Migration Choice under Risk and Liquidity Constraints

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Abstract

This paper develops and tests a migration choice model that incorporates two prominent migration strategies used by households facing risk and liquidity constraints. On the one hand, migration can be used as an ex-post risk-coping strategy after sudden negative income shocks. On the other hand, migration can be seen an as investment, but liquidity constraints may prevent households from paying up-front migration costs, in which case positive income shocks may increase migration. These diverging migratory responses to shocks are modeled within a dynamic migration choice framework that I test using a 20-year panel of internal migration decisions by 38,914 individuals in Indonesia. I document evidence that migration increases after contemporaneous negative income shocks as well as after an accumulation of preceding positive shocks. Consistent with the model, I find that migration after negative shocks is more often characterized by temporary moves to rural destinations and is more likely to be used by those with low levels of wealth, while investment migration is more likely to involve urban destinations, occur over longer distances, and be longer in duration. Structural estimation of the model reveals that migration costs are higher for those with lower levels of wealth and education, and suggests that the two migration strategies act as substitutes, meaning that those who migrate to cope with a negative shock are less likely to invest in migration. I use the structural estimates to simulate policy experiments of providing credit and subsidizing migration, and I explore the impact of increased weather shock intensity in order to better understand the possible impact of climate change on migration.

Keywords: Internal Migration, Risk-Coping, Liquidity Constraints, Dynamic Choice

JEL Classification: D14, D91, J61, O12, R23

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1 Introduction

Approximately 230 million individuals in the world are currently characterized as international migrants, and another 763 million as internal migrants, moving within the borders of their country (Bell and Muhidin, 2013). This migration is partially motivated by large income differences between countries, as well as between areas within a country, for example rural and urban areas. In Indonesia, the focus of this study, those living in rural areas earn 32 percent less than those living in urban areas and this number accounts for differences in prices and employment between rural and urban areas.

While a wide range of reasons may explain the choice to migrate, two primary rationales are often highlighted – especially in a developing country context – as reasons to migrate and, more broadly, as roles that migration can play in the process of economic development. On the one hand, migration can be used to cope with negative income shocks. If a household is hit by a negative shock, for example an agricultural shock due to drought, the household may decide to send a household member elsewhere to earn additional income. This migration strategy can be seen as an alternative to other ex-post risk-coping strategies, such as reducing savings, selling assets, increasing labor supply locally and decreasing consumption.

Alternatively, migration can be used as an investment strategy with the goal of increasing and diversifying future expected income and benefiting from higher wages elsewhere, for example in urban areas. However, as with any investment, this often requires large up-front costs. If a household is liquidity-constrained, it may not be able to make this investment, even if it would be profitable. Therefore, in the presence of liquidity constraints, an increase of wealth – for example due to one or more positive income shocks – may relax liquidity constraints and so increase migration.

While both migration strategies are closely related, they have opposite predictions in terms of the migratory response to shocks. When moving in order to cope with negative shocks, a strategy I will refer to as survival migration, migration increases after negative contemporaneous income shocks. Alternatively, if individuals are liquidity-constrained, migration may increase after (an accumulation of) positive income shocks that help relax liquidity constraints that prevented migration initially. I will refer to this strategy as investment migration.

Both migration strategies are widely observed and documented empirically but described as separate phenomena and in different papers. The survival rationale of migration is described for example in Kleemans and Magruder (2014) and Morten (2013), who find that sudden negative rainfall shocks induce people to migrate internally.[1] Evidence of the investment strategy is documented by Bryan, Chowdury and Mobarak (2014) and by Bazzi (2014), who find that beneficial migration is prevented by liquidity constraints and that overcoming these constraints by subsidizing migration or through positive income shocks increases out-migration. The difference between Kleemans and Magruder (2014) on the one hand and Bazzi (2014) on the other hand seems puzzling as both papers study the Indonesian context but find opposite responses to rainfall shocks. However, the discrepancy may be understood by recognizing that different types of migration are observed: Kleemans and Magruder (2014) focus on internal, short-distance migration, while Bazzi (2014) studies international migration that requires large up-front migration costs, making liquidity constraints more likely to be binding.

This paper provides a unified framework of migration choice that incorporates both survival and investment rationales for migration. I develop a migration choice model that encompasses both migration strategies and that improves on previous migration models by allowing for multiple moves over time, between multiple locations, and by incorporating wealth as an important determinant of migration choice. This model is dynamic in nature, to allow for people to plan future migrations and save up for migration over time to overcome liquidity constraints. It builds on the dynamic savings model by Deaton (1991), in which people have a certain amount of wealth and, after receiving a stochastic wage draw in each time period, must decide how much to save in order to smooth consumption and maximize utility over time. I extend this to become a migration choice model by including the current location as an additional state variable and migration choice as an additional control variable. The basic intuition can be explained by a simple three-location model in which a household can decide to migrate away from its home location to either a nearby rural area at a low migration cost, but where wages are only slightly higher than at home, or to a further-away urban area with higher costs and higher wages.

[1] Other papers that empirically observe increased migration after negative income shocks include Mueller, Gray and Kosec (2014), De Weerdt and Hirvonen (2013) and Boustan, Fishback and Kantor (2010).

In each period, the household observes a wage draw at its current location from a known distribution. If the household receives a bad wage draw and does not have sufficient savings built up, they may prefer to move to another location to receive a different wage. To avoid high migration costs, the household would likely prefer to move to a nearby rural location just to get another wage draw. I explicitly model a disutility of being away from the home location, which predicts that survival migration will be short in terms of distance as well as duration.

On the other hand, households may try to save up for migration as an investment to benefit from higher wages in a further-away city. If they are liquidity-constrained, then an accumulation of positive shocks may push them over the barrier, after which they are able to cover migration costs. The model therefore predicts that this type of migration is more likely to occur over longer periods of time.

I solve the dynamic migration choice model numerically and test the predictions of this model using a rich dataset of internal migrants in Indonesia. As part of the Indonesia Family Life Survey, all migration moves of 38,914 individuals were recorded over a 20-year period. Individuals were carefully tracked as they changed location, allowing me to study all migration decisions that individuals made, even if they are of short duration and over short distances. After showing that rainfall shocks are good proxies for income shocks, and that a sequence of positive rainfall years helps households accumulate wealth, I study the migration response to rainfall shocks. In line with the model, I find that migration increases both after contemporaneous negative rainfall shocks and after an accumulation of previous positive shocks. Also in agreement with the model, I find that survival migration is more likely to be temporary, have a rural destination, and be used by those with low levels of wealth. Investment migration, on the other hand, is more likely to occur over longer distances and to urban areas, and is longer in duration.

I then structurally estimate the model using maximum likelihood estimation in a mixed logit framework in order to retrieve individual migration cost parameters. The average migration costs of going to nearby rural area locations, which are used mostly for survival migration, are approximately equal to 20 percent of annual income. Investing in migration to a more distant, urban area is about 4 times as costly, slightly more than average annual income. Examining heterogeneous effects reveals that migration is about 30 percent more costly for those with lower levels of wealth and education, and approximately 50 percent less costly for younger individuals.

Studying the benefits of migration in terms of increased consumption and wages, I find that both migration strategies have positive returns to the mover. However, the magnitude of these benefits depends strongly on the migration rationale: those who migrated to cope with negative income shocks benefit to a lesser extent than those who invested in migration. Predicted consumption increases by 8 percent after survival migration and by 35 percent after investment migration; comparable numbers for wage increases are 8 and 46 percent for survival and investment migration, respectively. Comparing individuals with various degrees of prior migration experience moreover suggests that the two migration strategies act as substitutes, meaning that those who migrate to cope with a negative shock are less likely to invest in migration.

Taken together, these findings may have important policy implications. Those with lower levels of wealth and education pay higher migration costs while earning less. In addition, they are more likely to engage in the type of migration that yields lower returns, which reduces the opportunity to invest in migration to the extent that the two strategies act as substitutes. This may have important distributional implications and resonates with a recent debate on the existence of geographical poverty traps. Jalan and Ravallion (2002) introduced this term, defining it as a situation in which the characteristics of a household's area of residence are such that the household's consumption cannot rise over time, while an otherwise identical household that lives in a better-endowed area would enjoy a rising standard of living. In a recent paper, Kraay and McKenzie (2014) survey the empirical evidence on poverty traps. While finding sparse evidence in support of poverty traps in general, they argue that geographical poverty traps form an exception, stating that the evidence most consistent with poverty traps comes from poor households in remote rural regions. While not specifically testing for the existence of poverty traps, I find that liquidity constraints prevent profitable migration (as also shown by Bryan, Chowdhury, and Mobarak (2014) and Bazzi (2014)) that poor individuals face higher migration costs and engage in less profitable migration, which may subsequently limit their chances of investing in migration.

A policy instrument that may mitigate these distributional challenges and promote profitable migration is the provision of credit. In my model environment, where part of the population faces liquidity and credit constraints, I examine a policy experiment of providing credit at various interest rates. I find that, on the one hand, credit reduces the need for survival migration, as it provides an alternative ex-post risk-coping strategy by allowing individuals to borrow in order to finance consumption. On the other hand, credit increases the use of investment migration by allowing individuals to borrow the up-front cost of migrating, thereby confirming that liquidity constraints initially prevented migration with positive expected returns.

The findings in this paper also have implications for the expected future impacts of climate change on migration. Weather patterns are expected to change due to global warming, and rainfall shocks will likely increase in intensity. This may adversely impact those living rural areas, for whom weather shocks are a major source of income variation. While there is still considerable uncertainty about the impact of climate change on migration, this paper addresses a piece of the puzzle by studying how individual migration choices respond to weather shocks. I run a counterfactual experiment to examine the predicted change in migration patterns and welfare in response to increased intensity of weather shocks. I find that more extreme weather shocks increase the need to engage in survival migration as an ex-post risk-coping strategy while simultaneously limiting the opportunity to save up for profitable investment migration. This leads to a predicted reduction in overall welfare and disproportionately affects those at the bottom of the wealth distribution.

This paper advances our understanding of what drives people to migrate, a question that has engaged development economists for decades (e.g. for early references: Lewis, 1954 and Harris and Todaro, 1970). Still, existing income differences between countries and areas within a country, combined with evidence of profitable returns to migration, have led people to wonder why more people do not migrate.[2] Moreover, empirical evidence shows that those who migrate for longer distances and duration tend to benefit to a larger extent, which has made people wonder why these migration patterns are not observed more frequently (e.g. Banerjee and Duflo, 2007 and Munshi and Rosenzweig, 2005).

By bringing together two often-cited and empirically observed migration strategies, this paper contributes to the understanding of why people migrate, where they migrate to, and how long they

[2] This question has been examined in the international context for example by Clemens, Montenegro, and Pritchett (2008) and McKenzie, Gibson, and Stillman (2010), and in the context of internal migration for example by Bryan, Chowdhury, and Mobarak (2014) and Beegle, De Weerdt and Dercon (2011).

stay at their destination.[3] In an environment in which people face risk and liquidity constraints, I model these two strategies within a dynamic migration choice framework. The dynamics of the model allow for updating of preferred migration strategies in each period, making the model flexible by incorporating moves between various locations as well as multiple moves over time. As such, the model incorporates commonly observed migration patterns such as return migration and circular migration, which are not easily explained in models where people migrate merely in search of the best employment opportunity or models in which migration is treated as a one-shot decision. The importance of including multiple moves and a choice between multiple locations was also recognized by Kennan and Walker (2011), who develop a detailed dynamic model of optimal migration that explains migration choice based on expected income differentials in their data. There are considerable differences between their model and the model presented in this paper, primarily that Kennan and Walker (2011) consider a model in which wealth does not affect migration decisions. As such, individuals can borrow and lend without restriction to finance the cost of migration. This assumption may be warranted for their target group – young white males with a high school education in the United States – but has much less validity in the context of rural Indonesia. The model in this paper is therefore presented as an alternative model of migration choice applicable to developing country contexts in which wealth and liquidity constraints profoundly limit migration and destination choices.

This paper is structured as follows: First, I will present the dynamic migration choice model in Section 2. The data and empirical strategy are described in Section 3, and Section 4 provides reduced-form results. Section 5 introduces the structural estimation of the model, after which Section 6 presents the structural results. Various policy and counterfactual experiments are considered in Section 7, and Section 8 concludes.

2 Dynamic Migration Choice Model

This section develops a model incorporating both the survival and investment rationales for migration. This approach improves on previous models by allowing for multiple migration choices over

[3] The optimal duration of migration has been explored by Dustmann and Kirchkamp (2002) in relation to return migration, see also Dustmann (1997), Dustmann (2003) and Dustmann and Weiss (2007).

time and between multiple locations, and incorporating wealth as an important determinant of migration choice. The model is dynamic in nature, to allow people to save up for migration and to acknowledge the forward-looking nature of migration choice. It extends the dynamic savings model from Deaton (1991) by adding location as an additional state and control variable. In Deaton's savings model, individuals are not permitted to borrow to finance consumption. The model has one state variable, wealth, and one control variable, consumption. In each period, the decision maker receives an income draw from a known distribution and chooses how much to consume and how much to save for the next period in order to maximize utility. As such, savings serve as a precautionary motive to smooth consumption and maximize lifetime utility.

Recently, Bryan, Chowdury and Mobarak (2014) developed a migration model that also builds on Deaton (1991) by incorporating liquidity constraints. In their model, migration is risky while individuals find out whether or not they are good at migrating. If they are not, they lose the cost of migrating; for those close to subsistence, this will lead to underinvestment in migration in order to avoid the cost of failed migration. As such, their model incorporates liquidity constraints that may be relaxed by a migration incentive, which they randomly distribute in villages in rural Bangladesh. Indeed, the 8.50 US dollar incentive induces 22 percent of households to send a migrant. While they find empirical evidence in support of their model, the large magnitude of their effects is not fully accounted for. As is common in migration choice models, they focus on the binary choice of whether to migrate. In order to incorporate different migration strategies, I also include the choice of which location to migrate to. Therefore, I extend Deaton's dynamic savings model by adding current location as a state variable and next location as an additional control variable. Unlike wealth and consumption, which are continuous variables, there is a finite number of discrete locations to choose from. Initially, I will set up the model in which locations are defined as a function of distance from a $Home$ location, which is defined as the location where the person lives at age 18. After presenting this general set-up, I will introduce a three-location model upon which the main predictions are based, and that will later be structurally estimated.

Migration is modeled as an individual decision but can alternatively be thought of as a household decision problem, in which in each period, the household chooses whether or not to send a household member to another location. By treating the household as one unit, intra-household transfers and remittances are not modeled explicitly. I focus on individual migration choices in order to reduce the computational time needed to numerically solve the model, without losing its main objective of incorporating survival and investment migration.

This is a partial equilibrium model and assumes that wages are exogenous to the individual decision maker, which matches the micro-level focus of the data. Wages are furthermore assumed to be stationary, so the model does not account for upward trends in wages. In the empirical analysis, all monetary values are converted to their year 2000 equivalent using the Indonesian consumer price index and time fixed effects are included to account for annual variation that is the same across individuals.

The timing of the model is as follows: In the beginning of each period, the individual is at a certain location l and is endowed with wealth x. Then, a wage draw w_l is revealed from a known distribution. The person chooses to either accept this wage draw or to migrate to another location with a known wage distribution, but where the wage draw has not yet been revealed. In case of the latter, the individual has to pay the up-front migration cost that is a function of the current and next location, and in particular, a function of the distance between them: $m(l, l^{'}) = f(d)$. I assume that migration costs increase monotonically with the distance traveled:

$$\frac{\partial m(l, l^{'})}{\partial d} > 0 \quad \text{with} \quad m(l, l^{'}) = 0 \quad \text{if} \quad l^{'} = l \tag{1}$$

In case the person decides to move, he or she first pays the migration costs, then moves to the next location $l^{'} \neq l$ and, upon arrival at $l^{'}$, observes the new wage draw $w_l^{'}$. I will refer to the final wage received as $w_l^{'}$, which is equal to the original wage draw if the person decided not to migrate, $w_l = w_l^{'}$, and will generally be different if the person migrated to a different location.

Finally, based on the wage received and current wealth, the person chooses consumption c in order to maximize utility U. At the end of the period, he or she is left with wealth $x^{'}$ and at location $l^{'}$, which are the starting values of the state variables in the next period. Note that the primes indicate the next period's values, so $l^{'} = l$ if the person stayed in the same location, and $l^{'} \neq l$ if he or she migrated.

The equation of motion describes the evolution of wealth:

$$x^{'} = (1 + r)(x - c - m(l, l^{'}) + w), \tag{2}$$

where r is the interest rate and w is the wage at the location the individual lives when receiving the wage. Similar to Deaton (1991), the liquidity constraint is modeled as a borrowing constraint:

$$x \geq 0 \tag{3}$$

This gives the following Bellman equation:

$$V(x, l) = \max_{c,l^{'}} \left\{ U(c, l^{'}) + \beta \int V(x^{'}, l^{'} dF(w_{l^{'}}) \right\} \tag{4}$$

In line with Deaton (1991) and Bryan, Chowdury and Mobarak (2014), an isoelastic utility function is chosen that exhibits constant relative risk aversion. In addition to consumption, utility is a function of the location chosen in each period. This input argument is added as a constant disutility y of being away from home to reflect that, ceteris paribus, individuals prefer to be at home, and also to avoid the unrealistic scenario where everyone would migrate.

$$U(c, l^{'}) = \frac{c^{1-\rho}}{1-\rho} - y\mathbf{1}(l^{'}) \tag{5}$$

$$\text{with } \mathbf{1}(l^{'}) = 1 \text{ if } l^{'} \neq Home \tag{6}$$

While in the basic set-up the disutility y is incurred every period throughout the duration of the stay, one of the model extensions defines the disutility relative to the person's previous location (not necessarily where he or she lived at age 18) to reflect that the perception of $Home$ changes over time as people settle at a new location.

I consider migration decisions in which individuals are given the opportunity to choose between multiple locations. Each of these locations is associated with a certain migration cost and independent wage distribution. I focus on migration decisions driven by economic rationales, such that people will not migrate to locations that are both more costly and provide lower wages, allowing me to consider only locations that are not dominated by both costs and wages. Thus, assuming that people are optimally migrating, paying higher costs of migration must be associated with larger wage gains. While in principle this model allows for any finite number of locations, in practice, the model becomes computationally unfeasible when using all distinct locations in the data.[4] Therefore, I will now turn to a simplified three-location model that is sufficient to provide the main predictions and intuition underlying the survival and investment migration strategies.

First, I define a $Home$ location as the location where a person resides at age 18. While moves at younger ages are observed in the data as well, these migration choices are likely made by the individual's parents. For the vast majority of individuals in the data, the $Home$ location is characterized as a rural location, so, throughout the model and empirical implementation, I restrict my focus to individuals whose $Home$ location is rural (though results are robust to including all $Home$ locations). We can then think of the migration decision as choosing between the best nearby rural area (with low migration costs, but wage draws that are not much better than at $Home$) or migrating to a further-away city with higher costs and higher wages. In the description of the model, I will therefore interchangeably use the nearby and rural location on the one hand and the far and urban location on the other hand, and all analyses will be carried out using both distinctions. As such, each person's location choice set consists of three entries: $\{H, R, U\}$, corresponding to $\{Home, Rural, Urban\}$, or alternatively, $\{H, N, F\}$, corresponding to $\{Home, Near, Far\}$.

I solve this three-location model numerically in discrete time with an infinite time horizon using value function iteration, following Miranda and Fackler (2002). More details on the model solution are given in the computational Appendix. While I also solve the model in finite time horizon using backward induction, the infinite time horizon is preferred because this lines up directly with the data I observe. In the finite time horizon model solution, individuals no longer migrate or save as the last period approaches, when the value is zero. In the panel data, I observe individuals during 20 years at various stages of their lives, so there is no equivalent of the final period, which makes the infinite time horizon model more appropriate.

The model solution is shown in the form of three model realizations in Figures 1, 2 and 3. The

[4] As described in the next section, there are 3,317 separate locations observed in the data and using all of these would take approximately 400 days to solve the model.

individuals depicted in each graph start off at $Home$ with wealth equal to 2, and the model is solved for each period to obtain the individual's optimal choices. For illustration purposes, $Rural$ wages are only slightly higher than wages at $Home$, while wages in $Urban$ areas are significantly higher, as shown in Figure 4. While the wage distributions are certain and known to the decision maker, each wage draw is random. Figures 1, 2 and 3 give examples of an individual's behavior as predicted by the model under different wage draw trajectories during 20 time periods. Each figure shows cash-on-hand (in blue), consumption (in green), wage received (red squares) and original wage draw (grey crosses). In periods in which the individual does not migrate, the wage received (red squares) is equal to the wage draw in that period (grey crosses). When he or she migrates, however, the original wage draw in the starting location is usually not equal to the wage draw at the new location.

Figure 1 shows that wages follow a stochastic process over time and that cash-on-hand acts as a buffer to smooth consumption. Indeed, consumption is fairly constant during the first 13 periods. During this time period, wage draws are relatively good, allowing the individual to save and slowly increase his or her cash-on-hand up to the moment that, in period 14, wealth is high enough to cover migration costs to the urban area. As shown in the lower panel, the person moves from $Home$ to $Urban$ in period 14, where wages are higher, as shown earlier in Figure 4. The costs to cover this move are shown as a drop in cash-on-hand in the top panel. From period 14 onward, the individual indeed enjoys higher consumption and wages.

Figure 2 shows an individual with the same starting conditions but who is less fortunate with the wage draws he or she receives. In the first periods, poor wage draws prevent the individual from building up wealth. In period 6, cash-on-hand is not sufficient to buffer against the bad wage draw he or she receives at $Home$. As a result, the person would have to reduce consumption and therefore utility. To avoid this, he or she decides to migrate to a $Rural$ location in hope of receiving a better wage draw. Indeed, in period 6, the individual receives a better $Rural$ wage draw (red squares) than he or she would have received if he or she decided to stay at $Home$ (grey cross). As wealth remains low after migrating to a $Rural$ area, the situation reoccurs in period 10 and 11, and again in period 15. A person who stays at $Home$ throughout the 20 time periods is shown in Figure 3. He or she does not build up enough wealth to move to the $Urban$ location, nor does this person experience negative shocks that require migrating to a $Rural$ area.

These three examples of wage realization and resulting migration and consumption choices provide the basic intuition for the two migration motives often observed and studied. As in Figure 2, people may experience negative shocks, and, if they do not have sufficient wealth or savings to avoid the need to reduce consumption, migration can be used as an ex-post risk-coping strategy to allow the person to receive another random wage draw. To avoid high migration costs, it is preferred to migrate to a $Rural$ location under these circumstances. The long-term benefits of this strategy are limited because $Rural$ wages are only slightly higher than at $Home$ and being away from home comes at a utility cost y.

The investment potential of migration is illustrated in Figure 1. Migrating to the $Urban$ location is beneficial because wages are significantly higher than at $Home$, allowing migrants to increase consumption. However, if liquidity constrained, the individual may not be able to pay the up-front migration costs. As shown in Figure 1, individuals may be able to overcome liquidity constraints through positive wage draws, allowing them to build up wealth over time. If able to move, they would want to continue benefiting from higher wages, making this type of migration a longer-term strategy.

As shown by these realizations of the model solution, survival migration is used when individuals lack wealth to buffer against negative wage shocks. Investment migration is only possible after sufficient funds have been accumulated. It furthermore follows that migration to the $Rural$ area is more likely to be of short duration, while there are incentives to stay longer after migration to an $Urban$ area. As noted earlier, migration increases with contemporaneous negative shocks as well as with an accumulation of past positive shocks. Therefore, those who move in response to negative contemporaneous shocks stay at their destinations for shorter periods on average than those who move in response to an accumulation of previous positive shocks.

As individuals save up for migration further away or to urban areas, the migratory response to an accumulation of past positive shocks is predicted to be stronger for longer distances. The expected distance traveled after contemporaneous negative shocks is ambiguous. One the one hand, survival migration occurring after sudden negative shocks predicts short distance or rural migration to avoid high migration costs. On the other hand, conditional on having accumulated sufficient funds to invest in migration, it is still preferred to migrate when experiencing a negative shock that has reduced the opportunity costs of staying. So, while the migration response to an accumulation of positive shocks is expected to dominate for urban and faraway destinations, migration response after negative shocks is expected to occur at all destination types.

3 Data

I use the Indonesia Family Life Survey (IFLS) to study migration choice under risk and liquidity constraints and to test the migration choice model described in the previous section. Data was collected from the same households and individuals in four waves: 1993, 1997, 2000 and 2007. This panel dataset is particularly suitable to study migration due to its intensive efforts to track respondents and its resulting low rates of attrition: In the last wave in 2007, the recontact rate of original households interviewed in 1993 was 93.6 percent (Strauss et al., 2009 and Thomas et al., 2012). This longitudinal survey is representative of about 83 percent of the Indonesian population (Strauss et al., 2004). The analyses are based on all four waves of the IFLS, allowing me to construct a 20-year panel from 1988 through 2007 of 38,914 individuals.

3.1 Household panel dataset

Using the migration modules of the IFLS, a dataset is obtained of 38,914 individuals, who recorded when and where they migrated after the age of 12. All moves longer than 6 months are included. In addition to migration data based on recall between the four survey waves, the dataset contains information on where respondents were born and where they lived at age 12. This information is transformed into a panel dataset that reports the person's location in each year from 1988 to 2007. Children may move with their parents for reasons not included in the model, so for the main analyses I study people between age 18 and 65 and as noted earlier, a person's $Home$ location is where he or she resides at age 18. As women move for marriage more often than men, robustness checks are performed for men only. To improve the balance of the panel, the year 1988 is the first year for all individuals in the panel, even though all moves after age 12 are recorded, including those before 1988 if the individual was already old enough. This results in a panel dataset of individual location decisions of 38,914 individuals age 18 and above during the period 1988 − 2007, with a total of 558,425 individual-year observations.

More than 99 percent of moves in the sample took place within the borders of Indonesia, so this study focuses primarily on internal migration. Location information is available at three geographical levels. The largest level is the province, of which there are 34 in Indonesia, and these are further divided into kabupaten (districts) and kecamatan (sub-districts). To be able to study all migration choices, including those over short distances, this study uses all three geographical levels. As such, a migrant is someone who resides in a kecamatan different from the one he or she lived in at age 18. There are 3,317 separate kecamatan observed in the data, each having corresponding latitude and longitude coordinates, making it possible to calculate all distances travelled between kecamatan, some of which are only short distances.

Figure 5 gives an example of the migration choices observed in the data. Each line represents an individual's move observed in the data, starting at a red dot and ending at a green dot. In total, more than 22,500 moves are observed in the data, so this map only shows a subset of the moves, namely those taking place in August of 1995. This map shows that a large share of the moves occur over short distances and within islands. Figure 6 illustrates this more clearly by using pie charts to show migration within and between islands. The colors of the pie chart correspond with the colors of the destination islands. For example, the pie chart for Sumatra in the west of Indonesia shows that, during the study period of 20 years, 1565 individual migrants originated from Sumatra. Of those, 49.7 percent migrated to the islands in the south (marked in darker colors), including Java and Bali, and another 49.3 percent migrated to destinations within Sumatra. The remaining one percent migrated from Sumatra to Kalimantan and Sulawesi in the north and north-east. This map shows that a large share of moves takes places within islands, which is especially true for the prosperous areas in Java and Bali, where more than 90 percent of individuals migrated within the island group. Figures 7 and 8 show that the large cities are popular destinations. 5.9 percent of individuals residing in the Java-Bali area migrate to Jakarta, the capital and largest city, at least once during the study period; 4.3 of those residing in Sumatra make a trip to Jakarta; and comparable numbers for Kalimantan and Sulawesi are 1.1 and 1 percent, respectively. Indonesia's third largest city, Medan, located in the north-west of Sumatra, attracts 2.8 percent of individuals residing in Sumatra but fewer people from island groups that are farther away from Medan.

Table 1 provides summary statistics of this dataset. In almost 38 percent of the individual-year pairs, the person does not reside in the kecamatan in which he or she lived at age 18, which defines the migrant stock. The migrant flow is lower at 4.37 percent, which includes only the individual-year pairs in which a person changed location. The majority of these moves were away from the location at age 18, defined as $Home$. The median move lasted 4 years and took place over a distance of 100 km. In 64 percent of the moves, individuals traveled by themselves, and, in the cases when they did move together, they traveled on average with 2.58 persons.

In addition to detailed information on migration, data are available on individual and household characteristics as well as labor market outcomes. Similar to the construction of the annual migration panel, an annual panel of individual income is created using recall data between the survey years. Income in both formal and informal sectors is included, as well as income from both main and side jobs. Although an imperfect measure, assets are used to approximate wealth. Asset data from the individual and household asset module are summed up and, following Haagenars et al. (1994), the adult equivalent of assets is used to create the individual-level wealth variable. Asset data is only collected during the survey years, so wealth observations are available for 1993, 1997, 2000 and 2007. To facilitate interpretation, all annual monetary values are reported in 100,000 Indonesian Rupiah and converted to their year 2000 equivalent, using the Indonesian consumer price index that is part of the International Financial Statistics collected by the International Monetary Fund.

3.2 Weather data

Weather data are obtained from the Center for Climatic Research at the University of Delaware (Matsuura and Willmott, 2009). Monthly estimates of precipitation and temperature are available for grids of 0.5 by 0.5 degree, which corresponds to about 50 by 50 kilometers in Indonesia. These data are based on interpolated weather station data and are matched to IFLS respondent locations using GPS coordinates. Figure 9 shows all individuals' locations on a map of Indonesia as red dots, with blue grids representing the weather data to which each location is mapped. While this study explores various weather measures, precipitation levels are used as the main weather variable. This is in line with Maccini and Yang (2009), who argue that rainfall is the most important source of weather variation in Indonesia. Temperature shows less variation over time due to Indonesia's equatorial location. Instead of using annual data from each calendar year, all measures are created from July until June of the following year to reflect the growing seasons in Indonesia. In addition to precipitation, this study carries out robustness checks with various other weather variables. This includes precipitation z-scores and temperature, as well as precipitation squared and cubed to allow for nonlinear effects. To capture unusual weather patterns, robustness checks are performed with deviations from the mean, precipitation growth and extreme weather events.

4 Empirical Results

In order to study the migratory response to weather shocks, I estimate the following equation:

$$migrate_{it} = \alpha + \beta weather_{iT} + \delta_t + \lambda_i + \varepsilon_{it} \tag{7}$$

$migrate_{it}$ is a dummy variable for whether person i migrates in year t. $weather_{iT}$ is the precipitation level at the location of individual i at time T, in which T can take various values. In case of contemporaneous shocks, precipitation at time t, $weather_{i,t}$, is used, while previous shocks are accumulated over preceding time periods, for instance from time period $t-1$ until $t-3$: $weather_{i,(t-1,t-3)}$. All regression analyses include time fixed effects, δ_t, and individual fixed effects, λ_i, and are clustered at the location level, which is the level at which weather shocks are observed. In order to justify the use of accumulated previous rainfall shocks to proxy for wealth accumulation, I first regress wealth on previous rainfall shocks (see Table 3). These results confirm that wealth increases in the presence of positive weather shocks in the current year t, as well as in previous years.

The main empirical results on the migratory response to contemporaneous and preceding weather shocks are presented in Table 4. This table shows that migration away from the individual's rural Home location increases in response to both negative contemporaneous shocks and to an accumulation of previous positive shocks. This is true for various sets of previous shocks, ranging from year $t-1$ in column 1 to year $t-5$ in column 4, and is highly significant whether analyzed in the same regression or separately (not shown).

This confirms that the two diverging migratory responses to income shocks, which have been studied as separate phenomena, can be observed in the same dataset. The magnitudes of these effects are economically meaningful. Average rainfall in Indonesia is about 150 mm per month. If the equivalent of one month of rain is missed in a particular year, this induces 2.25 percent of individuals to leave. Similarly, an extra month of rain annually in previous years induces about 1.5 percent of individuals to migrate. Compared to the average migrant flow of 4.37 percent, such changes in weather patterns would account for almost half of the moves observed in the data.

To further examine differences in migration patterns in response to income shock, Table 5 is split between moves that lasted less than the median duration of four years, and those that lasted longer. The choice of how long to stay at a new destination is an endogenous choice that may be affected by subsequent income shocks. In order to account for possible bias, duration is recorded in the year of migration, when subsequent employment outcomes and shocks were unknown. This table confirms that individuals who move in response to negative contemporaneous shocks stay at their destination for a shorter period than those who move in response to an accumulation of previous positive shocks. Comparing columns 1 and 2 indicates that people save up for migration that lasts longer than 4 years, while there is no evidence of savings accumulation for shorter moves.

Before comparing changes in migration patterns to rural and urban destinations induced by various weather shocks, Table 2 shows the transition matrix between the locations $Home$, $Rural$ and $Urban$. The first row shows that, in 62.26 percent of the individual-year pairs, a person lives at his or her $Home$ location and decides to stay there; in 1.25 percent of individual-year pairs, a person migrates from the $Home$ location to a $Rural$ location and, in 1.01 percent of pairs, he or she moves from $Home$ to an $Urban$ area. The diagonal shows that, on average, people stay at a $Rural$ destination in 17.82 percent of individual-year pairs and at an $Urban$ destination in 15.88 percent of individual-year pairs. Technically, the diagonal also includes the situation in which a person moves between $Rural$ destinations or between $Urban$ destinations, but these moves are uncommon. Summing up all off-diagonal matrix entries gives a migration flow of 4.04 percent. The total migration flow as reported in Table 1 is 4.37 percent, so the remaining 0.33 percent can be attributed to moves between $Rural$ areas or between $Urban$ areas. The bottom panel of Table 2 shows the absolute number of individual-year pairs in each matrix cell. These sum up to 558,425, the number of individual-year pairs observed in the data.

Table 6 compares the migratory response to weather shocks when migrating to a rural (column 1) versus an urban (column 2) destination. As described in Section 2, investment migration is more likely to have an urban destination, while survival is expected to induce individuals to migrate to a nearby rural location. The second row confirms that accumulation of wealth through preceding positive shocks dominates for urban destinations, to which migration costs are higher. As expected, migration after a negative shock encourages individuals to leave $Home$ regardless of their destination, though individuals seem to be slightly more likely to move to a rural area. Table 7 repeats this exercise by comparing migratory responses to weather shocks when migrating less than 100 km (column 1) versus more than 100 km (column 2). As described in Section 2, investment migration is expected to dominate longer distance migration, while migration at all distances is expected to respond to current negative income shocks. This is confirmed by Table 7. An empirical challenge for comparing migration at various distances is that the distance itself is an endogenous choice. If there is positive serial correlation in rainfall patterns, a negative shock would tend to induce people to migrate farther away, while a positive shock would induce people to stay closer. However, the opposite pattern is observed in Table 7, so this is less of a concern, as it would merely bias the results downward.

5 Structural Estimation

In addition to the reduced-form evidence provided in the previous section, this section will structurally estimate the model in order to test its validity, estimate various model parameters and perform counterfactual policy analyses using these parameter values. The following table summarizes how the variables and parameters of the model match those observed in the data.

Location

Location is both a state and control variable in the model and, as described in Section 3, locations are defined at the kecamatan (sub-district) level, 3,317 of which are observed in the data. In line with the model, and in order to reduce computation time, the structural estimation distinguishes between three locations. $Home$ is the kecamatan where the person lives at age 18, and in the basic

Model parameter	Symbol	Empirical variable
State and control variables		
Location	l	Location $\{H, R, U\}$
Wealth	x	Adult-equivalent of household assets
Wages		
Wage distribution at *Home*	μ_h	Mean income non-migrants at *Home*
	σ_h	Variance income non-migrants
Wage distribution *Rural*	μ_r, μ_n	Mean income migrants $Rural, Near$
	σ_r, σ_n	Variance income migrants $Rural, Near$
Wage distribution *Urban*	μ_u, μ_f	Mean income migrants $Urban, Far$
	σ_u, σ_f	Variance income migrants $Urban, Far$
Wage draw at time t	w_t	Predicted wage model
Exogenous parameters		
Discount factor	β	Set exogenously ranging from 0.90 - 0.99
Interest rate	r	Set exogenously ranging from 0.01 to 0.10
Structurally Estimate		
Cost migrating *Rural*	m_n	One-time cost of moving to $Rural, Near$
Cost migration *Urban*	m_f	One-time cost of moving to $Urban, Far$
Disutility away from *Home*	y	Constant disutility of being away from *Home*
Coeff relative risk aversion	ρ	Set exogenously or structurally estimate

version of the model, the definition of $Home$ does not change over time. In accordance with the model and reduced-form results, two sets of criteria are used to distinguish migration destinations: $Rural$ and $Urban$ destinations on the one hand, and locations $Near$ and Far on the other hand, which are defined as those less and more than 100 km away from $Home$. Robustness checks are performed with alternative distance cut-offs ranging from 50 to 200 km. Figure 10 confirms the model assumption that $Urban$ wages first order stochastically dominate $Rural$ wages and Figure 11 shows that the same is true for wages Far compared to wages $Near$. To account for any possible selection in migrant status, Figures 12 and 13 show that the first order stochastic dominance still holds when only including individuals who ever migrate.

Wealth

As described in Section 2, asset data are used to approximate wealth. These data are available only during the survey years (no recall data on assets were collected), so wealth is observed in the four survey years: 1993, 1997, 2000 and 2007. Because this is an infinite time horizon model in which each individual-year pair is treated equally, and given that each period uses only data from that period, the structural estimation will be restricted to the four years in which survey data was collected.

Wages

While wages are observed for each individual in each year, these wages correspond to the wages at the location where the person chooses to be. For the model, the original wage draw is essential in determining whether or not a person migrates in response to a bad wage draw at the starting location that reduced the opportunity costs of moving. Original wage draws are not observed, however, and are likely lower than accepted wages if people indeed migrate away from negative shocks, making observed wages inadequate to use as wage shocks.

Instead, I use a wage model to predict original wage draws. Following Mincer (1974), I run basic Mincer regressions for the locations, $Home$, $Rural$, $Urban$, $Near$ and Far to predict income. In line with the reduced-form evidence presented in Section 4, I add current and lagged rainfall shocks to the common regressors, including education level, gender, age and age squared. Table 9 presents the results for all locations in columns 1, for $Home$, $Rural$ and $Urban$ in columns 2, 3, and 4, respectively, and columns 5 and 6 repeat the analyses for $Nearby$ and $Faraway$ destinations.

As expected, those with higher levels of education earn higher wages, and this relationship is the strongest in $Urban$ and $Faraway$ areas. A similar pattern is observed for men compared to women. Income increases with age at a declining rate, as indicated by the negative squared term. Current and lagged precipitation are reported as z-scores to facilitate interpretation. In line with earlier reduced-form results, precipitation terms are positive and slowly reduce predictive power as precipitation from earlier time periods is used. Comparing the Mincer regression at $Home$ in column 2 to those in other locations (columns 3 to 6) reveals that the precipitation terms are predictive of income at $Home$, but to a much lesser extent in other locations. As the main source of exogenous variation, this limits the use of income shocks at locations away from $Home$. Therefore, while the model is flexible in allowing for moves in any direction, the main estimation will focus on structural parameters estimated using wage shocks at $Home$. Robustness checks are performed with a broader range of structural parameters and are consistent with the main results but computation time increases sharply with the number of parameters estimated.

Parameter values estimated structurally

The cost of migrating has a fixed and variable component. In order to finance a move, a one-time migration cost m_r needs to be paid to move to a *Rural* location, and m_u needs to be paid to migrate to an $Urban$ area. Note that these migration costs include all one-time costs incurred when moving, such as transportation costs, as well as the cost of forgone income when employment is not immediately found. In addition to these one-time migration costs, individuals incur continuous costs, modeled directly in the utility function as a disutility of being away from home, y. While the migration cost and disutility of being away from home have different interpretations in the model, the main distinction in the structural estimation is provided by the difference in timing: migration cost is incurred only in the year of the move, while the disutility of being away from home is incurred as long as the individual is not present at $Home$. Both types of costs can be structurally estimated because people are observed in the year they move as well as in years they decide to stay at their destination.

5.1 Maximum likelihood estimation

I use maximum likelihood estimation in order to find the model parameter values underlying a series of simulated data that matches the observed data as closely as possible. For each set of parameter values, I solve the model, which leads to predicted choices for all state variable combinations.

Naturally, the predicted choices will not always correspond to actual choices I observe in the data. Following Rust (1987), I attribute deviations from predicted model decisions to unobserved state variables, ϵ, that are observed by the decision maker but unobserved by the econometrician. I assume that ϵ is distributed as a multivariate extreme value distribution, which leads to the logit formula as shown by Luce and Suppes (1965) and McFadden (1974). The conditional choice probabilities can then be expressed in the following closed form, in which x are the observed state variables and $d \in D$ the discrete decision variables:

$$P(d|x) = \frac{e^{(V(x,d))}}{\sum_{d' \in D(x)} e^{(V(x,d'))}} \tag{8}$$

I employ a nested fixed point algorithm that loops over various sets of parameter values in the outer loop. For a given set of parameter values, the inner loop solves the model by finding the value function of each location as a fixed point of the contraction mapping. Focusing on the discrete location choice consisting of the choice set, H, R, U, the following log likelihood function is calculated for each set of parameter values:

$$f = 1/N \sum_{i=1}^{N} log \left(\frac{e^{V_l}}{e^{V_h} + e^{V_r} + e^{V_u}} \right) \tag{9}$$

where N is the number of individual-year pairs in the data, which are all treated equally in the infinite time horizon model. The outer loop finds the set of parameter values that maximizes the log likelihood function. The computational Appendix describes the nested fixed point algorithm in more detail.

Migration costs likely vary across individuals. Therefore, after estimating the multinomial logit, I follow Berry, Levinsohn and Pakes (1995), Train (2003), and others by using a mixed logit model with random coefficients on migration costs. By applying a mixing distribution on the model parameters, I account for heterogeneity between individuals and exploit the panel structure of the data.

The choice probabilities for person i are

$$P(d|x)_{i\mathbf{j}} = \int \rho_{i\mathbf{j}}(\beta|\theta)f(\beta)d\beta, \tag{10}$$

where $\mathbf{j}$ is the sequence of choices $\mathbf{j} = \{j_{1,}j_2, j_3, j_4\}$ observed in the four survey years and $\rho_{i\mathbf{j}}$ is defined as before:

$$\rho_{i\mathbf{j}} = \frac{e^{(V_l')_{i\mathbf{j}}}}{e^{V_h} + e^{V_r} + e^{V_u}} \tag{11}$$

and $f(\beta|\theta)$ is the mixing distribution, which I take to be normal to allow for the cost parameters θ to be either positive or negative. The probabilities are approximated through simulation for any given value of θ.

Following Train (2003), I use simulated log likelihood to estimate the mean and standard deviation of the mixing distribution. This accounts for differences in migration costs between individuals, keeping these constant for the same individual over time. As such, the mixed logit framework uses the panel structure in which individuals are observed up to four times across all survey years.

Table 10 shows how well the structurally estimated model fits the data in terms of predicted migration patterns. Comparing the observed migration patterns in the top panel to the predicted ones in the bottom panel reveals that the structurally estimated model closely predicts the actual location choices. The model does particularly well when $Home$ is the starting location, which is expected given that the exogenous weather shocks are most predictive of wages at the $Home$ location, as shown earlier in Table 9. Indeed, model predictions deviate further from the observed data when predicting return migration. The next section will therefore focus on structural estimation of the costs of migrating away from $Home$.

6 Structural Results

The main results of the structural estimation are presented in Table 11. The top panel shows the estimated costs of migrating to a rural versus an urban area and the bottom panel uses the distinction between migrating more or less than 100 kilometers. To facilitate interpretation, the monetary values are presented in units of 100,000 Indonesian Rupiah, converted to their equivalent values in the year 2000. Multiplying each number by 12 gives approximate comparable values in US dollars.

Column 1 gives the estimated migration costs for the full sample. The average migration cost of moving to a rural area is 11.09, which is about 133 US dollars. With an average annual income of 56, people have to spend about 20 percent of their annual income on average to move to another rural area. The estimated costs of moving to an urban area are considerable larger at 72.32, which is equivalent to 868 US dollars and is more than average annual income. The disutility of being away from $Home$ is denoted y in the utility function and presented as the equivalent amount of consumption that people are willing to forgo to maintain the same level of utility. At 7.53, the disutility away from $Home$ is about 90 US dollars and this amount is incurred every year the person is away from $Home$.

The bottom panel shows that the migration cost of moving to a $Near$ area is 15.86 (190 US dollars) and moving to a Far area is 69.82 (838 US dollars). Compared to the rural-urban division, the difference in migration costs is smaller between $Near$ and Far. The disutility cost is slightly higher at 8.74 (105 US dollars).

Columns 2 to 5 show migration cost estimates by wealth quartile and reveal that, in general, migration costs are considerably larger for those with less wealth, as approximated by the adult-equivalent of household assets. Note that this discrepancy, on top of the fact that those with lower levels of wealth earn lower income, makes it harder for those at the bottom of the wealth distribution to migrate to other locations. Average migration costs for the poorest quartile are 16.87 (202 US dollars) to move to a rural area and 95.95 (1150) to move to an urban area. Both costs are higher than for the general population in column 1, and the rural-urban difference is also greater, indicating that moving to an urban area is particularly costly for those at the bottom of the wealth distribution. Migration costs initially decrease with greater wealth, but are slightly higher again for those in the highest wealth quartile, which may be explained by the fact that those with very high levels of wealth in rural areas own large landholdings and migrate less often. The structural estimation will attribute this pattern to high migration costs for this subgroup.

6.1 Heterogeneous migration costs

Table 11 showed that migrating is considerably more costly for those with lower levels of wealth. This section re-estimates the model to study how migration costs differ across various subgroups of the society.

Age and education

Table 12 compares migration costs across education and age groups. Those with no education or only primary education are defined as having low education and those with any secondary education (even if they did not complete their degree) are classified as having high education. Structural estimates reveal that migrating is about twice as costly for those with lower levels of education. Once they arrive at the destination, however, it seems less costly to stay away from $Home$, because the disutility is smaller for the group with low education. Given the difference in timing used in the structural estimates, this indicates that, once they have migrated, people with lower levels of education are more likely to stay.

Columns 4, 5 and 6 compare age groups and reveal that migration costs increase rapidly with age. For those age 25 and below, migrating to a rural area cost only 6.44 (77 US dollar), and migrating to an urban area cost 20.43 (245 US dollar). For individuals above age 50, these costs are about 3 and 5 times higher for rural and urban areas, respectively.

Gender and marital status

Differences across gender and marital status are explored in Table 13. At first, it may seem surprising that migrating is about twice as costly for men as for women. In Indonesia, however, women are more likely to migrate for marriage, which increases the number of moves by women and leads to lower structurally estimated costs. Comparing migration costs for married versus single individuals indeed reveals that migration is almost four times as costly for those who are married. When conditioned on being married in columns 6 and 7, the gender difference in migration costs is considerably reduced.

Prior migration experience and connection at destination

Migration costs are likely to be lower for those with previous experience migrating, especially to the same or similar areas, as people have gained information and potentially established contacts at the destination. This is explored in Tables 14 and 15, though it should be noted that the results in these tables are merely correlations and cannot be interpreted causally. To facilitate comparison, columns 2 through 6 of Table 14 include only individuals currently at *Home* after having gained migration experience, if any. Comparing columns 2 and 3 shows the somewhat surprising finding that urban migration costs are higher for those with some prior migration experience compared to no migration experience. This is further explained by comparing columns 4 and 5. Migrating to rural areas is less costly for those who migrated to rural areas before, while migration to urban areas is considerably more costly. The ratio of migration costs for those moving to urban versus rural areas is 6.5 in the general population (72.32/11.09) and increases to 10.3 for those with prior rural migration experience. This may suggest that those who used survival migration to a rural area are more likely to invest in urban migration subsequently. However, this can only be interpreted as a correlation, as low migration costs to rural areas may be precisely the reason these individuals migrated to rural areas before. The opposite pattern is observed for those with prior migration experience to urban areas, shown in column 5. The ratio of migration costs between urban and rural areas is merely 1.43 for this subgroup, indicating that those with prior migration experience to urban areas have much lower costs of migrating to an urban area again. In addition to the importance of migration experience, these results highlight the interaction between the two migration strategies. Those who have rural migration experience have higher urban migration costs and vice versa, which provides suggestive evidence that the migration strategies act as substitutes rather than complements.

This may have important policy implications. As shown earlier, those with lower levels of wealth and education pay higher migration costs while earning less. Moreover, the rural and nearby areas to which they are more likely to migrate yield lower returns to migration. To the extent that the migration strategies act as substitutes, this may further reduce their opportunity to investment in migration that would more likely improve their livelihoods. This may be one of the factors contributing to geographical poverty traps. As pointed out by Jalan and Ravallion (2002), geographical poverty traps exist when the characteristics of an area are such that household's consumption cannot rise while a similar household living in a geographically preferred area would enjoy rising standards of living. While migration can help people escape geographical poverty traps, the results in this study may indicate that the type of migration matters as well. If they engage in survival migration with low returns and low future opportunities to invest in migration, this may further perpetuate their disadvantageous rural position.

Finally, Table 15 compares migration costs between those who knew somebody at their destination prior to arrival and those who did not. This question was only included in the first survey wave of the IFLS, so this analysis is carried out for the year 1993 only. As a result of the small sample size, the standard errors are larger, but the pattern remains clear: those who report knowing someone at their destination have lower migration costs than those who did not. This is true for all four types of destinations considered, though the differences are not always statistically significant. Despite the small sample size, this result echoes the findings of earlier studies that emphasize the importance of migrant networks in determining migration choice.

6.2 Benefits of migration to the mover

The migration costs estimated in the previous section can be used to calculate predicted benefits of migration in terms of consumption and wage gains, as done in Table 16. Consumption changes on the top panel are those predicted by the model for the individual who moves and are relative to the model prediction if the person had not moved. Changes in annual consumption are calculated separately for those moving to a $Rural$ and an $Urban$ destination, and are comparable when using the distance metric of moving $Near$ and Far (results not shown). The first-year consumption changes are presented in the first two columns and show that those migrating to a $Rural$ area experience an average consumption increase of 2.04 percent and those who move to an $Urban$ area consume on average 3.62 percent more in the first year. Columns 3 and 4 repeat this analysis for annual consumption levels five years after the move and are not conditioned on whether the individual is still at the destination. Hence, although the person could have returned, the predicted consumption level is still observed five years after the move. These columns show that those who migrated to a *Rural* area have 5.82 percent higher annual consumption five years after moving; some of them may still be at the *Rural* destination. Those who migrate to an *Urban* area see a larger consumption gain at 30.71 percent, presumably because migrants tend to stay at their *Urban* destination for longer periods of time, enjoying higher wage and consumption levels.

The bottom panel of Table 16 calculates the change in wages for individuals who moved. Unlike consumption, the actual wages after moving are observed, and are used to estimate wage changes after migrating. The first two columns show that, in the year of migrating, wages increase by 8.36 percent when migrating to a rural area and by 38.44 percent when migrating to an urban area where wages are considerably higher. Wage gains after five years after 3.36 and 43.35 percent for rural and urban areas, respectively. Note that these wage gains are compared to predicted wages had the person stayed at *Home*. As shown earlier, migrants tend to move to rural areas when experiencing negative income shocks, which may explain why, when migrating to a rural area, the immediate wage gain is larger than the wage gain after five years.

7 Policy Experiments

The dynamic migration choice model with estimated migration cost parameters is used to explore predicted changes in welfare and migration, using counterfactual scenarios and policy experiments. First, I examine predicted changes in response to the provision of credit that allows people to borrow to fund migration and consumption. I then study the predicted effects of changes in migration costs, providing a subsidy to migrate, and restricting migration to urban areas. Finally, a counterfactual experiment of increased shock intensity is examined, in order to better understand the possible impact of climate change on migration.

7.1 Providing credit

The availability of credit may affect both migration strategies. Survival migration is used as a coping strategy after negative shocks to safeguard adequacy of consumption levels. When credit is available, people may prefer to borrow to guarantee sufficient consumption, thereby reducing the need for survival migration. Credit may furthermore relax liquidity constraints that prevented investment migration. So far, the model used here has followed Deaton (1991) by including a liquidity constraint stating that wealth needs to be weakly positive. In the numerical solution algorithm, any negative wealth value would results in zero consumption, causing utility and value functions to equal minus infinity, a value that will always be avoided by the decision maker. As such, an individual will be able to migrate only if he or she can cover the up-front migration cost. By providing credit, the policy maker can relax this constraint and allow people to borrow funds needed to invest in migration. Credit may therefore reduce the need for survival migration while increasing opportunities to engage in investment migration.

This section will explore changes in predicted migration rates and average consumption when providing credit at different rates and will distinguish between credit that can only be used to finance migration and credit provision for any purpose. All results are presented in panel A of Table 17.

The first row shows predicted effects of providing credit that can be used for any purpose, at an annual interest rate of 5 percent. As expected, survival migration is reduced considerably, from 1.25 percent as observed in the data to a predicted 0.87 percent. Note that these numbers refer to the migration flow, which counts only the year in which the move takes place. Also as expected, investment migration increases sharply from 1.01 to 1.61. As a results, columns 3 and 4 show that credit availability increases average consumption. The second row shows that, as the interest rate doubles, changes in migration rates and increases in consumption shrink disproportionately.

Various NGOs and development organizations have launched programs providing credit conditional on migrating. This policy experiment is examined in rows 3 and 4 at interest rates of 5 and 10 percent, respectively. Compared to unconditional credit provision, the impact is concentrated on investment migration because this is the type of migration where credit constraints are likely to be binding. The need for survival migration is only slightly reduced, which leads to lower welfare benefits, especially when interest rates are higher. Overall, these policy experiments reveal that credit acts as a substitute for survival migration and a complement to investment migration, and is welfare-enhancing overall.

7.2 Changes in migration costs

A number of policies can be used to directly affect migration costs, such as subsidizing migration. One such program was studied by Bryan, Chowdury and Mobarak (2014) and consisted of subsidies of 8.50 US dollars conditional on migrating. Panel B of Table 17 examines predicted changes in migration and consumption as a result of various changes in migration costs.

The first row shows that a 10 percent increase in migration costs reduces survival migration from 1.25 to 1.20 percent, while investment migration is reduced by a much greater degree, from 1.01 to 0.62 percent. This may be explained by a larger absolute change in $Urban$ migration costs, while the need to use survival migration remains large and consistent. Column 3 shows that average consumption increases initially as funds are used for consumption instead of for migration. However, the consumption effect turns negative in column 4 because fewer migration opportunities reduce long-term welfare, as measured by consumption.

The opposite pattern is observed for a 10 percent migration cost reduction in row 2 of Panel B. Survival migration increases from 1.25 to 1.35 percent, while investment migration sees a larger increase to 1.66 percent, after which there is more investment migration than survival migration. Consumption after 5 years increases significantly, though there is a small initial decrease as more people pay for migration.

Row 3 is a quantitative comparison with the experiment studied by Bryan, Chowdury and Mobarak (2014). The migration incentive of 8.50 US dollars has only a small effect on migration and consumption patterns. This stands in contrast to the 22 percent increase in migration rates they observed, but may be explained by the fact that, in addition to the price incentive, their intervention included information sessions that likely increased knowledge and awareness.

This migration choice model allows for estimating the welfare costs of restricting migration such as in the Chinese Hukou system. This system of household registration assigns rural or urban status to all citizens based on place of birth; if people move to another region, they lose access to various benefits and services, such as schooling. As such, the predicted migration rate to urban areas drops to zero. There is more need for survival migration as shown in column 1. Although there is a short period of increase from the lack of $Urban$ migration, long-term consumption decreases by a considerable 21.3 percent.

7.3 Increases in weather shock intensity

While there is still considerable uncertainty about the impact of climate change on migration, this paper addresses a piece of the puzzle by studying how individual migration choices respond to weather shocks. Those living in rural areas in developing countries with limited asset holdings are often particularly susceptible to large income fluctuations. This is especially true for those working in agriculture, for whom weather shocks are a major source of income variation. Weather patterns are expected to change due to global warming, and rainfall shocks will likely increase in intensity.

I run a counterfactual experiment to examine the predicted change in migration patterns and welfare in response to increased intensity of weather shocks. Panel C of Table 17 predicts changes in migration and consumption in response to a 5 and 10 percent increase in the standard deviation of weather shock. The first row shows that a 5 percent increase in weather shock intensity increases survival migration by 0.12 percentage points from 1.25 to 1.35 percent, and reduces investment migration from 1.01 to 0.89 percent. The second row reports the predicted changes for the poorest half of the wealth distribution and reveals that changes in migration rates are almost twice as large as for the general population. This suggests that poor individuals carry the largest burden of increased need for survival migration and reduced opportunities for investment migration. Welfare effects, as approximated by changes in consumption, are negative at 3.19 percent on average and are more than twice as negative for the poorest half of the population. The last two rows repeat the counterfactual analysis for a 10 percent increase in the standard deviation of shocks and reveal that this increases survival migration from 1.25 to 1.74 percent and reduces investment migration from 1.01 to 0.74 percent. Adverse effects, especially in terms of the need for survival migration, are considerably larger for poor individuals. Overall reductions in welfare, as approximated by consumption changes, range from 8.63 percent on average to 15.43 percent for the poorest half of the wealth distribution.

Overall, these counterfactual experiments reveal that more extreme weather shocks increase the need to engage in survival migration as an ex-post risk-coping strategy while simultaneously limiting the opportunity to save up for profitable investment migration. This leads to a predicted reduction in overall welfare and disproportionately affects those at the bottom of the wealth distribution.

8 Conclusion

This paper studies migration choice in the face of risk and liquidity constraints. On the one hand, households can use migration as an ex-post risk-coping strategy by moving after sudden negative shocks, such as agricultural crop loss. On the other hand, migration can be seen as an investment, but liquidity constraints may prevent households from paying the up-front migration costs. While both migration strategies have been observed and described in the literature, they have diverging predictions in terms of the migratory response to shocks. In the case of survival migration, the occurrence of contemporaneous negative shocks may induce people to migrate, while, in the presence of liquidity constraints, an accumulation of preceding positive shocks may relax those constraints and increase out-migration.

This paper develops a dynamic migration choice model that incorporates both migration strategies. It builds on Deaton's (1991) savings model and adds current location as a state variable and migration choice as an additional control variable. Predictions are derived based on the types of shocks that induce migration, characteristics of the move – including distance and duration – and characteristics of those who migrate. The main contributions of the model are that it allows for multiple choices over time and between multiple locations, and that it incorporates wealth as an important determinant of migration choice. My approach goes beyond that of Kennan and Walker (2011), who, as noted above, did not include wealth constraints among an educated cohort of migrants in a developed country. The model in this paper is therefore presented as an alternative model of migration choice applicable to developing country contexts in which wealth and liquidity constraints profoundly limit migration and destination choices.

The model is tested using a rich panel of more than 38,000 individuals in Indonesia, for whom all migration choices were recorded over a 20-year period. I document evidence of both migration strategies. In agreement with the models predictions, I find empirically that survival migration is more often characterized by temporary moves to rural destinations and is used by those with low levels of wealth. Investment migration, on the other hand, is more likely to involve urban destinations, occur over longer distances, and be longer in duration.

I structurally estimate the model and find the model parameter values underlying a series of simulated data that match the observed data as closely as possible. Migration costs are structurally estimated and average about 20 percent of annual income for survival migration, while corresponding costs for investing in migration average slightly more than annual income, making it reasonable that people have to save to afford such moves. There is considerable heterogeneity in the cost to migrate, which is 30 percent higher for those with lower levels of wealth and education and 50 percent higher for individuals above the median age. Furthermore, costs are lower for women than men, which seems to be driven by migration for marriage, as gender differences decrease sharply when conditioned on being married.

While both migration strategies have positive returns to migrants, those who invest in migration benefit to a greater degree. Suggestive evidence moreover reveals that the two migration strategies act as substitutes, meaning that those who migrate to cope with a negative shock are less likely to invest in migration. This may have important distributional implications and contributes to the debate on geographical poverty traps. While not testing for poverty traps directly, I find that liquidity constraints prevent profitable migration, and that poor individuals face higher migration costs while engaging in less profitable migration, which may limit their chances of investing in migration subsequently.

A policy instrument that may mitigate these distributional challenges and promote profitable migration is credit provision. I use the structural estimates to perform policy experiments and find that providing credit reduces the need for survival migration and increases the opportunity to invest in migration.

Finally, I explore how changes in the intensity of weather shocks affect migration patterns, which has implications for predicted migratory responses to climate change. I find that more extreme weather shocks increase the need to engage in survival migration while limiting the opportunity to invest in migration. This leads to an overall reduction in welfare and disproportionately affects those at the bottom of the wealth distribution.

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Figures

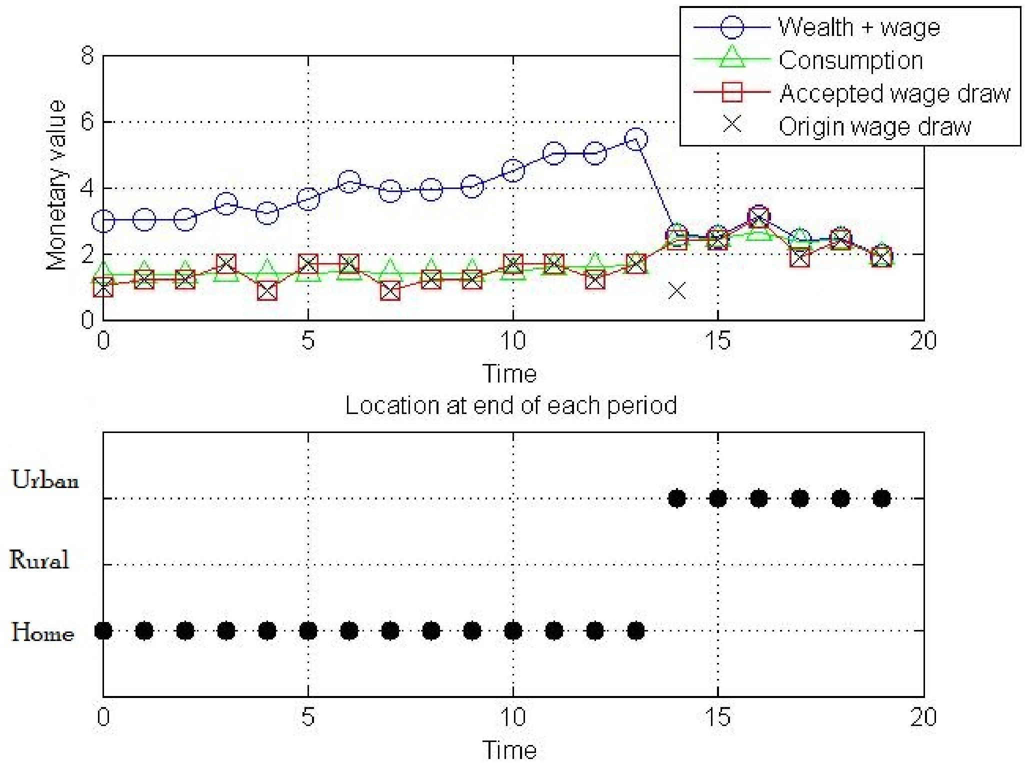

Figure 1: Model Solution: Moving to an Urban area

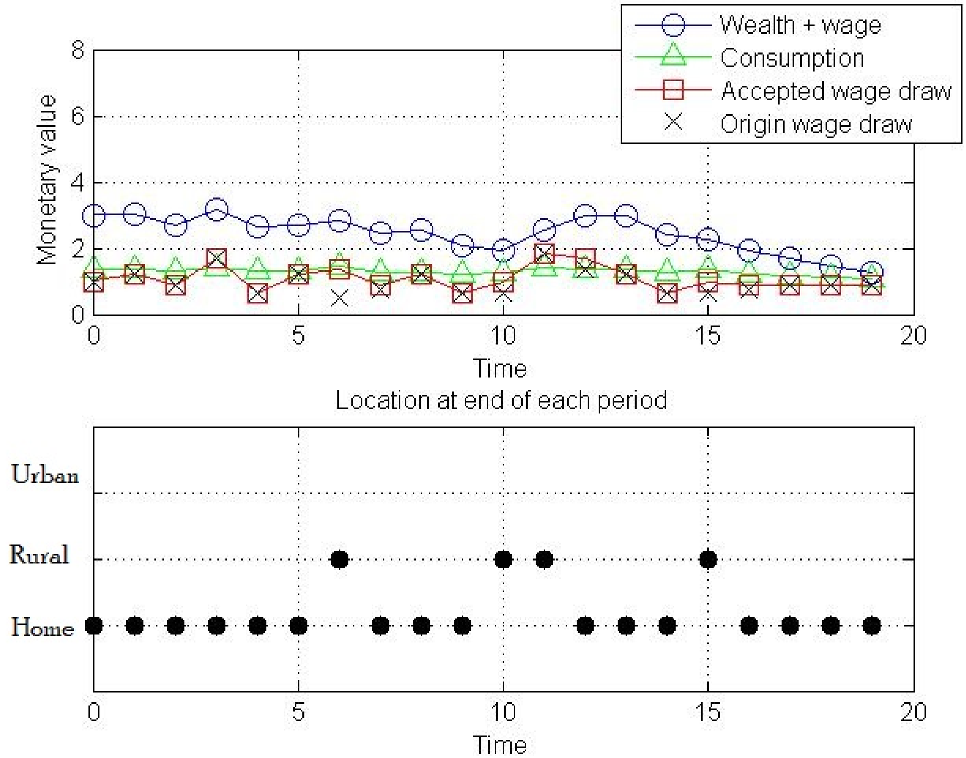

Figure 2: Model Solution: Moving to a Rural area

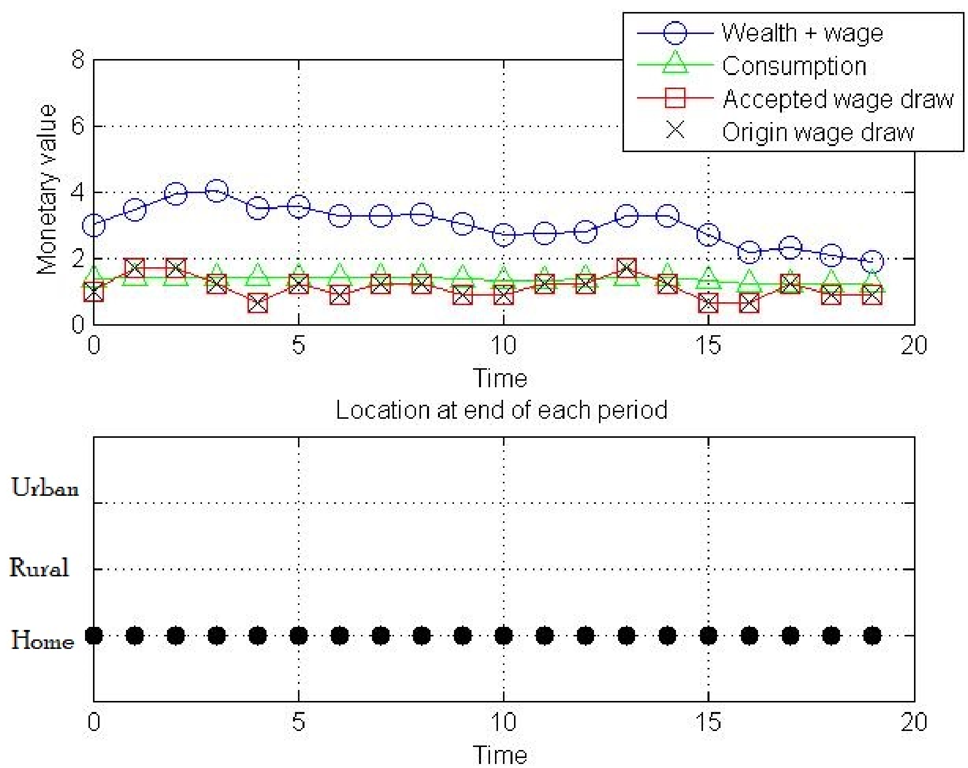

Figure 3: Model Solution: Staying Home

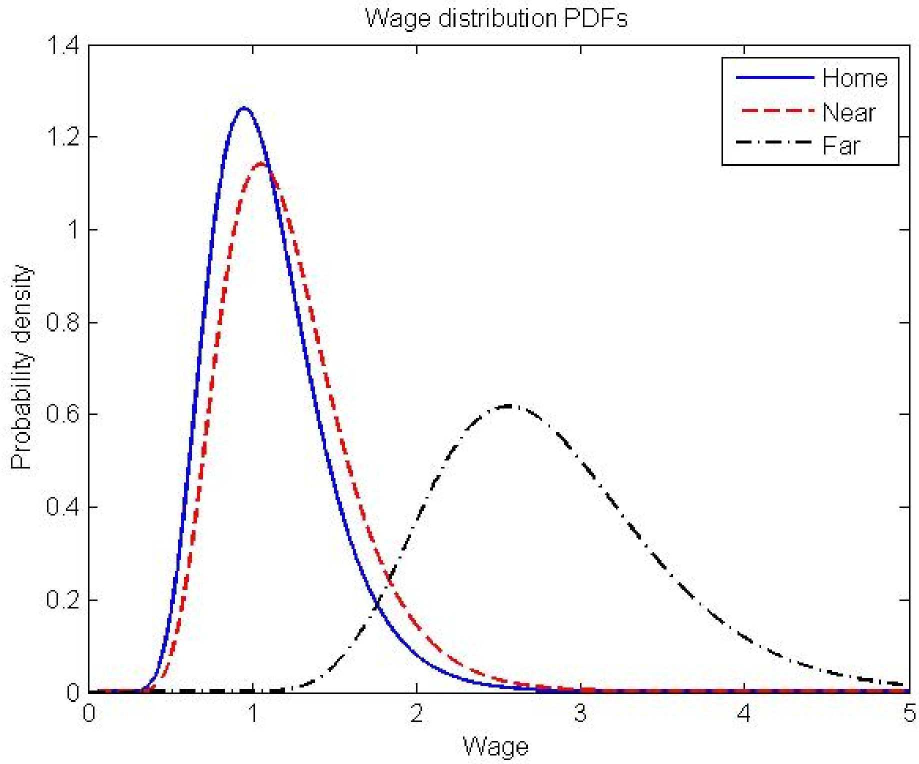

Figure 4: Wage Distributions used for model solutions shown in Figures 1, 2 and 3

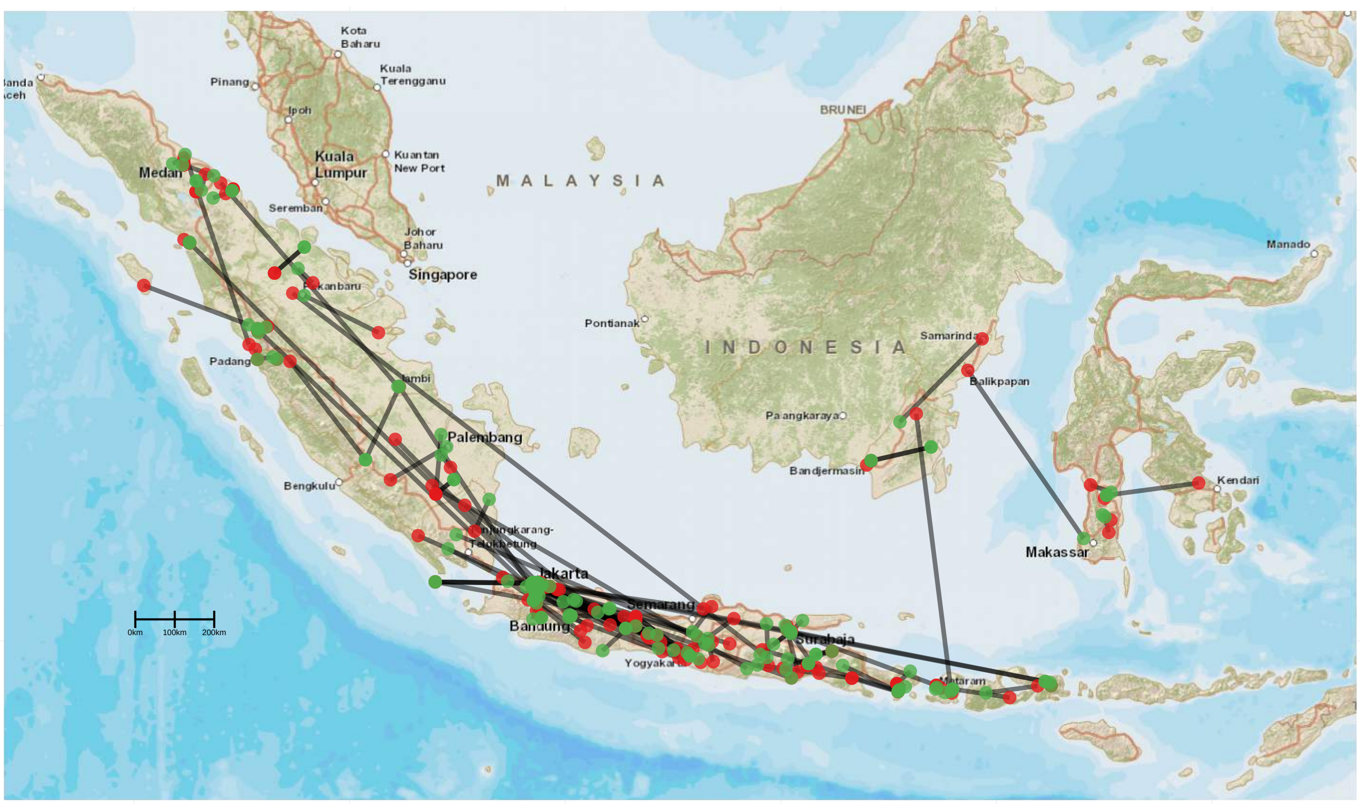

Figure 5: Monthly migration flow in August 1995

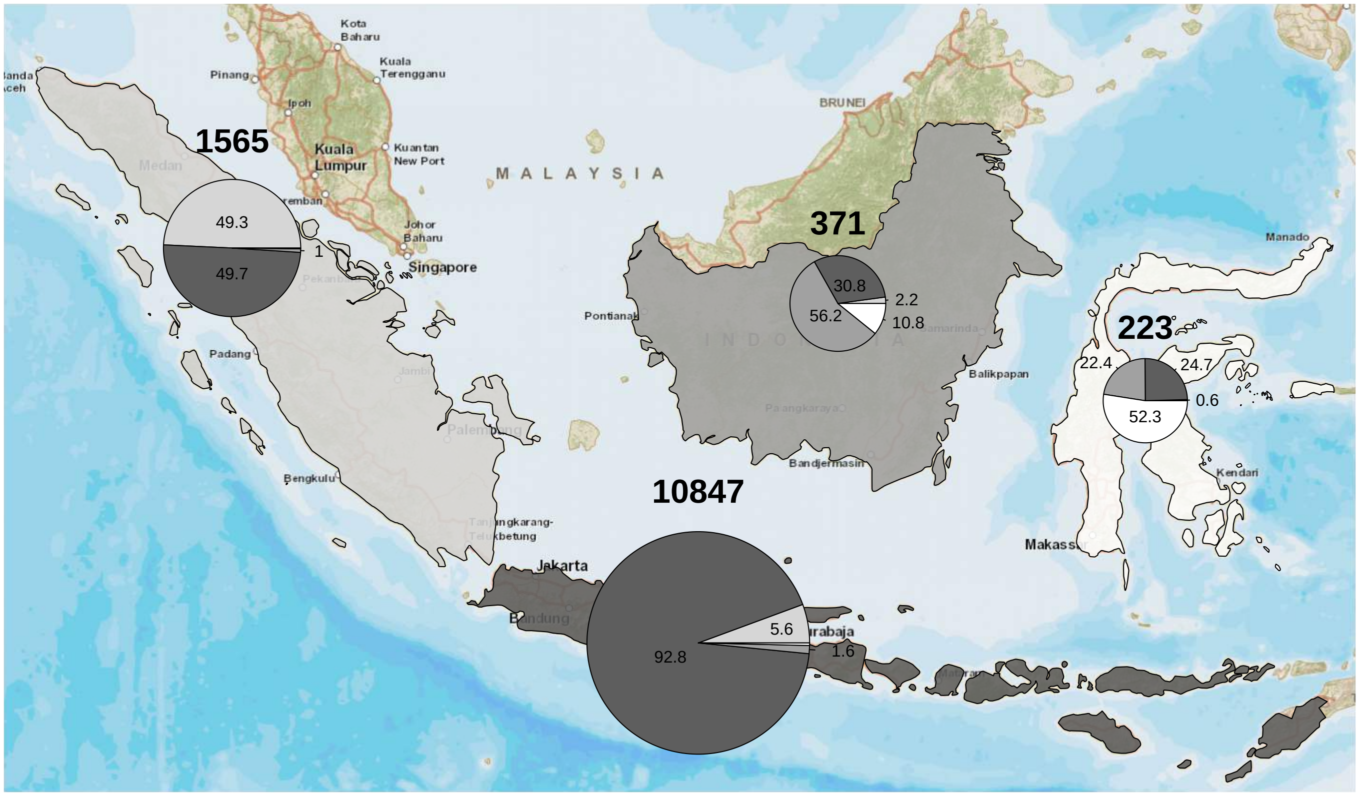

Figure 6: Migration flows between islands

Figure 7: Migration flow into Jakarta

Figure 8: Migration flow into Medan

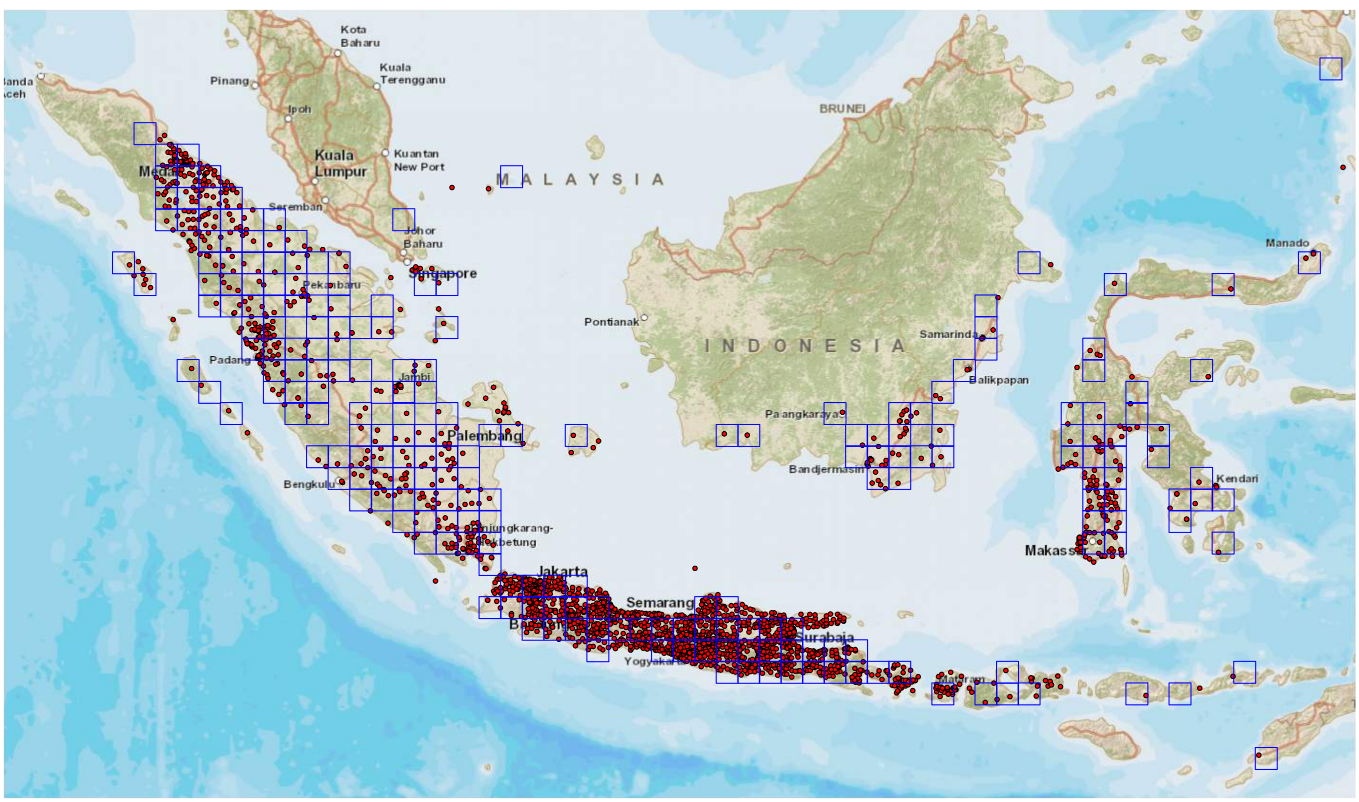

Figure 9: Household locations IFLS with weather data that locations are mapped to

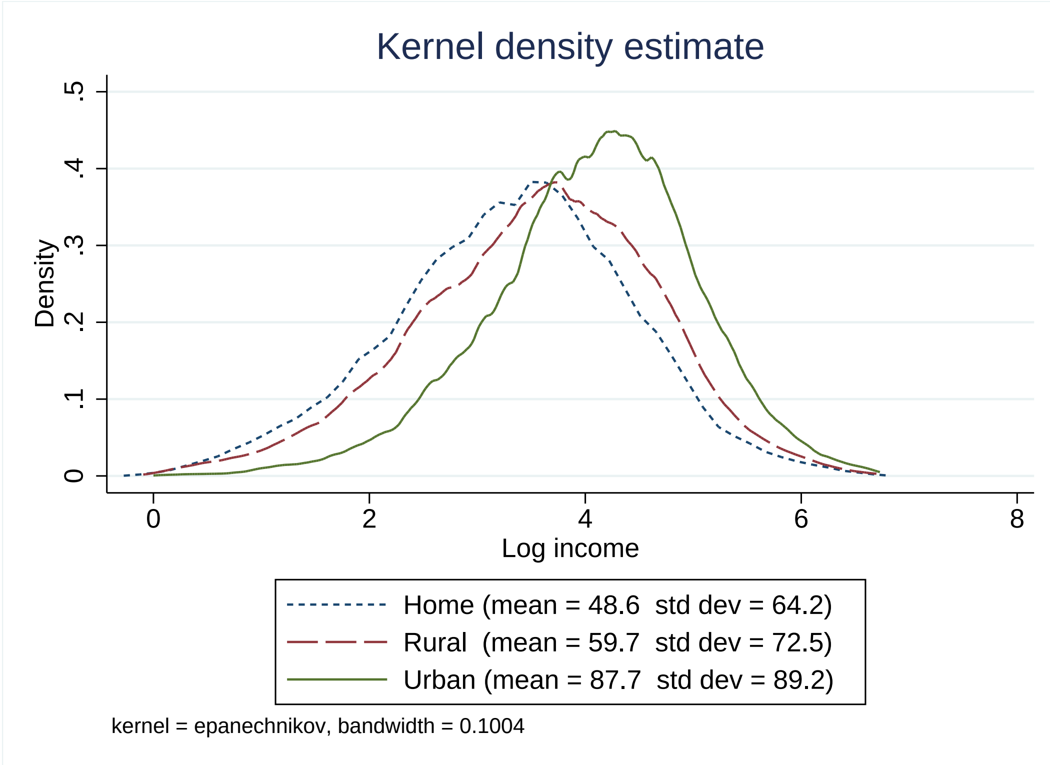

Figure 10: Kernel density wage distribution Home, Rural and Urban

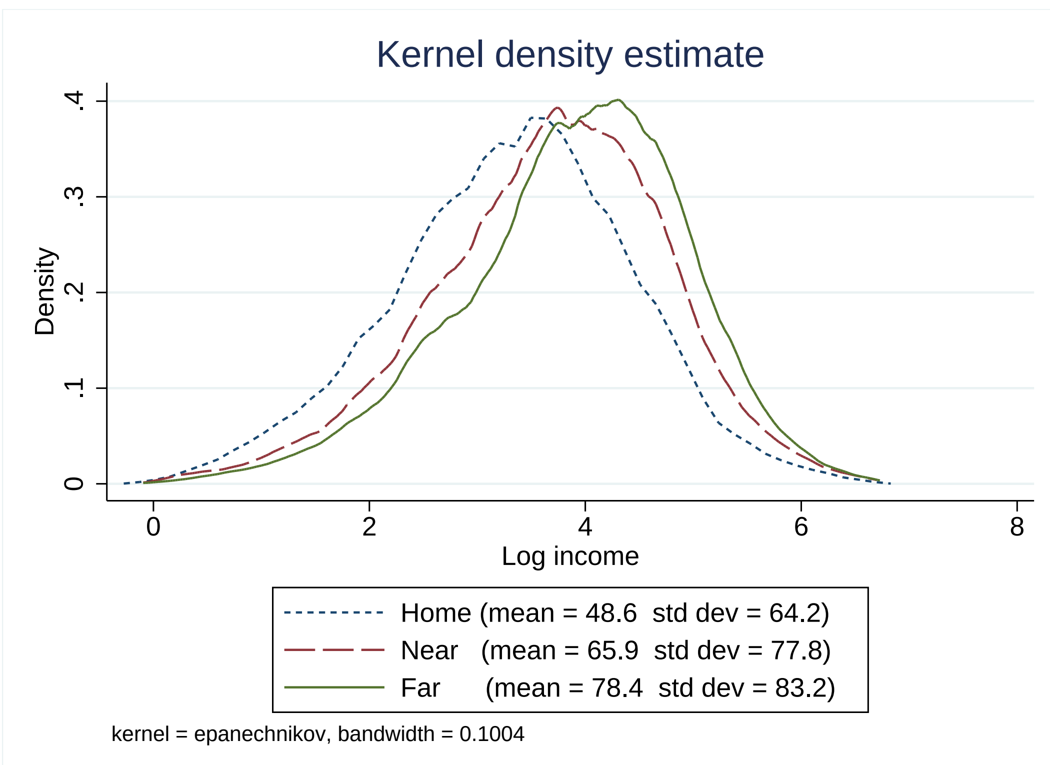

Figure 11: Kernel density wage distribution Home, Near and Far

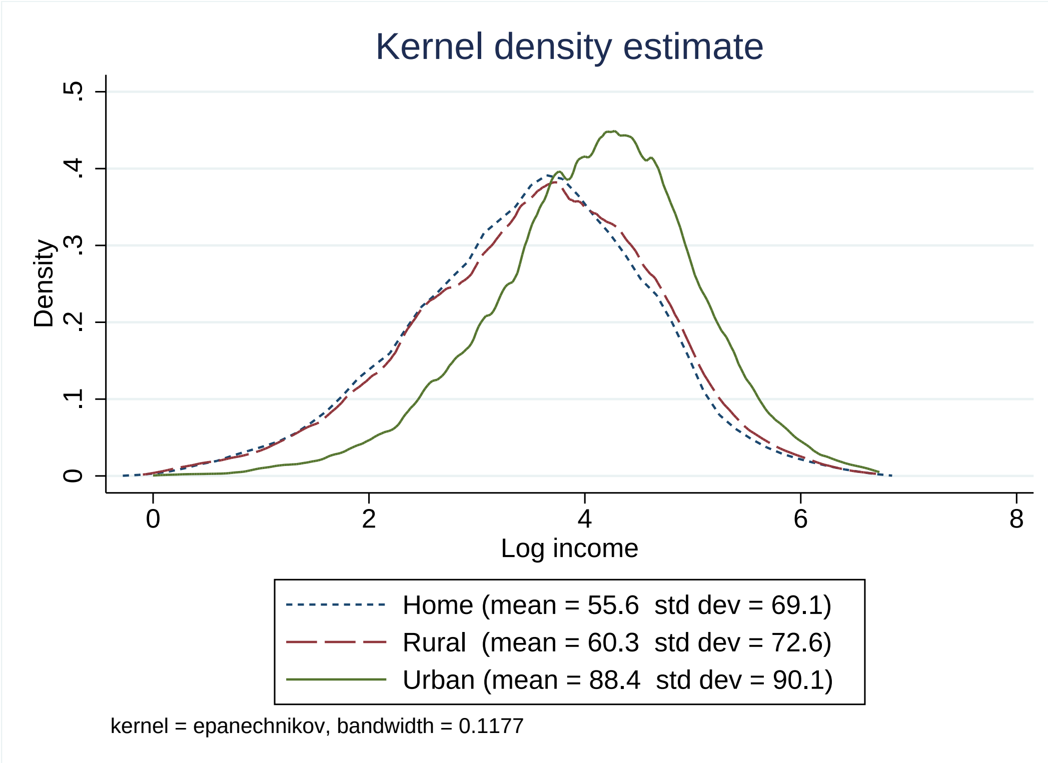

Figure 12: Kernel density wage distribution Home, Rural and Urban - Movers only

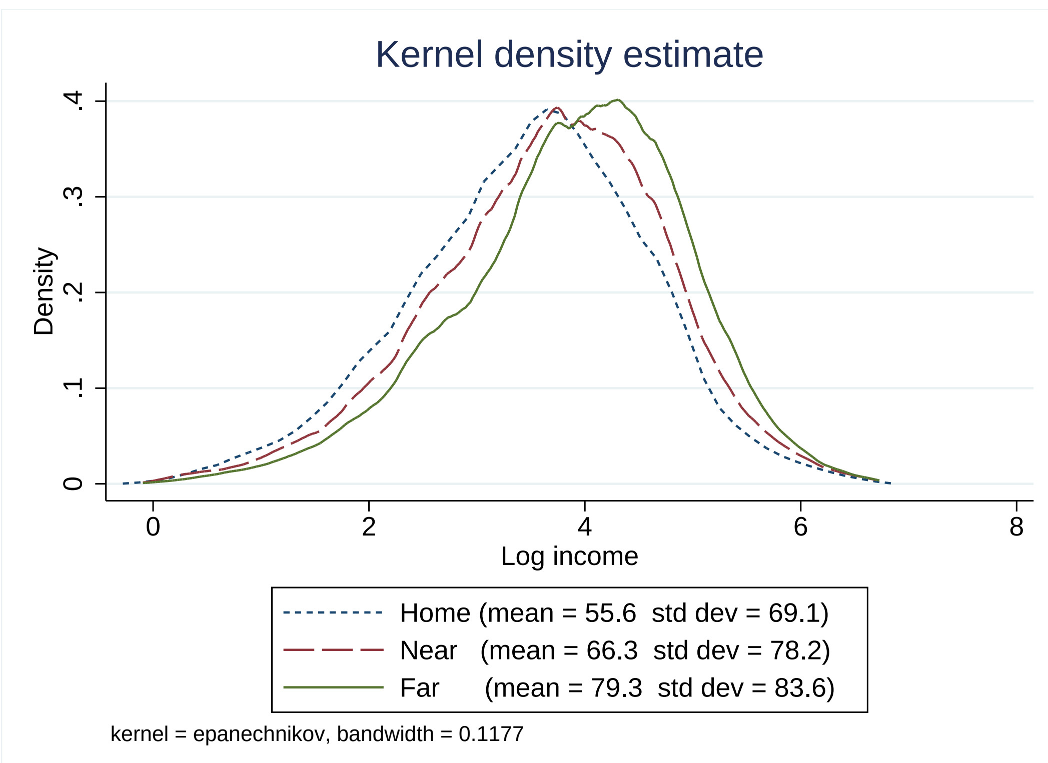

Figure 13: Kernel density wage distribution Home, Near and Far - Movers only

Tables

Table 1: Summary Statistics

Number of Individuals	38914
Number of Individuals-Year Pairs	558425
Migrant Stock (%)	37.74
Percentage of years as migrant	(48.65)
Migrant Flow (%)	4.37
Percentage of years migrating all directions	(20.44)
Duration Median (years away from home)	4.00
Mean	4.30
Standard Deviation	(4.12)
Distance Median (km away from home)	101.3
Mean	199.6
Standard Deviation	(304.4)
Migrating Together (%)	36.06
Of all moves, % with another person	(48.02)
Number of Persons	2.58
Conditional on moving together	(1.76)
Average Wealth	129.37
In 100,000 IDR ≈ 12 USD	(126.75)
Average Annual Income	56.33
In 100,000 IDR ≈ 12 USD	(71.55)

Source: Indonesian Family Life Survey. Means with standard deviations in brackets.

Table 2: Migration Transition Matrix

Percentages		End Location		
		Home	Rural	Urban
Starting Location	Home	62.26	1.25	1.01
	Rural	0.71	17.82	0.23
	Urban	0.55	0.28	15.88
Number of individual-year pairs		End Location		
		Home	Rural	Urban
Starting Location	Home	347675	7003	5623
	Rural	3962	99511	1290
	Urban	3071	1583	88678

Table 3: Wealth Accumulation in Response to Weather Shocks

	Dependent Variable: Individual Wealth			
	(1)	(2)	(3)	(4)
Rainfall at year t	0.642***	0.587***	0.590***	0.533***
	[0.181]	[0.182]	[0.183]	[0.186]
Sum rainfall year t-1 to t-2	1.220***			
	[0.129]			
Sum rainfall year t-1 to t-3		1.010***		
		[0.099]		
Sum rainfall year t-1 to t-4			1.043***	
			[0.086]	
Sum rainfall year t-1 to t-5				0.958***
				[0.075]
Time fixed effects	yes	yes	yes	yes
Individual fixed effects	yes	yes	yes	yes
Observations	99,379	96,416	93,046	89,737
R-squared	0.097	0.099	0.103	0.105
Number of pidlink	36,304	35,712	34,633	33,509

All regressions are clustered at the location level, standard errors in brackets, *** p<0.01, ** p< 0.05, * p<0.1. Rainfall is reported in average meter per month and wealth is reported in 100,000 (2000) Indonesian Rupiah ≈ $ 12 USD.

Table 4: Migration in Response to Weather Shocks

	Dependent Variable: Migrated away from Home Location			
	(1)	(2)	(3)	(4)
Rainfall at year t	-0.150***	-0.142***	-0.129***	-0.107***
	[0.014]	[0.014]	[0.014]	[0.014]
Sum rainfall year t-1 to t-2	0.042***			
	[0.009]			
Sum rainfall year t-1 to t-3		0.034***		
		[0.007]		
Sum rainfall year t-1 to t-4			0.030***	
			[0.006]	
Sum rainfall year t-1 to t-5				0.026***
				[0.005]
Time fixed effects	yes	yes	yes	yes
Individual fixed effects	yes	yes	yes	yes
Observations	354,320	354,320	354,320	354,320
R-squared	0.002	0.002	0.002	0.002
Number of pidlink	35,522	35,522	35,522	35,522

All regressions are clustered at the location level, standard errors in brackets, *** p<0.01, ** p< 0.05, * p<0.1. The dependent variable is a dummy of having migrated away from the individual's rural home location, where he/she lived at age 18; rainfall is reported in average meter per month (in Indonesia, average monthly rainfall equals 150 mm).

Table 5: Migration Strategies by Duration

	Dependent variable: Migrated away from Home Location	
	0 - 4 years	**> 4 years**
	(1)	(2)
Rainfall at year t	-0.096***	-0.046***
	[0.011]	[0.009]
Rainfall at year t-1 to t-3	0.003	0.031***
	[0.005]	[0.005]
Time fixed effects	yes	yes
Individual fixed effects	yes	yes
Observations	354,320	354,320
R-squared	0.003	0.003
Number of pidlink	35,522	35,522

All regressions are clustered at the location level, standard errors in brackets, *** p<0.01, ** p< 0.05, * p<0.1. The dependent variable is a dummy of having migrated away from the individual's rural home location, where he/she lived at age 18; rainfall is reported in average meter per month (in Indonesia, average monthly rainfall equals 150 mm).

Table 6: Migration Strategies by Destination

	Rural Destination	Urban Destination
Dependent Variable: Migrated away from Home Location		
	(1)	(2)
Rainfall at year t	-0.081***	-0.061***
	[0.009]	[0.011]
Rainfall at year t-1 to t-3	-0.002	0.036***
	[0.005]	[0.005]
Time fixed effects	yes	yes
Individual fixed effects	yes	yes
Observations	354,320	354,320
R-squared	0.001	0.002
Number of pidlink	35,522	35,522

All regressions are clustered at the location level, standard errors in brackets, *** p<0.01, ** p< 0.05, * p<0.1. The dependent variable is a dummy of having migrated away from the individual's rural home location, where he/she lived at age 18; rainfall is reported in average meter per month (in Indonesia, average monthly rainfall equals 150 mm).

Table 7: Migration Strategies by Distance

	0 - 100 km	> 100 km
Dependent variable: Migrated away from Home Location		
	(1)	(2)
Rainfall at year t	-0.037***	-0.106***
	[0.009]	[0.011]
Rainfall at year t-1 to t-3	-0.002	0.036***
	[0.005]	[0.005]
Time fixed effects	yes	yes
Individual fixed effects	yes	yes
Observations	354,320	354,320
R-squared	0.001	0.002
Number of pidlink	35,522	35,522

All regressions are clustered at the location level, standard errors in brackets, *** p<0.01, ** p< 0.05, * p<0.1. The dependent variable is a dummy of having migrated away from the individual's rural home location, where he/she lived at age 18; rainfall is reported in average meter per month (in Indonesia, average monthly rainfall equals 150 mm).

Table 8: Migration Strategies by Initial Wealth

Dependent variable: Migrated away from Home Location	
	(1)
Rainfall t * Intial Wealth 0-33%	-0.141***
	[0.036]
Rainfall t * Intial Wealth 34-66%	-0.122***
	[0.033]
Rainfall t * Intial Wealth 67-100%	-0.052*
	[0.035]
Rainfall (t-1 to t-3) * Intial Wealth 0-33%	0.050***
	[0.021]
Rainfall (t-1 to t-3) * Intial Wealth 34-66%	0.071***
	[0.020]
Rainfall (t-1 to t-3) * Intial Wealth 67-100%	0.045**
	[0.020]
Initial Wealth 34-66%	-0.000
	[0.012]
Initial Wealth 67-100%	-0.000
	[0.013]
Time fixed effects	yes
Individual fixed effects	yes
Observations	87,227
R-squared	0.005
Number of pidlink	34,537

All regressions are clustered at the location level, standard errors in brackets, *** p¡0.01, ** p¡ 0.05, * p¡0.1. The dependent variable is a dummy of having migrated away from the individual's rural home location, where he/she lived at age 18; rainfall is reported in average meter per month (in Indonesia, average montly rainfall equals 150 mm); initial wealth is based on the first wealth measurement of the individual and only years after this measurement are included.

Table 9: Wage Model

	Dependent Variable: Income					
	All	**Home**	**Rural**	**Urban**	**Near**	**Far**
	(1)	(2)	(3)	(4)	(5)	(6)
Education Level	16.50***	13.89***	16.32***	22.41***	17.69***	19.78***
	[0.57]	[0.60]	[0.937]	[1.560]	[1.08]	[1.68]
Male	18.95***	18.32***	17.62***	24.04***	20.39***	21.64***
	[0.81]	[0.96]	[1.792]	[2.324]	[1.83]	[2.46]
Age	4.21***	3.55***	3.95***	6.24***	4.58***	5.58***
	[0.18]	[0.19]	[0.374]	[0.429]	[0.40]	[0.48]
Age squared	-0.04***	-0.04***	-0.04***	-0.06***	-0.05***	-0.06***
	[0.002]	[0.002]	[0.005]	[0.005]	[0.005]	[0.006]
Rainfall at year t	1.97***	2.43***	0.65	0.08	1.27	0.63
	[0.43]	[0.50]	[0.84]	[1.15]	[0.81]	[1.10]
Rainfall at year t-1	1.67***	1.56***	1.30	1.26	1.59*	1.41
	[0.43]	[0.45]	[0.93]	[1.01]	[0.83]	[1.03]
Rainfall at year t-2	1.18***	1.58***	-0.84	0.60	0.31	0.39
	[0.45]	[0.48]	[1.01]	[1.05]	[0.89]	[0.98]
Rainfall at year t-3	0.51	0.81**	-2.08**	1.81	-0.86	1.35
	[0.39]	[0.36]	[1.05]	[1.17]	[0.84]	[1.45]
Rainfall at year t-4	0.72	0.79*	-0.85	0.80	0.78	-1.11
	[0.44]	[0.46]	[0.81]	[1.43]	[0.78]	[1.36]
Mean dependent variable	56.33	48.67	59.69	87.67	65.92	78.41
	(71.55)	(64.24)	(72.52)	(82.23)	(77.84)	(83.21)
Time fixed effects	yes	yes	yes	yes	yes	yes
Location fixed effects	yes	yes	yes	yes	yes	yes
Observations	154,179	94,499	35,129	24,551	34,826	23,208
R-squared	0.121	0.104	0.109	0.173	0.123	0.143
Number of locations	2,177	1,189	1,421	556	1,484	1,219

All regressions are clustered at the kecamatan level, standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1. Income is reported in 100,000 (2000) Indonesian Rupiah ≈ $ 12 USD. 'Home' is the person's location at age 18; 'Rural' refers to rural destinations; 'Urban' refers to urban destinations; 'Near' refers to destinations within 100 km from 'Home'; 'Far refers to destinations farther than 100 km from 'Home'.

Table 10: Model Fit

Observed Data		End Location		
		Home	Rural	Urban
Starting Location	Home	62.26	1.25	1.01
	Rural	0.71	17.82	0.23
	Urban	0.55	0.28	15.88
Model Predicton		End Location		
		Home	Rural	Urban
Starting Location	Home	62.28	1.22	1.03
	Rural	1.36	17.42	0.18
	Urban	0.39	0.00	16.11

Table 11: Mixed Logit Estimation of Migration Costs by Wealth Quartile

		Wealth Quartile			
	All	**0-25%**	**25-50%**	**50-75%**	**75-100%**
	(1)	(2)	(3)	(4)	(5)
Migration cost Rural	11.09	16.87	12.61	12.99	13.22
	(0.34)	(0.41)	(0.52)	(0.51)	(0.58)
Migration cost Urban	72.32	95.95	71.61	56.06	60.24
	(1.26)	(1.64)	(2.07)	(2.03)	(2.34)
Disutility away from home	7.53	7.14	9.06	10.21	11.62
(Consumption Equivalent)	(0.48)	(0.63)	(0.68)	(0.60)	(0.80)
Number of observations	100643	23122	23101	23095	23140
Migration cost Near	15.86	17.21	16.65	10.32	14.68
	(0.29)	(0.63)	(0.67)	(0.60)	(0.64)
Migration cost Far	69.82	92.39	70.84	54.81	59.15
	(1.12)	(1.83)	(2.27)	(2.18)	(2.53)
Disutility away from home	8.74	6.17	9.20	9.33	11.25
(Consumption Equivalent)	(0.49)	(0.60)	(0.79)	(0.63)	(0.86)
Number of observations	99589	22880	22955	22946	23001

Average wealth is 129 (std dev: 127) and average annual income is 56 (std dev: 72). All values are reported in 100,000 (2000) Indonesian Rupiah $\approx$ \$ 12 USD. Standard errors in brackets are not corrected for predicted wages. 'Rural' refers to rural destinations; 'Urban' refers to urban destinations; 'Near' refers to destinations within 100 km from the individual's home location at age 18; 'Far' refers to destinations farther than 100 km from the individual's home location at age 18. All parameters are estimated using mixed logit, which includes estimating standard deviations of all parameter values and of the classical measurement error on wealth. The following parameter values are set exogenously $\beta = .0.95$ $r = 0.03$ $\rho = 2$

Table 12: Mixed Logit Estimation of Migration Costs by Education Level and Age

		Education level		Age		
	All	**Low**	**High**	**25-**	**25-50**	**50+**
	(1)	(2)	(3)	(4)	(5)	(6)
Migration cost Rural	11.09	16.58	13.76	6.44	12.07	20.51
	(0.34)	(0.80)	(0.53)	(0.67)	(0.56)	(0.75)
Migration cost Urban	72.32	127.33	62.06	20.43	73.34	120.27
	(1.26)	(1.12)	(0.58)	(0.92)	(0.95)	(1.18)
Disutility away from home	7.53	6.80	10.52	11.13	9.44	7.70
(Consumption Equivalent)	(0.48)	(0.60)	(0.80)	(0.67)	(0.62)	(0.87)
Number of observations	100643	47585	44779	26737	46231	19425
Migration cost Near	15.86	21.16	13.83	7.40	14.19	23.61
	(0.29)	(0.69)	(0.48)	(0.63)	(0.46)	(0.67)
Migration cost Far	69.82	92.63	63.53	17.13	73.42	116.59
	(1.12)	(1.08)	(0.59)	(0.97)	(0.96)	(2.34)
Disutility away from home	8.74	8.82	11.05	12.17	8.89	7.05
(Consumption Equivalent)	(0.49)	(0.79)	(0.96)	(0.62)	(0.59)	(0.70)
Number of observations	99589	46985	44444	26539	45717	19197

Average wealth is 129 (std dev: 127) and average annual income is 56 (std dev: 72). All values are reported in 100,000 (2000) Indonesian Rupiah ≈ \$ 12 USD. Standard errors in brackets are not corrected for predicted wages. 'Rural' refers to rural destinations; 'Urban' refers to urban destinations; 'Near' refers to destinations within 100 km from the individual's home location at age 18; 'Far' refers to destinations farther than 100 km from the individual's home location at age 18. All parameters are estimated using mixed logit, which includes estimating standard deviations of all parameter values and of the classical measurement error on wealth. The following parameter values are set exogenously $\beta = .0.95$ $r = 0.03$ $\rho = 2$

Table 13: Mixed Logit Estimation of Migration Costs by Gender and Marital Status

	All	**Male**	**Female**	**Married**	**Single**	**Married Male**	**Married Female**	**Single Male**	**Single Female**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Migration cost Rural	11.09	16.67	10.65	23.86	7.45	48.94	30.85	13.61	6.05
	(0.34)	(0.46)	(0.72)	(0.66)	(0.69)	(0.83)	(0.74)	(0.93)	(0.65)
Migration cost Urban	72.32	97.78	43.82	114.82	34.07	133.04	115.22	48.45	24.44
	(1.26)	(1.02)	(0.99)	(1.72)	(0.86)	(2.46)	(1.62)	(1.92)	(1.44)
Disutility away from home	7.53	12.46	5.33	8.32	10.00	10.70	-3.25	12.03	12.83
(Consumption Equivalent)	(0.48)	(0.88)	(0.98)	(0.62)	(0.77)	(0.71)	(0.91)	(0.60)	(0.88)
Number of observations	100643	44158	48244	33902	22875	16487	17393	12874	10034
Migration cost Near	15.86	20.44	11.55	24.77	6.95	28.94	19.23	12.65	5.34
	(0.29)	(0.45)	(0.63)	(0.76)	(0.95)	(0.73)	(0.85)	(0.93)	(0.86)
Migration cost Far	69.82	94.69	45.76	110.90	36.87	123.50	79.20	54.68	32.82
	(1.12)	(0.97)	(0.76)	(1.42)	(0.86)	(2.26)	(1.68)	(1.77)	(0.99)
Disutility away from home	8.74	11.71	2.65	5.06	10.77	9.79	-6.35	10.97	11.21
(Consumption Equivalent)	(0.49)	(0.90)	(0.42)	(0.88)	(0.69)	(0.94)	(0.96)	(0.84)	(0.86)
Number of observations	99589	43694	47770	33595	22698	16333	17240	12776	9955

Average wealth is 129 (std dev: 127) and average annual income is 56 (std dev: 72). All values are reported in 100,000 (2000) Indonesian Rupiah $\approx$ \$ 12 USD. Standard errors in brackets are not corrected for predicted wages. 'Rural' refers to rural destinations; 'Urban' refers to urban destinations; 'Near' refers to destinations within 100 km from the individual's home location at age 18; 'Far' refers to destinations farther than 100 km from the individual's home location at age 18. All parameters are estimated using mixed logit, which includes estimating standard deviations of all parameter values and of the classical measurement error on wealth. The following parameter values are set exogenously $\beta = .95$ $r = 0.03$ $\rho = 2$

Table 14: Mixed Logit Estimation of Migration Costs by Migration Experience

		Migration Experience				
	All	**None**	**Some**	**Only Rural**	**Only Urban**	**Rural and Urban**
	(1)	(2)	(3)	(4)	(5)	(6)
Migration cost Rural	11.09	15.05	13.39	10.66	24.92	10.73
	(0.34)	(0.84)	(0.70)	(0.74)	(0.87)	(0.95)
Migration cost Urban	72.32	65.47	84.85	109.77	35.57	82.23
	(1.26)	(0.97)	(1.66)	(2.04)	(1.33)	(2.35)
Number of observations	100643	48293	41356	21138	11466	4505
		Migration Experience				
	All	**None**	**Some**	**Only Near**	**Only Far**	**Near and Far**
Migration cost Near	15.86	16.34	14.39	11.59	28.50	11.77
	(0.29)	(0.43)	(0.57)	(0.52)	(0.64)	(0.68)
Migration cost Far	69.82	60.79	89.60	106.05	37.95	87.64
	(1.12)	(1.73)	(2.26)	(2.08)	(2.55)	(2.71)
Number of observations	99589	48293	40450	21138	11466	4505

Average wealth is 129 (std dev: 127) and average annual income is 56 (std dev: 72). All values are reported in 100,000 (2000) Indonesian Rupiah $\approx$ \$ 12 USD. Standard errors in brackets are not corrected for predicted wages. 'Rural' refers to rural destinations; 'Urban' refers to urban destinations; 'Near' refers to destinations within 100 km from the individual's home location at age 18; 'Far' refers to destinations farther than 100 km from the individual's home location at age 18. All parameters are estimated using mixed logit, which includes estimating standard deviations of all parameter values and of the classical measurement error on wealth. The following parameter values are set exogenously $\beta = .0.95$ $r = 0.03$ $\rho = 2$

Table 15: Structural Estimation of Migration Costs by Migrant Network

		Know somebody at destination	
	All	**Yes**	**No**
	(1)	(2)	(3)
Migration cost Rural	11.09	8.50	12.73
	(0.34)	(2.84)	(5.07)
Migration cost Urban	72.32	57.25	72.51
	(1.26)	(9.25)	(8.47)
Number of Observations	100643	2282	9271
		Know somebody at destination	
	All	**Yes**	**No**
Migration cost Rural	15.86	6.84	17.88
	(0.29)	(2.21)	(4.62)
Migration cost Urban	69.82	68.71	74.12
	(1.12)	(9.82)	(6.25)
Number of Observations	99589	2269	9245

Average wealth is 129 (std dev: 127) and average annual income is 56 (std dev: 72). All values are reported in 100,000 (2000) Indonesian Rupiah $\approx$ \$ 12 USD. Standard errors in brackets are not corrected for predicted wages. 'Rural' refers to rural destinations; 'Urban' refers to urban destinations; 'Near' refers to destinations within 100 km from the individual's home location at age 18; 'Far' refers to destinations farther than 100 km from the individual's home location at age 18. All parameters are estimated using mixed logit, which includes estimating standard deviations of all parameter values and of the classical measurement error on wealth. The following parameter values are set exogenously $\beta = .0.95$ $r = 0.03$ $\rho = 2$

Table 16: Structural Estimation Benefits of Migrating

Change in Individual's Annual Consumption

1 year after migrating		5 years after migrating	
Moving Rural	Moving Urban	Moving Rural	Moving Urban
2.04%	3.62%	5.82%	30.71%

Change in Individual's Annual Wage

1 year after migrating		5 years after migrating	
Moving Rural	Moving Urban	Moving Rural	Moving Urban
8.36%	38.44%	3.36%	43.35%

Consumption changes are predicted by the model and compare consumption levels of those who moved to predicted consumption if the individual had not moved. Wage changes compare the actual wage the person received as observed in the data, to the predicted wage if the person had not moved. All numbers refer to annual averages and predicted changes after five years of moving are unconditional on whether the person is still at the destination.

Table 17: Counterfactual Experiments

	Predicted migration rates (%)		Predicted change average consumption	
	Home to Rural	**Home to Urban**	**1 year**	**5 year**
No Policy Status quo migration rates	1.25	1.01		
Providing credit at 5% interest rate Negative wealth at annual interest rate of 5%	0.87	1.61	6.86%	10.38%
Providing credit at 10% interest rate Negative wealth at annual interest rate of 10%	1.14	1.18	2.91%	4.36%
Credit at 5% conditional on migrating Negative wealth at annual interest rate of 5%	1.13	1.51	4.64%	7.93%
Credit at 10% conditional on migrating Negative wealth at annual interest rate of 10%	1.24	1.15	1.36%	2.49%
Migration 10% more costly 10% increase migration costs to Near and Far	1.20	0.62	1.41%	-6.30%
Migration 10% less costly 10% decrease migration costs to Near and Far	1.35	1.66	-0.73%	12.70%
Estimate Bryan et al (2014) $8.50 USD incentive conditional on migrating	1.31	1.05	-0.01%	0.45%
Restrict migration (Hukou) Migration to Far not allowed	1.46	0.00	1.20%	-21.30%
Increase Shock Intensity 5% increase standard deviation of shocks	1.37 (+ 0.12)	0.89 (- 0.12)	0.21%	-3.19%
Change amongst the poorest 50%	+ 0.23	- 0.21	-0.22%	-6.73%
Increase Shock Intensity 10% increase standard deviation of shocks	1.74 (+ 0.49)	0.74 (- 0.26)	-0.52%	-8.63%
Change amongst the poorest 50%	+ 0.93	- 0.38	-1.49%	-15.43%

Computational Appendix

Numerical Solution Dynamic Migration Choice Model

Infinite time horizon model

The dynamic choice model presented in Section 2 is solved numerically using value function iteration using the following algorithm:

1. Initialize a guess $V_0(A, l)$ for the value function using cubic spline interpolation over a grid of points in continuous A-space, where $A = x + w$ represents total cash on hand, x is an individual's wealth at the beginning of a period and w is the wage draw under consideration. The l-space is a set of discrete locations

2. Begin the iteration loop for $i = 1, 2, max_{iter}$, setting $V_{old} = V_0$ at the outset

   (a) For each combination of state variable values, (A_j, l_k), where A_j is a grid point in discretized A-space and l_k represents location k, calculate the value function $V_{new}(A_j, l_k)$ following equation 4

   (b) Update $V_{old} = V_{new}$

   (c) Repeat steps a and b until $max(V_{old} V_{new}) < tolerance\ level$

   (d) Once converged, save the value of the control variables (c, l') that maximizes the value function $V(A_j, l_k)$

   (e) Repeat steps b - d for all combinations of state variable values, (A_j, l_k). Update the resulting spline interpolation for the function $V(A, l)$

3. In order to derive general predictions of the model, simulate the choices an agent would make given a certain starting value of the state variables, (A, l)

   (a) In each period, the agent receives a random wage draw from his/her current location

   (b) Retrieve each location's value function from the model solution described in step 1

      i. Compute the value of staying at location l and accepting wage draw w_l by evaluating $v_l = V(x + w_l, l)$

ii. Retrieve the value of moving to each of the other locations based on expected wages at those locations (as the draw draws are still unknown to the agent), that is, $v_{l'} = \int V(x + w_{l'} - m(l, l^{'}), l^{'})dF(w_{l'})$ for $l^{'} \neq l$

iii. Make migration choice by choosing $max(v_1, v_2, , v_{nLoc})$

(c) After the migration choice, choose the consumption choice calculated in the model solution described in step 1. If the choice was to stay, then $A = x + w_l$ using the wage draw offered at the beginning of the period. If the choice was to move, then $A = x + w_{l'}$, where $w_{l'}$ is new wage value drawn at random from the wage distribution at the new location $l^{'}$

(d) Update the values of the state variables to $(x^{'}, l^{'})$ according to equation 2

(e) Repeat steps a - d for all time periods

(f) Repeat steps a - e for 10,000 agents

4. In order to derive comparative statics, repeat step 3 for different starting values of the state variables, (A, l), and various model parameters

Finite time horizon model

For the case of a finite time horizon, the model is solved numerically using a backwards induction procedure. The finite time version of the Bellman equation is

$$V_t(x, l) = \max_{c,l^{'}} \left\{ U_t(c, l^{'}) + \beta \int V_{t+1}(x^{'}, l^{'})dF(w_{l'}) \right\} \tag{12}$$

It is assumed that the ending condition for a time horizon consisting of T periods is $V_T(A, l) = 0$. The backwards induction procedure utilizes this fact and is performed as follows:

1. Initialize $V_T(A, l) = 0$

2. For each $t = T - 1, T - 2, ..., 0,$

   (a) For each combination of state variable values, (A_j, l_k), where A_j is a grid point in discretized A-space and l_k represents location k, calculate the value function $V_t(A_j, l_k)$ according to equation 13, using the known value of the function $V_{t+1}(A_j, l_k)$.

(b) Using the solution at each grid point, create a spline interpolation for $V_t(A, l)$ as well as for the associated optimal consumption decision (optimal migration decision is assumed to be chosen from a discrete set).

Structural Estimation using Nested Fixed Point Algorithm

I employ a two-loop nested fixed point algorithm for the structural estimation consisting of the following steps:

1. To initiate the outer loop, define a starting vector of model parameter values θ to be structurally estimated

2. In the inner loop, solve the infinite time-horizon model numerically in discrete time for the given set of model parameters θ using value function iteration as described above

3. Given the solution to the infinite time-horizon model, simulate the model solution for each individual-year pair observed in the data.

   (a) For each individual-year pair obtain the values of the state variables, (x, l), and the income shock, w_l, from the data

   (b) From the model solution described in step 2, obtain the values of the control variables $(c, l^{'})$, as predicted by the model

   (c) In the log likelihood function compare the predicted values of $(c, l^{'})$ to those observed in the data

   (d) Accumulate sum of terms in log likelihood function according to equation 10

   (e) Repeat steps a to c for all individual-year pairs in the data

4. In the outer loop, the vector of parameter values θ is varied and the inner loop is repeated to solve the model and simulate the data

5. Using extreme value assumptions on error between observed and predicted control variables, accounting for by the unobserved state variables ϵ, find θ that maximizes the log likelihood function