Economic Development and the Spatial Allocation of Labor: Evidence From Indonesia *

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Abstract

Nominal wages differ widely across space. Do these differences imply large productivity benefits to moving people across space, or are the differences driven by selection or amenity differences? To answer this question, we construct a general spatial equilibrium framework. Our framework allows us to decompose observed wage differences into four components: i) selection due to comparative advantage, ii) wedges due to migration costs, iii) endogenous amenity differences, and iv) endogenous agglomeration benefits. We show how migration costs can lead to lower aggregate productivity by hindering the movement of labor to where it is most productive. We then estimate the model using detailed micro data for Indonesia and the United States. Two counterfactuals illustrate the quantitative implications of migration costs on aggregate productivity. First, we estimate that between 1976 and 2012 migration costs declined by 35% in Indonesia; the improved allocation of labor to where it is most productive explains approximately 20% of Indonesia's GDP growth over this period. Second, we estimate that migration costs in the United States are 60% smaller than in Indonesia; higher costs of labor movement in Indonesia explain 4% of the GDP per-capita gap between the United States and Indonesia.

Keywords: Selection, Internal migration, Indonesia

JEL Classification: J61, O18, O53, R12, R23

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1 Introduction

Within country, nominal wages differ widely across space (Moretti 2011).[1] How to interpret these gaps is hotly debated, on one hand it has been argued that spatial wage gaps represent an unexploited opportunity to increase productivity and encourage relative development (e.g. Restuccia et al. 2008) on the other, the gaps may imply no such free lunch, simply reflecting rational selection of heterogeneous workers (Young, 2013). Determining which of these explanations is correct – or more importantly quantifying their relative importance – has clear policy implications: should governments focus on improving ways for people to move to highly productive areas, for example by constructing highways allowing easier migration, or should they instead allocate scare resources on policies that increase development in low productive areas, such as rural development schemes?

In this paper we provide a framework to ask whether productivity could be increased by moving people across space, and if there are such gains, then what causes people to not move. To do so, we build a model with four key features: i) workers draw location-specific productivity levels and select where they live and work to maximize utility, ii) there are costs of migrating, iv) locations offer different (partially endogenously determined) levels of amenity and, v) locations offer different (partially endogenously determined) levels of productivity. We show how migration costs can contribute to aggregate productivity losses by hindering the migration of labor to where it is most productive. We then estimate the model of labor sorting across space using census data from Indonesia and the United States. Two counterfactuals illustrate the quantitative effects. First, we estimate that between 1976 and 2012 migration costs declined by 35% in Indonesia; the improved allocation of labor to where it is most productive explains approximately 20% of Indonesia's GDP growth over this period. Second, we estimate that migration costs in the United States are 60% smaller than in Indonesia; higher costs of labor movement in Indonesia explain 4% of the GDP per-capita gap between the United States and Indonesia.

Our choice to construct a model with a role for both migration costs and unobserved migrant section is motivated by four, relatively novel, empirical facts that link together

[1] The data also suggests large differences in real wages, although this is harder to measure. See, for example, Kanbur and Rapoport (2005).

migration, distance and wages. Together, these four facts are consistent with the presence of both selection as well as barriers to mobility:

1. *Gravity:* We show that a gravity relationship holds for migration in Indonesia. That is, controlling for origin and destination fixed effects, the log of the proportion of migrants from origin g who migrate to destination i is decreasing in the log of the distance between i and g.

2. *The further a migrant travels to a destination, the higher their wage:* Controlling for a destination labor market fixed effect, the log of an individual's wage is increasing in the log of the distance migrated. We see this second fact as consistent with selection – the higher the cost of movement, the higher is the compensation required to make the move.

3. *The more people from an origin travel to a destination, the lower their wage:* Controlling for a destination fixed effect, the log of the wage is decreasing in the log of the portion of people from origin g that move to destination i. We again take this as consistent with selection: in our model higher migration costs from g to i will decrease the proportion of people born in g that move to i and these people will tend to have higher i specific skill levels.

4. *The distance effect appears to work through the extensive margin of how many people migrate:* Finally, we show that when the proportion of people moving from g to i and the distance from g to i are both included in a regression with the log of the wage on the left hand side, the importance of distance decreases, while the coefficient on the proportion of people moving remains unchanged. We see this as strongly consistent with a model of selection driven by migration costs: higher costs of movement (proxied by physical distance) induce a smaller portion of people to move from g to i and these people are more highly selected. Because the cost of movement should not directly affect the wage rate, except through selection, it is the proportion of people moving that should predict the wage, and not the distance moved.

The reduced form facts provide evidence consistent with the presence of both selection and migration costs, but the magnitude of such effects is not easily interpreted. Neither, can we provide counterfactual analysis of productivity differences of reducing such costs. Therefore, in order to quantity the contribution of selection to productivity we construct a framework with endogenous sorting of labor across space. The model we estimate allows locations to differ in three ways: first, locations may differ in their inherent productivity (for example, New York is a port while Atlanta is not); second, locations may differ in the natural amenity that they offer (for example, Sydney sits on a beautiful natural harbour, while Melbourne does not); and third, some places may be more costly to move between (for example, moving between Shanghai and Beijing is probably easy due to the cultural similarities of the people and the fast train. Moving between Lhasa and Beijing is probably harder due to both the cultural and physical distance). We then show that all four of the reduced form facts highlighted above are easily derived from our model. [2]

Amenity and productivity determine how attractive a location is to live, and movement costs determine how costly it is for a worker to move away from their place of birth and hence the gain they would need to make a move. We combine this structure with a model of human capital: each worker is characterized by a productivity level for each location, drawn from a multivariate Fréchet distribution. Given the costs and benefits or moving, workers select where they will live and work and this selection process endogenously determines the amount of human capital, and the total number of workers in each location. Amenity and productivity are also allowed to adjust in response to the movement of people due to congestion and agglomeration externalities.[3] The average wage of a location is determine by its endogenous productivity level and the amount of human capital working their, and aggregate GDP per worker is determined by the extent to which workers are able to move to high productivity locations, and the extent to which worker movement allows the country to take advantage of agglomeration externalities. We show how migration costs can cause workers to choose not to move to where they

[2] We have tried to make the list of ways in which locations differ all exogenous. Cultural differences are, however, potentially endogenous. We discuss this possibility and how to interpret our model in the light of this problem below.

[3] The model, therefore, distinguishes between inherent productivity and endogenous or current productivity as well as between natural amenity and endogenous or current amenity. We use the convention of always referring to the exogenous parameters as inherent or natural and the endogenous parameters simply as amenity or productivity.

are most productive; reducing such costs can then improve the allocation of workers and lead to an increase in productivity.[4]

We estimate the structural parameters of the model for each of four years for which we have data – 1976, 1995, 2011 and 2012. . One advantage of our model is that closed forms are easily computed and so identification is relatively transparent. Roughly, the extent to which the portion of people from g that move to i reduces the wage at i recovers the Fréchet parameter characterising the distribution of talent. Both amenities and productivities affect the migration rate, but in our model, productivity does not affect the wage of migrants. This follows from a convenient, but perhaps specific, feature of our model: an increase in productivity in destination i has two effects: first, it raises the wages of those already live there, and second, it increases the influx of low skill migrants. In our model these effects exactly offset meaning the wage level identifies amenities. Hence, wage differences can be used to infer amenities, and with these measured, migration rates can be used to infer differences in productivity. Finally, any "wedge" between average wages for migrants and non-migrants that exists both for migrants from i to g and for migrants from g to i is, combined with low migration rates between the two location, interpreted as a migration cost. Our structural estimates give us, for each location in Indonesia: the level of amenity relative to a benchmark, an absolute measure of productivity, the cost of migration between each pair of places and the total amount of human capital current living in each location. These measures can be used to do simple decompositions of the spatial wage gap, or combined with the full computational model to undertake counterfactual exercises.

Before making use of our estimates we show that our measures correlate with other measures available in the data. For example, our amenity measures are negatively correlated with measures of air, water, land and noise pollution. Our measures of migration cost are correlated with physical distance, both measured in straight line and using a measure of least cost transport cost, as well as with measures of the cultural and language

[4]Note, it is possible that reducing migration costs could lower productivity, if many very productive places have low amenity and reducing movement costs will tend to allocate people to lower productivity, higher amenity locations. In such a case, a policy of improving amenity in denser areas, or mitigating the costs of congestion seems a more promising policy approach.

differences between locations.

Our model can be used to undertake several counterfactual exercises. We consider several exercises that help to understand the aggregate effects of policies that encourage reallocation of workers across space. First, because we have four years of data we are able to understand what portion of GDP growth in Indonesia is caused by greater spatial integration of the labor market. We estimate that between 1976 and 2012 migration costs declined by 35% in Indonesia. We re-solve the model using parameters for 1976 imposing the migration costs from 2012 and find that the improved allocation of labor to where it is most productive explains approximately 20% of Indonesia's GDP growth over this period. Second, we consider what the GDP of Indonesia would be if average migration costs were the same as we find in the US. We find that migration costs in the United States are 60% smaller than in Indonesia. We then rescale our estimated migration costs in Indonesia to match the distribution of migration costs in the United States. This generates an increase in GDP per capita of 50% in Indonesia, a gap that is equivalent to 4% of the GDP per-capita gap between the United States and Indonesia.

Relative to the existing literature, we make three main contributions. First, we estimate a model a spatial sorting that allows both selection as well as migration barriers. A large literature debates the extent to which differences in nominal wages reflect differences in worker types, versus differences in absolute productivity across space. The distinction is conceptually important because if the wage distribution is entirely determined by selection – as argued, for example, by Young (2013) – then there are not productivity gains to be had by moving people across space – despite difference in average products, marginal products are equalized across space. We do find a role for selection, consistent with Young (2013) and Lagakos and Waugh (2013). However, we do not find that selection fully explains the gap. Our research clarifies this line of research by showing quantitatively that the answer lies somewhere in the middle – part of the productivity gap is drive by selection, and part by movement costs which prevent arbitrage.

Second, the model that we propose incorporates migration costs. Most of the existing literature on the spatial distribution of workers, notably that in the economic geography and urban economics traditions, assume that labor is freely mobile across space.[5] However, the small literature that incorporates migration costs find them to be substantial. For example, Kennan and Walker (2011) estimate that the fixed cost of migration for young men in the US is equivalent to 40% of the average wage. Morten (2013) estimates that the fixed costs of migration is equivalent to 30% of the mean consumption for rural Indian migrants, and Morten and Oliveira (2014) find that building roads in Brazil increased migration between locations, consistent with roads reducing migration costs. Bryan et al. (2014) show large returns to migration in North Western Bangladesh – a fact that is only consistent with a (broadly defined) cost of migration – and also directly ask migrants how much higher wage would be required to compensate for a *temporary* move. Over a quarter of those asked this question stated that their earnings as a migrant would have to be more than 150% of their earnings at home.

Third, we address the question of aggregate implications of worker heterogeneity. Quantitative work on the productivity gains of movement has received much less attention, and that work that does exist again concentrates on developed countries (Hsieh and Moretti, 2014) or quantifying the gains of liberalizing international migration (Clemens, 2011; Kennan, 2013). There is also a growing literature that examines the allocation of factors of production, both in developing and developed countries.This literature, which is largely quantitate, argues that it is not just factor accumulation that is important in determining relative development, but how factors are allocated. For example, in their seminal paper, Hsieh and Klenow (2009) document a large degree of misallocation of capital in Indian and Chinese firms relative to a US benchmark, and estimate productivity losses due to this misallocation in the order of 50%. In a more recent contribution, from which we draw much of our structure, Hsieh et al. (2013) estimate that 15-20% of factor productivity in the US between 1960-2000 was due to a reduction in implicit discrimination faced in the labor market for both blacks and women. With discrimination, group members were stopped from pursuing their comparative advantage. Our paper shows that cost of migration may have aggregate implications. A key policy implication is reducing the costs

[5]The spatial literature, building on Rosen and Small (1981) and Roback (1982) typically assumes that migration is, in the long run, costless. The first paper we are aware of to relax this assumption is Topel (1986).

of migration, for example by expanding highway access allowing for easier migration flows, would facilitate the movement to labor to where they are most productive.

And, finally, our paper addresses the issue of spatial equilibrium in a large developing country. While the question of what causes spatial dispersion has received a great deal of attention, most this work is in developed countries.[6] There are reasons, however, to think that answers may differ in developing and developed countries. A large literature in development follows the tradition of Lewis and sees developing countries as having dualistic labor markets. Part of the process of development is the movement of labor from traditional to modern sectors. Usually this movement is thought to encompass the physical movement of labor from rural to more urban areas. This sort of movement, and any reduction in constraints on labor movement, is captured in our work. Recent work suggests that any decomposition may differ across countries and depend on the state of development. For example, Desmet and Rossi-Hansberg (2013) decompose the causes of spatial diversion in the US and China. They find much greater welfare gains to decreasing dispersion in China than the US. This potentially reflects the general view that US labor markets are more tightly integrated than their developing country equivalents.

The remainder of the paper is structured as follows. Section 2 describes the data that we use and our setting, it also documents the four motivational facts discussed above. Section 3 outlines the model and we show how the structural parameters can be identified in Section 4. In this section we also discuss how our model differs from other models of selection and migration in the literature. Section 5 discusses the fit of the model to the data and shows the correlation between our structural measures of amenity, productivity, migration costs and human capital with other accepted measures. We also undertake quantitive exercises to evaluate the aggregate implications of improving the allocation of workers. Finally, Section 6 concludes and offers some suggestions for further research.

[6] Of course, understanding the rural-urban wage gap has been one of the key questions in development economics. Estimates of the rural/urban, or agricultural/manufacturing gap are staggering. For example, Caselli (2005) estimates that differences in productivity between agriculture and manufacturing can explain up to 40% of cross-country income differentials. More recently, after undertaking a thorough development accounting exercise using higher quality micro data from household surveys, Gollin et al. (2014) find that the productivity gap remains at least a factor of two.[7]

2 Data and Motivational Evidence

This section provides reduced form empirical evidence for the mechanisms in the model. We estimate the model using micro-level Census and survey data from Indonesia. For contrast, we replicate the specifications using the micro data from the US. This section first describes the data, and then carries out reduced form implications from the data that favors a model in which movement costs reduce the flow of migrants and lead to selection.

2.1 Census and survey data

The model we outline below provides a micro-foundation for the idea that migration is costly because it moves people away from their location of birth. While we micro found this notion using the idea of travel costs required to spend time with family and friends, it could also capture culture or psychological phenomena. For example, Atkin (2013) argues that people form a habit of consuming the food available at low cost in their home town, when they move they consume fewer calories because they continue to purchase this same food at a higher price. Therefore, to estimate the model we need data that reveals the location of birth, preferably at a reasonable level of geographic disaggregation, as well as current earnings data. To understand the time path of migration costs and to understand the development impact of spatial labor market integration we need data that covers several time periods.

We construct a rich regional database with these characteristics using individual level census and survey data from Indonesia. The Indonesia data come from the 1976 and 1995 SUPAS (Intercensal Population Survey) and from the 2011 and 2012 SUSENAS (National Socioeconomic Survey). While the decennial SUPAS collects data on the place of birth, the 76 and 95 SUPAS are unique in containing earnings data. Both were combined with the SAKERNAS or labor force survey, with the surveys were fielded at the same time. While the SUSENAS regularly collects earnings data, the 2011 survey round was the first to collect information on place of birth. All four surveys were sourced from the Indonesian Ministry of Statistics, and all four have place of birth at the district or regency (*kabupaten* level. We believe that Indonesia is the only country to have earnings and place of birth at a level smaller than the state available from one survey. For all surveys, we drop the provinces of Papua and West Papua. We generate a set of regencies which have maintained constant geographical boundaries between 1975 and 2010. This primarily involves merging together regencies that were divided in 2001. This leaves us with a sample of 304 regencies, where the average regency population surveyed in 2011 is 3700 people. Later, for the structural estimates we aggregate regencies up to the level of province, of which there are 25. We supplement this census data occasionally with data from the Indonesian Family Life Survey (IFLS) from 2007. This data has a much smaller sample, but collects more detailed information on incomes. This allows us to do some robustness checks.

We also construct a comparison dataset for the United States. However, the data are not as rich: location of birth is only collected at the state level, and not a smaller geographical level. Nonetheless, we construct samples from the 1990 5% Census sample, and the 2010 American Community Survey.

Summary stats for the Indonesian and the United States sample are given in Appendix Tables 1 and 2. We define a migrant as someone who has moved from their region of birth (either the regency in Indonesia, or the State in the United States). All wage variables are reported in monthly terms. All financial variables are converted into 2010 values in the local currency using a CPI deflator.[8] Monthly wages in Indonesia in 1976 were 0.49 million Rp, approximately $55USD, increasing to 1.81 million Rp in 2012 ($199 USD). Monthly wages for those who choose to migrate are 25% higher on average than wages of those who choose not to migrate; some of this is due to positive selection of migrants: the average migrant in 1976 has 5.3 years of school, compared with 3.3 years for the population; in 2012 the average migrant has 9.9 years of school, compared with 8 for the population. Migration rates are between 20-26% of the population.[9] For the US, mean monthly wags are $4,600 in 1990, increasing to $5,100 in 2010. The migration rate (defined as state-level

[8]We present wages in month units. However, hours worked are available in both datasets; we have re-estimated the models using hourly instead of monthly wages are results are robust.

[9]In addition, there is considerable heterogeneity between people born in rural and urban locations (not reported in table): out migration rates from rural areas is 17% in 1976, with approximately half migrating to a rural destination and half migrating to an urban destination. For those born in an urban area, the outmigration rate was 50%, with more than 2/3 migrating to another urban area and 1/3 migrating to a rural area. The same patterns (considerable rural-rural and urban-urban migration) hold across all 4 years.

moves) is approximately 40%, and migrants have slightly higher years of education and earning approximately 10% higher than non-migrants.

2.2 Four facts linking migration, selection and costs

Our choice to construct a model with a role for both migration costs and unobserved migrant section is motivated by four, relatively novel, empirical facts that link together migration, distance and wages. We believe these facts fairly convincingly show that to match the data one needs to build a model in which there are costs of moving, and in which these costs lead to selection, with those paying higher costs requiring a greater wage premium.

1. *Gravity:* Intuitively, a model in which costs of migration are important will imply that, controlling for origin and destination fixed effects, fewer people will migrate to areas that are more costly. While, as argued above, we wish to take a broad view of the costs of migration, a simple proxy is distance migrated. We, therefore, first document that a classic gravity relationship holds for Indonesian data.[10] We estimate

   $$\ln \pi_{ig} = \alpha_i + \gamma_g + \beta \ln d_{ig} + \epsilon_{ig}$$

   where π_{ig} is the portion of people born in origin g who move to destination i, α_i and γ_g are origin and destination fixed effects, d_{ig} is the euclidean distance between the centre or regency i and regency g and ϵ_{ig} is an error term. We estimate the equation for the four years of SUPAS/SUSENAS data. The results for the main sample are in Table 2, and in Appendix Table 3 for the IFLS sample. For all years we see a strong negative coefficient on log distance migrated, the elasticity of proportion migrating with respect to distance is between 0.32 and 0.4 depending on the sample and whether the regressions are run at the regency or province level.

2. *The further a migrant travels to a destination, the higher their wage:* Controlling for a destination labor market fixed effect, the log of an individual's wage is increasing

[10] For a discussion of the gravity equation in migration see, for example, Grogger and Hanson (2011); Ravenstein (1885).

in the log of the distance migrated.[11] We see this second fact as consistent with selection – the higher the cost of movement, the higher is the compensation required to make the move. The gravity relationship is also suggestive of selection: if there was no heterogeneity in the returns to migration (or the taste for different locations), then we would expect all people to move to the same place. The fact that we do not see this suggests that those that are paying higher migration costs are doing so to increase their utility and part of this is probably an attempt to increase their wage. If this story is true, then we would expect higher earnings for those that migrate further. To test whether this is true we estimate

$$\ln w_{kig} = \alpha_i + \beta \ln d_{ig} + \epsilon_{ig}$$

where w_{kig} is the wage of person k in destination i from origin g.[12] The results are presented in Table 3. We see a strong positive coefficient on log distance in all our data sets: depending on the year the elasticity of wage with respect to distance varies between 0.03 and 0.05. These results are also robust to looking at different sub populations - for example those that are self employed.

3. *The more people from an origin travel to a destination, the lower their wage:* Another implication of the selection story is that the reason that wages are higher for those that travel further is that those that travel further are more selected. The gravity results above tell us that this is true – fewer people travel to far away location, suggesting that they are a more select portion of the population. But if this is what is driving the wage effect of distance then we should also see that the smaller the proportion of people from o who move to d then the higher should be the wage. Controlling for a destination fixed effect, the log of the wage is decreasing in the log of the portion

[11] This results is robust to also including an origin fixed effect. The theory does not imply that this fixed effect should be included, as we discuss below.

[12] The model we present below implies that there should be destination fixed effects in this regression. The results we present here are robust to also including origin fixed effects.

of people from origin g that move to destination i. That is, we test

$$\ln w_{kig} = \alpha_i + \beta \ln \pi_{ig} + \epsilon_{kig}$$

We again take this as consistent with selection: in our model higher migration costs from g to i will decrease the proportion of people born in g that move to i and these people will tend to have higher i specific skill levels.

4. *The distance effect appears to work through the extensive margin of how many people migrate:* Further, if selection is the *only* driver of this result they we should see that, once we control for the how selected the migrants are (proxied by the proportion moving) then distance should not affect the wage.[13] To test these two implications the third column of Table 3 presents results from the regression

$$\ln w_{kig} = \alpha_i + \beta \ln \pi_{ig} + \gamma \ln d_{ig} + \epsilon_{kig}.$$

When we include both distance and proportion as predictors of the log wage we get reasonable support for the hypothesis that the distance effect is driven by selection. For nearly all of our census years the results show that with the two regressors the coefficient on log proportion remains strong and negative, while the coefficient on log distance decreases, often becoming insignificant. This is broadly true whether we look at the self-employed or wage earners. The results are somewhat more mixed for this final test when using the IFLS data. One interpretational caveat is that the correlation between log distance and log proportion is very high as indicated in the Tables. This may lead to problems interpreting the results. Overall, however, we see the evidence as suggestive that much of the distance effect on wages is driven by the increasing level of selectivity that we see over longer distances.

[13] At this point proportion should be seen as a proxy for the extent of selection and we could use any of a number of different moments. However, the Fréchet model that we present below implies that proportion is exactly the right control.

We see the results from this section as being suggestive of the presence of both selection and migration costs. However, the magnitude of such effects is not easily interpreted. Neither, can we provide counterfactual analysis of productivity differences of reducing such costs. Therefore, in order to quantity the contribution of selection to productivity we construct a framework with endogenous sorting of labor across space. We will show that we can theoretically derive results from the model that will match the four facts above.

2.2.1 Reduced form facts for the US

The above sets of results show that distance migrated, which we take as a proxy for the cost incurred to migrate, accentuates the selection effect: migrants who travel further earn more on average than migrates who don't travel as far, consistent with our selection story. To benchmark the results we repeat the analysis for the US, using data constructed from the American Community Survey. The results for the two specifications are in Appendix Tables 5 and 6. We find the small qualitative patterns, but with smaller coefficients: distance migrated still positively predicts wage, and proportion migrating negatively predicts wage, but there seems to be an additional negative effect of distance over and above the selection effect through the proportion migration. Note that this does not mean that there is no selection in migrants in the US; rather, it is consistent with costs of migration not being as dependent on distance traveled, which is consistent with for example greater access to infrastructure in the US compared with Indonesia.

The reduced form results are consistent with the mechanisms we explore in the model. However, to be able to decompose the observed wage differences into selection, wedges, amenities and agglomeration components, we need to estimate all the parameters in the model. This is what we turn to next.

3 Model

This section presents our theoretical framework. To capture the joint presence of selection and mobility constraints we build a model with four key features: i) workers draw location-specific productivity levels and select where they live and work to maximize utility, ii) there are costs of migrating, iv) locations offer different (partially endogenously determined) levels of amenity and, v) locations offer different (partially endogenously determined) levels of productivity.

We start by presenting a simple model of location choice with two locations and a symmetric cost of migration between the two. The simplified model is essentially that of Lagakos and Waugh (2013) without non-homothetic preferences, and incorporating migration costs. Throughout it should be emphasised that the migration cost we model should be thought of as encompassing any cost of moving from the location of birth to another location. This could include, but is not limited to: transportation costs, credit constraints, utility costs and psychological costs.[14] We use this model to build intuition for how migration costs decrease country level output and the relevance of our reduced form tests. We then present our full model which includes multiple locations, a micro foundation for migration costs and a more complete general equilibrium structure.

3.1 A Simple Rural Urban Example

In order to build intuition for the full model, we present a simple rural-urban selection model. First, we present the framework without migration costs. We then extend the simple model to include migration costs and show how this generates aggregate effects due to the misallocation of labor. Consider two locations, a village (v) and a city (c). The wage in the city is w_c per efficiency unit of labor and the wage in the village is w_v per efficiency unit. There are a measure 1 of individuals in each location, and each individual receives an iid productivity draw, which determines their labor efficiency if they live in the village (ϵ_v), and if they live in the city (ϵ_c). We assume that $\epsilon \sim$ Fréchet with parameter θ. Agents observe their productivity draws and then move to the location that provides them with the highest income. Therefore, an agent decides to live in the village if

$$\epsilon_v > \frac{w_c}{w_v}\epsilon_c$$

[14] See also, Notowidigdo (2013).

and decides to live in the city if

$$\epsilon_c > \frac{w_v}{w_c}\epsilon_v.$$

Given our Fréchet assumption it is easy to show that the fraction of people living in the city is

$$P(\epsilon_c w_c > \epsilon_v w_v) = \frac{w_c^\theta}{w_c^\theta + w_v^\theta},$$

and the average productivity of people in location i is

$$E(\epsilon_i) = \pi_i^{-1/\theta}\Gamma\left(1 - \frac{1}{\theta}\right)$$

where Γ is the gamma function. Finally, once the endogenous selection has occurred, the ratio of observed (nominal) wages earned by workers in the city and the village is:

$$\frac{\overline{wage}_c}{\overline{wage}_v} = 1.$$

This simple model allows us to demonstrate several of the characteristics that will follow through to our more complete structural model. First, the average quality of workers in location i is decreasing in the portion of the population that decides to live there (π_i). This makes sense: conditional on the free movement of labor, the more people living in location i the less selected are the people in that location. Second the portion of people that chose to live in location i is increasing in the base wage w_i, again this makes intuitive sense: the gains to living in a particular location are determined by the base wage. Third, in this model the ratio of average wages do not depend on w_c/w_v. This is an implication of our Fréchet assumption. There are two effects at work when the ratio of base wages w_c/w_v rises: first, those that are in location c now receive higher relative wages; second, people from location v move to location c meaning that the average quality of workers decreases. The Fréchet assumption means that these two effects exactly offset each other. We believe that this makes the Fréchet assumption a natural benchmark, it also means that migration costs are easy to identify in the model. We do, however, explore generalisations that relax this assumption in our work below. Fourth, this reasoning also implies that the location with the lowest base wage has the highest average productivity: the only people that will stay in the village if it has a low base wage are those that are particularly well suited to the village.

We now extend this simple model to incorporate a cost of migration and an option to invest in human capital. Given the Fréchet assumption, the simplest way to add incorporate migration costs is as a multiplicative cost of living somewhere other than where you were born.[15] We assume that the cost of moving is $\tau > 1$, with $\tau = 1$ if you do not move. We provide micro foundations for this approach in the next section and also explore alternative micro foundations in the Appendix.

Incorporating migration costs, we have that an individual born in location o will migrate to location d if

$$\epsilon_i w_i > \frac{\epsilon_{-i} w_{-i}}{\tau}$$

which then implies that the portion of people from location o that choose to move to location d is

$$\pi_{do} = \frac{\left(\frac{w_d}{\tau}\right)^{\theta}}{\left(\frac{w_d}{\tau}\right)^{\theta} + w_o^{\theta}}.$$

This then implies that average productivity in the village is

$$E(\epsilon_v) = [\frac{\pi_{vv}}{\pi_{vv} + \pi_{vc}} \pi_{vv}^{-\frac{1}{\theta}} + \frac{\pi_{vc}}{\pi_{cc} + \pi_{cv}} \pi_{vc}^{-\frac{1}{\theta}}]\Gamma(1 - \frac{1}{\theta})$$

so that total economy productivity is

$$[(\pi_{vv} + \pi_{vc})E(\epsilon_v) + (\pi_{cv} + \pi_{cc})E(\epsilon_c)]\Gamma(1 - \frac{1}{\theta}).$$

This simple model highlights two costs of spatial misallocation, driven by τ:

1. People are in the wrong place: people with a higher ϵ_d instead live in location o;

2. People are in the less efficient place: suppose that $w_c > w_v$ then, conditional on weakly more people being born in the village, there will be too few people living in the city; and

[15] Ahlfeldt et al. (2014) pursue a similar approach for capturing commuting costs.

In addition to these possibilities, in the richer model presented below, base wages may depend on the portion of the population living in c through an agglomeration externality. Migration costs will reduce the degree to which the economy takes advantage of these externalities.[16]

3.2 Full model

We now turn to the full model of comparative advantage with a location choice over N locations. We describe the aggregate production technology; the determination of human capital and wages; and the determination of utility and migration. We conclude by defining the GE solution to the model. The model we present here is closely related to the work of Hsieh et al. (2013) who use the same basic selection model to consider the impact of discrimination on labor market productivity.

3.2.1 Production

There are a (discrete) set of locations (or migration destinations), $i \in N$. Each location i produces a differentiated variety of a good. Total economy wide production is given by

$$Y = \left(\sum_{i=1}^{N} q_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where q_i is the total output of the good produced in location i.[17] Output of good i depends on the amount of human capital in location i according to the function

$$q_i = A_i H_i$$

where H_i is the total human capital (or effective labor units) available at location i and

$$A_i = \bar{A}_i H_i^{\gamma}$$

[16]Migration costs are effectively a tax on a product that has a marginal social product higher than its marginal social cost.

[17]If $\sigma \to \infty$ all products are perfect substitutes, so the case in which all location produce the same good is a limit case of our model.

is the productivity of location i. In this formulation, $\bar{A}_i$ can be thought of as the intrinsic productivity of location i, which is an exogenous parameter. Current productivity, A_i depends on intrinsic productivity and the total amount of human capital in location i with γ parameterising the extent of human capital spillovers, or productive agglomeration externalities.

3.2.2 Human Capital and Wages

Human capital for any individual depends on a destination specific skill h_i, which we assume is drawn from a multivariate Fréchet distribution:

$$F(h_1, \ldots, h_N) = \exp\left\{ - \left[\sum_{i=1}^{N} h_i^{-\theta} \right]^{1-\rho} \right\}$$

where θ measures the extent of skill dispersion (dispersion increases as θ decreases) and ρ measures the correlation in skills across locations .[18] The interpretation is that each different location has a different set of required skills.[19] There is correlation because some people may be good at everything and the case in which talent is unidimensional is a limiting case as $\rho \to 1$.

We assume that labor markets are competitive and that firms are price takers and are paid p_i for each unit. As a consequence, each unit of skill is paid

$$w_i = p_i A_i.$$

meaning that a person living in designation i with skill level h_i earns a wage $w_i h_i$.

[18]Throughout we follow the convention that the first subscript denotes the location of production and the second subscript the workers origin.

[19]The model can be extended to allow for human capital accumulation; this is an additional channel through which migration costs can affect human capital accumulation. The model with human capital is presented in Appendix A.

3.2.3 Utility and Labor Sorting

Workers care about three things: the amenity of the location where they live and work, α_i; total consumption c; and the amount of time they spend at home, t. Amenity in location d is determined by the number of workers living in the location according to the function

$$\alpha_i = \bar{\alpha}_i L_i^{\lambda}$$

where L_i is the total number of workers living in destination i and λ parameterises the extent of congestions costs. As with productivity, amenity is endogenous and composed of an exogenous element – natural productivity $\bar{\alpha}$ – and a congestion costs which depends on the exogenous variable L_i.

Individuals do not internalise their impact on amenity, and utility of an individual born in location (or origin) g and living in destination i is given by

$$U_{ig} = \alpha_i c^{\beta} t^{1-\beta}.$$

Individuals choose $\hat{t}$ (the amount of time away from work) to maximise utility subject to

$$\hat{t} \leq T,$$

$$c = wh(T - \hat{t}),$$

and

$$t = \hat{t}(1 - \tau)$$

where T is the total time endowment, w the hourly wage per unit of skill and τ is the number of hours required to return home from the location of work.[20] This maximisation problem leads to the solution

$$\hat{t}^* = (1 - \beta)T,$$

[20] We think of this as follows: individuals must go home multiple times, for example every weekend. If the individual lives far from home, then they will spend a portion $1 - \tau$ of their weekend at home. We, therefore, have that $\tau_{ii} = 0$ for all i.

implying that a constant portion of time is spent at work, regardless of τ. This is convenient as it implies all workers work the same number of hours, so we can interpret $w_i h_i$ as the hourly wage.

Total consumption for an individual does not depend on whether they are from, and is given by

$$c = wh\beta T.$$

So, total utility for someone from o migrating to d is

$$U_{ig} = \left(w_i \beta (\alpha_i T)^{\frac{1}{\beta}} \left((1-\beta)(1-\tau_{ig}) \right)^{\frac{1-\beta}{\beta}} h_i \right)^{\beta} \equiv (\bar{w}_{ig} h_g)^{\beta}. \tag{1}$$

With this background, known results regarding the Fréchet distribution imply the following facts.[21] First, let π_{ig} be the portion of people from origin o that choose to work in designation d. We have

$$\pi_{ig} = \frac{\tilde{w}_{ig}^{\theta}}{\sum_{s=1}^{N} \tilde{w}_{sg}^{\theta}} \tag{2}$$

where $\tilde{w}_{ig} = w_i(\alpha_i(1-\tau_{ig})^{1-\beta})^{\frac{1}{\beta}}$. Equation (2) is the key sorting equation and it asserts that sorting depends on relative returns, relative amenities and relative transport costs.

Second, we can use this characterisation to determine the average quality of workers from g working in i by noting that

$$E(h_{ig} \mid choose\ i) = \left(\frac{1}{\pi_{ig}}\right)^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta(1-\rho)}\right). \tag{3}$$

This equation implies that the more people from location g that move to location i, the lower is the average skill. This is intuitive as it implies that there is less selection. Finally, we can work out the average wage in a particular location, first note that the average wage of someone from location i living in location g is

$$\overline{wage}_{ig} = w_i E(h_i \mid choosei) = w_i \left(\frac{1}{\pi_{ig}}\right)^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta(1-\rho)}\right). \tag{4}$$

[21] See, for example, Hsieh et al. (2013)

We can further simplify to

$$\overline{wage}_{ig} = \left(\frac{\sum_s \tilde{w}_{sg}^{\theta}}{\left(\alpha_i (1-\tau_{ig})^{(1-\beta)}\right)^{\frac{\theta}{\beta}}} \right)^{\frac{1}{\theta}} \Gamma\Big(1 - \frac{1}{\theta(1-\rho)}\Big). \tag{5}$$

This gives the result that the average wage does not depend directly on the base wage w_i. Intuitively there are two forces at work: first, when the base wage rises it increase the wage for those that are currently in that location, which tends to increase the average wage; second, it also increases the number of migrants, and these migrants will, on average, be of lower skill than those that had already migrated, which tends to decrease the average wage at the destination. A priori it is hard to predict which force will dominate. The Fréchet model implies that these forces exactly offset to leaving the average wage unchanged. We think this is a reasonable starting point for a model, and will see what the data says below.

3.2.4 Deriving the reduced form facts

Before closing the production side of the model, we show that the four reduced form facts are easily derived from this model of labor sorting.

1. Gravity: taking logs of the migration decision (Equation 2) yields:

   $$\log(\pi_{ig}) = \theta \log(w_i) + \frac{\theta(1-\eta)}{\beta} \log(\alpha_i) + \frac{\theta(1-\beta)(1-\eta)}{\beta} \log(1-\tau_{ig}) - \log\left(\sum_s \tilde{w}_{sg}^{\theta}\right)$$

   The first two terms, $\theta \log(w_i) + \frac{\theta(1-\eta)}{\beta} \log(\alpha_i)$ are common to a destination labor market, so can be controlled for by a destination fixed effect. The last term, $\log\left(\sum_s \tilde{w}_{sg}^{\theta}\right)$ is common across all migrants, so can be controlled for by an origin fixed effect.

2. Wage at destination depends on distance travelled: taking logs of the wage equation (Equation 4) yields:

   $$\log(\overline{wage}_{ig}) = \log(\overline{\gamma}) - \frac{1}{\beta} \log \alpha_i + \frac{-(1-\beta)}{\beta} \log(1-\tau_{ig}) + \frac{1}{\theta(1-\eta)} \log\left(\sum_s \tilde{w}_{sg}^{\theta}\right)$$

The first two terms are common to the destination labor market, so can be controlled for by a destination fixed effect. The last term is common across individuals from the same origin, so the prediction is that the further you travel (i.e. the larger is τ_{ig}) the higher the wage at destination.

3. Share of people migrating negatively predicts wage at destination:

$$\log(\overline{wage}_{ig}) = \log(\overline{\gamma}) + \frac{1}{1-\eta}\log(w_i) - \frac{1}{\theta(1-\eta)}\log(\pi_{ig})$$

Here, the first two terms are common across the destination, so can be controlled for with a destination fixed effect. The prediction is a negative coefficient for the share of population migrating.

3.2.5 Aggregate Demand and The GE Solution to the Model

Above we have discussed the decisions of workers and firms in each location. The model is completed by assuming that a representative firm purchases goods from each location to solve

$$\max_{q_i}\left[\left(\sum_{i=1}^{N} q_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} - p_i q_i\right].$$

Solving this problem yields the requirement that

$$p_i = \left(\frac{Y}{q_i}\right)^{\frac{1}{\sigma}} \tag{6}$$

indicating that the price is a decreasing function of the total supply from each location.

A general equilibrium is then a set of prices p_i, base wages w_i and an allocation of workers and skills across apace H_i and L_i such that labor and goods markets clear. Intuitively, wages determine how many people move to each location, which in turn determines productivity and output. This in turn determines prices according to equation (6). Formally, an equilibrium consists of: prices p_i; base wages w_i; labor supply L_i and human capital H_i , such that:

1. Consumers maximize utility

2. Producers maximize profit

3. Labor markets clear

4. Goods markets clear

This definition gives rise to the following equilibrium conditions:

$$\pi_{ig} = \frac{\tilde{w}_{ig}^{\theta}}{\sum_{s=1}^{N} \tilde{w}_{sg}^{\theta}} \tag{7}$$

$$w_i = p_i \bar{A}_i H_i^{\gamma+1}$$

$$p_i = \left(\frac{Y}{q_i}\right)^{\frac{1}{\sigma}}$$

$$H_i = \sum_j \hat{L}_j \pi_{ig} E(h_{ig} \mid chooses\ i)$$

$$L_i = \sum_j \hat{L}_j \pi_{ig}$$

We take this model of comparative advantage and endogenous selection to the empirical setting of Indonesia, to quantify the aggregate effects of labor misallocation.

4 Identification of model parameters

After constructing the model, we now show how we can identify the parameters that define the model. One advantage of our model is that closed forms are easily computed and so identification is relatively transparent. Roughly, the extent to which the portion of people from g that move to i reduces the wage at i recovers the Fréchet parameter characterising the distribution of talent. Both amenities and productivities affect the migration rate, but in our model, productivity does not affect the wage of migrants. This follows from a convenient, but perhaps specific, feature of our model: an increase in productivity in destination i has two effects: first, it raises the wages of those already live there, and second, it increases the influx of low skill migrants. In our model these effects exactly offset meaning the wage level identifies amenities. Hence, wage differences can be used to infer amenities, and with these measured, migration rates can be used to infer differences in productivity. Finally, any "wedge" between average wages for migrants and non-migrants that exists both for migrants from i to g and for migrants from g to i is, combined with low migration rates between the two location, interpreted as a migration cost. Our structural estimates give us, for each location in Indonesia: the level of amenity relative to a benchmark, an absolute measure of productivity, the cost of migration between each pair of places and the total amount of human capital current living in each location. These measures can be used to do simple decompositions of the spatial wage gap, or combined with the full computational model to undertake counterfactual exercises.

We estimate the underlying parameters determining amenities (α), productivity (A), migration costs (τ) and the spread and correlation of talent (θ, ρ). We set the parameters determining amenity and productivity spillovers (λ, γ), share of consumption in the utility function (β), elasticity of substitution (σ) exogenously. In addition, we set time allocation to 1 (L), and assume that mean of the Frechet distribution is normalized to 1 (T_{ij}). We are only able to identify amenities to scale; further we assume that migration costs are symmetric and that own-migration costs are zero. This leaves us with $\frac{N(N-1)}{2} + 2N + 1$ parameters to estimate. Table 1 summarizes the parameters and their meaning in the model.

4.1 Identification of model parameters

Our model of spatial sorting yields the following three equations that determine the spatial sorting equilibrium:

$$\pi_{ig} = \frac{\left(w_i \alpha_i^{\frac{(1-\eta)}{\beta}} (1 - \tau_{ig})^{\frac{(1-\beta)(1-\eta)}{\beta}} \right)^{\theta}}{\sum_s \left(w_s \alpha_s^{\frac{(1-\eta)}{\beta}} (1 - \tau_{sg})^{\frac{(1-\beta)(1-\eta)}{\beta}} \right)^{\theta}} \tag{8}$$

$$\overline{wage}_{ig} = \overline{\gamma} w_i^{\frac{1}{1-\eta}} \pi_{ig}^{\frac{-1}{(1-\eta)\theta}} \tag{9}$$

where $\overline{\gamma} = \left(\frac{\eta\beta}{1-\eta+\eta\beta}\right)^{\frac{\eta}{1-\eta}} \Gamma\left(1 - \frac{1}{\theta(1-\eta)(1-\rho)}\right)$ is a constant determining the Frechet distribution. Substituting Equation 8 into Equation 9 yields

$$\overline{wage}_{ig} = \overline{\gamma} \frac{\alpha_i^{\frac{-1}{\beta}} (1 - \tau_{ig})^{\frac{-(1-\beta)}{\beta}}}{\left(\sum_s \tilde{w}_{sg}^{\theta}\right)^{\frac{-1}{\theta(1-\eta)}}} \tag{10}$$

Equations 8, 9 and 10 together identify the migration costs, comparative advantage parameter, productivities and relative amenities determining the spatial equilibrium. We now show how these equations can be used to identify each of the structural parameters in the model.

4.1.1 Frechet parameter

From Equation 9 we have:

$$\log(\overline{wage}_{ig}) = \underbrace{\log \overline{\gamma} + \frac{1}{1-\eta} \log w_i}_{\text{Destination fixed effect}} - \frac{1}{\theta(1-\eta)} \log(\pi_{ig})$$

That is, after controlling for the average utility in the destination with a destination fixed effect, the elasticity of the average wage with respect to the proportion of migrants identifies the Frechet parameter θ. This channel operates through the selection margin: the larger the share of migrants, the lower the average quality, and so the lower the bilateral wage. How responsive the wage is to an increased inflow of migrants is determined by the spread of talent: intuitively, if people are more similar, then θ is high, so the marginal migrant is not very less skilled than the previous migrant, and so they earn a wage that is close to the previous migrant. However, if the talent dispersion is large, then the marginal migrant is much less skilled than the previous, and so their wage is lower.

4.1.2 Migration costs

In the model, migration costs accentuate the selection margin. Migration costs introduce a wedge between migrants and non-migrants in the destination: the migrants that have chosen to pay the migration cost and move have a higher unobserved quality, and therefore earn a higher wage in the destination than non-migrants. We use this to identify the costs of migration. To see this explicitly, use equation 12. The difference between the home and away wage, for both migrants and non-migrants, identifies the cost of moving between two locations, assuming that migration costs are symmetric and own-migration costs are zero:[22]

$$\log \frac{\pi_{ig}}{\pi_{gg}} = \theta \log \frac{w_i}{w_g} + \frac{\theta(1-\eta)}{\beta} \log \frac{\alpha_i}{\alpha_g} + \frac{\theta(1-\beta)(1-\eta)}{\beta} \log(1-\tau_{ig})$$
$$\log \frac{\pi_{gi}}{\pi_{ii}} = -\theta \log \frac{w_i}{w_g} - \frac{\theta(1-\eta)}{\beta} \log \frac{\alpha_i}{\alpha_g} + \frac{\theta(1-\beta)(1-\eta)}{\beta} \log(1-\tau_{ig})$$

Adding these two equations,

$$\log \frac{\pi_{ig}\pi_{gi}}{\pi_{gg}\pi_{ii}} = 2\frac{\theta(1-\beta)(1-\eta)}{\beta} \log(1-\tau_{ig})$$

4.1.3 Amenities

Amenities make a location more attractive for workers. Amenities are not a productive asset of a location. In the model, amenities have two effects: they make a location more attractive, hence increase the migration rate, and as a result they lower the observed wage because they cause more in-migration and therefore bring in lower-skilled migrants who earn a lower wage.

We identify amenities as the difference between home and away wages for both migrants and non-migrants. To see this, use equation 14:

$$\log \frac{\text{wage}_{ig}}{\text{wage}_{gg}} = -\frac{1}{\beta} \log \frac{\alpha_i}{\alpha_g} - \frac{(1-\beta)}{\beta} \log(1-\tau_{ig})$$
$$\log \frac{\text{wage}_{gi}}{\text{wage}_{ii}} = -\frac{1}{\beta} \log \frac{\alpha_i}{\alpha_g} - \frac{(1-\beta)}{\beta} \log(1-\tau_{ig})$$

[22] Migration costs can also be identified the same way from 14.

Subtracting these two equations,

$$\log \frac{\text{wage}_{ig}\text{wage}_{ii}}{\text{wage}_{gi}\text{wage}_{gg}} = -2\frac{1}{\beta}\log\frac{\alpha_i}{\alpha_g}$$

This equation identifies the relative amenities between any two locations. Because amenities are unobserved, we do not have any more information to pin down the levels of amenities. For this reason, we make a normalization that $\alpha_1 = 1$.

The identification of amenities relies on one property of the Frechet distribution: once the choice probabilities are substituted into the wage level, as in Equation 10, the wage in location i cancels out. This is a particular feature of the Frechet distribution: an increase in the wage in location i would increase migration rates, but the incoming migrants are lower quality. Under the Frechet distribution these two effects exactly offset, so as a result the wage does not appear directly. This is a strong assumption, but seems a reasonable starting point.

4.1.4 Productivities

The productivity of a location is identified using the observed wages and the observed migration flows: a higher wage attracts more migrants, and a higher productivity translates into higher wages. From Equation 13 we have

$$\log(\overline{wage}_{ig}) = \log(\overline{\gamma}) + \frac{1}{1-\eta}\log(w_i) - \frac{1}{\theta(1-\eta)}\log(\pi_{ig})$$

where $\overline{\gamma} = \left(\frac{\eta\beta}{1-\eta+\eta\beta}\right)^{\frac{\eta}{1-\eta}}\Gamma\left(1-\frac{1}{\theta(1-\eta)(1-\rho)}\right)$ is a constant determining the Frechet distribution. Once we identify ρ (see below), then we can identify w_i in levels from the above equation.

4.1.5 Separating absolute advantage from comparative advantage

Using properties of the Frechet distribution, we can derive:

$$\frac{\text{var}(w_{ig})}{\left(\text{mean}(w_{ig})\right)^2} = \frac{\Gamma\left(1 - \frac{2}{\theta(1-\rho)(1-\eta)}\right)}{\left(\Gamma\left(1 - \frac{1}{\theta(1-\rho)(1-\eta)}\right)\right)^2} - 1 \tag{11}$$

Using observed data w_{ig} and the value for θ we already identified, this equation identifies ρ.

4.2 System of linear equations

To estimate the model, we transform the model into a system of constrained linear equations. Taking logs of equations 9, 8 and 10, and letting $\mathbb{I}_i$ indicate a dummy variables for destination i, $\mathbb{I}_{ig}$ for the pair ig, and $\mathbb{I}_g$ for the origin g, we get the following sets of equations:

$$\begin{aligned}\log(\pi_{ig}) = {} & \underbrace{\theta \log(w_i) + \frac{\theta(1-\eta)}{\beta} \log(\alpha_i)}_{\beta_i^1} \mathbb{I}_i + \underbrace{\frac{\theta(1-\beta)(1-\eta)}{\beta} \log(1-\tau_{ig})}_{\beta_{ig}^1} \mathbb{I}_{ig} + \\ & \underbrace{-\log\left(\sum_s \tilde{w}_{sg}^{\theta}\right)}_{\beta_g^1} \mathbb{I}_g\end{aligned} \tag{12}$$

$$\log(\overline{wage}_{ig}) = \underbrace{\log(\overline{\gamma}) + \frac{1}{1-\eta} \log(w_i)}_{\beta_i^2} \mathbb{I}_i - \frac{1}{\theta(1-\eta)} \log(\pi_{ig}) \tag{13}$$

$$\log(\overline{wage}_{ig}) = \underbrace{\log(\overline{\gamma}) - \frac{1}{\beta} \log \alpha_i}_{\beta_i^3} \mathbb{I}_i + \underbrace{\frac{-(1-\beta)}{\beta} \log(1-\tau_{ig})}_{\beta_{ig}^3} \mathbb{I}_{ig} + \underbrace{\frac{1}{\theta(1-\eta)} \log\left(\sum_s \tilde{w}_{sg}^{\theta}\right)}_{\beta_g^3} \mathbb{I}_g \tag{14}$$

In addition, to pin down ρ we use the relationship between the mean and variance:

$$\frac{\text{variance}}{\text{mean}^2} = \frac{\Gamma\left(1 - \frac{2}{\theta(1-\rho)(1-\eta)}\right)}{\left(\Gamma\left(1 - \frac{1}{\theta(1-\rho)(1-\eta)}\right)\right)^2} - 1 \tag{15}$$

Given a candidate vector $\beta(\alpha_i, w_i, \tau_{ig}, \theta, \rho)$ we estimate the system of 4 equations by GMM.

5 Structural Estimation

This section discusses the structural results. We first look more closely at correlates of the estimated costs and amenities, before turning to the aggregate implications of our results.

5.1 Parameter estimates

The estimated structural parameters, for both the United States and Indonesia, are in Table 4. The estimated correlation in talent is high - approximately 0.8 for Indonesia, and approximately 0.9 for the United States, indicating potentially a large role for absolute advantage. The estimated dispersion parameter is between 14.8 and 19 for Indonesia, depending on year, and between 48 and 45 for the United States. Recall that a higher dispersion parameters reflects a less disperse talent distribution, and hence a lower potential role for comparative advantage. Table 4 also shows the mean migration iceberg cost. Here the are two key facts to notice: first, the estimated migration cost, accounting for missing values which we assign a migration cost equal to 1, is decreasing over time in Indonesia (from 0.6 in 1976 to 0.4 in 2012). Second, the estimated costs in the United States are lower than that of the Indonesia - the mean iceberg cost is 0.16 across 1990 and 2010.

Migration costs

We plot the distribution of the iceberg costs for Indonesia and the United States in Figure 3 for the two years that are closest - 1990 and 2010 for the US, and 1995 and 2011 for Indonesia. Migration costs, for both the United States and India, are correlated with distance. Figure 4 plots the estimated bilateral iceberg cost of migrating between two locations against the (log) of the distance between them. There is a positive correlation for both the US and Indonesia, with a stronger relationship in Indonesia.

We next look at other measures of distance between two locations. Using the census data, we construct indices of religious and linguistic similarity. This index is constructed by calculating that a person selected at random from the origin will have the same characteristic (e.g. have the same religion) as a person selected at random from the destination. For example, if the origin is 50% Hindu and 50% Muslim, and the destination is 100% Hindu, then the religious similarity index would be 0.5. If the destination was also 50% Hindu and 50% Muslim, then the index would also be 0.5. Figure 5 plots the partial effect of these similarity indices on iceberg costs, after controlling for the distance between two locations. Both are statistically significant: the more similar two locations are in religion, the lower the estimated cost of migrating between the two pairs; and the more similar the two locations are linguistically, the lower the estimated cost of migrating between them.

Amenities

As discussed, we identify amenities up to scale. We note two characteristics of our estimated amenities. First, amenities are negatively correlated with productivities: this is shown in Figure 6. The negative correlation holds for both the United States and Indonesia, and for all the years we estimate the model. Second, we use the Village Potential Statistics survey (PODES) to compute measures of amenities at the village level. Our estimated amenities generally correlate as expected with these "real-world" measures - for example, Figure 7 uses the 1996 PODES data and our estimated amenities from the 1995 SUPAS data, and shows that areas that have higher levels of pollution have lower estimated amenities.[23] We provide further correlations of our estimated amenities with other measures of amenities in Appendix Table 7. Here, each entry in the table is the regression coefficient from separate regression of estimated amenities on amenities. As we only have 25 estimated parameters we do not expect individual signs to necessarily be statistically significant, but we note the general pattern in these results: overall, measures of pollution are negatively correlated with amenities; measures of health outbreaks such as malaria, tuberculosis and vomiting and also negatively correlated with amenities, although access

[23]Note that the slope in the Air Pollution is not driven by outliers. Removing the point in the lower right corner of the graph, the slope of the regression line is -0.72, with a standard error of 0.65.

to health care facilities seems also be to negatively correlated, village lighting and commercial banks are positively correlated and we see a mixed pattern for natural disasters such as flooding and earthquakes.

5.2 Migration costs have aggregate implications

We now look at the aggregate implications of movement costs for productivity in Indonesia. Migration costs have been decreasing in Indonesia between 1976-2012. How much did this improve productivity through improving the allocation of labor to where it is most productive? To answer this question, we reestimate our model using the 1976 values for the underlying amenities, exogenous components of productive, but with the estimated 2012 migration costs. The results are in Table 5. GDP would have been 19% higher in 1976 if migration costs were at the 2012 levels. We repeat the same analysis for each of the three variables: amenities, productivities and migration costs. Increasing the exogenous component of amenities in 1976 to 2012 levels would have caused GDP to be 33% higher; productivities 42% higher.

How do these numbers compare to actual GDP growth over the period? Column (5) of Table 5 provide the level of GDP per capita, normalized to 1976 levels, constructed by the model. [24] Between 1976 and 2012 we see a growth in within-model per capita GDP of 300%. Taking the sum of the contribution only accruing to migration costs (19%), the contribution only accruing to amenities (33%) and the contribution only accruing to productivity growth (42%) yields an increase in GDP of 94%, suggesting a role for important complementarities between these variables.[25]

We repeat the same exercise for the United States. The table is deferred to the Appendix; Appendix Table 8. Here we see that almost all the growth in per capita GDP between 1990 and 2010 is explained by changes in productivities; we estimate that migration costs marginally increased between 1990 and 2010 reducing GDP.

[24] Our model matches the observed real wages in the data, and so captures the growth in real wages over this period. The growth in real wages is broadly consistent with other measures of economic activity, but doesn't line up completely: for example, according to the World Bank development indicators per capital GDP (deflated into real terms), real GDP per capita in Indonesia relative to 1976 was 3.3 in 1995, 7.9 in 2011 and 8.3 in 2012.

[25] In addition, the allocation of people at a point in time is also changing across each year.

Next, we ask what the implications could be in Indonesia had migration costs at the same level as the United States. To answer this, we rescale the estimated distribution of migration costs. We do this in two ways: first, we rescale the entire distribution to have the same mean and standard deviation ("rescaling distribution") in the United States. Second, we rescale the distribution assuming that the correlation between distance and migration costs is the same as it is in the United States ("parametric"). These two methods are illustrated in Figure 8.

Then, we use these adjusted costs to simulate the counterfactual level of GDP in Indonesia. The results are given in Table 6. Using US-level costs would increase GDP between 50-50%, and the results are very similar for the two methods of adjustment. To benchmark these estimates, real GDP per capita (in 2010 prices) in 2012 was $48,900 in the US, and $3,300 in Indonesia, leading to a per capita gap of 14.7. Improving the allocation of labor through reducing Indonesia migration costs would reduce the GDP gap between the countries by 4%.

6 Conclusion

The persistence of large wage differences across space is an ongoing economic puzzle: given returns to labor differ, why do people not migrate to increase their income? At one extreme, do wage gaps reflect a large misallocation of labor? Or, at the other extreme, are wage gaps efficient because they are caused by selection on unobserved productivity levels? And further, if these gaps are due to wedges, what are the implications for aggregate productivity? The policy implications are vastly different if wage gaps are due to costs rather than selection, and hence understanding the determinants of observed wage gaps is key to be able to design effective urbanization and rural policies in developing countries.

Our answer to this question is that both channels matter: there is evidence of selection, contributing to wage gaps, but at the same time there is also evidence of barriers to mobility which mean that randomly moving people across space could increase their wage. To show this, we construct and estimate a spatial equilibrium model with endogenous sorting for a large developing country, Indonesia.

To motivate our model, we show four facts in the data that appear consistent of a world in which both selection and migration costs are important. First, people are less likely to migrate to locations that are further away, consistent with a role of migration costs. Second, within destination, workers who are migrated further earn higher wages, consistent with a selection story. We then show that again, within destination, workers who come from an origin where relatively more workers have migrated to this destination earn a lower wage, again consistent with selection. Finally, controlling for both the share of population migrating as well as the distance, the wage effects are driven by the share migrating: this last fact is consistent with migration costs affecting the extensive margin, and hence average quality, of migration.

Next, to more fully characterize the sources of spatial wage gaps, we construct a general spatial equilibrium framework. Our model has four key features: i) workers draw location-specific productivity levels and select where they live and work to maximize utility, ii) there are costs of migrating, iv) locations offer different (partially endogenously determined) levels of amenity and, v) locations offer different (partially endogenously determined) levels of productivity. We show how migration costs can contribute to aggregate productivity losses by hindering the migration of labor to where it is most productive. We estimate the the model using detailed micro data from Indonesia and use the model estimates to undertake several counterfactual exercises.

We find that migration costs have quantitatively important aggregate effects. First, because we have four years of data we are able to understand what portion of GDP growth in Indonesia is caused by greater spatial integration of the labor market. We estimate that between 1976 and 2012 migration costs declined by 35% in Indonesia. We re-solve the model using parameters for 1976 imposing the migration costs from 2012 and find that the improved allocation of labor to where it is most productive explains approximately 20% of Indonesia's GDP growth over this period. Second, we consider what the GDP of Indonesia would be if average migration costs were the same as we find in the US. We find that migration costs in the United States are 60% smaller than in Indonesia. We then rescale our estimated migration costs in Indonesia to match the distribution of migration costs in the United States. This generates an increase in GDP per capita of 50% in Indonesia, a gap that is equivalent to 4% of the GDP per-capita gap between the United States and Indonesia. Our results suggest that policies that reduce the costs of migrating, such as improved access to infrastructure, could improve GDP as well as welfare by reducing the costs of people to move to where they have the highest gains.

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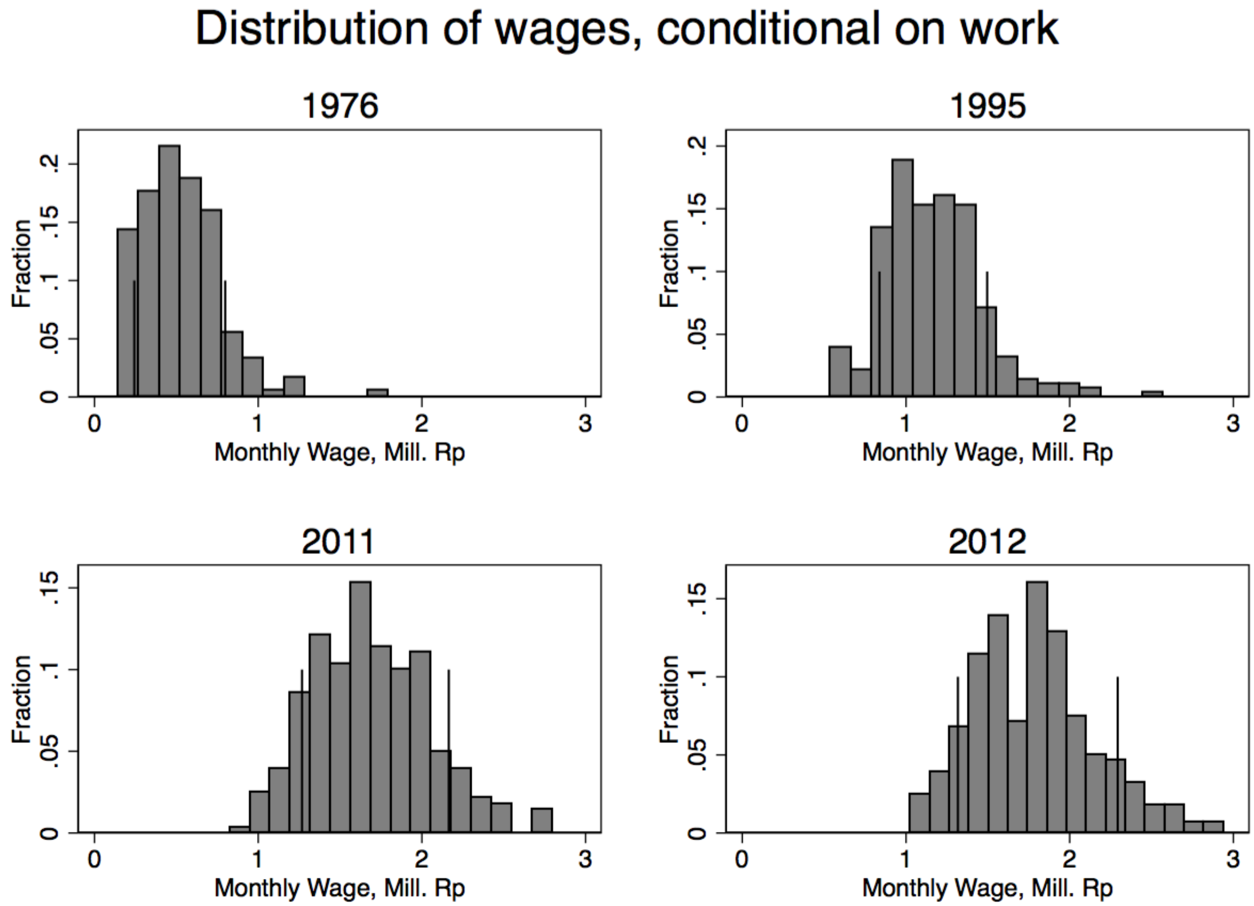

Figure 1: Spatial distribution of wages, Indonesia, 1976-2012

Figure shows the distribution of wage at the regency level. All values are in constant 2010 prices; 1 million rupiah approximately 85 USD.

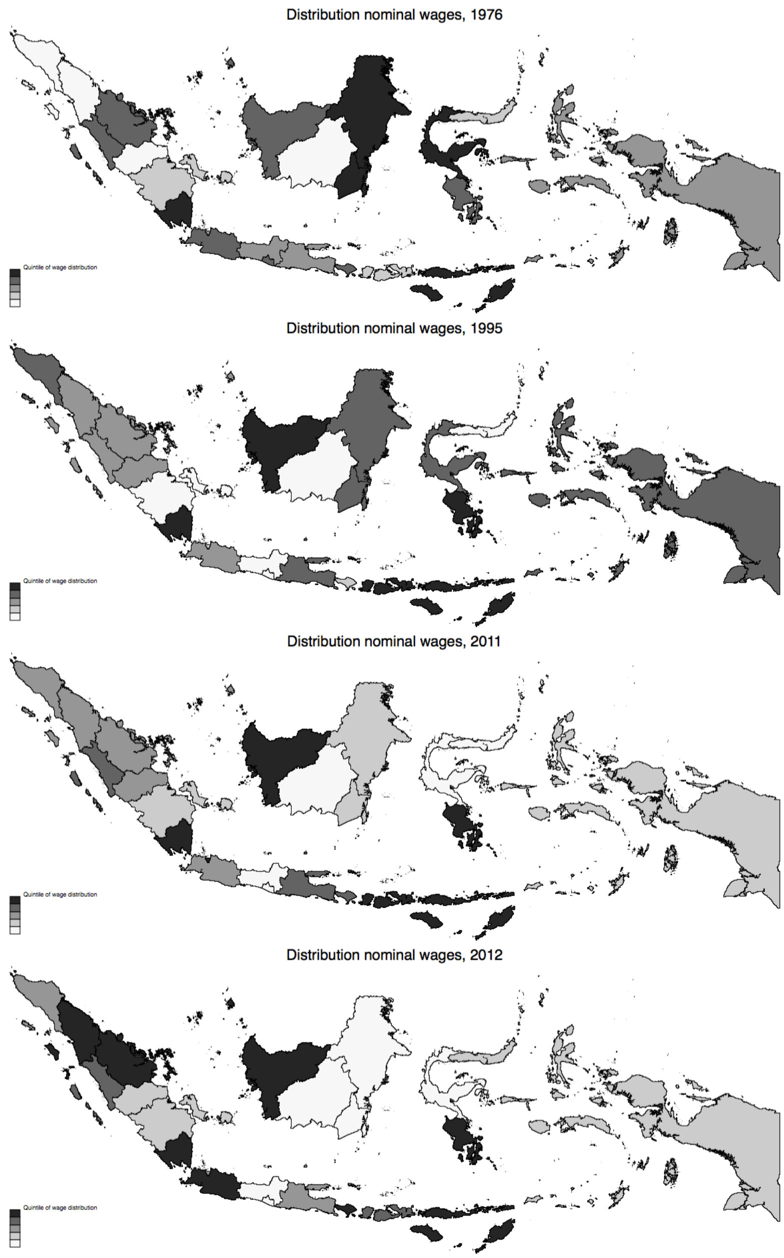

Figure 2: Map showing spatial distribution of wages, 1976-2012

Figure shows the mean nominal wage for each province. The distribution is divided into quintiles each year; with black representing the top quintile and light gray the lowest.

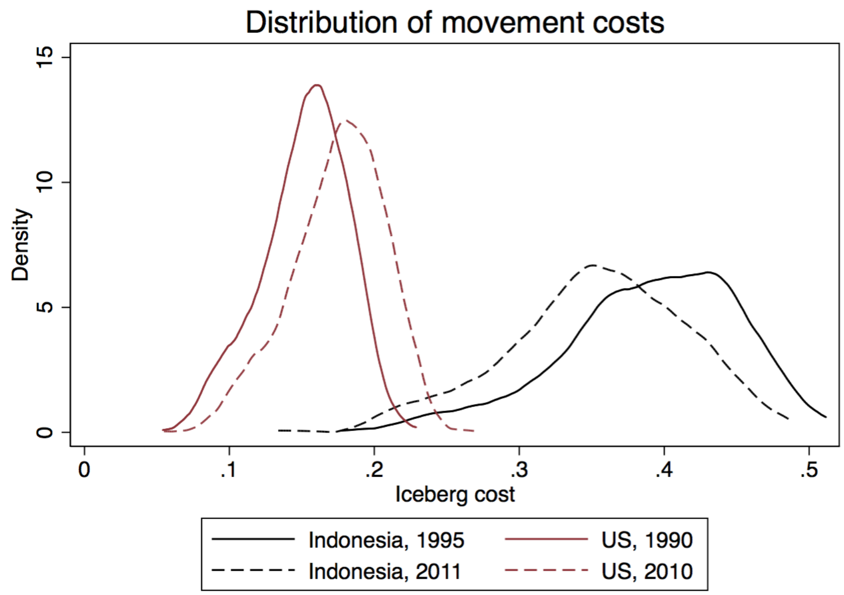

Figure 3: Distribution of estimated movement costs in Indonesia and the United States

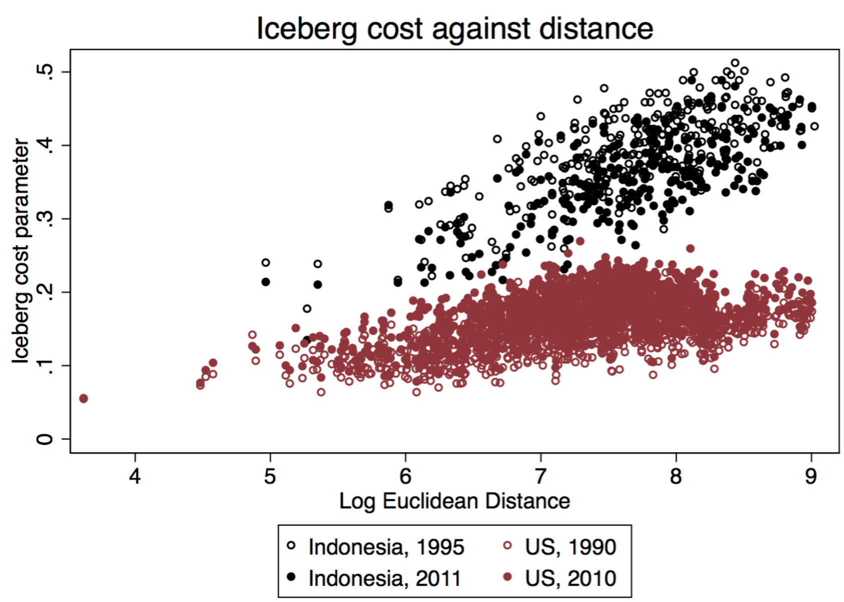

Figure 4: Relationship between iceberg costs and distance in Indonesia and the United States

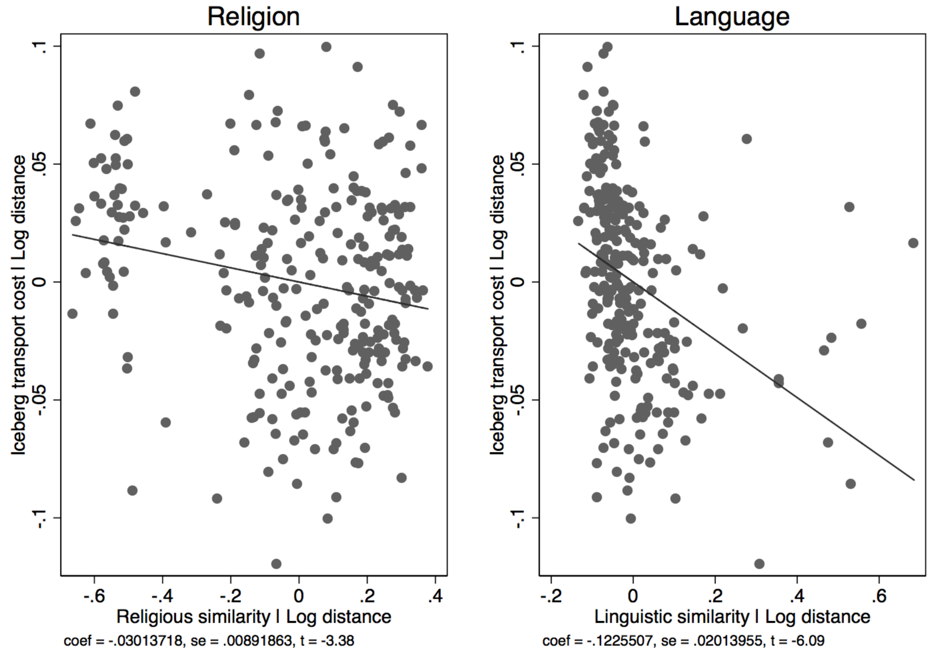

Figure 5: Partial regression plots of migration costs, controlling for log distance

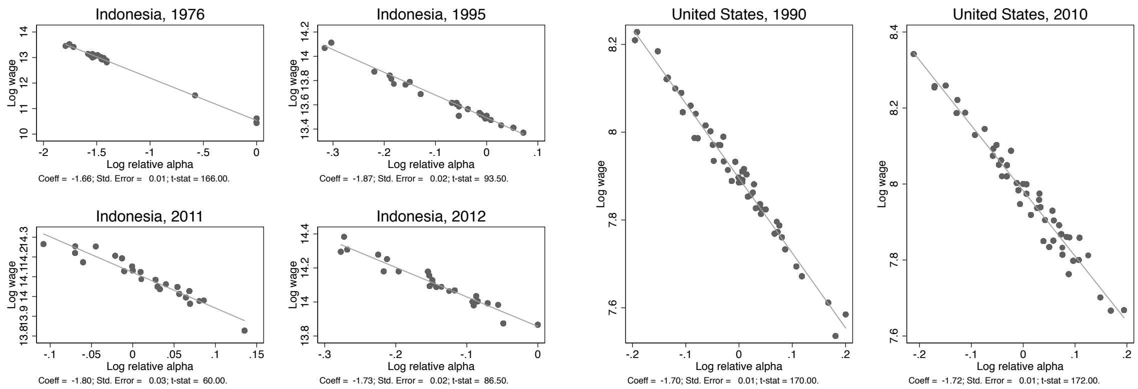

Figure 6: Amenities and wages negatively correlated

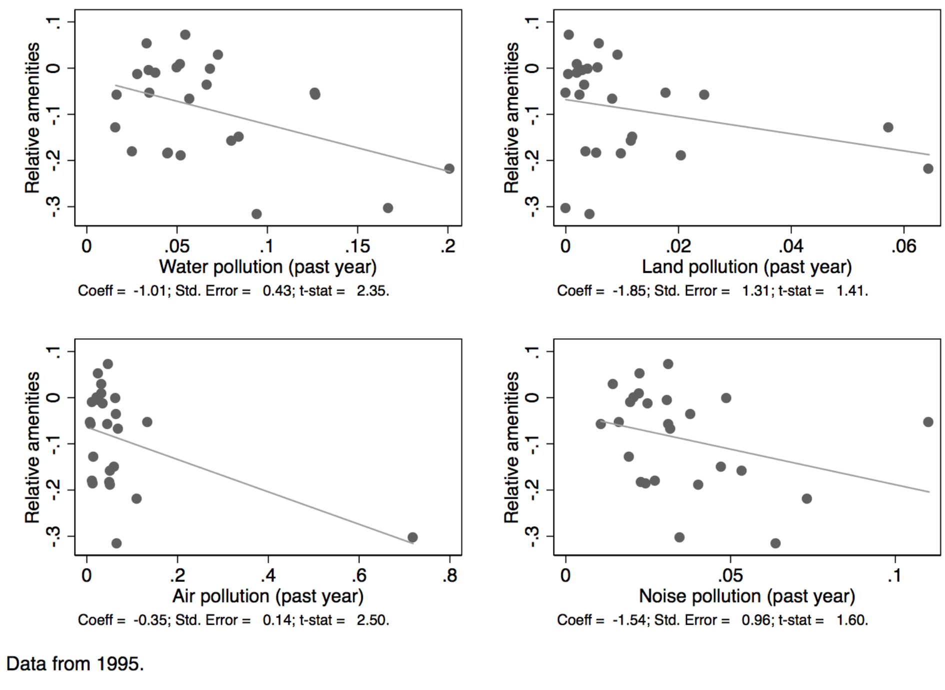

Figure 7: Amenities negatively correlated with pollution

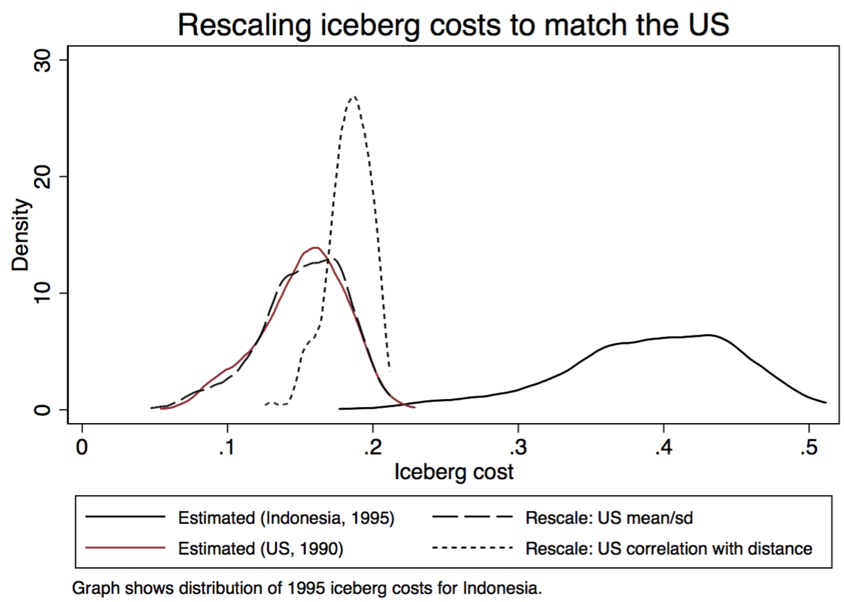

Figure 8: Rescaling the distribution

Table 1: Parameters of model

Type	Parameter	Usage	Number of parameters
Transport cost	τ_{ig}	$\tau_{ig} = \tau_{gi}; \tau_{ii} = 1$	$\frac{N(N-1)}{2}$
Base amenities	$\underline{\alpha}_i$	$\alpha_i = \underline{\alpha}_i L_i^{\lambda}; \underline{\alpha}_1 = 0$	N-1
Base productivity	$\underline{A}_i$	$w_i = A_i = \underline{A}_i H_i^{\gamma}$	N
Frechet	θ	Spread of talent	1
	ρ	Correlation of productivity	1
Set exogenously			
Time allocation	$L = 1$		
Frechet parameter	$T_{ij} = 1$		
Human capital	$\eta = 0$	e^{η}	
Congestion parameter	$\lambda =$	$\alpha_i = \underline{\alpha}_i L_i^{\lambda}$	
Agglomeration parameter	$\gamma =$	$w_i = A_i = \underline{A}_i H_i^{\gamma}$	
Utility function	$\beta =$	$c = \alpha_i c^{\beta} \tilde{l}^{1-\beta}$	
CES production fn	$\sigma =$	$Y = \left(\sum_i (A_i H_i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$	
Total			$\frac{N(N-1)}{2} + 2N + 1$

Table 2: The gravity equation

	(1)	(2)	(3)	(4)
	1976	1995	2011	2012
Dep var: Log Wage	b/se	b/se	b/se	b/se
Log Distance	-0.47***	-0.60***	-0.61***	-0.61***
	(0.0041)	(0.0017)	(0.0016)	(0.0016)
Destination FE	Yes	Yes	Yes	Yes
N	43160	166899	210373	210491

Notes: Regency

Table 3: Tests for selection and distance on wage

		1976			1995			2011			2012	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep var: Log Wage	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Log Distance	0.040***		-0.0035	0.038***		-0.0044**	0.036***		-0.0015	0.032***		0.0031*
	(0.0040)		(0.0045)	(0.0018)		(0.0021)	(0.0014)		(0.0015)	(0.0017)		(0.0018)
Log Proportion		-0.070***	-0.073***		-0.064***	-0.068***		-0.058***	-0.060***		-0.053***	-0.051***
		(0.0050)	(0.0064)		(0.0018)	(0.0024)		(0.0012)	(0.0019)		(0.0015)	(0.0023)
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
N	14883	14883	14883	58882	58882	58882	189972	189972	189972	67957	67957	67957
Correlation			-0.698			-0.750			-0.785			-0.782

Notes: Regency; Everyone.

Table 4: Estimated Frechet parameters

	Indonesia				United States	
	(1)	(2)	(3)	(4)	(5)	(6)
	1976	1995	2011	2012	1990	2010
ρ (correlation)	0.79***	0.81***	0.82***	0.83***	0.94***	0.93***
	(0.0072)	(0.0053)	(0.0096)	(0.0065)	(0.00038)	(0.00037)
θ (dispersion)	14.8***	16.6***	19.3***	19.0***	45.2***	37.9***
	(0.21)	(0.18)	(0.24)	(0.23)	(0.13)	(0.095)
Number missing migrant pairs	114	30	32	18	1	15
Mean mig cost (drop missing)	0.36	0.39	0.35	0.36	0.15	0.17
Mean mig cost (missing=1)	0.60	0.45	0.42	0.40	0.15	0.18

Notes: Income is at _month level.

Table 5: Productivity effects of changing migration costs, amenities and productivities, Indonesia

	(1) Use 1976	(2) Use 1995	(3) Use 2011	(4) Use 2012	(5) Per cap GDP (model)
Panel A: Migration costs					
1976	1.000	1.091	1.207	1.190	1.000
1995	0.991	1.000	1.106	1.093	2.175
2011	0.921	0.907	1.000	0.985	2.709
2012	0.919	0.913	1.016	1.000	3.006
Panel B: Amenities					
1976	1.000	1.251	1.305	1.333	1.000
1995	0.547	1.000	1.162	1.162	2.175
2011	0.656	1.040	1.000	1.068	2.709
2012	0.561	1.004	1.051	1.000	3.006
Panel C: Productivites					
1976	1.000	0.952	1.517	1.418	1.000
1995	0.633	1.000	1.575	1.537	2.175
2011	0.469	0.819	1.000	1.078	2.709
2012	0.462	0.771	1.047	1.000	3.006
Share cons. utility	0.600	0.600	0.600	0.600	
Amenity spillover	0.000	0.000	0.000	0.000	
Productivity spillover	0.050	0.050	0.050	0.050	
CES parameter	8.000	8.000	8.000	8.000	

Notes: Estimated at the province level. Estimates derived from structural results and GE solution to model. Wage type is month.

Table 6: Aggregate effects if had US migration costs in Indonesia

	(1) Rescaling distribution	(2) Parametric form	(3) Ratio GDP per cap (WB)
1995	1.553	1.543	31.006
2011	1.510	1.492	15.197
2012	1.566	1.543	14.655
Share cons. utility	0.600	0.600	
Amenity spillover	0.000	0.000	
Productivity spillover	0.050	0.050	
CES parameter	8.000	8.000	

Notes: Column (3) shows the ratio of real GDP per capita, in 2010 USD, calculated from deflating the nominal series from the World Bank Development Indicators Database and applying an exchange rate of 0.0001 IDR: 1 USD. Model is estimated at the province level. Estimates derived from structural results and GE solution to model. Wage type is month.

Appendix Table 1: Summary statistics, Indonesia

	(1) 1976	(2) 1995	(3) 2011	(4) 2012
Demographic				
Average age	40.34	41.01	42.39	42.62
Average age (migrant)	39.79	40.51	41.53	41.79
Share female	0.00	0.00	0.00	0.00
Share female (migrant)	0.00	0.00	0.00	0.00
Years school	3.30	6.17	7.80	8.00
Years school (migrant)	5.30	8.28	9.74	9.88
Financial				
Monthly wage	0.14	1.18	1.38	0.68
Monthly wage (drop zeros)	0.49	1.18	1.41	1.81
Monthly wage (migrant)	0.35	1.59	1.96	1.19
Monthly wage (migrant, drop zeros)	0.74	1.59	1.98	2.24
Migration				
Share migrating	0.20	0.26	0.25	0.26
Number of obs	43160	166899	210373	210491

Notes: Data source: 1976 SUPAS, 1995 SUPAS, 2011 SUSENAS and 2012 SUSENAS. All wages in constant millions of Rp. 1 mill Rp approximately 110 USD.

Appendix Table 2: Summary statistics, United States

	(1) 1990	(2) 2010
Demographic		
Average age	39.91	43.33
Average age (migrant)	40.35	43.76
Share female	0.00	0.00
Share female (migrant)	0.00	0.00
Years school	13.52	15.13
Years school (migrant)	14.08	15.52
Financial		
Monthly wage	4011.77	4210.91
Monthly wage (drop zeros)	4589.66	5087.33
Monthly wage (migrant)	4428.71	4853.11
Monthly wage (migrant, drop zeros)	5005.02	5765.82
Migration		
Share migrating	0.39	0.40
Number of obs	2154720	362756

Notes: Data source: 1990 Census and 2010 ACS survey. All wages in constant 2010 USD.

Appendix Table 3: The gravity equation (IFLS)

Dep var: Log Proportion Mig.	(1) 1993 b/se	(2) 1997 b/se	(3) 2000 b/se	(4) 2007 b/se
Log Distance	-0.27***	-0.26***	-0.30***	-0.32***
	(0.0076)	(0.0079)	(0.0071)	(0.0064)
Destination FE	Yes	Yes	Yes	Yes
N	5415	5442	6957	9018

Notes: Regency.

Appendix Table 4: Tests for selection and distance on wage (IFLS)

Dep var: Log Wage	(1) b/se	1993 (2) b/se	(3) b/se	(4) b/se	1997 (5) b/se	(6) b/se	(7) b/se	2000 (8) b/se	(9) b/se	(10) b/se	2007 (11) b/se	(12) b/se
Log Distance	0.040***		0.017	0.026**		0.014	0.031***		0.035***	0.024***		0.015**
	(0.014)		(0.012)	(0.011)		(0.0089)	(0.0089)		(0.0084)	(0.0076)		(0.0070)
Log Proportion		-0.082***	-0.066***		-0.085***	-0.072***		-0.076***	-0.044***		-0.084***	-0.071***
		(0.019)	(0.022)		(0.015)	(0.017)		(0.013)	(0.015)		(0.010)	(0.012)
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
N	3960	4006	4006	3792	3816	3816	5393	5431	5431	6967	7142	7142
Correlation			-0.606			-0.595			-0.618			-0.596

Notes: Regency; Everyone.

Appendix Table 5: The gravity equation (US)

Dep var: Log Wage	(1) 1990 b/se	(2) 2010 b/se
Log Distance	-1.17***	-1.00***
	(0.0012)	(0.0034)
Destination FE	Yes	Yes
N	817894	142331

Notes:

Appendix Table 6: Tests for selection and distance on wage: US

		1990			2010	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep var: Log Wage	b/se	b/se	b/se	b/se	b/se	b/se
Log Distance	0.016***		-0.029***	0.033***		-0.024***
	(0.0018)		(0.0029)	(0.0053)		(0.0082)
Log Proportion		-0.031***	-0.036***		-0.046***	-0.041***
		(0.00038)	(0.0021)		(0.0012)	(0.0064)
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	No	No	Yes	No	No
N	720134	1870318	720134	120033	300479	120033
Correlation			-0.279			-0.355

Notes: At state level; wage is _month

Appendix Table 7: Correlation of estimated amenities with data

	(1) 1995 b/se	(2) 2011 b/se	(3) 2012 b/se
Water pollution (past year)	-1.01** (0.43)	-0.12 (0.17)	-0.30 (0.21)
Land pollution (past year)	-1.85 (1.31)	-1.02 (0.73)	-2.12** (0.84)
Air pollution (past year)	-0.35** (0.14)	0.45** (0.19)	0.26 (0.25)
Noise pollution (past year)	-1.54 (0.96)		
Number of hospitals	-0.84*** (0.27)	-0.032 (0.12)	-0.20 (0.14)
Number of supported puskesmas	-0.0093 (0.14)	0.060 (0.061)	0.029 (0.078)
Number of doctors' practices	-0.028*** (0.011)	-0.0012 (0.0057)	-0.010 (0.0069)
Number of drug stores	-0.12*** (0.028)	-0.044 (0.062)	-0.14* (0.072)
Number of markets with permanent buildings	-0.30 (0.63)		
Main road village lighting	0.36 (0.34)	0.13 (0.15)	0.54*** (0.15)
Number of commerical banks	1.06 (1.73)	0.11 (0.69)	1.95** (0.76)
Has movie theater	-3.69 (3.73)	-4.54 (15.6)	-16.4 (19.2)
Ease of reaching hospital	-0.0038 (0.074)	-0.055 (0.048)	-0.0064 (0.062)
Ease of reaching puskesmas/other health facility	0.10 (0.13)	-0.076 (0.074)	-0.027 (0.094)
Ease of reaching market with permanent building	-0.016 (0.081)		
Ease of reaching shopping complex	-0.0053 (0.075)		
Number of commerical banks	1.06 (1.73)		
Flooding		0.033 (0.19)	-0.013 (0.23)
Earthquake		-0.030 (0.078)	-0.014 (0.098)
Whirlwind/tornado/hurricane		0.33** (0.14)	0.16 (0.20)
Drought		-0.85** (0.42)	-0.83 (0.54)
Outbreak (last year): Vomiting/diarrhea		-0.45* (0.26)	-0.67** (0.32)
Outbreak (last year): Malaria		-0.21 (0.15)	0.0077 (0.20)
Outbreak (last year): Bird flu (1 case is considered an outbreak)		3.94 (3.24)	-0.92 (4.17)
Outbreak (last year): Tuberculosis		-0.17 (0.43)	-0.96* (0.49)
Number of stores		0.0084** (0.0037)	0.0085* (0.0049)
Number of restaurants		-0.039 (0.11)	0.070 (0.14)
Number of hotels		0.032 (0.12)	-0.055 (0.15)

Notes:

Appendix Table 8: Productivity effects of changing migration costs, amenities and productivities, United States

	(1) Use 1990	(2) Use 2010	(3) Per cap GDP (model)
Panel A: Migration costs			
1990	1.000	0.858	1.000
2010	1.099	1.000	1.140
Panel B: Amenities			
1990	1.000	0.883	1.000
2010	1.010	1.000	1.140
Panel C: Productivites			
1990	1.000	1.173	1.000
2010	0.760	1.000	1.140
Share cons. utility	0.600	0.600	
Amenity spillover	0.000	0.000	
Productivity spillover	0.050	0.050	
CES parameter	8.000	8.000	

Notes: Estimated at the province level. Estimates derived from structural results and GE solution to model. Wage type is month.

A Model with education

– Need to fill this in