Migration Choice under Risk and Liquidity Constraints

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Abstract

There are many reasons why people migrate, and different motivations may lead to different types of migration. I study the choice to migrate within a developing country, where people may face substantial 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. I model these diverging migratory responses to shocks in a dynamic migration choice model that I test using a 28-year panel of internal migration decisions by more than 45,000 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, migration after negative shocks is more often characterized by temporary moves to nearby, rural destinations, while migration as an investment strategy is more likely to involve urban destinations and take place over longer durations and distances.

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1 Introduction

There are many reasons why people migrate, and different motivations may lead to different types of migration. Yet, most classical migration models tend to treat the choice to migrate as a one-time decision to relocate to the optimal destination. Actual migration patterns, however, are diverse and for example include substantial temporary migration, circular migration and rural-rural migration; patterns that cannot be fully understood in traditional frameworks.

In this paper, I study the choice to migrate within a developing country, where people may face substantial risk and liquidity constraints. In this context, two primary rationales are often highlighted 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 to another location to earn additional income and make ends meet. 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.

On the other hand, 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 'ex-post risk-coping 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 ex-post risk-coping rationale of migration is described for example in Kleemans and Magruder (2018) and Morten (2019), who find that sudden negative rainfall shocks induce people to migrate internally.[1] Evidence of the investment strategy is documented by Bryan, Chowdhury and Mobarak (2014) and by Bazzi (2017), 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 Bazzi (2017) on the one hand and Kleemans and Magruder (2018) 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 (2018) focus on internal, short-distance migration, while Bazzi (2017) studies international migration that requires large up-front migration costs, making liquidity constraints more likely to be binding.

This paper aims to provide a unified framework of migration choice that incorporates both ex-post risk-coping and investment rationales for migration. I develop a migration choice model that encompasses both migration strategies and that allows for multiple moves over time and between multiple locations. 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.

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

[1] Other papers that empirically observe increased migration after negative income shocks include Mueller, Gray and Kosec (2014), De Weerdt and Hirvonen (2016) and Boustan, Fishback and Kantor (2010).

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 ex-post risk-coping 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 (henceforth "IFLS"), all migration moves of 45,946 individuals were recorded over a 28-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 ex-post risk-coping 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.

This paper aims to advance 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

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

why these migration patterns are not observed more frequently (e.g. Banerjee and Duflo (2007) and Munshi and Rosenzweig (2005)).

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

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

[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).

studying how individual migration choices respond to weather shocks.

This paper is structured as follows: First, I will present the dynamic migration choice model in Section 2. The data and empirical strategy are introduced in Section 3. Section 4 describes the results and Section 5 concludes.

2 Dynamic Migration Choice Model

This section develops a model incorporating both the ex-post risk-coping and investment rationales for migration. This approach improves on previous models by allowing for multiple migration choices over 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 (1991)'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.

In order to gain insights in seasonal migration patterns, Bryan et al. (2014) develop 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. As is common in migration choice models, they focus on the binary choice of whether to engage in seasonal migration. In order to incorporate different migration strategies, I also include the choice of which location to migrate to. I do so by extending Deaton (1991)'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 16. After presenting this general set-up, I will introduce a three-location model upon which the main predictions are based.

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, I do not include intra-household transfers and remittances in the model. This is a partial equilibrium model and assumes that wages are exogenous to the individual decision maker. 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:

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

Similar to Deaton (1991) and Bryan et al. (2014), I choose an isoelastic utility function 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 the finding by Lagakos, Mobarak and Waugh (2018) that most individuals prefer to be at home.

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

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

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. Therefore, I will now turn to a simplified three-location model that is sufficient to provide the main predictions and intuition underlying the ex-post risk-coping and investment migration strategies.

2.1 Three Location Model

First, I define a '*Home*' location as the location where a person resides at age 16. 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).[4] The model solution is shown in the form of three model realizations in Figures 1, 2 and 3. The 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 A1. While

[4]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 28 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 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 the sum of wealth and wage as '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, the initial wage draw and wage received are different.

Figure 1 shows that wages follow a stochastic process over time and that cash-on-hand acts as a buffer to smooth consumption as predicted by Deaton (1991). 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 bottom panel, the person moves from $Home$ to $Urban$ in period 14, where wages are higher, as shown earlier in Figure A1. 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. During periods 10 and 11, the person decides to stay for two periods because of the high wage draw in the $Rural$ area in period 11. 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, ex-post risk-coping 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, ex-post risk-coping 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. Data was collected from the same households and individuals in five waves: 1993, 1997/1998, 2000, 2007/2008 and 2014/2015. When it was first fielded in 1993, this longitudinal survey was representative of about 83 percent of the Indonesian population living in 13 of the then 26 provinces (Strauss, Beegle, Sikoki, Dwiyanto, Herawati and Witoelar, 2004). 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 conducted in 2014 and 2015, the recontact rate of original households interviewed in 1993 was 92 percent (Strauss, Witoelar and Sikoki, 2016). The analyses are based on all five waves of the IFLS, from which I construct a 28-year panel from 1988 to 2015 of 45,946 individuals with annual information on migration and labor market outcomes. This section gives a brief introduction of the data; please refer to the data appendix for further details.

3.1 Individual panel dataset

The migration modules of the IFLS collect individual-level data of all migration a person undertook from age 12 onwards. All moves that cross a village boundary are included, so the data includes short-distance moves.[5] Only moves that lasted at least 6 months are included, so most seasonal migration patterns such as those studied by Bryan et al. (2014) at excluded. In addition to migration data based on recall between the five survey waves, the dataset contains information on where respondents were born and where they lived at age 12. I use a person's location at age 12 as their $Home$ location. This information is transformed into a panel dataset that reports the person's

[5]Throughout the analyses, I use a minimum distance of 20 km to identify migrations. Robustness checks show that the results are not sensitive to the value of the distance cutoff and to having no distance cutoff.

location in each year from 1988 to 2015. Children may move with their parents for reasons not included in the model, so for the main analyses I study people older than 16 years old.[6] Employment information is available starting 1988, so I start the panel in 1988 even though all moves after age 12 are recorded, including those before 1988. This results in a panel dataset of individual location decisions of 45,946 individuals age 16 and above during the period 1988 – 2015, with a total of 741,227 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 12. There are 3,317 distinct kecamatan observed in the data, each having corresponding latitude and longitude coordinates, making it possible to calculate all distances travelled between kecamatan.

Figure 4 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, 18,649 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 occurs over short distances and within islands. Figure 5 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 28 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

[6]Women migrate for marriage more often than men do, so I repeat the analysis for men only as a robustness check.

the prosperous areas in Java and Bali, where more than 90 percent of individuals migrated within the island group. Figures 6 and 7 show that 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 28 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 3.08 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 12, defined as $Home$. The median move lasted 4 years and took place over a distance of 90 km. The mean duration and distance are considerably larger indicating a large right tail with longer duration and distance moves. In 38 percent of moves, individuals migrate together with others and if they do, they migrate on average in a group of 2.47 persons.

In addition to detailed information on migration, data are available on individual and household characteristics and labor market outcomes. Similar to the the annual migration panel, I construct an annual panel of individual income and employment 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 Hagenaars, De Vos and Asghar Zaidi (1994), the adult equivalent of assets is used to create the individual-level wealth variable. Asset data is only collected during the survey years. 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 8 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, I follow the literature by using an indicator for drought as the main weather variable.[7] Various papers have shown that in Indonesia drought reduces agricultural productivity, income, and wealth, as many farmers continue to rely on rain-fed agriculture (Kishore, Subbiah, Sribimawati, Diharto, Alimoeso, Rogers and Setiana (2000) and Levine and Yang (2014). Drought is defined as precipitation at least one standard deviation below the location's mean. 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 an indicator for drought, this study carries out robustness checks with various other weather variables, including precipitation levels and z-scores, as well as precipitation squared to allow for nonlinear effects.

4 Results

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

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

$migrate_{it}$ is a dummy variable for whether person i migrates in year t. $drought_{iT}$ is an indicator for a drought occurring at the location of individual i at time T, meaning that precipitation was less than one standard deviation below the mean. T can take various values: in case of contemporaneous shocks, drought at time t, $drought_{it}$, is used, while previous shocks are accumulated over preceding

[7] For example see Corno, Hildebrandt and Voena (2020). 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.

time periods, for instance from time period $t-1$ until $t-3$: $drought_{i(t-1,t-3)}$. 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 A1). 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 3. 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 the previous 2 years in column 1 to the previous 5 years in column 4. The opposing effects are highly significant whether analyzed in the same regression as in Table 3 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 4 is split between moves that lasted less than the median duration of four years, and those that lasted longer. Duration is recorded in the year of migration, when subsequent employment outcomes and shocks were unknown, but may later be affected by those outcomes. This table shows that negative contemporaneous shocks encourage migration of all durations, but that those who move in response to an accumulation of previous positive shocks (meaning fewer droughts), tend to stay longer. 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 64.31 percent of the individual-year pairs, a person lives at his or her *Home* location and decides to stay there; in 0.55 percent of individual-year pairs, a person migrates from the *Home* location to a *Rural* location and, in 1.05 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 12.35 percent of individual-year pairs and at an *Urban* destination in 20.55 percent of individual-year pairs. While uncommon, the diagonal also includes moves between *Rural* destinations or between *Urban* destinations. Summing up all off-diagonal matrix entries gives a migration flow of 2.78 percent. The total migration flow as reported in Table 1 is 3.08 percent, so the remaining 0.3 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 that sum up to 741,227.

Table 5 compares the migratory response to weather shocks when migrating to a rural (column 1) versus an urban (column 2) destination. The model predicts that ex-post risk-coping induces individuals to migrate to rural locations and investment migration is more likely to have an urban destination. This table provides evidence supporting these predictions. Migration after a negative shock encourages individuals to leave *Home* to both types of destinations and especially to *Rural* destination. The second row confirms that accumulation of wealth through preceding positive shocks dominates for urban destinations, to which migration costs are higher.

Table 6 tests the model prediction on migration distance comparing migratory responses to weather shocks when migrating less than 100 km (column 1) versus more than 100 km (column 2). As predicted by the model, ex-post risk-coping migration is expected to lead to short-distance moves, while individuals may need to save up to invest in farther-distance, more costly migration. The results are qualitatively in line with these predictions, but the coefficients in columns 1 and 2 are not statistically different from each other. One potential explanation for the lack of precision is that distance itself is an endogenous choice and can be a function of weather. 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. This would bias results in the opposite direction compared to the predictions made by the model.

5 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 due to drought. 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 ex-post risk-coping 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 (1991)'s 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. It is complementary to the model by Kennan and Walker (2011) that has no borrowing constraint and is applied to a cohort of educated men in the United States. The model in this paper is an alternative model of migration choice applicable to developing country contexts in which risk and liquidity constraints profoundly limit migration and destination choices.

The model is tested using rich data on more than 45,000 individuals in Indonesia, for whom all migration choices were recorded over a 28-year period. I confirm that the two diverging migratory responses to income shocks, which have been studied as separate phenomena, can be observed in the same dataset. Migration increases both after a sudden occurrence of drought as a way to cope with the negative income shock, as well as after the absence of drought in preceding years, allowing individuals to save up for more costly migration. In agreement with the model's predictions, I find that ex-post risk-coping migration is more often characterized by temporary moves to rural destinations and is used by those with low levels of wealth. Migration as an investment strategy is more likely to involve urban destinations, occur over longer distances, and be longer in duration.

References

Abramitzky, Ran, Leah Platt Boustan, and Katherine Eriksson (2013) "Have the poor always been less likely to migrate? Evidence from inheritance practices during the age of mass migration," *Journal of Development Economics*, 102, 2–14.

Adda, Jérôme, Christian Dustmann, and Joseph-Simon Görlach (2022) "The Dynamics of Return Migration, Human Capital Accumulation, and Wage Assimilation," *The Review of Economic Studies*, rdac003.

Akram, Agha Ali, Shyamal Chowdhury, and Ahmed M. Mobarak (2017) "Effects of Emigration on Rural Labor Markets," Working Paper 23929, National Bureau of Economic Research.

Angelucci, Manuela (2015) "Migration and financial constraints: Evidence from Mexico," *Review of Economics and Statistics*, 97 (1), 224–228.

Banerjee, Abhijit V. and Esther Duflo (2007) "The Economic Lives of the Poor," *Journal of economic perspectives*, 21 (1), 141–168.

Bazzi, Samuel (2017) "Wealth Heterogeneity and the Income Elasticity of Migration," *American Economic Journal: Applied Economics*, 9 (2), 219–55.

Bazzi, Samuel, Arya Gaduh, Alexander D. Rothenberg, and Maisy Wong (2016) "Skill transferability, migration, and development: Evidence from population resettlement in Indonesia," *American Economic Review*, 106 (9), 2658–98.

Beegle, Kathleen, Joachim De Weerdt, and Stefan Dercon (2011) "Migration and Economic Mobility in Tanzania: Evidence from a Tracking Survey," *Review of Economics and Statistics*, 93 (3), 1010–1033.

Bell, Martin, Elin Charles-Edwards, Aude Bernard, and Philipp Ueffing (2017) "Global trends in internal migration," in *Internal Migration in the Developed World*, 76–97: Routledge.

Bertoli, Simone, J. Fernández-Huertas Moraga, and Francesc Ortega (2013) "Crossing the border: Self-selection, earnings and individual migration decisions," *Journal of Development Economics*, 101, 75–91.

Bilal, Adrien and Esteban Rossi-Hansberg (2021) "Location as an Asset," *Econometrica*, 89 (5), 2459–2495.

Bohra-Mishra, Pratikshya, Michael Oppenheimer, and Solomon M. Hsiang (2014) "Nonlinear permanent migration response to climatic variations but minimal response to disasters," *Proceedings of the National Academy of Sciences*, 111 (27), 9780–9785.

Borjas, George (1990) "Self-Selection and the Earnings of Immigrants: Reply," *American Economic Review*, 80 (1), 305–08.

Boustan, Leah Platt, Price V. Fishback, and Shawn Kantor (2010) "The Effect of Internal Migration on Local Labor Markets: American Cities during the Great Depression," *Journal of Labor Economics*, 28 (4), 719–746.

Boustan, Leah Platt, Matthew E. Kahn, and Paul W. Rhode (2012) "Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century," *American Economic Review*, 102 (3), 238–44.

Bryan, Gharad, Shyamal Chowdhury, and Ahmed M. Mobarak (2014) "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica*, 82 (5), 1671–1748.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller (2008) "Bootstrap-based improvements for inference with clustered errors," *The review of economics and statistics*, 90 (3), 414–427.

Carrington, William J., Enrica Detragiache, and Tara Vishwanath (1996) "Migration with Endogenous Moving Costs," *American Economic Review*, 86 (4), 909–30.

Clemens, Michael A., Claudio E. Montenegro, and Lant Pritchett (2008) "The Place Premium: Wage Differences for Identical Workers across the US Border," Policy Research Working Paper Series 4671, The World Bank.

Corno, Lucia, Nicole Hildebrandt, and Alessandra Voena (2020) "Age of marriage, weather shocks, and the direction of marriage payments," *Econometrica*, 88 (3), 879–915.

De Weerdt, Joachim and Kalle Hirvonen (2016) "Risk Sharing and Internal Migration," *Economic development and cultural change*, 65 (1), 63–86.

Deaton, Angus (1991) "Saving and Liquidity Constraints," *Econometrica*, 59 (5), 1221–48.

Dustmann, Christian (1997) "Return Migration, Uncertainty and Precautionary Savings," *Journal of Development Economics*, 52 (2), 295–316.

——— (2003) "Return migration, wage differentials, and the optimal migration duration," *European Economic Review*, 47 (2), 353–369.

Dustmann, Christian and Joseph-Simon Görlach (2016) "The economics of temporary migrations," *Journal of Economic Literature*, 54 (1), 98–136.

Dustmann, Christian and Oliver Kirchkamp (2002) "The Optimal Migration Duration and Activity Choice After Re-migration," *Journal of Development Economics*, 67 (2), 351–372.

Dustmann, Christian and Yoram Weiss (2007) "Return Migration: Theory and Empirical Evidence from the UK," *British Journal of Industrial Relations*, 45 (2), 236–256.

Frankenberg, Elizabeth, Lynn A. Karoly, Paul Gertler, Sulistinah Achmad, I. G. N. Agung, Sri Harijati Hatmadji, and Paramita Sudharto (1995) *The 1993 Indonesian Family Life Survey: Overview and Field Report*, Santa Monica, CA: RAND Corporation.

Frankenberg, Elizabeth and Duncan Thomas (2000) "The Indonesia Family Life Survey (IFLS): Study Design and Results from Waves 1 and 2," *RAND, Santa Monica, CA. DRU-2238/1-NIA/NICHD*.

Gollin, Douglas, David Lagakos, and Michael E. Waugh (2014) "The agricultural productivity gap," *The Quarterly Journal of Economics*, 129 (2), 939–993.

Görlach, Joseph-Simon (2022) "Borrowing Constraints and the Dynamics of Return and Repeat Migrations," *Journal of Labor Economics*, forthcoming.

Gröger, André (2021) "Easy come, easy go? Economic shocks, labor migration and the family left behind," *Journal of International Economics*, 128, 103409.

Grogger, Jeffrey and Gordon H. Hanson (2011) "Income maximization and the selection and sorting of international migrants," *Journal of Development Economics*, 95 (1), 42–57.

Hagenaars, Aldi, Klaas De Vos, and M. Asghar Zaidi (1994) "Poverty Statistics in the Late 1980s: Research Based on Micro-data, Office for Official Publications of the European Communities.," *Luxemborg*.

Halliday, Timothy (2006) "Migration, Risk, and Liquidity Constraints in El Salvador," *Economic Development and Cultural Change*, 54 (4), 893–925.

Hamory, Joan, Marieke Kleemans, Nicholas Y. Li, and Edward Miguel (2021) "Reevaluating agricultural productivity gaps with longitudinal microdata," *Journal of the European Economic Association*, 19 (3), 1522–1555.

Harris, John R. and Michael P. Todaro (1970) "Migration, Unemployment & Development: A Two-Sector Analysis," *American Economic Review*, 60 (1), 126–42.

Herskowitz, Sylvan, Marieke Kleemans, and Cristhian Pulido (2021) "Kin transfers as safety nets in response to idiosyncratic and correlated shocks," IFPRI Discussion Paper 02097, International Food Policy Research Institute.

Jayachandran, Seema (2006) "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries," *Journal of Political Economy*, 114 (3), 538–575.

Kennan, John and James R. Walker (2011) "The Effect of Expected Income on Individual Migration Decisions," *Econometrica*, 79 (1), 211–251.

Kishore, Kamal, A.R. Subbiah, Tien Sribimawati, Ir. Sri Diharto, Sutarto Alimoeso, Peter Rogers, and Adang Setiana (2000) "Indonesia Country Study. Asian Disaster Preparedness Center (ADPC) with sponsored by UNEP,"Technical report, NCAR/WMO/UNU/ISDR and Office of Foreign Disaster and NOAA. Pathumthani, Thailand.

Kleemans, Marieke and Jeremy Magruder (2018) "Labour Market Responses To Immigration: Evidence From Internal Migration Driven By Weather Shocks," *Economic Journal*, 128 (613), 2032–2065.

Lagakos, David (2020) "Urban-rural gaps in the developing world: Does internal migration offer opportunities?" *Journal of Economic perspectives*, 34 (3), 174–92.

Lagakos, David, Samuel Marshall, Ahmed M. Mobarak, Corey Vernot, and Michael E Waugh (2020) "Migration costs and observational returns to migration in the developing world," *Journal of Monetary Economics*, 113, 138–154.

Lagakos, David, Ahmed M. Mobarak, and Michael E Waugh (2018) "The Welfare Effects of Encouraging Rural-Urban Migration," Working Paper 24193, National Bureau of Economic Research.

Levine, David I. and Dean Yang (2014) "The Impact of Rainfall on Rice Output in Indonesia," Working Paper 20302, National Bureau of Economic Research.

Lewis, Arthur (1954) "Economic Development with Unlimited Supplies of Labour," *The Manchester School*, 22 (2), 139–191.

Maccini, Sharon and Dean Yang (2009) "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall," *American Economic Review*, 99 (3), 1006–26.

Mahajan, Parag and Dean Yang (2020) "Taken by storm: Hurricanes, migrant networks, and US immigration," *American Economic Journal: Applied Economics*, 12 (2), 250–77.

Matsuura, Kenji and Cort J. Willmott (2009) "Terrestrial Air Temperature and Precipitation: Monthly Climatologies," *Center for Climatic Research, Department of Geography, University of Delaware.*

McKenzie, David, Steven Stillman, and John Gibson (2010) "How Important Is Selection? Experimental vs. Non-Experimental Measures of the Income Gains from Migration," *Journal of the European Economic Association*, 8 (4), 913–945.

McKenzie, David, Caroline Theoharides, and Dean Yang (2014) "Distortions in the International Migrant Labor Market: Evidence from Filipino Migration and Wage Responses to Destination Country Economic Shocks," *American Economic Journal: Applied Economics*, 6 (2), 49–75.

Meghir, Costas, Ahmed M. Mobarak, Corina Mommaerts, and Melanie Morten (2022) "Migration and Informal Insurance: Evidence from a Randomized Controlled Trial and a Structural Model," *The Review of Economic Studies*, 89 (1), 452–480.

Miranda, Mario J. and Paul L. Fackler (2002) *Applied Computational Economics and Finance*: The MIT Press.

Monras, Joan (2020) "Economic shocks and internal migration," Working Paper DP12977.

Morten, Melanie (2019) "Temporary Migration and Endogenous Risk Sharing in Village India," *Journal of Political Economy*, 127 (1), 1–46.

Mueller, Valerie, Clark Gray, and Katrina Kosec (2014) "Heat Stress Increases Long-term Human Migration in Rural Pakistan," *Nature Climate Change*, 4 (3), 182–185.

Munshi, Kaivan (2003) "Networks In The Modern Economy: Mexican Migrants In The U.S. Labor Market," *The Quarterly Journal of Economics*, 118 (2), 549–599.

Munshi, Kaivan and Mark Rosenzweig (2005) "Economic Development and the Decline of Rural and Urban Community-based Networks," *The Economics of Transition*, 13 (3), 427–443.

Olken, Benjamin (2009) "Merged Indonesia Kecamatam Codes," *NBER electronic data set.*

Pulido, José and Tomasz Swiecki (2019) "Barriers to mobility or sorting? sources and aggregate implications of income gaps across sectors and locations in indonesia," *Unpublished Working Paper.*

Rosenzweig, Mark R. and Oded Stark (1989) "Consumption Smoothing, Migration, and Marriage: Evidence from Rural India," *Journal of Political Economy*, 97 (4), 905–26.

Shrestha, Maheshwor (2017) "Push and pull: A study of international migration from Nepal," *World Bank Policy Research Working Paper* (7965).

Strauss, John, Kathleen Beegle, Bondan Sikoki, Agus Dwiyanto, Yulia Herawati, and Firman Witoelar (2004) "The Third Wave of the Indonesia Family Life Survey (IFLS): Overview and Field Report," *WR-144/1-NIA/NICHD*.

Strauss, John, Firman Witoelar, and Bondan Sikoki (2016) "The fifth wave of the Indonesia family life survey: overview and field report," *WR-1143/1- NIA/NICHD*, 1.

Strauss, John, Firman Witoelar, Bondan Sikoki, and Anna M. Wattie (2009) "The Fourth Wave of the Indonesian Family Life Survey (IFLS4): Overview and Field Report," *WR-675/1-NIA/NICHD*.

Thomas, Duncan, Elizabeth Frankenberg, and James P Smith (2001) "Lost but Not Forgotten: Attrition and Follow-up in the Indonesia Family Life Survey," *Journal of Human Resources*, 36 (3), 556–592.

Thomas, Duncan, Firman Witoelar, Elizabeth Frankenberg, Bondan Sikoki, John Strauss, Cecep Sumantri, and Wayan Suriastini (2012) "Cutting the costs of attrition: Results from the Indonesia Family Life Survey," *Journal of Development Economics*, 98 (1), 108–123.

Todaro, Michael (1969) "A Model for Labor Migration and Urban Unemployment in Less Developed Countries," *American Economic Review*, 59 (1), 138–48.

Townsend, Robert M. (1994) "Risk and Insurance in Village India," *Econometrica*, 62 (3), 539–91.

Train, Kenneth (2009) *Discrete Choice Methods with Simulation*, Cambridge Books: Cambridge University Press.

Yang, Dean (2008a) "International migration, remittances and household investment: Evidence from Philippine migrants' exchange rate shocks," *The Economic Journal*, 118 (528), 591–630.

——— (2008b) "Risk, Migration, and Rural Financial Markets: Evidence from Earthquakes in El Salvador," *Social Research*, 75.

Figures

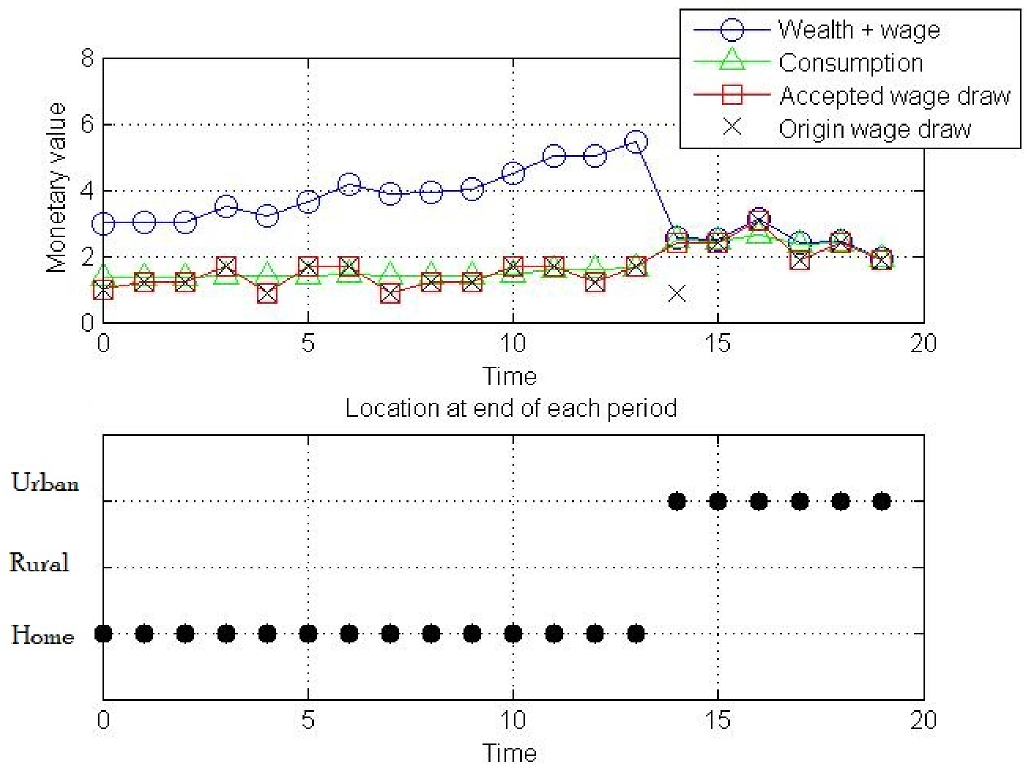

Figure 1: Model Solution: Moving to an Urban area

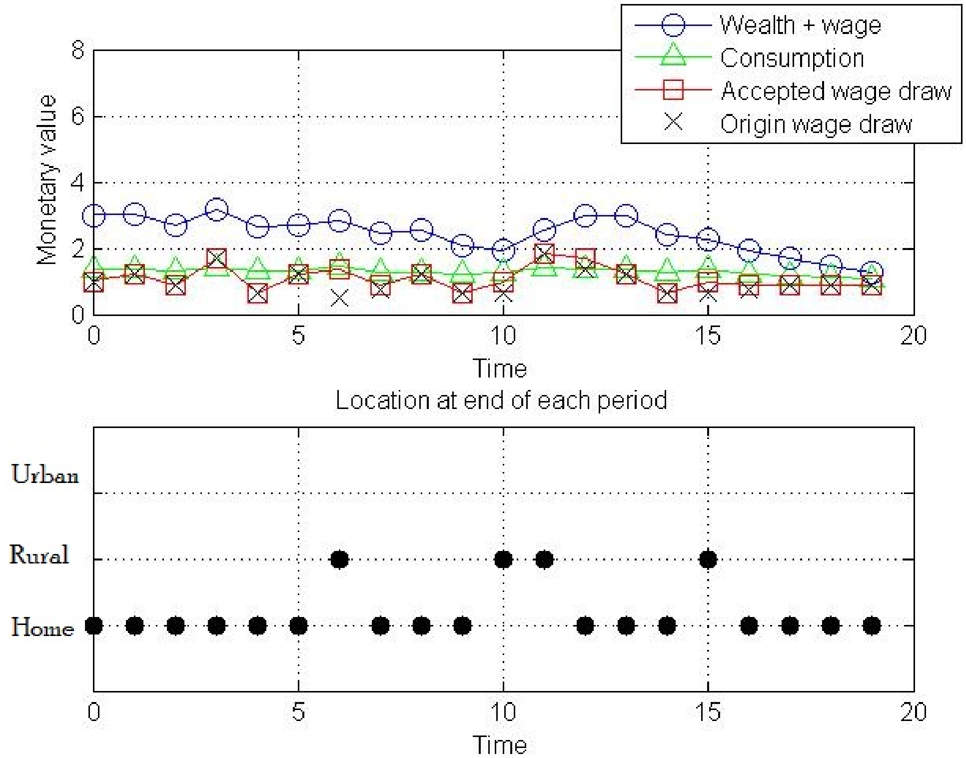

Figure 2: Model Solution: Moving to a Rural area

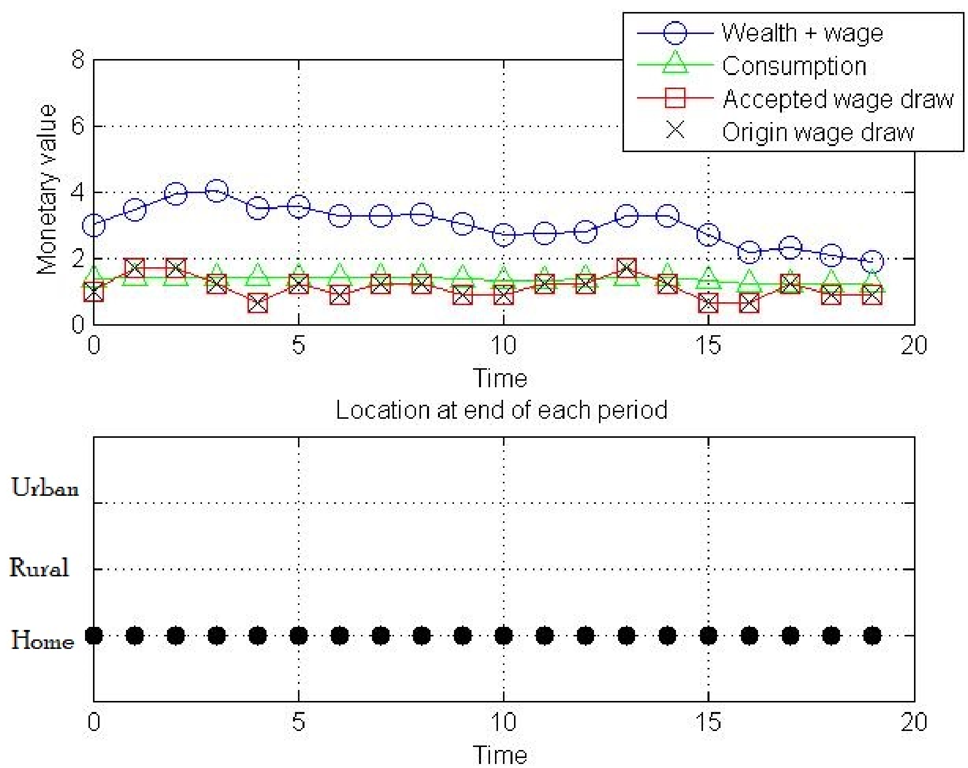

Figure 3: Model Solution: Staying Home

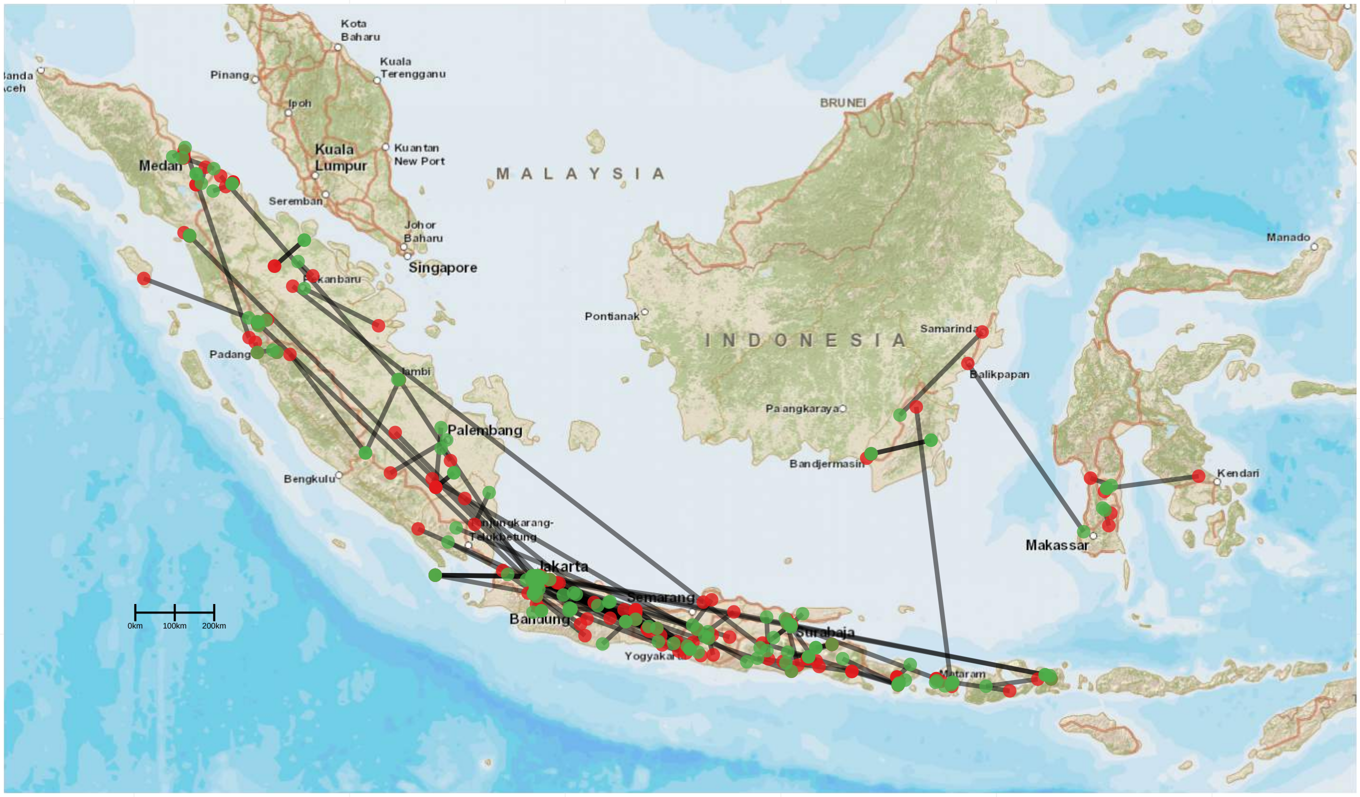

Figure 4: Monthly migration flow in August 1995

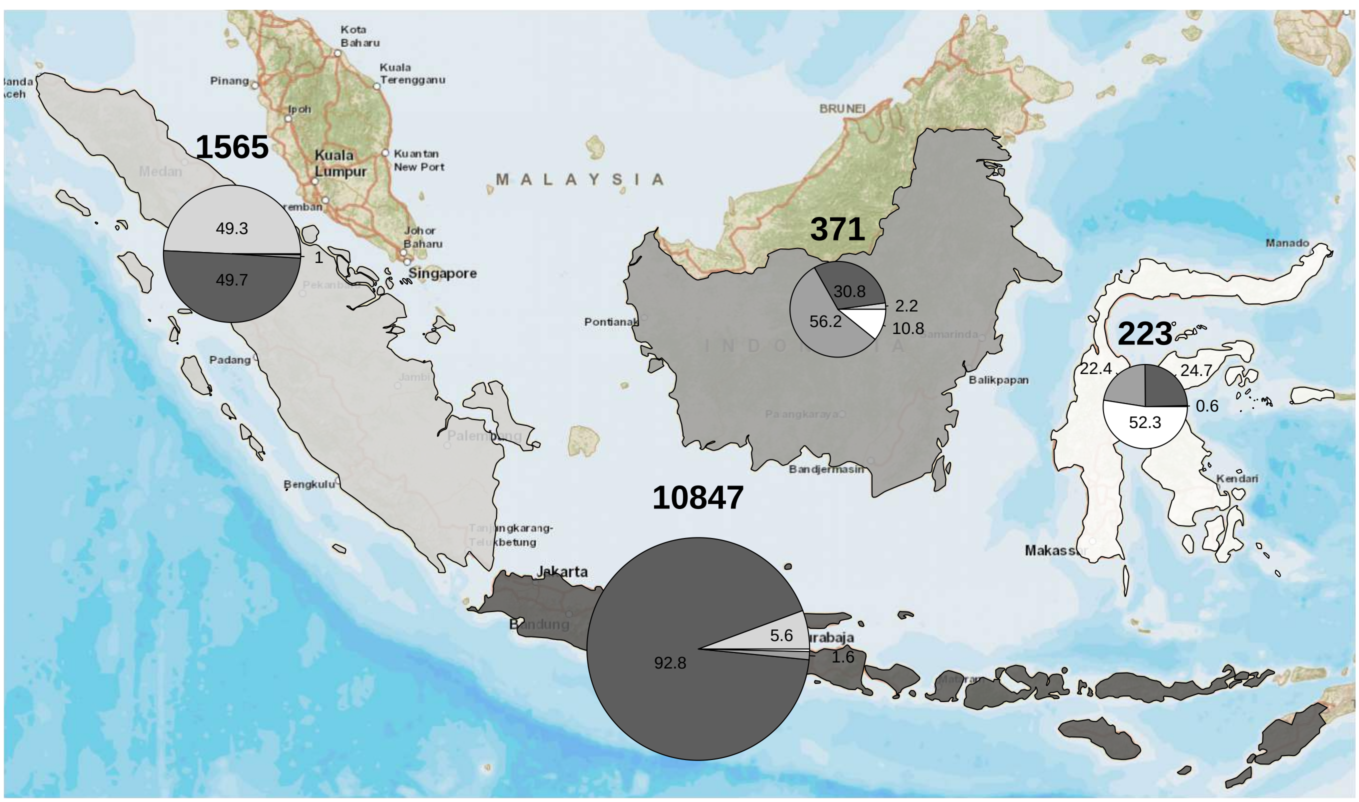

Figure 5: Migration flows between islands

Figure 6: Migration flow into Jakarta

Figure 7: Migration flow into Medan

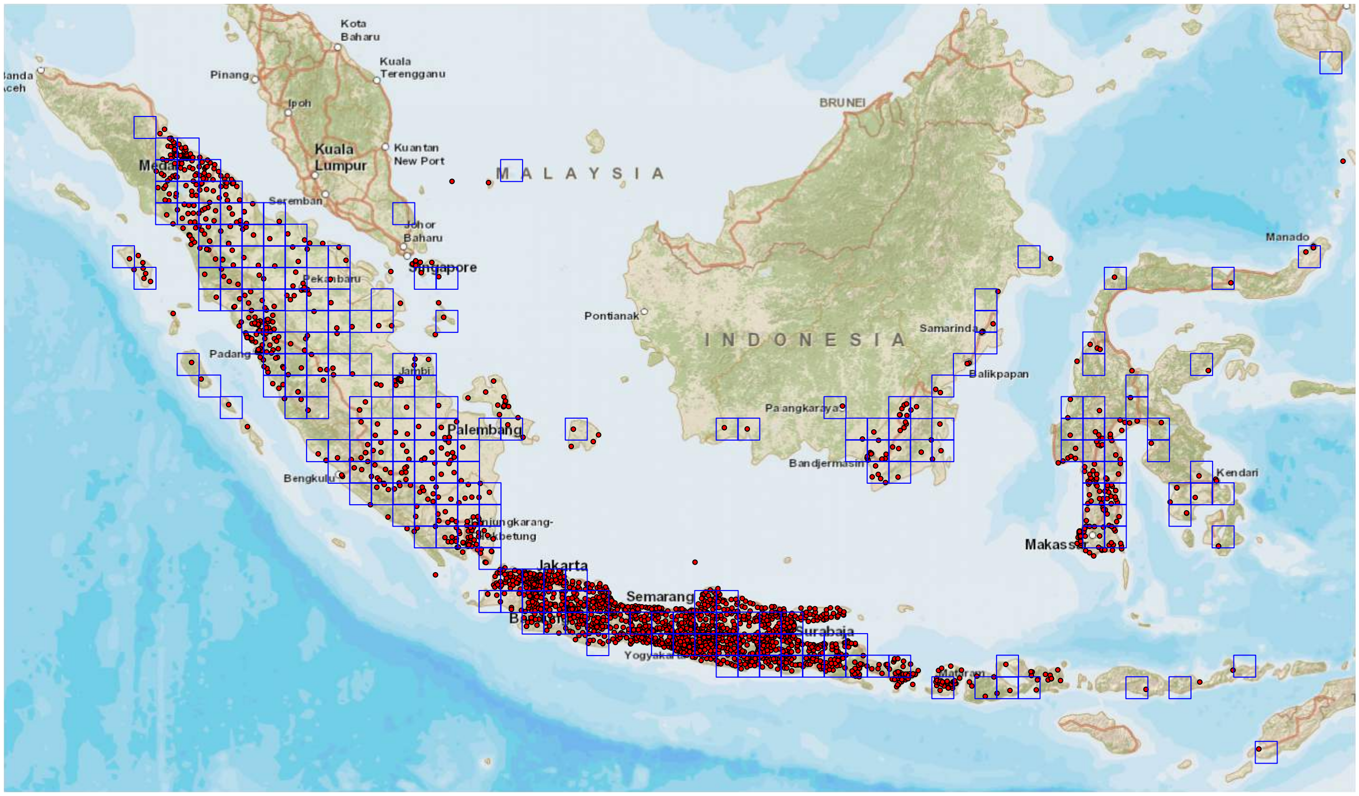

Figure 8: Household locations IFLS with weather data that locations are mapped to

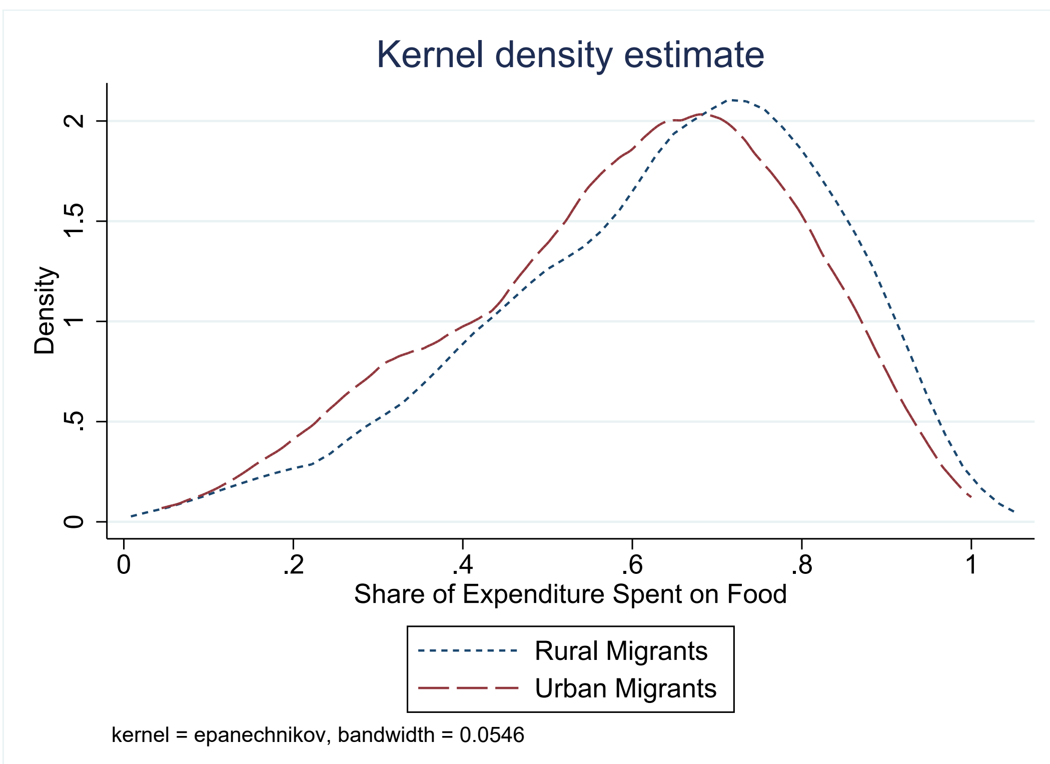

Figure 9: Share Expenditure Spent on Food by Migrant Destination

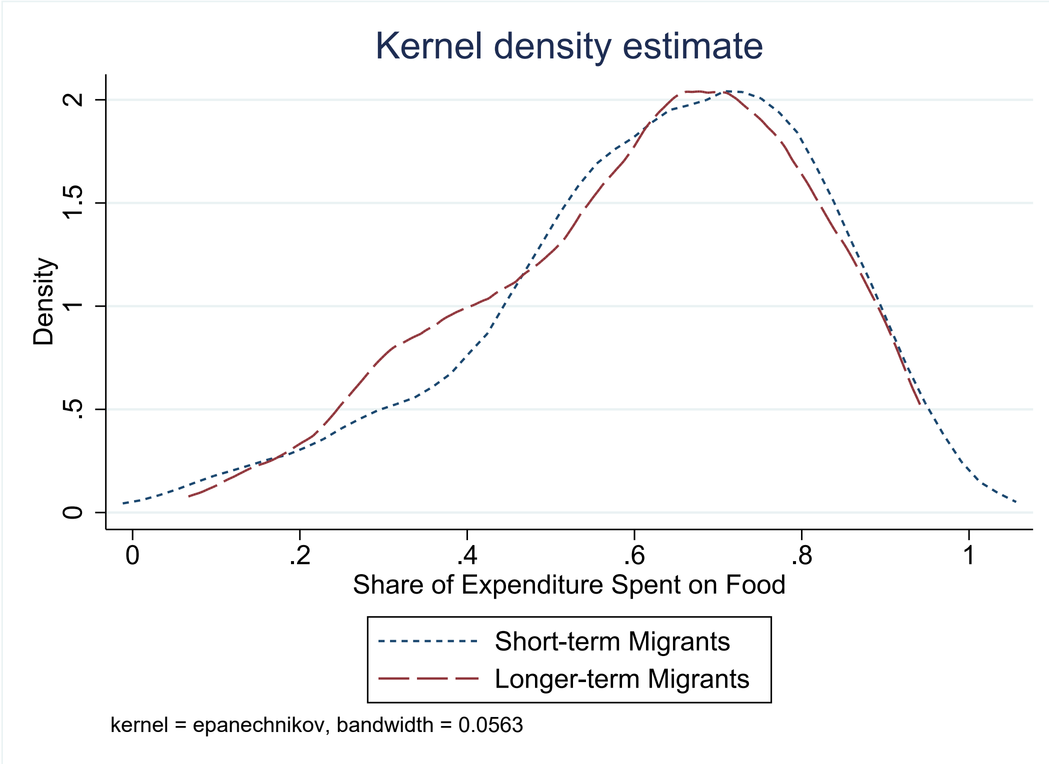

Figure 10: Share Expenditure Spent on Food by Migrant Duration

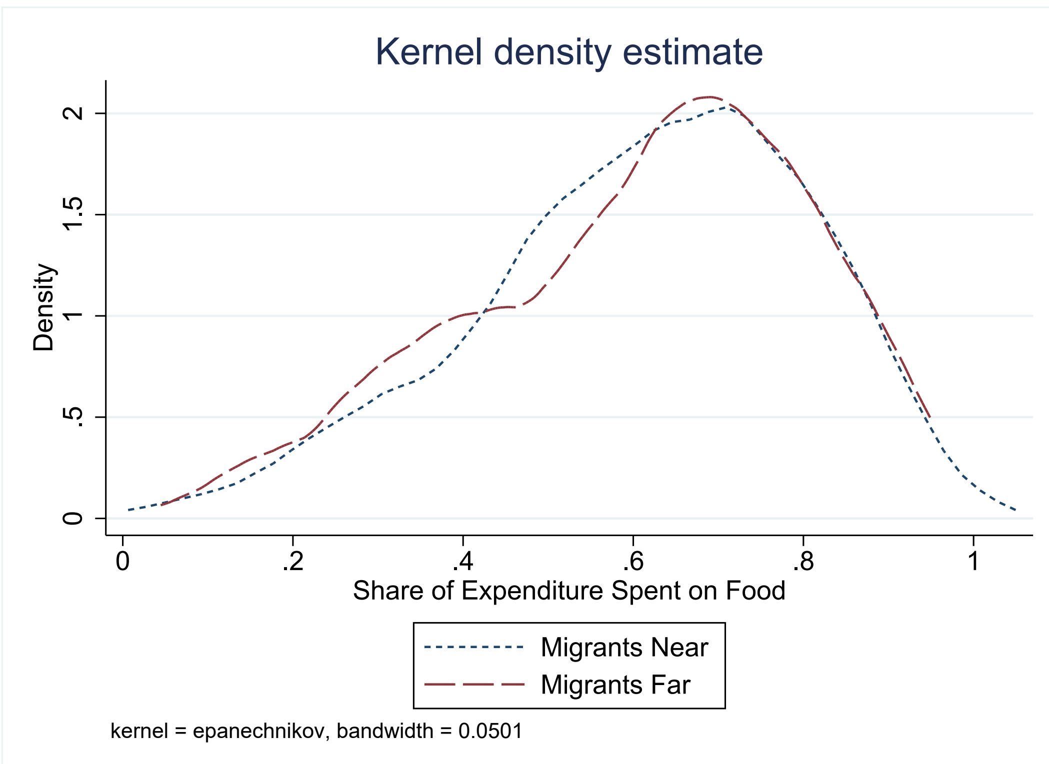

Figure 11: Share Expenditure Spent on Food by Migrant Distance

Tables

Table 1: Summary Statistics

Number of Individuals	45,946
Number of Individuals-Year Pairs	741,227
Migrant Stock (%)	28.35
Percentage of years as migrant	(45.07)
Migrant Flow (%)	3.08
Percentage of years migrating all directions	(17.29)
Duration Median (years away from home)	4.00
Mean	6.20
Standard Deviation	(5.68)
Distance Median (km away from home)	90.1
Mean	238.3
Standard Deviation	(353.4)
Migrating Together (%)	37.25
Of all moves, % with another person	(48.35)
Number of Persons	2.47
Conditional on moving together	(1.59)
Average Wealth	159.68
In 100,000 IDR ≈ 12 USD	(239.91)
Average Annual Income	61.98
In 100,000 IDR ≈ 12 USD	(64.71)

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

Table 2: Migration Transition Matrix

Percentages		End Location		
		Home	Rural	Urban
Starting Location	Home	64.31	0.55	1.05
	Rural	0.27	12.35	0.17
	Urban	0.54	0.20	20.55
Number of individual-year pairs		End Location		
		Home	Rural	Urban
Starting Location	Home	431,101	3,667	7,068
	Rural	1,816	82,803	1,137
	Urban	3,636	1,325	137,744

Table 3: Migration in Response to Weather Shocks

	Dependent Variable: Migrated away from Home Location			
	(1)	(2)	(3)	(4)
Drought at year t	0.678***	0.681***	0.700***	0.682***
	[0.144]	[0.143]	[0.145]	[0.138]
Sum drought year t-1 to t-2	-0.057			
	[0.162]			
Sum drought year t-1 to t-3		-0.572***		
		[0.184]		
Sum drought year t-1 to t-4			-0.641***	
			[0.170]	
Sum drought year t-1 to t-5				-0.407***
				[0.153]
Time fixed effects	yes	yes	yes	yes
Individual fixed effects	yes	yes	yes	yes
Mean dependent variable	1.865	1.865	1.865	1.865
R-squared	0.186	0.186	0.187	0.201
Observations	354,320	354,320	354,320	354,320
Number of individuals	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 4: Migration Strategies by Duration

	Dependent variable: Migrated away from Home Location	
	0 - 4 years	**> 4 years**
	(1)	(2)
Drought at year t	0.252***	0.379***
	[0.074]	[0.091]
Drought at year t-1 to t-3	-0.185	-0.427***
	[0.129]	[0.118]
Time fixed effects	yes	yes
Individual fixed effects	yes	yes
Mean dependent variable	0.762	0.953
R-squared	0.169	0.186
Observations	354,320	354,320
Number of individuals	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 Destination

	Dependent Variable: Migrated away from Home Location	
	Rural Destination	**Urban Destination**
	(1)	(2)
Drought at year t	0.436***	0.245***
	[0.101]	[0.091]
Drought at year t-1 to t-3	-0.151	-0.421***
	[0.100]	[0.152]
Time fixed effects	yes	yes
Individual fixed effects	yes	yes
Mean dependent variable	0.706	1.158
R-squared	0.170	0.194
Observations	354,320	354,320
Number of individuals	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 Distance

	Dependent variable: Migrated away from Home Location	
	0 - 100 km	**> 100 km**
	(1)	(2)
Drought at year t	0.396***	0.285***
	[0.089]	[0.087]
Drought at year t-1 to t-3	-0.240*	-0.332**
	[0.127]	[0.131]
Time fixed effects	yes	yes
Individual fixed effects	yes	yes
Mean dependent variable	1.016	0.779
R-squared	0.178	0.194
Observations	354,320	354,320
Number of individuals	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).

A. Appendix Figures and Tables

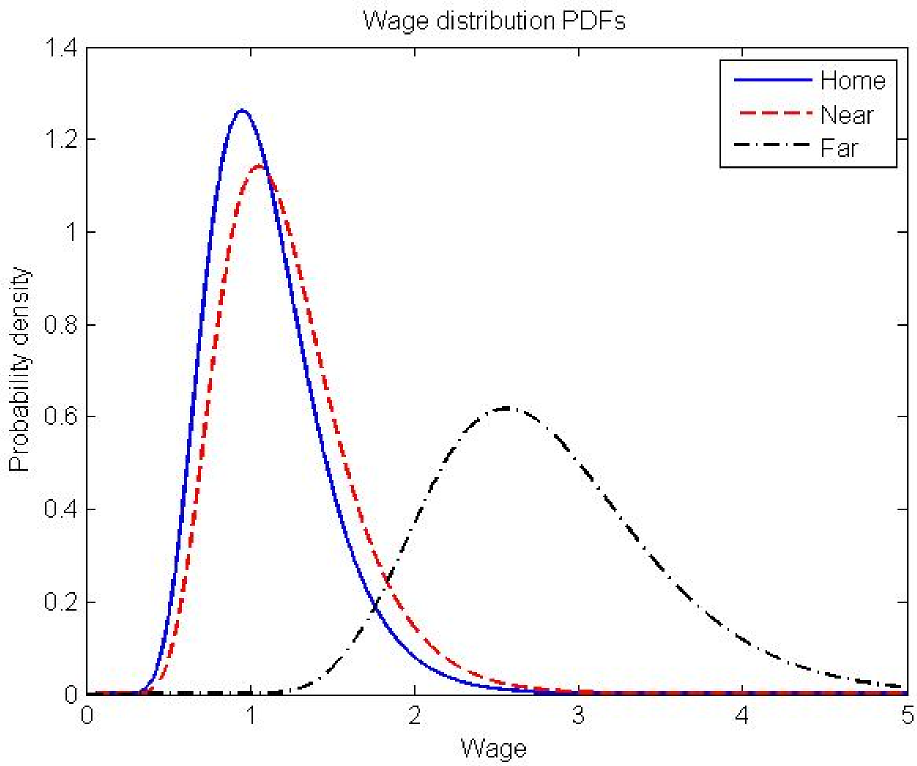

Figure A1: Wage Distributions used for model solutions shown in Figures 1, 2 and 3

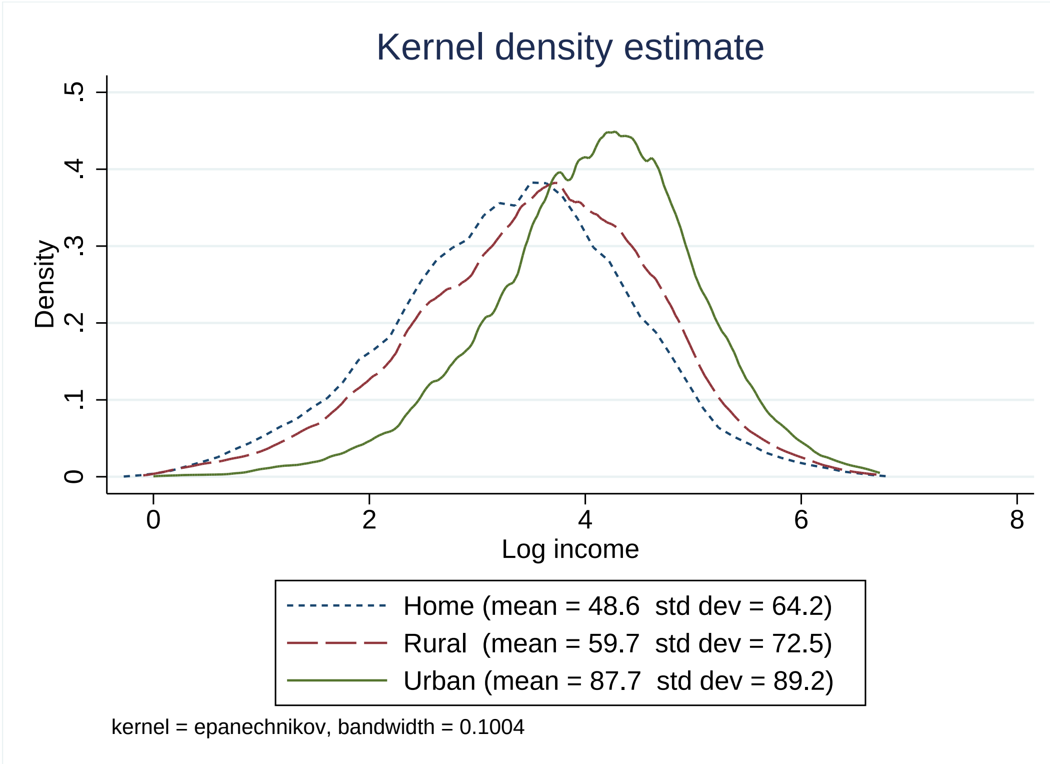

Figure A2: Kernel density wage distribution Home, Rural and Urban

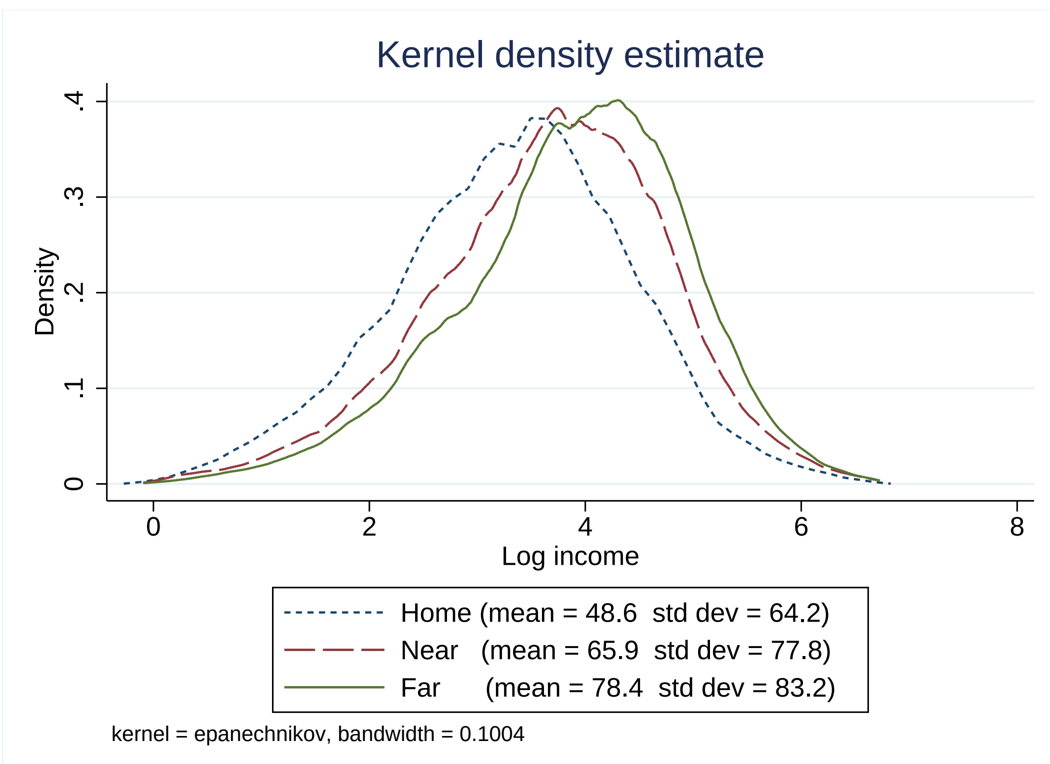

Figure A3: Kernel density wage distribution Home, Near and Far

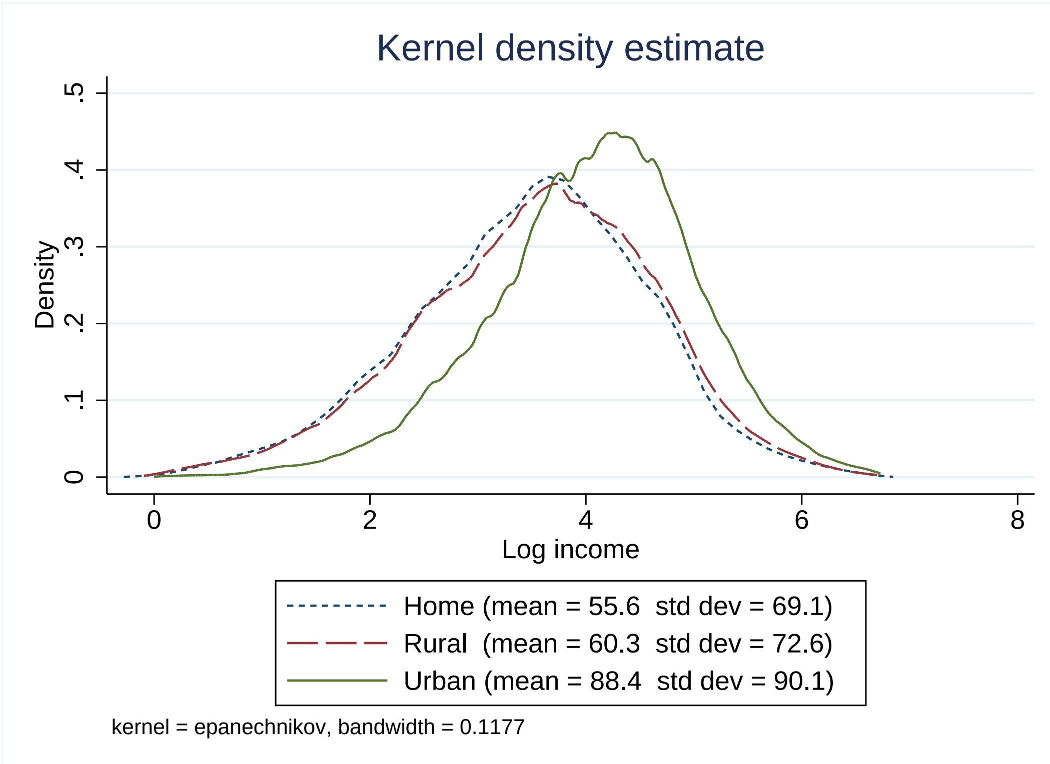

Figure A4: Kernel density wage distribution Home, Rural and Urban - Movers only

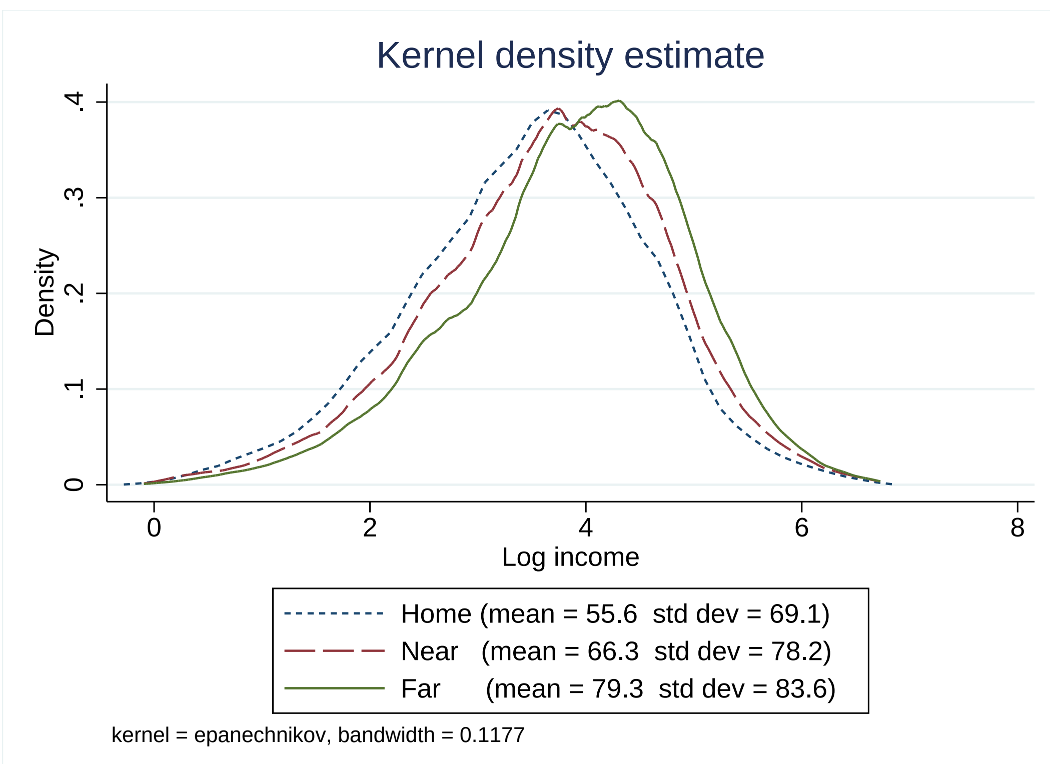

Figure A5: Kernel density wage distribution Home, Near and Far - Movers only

Table A1: 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 individuals	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 $\approx$ \$ 12 USD.

Table A2: 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'.

B. 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 $i = 1, 2, \dots max_{iter}$, 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 $max(v_1, v_2, \ldots, v_{nLoc})$

(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

$$V_t(x, l) = \max_{c, l^{'}} \left\{ U_t(c, l^{'}) + \beta \int V_{t+1}(x^{'}, l^{'}) dF(w_{l'}) \right\} \tag{8}$$

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).