants of migration and changes in well-being that might accrue slowly over time after migration. Consistent with Hamory et al. (2021), the event studies, two-way fixed effects results and findings from the sequential difference-in-differences approach, where we compare recent movers with respondents who would move in the future, show that migrants tend to have better, not worse, well-being after migration.

However, event studies and sequential difference-in-differences do not account for selection into and timing of migration and may, therefore, reflect the differences between migrants and non-migrants or respondents who choose to migrate at different points in time. To overcome this issue, we implement an instrumental variable design. We instrument the decision to migrate using 'rainfall shock' at the respondents' origin districts. The 'rainfall shock' is defined by the extent to which the amount of total rainfall in the year prior to the year of migration in the migrant origin district differs from the district's 50-year average annual rainfall. We show that a respondent is more likely to migrate if the rainfall in their origin district is lower than the long-term district annual average rainfall. The instrument is unlikely to impact the health of the migrant directly because the health measures are recorded one to seven years after the rainfall shock. In fact, worse health due to rainfall deviations would limit migration rather than encourage it. We also show that the rainfall shock did not impact the well-being of any non-migrating member in the migrant's origin household and, therefore, is unlikely to have directly impacted the migrant's well-being right before the migration. We then use the predicted migration decision to estimate the impact of migration on the well-being of the migrant. Here, too, we find no evidence of a deterioration of migrant health after migration. Taken together, our findings suggest that compensating amenity differentials, at least of the type that can impact health, might not be a deterrent for internal migration.

Secondly, our paper adds to the small number of studies that examine the impact of domestic migration on migrant health (Finkelstein et al., 2021). Previous studies in this field focus on the impact of immigration to developed countries on the health of both immigrant and native populations (Antecol and Bedard, 2006; Giuntella and Mazzonna, 2015; Giuntella et al., 2018). However, differences in the costs and benefits of international and domestic migration imply differences in the composition of the two types of movers. Additionally, the scale at which internal migration occurs is much larger than the scale of international migration (Bell and Charles-Edwards, 2013). This has implications for amenities, like congestion, and, therefore, well-being. On the positive side, domestic migrants may not face language barriers at the destination and might be better able to maintain their networks and family ties. Similarly, the reasons for and the implications of internal migration may differ across developed and developing countries. Weaker institutions and lower government capacity in developing countries could mean that internal migrants lose their social security benefits when they migrate or do not receive any assistance at the destination. Several studies have compared the health of migrants with natives in Indonesia or other developing countries (Lu, 2008, 2010; Tong and Piotrowski, 2012; Sun and Yang, 2021). To the best of our knowledge, no previous study controls for selection into migration. We believe ours is the first study that tries to estimate the **effect** of domestic migration on migrant health after accounting for selection.

Our study also contributes to the literature on the association between amenity differentials and migration (Munshi and Rosenzweig, 2016; Gollin et al., 2021), specifically focusing on domestic migration and accounting for selection effects using longitudinal data. We are unaware of any other studies that compare the health of migrants before and after migration to infer whether compensating amenities differential deter internal migration.

2 Data

Our analyses use data from five waves of the Indonesian Family Life Survey (IFLS). The IFLS is a longitudinal socioeconomic and health survey conducted by the RAND Corporation. It is representative of around 83 percent of the population that were living in 13 out of 26 provinces in Indonesia in 1993. The first wave, IFLS1, was conducted in 1993–1994 with follow-up waves in 1997-1998, 2000, 2007-2008, and 2014-2015. The IFLS is known for its impressive tracking with one of the lowest attrition rates among lon-

gitudinal datasets worldwide. 86.9% of IFLS 1 dynasty households were interviewed in all five waves (Strauss et al., 2016).

There are several reasons for choosing IFLS for our analysis. First, the IFLS is currently the only household-level panel dataset available for Indonesia. It contains rich migration data that allows us to construct complete migration profiles for respondents from the first time they are interviewed. It also collects retrospective information on the place of birth and residence at twelve years of age. Such rich information on migration is difficult to find in longitudinal surveys from developing countries. IFLS takes extra care in following respondents who migrate, even if they migrate outside IFLS-provinces. Their impressive recontact rates mean that our estimates are less prone to biases due to selective attrition, which is particularly concerning when studying migration. Another big advantage of using IFLS is the breadth and quality of health data it collects. The survey collects anthropometric measures, prevalence of acute and chronic health conditions, self-reported health status measures, and information on health behavior. Importantly, key summary health measures, like weight, height, lung capacity, grip strength, and hemoglobin count, are collected by trained enumerators or accompanying nurses.

2.1 Dependent Variables

We use three criteria to select the well-being measures that we use for our empirical analysis. First, we choose measures that are consistently collected throughout the five survey waves. Although this greatly limits our choices, it is critical to ensure that we have enough variation in our variables of interest (especially migrant status over survey waves for the same respondents). Second, to ensure that we do not confound the effect of migration on well-being with the effect of migration on changes in health-reporting behaviors, we select a mix of objective biomarkers and subjective self-assessments of well-being.

Migration can lead to changes in the ability to self-diagnose or get diagnosed with medical conditions. It can also affect people's perception of their physical capabilities. Our mix of measures allows us to distinguish between changes in underlying health and changes in respondent's perceptions of health. The objective biomarkers that we use are the respondent's Body Mass Index (BMI)-based measures, hemoglobin count, and lung capacity. Another advantage of using these measures is that they are collected by trained professionals, reducing the chances of mismeasurements. To understand changes in self-assessments of health, we use information on the level of difficulty faced in performing activities of

daily living (ADL) and self-reported health on a four-point scale that runs from 'very unhealthy' to 'very healthy'. Finally, we also want a mix of short-term, medium-term, and long-term health indicators. While BMI-related measures capture medium- to long-term health status, lung capacity and hemoglobin count can indicate short-term fluctuations in health. Level of difficulty in performing ADL and self-reported health are likely to factor in both short-term and long-term health. Based on these criteria, our chosen set of health measures are BMI-related measures, lung capacity, hemoglobin count, level of difficulty in performing ADL, and self-reported health.

BMI is commonly used as a screening tool to identify individuals at risk of chronic health conditions, like cardiovascular disease, diabetes, and certain cancers. For adults, BMI values between 18.5 and 24.9 are considered to be within the healthy range. Individuals with BMI values below 18.5, between 25 to 29.9, and above 30 are considered to be underweight, overweight, and obese, respectively. For our analysis, we use BMI measurements to construct separate indicators for whether a respondent is in the underweight or overweight category. Lung capacity refers to the amount of air that a person can inhale or exhale during a respiratory cycle. It is measured using a variety of tests, including spirometry. Analysis of lung capacity can provide information about a person's respiratory function and overall health status, and also indicate if they have respiratory diseases, such as asthma, chronic obstructive pulmonary disease (COPD), and lung fibrosis. A low hemoglobin count indicates iron deficiency or sickle-cell anemia, which compromises an individual's s ability to absorb nutrients from food.

Activities of daily living (ADL) assess a person's ability to perform everyday tasks. The IFLS survey asks respondents several questions on their ability to perform a range of everyday tasks including their ability to carry a heavy load, walking for 5 km, and their ability to squat and kneel. To reflect the overall level of difficulty in ADL, we add the scores for each of the eight activities for which information is collected in all waves. These are carrying a heavy load, walking 5 km, sweeping the house floor, drawing a pail of water, squatting and kneeling, standing up from sitting on chair, and standing up from sitting on the floor. A higher score indicates higher levels of difficulty in ADL.

2.2 Explanatory Variable

The main explanatory variables in our analysis are whether there is a change in a respondent's migration status since the first time they were interviewed in the survey and, if yes,

in which year did the change occur. Indonesia consists of 34 provinces that are subdivided into regencies or districts, referred to as *Kabupaten*. The IFLS survey, in each wave, collects information on the current residence district of the respondents. We use this information to define 'migrants' as those respondents who changed their district of residence in two successive wave. We use the district codes from 1998 to standardize and merge the IFLS information across waves. At that time, the country consisted of 301 districts. Since then, various delimitations have occurred, whereby the number of districts expanded to 346 districts in 2000, 465 districts in 2007, and 512 districts in 2014. All split-off districts are mapped to their parent district in 1998.

3 Empirical Methodology

We begin our analyses with event study graphs that graphically examine changes in migrant well-being before and after migration. All event study figures control for respondent fixed effects, residence district-survey year fixed effect, and fixed effects for the age of the respondents. Next, we perform a comparable regression analysis using the following two-way fixed effect (TWFE) model:

$$\begin{aligned} H_{idt} = \alpha^{TW} + \beta_1^{TW}\text{Migrant}_{idt} + \beta_2^{TW}(\text{Time relative to the migration event})_{idt} \\ + \beta_3^{TW}\text{Migrant}_{idt} \times (\text{Time relative to the migration event})_{idt} \\ + \gamma_i^{TW} + \omega_d^{TW} \times \delta_t^{TW} + \varepsilon_{idt}^{TW} \end{aligned} \quad (1)$$

Here, H_{idt} denotes the well-being of respondent i living in district d recorded during survey wave t. Migrant_{idt} is an indicator variable that takes on the value '1' if the respondent reports living in a district other than their birth district in survey wave t. $(\text{Time relative to the migration event})_{idt}$ is the distance of the survey wave t from the wave in which the Migrant_{idt} changes from '0' to '1'. We control for respondent-level time-invariant characteristics using individual fixed effects, denoted by γ_i. We also include for residence district-wave fixed effect ($\omega_d \times \delta_t$) to control for district-level characteristics changes across survey waves. Here, we cluster the standard errors at the level of district of residence. The estimate of β_1 captures the change in the health measures of the average respondents with change in time relative to the migration event after controlling for any time-invariant respondent-level and district-level characteristics.

Note that the event studies and the two-way fixed effects estimations use the sample of

respondents who migrated at least once between 1993 and 2014. While these results serve as the first level of our inquiry into the health effects of migration, there are several weaknesses. For instance, the timing of migration is not exogenously determined, leading to the concern that any observed relationship in the figures could be driven by selection. People who decide to migrate may do so when they sense a deterioration (or improvement) in their health.[5] We account for this form of selection using two different identification approaches.

Following the recent advances in the difference-in-differences (DiD) methodology, we use the estimation approach in Callaway and Sant'Anna (2021) comparing people who migrated in a specific wave with those who had not migrated at that point, but would eventually migrate by 2014 ('not-yet-treated'). Since we do not observe the health status of IFLS respondents before the first wave and all our specifications include respondent fixed effects, we cannot make this comparison for respondents identified as migrants in the first wave of the survey. Similarly, for respondents migrating in the fifth survey wave, we do not have a 'not-yet-treated' comparison group. For $\tau \in \{2, 3, 4\}$, we implement this 'Sequential DiD' by comparing the change in health of respondents who moved in wave τ with respondents who would move in a later wave, using data until wave τ. We estimate the following equation:

$$H_{idt} = \alpha^{TW} + \beta^{TW}[\text{Migrated b/w waves } (\tau-1) \text{ and } \tau]_{idt} \times I(\text{survey wave} = \tau) + \gamma_i^{TW} + \omega_d^{TW} \times \delta_t^{TW} + \varepsilon_{idt}^{TW}, \quad \forall \tau \in \{2, 3, 4\} \quad (2)$$

This within-migrants migrants comparison accounts for selection into becoming a migrant. The parallel trends assumption is much more likely to hold for these two groups of migrants who differ just in the timing of migration.

Robustness tests: Instrumental variabe anaysis

The sequential DiD does not account for endogeneity in the timing of migration. Migration in different calendar years or different ages might be motivated by different underlying factors that might or might not have a bearing on health. Next, we implement an instrumental variable design that accounts for both selection into being a migrant and the timing of migration.

[5]For example, people with worsening health could migrate to avail better health support at the destination. Or, people in good health could migrate to leverage their productivity benefits of their good health in a market that values their skills and expertise.

Our instrument for migration is a location-specific rainfall shock. The rationale is as follows. Agriculture is one of the most important sources of livelihood in Indonesia. According to World Bank indicators, close to 40 percent of the country's labor force was engaged in agriculture in the early 2000s. Agriculture in Indonesia is highly dependent on the timing and amount of rainfall (Kishore et al., 2000; Levine and Yang, 2014). Monsoon trajectories vary across years leading to variations in the timing, intensity, and duration of precipitation in different regions of the country in any given year and across years within a region. Studies by Levine and Yang (2014) find that higher rainfall in Indonesia is associated with higher rice yields. Maccini and Yang (2009) and Banerjee et al. (2025) find that the agricultural benefits of rainfall do not diminish even at very high levels of rainfall. Due to Indonesia's equatorial location, other weather-related factors, such as temperature, shows little variation within years and across years.

The impact rainfall fluctuations have on agriculture output have long-lasting implications. Maccini and Yang (2009) find that better rainfall was associated with better health, educational, and socio-economic outcomes for women born between 1953 and 1974 in Indonesia. They argue that better rain, through higher income, improves the ability of parents to provide better "nutrition, medical inputs, and generally more nurturing environments for infant girls".[6] Therefore, it not surprising that regions that experience negative rainfall shocks witness more out-migration (Kleemans and Magruder, 2017). Out-migration during difficult agricultural seasons allows agricultural households to mitigate the adverse effect of low rainfall Bryan et al. (2014).

Rainfall could also affect health through other channels like disease environment and availability of potable water (Cornwell and Inder, 2015). Therefore, instrumenting migration decision with rainfall shocks could violate the exclusion restriction in our setting. But the context makes this unlikely. First, we use the rainfall shock in a year prior to the migration year. Changes in disease environment in twelve months before migration are unlikely to have persistent effects on health of adults. Controlling for rainfall shocks in the year of migration does not affect the relationship between lagged year rainfall and migration. Moreover, rainfall usually affects the spread of infectious disease, which are unlikely to have sustained effect on the long-term adult health markers we examine. Second, we show that the rainfall shocks do not impact the health of migrant's household members

[6] Banerjee et al. (2025) confirm these findings for all genders.

who do not migrate.[7]

For the instrumental variable analysis, we predict migration decisions using rainfall variation at the migrant's origin district. In all stages of the instrumental variable analysis, we also control for temperature variations at the district of origin. The weather measures are constructed using data from the University of Delaware's Terrestrial Precipitation and Air Temperature. The dataset provides estimated daily precipitation and temperature information for 0.5 by 0.5 degree grids going back to 1900. We begin by collapsing the grid-day level data to gridyear) level. We then convert the grid-level data into district-level data using the following process. First, for each district surveyed by IFLS, we calculate the district's geographical centroid. Next, we match each district centroid with the five nearest grid points. We then calculate a weighted average of the weather variables across these five grid points for each district and month, with the inverse of the distance between the district centroid and the grid point as the weight. Next, for each district and year, we use this weighted average to calculate the district's daily average in the preceding fifty years. We subtract this historical average from the weighted daily average for every year to obtain the weather shock measures. Therefore, the rainfall shock for a district in a specific year is the extent to which the average daily rainfall in that year deviates from the daily average rainfall in the fifty years before that year.

The first-stage estimation equation for the IV model can be formally written as:

$$\text{First Stage: } \text{Mig}_{iodt} = a + b \times \text{Rain shock}_{ido,(\tau-1)} + \zeta_i + \eta_d \times \theta_t + \mu_o \times \theta_t + \epsilon_{iodt}. \quad (3)$$

where subscripts t denote survey waves and $(\tau - 1)$ denote years relative to the migration year. Mig_{iodt} is an indicator variable that takes on a value '1' if individual i interviewed in survey wave t migrated from origin district o between waves $t-1$ and t. $\text{Rain shock}_{ido,(\tau-1)}$ is the average of the deviations of the rainfall in origin o from the district-specific 50-year historical rolling average daily rainfall in a year before the year of migration (denoted by τ). The specification includes respondent-level fixed effects (ζ_i), destination district-wave fixed effects ($\zeta_i + \eta_d$), and origin district-wave fixed effects ($\mu_o \times \theta_t$), as both locations are affected by rainfall shocks.As before, respondent FE allow us to account for respondent-level time-invariant characteristics, like openness to new ex-

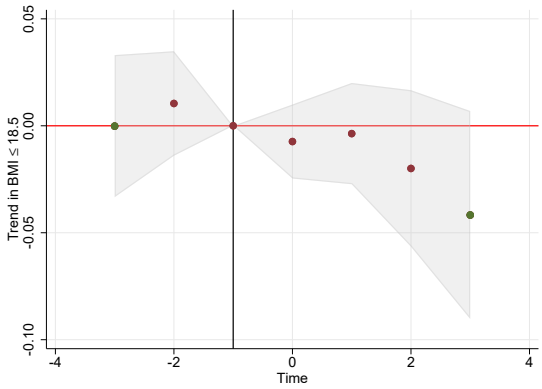
[7]As we show below, 90% of all Indonesian internal migrants migrate for work, education, marriage, or to be with family. Bad health due to rainfall shocks is likely to deter all these types of migration, not trigger it.

perience, that can impact migration decision. Destination and origin district-wave fixed effects now allow us to additionally control for all district level changes over time, including changes in infectious disease environment. Throughout the IV analysis, we cluster the standard errors at the respondent level. We use the predicted value of Mig_{iodt} from this first-stage model in the following second stage:

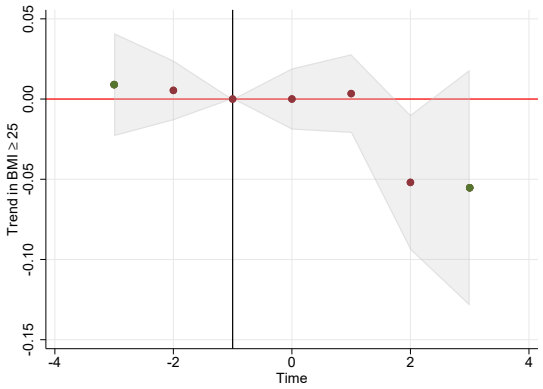
$$\text{Second Stage: } H_{iodt} = \alpha^{IV} + \beta^{IV} \times \widehat{\text{Mig}}_{iodt} + \gamma_i^{IV} + \omega_d^{IV} \times \delta_t^{IV} + \varepsilon_{iodt}^{IV} \tag{4}$$

Throughout the analysis, we cluster standard errors at the residence district level. The results are robust to changes in the geographical level at which we cluster standard errors.

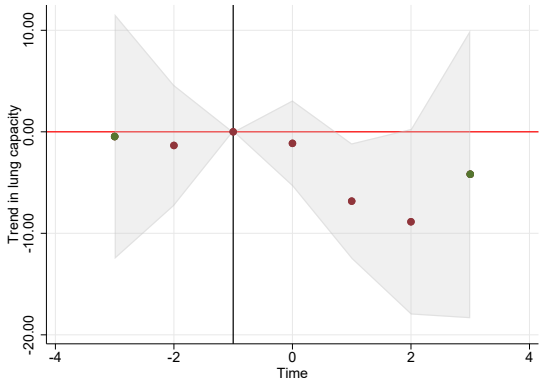
Figure 1: Trends in health measures before and after migration



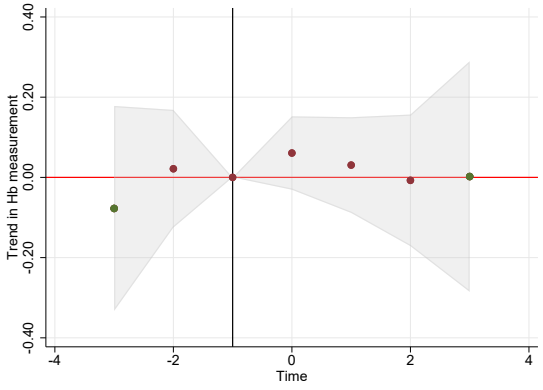
(a) BMI $\leq$ 18.5



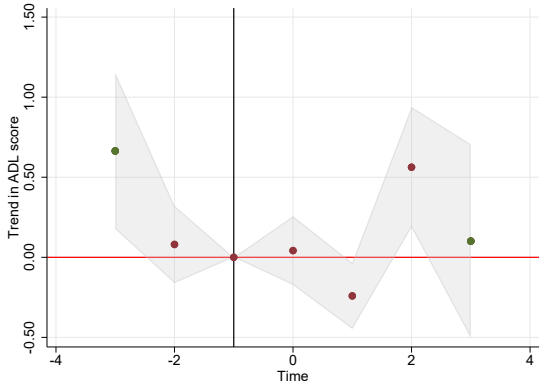
(b) BMI $\geq$ 25



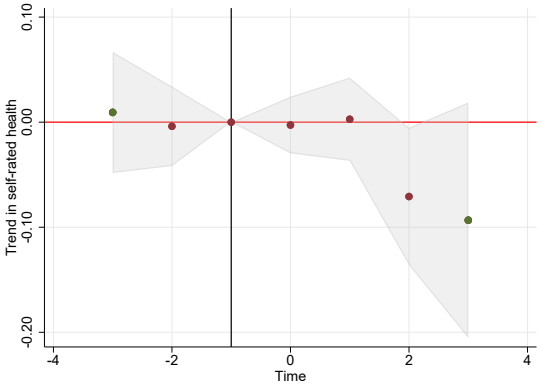
(c) Lung capacity



(d) Hemoglobin count



(e) Difficulty in performing ADL (score)



(f) Self-rated current health (1-4)

Source: Indonesia Family Life Survey waves 1-5.
Notes: The gray bands depict 95% confidence intervals. The vertical black line denotes the last interview before migration. All specifications control for respondent fixed effects, residence district-survey wave fixed effects, and age fixed effects. The standard errors are clustered at the residence district level.

4 Results

4.1 Event Study Analysis

We begin by presenting the change in the health status of migrants, comparing their health measures in the waves before and after their migration move. Figure 1 illustrates the results. In all figures, we control for respondent fixed effects to capture time-invariant individual characteristics, like genetics, and district-wave fixed effects to account for district-level changes, like disease breakout, crime or weather conditions, that could impact respondent well-being. Additionally, we also control for age of the respondents. The figures present a mixed picture. While there are no significant changes in any of the health measures immediately after the move, the probabilities of being underweight and overweight, and the difficulty in performing activities of daily living (ADL) decline with time.

Over the long run, lung capacity and self-rated health seems to deteriorate, but the difference is not always statistically significant. The figures suggest that there might not be any across-the-board negative effect of migration, but further analysis is required for a better understanding of the effects of migration.

Table 1: Association of migration and health

	(1) Underweight	(2) Overweight	(3) Lung Capacity	(4) Hb Levels	(5) ADL Score	(6) Self-rated Health
Migrant	-0.016*	0.020*	7.252***	0.116***	-0.443***	0.046***
	(0.008)	(0.010)	(1.970)	(0.044)	(0.094)	(0.013)
Migrant × Waves since migration	0.003	0.010	0.882	0.039	-0.539***	0.031**
	(0.006)	(0.011)	(2.898)	(0.050)	(0.151)	(0.015)
Respondent FE	✓	✓	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓	✓	✓
Mean of DV	0.168	0.203	319.805	13.361	8.304	2.987
# of districts	198	198	197	197	193	199
Observations	12,302	12,302	11,250	11,198	9,821	12,959

Source: Indonesia Family Life Survey waves 1-5.
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at the residence district level, are reported in parentheses.

In Table 1, we present results from a two-way fixed effects estimation that uses a specification similar to the event studies. The only difference is that we now impose independent linear trend structures on the evolution of migrant health before and after migration. The benefit of this specification is that it helps us ascertain if there is structural break (significant changes in the intercept and the slope) in health of migrants around the time of

migration. In contrast to the event studies, we find that migration is associated with an immediate improvement in health across all measures except a small rise in the probability of being overweight.[8] Interestingly, ADL scores and self-rated health improve with time after migration.[9] If people choose migration expecting a better life at the destination, we should expect to see improvements in health over time after migration.

Next, we consider the possibility that migration motivated by different reasons might have different relationships with health. IFLS has a range of information on why respondent moved out from their origins. We group the reasons into five categories: work-related, education-related, marriage and divorce, other family-related, and other reasons (such as transmigration program, natural disasters, health, and political disturbance). Using lung capacity as the outcome variable, Table 2 shows that migration of almost all types are correlated with improvements in lung capacity, but the association is statistically significant for only work and marriage-related migration.[10] The only significant negative coefficient is the change in lung capacity over time for respondents migrating for other reasons. But here too the effect is barely significant, and the sample for the group the smallest among the five.

[8] In Indonesia, being overweight is often associated with material comfort and wealth. See Aizawa and Helble (2017) and Oddo et al. (2019).

[9] As discussed before, a lower ADL score reflects lower levels of reported difficulty in performing activities of daily life.

[10] The result of migration effect by each reason on other health indicators are reported in the appendix. In general, there is no clear evidence of deterioration on any health indicators regardless of the reason for migration.

Table 2: Heterogeneity by Reason for Migration

	(1)	(2)	(3)	(4)	(5)
	Lung Capacity				
Migrant	12.286***	9.929	7.878**	1.567	-0.53
	(3.686)	(8.826)	(3.754)	(3.299)	(6.773)
Migrant × Waves since migration	-4.839	3.332	5.84	4.934	-15.686*
	(3.729)	(6.206)	(4.098)	(4.497)	(8.618)
Respondent FE	✓	✓	✓	✓	✓
District-Wave FE	✓	✓	✓	✓	✓
Reason for migration	work	educ	marriage	family	other
Mean of DV	344.611	347.654	312.851	318.884	320.696
# of districts	179	124	137	154	82
Observations	3,937	1,084	2,789	3,573	890

Source: Indonesia Family Life Survey waves 1-5.
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at the residence district level, are reported in parentheses.

While the TWFE accounts for time-invariant respondent-level characteristics, they do not account for selection into migration. It is possible that individuals who choose to migrate have a different health trajectory than individuals that do not migrate. To accommodate this concern, we use a modified version of a Difference-in-differences design proposed in Callaway and Sant'Anna (2021). The method, as described in Section 3, compares migrants in a specific wave with respondents who have never migrated but would migrate, but at a later date, using observations on these two groups of people collected until the specific wave. Since the method involves comparing two groups of migrants who differ only in the timing of their move, the parallel trends assumption is more likely to hold than when comparing migrants with natives. The findings from the analysis are presented in Table 3.

Table 3: Sequential difference-in-differences (Untreated Control)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Underweight			Overweight			Lung Capacity	
Migrant in Wave 2 × Survey wave ≤ 2	-0.000			-0.403				
	(0.000)			(0.269)				
Migrant in Wave 3 × Survey wave ≤ 3		-0.033			0.016		4.872	
		(0.040)			(0.027)		(10.092)	
Migrant in Wave 4 × Survey wave ≤ 4			-0.029			0.075**		10.822
			(0.035)			(0.030)		(7.699)
Respondent FE	✓	✓	✓	✓	✓	✓	✓	✓
Destination-wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	0.149	0.223	0.186	0.200	0.122	0.159	317.585	312.137
# of districts	59	150	181	59	150	181	135	179
Observations	504	2,520	8,527	504	2,520	8,527	1,978	7,479
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Hb Levels			ADL Score			Self-rated Health	
Migrant in Wave 2 × Survey wave ≤ 2			0.245			-0.366		
			(0.457)			(0.224)		
Migrant in Wave 3 × Survey wave ≤ 3	0.299			-0.111			0.019	
	(0.213)			(0.252)			(0.070)	
Migrant in Wave 4 × Survey wave ≤ 4		0.198			-0.197			0.007
		(0.166)			(0.614)			(0.050)
Respondent FE	✓	✓	✓	✓	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean of DV	13.264	13.294	7.674	7.824	7.923	3.035	3.022	3.005
# of districts	136	178	74	160	167	74	160	183
Observations	1,970	7,443	644	2,816	6,281	648	2,815	9,070

Source: Authors' calculation using Indonesia Family Life Survey waves 1-5.
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at the residence district level, are reported in parentheses.

We do not have enough observations by migrant status in waves 1 and 2 to estimate the association between migration with lung capacity and hemoglobin. Besides that, all the associations are statistically insignificant barring the association between the health status of migrants who migrate in wave 4 and the probability of being overweight. As previously mentioned, in Indonesia, being overweight indicates better levels of material consumption and may not be seen as a deterioration in health. A more serious concern is that while the sequential DiD design accounts for selection into migration, it does not account for the endogenous timing of the move. Next, we report results from our Instrumental variables model that takes into account the potential endogeneity of migration timing.

We begin by documenting the significant association between rainfall shock in the year before year t in the migrant's origin district, calculated as the difference between the district's average daily rainfall in year $t-1$ and the 50-year historical rolling average daily rainfall in that district, and the probability of migration. Table 4 presents the first-stage

results of our IV etimation. In all specifications, we control for the temperature shocks analogous of the inclusion of rainfall shocks. Across all specifications with different levels of fixed effects, we find that lower rainfall in the year preceding year t in a district is associated with higher out-migration in year t. This is consistent with findings from Kleemans and Magruder (2017) and Bryan et al. (2014).

Table 4: Impact of rainfall at origin on likelihood of migration (First Stage)

	(1)	(2)	(3)	(4)	(5)
	Respondent is a migrant				
Rain shock$_{ido,(\tau)}$				-0.0001	0.0003
				(0.0003)	(0.0003)
Rain shock$_{ido,(\tau-1)}$	-0.0011**	-0.0020***	-0.0015***	-0.0015***	-0.0011***
	(0.0004)	(0.0007)	(0.0003)	(0.0004)	(0.0004)
Rain shock$_{ido,(\tau-2)}$					0.0003
					(0.0004)
Respondent FE	✓	✗	✓	✓	✓
Destination-wave FE	✓	✓	✓	✓	✓
Origin-wave FE	✗	✓	✓	✓	✓
Temperature control	✓	✓	✓	✓	✓
Mean of DV	0.302	0.301	0.301	0.301	0.301
# of destination districts	223	224	221	221	221
Observations	105,478	119,948	105,351	105,351	105,301

Source: Authors' calculation using Indonesia Family Life Survey waves 1-5.
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at the residence district level, are reported in parentheses.

For the instrument to be valid, the rainfall shock needs to satisfy the exclusion criteria. While it is impossible to test whether the exclusion restriction holds, it is useful to think of possible scenarios in which it may fail to hold and then reflect on how likely these scenarios are going to be. The most obvious scenario is when a rainfall shock in year $t-1$ directly impacts the health of respondents. However, this is unlikely for several reasons. As previously discussed, rainfall-induced changes in nutritional availability and disease environment, if they do exist, are unlikely to impact outcomes one year later. Notice that controlling for rainfall in the year of migration, which is much more likely to move these alternative channels, does not impact the probability of migration. They also do not affect our second-stage results. This is not surprising because rainfall shocks usually affect the spread of infectious diseases or short-term health indicators like wasting, and are unlikely to be reflected in the long-term adult health markers included in this study. However, if there are any direct effects of lagged year rainfall shocks on health that persist to the

year of migration, there is no reason why they should exist only for respondents who have migrated out. In Table 5, we show that the rainfall shock in the year before migration had no significant effect on the health of migrants' family members who did not migrate with them. Given the context and these results, the instrument is likely to satisfy the exclusion restriction.

Table 5: The Impact of Rainfall Shock on Migrant Household Members

	(1) Underweight	(2) Overweight	(3) Lung Capacity	(4) Hb Levels	(5) ADL Score	(6) Self-rated Health
Rain shock$_{ido,(\tau-1)}$	-0.000	-0.001	-0.020	-0.008	0.004	-0.003*
	(0.001)	(0.001)	(0.212)	(0.005)	(0.009)	(0.001)
Respondent FE	✓	✓	✓	✓	✓	✓
Origin-Wave FE	✓	✓	✓	✓	✓	✓
Destination-Wave FE	✓	✓	✓	✓	✓	✓
Mean of DV	0.166	0.205	309.335	13.276	8.860	2.958
# of destination districts	178	178	178	177	163	181
Observations	65,835	65,835	56,914	57,242	52,659	68,378

Source: Authors' calculation using Indonesia Family Life Survey waves 1-5.
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at the residence district level, are reported in parentheses.

Since rainfall shocks are unanticipated, they instrument for both selection into and timing of migration. Next, we use the first-stage IV predictions to examine the impact of migration on health. The findings are reported in Table 6. Even with a reasonably strong instrument, none of the estimated effects on health are significant. Moreover, the direction of all the estimated coefficients suggests an improvement in health due to migration.

Overall, across different estimated models, we consistently find no negative effects of migration on health. These results are consistent with findings from Gollin et al. (2021), who found that amenities differentials run in the opposite direction. This is understandable since the quality of public infrastructure and services (including the health sector) is more likely to be better in urban areas – places that predominantly become migration destinations.

Table 6: Impact of internal migration on health (Second Stage)

	(1) Underweight	(2) Overweight	(3) Lung Capacity	(4) Hb Levels	(5) ADL Score	(6) Self-rated Health
Migrant	0.3746	-0.1575	20.4232	3.0983	-1.2143	1.1876
	(0.3475)	(0.4314)	(95.5813)	(2.0375)	(3.2459)	(0.7915)
Respondent FE	✓	✓	✓	✓	✓	✓
Destination-wave FE	✓	✓	✓	✓	✓	✓
Origin-wave FE	✓	✓	✓	✓	✓	✓
Temperature control	✓	✓	✓	✓	✓	✓
First-stage F-stat	17.095	17.095	13.802	12.904	24.902	17.065
Mean of DV	0.156	0.222	310.899	13.295	8.765	2.959
# of destination districts	217	217	215	213	206	221
Observations	96,941	96,941	83,688	83,907	78,477	100,964

Source: Authors' calculation using Indonesia Family Life Survey waves 1-5.
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at the residence district level, are reported in parentheses.

5 Conclusion

Standard models of migration predict a movement of people from low- to high-wage regions to benefit from the wage differentials. Empirically, we find that people are reluctant to move to high-wage regions even when these benefits exist and even if they are aware of the potential gains. The sorting hypothesis based on individual characteristics explains part but not all of the 'missing' migration. Amenity differentials are the most likely explanation but are extremely hard to empirically document. The difficulty arises from the broad definition of amenities, which makes it impossible to measure them all.

In this paper, we propose a simple solution. Since amenities are, by definition, facilities that make life more comfortable, any decline in health due to migration must indicate a loss of certain amenities when moving. We use information on migrants before and after their move using data from the Indonesian Family Life Survey to examine if migration leads to a deterioration in the health of the migrants. The longitudinal nature of the survey allows us to control for time-invariant individual characteristics, including genetic endowment and early-life conditions, and extract the effects of migration. Across different models, including a sequential variation of the DiD design and instrumental variable approach, we find no evidence of adverse health effect of migration. Our findings cast doubt on the compensating amenity differential as an explanation for low rates of migration.

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Appendix

Table A1: Heterogeneity Analysis - Migration Effect on Health Outcomes by Reason

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Underweight						Overweight				Lung Capacities				
Migrant	-0.033*	0.042	-0.029*	-0.008	0.050	-0.014	-0.011	0.022	0.013	0.019	12.286***	9.929	7.878**	1.567	-0.530
	(0.018)	(0.030)	(0.017)	(0.015)	(0.036)	(0.018)	(0.047)	(0.020)	(0.019)	(0.038)	(3.686)	(8.826)	(3.754)	(3.299)	(6.773)
Migrant × Waves since migration	0.031**	0.022	-0.001	-0.012	0.021	0.001	0.010	-0.014	0.010	-0.044	-4.839	3.332	5.840	4.934	-15.686*
	(0.013)	(0.026)	(0.013)	(0.013)	(0.032)	(0.017)	(0.028)	(0.016)	(0.014)	(0.038)	(3.729)	(6.206)	(4.098)	(4.497)	(8.618)
Respondent FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
District-Wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Reason for migration	work	educ	marriage	family	other	work	educ	marriage	family	other	work	educ	marriage	family	other
Mean of DV	0.172	0.186	0.160	0.148	0.124	0.175	0.202	0.209	0.237	0.279	344.611	347.654	312.851	318.884	320.696
# of districts	179	124	138	156	85	179	124	138	156	85	179	124	137	154	82
Observations	4,209	1,132	3,095	3,892	1,021	4,209	1,132	3,095	3,892	1,021	3,937	1,084	2,789	3,573	890
	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
	HB Levels						ADL Score					Self-Rated Health			
Migrant	0.000	-0.236	0.017	0.019	0.061	-0.103	-0.785**	-0.416**	-0.355**	-0.830*	0.009	0.128**	-0.000	0.018	0.043
	(0.083)	(0.154)	(0.084)	(0.071)	(0.164)	(0.140)	(0.360)	(0.184)	(0.152)	(0.430)	(0.025)	(0.060)	(0.024)	(0.025)	(0.066)
Migrant × Waves since migration	0.115	0.005	0.048	0.047	-0.221	-0.186	-0.383	-0.295	-0.202	-0.342	0.015	0.051	0.020	-0.012	0.031
	(0.070)	(0.153)	(0.083)	(0.072)	(0.207)	(0.125)	(0.404)	(0.202)	(0.125)	(0.516)	(0.021)	(0.041)	(0.028)	(0.019)	(0.043)
Respondent FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
District-Wave FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Reason for migration	work	educ	marriage	family	other	work	educ	marriage	family	other	work	educ	marriage	family	other
Mean of DV	13.741	13.812	13.271	13.230	13.288	7.941	7.920	8.233	8.369	8.524	2.995	3.044	2.988	2.974	2.944
# of districts	179	122	137	154	82	168	103	129	152	71	180	127	142	160	87
Observations	3,894	1,066	2,788	3,557	887	3,104	687	2,508	3,111	858	4,439	1,200	3,235	4,123	1,071

Source: Indonesia Family Life Survey waves 1-5.
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors, clustered at the residence district level, are reported in parentheses.