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? 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 2011 migration costs declined by 21% in Indonesia; the improved allocation of labor to where it is most productive explains a 37% increase in 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.

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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 five 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, iii) locations differ in how effective they are in creating human capital for children born there, 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 2011 migration costs declined by 21% in Indonesia; the improved allocation of labor to where it is most productive explains approximately a 37% increase in 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

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

migrant section is motivated by four, relatively novel, empirical facts about migration in Indonesia that link together 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 o who migrate to destination d is decreasing in the log of the distance between d and o.

2. *The further a migrant travels to a destination, the higher their wage:* Controlling for destination and origin fixed effects, 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 destination and origin fixed effect, the log of the wage is decreasing in the log of the portion of people from origin o that move to destination d. We again take this as consistent with selection: in our model higher migration costs from o to i will decrease the proportion of people born in o that move to d and these people will tend to have higher d 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 o to d and the distance from o to d are both included in a regression with the log of the wage on the left hand side, the importance of distance decreases, becoming insignificant, while the coefficient on the proportion of people moving remains largely 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 o to d 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.

We also show that these facts are broadly true in US data from the American Community Survey in 1990 and 2010 which we use as a source of comparison.

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 four 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); third, some places may be better at providing human capital for the children born there; and fourth, 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 skill: each worker is characterized by a productivity level for each location, drawn from a multivariate Fréchet distribution. This productivity also depends on the quality of institutions for improving human capital in their location of birth. 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]

[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

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 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 o that move to d reduces the wage at d recovers the Fréchet parameter characterising the distribution of talent. Both amenities and productivities affect the migration rate, but in our model, amenity does not affect the nominal wage of migrants once selection is controlled for. This allows for separate identification of amenities and productivities. Finally, any "wedge" between average wages for migrants and non-migrants that exists both for migrants from o to d and for migrants from d to o 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

simply as amenity or productivity.

[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.

measure of least cost transport cost, as well as with measures of the cultural and language 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 40% 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 an 80% increase in Indonesia's GDP 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. We also consider counterfactuals involving changes in amenity and find similar predictive power.

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, 2012). 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 mi-

[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).

gration may have aggregate implications. A key policy implication is reducing the costs 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 7 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 documents four facts that are consistent with wage gaps being driven both by movement costs and by selection.We document these facts using micro-level Census and survey data from Indonesia. The same data is used for the structural estimation. For comparison, we also replicate the specifications using the data from the US. This section first describes the data, and then documents the facts and discusses why they suggest a model in which movement costs reduce the flow of migrants and lead to selection on skill type.

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. To estimate the model we need data that documents an individuals current earrings as well as location of birth and current working location, preferably at a reasonable level of geographic disaggregation. 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 being 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, we understand that this will now be collected in all future SUSENAS surveys. 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.[8] We believe that Indonesia is the only developing country to have earnings and place of birth at a level smaller than the state available from one survey. For all surveys, we drop

[8] Regency is a second level administrated subdivision below a province and above a district.

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 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. [9] 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.[10] For the US, mean monthly wags are $4,600 in 1990, increasing to $5,100 in 2010. The migration rate (defined as state-level moves) is approximately 40%, and migrants have slightly higher years of education and earning approximately 10% higher than non-migrants.

[9]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.

[10]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.

2.2 Four facts linking migration, selection and costs

In this section we document four facts, which we think show that moving across space is costly and that the cost of movement lead to selection: only those types who would gain most are willing to pay the costs of movement. These facts motivate and are captured by the model we estimate in Section 5.

1. *Gravity:* If migration is costly, we expect that an increase in costs will decrease migration rates. To test this, we proxy migration cost with distance and document that a classic gravity relationship holds for Indonesian data.[11] That is, we estimate

$$\ln \pi_{do} = \alpha_d + \gamma_o + \beta \ln dist_{do} + \epsilon_{do}$$

   where π_{do} is the portion of people born in origin o who move to destination d, α_d and γ_o are destination and origin fixed effects, $dist_{do}$ is the euclidean distance between the centre or regency d and regency o and ϵ_{do} is an error term. We include origin fixed effects to control for the favourability of staying at the origin, or of migrating elsewhere from that particular location (similar to multilateral resistance in the trade literature), while destination fixed effects control for the productivity or amenity of the destination. We estimate the equation for the four years of SUPAS/SUSENAS data as well as for the 1993, 1997, 2000 and 2007 IFLS samples. 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 0.7 and 0.6 depending on the sample, the estimated coefficients are somewhat smaller for the IFLS sample. We interpret these results as confirming that there are costs of moving across Indonesia, and that costs are decreasing with distance.

2. *The further a migrant travels to a destination, the higher their wage:* The gravity equation itself is suggestive of selection: if there were no heterogeneity in migration returns or tastes then all people would move to the same place. To investigate whether

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

taste heterogeneity and/or return heterogeneity is driving the result, we run the regression

$$\ln w_{ido} = \alpha_d + \gamma_o + \beta \ln dist_{do} + \epsilon_{ido}.$$

where w_{ido} is the wage of person i in destination d from origin o. In this regression, the destination fixed effect controls for any fixed productivity differences across destinations, while the origin fixed effect controls for any human capital differences common to people from the same origin. Results from this regression 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. We see this second fact as consistent with selection on skill type. If workers are paid their marginal product, then the only way for distance to lead to higher average wages is if distance changes the composition of the marginal products of workers.

3. *The more people from an origin travel to a destination, the lower their wage:* If the argument above is correct, and distance affects the wage by altering the skill composition of workers, 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. To test this we estimate

$$\ln w_{ido} = \alpha_d + \gamma_o + \beta \ln \pi_{do} + \epsilon_{ido}$$

Results from this regression are also presented in Table 3 and show that the elasticity of the wage with respect to the proportion migrating is negative and between 0.055 and 0.085 depending on the year.

4. *The distance effect is not present after controlling for selection:* Our argument so far is that distance leads to fewer people migrating and that fewer people migrating means they are more selected, pushing up there wage. If this is correct, then distance should have no further effect on the wage after we control for selection, proxied

by the portion of people migrating.[12] To test this Table 3 presents results from the regression

$$\ln w_{ido} = \alpha_d + \gamma_o + \beta \ln \pi_{do} + \gamma \ln d_{do} + \epsilon_{ido}.$$

When we include both distance and proportion as predictors of the log wage we get support for the hypothesis that the distance effect is driven by selection. For 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, becoming insignificant. The results for the IFLS data presented in Appendix Table 4 and also support the same basic pattern. 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.

We see the results from this section as being suggestive of the presence of both selection on productivity levels and migration costs. The results are particularly suggestive of a model in which migration costs (proxied by distance) lead to selection, with the implication that those who pay higher migration costs receive higher wages. 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 set 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

[12] 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.

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 similar 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 presence of selection on producivity type, as well as 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, iii) locations offer different (partially endogenously determined) levels of amenity and, iv) locations offer different (partially endogenously determined) levels of productivity. In the following sections we describe the aggregate production technology; the determination of human capital and wages; and the determination of utility and migration. We then show that the model is consistent with the facts presented above, before defining the GE solution to the model. The model we present is closely related to the work of Hsieh et al. (2013) who use the same basic selection model to study the impact of discrimination on labor market productivity.[13] The model is also closely related to Ahlfeldt et al. (2014) which features a cost of movement,

[13]Hsieh et al. (2013) in turn draw heavily on the pioneering work of Eaton and Kortum (2002). See Costinot and Vogel (2014) for a review of the literature.

and worker selection, but concentrates on the commuting decision.

3.1 Production

We think of the economy as broken into a discrete set of locations N, each of which is a place of birth (or origin "o") and a potential migration destination "d". To ease notation, we generally index locations by d. Each destination produces a different good. Total economy wide production is given by the CES aggregate

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

where q_d is the total output of the good produced in location d, and σ captures the degree of substitutability between products.[14] Output of good d depends on the amount of human capital in location d according to the function

$$q_d = A_d H_d$$

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

$$A_d = \bar{A}_d H_d^{\gamma}$$

is the productivity of location d. In this formulation, $\bar{A}_d$ can be thought of as intrinsic productivity – an exogenous parameter, which may change over time. For example, New York may presently have high productivity due to its proximity to a port, but this may have been even more important 100 years ago. Current labor productivity, A_d depends on intrinsic productivity and the total amount of human capital in location d with γ parameterising the extent of human capital spillovers, or productive agglomeration externalities.

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

3.2 Human Capital and Wages

Human capital for any individual i born in origin o who chooses to work in destination d is

$$h_{doi} = s_{di} q_o$$

where q_o captures the quality of the human capital formation environment in o (for example basic nutrition or schooling availability) and s_{di} is a destination specific skill (a natural talent), which we assume is drawn from a multivariate Fréchet distribution

$$F(s_1, \ldots, s_N) = \exp\left\{ - \left[\sum_{d=1}^{N} s_d^{-\frac{\tilde{\theta}}{1-\rho}} \right]^{1-\rho} \right\}.$$

Here $\tilde{\theta}$ measures the extent of skill dispersion (dispersion increases as $\tilde{\theta}$ decreases) and ρ measures the correlation in skills across locations.[15] Throughout it is useful to work with $\theta = \tilde{\theta}/(1-\rho)$ rather than $\tilde{\theta}$, but we report results for $\tilde{\theta}$ as this corresponds to the Fréchet parameter often estimated in the trade literature when $\rho = 0$. The interpretation is that each different location has a different set of required skills. To the extent that the estimated $\tilde{\theta}$ is estimated to be high, then locations do not differ greatly in their skill requirements. We allow for correlation between skill draws because some people may be good at everything and the case in which talent is unidimensional is a limiting case as $\rho \to 1$.

All firms in location d produce a non-differentiated product and sell at price p_d, which they take as given. Within destination labor markets are assumed to be competitive, implying each unit of human capital is paid

$$w_d = p_d A_d$$

meaning that a person living in designation d with human capital level h_d earns a wage $w_d h_d$.

[15] The distribution has Fréchet marginals with parameter $\tilde{\theta}$ combined with a Gumbul copula with parameter $1/(1-\rho)$.

3.3 Utility and Labor Sorting

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

$$\alpha_d = \bar{\alpha}_d L_d^{\lambda}$$

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

Individuals do not internalise their impact on amenity, and utility of an individual born in origin o and living in destination d is given by

$$U_{do} = \alpha_d c^{\beta} t^{1-\beta}.$$

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 human capital and τ is the number of hours required to return home from the location of work.[16] This maximisation problem leads to the solution

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

[16] 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 $\tau_{oo} = 0$ for all o.

implying that a constant portion of time is spent at work, regardless of τ and s. Total consumption of an individual does not depend on where they are from, and is given by

$$c = wh\beta T.$$

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

$$U_{do} = \left(w_d \beta (\alpha_d T)^{\frac{1}{\beta}} \left((1-\beta)(1-\tau_{do})\right)^{\frac{1-\beta}{\beta}} s_d q_o \right)^{\beta} \equiv (\bar{w}_{do} s_d)^{\beta}. \tag{1}$$

With this background, known results regarding the Fréchet distribution imply the following facts.[17] First, let π_{do} be the portion of people from origin o that choose to work in designation d. We have

$$\pi_{do} = \frac{\tilde{w}_{do}^{\theta}}{\sum_{j=1}^{N} \tilde{w}_{jo}^{\theta}} \tag{2}$$

where $\tilde{w}_{do} = w_d (\alpha_d (1-\tau_{do})^{1-\beta})^{\frac{1}{\beta}}$. Equation (2) is the key sorting equation and it asserts that sorting depends on relative returns, relative amenities and relative transport costs – it does not depend on the quality of human capital formation in the origin, q_o.

Second, we can use this characterisation to determine the average skill of workers from o working in d by noting that

$$E(s_{do} \mid choose\ i) = \left(\frac{1}{\pi_{do}}\right)^{\frac{1}{\theta}} \bar{\Gamma}, \tag{3}$$

where $\bar{\Gamma} = \Gamma\Big(1 - \frac{1}{\theta(1-\rho)}\Big)$ and $\Gamma(\cdot)$ is the gamma function. This equation implies that the more people from o that move to d, the lower is their 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

$$\overline{wage}_{do} = w_d q_o E(s_d \mid choose\ \ d) = w_d q_o \left(\frac{1}{\pi_{do}}\right)^{\frac{1}{\theta}} \bar{\Gamma}. \tag{4}$$

Equations (2) and (4) are our main estimating equations.

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

We can further simplify (4) to

$$\overline{wage}_{do} = q_o \left(\frac{\sum_j \tilde{w}_{jo}^{\theta}}{\left(\alpha_d (1-\tau_{do})^{(1-\beta)}\right)^{\frac{\theta}{\beta}}} \right)^{\frac{1}{\theta}} \bar{\Gamma}, \tag{5}$$

which gives the result that the average wage does not depend directly on the base wage w_d. Intuitively there are two forces at work: first, when the base wage rises it increase the wage for those that are currently at the destination d, 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. A priori it is hard to predict which force will dominate. The Fréchet model implies that these forces exactly offset each other leaving the average wage unchanged.[18] As we discuss further below, this basic property implies that if there are average wage gaps between destinations, then these gaps must be driven by either differences in amenity or differences in movement costs. Thus, our model maintains a basic property of traditional models in urban economics: differences in average wages should be arbitraged away, unless there are frictions which prevent movement (in our case movement costs and amenity differences).

3.4 Deriving the reduced form facts

Before turning to the GE solution to the model, we show that the four reduced form facts are easily derived from this simple model of labor sorting.

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

$$\ln(\pi_{do}) = \theta \ln(w_d) + \frac{\theta}{\beta} \ln(\alpha_d) + \frac{\theta(1-\beta)}{\beta} \ln(1-\tau_{do}) - \ln\left(\sum_j \tilde{w}_{jo}^{\theta}\right). \tag{6}$$

   The first two terms, are common to a destination labor market, so can be controlled for by a destination fixed effect. The last term can be controlled for by an origin fixed effect. Hence, the model predicts that, after controlling for origin and destina-

[18] Similar implications from the Fréchet are noted in many papers. See, for example, Hsieh et al. (2013) and Young (2014).

tion fixed effect, higher movement costs between o and d lead to less migration. In documenting this fact above, we approximated movement costs with distance, but this need not be all that determines movement costs.

2. *The Distance Wage Effect*: taking logs of the wage equation (Equation 5) yields:

$$\ln(\overline{wage}_{do}) = \ln(\overline{\Gamma}) - \frac{1}{\beta}\ln\alpha_d - \frac{(1-\beta)}{\beta}\ln(1-\tau_{do}) + \frac{1}{\theta}\ln\left(\sum_j \tilde{w}^{\theta}_{jo}\right) + \ln(q_o).$$

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

3. *The Origin Proportion Wage Effect*:

$$\ln(\overline{wage}_{do}) = \ln(\overline{\Gamma}) + \ln(w_d) - \frac{1}{\theta}\ln(\pi_{od}) + \ln(q_o). \tag{7}$$

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

4. *The Proportion Effect Dominates*: After controlling for origin and destination fixed effects, as well as the proportion of people moving, equation (7) implies that movement costs between o and d should not predict average wages. In the model, the proportion effect dominates because movement costs have no direct impact on wages, their only effect is in determining the number of people who move, and hence the extent of selection.

As documented above, all four of these reduced for relationships are present in the data.

3.5 Aggregate Demand and The GE Solution to the Model

The model is closed by assuming that a representative firm (or consumer) purchases goods from each location (taking prices as given) to solve

$$\max_{q_d} \left[\left(\sum_{d=1}^{N} q_d^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} - p_d q_d \right].$$

First order conditions for this problem yield the requirement that

$$p_d = \left(\frac{Y}{q_d} \right)^{\frac{1}{\sigma}}, \tag{8}$$

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

Given an initial allocation of people $\hat{L}_o$ for each $o \in N$, a general equilibrium is a set of prices p_d, base wages w_d and an allocation of workers L_d and skills H_d across space such that labor markets clear in each location and goods markets clear across the economy. Intuitively, base wages determine how many people move to each location, which in turn determines productivity and output. This in turn determines prices according to equation (8); as more people move to a location goods supply increases, which pushes down prices and wages restoring equilibrium.

Formally, given an initial allocation $\hat{L}_o$, an equilibrium consists of, prices p_d; base wages w_d; labor supply L_d and human capital H_d for each location $d \in N$, such that:

1. Consumers maximize utility
$$\pi_{do} = \frac{\tilde{w}_{do}^{\theta}}{\sum_{j=1}^{N} \tilde{w}_{jo}^{\theta}}$$

2. Producers maximize profit
$$w_d = p_d \bar{A}_d H_d^{\gamma+1}$$
where
$$H_d = \sum_o q_o \hat{L}_o \pi_{do} E(h_{do} \mid chooses\ d)$$

3. Labor markets clear

$$L_d = \sum_o \hat{L}_o \pi_{do}$$

4. Goods markets clear

$$p_d = \left(\frac{Y}{q_d}\right)^{\frac{1}{\sigma}}.$$

4 Identification and Estimation

In our empirical application, we will use the data to identify $\{\theta, \rho, q_o, w_d, \alpha_d, \tau_{do}\}$ and will set $\{\gamma, \lambda, \sigma\}$ using estimates from the literature and commenting on robustness. In this section we show how we can identify $\{\theta, \rho, q_o, w_d, \tau_{do}\}$. To do this we have to make several normalizations. First, we assume that $\tau_{oo} = 0$ and $\tau_{do} = \tau_{od}$: movement costs are symmetric and it is costless to live at home. Second, we normalize $\alpha_1 = 1$: because we do not observe utility levels, the only variation we have to identify α comes from people's relative preferences for locations. Third, we normalize $q_1 = 1$: we identify only relative qualities of human capital generation. Intuitively this normalizes the wage w_d as well: the wage w_d is what would be earned by someone living at location d who was born in location 1 and who has a skill draw of 1.

The parameter β plays an important role in translating movement costs (measured in time) and amenities (measured in utils) into the same units as consumption and wages (dollars). To transform time into dollars we must take our estimates of $(1 - \tau)$ to the power $(1 - \beta)/\beta$. For amenities, we must take our estimates α to the power $1/\beta$ to turn them from dollars in to utils. Therefore, what we want to estimate is $(1 - \tau_{do})^{\frac{1-\beta}{\beta}}$ and $\alpha_d^{\frac{1}{\beta}}$. We show below that these are estimable from the data without knowledge of β and as a consequence we do not need to know β, either for the structural estimation or the counterfactual simulations.

One advantage of our model is that closed forms are easily computed and so identification is relatively transparent and intuition for identification is easy to give. Roughly, the extent to which the portion of people from o that move to d reduces the wage at d recovers the Fréchet parameter characterising the distribution of talent. Both amenities and productivities affect the migration rate, but as discussed above, productivity does not affect the wage of migrants. Hence, wage differences can be used to infer amenities, and with these measured, migration rates can be used to infer differences in productivity. Finally, assuming that movement costs are symmetric ($\tau_{do} = \tau_{od}$) any "wedge" between average wages for migrants and non-migrants that exists both for migrants from d to o *and* for migrants from o to d is, combined with low migration rates between the two location, interpreted as a movement 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, the quality of human capital in each location relative to a benchmark, and the total amount of human capital currently 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. To help with the discussion, Table 1 summarizes the parameters that we estimate and calibrate and their meaning in the model. We first discuss identification and then estimation.

4.1 Identification of model parameters

Identification of model parameters is based on the wage and sorting equations derived above. Identification does not require the GE solution to the model.

4.1.1 Frechet parameters: $\{\theta, \rho\}$

Repeating equation (7) for convenience we have

$$\ln(\overline{wage}_{do}) = \underbrace{\ln(\overline{\Gamma}) + \ln(w_d)}_{\text{Destination fixed effect}} - \frac{1}{\theta}\ln(\pi_{do}) + \underbrace{\ln(q_o)}_{\text{Origin fixed effect}} . \tag{9}$$

That is, after controlling for origin and destination fixed effects, the elasticity of the average wage with respect to the proportion of migrants identifies the Fréchet parameter θ. Variation in π_{do} is generated in the model by differences in the costs of migration and differences in ratio of productivities. Differences in the extent of selection then implies differences in average wages: the larger the share of the origin population that moves, the lower the average quality, and so the lower the average 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 (or destinations differ little in their skill needs), then θ is high, so the marginal migrant is not very less skilled than the previous migrant. However, if the talent dispersion is large (or there are large differences in the skill needs in different destinations), then the marginal migrant is much less skilled than the previous, and so their wage is lower.

To separate comparative and absolute advantage, the properties of the Fréchet distribution imply:

$$\frac{\mathrm{var}(w_{do})}{(\overline{wage}_{do}))^2} = \frac{\Gamma\left(1 - \frac{2}{\theta(1-\rho)(1-\eta)}\right)}{\left(\Gamma\left(1 - \frac{1}{\theta(1-\rho)(1-\eta)}\right)\right)^2} - 1. \tag{10}$$

Using data on individual wages, combined with the θ identified as above, this equation identifies ρ. Intuitively, if there is little correlation in skill types, so that everyone has some destination in which they excel, then the within destination origin pair wage variance will be low. If, in contest, the variance is high, then we believe that many people of different skill levels find the same place to be their best option, suggestion there is high dependence between skill draws and that ρ is high.

4.1.2 Location Characteristic Affecting the Wage: $\{w_d, q_o\}$

Considering again equation (9), because we know ρ and θ we can identify w_d in levels using the normalization that $q_1 = 1$. Intuitively, after controlling for selection through π_{do} and the quality of human capital through q_o any differences in wages between locations must be driven by differences in productivity. The quality of the human capital environment q_o can be similarly determined: after controlling for productivity differences the destination, as well as selection, any differences in wages earned by people from different origins must be accounted for by the relative quality of human capital formation opportunities.

4.1.3 Characteristics Affecting Movement: $\{\tau_{do}, \alpha_d\}$

Movement costs and amenity differences are recovered from the gravity relationship (6), we repeat the equation for ease of reference:

$$\ln(\pi_{do}) = \theta \ln(w_d) + \frac{\theta}{\beta} \ln(\alpha_d) + \frac{\theta(1-\beta)}{\beta} \ln(1-\tau_{do}) - \ln\left(\sum_j \tilde{w}_{jo}^{\theta}\right). \tag{11}$$

Identification of movement costs comes from low levels of movement relative to the amount of people staying home. Intuitively low movement could be caused by amenity difference, productivity differences or movement costs. Movement costs, however, are the only force which would lead both people from o to be unlikely to move to d *and* people from d to be unlikely to move to o. This intuition is confirmed by rearranding the gravity equation to give:

$$(\ln \pi_{do} - \ln \pi_{oo}) + (\ln \pi_{od} - \ln \pi_{dd}) - \ln(2) = \left(\frac{\theta(1-\beta)}{\beta}\right) \ln(1-\tau_{do}).$$

θ is identified as above, and β is calibrated implying that we can identify τ_{do} from this equation. Note here that we effectively estimate $(1-\tau_{do})^{\frac{1-\beta}{\beta}}$ which means we estimate the dollar costs of movement without needing to know β.

Finally, identification of relative amenities also comes from the gravity equation. Having identified w_d, θ and τ_{do} the only unknown in (11) are the α_d. Amenities are things which lead to skewed movement in a particular direction, but which do not cause changes in wages, after controlling for selection. We can only identify them up to a normalization because the amenities are also present in the term $\ln\left(\sum_j \tilde{w}_{jo}^{\theta}\right)$. Again, we esimate $\alpha_d^{\frac{1}{\beta}}$ which, as discussed above means we can estimate the dollar value of amenities without knowing β.

4.2 Estimation

To estimate the model, we assume that the observable data is measured with error. That is

$$\hat{\pi}_{do} = \pi_{do}\epsilon_{do}, \text{ and } \hat{wage}_{do} = \overline{wage}_{do}\eta_{do}$$

where $\hat{}$ denotes the measure observed in the data and ϵ_{do} and η_{do} are log normally distributed mean zero disturbances assumed to be uncorrelated with each other or any of independent variables. Denoting our vector of independent variables x we make use of the assumptions $E(\ln \eta\ x) = 0$ and $E(\ln \epsilon\ x) = 0$ to create $2(N(N-1))$ moment conditions. We combine these with an additional moment condition requiring that

$$E\left(\frac{\text{var}(w_{do})}{(\hat{wage}_{do})^2}\right) - \left(\frac{\Gamma\left(1 - \frac{2}{\theta(1-\rho)(1-\eta)}\right)}{\left(\Gamma\left(1 - \frac{1}{\theta(1-\rho)(1-\eta)}\right)\right)^2} - 1\right) = 0,$$

and estimate by GMM. When doing so, we ensure that the term $\ln\left(\sum_j \tilde{w}_{jo}^{\theta}\right)$ in equation (11) is consistent with the model.

In implementing the procedure we make several adjustments. First, if there is no movement in either direction between a pair do then we set $\tau_{do} = 1$. Second, if there is movement in only one direction, we are still able to estimate τ_{do} because we can estimate the fixed effects w_d, α_d and q_o using other equations. Third, if fewer than five people migrate between two locations do then we do not use data on the wage for those migrants in our estimation. This limits the impact of outliers on estimated parameters.

5 Estimation Results

5.1 Parameter estimates

The next sections present our parameter estimates. Recall that for these estimate we do not need to take a stand on the value of the exogenous parameters $\{\sigma, \gamma, \lambda\}$. Also, as argued above, β serves merely to transform variables between time, utils and money. All the parameters we present are in terms of money.

5.2 Fréchet Parameters

Table 4 presents out estimates of ρ and $\tilde{\theta}$ for both Indonesia and the US. The estimated correlation in talent is high - approximately 0.8 for Indonesia, and approximately 0.9 for the United States. These results, which are driven by a high variance in within origin/destination pair wages suggest that there is a lot of dependence in the skill distribution: those who are good in one places, are also good in other places. We estimate a high ρ because the within destination original pair wage variance is high relative to the mean wage. The estimated dispersion parameter is around 3 for Indonesia and a little less than 3 for the US. Recall that a higher dispersion parameter reflects a less disperse talent distribution, and hence a lower potential role for comparative advantage. Figure 5 shows one hundred draws from a bivariate version of the distribution for Indonesia in 2011 and the US in 2010, each axis shows a draw s of a different location. Overall, we find that there is high dependence in the data, people who have high skill in one location have high skill in all locations, this is particularly true in the US. There are also large skill differences across people driven by the high ρ.

5.3 Migration costs

Table 4 shows the mean migration 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 0.59 in 1976 to 0.35 in 2012). These are large costs. As discussed above, the units are monetary and hence the results implies that the average district to district move in 2012 would need to be compensated with about a 60% pay rise. Second, the estimated costs in the United States are lower than that of the Indonesia - the mean iceberg cost is between 0.18 and 0.16 across 1990 and 2010. This implies that the average state to state move in the US would need to be compensated with about a 15-10% pay rise.

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.[19] We see two points. First, in addition to having higher mean movement costs, Indonesia also has greater dispersion in movement costs. Second, reduction in movement costs in Indonesia have been across the board: the distribution has shifted to the left.

Migration costs, for both the United States and Indonesia, are also 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. Particularly striking is the much lower correlation between distance and movement costs in the US. This could be caused by several mechanisms. First, it may be that actual transportation costs are cheaper in the US. Second, it may be that people in the US are more welcoming of migrants from more physically distant communities.

Our measured movement costs are also correlated with measures of social distance between locations. Using the census data, we construct indices of religious and linguistic similarity. This index is constructed by calculating the probability that a person selected at random from the origin will have the same characteristic (religion or language) 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 6 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.

5.4 Amenities

As discussed above, we identify amenities up to scale. We note two characteristics of our estimated amenities. First, amenities are negatively correlated with productivities: this is

[19] The plots to do not show the costs that are estimated to be 1, because we see no migration in either direction.

shown in Figure 7. The negative correlation holds for both the United States and Indonesia, and for all the years we estimate the model. This correlation implies that places that are most productive are also places that are least pleasant to live, and amenity differences across space are therefore mean that some people choose not to live and work in the most productive places. Recalling our identification discussion above, the negative correlation occurs because places we estimate to have high productivity (high wages after controlling for workers selection) do not attract as many migrants as the high wages would imply. A negative correlation of this sort is implied by the equilibrium logic of the model: a very productive place will see more migrants, which will tend to decreases the amenity of living in that location.Policies that reduce the amenity/productivity correlation are potential sources of productivity growth.

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 8 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.[20] 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 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.

[20] 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.

6 Aggregate implications

Our structural estimates imply two broad facts about spatial labor market integration in Indonesia. First, it appears that spatial integration of the labor market has improved over time: movement costs have decreased across the board, and the negative correlation between amenity and productivity has also decreased.Second, costs of moving across space are higher in Indonesia in the US. In this section we explore the implications of these facts for changes in Indonesia's labor productivity over time and the relative productivity of Indonesia and the US.. We begin by discussing how we choose the three remaining parameters $\{\gamma, \lambda, \sigma\}$.

6.1 Exogenous Parameters: $\{\gamma, \lambda, \sigma\}$.

We set the remaining exogenous parameters using estimates from the literature, and then consider how sensitive our results are to these estimates.

There is a large literature which attempts to estimate agglomeration effect (γ) across many countries. The literature is reviewed in Rosenthal and Strange (2004) and Combes and Gobillon (2014). Recent consensus estimates suggest a γ of between 0.01 and 0.02 for the developed world, although some studies (e.g. Greenstone et al. (2010)) suggest much higher numbers. Estimates for developing countries are more sparse and suggest a γ up to 1. We present our main estimate for $\gamma = 0.05$, but also consider robustness for numbers between 0 and 0.08. We expect that spatial integration will be more important when γ is high.

A much smaller literature attempts to estimate λ. On one hand, the work in Albouy (2012) could be seen as suggesting that $\lambda = 0$ in the US. In contrast, work by Combes et al. suggests a λ of around -0.04. We take 0 as our starting point and consider values beteween 0 and -0.08. As λ decreases (as congestion becomes more important), we expect that movement costs will become less important because it will be hard to move people in to productive areas even if movement costs are low.

Accurate estimates the elasticity of substitution across regions are also hard to obtain. Allen and Arkolakis (2014) use a figure of 8 and we follow them in our main results. We also consider values between 2 and 8. We expect that as σ increases there will be larger benefits to spatial integration: a high elasticity of substitution means that the products from different locations become less substitutable and so there are larger costs to low production of some goods.

6.2 Counterfactual Experiments

Changes Over Time

In this section we consider how much of the labor productivity growth in Indonesia over time can be accounted for by improvements in labor market integration over time. We first consider the impact of decreasing movement costs. To estimate the aggregate implications of decreasing movement costs we estimate the model for a particular year (e.g. 1995) and keeping everything else constant (base wages w_d, amenities α_d, and human capital q_o) we consider the impact of changing movement costs to those estimated from another year (e.g. 2011). These can be compared to the change in GDP (Y) from the model over the same time period. Results from this exercise are reported in panel A of Table 5 with robustness to alternative values of the exogenous variables reported in Appendix Table 9. We note two things. As a source of comparison, panel c of the table reports the change in GDP accounted for by changes in the base wages w_d over time. We compute relatively large impacts of reduced movement costs. As noted earlier, movement costs decrease between 76 and 2011, and we calculate that this leads to an 34% increase in output. The change from 95 to 2011 is smaller, but still substantial at 27%. This compares with 420% increase in labor productivity from 1976 to 2011.

The results in Appendix Table 9 suggest that the results are robust to different choices of the exogenous variables: changes are as expected with larger estimates for higher elasticities of substitution, smaller congestion externalities and larger agglomeration externalities, but the differences are not quantitatively large.

Second, we consider the effect of changes in amenities over time. If high productivity places have become more pleasant places to live, then we expect to see increase in overall productivity. To investigate we run experiments similar to those for migration costs: keeping everything else constant we replace relative amenities estimated in one year with amenities from a different year. Panel B of Table 5 shows results of the experiments. Again, the impacts are reasonably large. The change in amenities from 1976 to 2011 accounts for a 38% increase increase in labor productivity, while from 1995 to 2011 we ascribe a 8% increase in labor productivity to changes in amenities.

By way of comparison, we also look at the change in labor productivity caused by a change in labor productivities w_d over time, keeping amenities and movement costs fixed. These effects are larger than those due to amenity, but are of the same order of magnitude It should be noted that there is a potential complementarity or substitutability between changes in the model. For example, a particular change in productivities may be enhanced by a reduction in movement costs. In particular, changes in productivities in urban areas may be more effective in raising labor productivity if it is less costly to move to those areas. Hence, each adding the three changes, those due to movement costs, amenities and productivities over time, does not necessarily add up to the size of the change in labor productivity over time. Overall, our results suggest that a large portion of the increase in labor productivity over time can be accounted for by improvements in labor market integration.

For completeness, we repeat the same exercises for the United States. The table is deferred to the Appendix; Appendix Table 8. The model calculates a 32% increase in GDP over the period 1990 - 2010.We calculate a 34% increase due to only a decrease in movement costs. In contrast, and inline with the work of Hsieh and Moretti (2015) we see a worsening of the situation with respect to amenities, the model implies that higher productivity locations have seen a relative reduction in their amenity with the impact of a 11% reduction in labor productivity. Hsieh and Moretti (2015) ascribe this fact to housing market policies that push up housing prices in high productivity areas. By way of comparison, we calculate that increasing productivity alone would have increased GDP by 125%. In the US case it appears that improved mobility and increased productivity have been substitutes over this period.

Relative to the US

Next, we apply model to understanding the productivity differences between Indonesia and the US. In particular, we ask what labor productivity would be in Indonesia if it had migration costs at the same level as the United States in 2010. To answer this question, 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 9. We then use these adjusted costs to simulate the counterfactual level of GDP in Indonesia. The results are given in Table 6. We estimate that if Indonesia had as low movement costs as the US then its GDP would be between 45 and 60% higher than currently. While this number is large, it is small in comparison to the current 140% gap between the two countries.

7 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 2011 migration costs declined by 21% 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 a 37% increase in 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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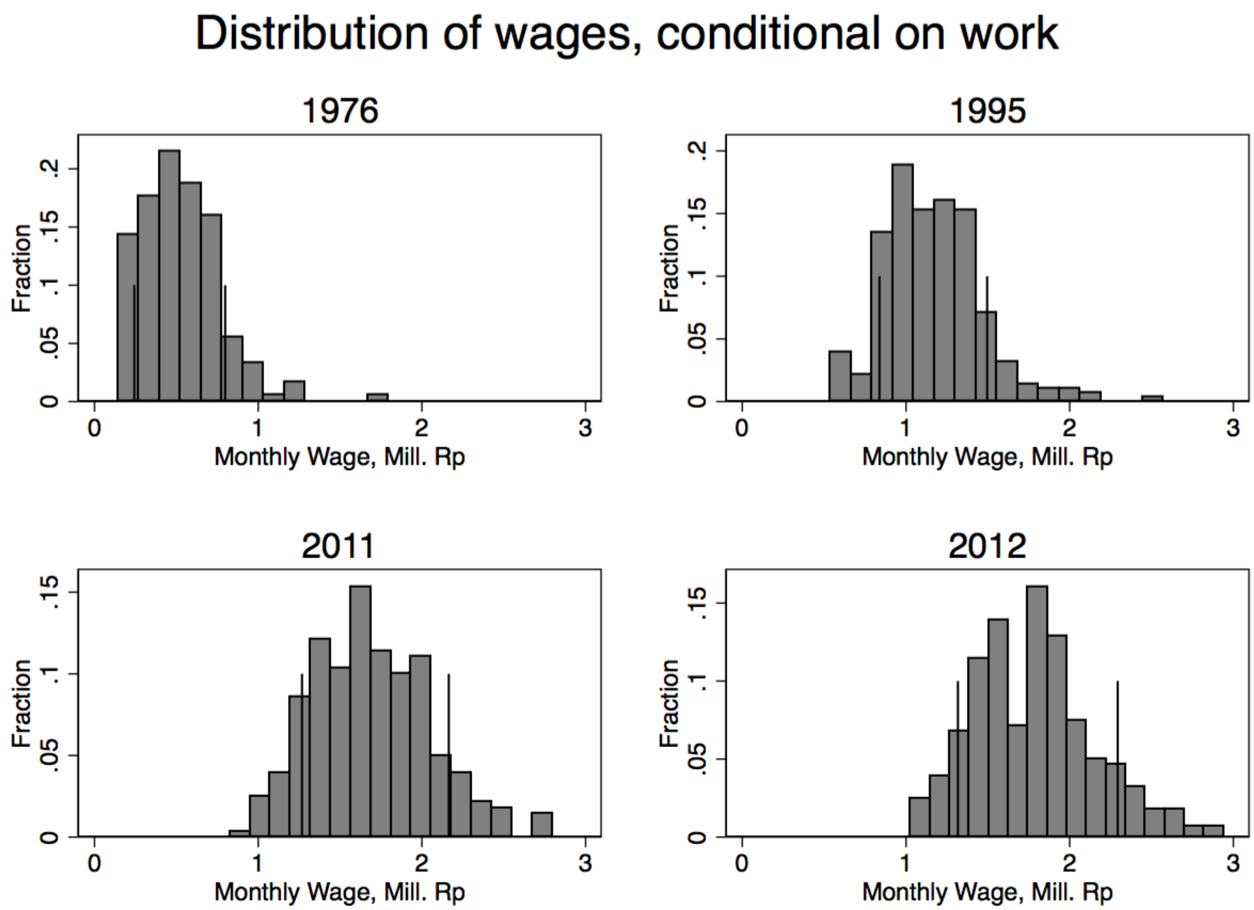

Figure 1: Spatial distribution of wages, Indonesia, 1976-2012

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

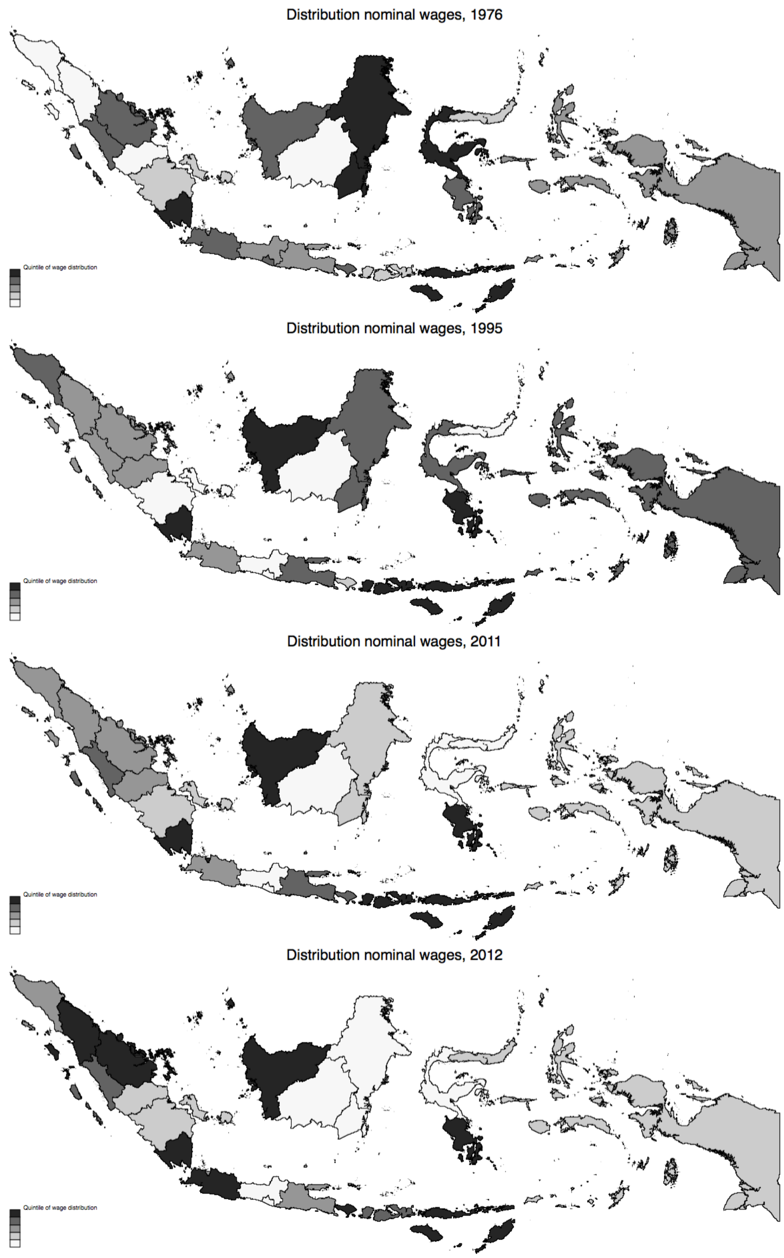

Figure 2: Map showing spatial distribution of wages, 1976-2012

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.

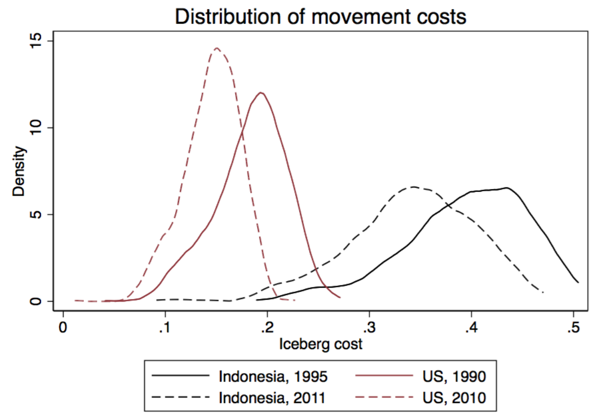

Figure 3: Distribution of estimated movement costs in Indonesia and the United States

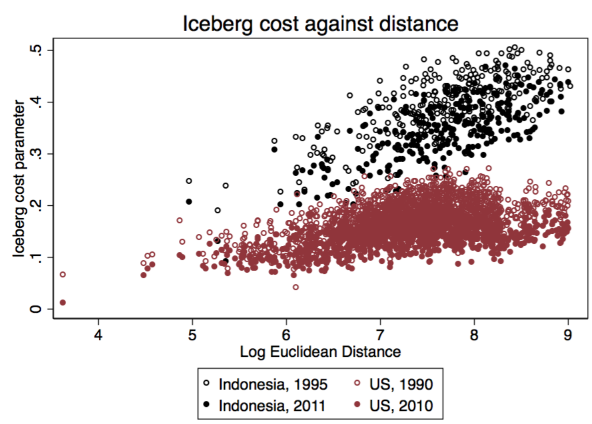

Figure 4: Relationship between iceberg costs and distance in Indonesia and the United States

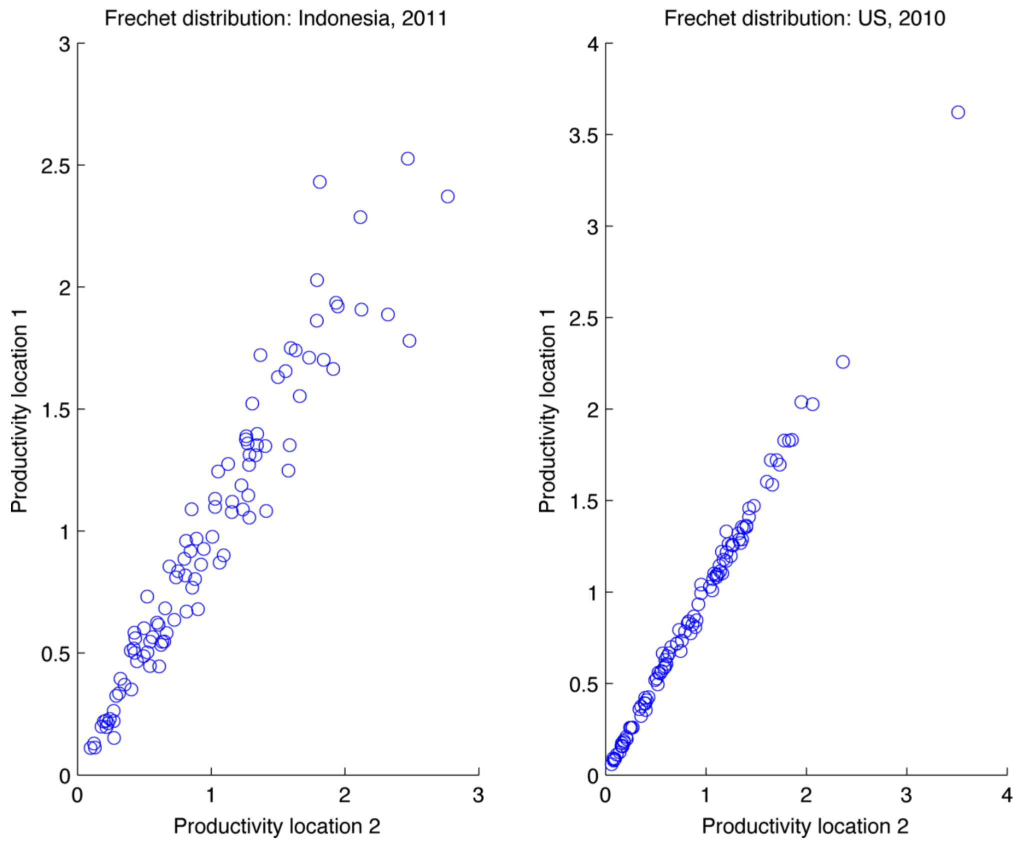

Figure 5: Simulated Frechet Distribution

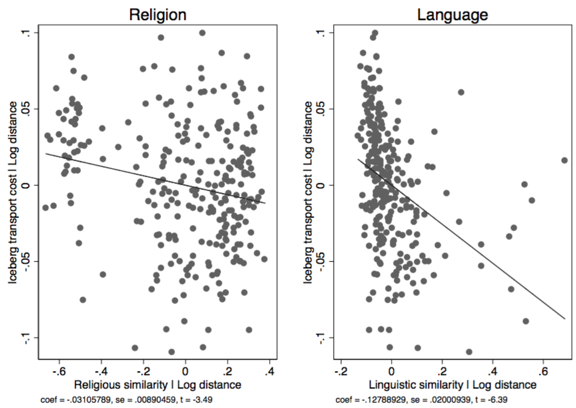

Figure 6: Partial regression plots of migration costs, controlling for log distance

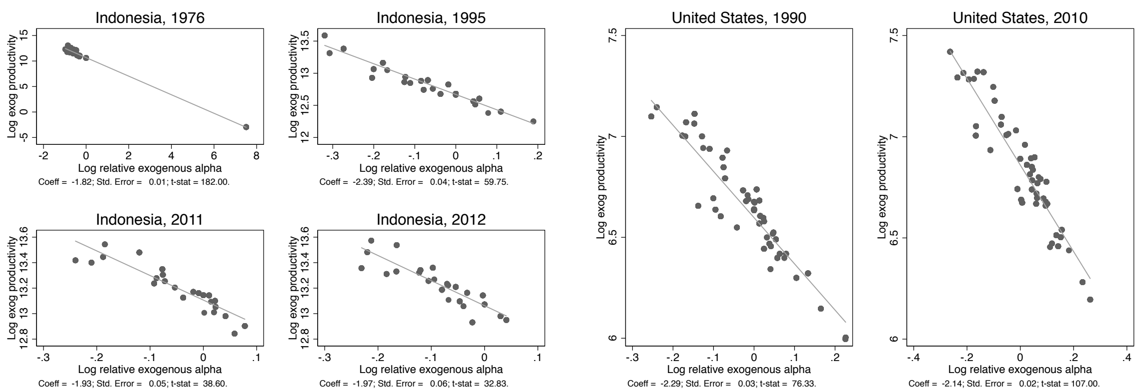

Figure 7: Amenities and wages negatively correlated

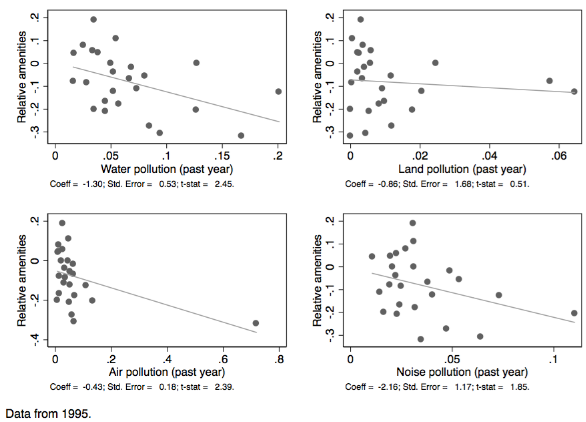

Figure 8: Amenities negatively correlated with pollution

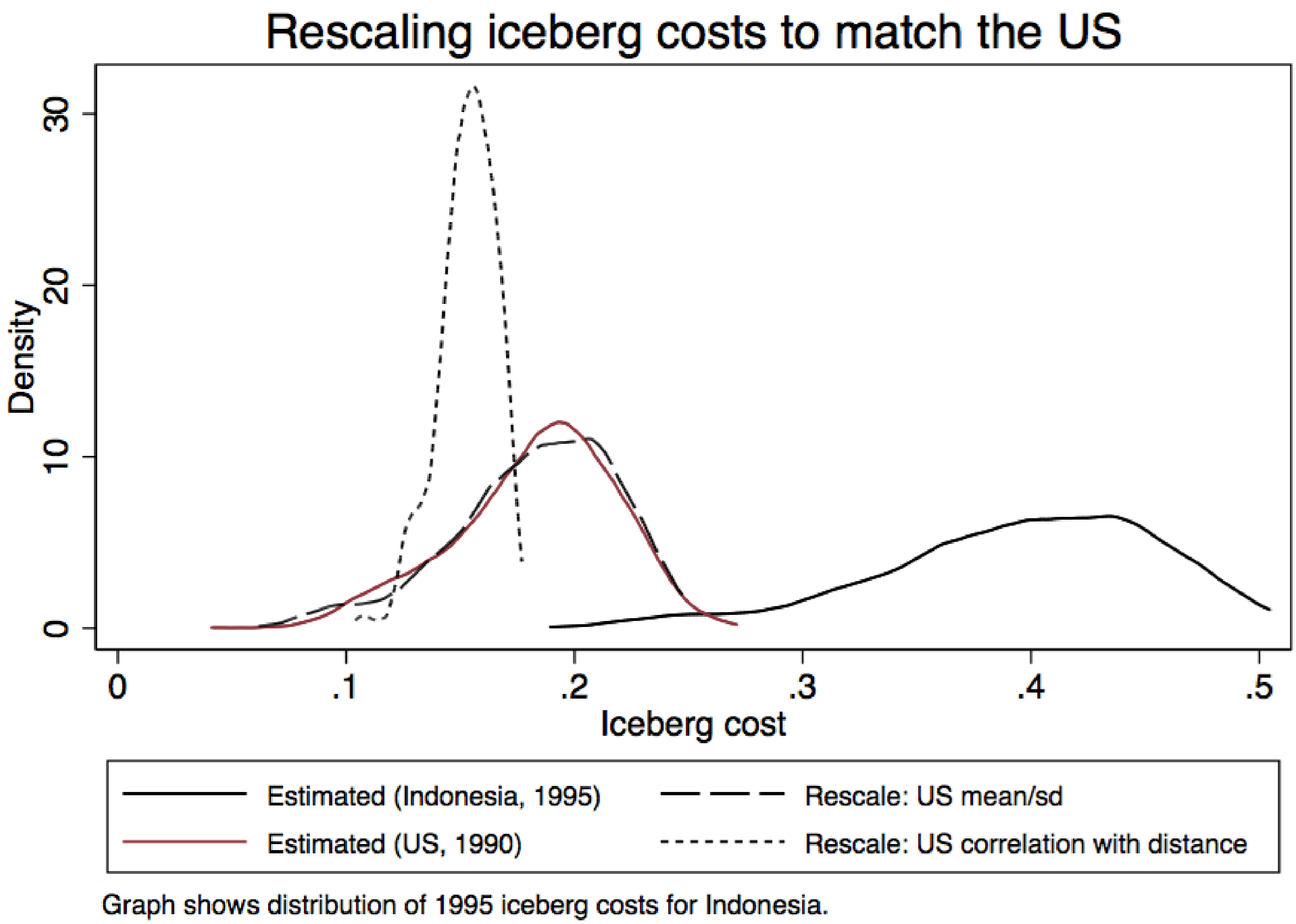

Figure 9: Rescaling the distribution

Table 1: Parameters of model

Type	Parameter	Usage	Number of parameters
Transport cost	τ_{do}	$\tau_{do} = \tau_{od}; \tau_{oo} = 1$	$\frac{N(N-1)}{2}$
Base amenities	$\bar{\alpha}_d$	$\alpha_d = \bar{\alpha}_d L_d^{\lambda}; \bar{\alpha}_1 = 1$	N-1
Base productivity	$\bar{A}_d$	$w_d = A_d = \bar{A}_d H_d^{\gamma}$	N
Frechet	θ	Spread of talent	1
	ρ	Correlation of productivity	1
Set exogenously			Notes
Congestion parameter	λ	$\alpha_d = \underline{\alpha}_d L_d^{\lambda}$	
Agglomeration parameter	γ	$w_d = A_d = \underline{A}_d H_d^{\gamma}$	
Utility function	β	$c = \alpha_d c^{\beta} t^{1-\beta}$	Does not need to be known
CES production fn	σ	$Y = \left(\sum_d (A_d H_d)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$	
Total			$\frac{N(N-1)}{2} + 2N + 1$

Table 2: The gravity equation

Dep var: Log Wage	(1) 1976 b/se	(2) 1995 b/se	(3) 2011 b/se	(4) 2012 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***		0.0022	0.038***		-0.00099	0.036***		-0.0028	0.032***		-0.0016
	(0.0040)		(0.0051)	(0.0018)		(0.0023)	(0.0014)		(0.0019)	(0.0017)		(0.0023)
Log Proportion		-0.083***	-0.082***		-0.067***	-0.068***		-0.061***	-0.063***		-0.056***	-0.057***
		(0.0057)	(0.0070)		(0.0019)	(0.0025)		(0.0015)	(0.0020)		(0.0019)	(0.0025)
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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) 1976	(2) 1995	(3) 2011	(4) 2012	(5) 1990	(6) 2010
ρ (correlation)	0.82***	0.84***	0.88***	0.86***	0.92***	0.96***
	(0.21)	(0.0048)	(0.00034)	(0.0061)	(0.000087)	(0.00012)
$\tilde{\theta}$ (dispersion)	2.93	3.00***	3.27***	3.33***	2.83***	2.66***
	(2.68)	(0.011)	(0.23)	(0.0048)	(0.0037)	(0.0078)
Number missing migrant pairs	114	30	32	18	1	15
Mean mig cost (drop missing)	0.34	0.35	0.27	0.30	0.19	0.11
Mean mig cost (missing=1)	0.59	0.42	0.34	0.35	0.19	0.12

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) Labor productivity (model)
Panel A: Migration costs				
1976	1.000	1.105	1.370	1.000
1995	0.956	1.000	1.271	2.227
2011	0.778	0.777	1.000	4.275
Panel B: Amenities				
1976	1.000	1.203	1.385	1.000
1995	0.838	1.000	1.079	2.227
2011	0.690	1.088	1.000	4.275
Panel C: Productivites				
1976	1.000	1.075	1.493	1.000
1995	0.794	1.000	1.627	2.227
2011	0.634	0.801	1.000	4.275
Share cons. utility	0.600	0.600	0.600	
Amenity spillover	0.000	0.000	0.000	
Productivity spillover	0.050	0.050	0.050	
CES parameter	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	1.475	1.434	31.006
2011	1.588	1.577	15.197
2012	1.627	1.620	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***		0.015	0.026**		0.0023	0.031***		0.012	0.024***		-0.013
	(0.014)		(0.015)	(0.011)		(0.012)	(0.0089)		(0.010)	(0.0076)		(0.0087)
Log Proportion		-0.094	-0.084***		-0.076***	-0.075***		-0.067***	-0.057***		-0.092***	-0.10***
		(.)	(0.028)		(0.018)	(0.021)		(0.015)	(0.018)		(0.012)	(0.014)
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3960	3960	3960	3792	3792	3792	5393	5393	5393	6967	6967	6967
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

Dep var: Log Wage	(1) b/se	1990 (2) b/se	(3) b/se	(4) b/se	2010 (5) b/se	(6) b/se
Log Distance	0.016***		-0.032***	0.033***		-0.0079
	(0.0018)		(0.0033)	(0.0053)		(0.0096)
Log Proportion		-0.028***	-0.040***		-0.042***	-0.037***
		(0.00039)	(0.0024)		(0.0012)	(0.0074)
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
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)	-1.28***	-0.46*	-0.52**
	(0.44)	(0.25)	(0.21)
Land pollution (past year)	0.019	-2.60**	-2.74***
	(1.46)	(1.02)	(0.85)
Air pollution (past year)	-0.43***	0.34	0.027
	(0.15)	(0.31)	(0.28)
Noise pollution (past year)	-1.44		
	(1.05)		
Main road village lighting	0.17	0.29	0.37*
	(0.38)	(0.22)	(0.19)
Has movie theater	-6.16	-15.9	-40.4**
	(3.88)	(23.5)	(19.3)
Ease of reaching hospital	0.16**	0.019	0.11*
	(0.072)	(0.075)	(0.062)
Ease of reaching puskesmas/other health facility	0.28**	-0.0025	0.13
	(0.13)	(0.11)	(0.098)
Ease of reaching market with permanent building	0.16**		
	(0.080)		
Ease of reaching shopping complex	0.19***		
	(0.070)		
Flooding		-0.28	-0.059
		(0.28)	(0.25)
Earthquake		-0.057	-0.064
		(0.12)	(0.11)
Whirlwind/tornado/hurricane		0.43*	0.0097
		(0.23)	(0.22)
Drought		-0.43	0.15
		(0.68)	(0.61)
Outbreak (last year): Vomiting/diarrhea		-0.62	-0.62*
		(0.40)	(0.35)
Outbreak (last year): Malaria		0.082	0.30
		(0.24)	(0.21)
Outbreak (last year): Bird flu (1 case is considered an outbreak)		-3.32	-3.79
		(5.03)	(4.44)
Outbreak (last year): Tuberculosis		-0.26	-1.00*
		(0.65)	(0.54)

Notes:

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

	(1) Use 1990	(2) Use 2010	(3) Labor productivity (model)
Panel A: Migration costs			
1990	1.000	1.346	1.000
2010	0.542	1.000	1.318
Panel B: Amenities			
1990	1.000	0.884	1.000
2010	1.049	1.000	1.318
Panel C: Productivites			
1990	1.000	1.251	1.000
2010	0.664	1.000	1.318
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.

Appendix Table 9: Robustness: productivity effects of reducing migration costs

	(1) Sub. elasticity = 4	(2) Sub. elasticity= 6	(3) Sub. elasticity = 8
Productivity spillover = 0			
$\lambda = -0.08$	1.237	1.237	1.238
$\lambda = -0.05$	1.239	1.241	1.242
$\lambda = 0$	1.244	1.249	1.252
Productivity spillover = 0.05			
$\lambda = -0.08$	1.250	1.251	1.251
$\lambda = -0.05$	1.253	1.255	1.256
$\lambda = 0$	1.260	1.266	1.271
Productivity spillover = 0.08			
$\lambda = -0.08$	1.259	1.259	1.259
$\lambda = -0.05$	1.262	1.264	1.265
$\lambda = 0$	1.269	1.277	1.284

Notes: Table shows the effect on 1995 GDP of imposing 2011 migration costs. Table shows different combinations of amenity and productivity spillovers, for different values of substitution parameter.

Appendix Table 10: Robustness: productivity effects of equalizing amenities

	(1) Sub. elasticity = 4	(2) Sub. elasticity= 6	(3) Sub. elasticity = 8
Productivity spillover = 0			
$\lambda = -0.08$	1.016	1.023	1.028
$\lambda = -0.05$	1.022	1.030	1.035
$\lambda = 0$	1.042	1.055	1.064
Productivity spillover = 0.05			
$\lambda = -0.08$	1.020	1.030	1.038
$\lambda = -0.05$	1.026	1.037	1.045
$\lambda = 0$	1.050	1.067	1.079
Productivity spillover = 0.08			
$\lambda = -0.08$	1.022	1.035	1.045
$\lambda = -0.05$	1.030	1.043	1.052
$\lambda = 0$	1.055	1.076	1.090

Notes: Table shows the effect on 1995 GDP of imposing 2011 amenities. Table shows different combinations of amenity and productivity spillovers, for different values of substitution parameter.

Appendix Table 11: Robustness: productivity effects of US migration costs

	(1) Sub. elasticity = 4	(2) Sub. elasticity= 6	(3) Sub. elasticity = 8
Productivity spillover = 0			
$\lambda = -0.08$	1.530	1.530	1.529
$\lambda = -0.05$	1.533	1.534	1.534
$\lambda = 0$	1.540	1.545	1.549
Productivity spillover = 0.05			
$\lambda = -0.08$	1.563	1.562	1.560
$\lambda = -0.05$	1.567	1.567	1.567
$\lambda = 0$	1.576	1.583	1.588
Productivity spillover = 0.08			
$\lambda = -0.08$	1.583	1.581	1.579
$\lambda = -0.05$	1.587	1.588	1.587
$\lambda = 0$	1.598	1.607	1.613

Notes: Table shows the effect on Indonesian GDP in 2011 of imposing (rescaled) US migration costs. Table shows different combinations of amenity and productivity spillovers, for different values of substitution parameter.