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Assimilation of rural–urban migrants under a less restrictive internal migration policy: Evidence from Indonesia

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Assimilation of rural–urban migrants under a less restrictive internal migration policy: Evidence from Indonesia

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Abstract

This paper provides new evidence on how a relatively open internal migration policy can influence migrant assimilation outcomes. We revisit the findings of previous studies on international labour migration in developing countries by investigating the economic consequences of moving people from rural areas to four Indonesian cities in which international migration is relatively free. The empirical investigation uses cross-sectional and individual-level panel data techniques. The results suggest that Indonesian migrants do not experience earnings penalties following their arrival in urban areas but have persistently higher earnings than their urban non-migrant counterparts. However, the higher earnings are accompanied by a worrying decline in migrant mental health. The finding of persistently higher earnings contrasts with the results of studies in countries such as China and Vietnam, which have more restrictive policies for rural–urban migration. We argue that economic assimilation can be highly successful in developing economies if the internal migration regime is relatively open, yet it creates an adverse mental health consequence.

Keywords: Indonesia, rural–urban migration, migration policy, mental health of internal migrants

JEL: O15, R23, R28

Assimilation of rural–urban migrants under a less restrictive internal migration policy: Evidence from Indonesia

1. Introduction

People the world over have tried to achieve better livelihoods by migrating either internally or internationally. Motivation to migrate also could originate from relative deprivation in income or skills (Stark and Bloom 1985). In other words, people move from one to another place to change their relative economic position in the current reference group or to change their reference group. Whether migrant finally achieve or not their objective in the destination is an open empirical question and this is what this present study provides in the context non-restricted internal migration setting.

Both international and internal migrations face natural barriers, such as distance or language. In addition to natural barriers, policy barriers are often enforced, such as the restrictive policies for international immigrants in the US (Abramitzky, Boustan, and Eriksson 2014) and the household registration (Hukou) system in China (Frijters, Meng, and Resosudarmo 2011). These policies can impede economic efficiency of migration.

Natural barriers (distance or language) and restrictive migration policies may shape the assimilation profile, and their influence depends on two factors. The first is how the natural barriers and restriction policies affect migrant selection. The second is how the policy dynamic alters migrant quality in the labour market over time.

For example, up to 1924, US borders were completely open to immigrants, especially those from Europe. Abramitzky, Boustan, and Eriksson (2014) observed that the gradual imposition of stricter US immigration policies since 1924 has led to a decline in the quality of immigrants to that country. As a result, they found that the assimilation profile of the immigrants shows a persistent gap between their wages and those of non-immigrants rather than the standard assimilation profile, in which recent migrants experience wage penalty and lifetime migrants' earnings overtake those of non-migrants.

Another example is that of China and Vietnam, which impose internal migration restrictions through a household registration system, known in China as Hukou. This system prevents rural–urban migrants from accessing social services equal to those of urban non-migrant workers. The registration system has also created significant labour-market segregation between rural–urban migrant workers and urban workers (Frijters, Meng, and Resosudarmo 2011). Although the Hukou system has been significantly relaxed since the mid-1980s (Meng and Zhang 2001), recent empirical estimates show that the typical economic assimilation profile that results from such a policy produces an inferior outcome for migrants relative to urban non-migrants (Ge 2017). The economic assimilation of the migrant is defined as the rate of convergence of his or her wages with those of non-migrants – or natives – in the hosting destinations (Chiswick 1978; Borjas 1985).

A number of studies have analysed the assimilation process for international migrants (Chiswick 1978; Borjas 1985; Cobb-clark, Broadway, and McVicar 2012; Breunig, Hasan, and Salehin 2013; Abramitzky, Boustan, and Eriksson 2014), and a few have examined internal migration (Meng and Zhang 2001; Ge 2017). Moreover, most studies have focused on the experiences of developed countries. Only a few studies on developing countries where there are restrictions on rural–urban migration. This paper aims to add variety to this literature by examining the experience of Indonesia where there are no binding constraints on internal labour mobility.

This paper focuses on internal migrants' performance, investigating economic assimilation, as a form of labour-market integration, and mental health assimilation, as a form of social integration, of rural–urban migrants. This paper examines the assimilation processes of rural–urban migrants in Indonesia, where the environment for internal migration is less restrictive than in places such as China and Vietnam. The investigation allows us to infer the consequences for the assimilation profile of migrants of relaxing internal migration restrictions. It determines whether migrants in a less restricted system can derive greater benefits from migrating than those in a more restrictive system, and whether migrant welfare converges faster towards that of urban non-migrants in a more liberal system than in a more restrictive one. In other words, the Indonesian case is chosen to benchmark the economic assimilation of internal migrants in countries such as China and Vietnam where rural–urban migrants face policies that are more restrictive.

The findings of this paper suggest that the Indonesian rural-urban assimilation profile is quite similar to that in India (Khan 2017), but contrasts with that of a restricted internal migration setting such as China (Ge 2017) or Vietnam (Liu 2017). Indonesia's rural–urban migrants do not experience an earnings penalty upon arrival in the cities, and their earnings remain persistently higher than those of urban non-migrants over time. However, the earnings assimilation profile is accompanied by a worrying in mental health assimilation profile: initially there is no mental health gap between migrants and urban non-migrants, but a modest deterioration in mental health occurs for every year since migration. Further, the estimates suggest that worsening mental health is strongly correlated with a lack of social support, and less well correlated with pressure caused by migrants extended working hours, as predicted by existing empirical studies.

The expected contribution of this paper is twofold. First, it provides empirical estimates of the assimilation process of internal migrants in a less restricted internal migration regime. Second, this is the first study to link two important outcomes in the analysis of the economic and social assimilation of internal migrants, namely, earnings and mental health.

The paper is organised as follows. Section 2 provides a literature review and summarises the estimating equation used in the literature on economic assimilation of migrants. Section 3 formulates our empirical strategy. Section 4 describes the data. Section 5 presents the results of our analysis of the economic assimilation profiles, the channels, and the heterogeneity profiles. Section 6 concludes.

2. Literature Review

In the context of developing economies, there are relatively few studies examining the wage gap between rural–urban migrants and urban non-migrants. Among them are Zhang and Meng (2007) and Ge (2017) in China, Liu (2017) in Vietnam, and Khan (2017) in India. These studies explicitly examine the economic assimilation of migrants relative to non-migrants. However, they use only cross-sectional or synthetic-cohort data. Liu (2017), with a particular focus on occupational segregation, examines the wage gap between rural–urban migrants and urban non-migrants in Vietnam in a static comparative perspective. For the case of Indonesia, Manning and Alisjahbana (2010) also attempt to examine the relative performance of rural–urban migrants' earnings from a dynamic perspective, but uses only a cross-sectional data set.

These studies yield diverse patterns or assimilation profiles. A primary explanatory factor is the different settings of the internal migration regime. While China and Vietnam have been restricting migration through the Hukou system, which limits rural–urban migrants' access to service delivery, the Indian system has been relatively less restrictive. The similarity of the internal migration regimes in China and Vietnam seems to yield relatively similar assimilation profiles for both countries, although we cannot infer this directly from the available static results for Vietnam.

Zhang and Meng (2007) find that the earnings of rural–urban migrants in China generally assimilate to those of their urban counterparts at the rate of 3.2% for each additional year spent in the host city. A recent study by Ge (2017) finds that rural–urban migrants in China start with a wage penalty of 32% relative to non-migrants, with a rate of convergence of 1.5% for each additional year spent in the city, and a decreasing rate of 0.25% of years-squared. The combined effect of these results is that migrants' wages cannot catch up with those of urban workers even in the long run. Liu (2017) estimates that the earnings of rural–urban migrants in Vietnam, in aggregate, are lower by 31.4% than those of non-migrants, using a standard Mincerian equation (Mincer 1974). Since the estimates are based on a static setting, Liu's results cannot be used to infer how these earnings evolve over time spent in the city.

The attempt by Manning and Alisjahbana (2010) to infer the assimilation profile of internal migrants who can freely move from rural to urban areas yields a quite different result. They indicate that Indonesian rural–urban migrants in the four cities tend to experience the standard assimilation profile, with the recent migrant experiencing wage penalty and the lifetime migrant's earnings overtaking those of the urban non-migrant. From this tentative result and those from China and Vietnam, it seems that restrictive internal migration regimes such as the Hukou system may play a significant role in shaping the assimilation profile of rural–urban migrants.

3. Empirical Strategy

Empirical studies of the economic assimilation of migrants commenced with the international migration context and the use of cross-section data in the 1970s. One of the earliest assimilation models was developed by Barry R. Chiswick in 1978; it focused on distinguishing (a) the effect of dynamic quality of successive migrant cohorts and individual heterogeneity from (b) the effect of Years Since Migration (YSM) for measuring economic assimilation. The core of the model by Chiswick (1978) using cross-section data is:

$$logW_i = \boldsymbol{X}_i.\boldsymbol{\beta}_0 + \beta_1.I_i + \beta_2.YSM_i + \beta_3.AGE_i + \beta_4.AGE_i^2 + \varepsilon_i \quad (1)$$

where i indexes individuals.

The estimating equation prescribes a linear regression of the natural logarithm of annual earnings $logW_i$ on a set of exogenous variables: I_i, a dummy variable that equals unity if the person is foreign-born and zero if a non-migrant; YSM_i, the number of years the migrant has resided in the host country, which equals zero for non-migrants; X_i, a vector of socioeconomic characteristics (mainly years of schooling, geographical dummies and weekly hours worked); and AGE, the calendar age to proxy gross labour-market experience.

Equation 1 estimates the earnings assimilation profile of migrants relative to non-migrants using two parameters: β_1, whether there is a wage penalty or premium upon arrival, and β_2, the yearly change in the relative earnings as migrants assimilate in the host country. Since the total (labour market) experience effect (measured by age) and the gross education effect (measured by years of schooling) have been controlled for, the assimilation coefficients are often attributed to host country's specific training or skills acquired in the labour market, or host country's human capital transferability (Borjas 1985).

Two important critiques emerge in responding to this core model with cross-section data: (a) the model cannot control dynamic change in cohort quality in the labour market which empirically is a noticeable explanatory factor of the assimilation process and (b) static nature of a cross sectional data is vulnerable to bias associated with non-random process of re-migration (Borjas 1985). The solution to the first concern is to include a cohort effect in equation 1, which requires the use of repeated cross-section data to avoid further identification problems; this is known as a synthetic-cohort approach. As for the second concern, nothing more can be done if complete re-migration data are lacking. The use of the synthetic-cohort model as prescribed by Borjas (1985) has now become the norm.

In his synthetic-cohort model, Borjas (1985) uses a repeated cross-section data set obtained in a calendar census ($Year = \{1, \dots, t\}$) , injects migrant time arrival ($COHORT_i$), or "cohort fixed effect", into the equation, and separates the equation into two because of the identification problem.

Migrant equation:

$$\begin{aligned} logW_{it} = \boldsymbol{X}_{it}.\boldsymbol{\beta}_0 + \beta_2.YSM_i + \beta_3.AGE_{it} + \beta_4.AGE_{it}^2 + \boldsymbol{COHORT}_i \\ + \boldsymbol{YEAR}_t + \varepsilon_{it} \end{aligned} \quad (2)$$

Non-migrant equation:

$$logW_{it} = \boldsymbol{X}_{it}.\boldsymbol{\beta}_0 + \beta_3.AGE_{it} + \beta_4.AGE_{it}^2 + \boldsymbol{COHORT}_i + \boldsymbol{YEAR}_t + \varepsilon_{it} \quad (3)$$

where t indexes census year, $COHORT$ is a vector of arrival cohort fixed effect and $YEAR$ is a vector of census year fixed effect.

While the synthetic-cohort model refines the estimates from an unobserved secular change of migrant quality at the cohort level, it does not address the unobserved heterogeneity of migrants over time at the individual level. The synthetic-cohort model also assumes that the composition of migrants by cohort is constant over time, which is a strong assumption in the presence of remigration.

Cobb-clark, Broadway, and McVicar (2012) and Abramitzky, Boustan, and Eriksson (2014) hence suggest inclusion of individual effects in the estimating equation. Certainly, such an approach needs panel data at the individual level that tracks the same individual over time. Data of this type are often unavailable or expensive to obtain. The specifications use YSM in an integer (Cobb-clark, Broadway, and McVicar 2012) or a categorical group (Abramitzky, Boustan, and Eriksson 2014). The categorical approach allows the use of the variable that identifies a penalty or a premium upon arrival in a pooled migrant and non-migrant sample with a panel data fixed-effect estimator. The Abramitzky, Boustan, and Eriksson (2014) model is as follows:

$$Occupation\_score_{it} = \boldsymbol{\alpha}_i + \boldsymbol{\mu}_i + \boldsymbol{\theta}_t + \boldsymbol{\gamma}_{it}.\boldsymbol{\beta}_2 + \beta_3.AGE_{it} + \beta_4.AGE_{it}^2 + \beta_5.AGE_{it}^3 + \beta_6.AGE_{it}^4 + \varepsilon_{it} \quad (4)$$

where: *occupation score* is a proxy for labour-market earnings that varies between (but not within) occupations; α denotes the country place of origin fixed effect; μ is the year of arrival in the hosting country fixed effect; and θ is the census (survey wave) year fixed effect. $\boldsymbol{\gamma}$ is a vector of variables γ which separates the foreign-born individuals into five categories according to time spent in the host country (0–5 years, 6–10 years, 11–20 years, 21–30 years, and 30 or more years), with the native-born individuals constituting the omitted category.

The sign and magnitude of the coefficient on the first dummy variable (0–5 years) indicate whether migrants received an occupation-based earnings penalty (or premium) upon first arrival in the host country, whereas the remaining dummy variables reveal whether migrant earnings eventually catch up with or surpass the occupation-based earnings of non-migrants. As for the concern about the cohort effect, the specification in equation (4) divides the foreign-born into two year-of-arrival cohorts indicated by μ (arrivals before and after 1890), as for the context of the US immigration policy dynamic.

In this paper, in which we are analysing the assimilation process of rural–urban migrants in Indonesia, we extend the specification in equation (1) by applying the framework of Abramitzky, Boustan, and Eriksson (2014), to control for the unobserved time-invariant heterogeneity of individual migrants. We implement an individual fixed-effect (FE) approach as the preferred estimating equation for this reason. For the purpose of a robustness check, we also provide Pooled OLS estimation and Hausman-Taylor (HT) estimation (Hausman and Taylor, 1981). The HT estimation uses an instrumental variable (IV) estimator for panel data that controls for possible correlation between included variables and unobserved individual effects (Breunig, Hasan, and Salehin 2013). The model used in this paper is as follows.

$$outcome_{it} = \boldsymbol{X}_{it}.\boldsymbol{\beta}_1 + \boldsymbol{\theta}_t + \boldsymbol{GROUP}_{it}.\boldsymbol{\beta}_2 + \beta_3.AGE_{it} + \beta_4.AGE_{it}^2 + \boldsymbol{COHORT}_i + \varepsilon_{it} \quad (5)$$

Our main outcome variables are earnings and mental health status. Not like γ in the Abramitzky, Boustan, and Eriksson (2014) model, $GROUP$ is a vector of dummies separating rural–urban migrants into five categories according to time spent in the cities (0–5 years, 6–15 years, 16–25 years, 26–35 years, and 36 or more years), with non-migrant as the omitted category. Our set of coefficients of interest are $\boldsymbol{\beta_2}$ which represents each migrant-cohort's earning or mental health gap relative to non-migrant.

The sign and magnitude of the coefficient on the first dummy (0–5 years) indicate whether a migrant received an earnings penalty (or premium) upon arrival. This coefficient is interpreted slightly differently for mental health outcomes. It is attributed to relative mental health status upon arrival of migrant to non-migrant. The specification also includes time of survey (waves) dummies, θ.

The remaining dummy variables reveal whether the migrants' earnings and mental health status assimilate with those of non-migrants in the host city over time. For robustness purposes, we also implement the alternative specification with only a dummy of (0–5) years as the indicator for the earnings penalty/premium and YSM as the indicator for the speed of convergence. This specification is used by Cobb-clark, Broadway, and McVicar (2012).

The point estimate $\boldsymbol{\beta_2}$ leads to two possible hypothesized assimilation profiles. Type 1 of the hypothesized assimilation profile is, in the case of economic assimilation, an earnings penalty followed by a convergence when β_2 for the first dummy (0-5) years is negative and β_2 for all the rest of the dummies are positive. Type 2 of the hypothesized assimilation profile is a persistent earnings gap relative to non-migrants, either lower when all $\beta_2 < 0$ or higher when all $\beta_2 > 0$. Similar interpretation can be applied for the case of mental health status.

4. Data

The dataset used in this paper in compiled from the longitudinal Rural–Urban Migration in Indonesia (RUMiI) surveys in four major Indonesian cities: Medan, Tangerang (as a proxy for Jakarta), Samarinda, and Makassar. These cities are the main migrant destination cities in

Indonesia's major island groups: Sumatra, Java and Bali, Kalimantan and Eastern Indonesia, respectively. The survey waves are four consecutive years from 2008 to 2011. RUMiI tracked both rural–urban migrants and urban non-migrant households, with an initial number of 1,521 migrant households and 850 non-migrant households – a total of 2,371 households, in 2008 (Resosudarmo, Yamauchi, and Effendi 2010).

In this survey, rural–urban migrants are defined as individuals who stay continuously in the rural area for at least five years until they turned 12 years old, and at the time of the survey resided in an urban area. Recent migrants are those who moved to a city in the five years preceding the survey, and lifetime migrants are those who moved to a city more than five years before the time of the first survey.

The focus of analysis in this paper is on earnings and mental health on internal migrants. Earnings are defined as the total earnings of workers in three types of occupational categories (employee; public employee; and self-employed) in the month before the survey. These earnings include fringe benefits (food, transport, housing, and the value of in-kind payments). Mental health is measured using the 12-item General Health Questionnaire (GHQ), and the surveys follow the standard approach of summing the 12 GHQ responses to form an index running from 0 to 36 (the Likert scale) (Frijters, Johnston, and Meng 2009; Meng and Xue 2017). A higher score corresponds to a higher number of depressive symptoms affirmed.

To better understand mental health issues this paper also pays attention to social support and hours worked. Social support is defined as the number of people in an individual's social network who are helping, for example, lending money, helping with job search, taking care of children, sharing their resources and providing advice. The number of people is weighted by their education level and relationship (family, extended family, and friend). Hours worked is measured from a question on the average number of hours per week the respondent worked in the main job in the previous year. Table 1 summarises the key variables of the sample in the baseline survey in 2008 (see also Appendix 1 for distribution patterns for some of the key variables).

<<Table 1 is about here>>

5. Results

5.1 The cohort effects

One empirical task is to disentangle the roles of the cohort effect, individual heterogeneity and cities' human capital transferability in determining the internal migrants' economic assimilation. First, the estimates examine whether the cohort effect plays a role in bias formation for the assimilation estimates. To do so, we quantify the extent to which the unobserved factors explain the wage gap between non-migrants and migrants relative to observable factors by each cohort. A standard Blinder–Oaxaca decomposition (B–O) decomposition (Blinder 1973; Oaxaca 1973) is used, and the decomposition assumes that there is discrimination by wage between the two groups based on migration status. The discrimination is attributed to both the skill gap and a latent trait that can explain the gap, such as ability or motivation.

The B–O decomposition implements a twofold decomposition of the RUMiI dataset, comprising endowment and unknown parts, with the pooled coefficients as the benchmark for the two groups. Although another technique, such as the Nopo decomposition (Pakrashi and Frijters 2016) could be used, identical distributions of all key variables in our data support the use of the standard B–O decomposition.

The included covariates are age, education (proxied by years of schooling), gender; occupational type (employee, self-employed, public employee, and unpaid domestic worker); and city dummies. Figure 1 shows the decomposition results. It tells us that, apart from the observables, individual heterogeneity helps to explain the gap (net of city factors). The shares of the unexplained part vary across the cohort, which indicates that the cohort effect should be controlled for in the main estimate. For the recent migrants, the earnings gap is explained more by the endowment effect than by the unobserved effect. The opposite case applies for the oldest age cohort, since they belong to the lifetime migrant group.

<<Figure 1 is about here>>

We use three definitions of *COHORT* to estimate equation 5. The first divides the waves of migrants into pre– and post–1998 Asian financial crisis groups, which differ systematically due to labour market structural change (Manning and Alisjahbana 2010). The second divides the waves into three periods by presidency; this can lead to different rural–urban migrant types (Effendi et al. 2010). One of examples is *Transmigration* program during the Soeharto presidency. The program called voluntary internal migrant in which the government decide hosting destination for them. This program created labour movement especially in the agriculture sector from Java and Bali to Sumatra (Bazzi et al. 2016). The last divides the waves by each calendar year of arrival. We prefer the last definition as it is the most conservative.

Table 2 presents the estimates without and with cohort dummies and confirms the need to control for the cohort effect, as the B-O decomposition results suggest.

<<Table 2 is about here>>

5.2 Main outcomes estimates

Key results are presented in Table 3. To facilitate interpretation of results Figure 2 depicts the assimilation profile for each outcome with each specification (Pooled OLS, FE, and HT specification), in which cohort effect is controlled and balanced panel observations is utilized. Discussion about attrition bias is provided in the Appendix 3. In general, the decomposition results show type 2 of the hypothesized assimilation profile: a persistent gap of earnings (higher) and mental health (lower) for migrants relative to urban non-migrants.

<<Table 3 is about here>>

<<Figure 2 is about here>>

Our preference is FE estimation, because it eliminates the time-invariant and relevant unobserved factors, such as motivation at the time of migration. The FE estimates show that rural–urban migrants in Indonesia's four big cities did not experience a wage penalty upon arrival (see in Table 3-column 1-4 or Figure 2-Panel A). Instead, their income overtook the average income of urban non-migrants by about 22% soon after their arrival in the cities. These superior relative earnings persisted and had quadrupled after 36 years spent in the city. The profile is robust to the alternative specification and attrition bias as reported in Appendix 2.

However, along with earnings superiority, the migrants suffer mental health problems (see Table 3-column 5-8 or Figure 2-Panel B). The estimates based on the FE model, which controls for time-invariant individual heterogeneity, show that the migrants have consistently higher mental illness scores than urban non-migrants, ranging from about 3 to 6 (out of 36) above the average score of the latter.

5.3 Channels for deterioration of mental health

Further estimates test two possible channels that have been used in the literature for testing the hypothesis that rural–urban migrants suffer greater deterioration in mental health status than non-migrants. The first channel is extended hours of work. In the context of negative selection of migrants from rural areas, it has been argued that internal migrants often spend more hours in the labour force to compensate for their lower productivity and to maintain a level of earnings comparable with that of non-migrants (Fritjers, Johnston, and Meng, 2009).

The situation in Indonesia is rather different. We have seen that migrants have persistently higher incomes following arrival. If working hours is the channel for superior earnings and deteriorating mental health, we would expect persistently higher working hours for migrants than for non-migrants. In contrast, the estimates based on FE specification show that rural–urban migrants indeed work longer hours (about 8 per week) upon arrival, but the hours converge towards those of non-migrants about 16 years after migration (see Table 4 columns 1–4 or Figure 3 Panel A).

<<Table 4 is about here>>

<<Figure 3 is about here>>

Since factors related to the labour market do not seem to explain the mental health assimilation profile, we test a non-labour market factor: a lack of social support. Lu (2010) tested this for the case of Indonesia using IFLS data and showed that mental health problems are associated with reduced social support. For this purpose, we replicate the earnings assimilation specifications for social support and add a relevant covariate, namely hours worked. In the estimating equation for social support, we want to limit the influence of between variation in hours worked, so we use hours worked as the covariate. Figure 3 (Panel B) shows that social support declines more for migrants than for non-migrants over time spent in cities (see Table 4 column 1–4 as well). This profile is in line with the mental health and earnings assimilation profile. The social support estimate suggests that for internal migrants in Indonesia a lack of social support may drives mental health problems.

5.4 Interpretation of the economic assimilation profile

Figure 4 presents the FE estimates (dashed line) and the simple average difference (solid line) of the earnings gap between migrants and urban non-migrants. The solid line is obtained from an Ordinary Least Square (OLS) estimate without controlling for heterogeneity among cohorts. If we infer from this line, it seems that migrants experience a standard assimilation process, as predicted by the general Immigrant Assimilation Hypothesis (IAH) with an inverted U shape.

In other words, they seem to experience an earnings penalty upon arrival, followed by a convergence toward that the earnings of urban non-migrants, with diminishing returns.

However, research on immigrant assimilation, such as the study by Borjas (1985), has argued that such inference is incorrect. It is not an economic assimilation measures because they do not control for heterogeneity among cohort groups as well as among individuals. This implies that the simple average difference captures an understated economic assimilation process. In addition, the pattern is also can be influenced by a dynamic change in the cohort's quality.

<<Figure 4 is about here>>

The true measure of assimilation or the human capital transferability by time spent in the city is provided by the FE estimates which conditionals on other migrant's performance with different time spent in the city, i.e. Equation 5 and results in Table 3 or dashed line in Figure 4.

It reveals that the actual speed of "convergence" of the migrants' earning relative to those of urban non-migrants differs after the cohort effect and individual heterogeneity effect have been ruled out. The FE estimate measures an earnings premium of nearly 50% upon arrival, followed by a moderate increase in later years, up to more than 100% in 36 years after migrating.

The widening gap between coefficients of the specification with and without cohort effect (Figure 2, Panel A) also tells us about the tendency of a declining quality in the labour market of migrant cohorts over time. Our interpretation is that the positive selection out of village has occurred strongly in the early periods of internal migration when the hurdle to migrate associated with the cost of moving from rural-to-urban areas is relatively still high. This positive selection trend across cohorts mainly explains the persistence gap of earning of migrants relative to that of urban non-migrants. The comparison of the coefficients between those of the full observation and balanced panel shows that the remigration effect is relatively low. In contrast with the international migration context, it seems that the internal migration–re-migration dynamic displays a more random processes across cohorts owing to non-systematic changes to the migration policy in various period.

5.5 Heterogenous economic assimilation profiles

We extend the analysis with subsampling the estimates for main outcomes by demography and geography variables that matters for migrant quality selection in the labour market. The results are presented in the Table 6. They reveal that the extent of the superior earnings assimilation profile varies between cities, by category of intermarriage and by migration distance, but not by gender. In one hand, the key results hold in fast growing and more developed cities such as Tangerang, which is a proxy for Jakarta, and Makassar. On the other hand, less developed and less attractive cities such as Samarinda yield a contrasting economic assimilation profile for migrants, in which their earnings are persistently lower than those of non-migrants. We argue that different degrees of city maturity might have attracted migrants who differ in labour market quality (Effendi et al. 2010), and hence the economic assimilation profiles could differ among cities. Important to note is that both Samarinda and Makassar are located in the Eastern part of Indonesia. The size of migrants in Makassar has been much larger than that in Samarinda. Hence, Makassar is a much more important city of destination for migrants in Eastern Indonesia.

The main estimates mask several possible heterogeneities of economic assimilation profiles of the rural–urban migrant. Meng and Gregory (2005), in the Australian context, show that people who are intermarried, including migrants, have significantly higher earnings than those who are endogamous. As for the Indonesian case, intermarriage seems to be the main explanation for the rapid assimilation profile of earnings. Intermarriage seems to be the mechanism for the intermarried migrant to absorb the city's lifestyle more rapidly than those who are endogamous.

Inter– or within–island migration also matters for migrants' economic assimilation profile. Estimates by inter- or within-island migration suggest that within-island migration is a case of a positive selection of migrant workers from rural areas to cities. They indicate that within-island migration is a higher priority for rural-urban migrants in Indonesia; i.e. rural people prefer to migrate to a city in the same island as their villages of origin, than inter-island migration. This is understandable, since rural people have more information on how to survive in a city within their islands than that of a city in other islands and, after migrated, it is easier for them to visit their left-behind families in their villages of origin.

Lastly, female and widowed female perform as well as male workers in the assimilation process. This indicates that among household heads there is no quality difference between female and male migrant workers in the city labour market, with females being as strongly positively selected as the male from the sending regions.

6. Conclusion

This paper provides new evidence of existing internal migration studies about the assimilation of migrants in developing economies. We examine rural–urban migrants' economic and social assimilation in Indonesia, a country that has adopted a relatively open internal migration policy. Using individual panel data for four cities in Indonesia, our empirical models are able to eliminate cohort effect and individual heterogeneity biases that have bedevilled previous empirical work on this topic.

Our results show that, in general, Indonesia's rural–urban migrants do not experience an earnings penalty upon arrival in the cities. The rural–urban migrant economic assimilation profiles that we observe exhibit increasing permanent gaps between migrants and their urban non-migrant counterparts. In these gaps, migrants are superior to their non-migrant counterparts in earnings, but inferior with regard to mental health. In other words, rural–urban migrants have persistently higher earnings than their urban non-migrant counterparts over time, but their mental health is persistently worse than that of their non-migrant counterparts. We argue that this decline in mental health is associated with a lack of access to social support from relatives and friends.

The evidence of migrants' higher earning in in host cities persists when we divide the sample based on gender and on intermarriage with urban non-migrants. However, it is not the case for inter-island migrants. Among the four cities we observe, this migrant superiority in earnings particularly happens in relatively developed cities such as Makassar and Jakarta (proxied by Tangerang). It does not hold in a less developed city that is less attractive to rural–urban migrants.

Our results contrast with those for developing countries with more restrictive internal migration settings, such as China and Vietnam. By comparing our results with those of previous studies conducted in these two countries, we argue that the assimilation of internal migrants in developing economies is likely to be more successful under a less restricted or more open internal migration policy regime. We therefore support the implementation of such regimes in developing countries. Nonetheless, we point to the need for a policy response to the problem of declining mental health among rural–urban migrants.

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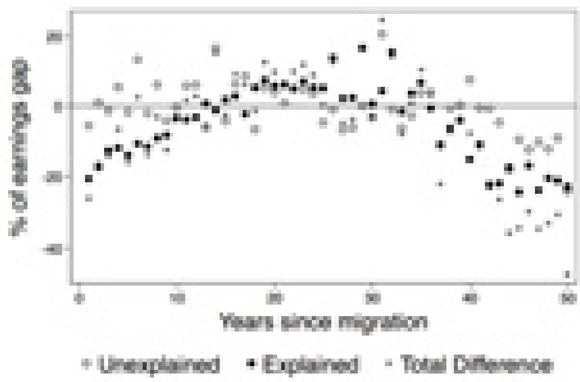
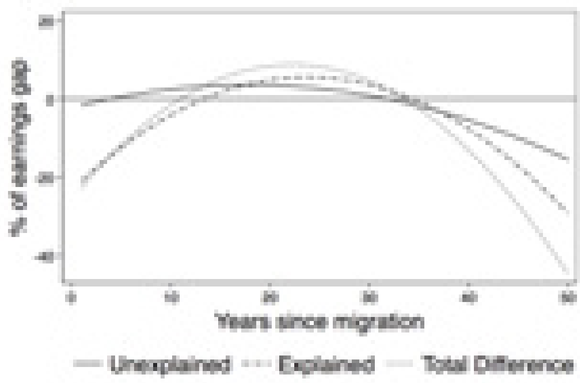
Figures



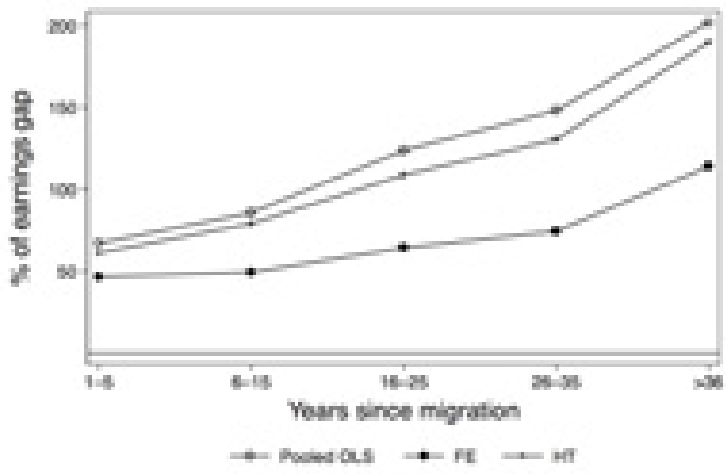
Panel A. Scatter



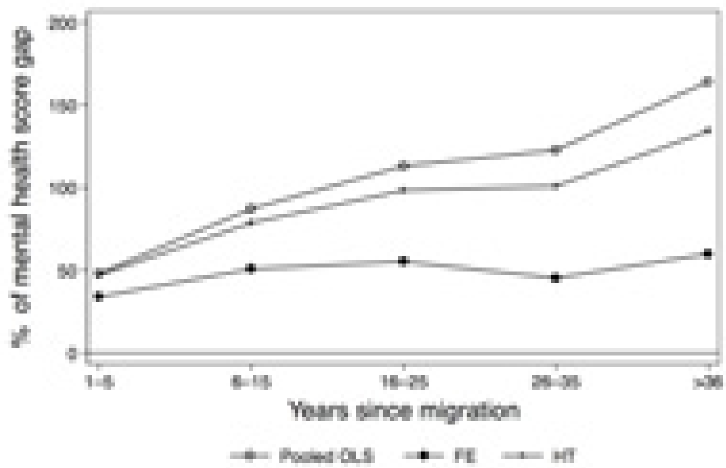
Panel B. Quadratic fit

Figure 1. B–O decomposition

Note: B–O decomposition refers to Blinder–Oaxaca decomposition results.

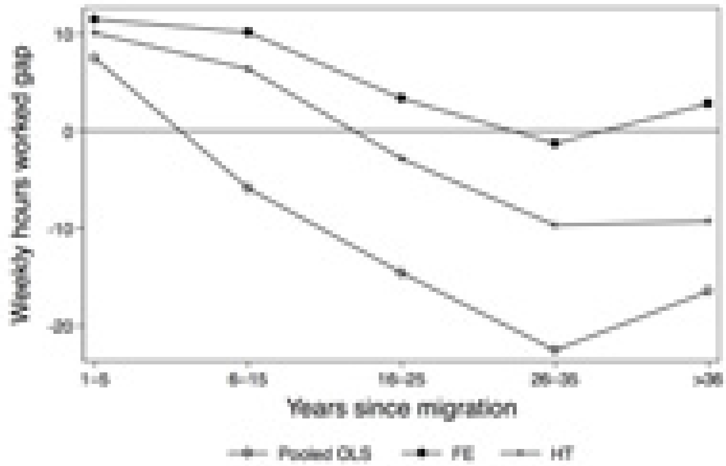


Panel A. Earnings assimilation profile

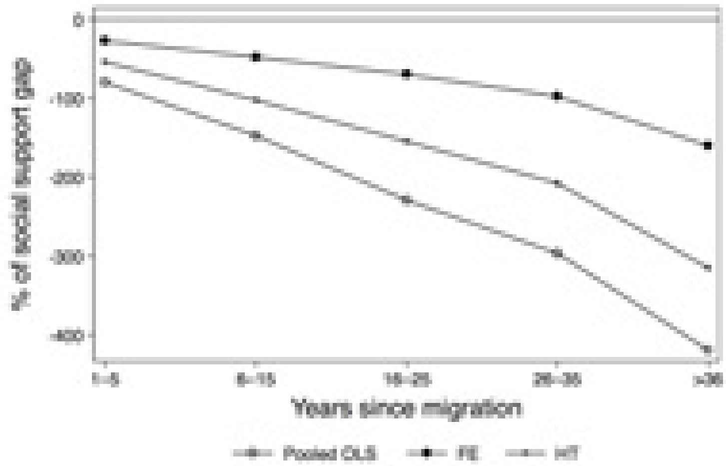


Panel B. Mental health assimilation profile

Figure 2. Economic and mental health assimilation profiles



Panel A. Working hours



Panel B. Social support

Figure 3. Working hours and social support assimilation profiles

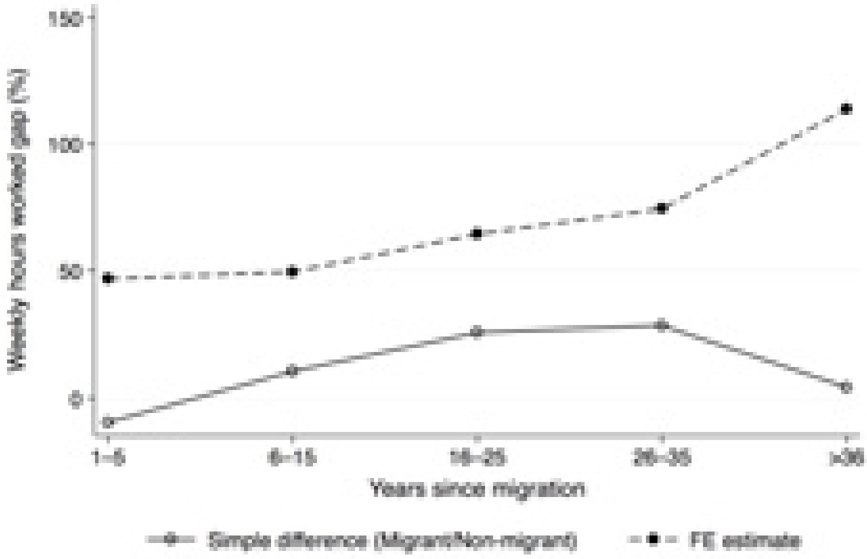
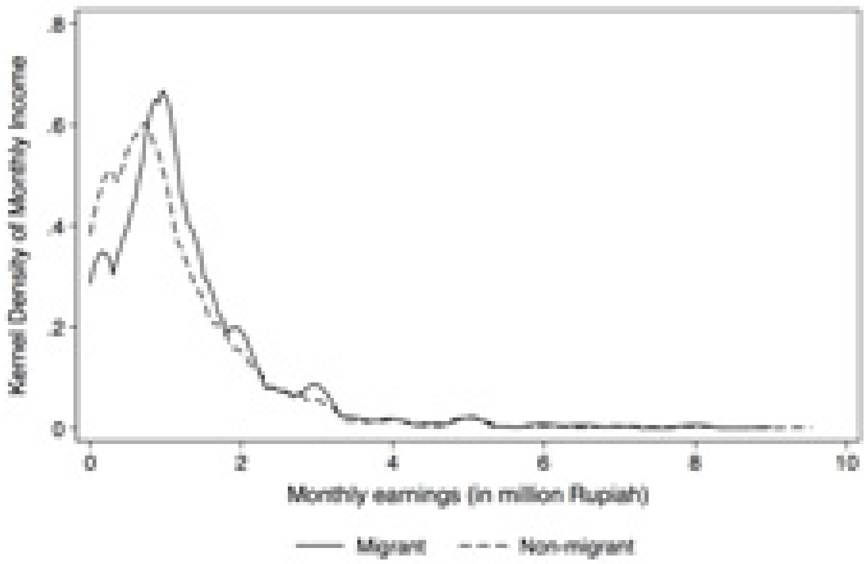
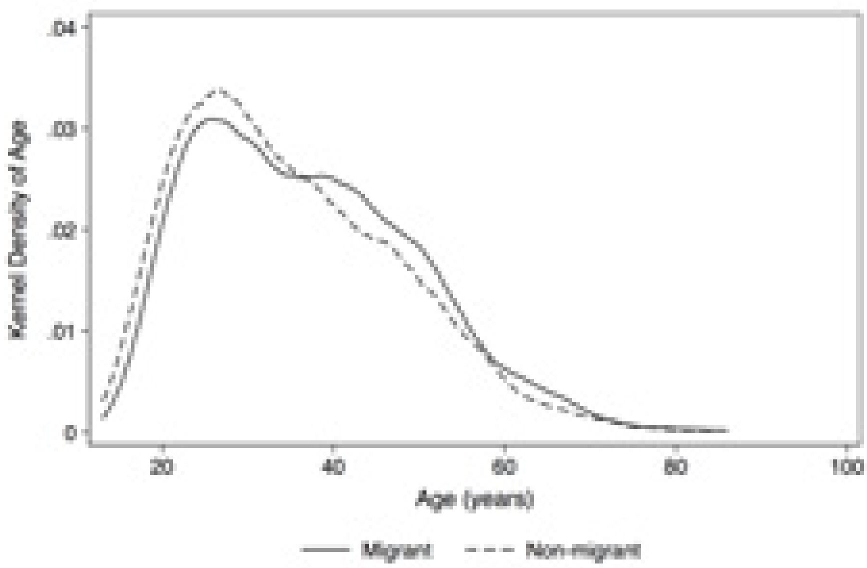


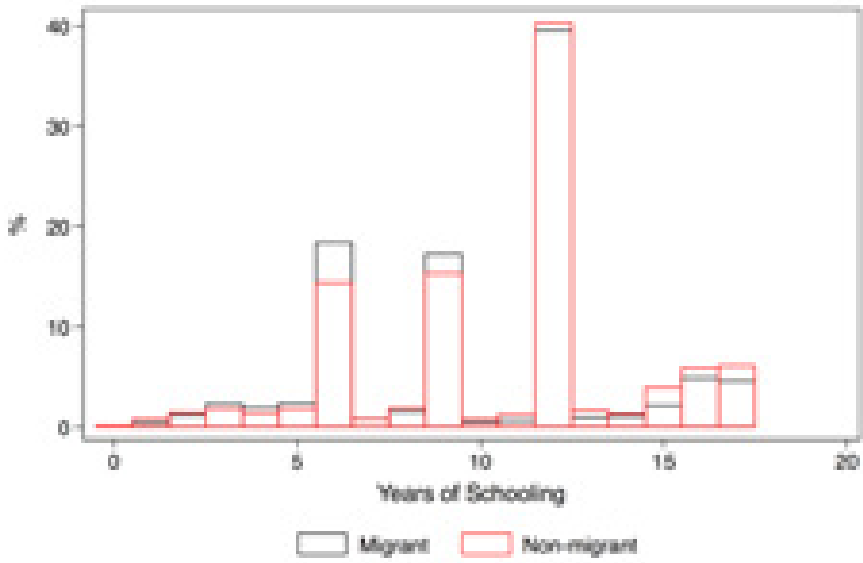
Figure 4. FE vs simple average difference–estimates



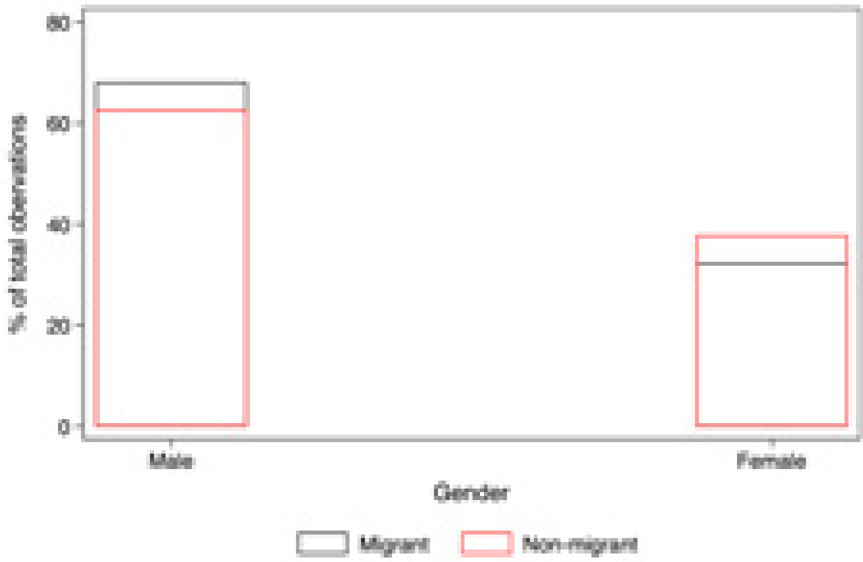
Panel A. Monthly earnings



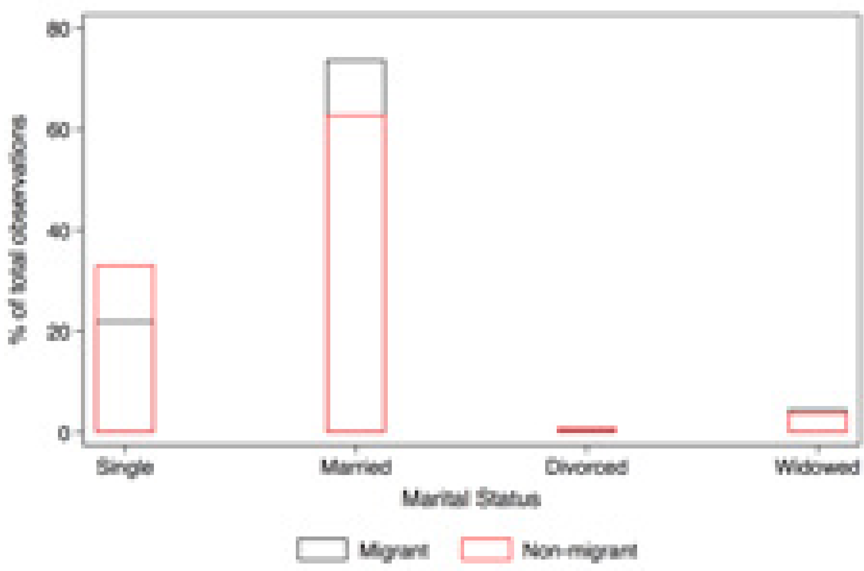
Panel B. Age



Panel C. Years of schooling



Panel D. Gender



Panel E. Marital status

Figure A1. Distribution of key variables

Table 1. Summary statistics

Variables	Recent		Lifetime		Urban Non-migrant		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age	28.55	8.78	43.96	10.90	43.57	10.74	41.04	11.99
Years of schooling	10.25	3.14	10.34	3.78	9.94	3.93	10.16	3.74
Married	0.51	0.50	0.89	0.31	0.90	0.31	0.83	0.38
Share of male	0.78	0.41	0.92	0.27	0.92	0.27	0.90	0.30
Earnings (million Rupiah)	1.36	1.08	2.45	12.91	1.98	5.92	2.06	9.10
Hours worked	52.33	33.24	52.67	39.92	49.76	26.44	51.40	33.72
Mental health score	11.73	3.96	11.13	4.27	11.34	4.44	11.32	4.30
Social support score	17.16	11.33	14.66	10.86	13.56	10.65	14.65	10.93
Share of employee	0.74	0.44	0.56	0.50	0.57	0.50	0.60	0.49
Share of public employee	0.02	0.14	0.09	0.29	0.07	0.26	0.07	0.26
Share of self-employed	0.24	0.43	0.34	0.47	0.36	0.48	0.33	0.47

Source: The summary statistic is calculated from 2008 wave of RUMiI.

Note: Recent is between 0–5years and lifetime is above 5 years.

Table 2. Cohort effects

	Without COHORT	With COHORT		
		Finest	Crisis dummy	3-period
YSM group				
1–5 years	0.046	0.671	0.262	0.261
	(0.082)	(0.035)	(0.047)	(0.049)
6–15 years	0.060	0.857	0.281	0.287
	(0.066)	(0.049)	(0.093)	(0.086)
16–25 years	0.073	1.237	0.296	0.310
	(0.047)	(0.204)	(0.106)	(0.097)
26–35 years	(0.020)	1.480	0.204	0.216
	(0.045)	(0.214)	(0.117)	(0.103)
≥ 36 years	0.125	2.017	0.349	0.494
	(0.069)	(0.236)	(0.106)	(0.099)
R^2	0.25	0.28	0.25	0.25
Observations	2340	2340	2340	2340

Source: Authors' estimate.

Table 3. Economic assimilation estimates

Variables	Earnings				Mental health			
	Pooled OLS		FE	HT	Pooled OLS		FE	HT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1–5 years	0.643	0.671	0.466	0.611	0.430	0.481	0.339	0.470
	(0.032)	(0.035)	(0.103)	(0.068)	(0.019)	(0.014)	(0.037)	(0.030)
6–15 years	0.850	0.857	0.494	0.790	0.770	0.872	0.508	0.787
	(0.060)	(0.049)	(0.160)	(0.101)	(0.037)	(0.027)	(0.058)	(0.055)
16–25 years	1.253	1.237	0.643	1.087	1.005	1.131	0.553	0.983
	(0.182)	(0.204)	(0.265)	(0.218)	(0.101)	(0.121)	(0.140)	(0.135)
26–35 years	1.329	1.480	0.744	1.303	1.128	1.227	0.453	1.009
	(0.206)	(0.214)	(0.280)	(0.217)	(0.123)	(0.175)	(0.240)	(0.201)
≥ 36 years	1.875	2.017	1.139	1.896	1.498	1.642	0.599	1.343
	(0.235)	(0.236)	(0.308)	(0.231)	(0.203)	(0.240)	(0.317)	(0.276)
Cohort dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Balanced panel	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	0.27	0.28	0.16		0.08	0.08	0.14	
Observations	2991	2340	2340	2340	3091	2410	2410	2410

Source: Authors' estimate.

Table 4. Channels estimates for mental health

	Working hours				Social support			
Variables	Pooled OLS		FE	HT	Pooled OLS		FE	HT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
YSM group								
1–5 years	-4.974	7.478	11.471	10.072	-0.691	-0.796	-0.272	-0.613
	(1.071)	(0.807)	(1.651)	(1.545)	(0.028)	(0.023)	(0.062)	(0.049)
6–15 years	-13.994	-5.886	10.142	6.378	-1.449	-1.474	-0.479	-1.225
	(2.165)	(4.600)	(3.344)	(3.533)	(0.116)	(0.158)	(0.161)	(0.151)
16–25 years	-40.570	-14.573	3.339	-2.848	-2.224	-2.292	-0.696	-1.833
	(13.057)	(6.168)	(6.030)	(6.043)	(0.125)	(0.181)	(0.186)	(0.171)
26–35 years	-49.527	-22.523	-1.269	-9.676	-2.987	-2.966	-0.976	-2.396
	(13.398)	(6.992)	(7.616)	(7.013)	(0.189)	(0.189)	(0.288)	(0.202)
≥36 years	-52.310	-16.470	2.807	-9.278	-4.182	-4.194	-1.602	-3.457
	(13.667)	(6.959)	(8.395)	(7.442)	(0.198)	(0.200)	(0.299)	(0.206)
Cohort dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Province dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Balanced panel	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	0.05	0.08	0.03		0.15	0.14	0.37	
Observations	2986	2336	2336	2336	2889	2264	2264	2268

Source: Authors' estimate.

Note: YSM stands for years since migrating. All specifications except FE include *earnings, age, education (years of schooling), gender, marital status–dummies, occupation dummies, city dummies, sending province–dummies*, and *arrival cohort–dummies*. FE estimate uses time variant controls of earnings, age and marital status–dummies. *Arrival cohort-dummies* uses the finest definition. Standard errors are in parentheses.

Table 5. Full estimates for main outcomes and channels for mental health problem

Panel A. Main estimates

	Earnings				Mental health			
Variables	Pooled OLS		FE	HT	Pooled OLS		FE	HT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
YSM group								
1–5 years	0.643	0.671	0.466	0.611	0.430	0.481	0.339	0.470
	(0.032)	(0.035)	(0.103)	(0.068)	(0.019)	(0.014)	(0.037)	(0.030)
6–15 years	0.850	0.857	0.494	0.790	0.770	0.872	0.508	0.787
	(0.060)	(0.049)	(0.160)	(0.101)	(0.037)	(0.027)	(0.058)	(0.055)
16–25 years	1.253	1.237	0.643	1.087	1.005	1.131	0.553	0.983
	(0.182)	(0.204)	(0.265)	(0.218)	(0.101)	(0.121)	(0.140)	(0.135)
26–35 years	1.329	1.480	0.744	1.303	1.128	1.227	0.453	1.009
	(0.206)	(0.214)	(0.280)	(0.217)	(0.123)	(0.175)	(0.240)	(0.201)
≥36 years	1.875	2.017	1.139	1.896	1.498	1.642	0.599	1.343
	(0.235)	(0.236)	(0.308)	(0.231)	(0.203)	(0.240)	(0.317)	(0.276)
Age	0.079	0.075	0.155	0.136	0.006	0.004	0.059	0.040
	(0.010)	(0.012)	(0.036)	(0.019)	(0.004)	(0.005)	(0.020)	(0.008)
Age-squared	-0.001	-0.001	-0.001	-0.001	0.000	0.000	0.000	-0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Years of schooling	0.071	0.068	0.014	0.043	-0.020	-0.018	-0.002	0.024
	(0.007)	(0.010)	(0.012)	(0.014)	(0.003)	(0.003)	(0.023)	(0.018)
Log of monthly earnings								0.127
								-0.059
Gender = female	-0.243	-0.308		-0.407	0.048	0.120		-0.175
	(0.060)	(0.080)		(0.083)	-0.035	-0.041		(0.094)

Marital = married	-0.032	-0.069	-0.172	-0.201	-0.069	-0.021	-0.145	-0.244
	(0.074)	(0.089)	(0.234)	(0.207)	(0.027)	(0.033)	(0.077)	(0.155)
Marital = divorced	-0.271	-0.399	0.087	0.041	-0.016	-0.007	-0.219	-0.181
	(0.090)	(0.101)	(0.310)	(0.230)	(0.038)	(0.033)	(0.114)	(0.107)
Marital = widowed	-0.458	-0.577	-0.432	-0.569	-0.028	-0.006	-0.066	-0.236
	(0.110)	(0.135)	(0.163)	(0.141)	(0.056)	(0.056)	(0.102)	(0.085)
Occupation = public employee	0.397	0.421	0.480	0.471	-0.028	-0.028	-0.254	0.065
	(0.046)	(0.056)	(0.144)	(0.073)	(0.029)	(0.039)	(0.213)	(0.030)
Occupation = self-employed	0.082	0.130	0.237	0.158	0.030	0.042	0.054	0.172
	(0.061)	(0.07)	(0.11)	(0.08)	(0.016)	(0.015)	(0.028)	(0.07)
City = Tangerang	0.087	0.129		0.553	-0.006	0.02		0.151
	(0.094)	(0.133)		(0.155)	(0.04)	(0.04)		(0.102)
City = Samarinda	0.129	0.235		0.738	-0.092	-0.015		0.189
	(0.122)	(0.166)		(0.211)	(0.052)	(0.047)		(0.161)
City = Makassar	0.037	0.096		0.805	-0.102	-0.026		-4.331
	(0.140)	(0.178)		(0.230)	(0.057)	(0.057)		(2.260)
Constant	-3.207	-2.821	-4.909	-18.156	2.207	2.212	-0.412	
	(0.409)	(0.358)	(0.772)	(8.946)	(0.110)	(0.153)	(0.460)	
Cohort dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Province dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Balanced panel	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	0.27	0.28	0.16		0.08	0.08	0.14	
Observations	2991	2340	2340	2340	3091	2410	2410	2410

Panel B. Channel estimates for mental health problem

	Working hours				Social support			
Variables	Pooled OLS		FE	HT	Pooled OLS		FE	HT
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
YSM group								
1–5 years	-4.974	7.478	11.471	10.072	-0.691	-0.796	-0.272	-0.613
	(1.071)	(0.807)	(1.651)	(1.545)	(0.028)	(0.023)	(0.062)	(0.049)
6–15 years	-13.994	-5.886	10.142	6.378	-1.449	-1.474	-0.479	-1.225
	(2.165)	(4.600)	(3.344)	(3.533)	(0.116)	(0.158)	(0.161)	(0.151)
16–25 years	-40.570	-14.573	3.339	-2.848	-2.224	-2.292	-0.696	-1.833
	(13.057)	(6.168)	(6.030)	(6.043)	(0.125)	(0.181)	(0.186)	(0.171)
26–35 years	-49.527	-22.523	-1.269	-9.676	-2.987	-2.966	-0.976	-2.396
	(13.398)	(6.992)	(7.616)	(7.013)	(0.189)	(0.189)	(0.288)	(0.202)
≥36 years	-52.310	-16.470	2.807	-9.278	-4.182	-4.194	-1.602	-3.457
	(13.667)	(6.959)	(8.395)	(7.442)	(0.198)	(0.200)	(0.299)	(0.206)
Age	0.067	-0.201	0.008	0.134	-0.049	-0.045	-0.269	-0.164
	(0.525)	(0.400)	(0.782)	(0.551)	(0.009)	(0.008)	(0.053)	(0.021)
Age-squared	-0.003	-0.001	-0.018	-0.005	0.000	0.000	0.001	0.001
	(0.005)	(0.004)	(0.009)	(0.006)	0.000	0.000	(0.001)	0.000
Years of schooling	-0.445	-0.547	0.168	-0.499	0.037	0.036	-0.033	-0.076
	(0.174)	(0.196)	(0.542)	(0.383)	(0.006)	(0.007)	(0.015)	(0.017)
Log of monthly earnings	0.527	2.456	3.542	2.155	0.001	0.002	0.002	
	(1.115)	(0.743)	(1.128)	(0.900)	0.000	0.000	(0.001)	
Gender = female	1.234	1.244		-2.437	0.012	0.046		-0.034
	(1.605)	(1.757)		(2.541)	(0.055)	(0.058)		(0.098)
Marital = married	7.681	11.055	3.152	2.993	-0.059	-0.058	0.067	0.119
	(2.717)	(3.011)	(2.825)	(3.534)	(0.054)	(0.059)	(0.112)	(0.117)

Marital = divorced	14.575	20.659	16.126	15.868	-0.153	-0.140	-0.203	-0.132
	(3.511)	(4.419)	(6.647)	(9.585)	(0.075)	(0.065)	(0.195)	(0.234)
Marital = widowed	0.447	4.745	-0.593	0.407	0.005	-0.041	0.031	0.286
	(3.204)	(3.144)	(3.396)	(4.344)	(0.073)	(0.069)	(0.145)	(0.205)
Occupation = public employee	-7.540	-10.041	1.135	-9.075	0.130	0.194	-0.036	0.471
	(2.140)	(2.755)	(4.821)	(2.312)	(0.047)	(0.043)	(0.217)	(0.104)
Occupation = self-employee	3.752	0.819	-0.134	0.846	-0.048	-0.067	-0.134	-0.122
	(1.833)	(1.062)	(1.902)	(1.047)	(0.028)	(0.034)	(0.051)	(0.068)
City = Tangerang	-2.268	-4.968		-5.917	0.249	0.177		0.153
	(4.122)	(3.978)		(3.944)	(0.077)	(0.094)		(0.141)
City = Samarinda	-1.526	-3.729		-4.106	0.251	0.172		0.350
	(3.580)	(4.233)		(4.325)	(0.086)	(0.122)		(0.186)
City = Makassar	-7.886	-10.695		-11.648	0.239	0.158		0.347
	(3.494)	(4.590)		(4.631)	(0.117)	(0.159)		(0.233)
Constant	75.107	67.245	74.090	-2.777	4.342	4.831	12.525	8.463
	(12.018)	(7.922)	(20.187)	(117.637)	(0.140)	(0.237)	(1.025)	(0.525)
Cohort dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Province dummies	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Balanced panel	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	0.05	0.08	0.03		0.15	0.14	0.37	
Observations	2986	2336	2336	2336	2889	2264	2264	2268

Source: Authors' estimate.

Note: Standard errors are in parentheses and clustered at year-of-arrival level.

Table 6. Heterogeneous earnings assimilation profiles

Panel A. Sub-sampling by city and by inter-island category

	Cities				Inter- or Within-island Migration	
	Medan	Tangerang	Samarinda	Makassar	Inter-island	Within-island
YSM group						
1–5 years		0.798	-0.995	0.727	-0.769	0.688
		(0.148)	(0.131)	(0.054)	(0.282)	(0.106)
6–15 years	-0.004	0.916	-1.216	0.813	-0.614	0.671
	(0.108)	(0.202)	(0.159)	(0.182)	(0.403)	(0.151)
16–25 years	0.096	1.012	-1.207	1.489	-0.445	0.822
	(0.124)	(0.270)	(0.497)	(0.490)	(0.619)	(0.192)
26–35 years	0.169	1.125	-1.423	1.896	-0.429	0.934
	(0.167)	(0.296)	(0.537)	(0.582)	(0.655)	(0.223)
≥36 years	0.754	0.991	-1.377	2.935	-0.425	1.444
	(0.536)	(0.321)	(0.578)	(0.720)	(0.738)	(0.250)
Age	0.165	0.151	0.162	0.197	0.087	0.174
	(0.055)	(0.060)	(0.057)	(0.070)	(0.072)	(0.034)
Age-squared	-0.001	-0.001	-0.001	-0.002	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	0.000
Years of schooling	0.034	0.02	0.017	-0.043	0.034	0.005
	(0.033)	(0.012)	(0.031)	(0.035)	(0.056)	(0.009)
Marital = married	0.455	-0.267	-0.129	-0.929	-0.26	-0.14
	(0.388)	(0.183)	(0.196)	(0.599)	(0.188)	(0.285)
Marital = divorced	0.758	-0.129	0.26	-0.294	0.645	0.059
	(0.428)	(0.265)	(0.386)	(0.668)	(0.293)	(0.413)
Marital = widowed	-0.017	-0.648	-0.168	-0.86	-0.328	-0.432

	(0.389)	(0.138)	(0.242)	(0.636)	(0.493)	(0.210)
Occupation = public employee	0.212	1.093	1.314	0.427	0.000	0.474
	(0.132)	(0.482)	(0.138)	(0.319)		(0.145)
Occupation = self-employed	0.188	0.137	0.388	0.371	0.327	0.236
	(0.154)	(0.115)	(0.140)	(0.336)	(0.251)	(0.111)
Constant	-6.537	-4.542	-4.155	-4.846	-2.16	-5.488
	(0.824)	(1.203)	(1.285)	(1.829)	(1.776)	(0.655)
R^2	0.25	0.18	0.13	0.20	0.17	0.14
Observations	659	753	504	424	411	1929

Panel B. Sub-sampling by gender and by marital status

	Intermarriage status		Gender	
	Endogamous migrant	Exogamous migrant	Male	Female
YSM group				
1–5 years	-0.101		0.416	
	(0.036)		(0.106)	
6–15 years	-0.032	0.169	0.459	0.053
	(0.069)	(0.143)	(0.164)	(0.238)
16–25 years	0.146	0.365	0.646	-0.288
	(0.295)	(0.170)	(0.272)	(0.397)
26–35 years	0.264	0.506	0.760	-0.762
	(0.297)	(0.242)	(0.286)	(0.544)
≥36 years	0.669	0.994	1.146	
	(0.318)	(0.248)	(0.312)	
Age	0.153	0.153	0.150	0.216
	(0.033)	(0.037)	(0.039)	(0.094)
Age-squared	-0.001	-0.001	-0.001	-0.002
	0.000	0.000	0.000	(0.001)
Years of schooling	0.009	0.018	0.022	-0.093
	(0.012)	(0.008)	(0.013)	(0.056)
Marital = married	0.350	0.333	-0.019	-0.727
	(0.138)	(0.146)	(0.232)	(0.391)
Marital = divorced	0.758	0.731	0.326	-0.736
	(0.140)	(0.132)	(0.198)	(0.570)
Marital = widowed	0.026	-0.13	0.035	-1.308
	(0.129)	(0.118)	(0.179)	(0.390)

Occupation = public employee	0.563	0.495	0.489	0.167
	(0.102)	(0.204)	(0.169)	(0.324)
Occupation = self-employed	0.285	0.394	0.268	-0.124
	(0.084)	(0.093)	(0.103)	(0.429)
Constant	-5.198	-5.336	-5.017	-4.24
	(0.585)	(0.666)	(0.828)	(2.228)
R^2	0.17	0.17	0.16	0.32
Observations	1736	1383	2141	199

Source: Authors' estimate.

Note: All columns represent FE specification. Standard errors are in parentheses and clustered at year-of-arrival level.

Table A1. Alternative specification

Variables	Pooled OLS		FE	HT
	(1)	(2)	(3)	(4)
1–5 years	0.127	0.194	0.153	0.151
	(0.070)	(0.058)	(0.062)	(0.094)
Time spent in city	0.107	0.126	0.089	0.124
	(0.027)	(0.028)	(0.038)	(0.023)
Time spent in city-squared/100	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	0.000
Cohort dummies	Yes	Yes	No	Yes
Balanced panel	No	Yes	Yes	Yes
R^2	0.28	0.30	0.18	
Observations	2991	2340	2410	2340

Source: Authors' estimate.

Note: All specifications except FE include *age, education, gender, marital status–dummies, occupation dummies, city dummies, sending provinces–dummies. Arrival cohort-dummies* uses the finest definition. Standard errors are in parentheses.

Table A2. Estimates to address potential attrition bias

Variables	Pooled OLS		FE	
	without IPW	with IPW	full sample	balanced panel
	(1)	(2)	(3)	(4)
YSM group				
1–5 years	0.643	0.628	0.483	0.483
	(0.032)	(0.030)	(0.097)	(0.097)
6–15 years	0.850	0.881	0.555	0.555
	(0.060)	(0.075)	(0.142)	(0.142)
16–25 years	1.253	1.286	0.712	0.712
	(0.182)	(0.184)	(0.250)	(0.251)
26–35 years	1.329	1.399	0.816	0.816
	(0.206)	(0.215)	(0.263)	(0.263)
≥36 years	1.875	1.844	1.219	1.219
	(0.235)	(0.258)	(0.291)	(0.291)
Age	0.079	0.074	0.152	0.152
	(0.010)	(0.010)	(0.036)	(0.036)
Age-squared	-0.001	-0.001	-0.001	-0.001
	0.000	0.000	0.000	0.000
Years of schooling	0.071	0.073	0.01	0.01
	(0.007)	(0.006)	(0.012)	(0.012)
Gender = female	-0.243	-0.242		
	(0.060)	(0.071)		
Marital = married	-0.032	-0.049	-0.199	-0.199
	(0.074)	(0.067)	(0.225)	(0.225)
Marital = divorced	-0.271	-0.126	0.075	0.075

	(0.090)	(0.128)	(0.299)	(0.300)
Marital = widowed	-0.458	-0.467	-0.413	-0.413
	(0.110)	(0.105)	(0.150)	(0.150)
Occupation = public employee	0.397	0.393	0.427	0.427
	(0.046)	(0.040)	(0.149)	(0.149)
Occupation = self-employed	0.082	0.079	0.227	0.227
	(0.061)	(0.063)	(0.111)	(0.112)
City = Tangerang	0.087	0.083		
	(0.094)	(0.091)		
City = Samarinda	0.129	0.149		
	(0.122)	(0.121)		
City = Makassar	0.037	0.082		
	(0.140)	(0.134)		
Province fixed effect	Yes	Yes	No	No
Constant	-3.207	-3.194	-4.720	-4.752
	(0.409)	(0.402)	(0.730)	(0.742)
R^2	0.27	0.27	0.16	0.16
Observations	2991	2887	2991	2409

Source: Authors' estimate.

Note: The number of observations in the second column is slightly lower because of failure in generating weights for some observations owing to nonconvergence with the full sample. Standard errors are in parentheses and clustered at year-of-arrival level.

Appendixes

Appendix 1: Distribution patterns for some of the key variables

Figure A1 shows the distributions patterns for some of the key variables utilize in the analysis in this paper.

<<Figure A1 is about here>>

Appendix 2: Robustness check for different *GROUP* specifications

Table A1 shows that our conclusions are robust for different *GROUP* (the grouping for migrant arrival-years) specifications which is an integer value of the time spent in the cities instead of dummies for group of time spent in the cities as is used in the main text.

<<Table A1 is about here>>

Appendix 3: Attrition issue

The attrition of household heads in the sample entails two possible cases: a common dropout and a truncation such as death. Attrition might affect the outcome estimate, and it depends on the nature of the attrition bias. One favourable condition is if the outcomes are missing completely at random in which case, the missingness is independent of any outcome. If the outcome missing is independent of all missing outcomes conditional only on observed outcomes, the outcomes are missing at random (Daza, Hudgens, and Herring 2017). However, the nature of attrition of dropouts in the migration survey, in general, is about the missing at random case. Concerning the attrition bias of this category, the inverse-probability weights (IPW) may be used to ensure the consistency of the estimates provided that the data missingness model is correctly specified from observed covariates (Wooldridge 2007). To test whether there are influencing observed variables to the dropout and then apply the IPW, we use the **xtrccipw** command provide by Daza, Hudgens, and Herring (2017). The first two columns of Table A2 present estimates with and without the weighting and it barely changes the magnitude of the estimate, which suggests that the presence of bias owing to missing at random outcomes is not severe.

<<Table A2 is about here>>

Another viewpoint for considering the attrition in the migration dataset is the remigration process. It is likely that the dropout samples are individuals who decide to return to the village (negative selection out of the city) or leave the city towards a higher-wage city or country (positive selection out of the city). In general, the remigration or stepwise migration processes are driven by an unobserved factor, such as ability, of which we do not have the measure. The use of panel data fixed effect might eliminate the bias originating from remigration assuming the conditional dependence of the missingness on unobserved that is time invariant, such as ability (Abramitzky, Boustan, and Eriksson 2014). The ability components will be eliminated in both the comparison of migrant and non-migrant and the comparison of migrants in each cohort. The last two columns of Table A2 present the fixed-effect estimates between two specifications with a full sample and only with a balanced sample, and it shows insignificant differences in the coefficients.