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DISCUSSION PAPER SERIES

IZA DP No. 13612

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Michael A. Clemens
Center for Global Development and IZA

Mariapia Mendola
Università degli Studi di Milano Bicocca and IZA

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ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Migration from Developing Countries: Selection, Income Elasticity, and Simpson's Paradox*

How does immigration affect incomes in the countries migrants go to, and how do rising incomes shape emigration from the countries they leave? The answers depend on whether people who migrate have higher or lower productivity than people who do not migrate. Theory on this subject has long exceeded evidence. We present estimates of emigrant selection on both observed and unobserved determinants of income, from across the developing world. We use nationally representative survey data on 7,013 people making active, costly preparations to emigrate from 99 developing countries during 2010–2015. We model the relationship between these measures of selection and the income elasticity of migration. In low-income countries, people actively preparing to emigrate have 30 percent higher incomes than others overall, 14 percent higher incomes explained by observable traits such as schooling, and 12 percent higher incomes explained by unobservable traits. Within low-income countries the income elasticity of emigration demand is 0.23. The world's poor collectively treat migration not as an inferior good, but as a normal good. Any negative effect of higher income on emigration within subpopulations can reverse in the aggregate, because the composition of subpopulations shifts as incomes rise—an instance of Simpson's paradox.

JEL Classification: F22, J61, O15
Keywords: international migration, economic development, self-selection

Corresponding author:
Mariapia Mendola
Department of Economics
Università di Milano Bicocca
Piazza dell'Ateneo Nuovo 1
20126 Milano
Italy
E-mail: mariapia.mendola@unimib.it

* We acknowledge collaboration from the Food and Agriculture Organization of the United Nations and helpful comments from Benjamin Elsner, Gaurav Khanna, Samuel Bazzi, Thomas Ginn, Joseph-Simon Görlach, Alexis Le Nestour, Hannah Postel, and Justin Sandefur, as well as technical pointers from Peter Q. Blair and Paul Goldsmith-Pinkham, but any errors are ours alone. We acknowledge support from the Open Philanthropy Project. The paper represents the views of the authors alone and not necessarily those of their employers, funders, or any other institutions. Pre-analysis plan irreversibly registered at https://osf.io/ujzks.

The self-selection of international migrants is central to migration theory and to the impact of migration on destination countries (LaLonde and Topel 1997). If people with relatively low intrinsic determinants of income are more prone to migrate, migrants may integrate more slowly into destination-country labor markets. The opposite would be true if high migration costs prevent migration by low-income workers. But little is known about the empirical magnitude of migration costs, their relationship to observed and unobserved skill, and how those costs shape selection (Hanson 2010, 4403; Bertoli et al. 2013). There are few estimates of migrant self-selection on the unobserved or overall determinants of income. These require data on migrants prior to migration, which is available only in uncommon settings (e.g. Chiquiar and Hanson 2005; McKenzie, Stillman and Gibson 2010; Fernández-Huertas 2011; Abramitzky, Boustan and Eriksson 2012).

The question of migrant self-selection is closely linked to another question that has been important in the literature, how to estimate the income elasticity of migration (e.g. Hatton and Williamson 1998; Djajić, Kırdar and Vinogradova 2016; Bazzi 2017; Dao, Docquier, Parsons and Peri 2018). If developing-country migrants are indeed self-selected from among those with the lowest earnings, then households treat the purchase of migration as an inferior good: Higher incomes for the poor in the origin country will deter migration. Migrant-destination countries desiring smaller, more productive inflows of developing-country migrants could achieve this goal by assisting income growth and poverty reduction overseas. But evidence on this closely related question is likewise rare.

In this paper, we estimate the degree of self-selection and the income elasticity of emigration across the developing world. We begin by showing in theory that the magnitudes of self-selection and income elasticity are closely related. Basic theory suggests that in developing countries, large portions of the population are likely to exhibit positive selection and positive income elasticity. We then estimate both quantities using nationally representative survey data on 653,613 people in 99 developing countries, of whom 7,013 were making active, costly preparations to emigrate when they were interviewed during 2010–2015.

This rich dataset allows us to estimate self-selection on both observable and unobservable determinants of income, as well as the effect of rising incomes on emigration demand. We test for observable implications of any bias from unobserved migration behavior (preparing to migrate but not migrating), or bias from differential coverage of regular and irregular migrants. Finally, we discuss the implications for the effect of economic development on emigration and why this effect might be positive. This finding can be as counterintuitive as any other instance of Simpson's paradox: The emigration-income relationship within subgroups can be very different from the relationship in the aggregate population, because the composition of those subgroups changes as incomes rise.

We find that self-selection on the overall determinants of earnings is overwhelmingly positive, for developing-country migrants collectively and for 93 of the 99 countries separately. In low-income countries on average, people actively preparing to emigrate have 30.0 percent higher incomes than those not actively preparing to emigrate. They are positively selected on observed determinants of income such as schooling, with actively preparing emigrants exhibiting 14.1 percent higher incomes predicted by their observed traits than others. And they are positively selected on *unobserved* determinants of income, exhibiting 12.0 percent higher income residuals—after controlling for observables—than others. These measures are for prospective migrants to all destinations, including neighboring poor countries. Restricting the sample to those moving to rich countries increases all three selection measures to 72.6 percent (overall), 27.9 percent (observables), and 33.1 percent (unobservables).

We then set out theoretical conditions under which these selection estimates are a sufficient statistic for the sign and broad magnitude of the within-country income elasticity of migration, and show that these conditions are generally met in the data. We test this idea by simulating the effect on emigration demand of rising incomes in the microdata. Within low-income countries, the income elasticity of emigration demand is 0.229, and higher in middle-income countries. For large portions of the world's poor, this positive within-country income elasticity more than offsets the migration-deterrent effect of higher incomes at the country level.

That is, across the developing world, households *collectively* treat migration not as an inferior good, but as a normal good. Together, these findings imply that economic growth in a developing country can *raise* the number of migrants, and when it does, the new migrants will be positively selected at the margin. We show that the opposite conclusions could have been reached by analyzing subgroups whose composition changes over the course of economic development, which is often done in studies of the relationship between migration and development.

The first contribution of this paper is to present empirical estimates of migrant self-selection, on both observed and unobserved determinants of income, from across the developing world. Little evidence has been available to test theories of migrant selection from poor countries on unobserved traits (Grogger and Hanson 2011, 44; Belot and Hatton 2012; Clemens et al. 2019, 205). Information on migrants' income before migration is rare; in the developing world it exists only for a handful of countries. Pre-migration data on migrants has revealed intermediate or slightly negative self-selection on unobserved determinants of earnings in Mexico (e.g. Chiquiar and Hanson 2005; Fernández-Huertas 2011; Ambrosini and Peri 2012), positive selection in Poland (Dustmann et al. 2015), and positive selection in the Pacific island nations of Tonga, Micronesia, and Samoa (McKenzie et al. 2010; Akee 2010; Gibson et al. 2013). Other direct evidence from developing countries is scarce.[1]

The second contribution is to specify the theoretical conditions under which selection estimates inform a different but closely related empirical question: How will demand for emigration change as incomes rise in developing countries? Development brings various complex changes that could raise or lower the demand to emigrate (de Haas 2007; Mendola 2012). In cross-country panel data on bilateral migration flows to OECD countries, origin-country income per capita correlates positively with emigration rates (all developing countries: Clark et al. 2007; Vogler and Rotte 2000; lowest-income countries: Pedersen et al. 2008; Mayda 2010), though not in some regression specifications (Ortega and Peri 2013). Sustained rises in income per capita at the national level are associated with higher emigration rates from developing countries, both in cross-section (Clemens 2014; Dao et al. 2018) and time series (Clemens 2020).

But evidence beyond country averages is rare. In a handful of developing countries, studies have directly measured the elasticity of migration demand to exogenous increases in income at the household level. They find the elasticity to be positive for international migration by poor

[1] Bertoli, Fernández-Huertas and Ortega (2013) investigate the effect of individual-level earnings in Ecuador on migration to the United States and Spain. In the context of a sudden collapse in the Ecuadorian economy, and using modeled rather than directly-observed origin-country earnings, they find that people who would have experienced a large loss of earnings in Ecuador during the crisis were more likely to emigrate. We investigate the effect of long-term sustained earnings growth on migration.

households in Mexico (Orrenius and Zavodny 2005; McKenzie and Rapoport 2007) and Indonesia (Bazzi 2017). Cash transfers have been found to positively affect international migration in Mexico (Angelucci 2015; Görlach 2019), Honduras (Millán et al. 2020), and Comoros (Gazeaud et al. 2019).[2] For almost all developing countries, no such estimates exist.

The paper begins by setting out a minimal model of migration and earnings, pointing out the close links between migrant selection and the income elasticity of migration. It proceeds to describe the survey data, and point out the broad relationship between migration and income across the 99 countries. It then presents estimates of selection on observables and unobservables for country groups and individual countries. This is followed by a discussion of the theoretical conditions under which the degree of self-selection on income determines the income elasticity of emigration, with a simulation to test those conditions. Finally, it discusses the implications for the effect of economic development on migration, why that effect might seem counterintuitive, and the connection of these results to unemployment and informal migration.

1 Self-selection and the income elasticity of migration

Two separate literatures have considered migration self-selection and the income elasticity of migration. We begin by pointing out the connection between those research programs and why theory can counterintuitively predict that emigration rises with home-country income.

1.1 Migrant selection on observed and unobserved skill

Suppose that there are workers in two countries $k \in \{0, 1\}$. The migrant origin country, 0, is poorer than the destination country, 1. Extending Hanson's (2010, 4380) formalization of the Roy (1951) selection model, workers earn a Mincerian (1958) wage determined by

$$\ln w_k = \mu_k + \delta_k s + \tilde{\delta}_k \tilde{s}, \tag{1}$$

[2] Considering rural-urban migration by poor households *within* developing countries, Cai (2020) finds a positive effect of pure cash transfers on domestic migration in China, found also by Tiwari and Winters (2019) in Indonesia, while Bryan et al. (2014) find a positive effect of a small labeled cash transfer on rural-urban migration in Bangladesh. Imbert and Papp (2020) find a negative effect of a make-work program in India on domestic migration—though receipt of the subsidized jobs is tied to presence in the rural area of origin, so the intervention represents a bundled treatment including elements beyond an income shock.

where μ sets the base wage for the unskilled, s is observable skill with return δ, and $\tilde{s}$ is unobservable skill with return $\tilde{\delta}_k$ (such that $E[\tilde{s}|s] = 0$). For a given individual specified by $s, \tilde{s}$, the net gain to migrating from 0 to 1 is

$$g(w_0) = \Big(w_1 - w_0\Big) - \Big(c + \theta s + \tilde{\theta}\tilde{s}\Big). \tag{2}$$

The first term captures the wage gain between country 1 and country 0. The second term captures migration cost, with a part c that is fixed and a part that varies with observable and unobservable skill by the factors $\theta, \tilde{\theta}$, respectively. Suppose that the probability of migration as a function of origin-country wage rises with the gain (2), as in a standard McFadden (1974) random utility model,

$$p = p\big(g(w_0)\big), \quad p' > 0. \tag{3}$$

Selection in this model is ambiguous. Selection is positive on observed skill if an increase in skill, s, raises the net gain (2). A positive derivative of (2) with respect to s implies

$$w_0 < \frac{\delta_1}{\delta_0} w_1 - \frac{\theta}{\delta_0} \quad \equiv \quad w^*. \tag{4}$$

That is, the probability of migration (3) rises with observed skill s for workers whose origin-country wages lie under some critical value, and falls when origin-country wages are above that value.

In a typical developing country, this would imply positive selection on schooling across most of the population, except for the richest extreme. For example, suppose that the return to schooling, s, in the origin country is $\delta_0 = 0.10$, and in the destination country $\delta_1 = 0.06$. The unskilled wages in the two countries are $e^{\mu_0} = \$7{,}000$ and $e^{\mu_1} = \$20{,}000$, respectively. Suppose total migration costs are fixed at $c = \$12{,}000$ (so $\theta = 0$). From (2) and (3), the net gain and thus the probability of migration rise with schooling: The net gain is \$3,912 at 6 years of schooling, and \$5,848 at 12 years. The net gain keeps rising with schooling until $s^* = 13.5$ years, where workers in the origin country earn $w_0(s^*) = w^* = \$27{,}000$. That is, selection would be positive for the average worker at all levels of schooling below tertiary—the vast majority of a typical developing country.[3]

[3] These numbers are broadly realistic for many developing countries (Psacharopoulos and Patrinos 2018; Clemens et al. 2019). Alternative formulations of the Roy (1951) selection model in (2) assume instead that migration probability rises with the gap in *log* wages and that migration costs are a multiple of the origin-country wage (Borjas 1987). That is, we could instead assume $g \equiv (\ln w_1 - \ln w_0) - c$. This would require implicitly assuming that the dollar-equivalent

This result obtains without capital constraints. Even more workers would exhibit positive selection on observed skill if workers with higher skill have lower migration costs ($\theta < 0$), since $\partial w^*/\partial\theta < 0$. This could arise because skilled workers have more wealth and are less capital-constrained to pay migration costs (Orrenius and Zavodny 2005; Hanson 2006, 901; McKenzie and Rapoport 2010; Belot and Hatton 2012; Assunção and Carvalho 2013). It could also arise from skill-selective policy barriers to migration.

By the same reasoning, selection on *unobserved* skill is positive if

$$w_0 < \frac{\tilde{\delta}_1}{\tilde{\delta}_0} w_1 - \frac{\tilde{\theta}}{\tilde{\delta}_0} \quad \equiv \quad \tilde{w}^*. \tag{5}$$

That is, at a given level of unobserved skill, selection on unobservables is positive if the average origin wage is less than the destination wage scaled by the relative returns to unobserved skill in the two countries. The poorest people at any level of unobserved skill exhibit positive selection on unobservables, because for them a marginal increase in unobserved skill raises the probability of migration. For any given individual, positive selection on observables does not require positive selection on unobservables (Borjas 1991, 30).[4]

1.2 The income elasticity of migration and Simpson's paradox

This model of selection yields a counterintuitive prediction about the income elasticity of migration. What happens to migration behavior as households' incomes increase? The answer depends on the cause of rising incomes. We discuss two distinct income elasticities of emigration: one *intrinsic* because it reflects income determinants carried within the worker, such as schooling, and one *extrinsic* because it reflects income determinants affecting all workers in a

migration cost is higher for more highly educated workers, since migration cost is constant in terms of labor time. This would yield $g = (\mu_1 - \mu_0) + (\delta_1 - \delta_0)s - c$, which by construction requires universally negative selection on observed skill ($dg/ds < 0$) as long as skills are relatively scarce in the developing country of migrant origin ($\delta_0 > \delta_1$). The sensitivity of this prediction to the assumed functional form is pointed out by Chiswick (1999). Rosenzweig (2007) and Grogger and Hanson (2011) test and reject this alternative formulation given its false prediction: There is now "overwhelming evidence that emigrants are positively selected in terms of schooling" from essentially all developing countries (Hanson 2010, 4378), as Lazear (2020) verifies for the United States.

[4] In a developing country with relatively high average incomes and extensive networks of low-income migrants to assist other low-income migrants ($\tilde{\theta} > 0$), such as Mexico, selection on unobservables might be intermediate or slightly negative (Fernández-Huertas 2011; Ambrosini and Peri 2012). A richer model would include the decision effects of uncertainty in the destination wage, w_1, which could further raise the slope of $p(w_0)$ (Batista and McKenzie 2019; Bah and Batista 2018), particularly if higher-income families are better able to self-insure (Gazeaud et al. 2019).

particular country, such as infrastructure.

Consider a rise in the origin-country wage caused by a rise in a worker's intrinsic, observable trait, s. From (3) and (4), this raises the probability of migration for workers with $w_0 < w^*$,

$$\frac{dp}{dw_0(s)} > 0. \tag{6}$$

Demand for migration rises with the home-country wage, as it does for a normal good. In the numerical example above, this rise occurs among any workers in the origin country earning less than 60 percent of what they could earn in the destination country. This would encompass the large majority of many developing countries, even with no capital constraints.

In contrast, consider a universal rise in the origin-country wage caused by a rise in the base wage parameter, μ_0, produced by conditions extrinsic to all workers. In this case, $dg/dw_0(\mu_0) = -1$ regardless of w_0. That is, such a wage increase reduces migration probability for *all* workers:

$$\frac{dp}{dw_0(\mu_0)} < 0. \tag{7}$$

For this type of wage increase, demand for migration falls with a rise in the home-country wage, as would demand for an inferior good. Such a wage increase cannot be observed within a country because by assumption, μ_0 is fixed for all workers in that country. Across workers in a country we expect to observe (6). We will discuss change at the country level below.

There is no conflict between equations (6) and (7). The intrinsic income elasticity of migration can be positive while the extrinsic elasiticity is negative. This is an instance of Simpson's (1951) paradox, in which a statistical relationship observed within subgroups can reverse in the aggregate.[5] Holding an individual trait, s, fixed, any given subpopulation of workers might be less likely to emigrate if their earnings in the home country were higher. This would occur if their earnings rose without any change in individual traits, as in (7). But if their earnings rose due to a change in traits, s, their earnings also rise in the destination country. The net effect on the migration incentive can be positive, as in (6). A population as a whole can treat emigration as a normal good *even if every subpopulation treats it as an inferior good.*

[5] Simpson's paradox is also known as the "ecological fallacy" (Selvin 1958).

2 Data

We estimate the relationship between migration and earnings (dp/dw_0), observable traits (dp/ds), and unobservable traits ($dp/d\tilde{s}$) using nationally representative survey microdata on people actively preparing to emigrate from 99 developing countries. The Gallup World Poll is an annual, nationally representative survey conducted in most countries worldwide (Gallup 2015). We pool six annual waves of the survey, 2010–2015. The questions to each respondent include three nested questions about prospective emigration, as well as numerous other questions about income, education, and other traits. No other data source has collected such extensive information on prospective migrants worldwide. We utilize a question from the survey that has been little exploited in the literature, in order to better proxy for actual migration behavior.

The first survey question about migration assesses abstract **desire** to emigrate: "*Ideally, if you had the opportunity, would you like to move permanently to another country, or would you prefer to continue living in this country?*" Those who answer yes receive a follow-up question about concrete **plans** to emigrate—"*Are you planning to move permanently to another country in the next 12 months, or not?*"—and are asked where they plan to move. Those who answer yes to both the questions about desire and plan are asked a third question about active **preparation** to emigrate: "*Have you done any preparation for this move (for example, applied for residency or visa, purchased the ticket, etc.)?*" This survey is widely used in the literature to study migration behavior (Dustmann and Okatenko 2014; Dao, Docquier, Parsons and Peri 2018; Delogu et al. 2018, Manchin and Orazbayev 2018, Mendola 2019).

Since the above questions are asked before departure, actual emigration is not observed. This is a limitation of the data, particularly important given that most prior studies have used the responses on hypothetical *wishes* or possibly uncertain *plans*, responses that do not require any costly action by the respondent (e.g. Docquier et al. 2014).

We address this concern by using only the data on people making active, costly preparations to emigrate in the next several months. "Questions regarding steps taken to prepare for migration, such as obtaining a passport or applying for a visa … are … factual questions and therefore fundamentally different from the two other types of question" (Carling 2019, 5). Such preparations are a very strong predictor of actual subsequent migration behavior (Bertoli and Ruyssen 2018). Tjaden et al. (2019) compare the Gallup World Poll responses on migration *preparation* with actual bilateral migration flows the following year across country dyads, finding a statistically precise elasticity of 0.8. Below, we conduct our own analysis of the composition of actual recent migration flows and the composition of *preparing* migrants in selected migration corridors.

Beyond this, the survey data themselves indicate that responses about active preparation to emigrate contain large amounts of information not present in responses about abstract wishes or unlikely plans. In the data on 99 developing countries that we use here, the mean of an indicator for emigration *desire* is 0.232, the mean emigration *plan* is 0.031, and the mean emigration *preparation* is just 0.010. That is, only one in seven people expressing an abstract desire to emigrate is planning to emigrate within a year, and among those planning to emigrate, only one in three is making active and costly preparations for the move. More important, as shown below, the gap between *desire* and *preparation* falls sharply with income, as does the gap between *plan* and *preparation*. This strongly suggests that any gap between *preparation* and actual migration likewise narrows with income. In other words, richer people are better able to turn their desires into plans, their plans into preparation, and their preparation into migration. This direction of bias, as we discuss below, would imply that our estimates of selection and income elasticity are lower bounds.

A second limitation of the data is that the sample for each country in each year is the same size (about 1,000). People preparing to emigrate are rare. In the average country of our 99-country sample, in six years of pooled data, the number of respondents is 6,604 and the number who report active preparation to emigrate is 70.8. A fixed sample size means that there is a lower absolute number of observations of people preparing to migrate when 1) for a given country size, the migration prevalence is lower, or 2) for a given migration prevalence, the country size is smaller. This may be why the *preparation* variable has been barely used in prior research (Migali and Scipioni 2019). We address this limitation by pooling data from groups of countries to improve statistical power.[6] We also present country-level results, and test the robustness of

[6]We use the official country classifications by income used by the World Bank. At the beginning of the survey data period (2010), these were set according to gross national income per capita (Atlas exchange rate US dollars, not purchasing power parity) as follows: "Low income" is $\leqslant$ \$1,005; "lower middle income" is \$1,006–\$3,975; "upper

the results to excluding countries with small samples.

A third limitation of the data is that income is reported at the household level. This is standard in developing-country settings, where household earnings may not be easily attributed to single members (e.g. Mukherjee et al. 2013). But because only one respondent per household is interviewed, the survey questions on migration preparation, education, age, gender, an so on are asked of the *individual* respondent.

This limitation is mitigated by the fact that the survey respondent for each household is chosen at random (among adults ages 15+) using a Kish (1949) grid. Thus the respondent's reported individual traits are unbiased estimates of the traits of the average adult in the household. Our core analysis, then, in effect regresses (the natural logarithm of) household income per adult on traits such as, for example, the average education level of adults in each household. Alternative approaches exist, such as defining regressors based on the traits of the head of household. But theory suggests that using average adult traits by household, as we do, better captures the effect of worker traits on their productivity (Yang 1997). Empirical tests of the alternative approaches find that average adult traits are more informative about on-farm and off-farm household income in developing-country settings than traits of the head of household (Jolliffe 2002).

The dataset we use pools responses from 653,613 respondents in 99 developing countries, of whom 7,013 (1.07 percent) reported active preparation to emigrate. In each country the survey is probability based and nationally representative of the resident population at age 15 and older, covering the entire country including rural areas (Gallup 2015).

3 Descriptive results on income and migration

We begin by estimating the emigration-income profile $p(w_0)$. We do this with a simple bivariate nonparametric Nadaraya-Watson (1964) kernel regression of an indicator for preparing to emigrate, on the natural log of household income per adult. For each country, this regression is

middle income" is \$3,976–\$12,275.

superimposed on the kernel density of the income variable.[7]

3.1 The income elasticity of migration across the income distribution

The empirical relationship between income and emigration demand is generally and strongly positive. Figure 1 shows this for six selected countries where emigration is important. In each case the propensity to prepare for emigration rises sharply with income across most of the distribution. In four of the countries, migration may fall with income for limited numbers of the highest-income respondents.

The countries chosen for Figure 1 are typical of the developing world. Figure 2 shows the same analysis, with all individuals in three large groups of countries pooled in the same regression. Individual income is de-meaned at the country level. For people in low-income countries collectively, those with household income per adult 1 log point above the country mean are 0.7 percentage points more likely to report active preparation to emigrate than people 1 log point below the country mean. The rise is even sharper in lower-middle-income and upper-middle-income countries.

The model predicts that the income elasticity of migration will be positive ($dp/dw_0 > 0$) either 1) when selection is positive on both observables and unobservables ($w_0 < \textsc{min}(w^*, \tilde{w}^*)$), or 2) when positive selection on either observables or unobservables is large enough to overwhelm negative selection in the other. That is, the generally positive income elasticity is sufficient for positive selection on the overall determinants of income, but not sufficient for positive selection on either observables or unobservables considered separately. We will consider those in section 4.

3.2 Potential bias from unobserved migration

A concern might be that actual emigration is not observed, leading to bias if the difference between *preparation* and actual migration is not constant across the income distribution. If actual

[7]Both the regression and the density are weighted by the inverse probability of household sampling within countries. This makes the results represent the relationships in the average country, regardless of size. An alternative is to use frequency weights, effectively giving more weight to larger countries. Results using frequency weights are similar and are presented in the online appendix.

migration behavior were to fall with income relative to stated migration *preparation*, this would cause upward bias in the preceding selection estimates. It would likewise cause upward bias in the regression line slopes of Figure 1 and Figure 2.[8]

Such a bias would require relatively richer people—who desire migration, are planning for emigration, and have already taken costly steps to prepare for migration—to be less and less able than poorer people to convert their desire, plans, and active preparation into actual migration within a given period. This might seem prima facie implausible. Conditional on the presence of clear demand for migration, we would expect relatively richer people to be better able to realize that demand within any given period of time.

And even if the opposite were true, in order to reverse the sign on the slope of $p(w_0)$, rich people would have to self-select out of true migration (conditional on preparation) at a very high rate relative to poor people. For example, in Figure 2a, the richest people in poor countries are about four times as likely as the poorest people to be actively preparing for migration (0.027 versus 0.007). Suppose that for every true migrant among the poorest people, one additional person was preparing to migrate but did not (so the true migration rate is 0.0035). If the true $p(w_0)$ slopes down, then for every true migrant among the richest people, *seven* others were preparing to migrate but did not ($0.027/0.0034 - 1 = 6.9$). It would require an extraordinary mechanism for the richest people to be unable to consummate their desires, plans, and costly preparations at a rate seven times higher than among the poorest. We would expect the opposite.

We can test this idea in the data. The nested survey questions on emigration *desire*, *plans*, and *preparation* reflect increasingly costly behaviors. Stating a desire is nearly costless, making plans requires some costs, and making active preparation, such as paying for a travel arrangement or visa application, requires large and direct costs. Suppose further that emigration itself carries an additional cost, beyond the cost of preparation. A person who arranged travel for a potential migrant could abscond with the money; a visa application could be denied. Richer households should be better able to pay such costs, such as finding another person to arrange travel, or ap-

[8] An alternative form of the same concern would be that people with higher incomes take consistently longer to prepare for migration than people with lower incomes, and thus are more likely to be found in the origin country by the survey enumerators. This is simply another mechanism by which the probability of true migration within any given period, conditional on reporting *preparation* for migration, would fall with income.

plying for another visa to a different destination. This implies that any gap between preparation and true emigration should fall with income. That is untestable. But we can test the closely related ideas that the gap between *desire* and *plan*, and the gap between *plan* and *preparation*, likewise fall with income.

This is presented in Table 1a. In column 1, the dependent variable is the difference between an indicator for *desire* and an indicator for *plan* at the individual level, among all individuals indicating *desire*, with fixed effects for the origin country. This gap between *desire* and *plan* falls by about 1 percentage point (0.00944) for each rise of 1 log point in household income per adult. Column 2 allows for country random effects in the slopes (and intercepts) in a mixed-effects regression with no restrictions placed on the variance and covariance of residuals between countries. The *desire-plan* gap still falls with individual income, to a slightly lesser degree (0.00717). Columns 3 and 4 run the same tests for the gap between *plan* and *prepare*, among all individuals reporting a *plan* to emigrate. This gap falls by 6 percentage points (0.0641) for each rise of 1 log point in household income per adult. The same analysis is repeated for rich destination countries only, in Table 1b. There, the *desire-plan* gap is similarly negatively related to income, and the *plan-prepare* gap is more negatively related.[9]

In other words, richer people are better able to overcome the costs of converting migration *desire* into active migration *plans*, and even better able to overcome the costs of converting migration *plans* into active migration *preparation*. Conditional on migration *desire*, migration *planning* is a normal good. Conditional on having made migration *plans*, expenditures to *prepare* for emigration are normal goods. This suggests that richer people should likewise be better able to bear the additional costs of converting migration *preparation* into migration. In other words, conditional on having made expenditures to *prepare* for migration, migration is a normal good. Such a relationship would make the preceding estimates of selection lower bounds on the true values.

[9] The results are similar when, rather than actual income, the exercise in Table 1 is repeated using income predicted by observable traits. In other words, people with higher observed determinants of earnings such as education are much more likely to convert emigration *desire* into emigration *plans*, and to convert emigration *plans* into costly *preparation*. We therefore consider it unlikely that, for example, better educated people are relatively less able to follow up their costly expenditures on migration *preparation* with migration itself. In other words, the regressions in Table 1 can be interpreted as tests of the sign on θ in subsection 1.1, strongly rejecting migration costs that rise with observable skill such as education.

3.3 Irregular migration

A different form of bias might arise, in principle, in migration corridors with a high prevalence of irregular migration. By the strict wording of the survey questionnaire, responses about migration preparation should include both regular and irregular migration (Manchin and Orazbayev 2018, 362). But it is possible that the wording of one question cued respondents to think about regular migration. First, respondents were asked if they were "*planning to move permanently to another country in the next 12 months*," without reference to regular or irregular channels. Then they were asked if they had "*done any preparation for this move (for example, applied for residency or visa, purchased the ticket, etc.)*." This latter question (the one used in our analysis) likewise makes no explicit reference to regularity. The "etc." in the question would logically include preparations for irregular migration such as paying a smuggler. But the mere fact of mentioning visas might cue some respondents to think of regular channels. If such an effect is present and substantial, the survey sample would underrepresent prospective irregular migrants.

We address this concern in two ways. First, we test the sensitivity of the results to using the "planning" response instead of the "preparation" response. This response has the disadvantage that it is less directly connected to actual migration behavior, but the advantage that the wording of the question is fully inclusive of irregular migration. The within-country income elasticity of migration "planning" remains broadly and strongly positive, resembling the graphs in Figure 2. This result is presented in Figure A4 in the online appendix.[10]

Second, we compare the educational composition of *preparing* emigrants in the survey data with the actual composition of all recently arrived migrants—regular and irregular—from selected countries where irregular migration is very common. For example, we consider migrants to the United States from Mexico, Guatemala, and Honduras, roughly half of whom had irregular status during this period (Rosenblum and Ruiz Soto 2015). And we compare prospective and actual migrants to Europe from Afghanistan, Niger, and Tunisia, some of the most important

[10] Likewise in the online appendix we repeat the selection analysis in the following section using emigration *planning* rather than *preparation.* The results show that selection remains positive among "planning" emigrants for both overall and observable determinants of income, but selection becomes intermediate on unobservable determinants of income (the hypothesis of zero selection on unobservables cannot be rejected)—except for "planning" emigrants from upper-middle-income countries to all other countries, where selection on unobservables is positive and statistically significant at the 5 percent level. The income elasticity of migration accordingly remains positive and substantial. Aksoy and Poutvaara (2019) study self-selection among irregular migrants specifically.

origin countries for irregular migration during this period (Frontex 2012).[11]

This comparison for migrants to the United States is shown in Table 2a. It compares the education level of prospective and actual migrants to the United States from Mexico, Central America, and Haiti. Whether education is measured as secondary or tertiary schooling, prospective migrants in the survey are broadly similar to actual migrants. For secondary schooling, actual migrants are slightly more educated than prospective migrants from Mexico, El Salvador, and Haiti, and slightly less educated than those from Guatemala and Honduras. For tertiary education, actual migrants are slightly more educated than prospective migrants from Guatemala and Haiti, and slightly less than those from Mexico, Honduras, and El Salvador. There is no clear pattern of more negative selection on education among actual recent migrants than among prospective migrants during the same period.

This conclusion broadly holds for migrants to Europe as well. Table 2b shows the same comparison as above for selected countries of origin with high prevalence of irregular migration to Europe. For secondary education, selection is somewhat more positive among prospective migrants than actual migrants from Senegal, Tunisia, Cameroon, and Nigeria. Selection is similar among prospective and actual migrants from Iraq, Mali, and Niger. Selection is more positive among actual migrants than prospective migrants for Afghanistan, Algeria, Côte d'Ivoire, and Sudan. For tertiary education, selection is more positive among actual migrants than prospective migrants from *all* of these countries whose data allow this test. Here again, there is no pattern of more positive selection on education among the prospective migrants in the survey data than among actual migrants, including both irregular and regular migrants.

This analysis suggests one of two possibilities. Respondents to the survey might simply answer the question as it is asked, reporting preparation for irregular migration in roughly the same terms as regular migration. We find this interpretation the most plausible. Alternatively, respondents might be more likely to answer about preparation for regular migration, but irregular migrants might be selected similarly to regular migrants on key observables. We find this less

[11] The education categories for both data sources are harmonized as follows: "Elementary" = completed elementary education or less (up to 8 years of basic education), International Standard Classification of Education (ISCED) 0–2; "Secondary" = completed some secondary education and/or up to three years of tertiary education (9 to 15 years of education), ISCED 3–4; "Tertiary" = completed 4 years of education beyond high school and/or received a 4-year college degree, ISCED 5+.

plausible, though the conjecture cannot be ruled out with this dataset. Neither of these possibilities implies large bias in interpreting the following selection estimates as covering migrants in general, given their current mix of regular and irregular status.

4 Estimates of emigrant selection

The preceding results suggest that $p(w_0)$ is upward-sloping for large parts of the developing world. This does not mechanically require positive selection of emigrants. In the model, net selection depends on the shape of the income distribution and the local slope of $p(w_0)$ across that distribution. In individual countries where the migration function does not rise monotonically with income, such as Senegal (Figure 1f), overall selection could be positive or negative. We require a general test for selection.

4.1 Selection conditions

We can formulate direct, nonparametric tests for selection as follows. Suppose home wages are distributed according to the probability density function $f(w_0)$. Average self-selection on overall wages is positive if and only if the mean home wage for migrants exceeds the mean wage in the home population,

$$E[w_0|\text{migrate}] = \frac{\int_0^\infty p_i(w_0) \cdot w_0 f(w_0)\, dw_0}{\int_0^\infty p_i(w_0)\, dw_0} > \int_0^\infty w_0 f(w_0)\, dw_0 = E[w_0]. \tag{8}$$

The same reasoning gives a simple condition for selection on *unobserved* determinants of the wage. Conditional on observed skill, s, the condition for positive selection on unobserved determinants of the wage becomes

$$E[w_0|s, \text{migrate}] = \frac{\int_0^\infty p_i(w_0|s) \cdot w_0 f(w_0|s)\, dw_0}{\int_0^\infty p_i(w_0|s)\, dw_0} > \int_0^\infty w_0 f(w_0|s)\, dw_0 = E[w_0|s]. \tag{9}$$

Both of the conditions (8) and (9) are untestable in standard datasets gathered from migrant-destination countries, where migrants' counterfactual position in the home-country wage distribution is unknown.

4.2 Tests for selection on observed and unobserved traits

We first test for positive selection on the overall determinants of earnings by testing the selection condition (8). Table 3a, column 1, reports estimates of the difference between log household income per adult for respondents who report preparing to emigrate versus all others. Respondents are again pooled by country income class, with log household income per adult de-meaned by country as in Figure 2. In low-income countries, respondents who report active preparation to emigrate have 0.262 log points (30.0 percent) higher overall income than those who do not report active preparation to emigrate. This difference is greater in lower-middle-income countries (0.314 log points, or 36.9 percent) and upper-middle-income countries (0.294 log points, or 34.2 percent).

We can furthermore test separately for selection on observed and unobserved determinants of income. To test for selection on observables, we first regress log household income per capita on indicator variables for education, age, gender, and rural/urban location of the respondent, with an indicator for country.[12] We use this regression to predict income for each individual, and repeat the selection analysis, replacing true income with income predicted by observed traits. Selection on unobservables (9) is estimated by replacing true income with the residual from the same income regression.

The results are shown in Table 3a, columns 3 and 5. Column 3 shows the selection estimates using income predicted by observable traits: education, age, gender, and rural/urban location. Selection is highly positive in the average country in all three country classes. Respondents reporting active preparation to migrate have 0.13–0.14 log points higher household income per adult *explained by observed traits* than those not reporting active preparation to emigrate. This matches prior evidence that migrant selection is generally and strongly positive on education (Hanson 2010, 4378), but also takes into account the additional observable traits of age, gender, and rural/urban location.

[12]The education indicators are one indicator each for secondary and tertiary education, with primary education or less as the base group. The age indicators are for ages 20–29, 30–39, 40–49, 50–59, 60–69, and 70+, with under 20 as the base group. "Urban" is defined as reporting living in a "large city" or "suburb of a large city", with "small town/village" or "rural" as the base group.

Column 5 of Table 3a reports the selection estimates on unobserved determinants of income. These, too, are positive overall, suggesting that the level of earnings with the highest migration rate, $\hat{w}$, within groups of individuals defined by observables generally lies to the right of mean earnings in those same groups. In low-income countries, respondents reporting active preparation to emigrate have 0.113 log points (12.0 percent) higher incomes *unexplained by observed traits* than respondents who do not report active preparation to emigrate. Selection on unobservables is even higher in lower-middle-income countries (0.172 log points, or 18.8 percent) and upper-middle-income countries (0.149 log points, or 16.1 percent).

4.3 Tests separated by country

Figure 3 reports the same tests, for selection on the overall determinants of earnings, separately for each of the 99 countries. The estimates are positive for 93 countries, negative for 6. Figure 4 reports the tests for selection on observables and unobservables, again separately for each country. Selection on observables is positive in 95 countries, negative in 4. In 17 countries, selection on observables and unobservables have different signs—though confidence intervals are large. These estimates support the proposition of Borjas (1991, 30) that positive selection on observables like education does not require positive selection on unobservables, for any given country. Nevertheless, the coefficient estimates for selection on unobservables are positive in 83 of the 99 countries.

Finally, we repeat the preceding analysis, restricting the sample to respondents who state that they are preparing to emigrate to a country classified as "rich". These make up 54 percent of the original global sample of those making preparations to emigrate.[13] This restriction eliminates less costly, regional migration within the developing world. Equation (2) predicts that selection will be more positive in this subsample bound only for rich countries. For short-range migration within the developing world, any costs that decline with skill ($\theta < 0$) would be less constraining, and selection could be less positive for migration to neighboring countries with large networks to facilitate it (Munshi 2020; Lazear 2020). This change in selection should be greater in poor countries, where the average wage is low compared with the migration cost.

[13] "Rich" destination countries are herein defined as United States, United Kingdom, France, Germany, the Netherlands, Belgium, Spain, Portugal, Italy, Sweden, Greece, Denmark, Japan, Canada, Australia, New Zealand, and South Korea. (Others, such as Ireland or Norway, were not reported as a planned destination in the sample.)

Both of these predictions are observed in the data. Table 3b presents the selection regressions for respondents with rich destination countries only. Selection on overall determinants of income is much higher: In low-income countries, respondents reporting active preparation to emigrate to a rich country have 0.546 log points (72.6 percent) higher overall incomes than respondents who do not report such preparation. This is more than twice the degree of positive selection seen when all destinations are included, in Table 3a. In upper-middle-income countries the degree of positive selection for those preparing to migrate to rich countries is also higher than for all destinations, but the difference is much smaller. Figures 5 and 6 report the same analysis for each of the 99 countries separately. Self-selection on overall income, and on observables and unobservables, is more positive for those preparing to move to rich countries than for migrants in general. This positive selection is strongest in the poorest countries, where migration costs are highest relative to income.

5 Estimates of income elasticity within countries

Here we show that our tests of the sign and magnitude of selection in equations (8) and (9) across 99 developing countries are close to sufficient for testing the sign and broad magnitude of the income elasticity of emigration demand within countries. We begin by discussing the theoretical conditions under which the sign on selection and the sign on income elasticity must be identical.

5.1 The relationship between selection and income elasticity

Consider the relationship between the migration function, $p(w_0)$, and the income elasticity of migration. The overall prevalence of migration is

$$E[p(w_0)] = \int_0^\infty p_i(w_0) f(w_0)\, dw_0. \tag{10}$$

Suppose that we simulate economic development as a rightward shift of the entire home wage distribution via a rise in the mean wage, $\hat{w}_0$. The change in the migration rate, by the Leibniz rule, is

$$\frac{dE[p]}{d\hat{w}_0} = \int_0^\infty p_i(w_0) \frac{df(w_0)}{d\hat{w}_0}\, dw. \tag{11}$$

Note that if $p(w_0)$ is strictly and monotonically increasing, and the wage distribution $f(w_0)$ is strongly unimodal, the derivative (11) must be strictly positive. That is, rising incomes across the entire distribution must increase the emigration rate.

This can be proven intuitively by noting that the strong unimodality assumption requires there to be (exactly) two wages, w_ℓ, w_h, corresponding to any given density value, $f(w)$, such that $w_h > w_\ell$, with the monotonicity assumption yielding $p^*(w_h) > p^*(w_\ell)$. Strong unimodality thus implies that shifting the wage distribution to the right raises the density at w_h, where migration propensity is higher, and reduces the density at w_ℓ. The same reasoning can be repeated for any value in the range of $f(w)$. Under these assumptions, estimating migrant self-selection is the dual of estimating the income elasticity of migration.

In other words, a test for positive selection (8) and a test for positive income elasticity of migration (11) are *identical*—if the income distribution is strongly unimodal, and provided that the emigration-income function, $p(w_0)$, monotonically increases. Figure 2 suggests that both of these conditions are met in large parts of the developing world. This indirectly suggests that the earlier tests for migrant selection are also informative about whether migration might rise or fall as incomes rise.

5.2 Nonparametric simulation of the income elasticity of emigration

But what if $p(w_0)$ is not strictly monotonic? Rather than assume the form of $p(w_0)$, we can directly estimate the income elasticity of migration with a simulation. The effect of overall development on migration in (11) has no closed-form analytic solution for standard bell-shaped functional form assumptions on $p_i^*(w)$ and $f(w)$. But it can be numerically and nonparametrically estimated in an arbitrarily fine discrete approximation. This approach has the advantage that no assumptions are needed regarding the shape of the income distribution nor the monotonicity of $p^*(w)$.

We simulate the effect of broadly rising incomes on emigration demand as follows. For each country separately, we estimate the average propensity to prepare for emigration within each income ventile, p_v. We simulate a generalized 50 percent increase in income by raising each individual's true log income, w, to the new log income, $\tilde{w} \equiv w + ln(1.5)$. We then assign that person a new migration probability by determining their new income ventile and assigning them the average probability of emigration in that ventile of the original income distribution.

In other words, we estimate a discrete approximation of equation (11), so that the change in the nationwide probability of preparing to emigrate is

$$\frac{\Delta E[p_i]}{\Delta w} = \sum_{v=1}^{20} p_v \left(\frac{\tilde{N}_v - N_v}{N_v} \right), \tag{12}$$

where N_v is the number of people in ventile v at the original income, w, and $\tilde{N}_v$ is the number whose raised income $\tilde{w}$ would have placed them in ventile v.[14] For a 50 percent increase in incomes, the change in probability in (12) is converted into an income elasticity by dividing by 0.5.

The results, pooling individuals from groups of countries, are presented in Table 4. In low-income countries, the income elasticity of emigration preparation is 0.229. That is, a 50 percent increase in income for all people, without any other change in the income distribution, raises the probability of preparing for emigration by 0.115. This elasticity is higher in middle-income countries.

What if the income distribution does not remain the same? We can furthermore simulate changes in the income distribution as follows. If we plausibly assume that incomes are log-normally distributed with standard deviation σ, the Gini coefficient is known to have the simple form $G = 2\phi\left(\frac{\sigma}{\sqrt{2}}\right) - 1$, where ϕ is the cumulative distribution function of the standard normal; thus $\sigma = \sqrt{2} \cdot \phi^{-1}\left(\frac{G+1}{2}\right)$. Consider a change in the income distribution such that the mean ln income, μ_w, rises by ln(1.5) and the Gini coefficient rises by 5 points to $\tilde{G} \equiv G + 0.05$, yielding the new standard deviation $\tilde{\sigma}$.[15] Thus the mean of unlogged income, w, will rise 50 percent and the Gini will rise by 5 points if we transform each individual's ln income, w_i, to the counterfactual ln

[14] People whose raised income, $\tilde{w}$, lies above the highest ventile of the original income distribution are assigned the migration probability of the highest ventile, p_{20}.

[15] This is a large change in inequality. In World Bank data the standard deviation of the Gini coefficient across all countries is 7.8.

income

$$\tilde{w}_i = (\mu_w + \ln 1.5) + (w_i - \mu_w)\frac{\tilde{\sigma}}{\sigma}. \tag{13}$$

The same method can be used to simulate a fall in inequality, with $\tilde{G} \equiv G - 0.05$. Plugging these counterfactual incomes into the simulation (12), we can simulate the income elasticity of emigration preparation if the simulated rise in average incomes is accompanied by rising or falling inequality.

These results are shown in Table 4, columns 2 and 3. In low-income countries, the income elasticity of emigration preparation falls from 0.229 to 0.208 if the 50 percent rise in incomes is accompanied by a 5-Gini-point fall in inequality. The elasticity rises to 0.278 if it is accompanied by a 5-Gini-point rise in inequality. But the conclusion of a generalized, large, positive elasticity is unaffected by substantial changes in the distribution of income. The same is true in middle-income countries, where elasticities are higher in all three columns.

Figure 7 presents the results of the same simulation for each of the 99 developing countries. The round dot shows the income elasticity of preparing to emigrate, assuming no change in inequality. The downward-pointing triangle shows the result with a 5 Gini point fall in inequality, the upward-pointing triangle shows the result with a 5 Gini point rise in inequality. The income elasticity is positive in 91 of the 99 countries. This conclusion is not substantially affected by relaxing the assumption of no change to inequality.

Beyond this, the results for selection on overall income contain much of the same information as the results for income elasticity, as theory predicts. Figure 8 plots one against the other, country by country. In 93 of the 99 countries, selection and income elasticity have the same sign. In three of the countries with discordant signs, both measures are close to zero. In other words, in practice, the sign of the overall selection measure is close to a sufficient statistic for the sign of the income elasticity. Beyond this, the magnitude of the selection measure is highly informative about the magnitude of the income elasticity. The linear regression line in the figure (no constant term) has slope 0.765, standard error 0.042, and an R^2 of 0.777.

6 Economic development and migration

Economic development implies more than just changing incomes at the household level. It involves changes in capital, technology, and unobserved human capital that can change the marginal product of all workers in complex ways—including the marginal product of those workers if they were to migrate. Consider national-level changes that result in higher average incomes for the workers modeled in section 1.

6.1 The inverse-U relationship between migration and development

Average incomes in an economy could rise by various mechanisms as the economy develops. Average incomes could rise due to increases in observed traits, s, such as education, which would tend to raise the migration rate in a poor economy (where for most workers, $w_0 < w^*$) by (6). Average incomes could also rise due to increases in the base wage parameter, μ_0, such as increases in capital per worker, which would tend to reduce the migration rate by (7). Average incomes could furthermore rise due to increases in the returns to observed trait, δ_0—such as better nutrition, better quality of education, increased female labor force participation, or global skill-biased technological change. Such changes would not affect the migration rate ($dg/d\delta_0 = 0$, by (2)), provided that they equally raise the return to workers' observed skill in migrant-destination countries ($d\delta_1/d\delta_0 = 1$).

Pooling workers from different countries, then, we could observe a nonmonotonic relationship between income and migration. Across poor countries, where development is driven by investment in human capital and the returns to that investment, the income elasticity of migration could be dominated by the positive slope in (6). In richer countries, where development is driven by capital investment affecting all workers, the income elasticity of migration could turn negative. This could occur both because the elasticity is increasingly driven by country-level differences in μ, as in (7), and because more and more workers earn a wage in the origin country that is sufficiently close to what they could earn abroad (for whom $w_0 > w^*$).

This is indeed what we observe when pooling workers across all countries and considering the relationship between migration propensity and *absolute* income. Figure 9a shows the same emigration-income kernel regressions from Figure 2 but with all individuals in the 99 developing countries pooled into a single sample, and without de-meaning income at the country level. The probability of actively preparing to migrate first rises and then falls with individual income. It is steeply rising at the median household income per adult in low-income countries (US$841 at purchasing power parity (PPP)) and the median in lower-middle-income countries (PPP$1,590), and is just beginning to fall by the median in upper-middle-income countries (PPP$3,714). This produces the inverse-U relationship between income and migration known as the "emigration life cycle" (Hatton and Williamson 1998; Williamson 2015; Clemens 2020) observed for typical developing countries over the last two centuries.

6.2 Structural change during development

The positive elasticity of migration for poor workers in Figure 9a strikes many observers as counterintuitive, given that individual migrants often mention joblessness and poverty as reasons to migrate (Clemens and Postel 2018; Eziakonwa et al. 2019). We argued in subsection 1.2 that this could arise from Simpson's paradox: The income elasticity of migration could be negative for any given worker or type of worker, even as the income elasticity for a population is positive.

We can illustrate the importance of Simpson's paradox in the data. We could entirely miss the inverse-U pattern in Figure 9a if we analyzed the same data controlling for individual traits whose distribution tends to shift during the development process. Consider education. Figure 9b shows the same regression as Figure 9a, with respondents separated according to whether or not they have secondary education. At any given level of income, people with more schooling are much more likely to be preparing to emigrate.

Within each subgroup defined by schooling, there is little tendency for emigration demand to rise with rising incomes. Yet the fraction of respondents at each income level who have secondary education rises massively with income (the dashed line). Conditional on having secondary education, people earning PPP$3,000 per year are somewhat less likely to emigrate than people earning PPP$1,000 per year (Figure 9b). But the pattern in the overall population is reversed: People earning PPP$3,000 are much more likely to emigrate than those earning PPP$1,000 (Figure 9a).

In other words, the development process is not only movement along either the low-education curve or the high-education curve. It is that, but it is also a gradual shift from one curve to the other. At high levels of education this structural change slows to completion, and further increases in income arise from within-group effects. Thus toward the right side of Figure 9a, migration falls with rising income.

This need not occur if within-country positive selection and income elasticity fall at higher levels of economic development. We have reason to doubt this from the indirect evidence of Figure 2, showing that the slope of the emigration-income profile, $p(w_0)$, is even higher on average in upper-middle-income countries than in low-income countries. But we can test this hypothesis directly, in country cross-section. Figure 10a plots the overall selection measure from Figure 3 against real GDP per worker measured at PPP. The line is again a simple moving-average kernel regression. There is no sign of a generalized decline in selection in relatively richer developing countries. If anything, the selection measure rises in middle-income countries relative to low-income countries, as Figure 2 implied. The same is true for the income elasticity measure from Figure 7, plotted against GDP per worker in Figure 10b.

6.3 Short- and long-term effects

Beyond structural change, some factors that encourage emigration can fall in importance as development proceeds. Consider unemployment, an important driver of emigration at the individual level (e.g. Giambra and McKenzie 2019). In our dataset, people who report that they desire work but are unemployed are much more likely to report preparing to emigrate, at almost every income level.[16] Figure 11 shows the regressions from Figure 2 split by unemployment. In all three income classes of developing countries, at the mean household income per adult, the probability of preparing to emigrate is roughly double among unemployed adults from that household.

[16] "Unemployed" people are those who neither report full-time employment, nor report part-time employment, nor report being "out of the workforce."

This suggests that a policy intervention to reduce unemployment, whether among the relatively poor or the relatively rich, could reduce emigration demand in the short term. Yet it does not imply that sustained reductions in unemployment over the course of successful economic development would have the same effect in the long term. Figure 11 also shows the fraction of people at each income level reporting unemployment (the dashed line). It is low, in all three country groups, and declines with rising income: Reported unemployment is roughly 8–13 percent among the relatively poorest people and 4–5 percent among the relatively richest. This has two implications.

First, even reducing unemployment in the short term would do little to reduce emigration demand. Consider people with average incomes in low-income countries. The unemployed are about twice as likely to demand emigration, but constitute only about 7 percent of the sample. This implies that at mean income, eliminating *all* unemployment would reduce the emigration probability by just seven one-hundredths of a percentage point (0.0007). The very small effect arises because the effect on emigration is concentrated in a small subpopulation.[17]

Second, over the longer term, even this small reduction in emigration pressure is likely to be overwhelmed by other factors accompanying development—such as increased schooling—that raise emigration demand. Figure 11 makes clear that falling unemployment goes hand-in-hand with greater earnings, which *raise* migration pressure. In low-income countries, where the income elasticity of migration demand is 0.229 (Table 4), the above decline of 0.0007 in emigration probability from the elimination of unemployment would be reversed by a mere 0.3 percent rise in incomes across the distribution. Greater income opportunities in the long term do not imply reduced unemployment and lower migration; they imply reduced unemployment and *greater* migration.

7 Conclusion

"Positive selection of emigrants appears to be a nearly universal phenomenon," concludes Hanson (2010, 4378), discussing migrants' observed education. We confirm and extend this finding

[17] $(0 \times 0.07 + 0.01 \times 1) - (0.02 \times 0.07 + 0.01 \times (1 - 0.07)) = -0.0007$.

to document nearly universal positive selection on other observed determinants of earnings beyond education, and generally positive selection on the collective unobserved determinants of earnings. This suggests that textbook models requiring negative selection of developing-country migrants are not empirically descriptive. Because these selection patterns are shaped by costs that include policy barriers to migration—such as the cost of visas or the cost of educational requirements for visas—these findings on selection at the margin need not hold under low or no policy barriers (Abramitzky et al. 2013; Spitzer and Zimran 2018; Lazear 2020).

We likewise find that the income elasticity of emigration at the household level is positive across the developing world. This is corroborated by prior household-level studies from a handful of countries. It furthermore implies that income elasticity at the country level, across countries or within countries over time, has an ambiguous sign at low levels of development. This is corroborated by historical evidence at the country level. The takeoff into modern economic growth across peripheral Europe a century ago, from Sweden to Italy, was accompanied by a large increase in emigration (Hatton and Williamson 1998). This has been the norm over the last half century as well. Between 1960 and 2019, the within-country elasticity of emigration flows to GDP per capita growth in countries with GDP per capita below PPP$10,000 has been positive, estimated at 0.35 (Clemens 2020).

This striking feature of past development arises in large measure from structural changes inherent to the economic development process (de Haas et al. 2019, 9). This evidence is relevant to the common policy of delivering overseas development assistance as a broad deterrent to migration: In poor countries, rising incomes at the household level and the national level are associated with a rising propensity to migrate. Future research can learn much from longitudinal surveys observing migrants on both sides of the border. But given the great expense and tracking difficulties involved in that work, such surveys are likely to remain uncommon.

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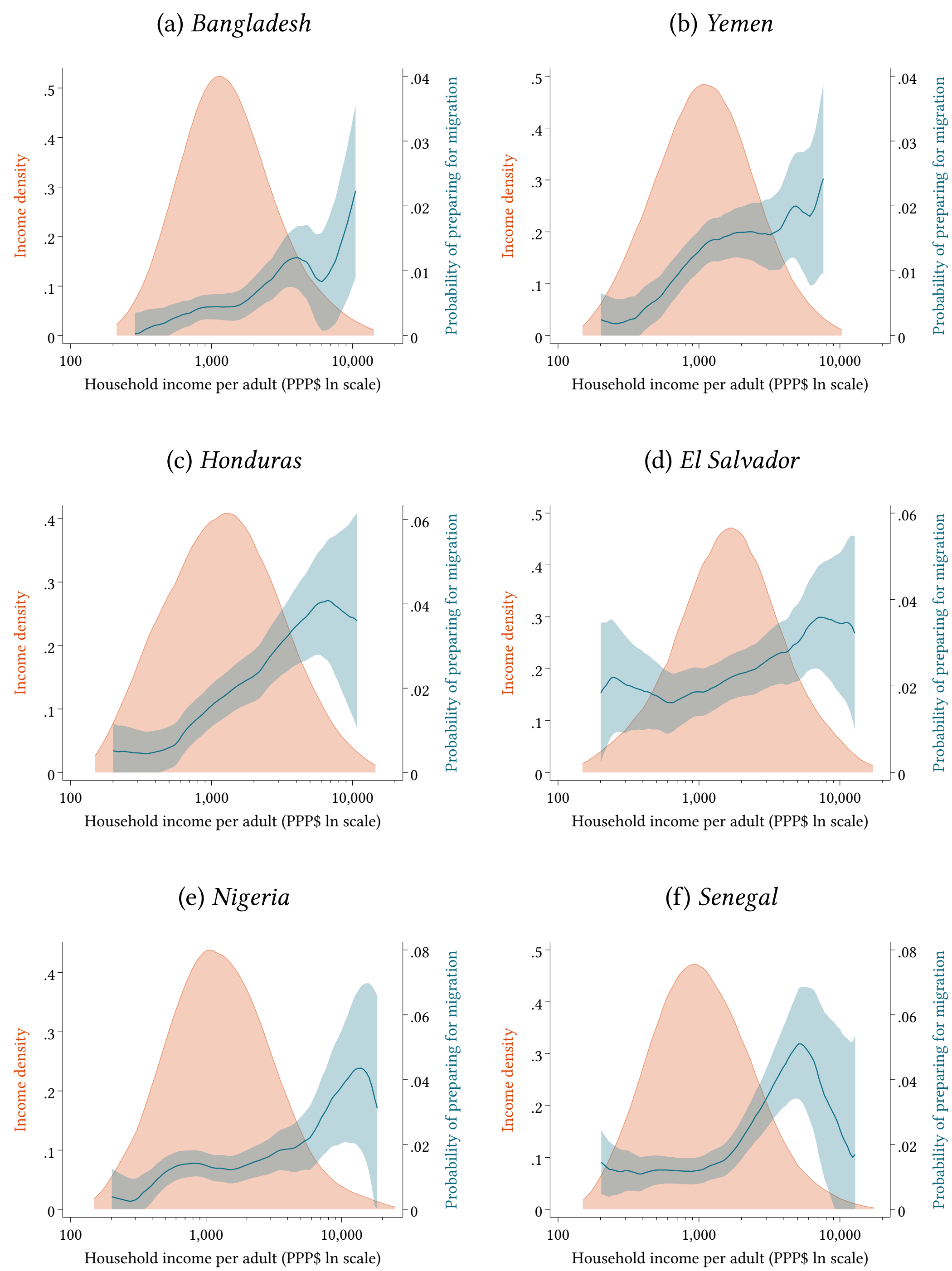
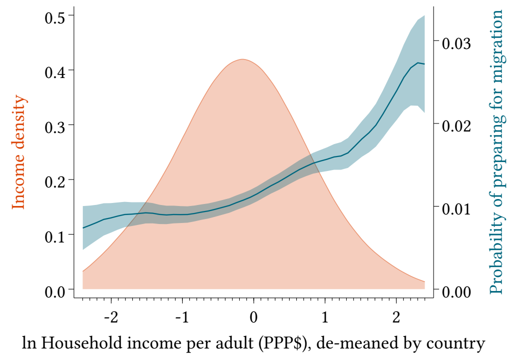
Figure 1: Active preparation to emigrate across the income distribution, selected countries



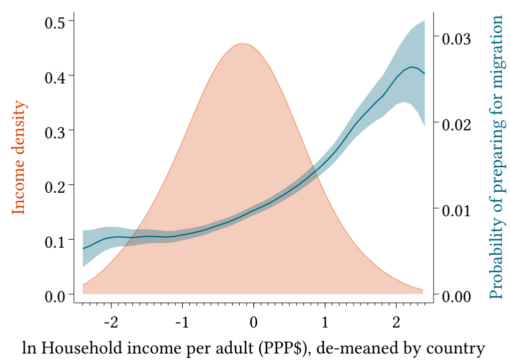
Data for individuals, pooled 2010–2015. Sample sizes: Bangladesh 7,969; Yemen 8,669; Honduras 5,566; El Salvador 5,874; Nigeria 6,459; Senegal 5,691. Income distribution shown as Epanechnikov kernel density, bandwidth 0.3 natural log points, weighted by the inverse probability of household sampling within countries. Migration preparation probability shown as Nadaraya-Watson regression, bandwidth 0.3 natural log points, also weighted by sampling weight. Light blue band shows 95 percent confidence interval on the local mean probability.

Figure 2: Active preparation to emigrate across the income distribution, by country class

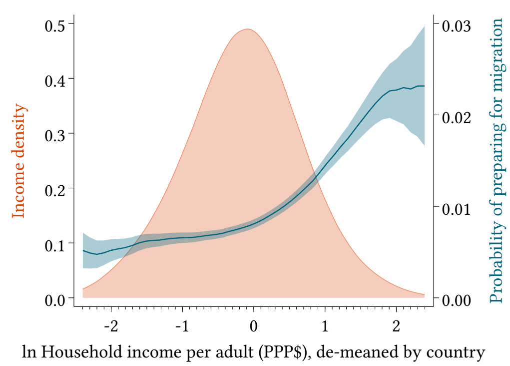
(a) *People in low income countries*



(b) *People in lower middle income countries*



(c) *People in upper middle income countries*



Data for individuals, pooled 2010–2015. Sample sizes: Low-income 120,420; lower-middle-income 236,146; upper-middle-income 261,059. Income distribution shown as Epanechnikov kernel density, bandwidth 0.3 natural log points, weighted by inverse probability of household sampling within countries. Migration preparation probability shown as Nadaraya-Watson regression, Epanechnikov kernel, bandwidth 0.3 natural log points, also weighted by sampling weight, with 95 percent confidence interval. Income classes are those used by the World Bank in 2010, according to gross national income per capita (Atlas exchange rate US$): “Low” is ⩽ $1,005; “lower middle” is $1,006–$3,975; “upper middle” is $3,976–$12,275.

Table 1: Testing for bias from unobserved migration

(a) *All destination countries*

Dep. var.	Gap between *desire* and *plan*		Gap between *plan* and *prepare*	
Included if	Desire	Desire	Plan	Plan
ln Household income/adult	−0.00944	−0.00717	−0.06414	−0.06738
	(0.00113)	(0.00176)	(0.00385)	(0.00430)
Country fixed effects	X	–	X	–
Country random effects in slope & intercept	–	X	–	X
N	168,775	168,775	21,430	21,430

(b) *Rich destinations only*

Dep. var.	Gap between *desire* and *plan*		Gap between *plan* and *prepare*	
Included if	Desire	Desire	Plan	Plan
ln Household income/adult	−0.00952	−0.00671	−0.07941	−0.08096
	(0.00144)	(0.00199)	(0.00520)	(0.00460)
Country fixed effects	X	–	X	–
Country random effects in slope & intercept	–	X	–	X
N	100,090	100,090	11,648	11,648

Data for individuals, pooled 2010–2015, weighted by sampling weight. Robust standard errors in parentheses. Columns 1 and 3 are country fixed-effects regressions, columns 2 and 4 are mixed-effects regressions with country random effects in the slope and intercept. "Rich destinations" are: United States, United Kingdom, France, Germany, the Netherlands, Belgium, Spain, Portugal, Italy, Sweden, Greece, Denmark, Japan, Canada, Australia, New Zealand, and South Korea. (Others, such as Ireland or Norway, were not reported as a planned destination in the sample.)

Table 2: Comparing observed education among actual, recently arrived immigrants with education among prospective emigrants, in corridors of high irregular migration prevalence

(a) *Destination: United States*

	Secondary education or more			Tertiary education		
Origin:	Prospective emigrants	Actual immigrants	*Relative selection*	Prospective emigrants	Actual immigrants	*Relative selection*
Mexico	0.64	0.74	+	0.16	0.14	≈
Guatemala	0.64	0.55	−	0.03	0.06	≈
Honduras	0.73	0.67	−	0.14	0.08	−
El Salvador	0.60	0.66	+	0.21	0.09	−
Haiti	0.76	0.89	+	0.11	0.15	+

(b) *Destination: Europe*

	Secondary education or more			Tertiary education		
Origin:	Prospective migrants	Actual migrants	*Relative selection*	Prospective migrants	Actual migrants	*Relative selection*
Algeria	0.42	0.55	+	0.02	0.28	+
Afghanistan	0.16	0.34	+	0.02	0.13	+
Cameroon	0.78	0.68	−	0.05	0.32	+
Côte d'Ivoire	0.28	0.49	+		0.23	
Iraq	0.55	0.52	≈	0.11	0.33	+
Mali	0.33	0.31	≈		0.14	
Niger	0.53	0.54	≈		0.32	
Nigeria	0.88	0.77	−	0.05	0.53	+
Sudan	0.46	0.59	+	0.31	0.38	+
Senegal	0.48	0.34	−	0.01	0.13	+
Tunisia	0.66	0.56	−	0.11	0.27	+

"+" means actual recent migrants more positively selected on education than *preparing* migrants in survey data, "≈" means similarly selected (difference $\leqslant 0.03$), "−" means actual migrants selected more negatively on education than *preparing* migrants. Blank cell means no observation in that country's sample. "Prospective migrants" are the sample of people in each origin country 2010–2015 *preparing* to emigrate to each destination. "Secondary education" means completed 9 to 15 years of education (or more). "Tertiary education" means completed 16+ years of education. *United States:* "Actual migrants" are respondents to the Current Population Survey (Annual Social and Economic Supplement; Flood et al. 2018) 2011–2019—which seeks to include irregular migrants—who arrived in the United States during 2010–2015, by country of birth. We omit people who likely received their highest level of schooling in the United States. That is, we omit people who arrived below age 15, who arrived at age 15–16 and have "some college," who arrived at age 17–18 and have a bachelor's degree, who arrived at 19–20 and have a master's professional degree, or who arrived by age 23 and have a doctorate. *Europe:* Europe includes all of Eastern Europe but not Russia or Turkey. "Actual migrants" are the foreign-born listed in the OECD DIOC 2011 (Database on Immigrants in OECD and non-OECD Countries; Arslan et al. 2015) who arrived within the past five years. These are compiled from censuses and labor force surveys that seek to include irregular migrants.

Table 3: Selection estimates by country income class

(a) *All destination countries*

	Selection overall		Selection on observables		Selection on unobservables	
	Diff	s.e.	Diff	s.e.	Diff	s.e.
Low income	0.262	(0.030)	0.132	(0.010)	0.113	(0.029)
Lower middle income	0.314	(0.021)	0.137	(0.006)	0.172	(0.020)
Upper middle income	0.294	(0.022)	0.133	(0.008)	0.149	(0.022)

(b) *Rich destinations only*

	Selection overall		Selection on observables		Selection on unobservables	
	Diff	s.e.	Diff	s.e.	Diff	s.e.
Low income	0.546	(0.042)	0.246	(0.016)	0.286	(0.043)
Lower middle income	0.364	(0.028)	0.151	(0.009)	0.207	(0.028)
Upper middle income	0.323	(0.027)	0.135	(0.010)	0.176	(0.026)

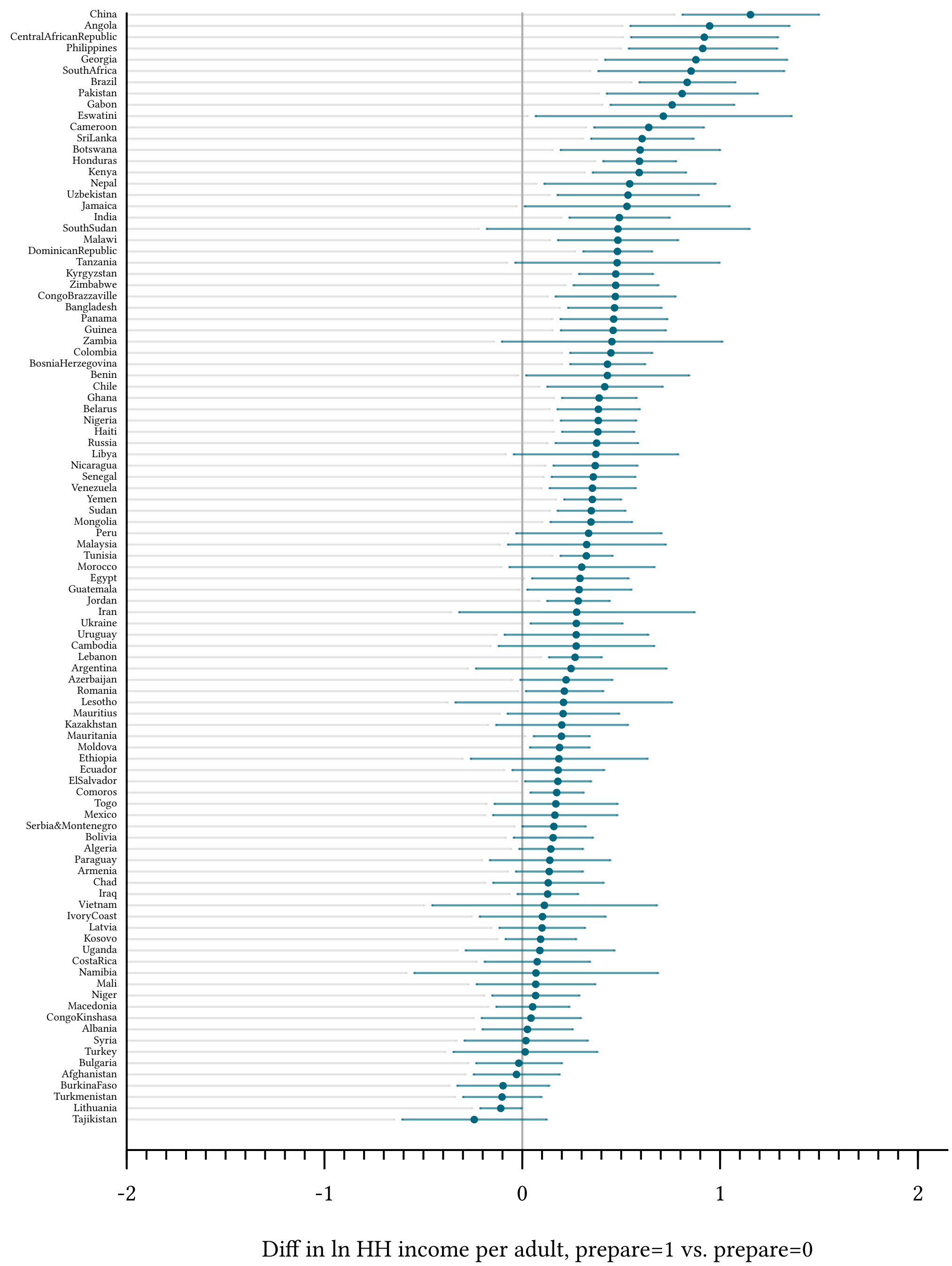
Estimates of difference in ln income between preparing emigrants and others. Data for individuals, pooled 2010–2015. Robust standard errors in parentheses. Sample sizes: *All destination countries*, low income 122,396; lower middle income 237,508; upper middle income 263,695. *Rich destination countries*, low income 121,444; lower middle income 236,304; upper middle income 262,830. "Rich destinations" are: United States, United Kingdom, France, Germany, the Netherlands, Belgium, Spain, Portugal, Italy, Sweden, Greece, Denmark, Japan, Canada, Australia, New Zealand, and South Korea. (Others, such as Ireland or Norway, were not reported as a planned destination in the sample.) Income classes are those used by the World Bank in 2010, according to gross national income per capita (Atlas exchange rate US$): "Low" is $\leqslant$ \$1,005; "lower middle" is \$1,006–\$3,975; "upper middle" is \$3,976–\$12,275.

Table 4: Simulation: Income elasticity of emigration preparation

	No change in Gini	With −5 Gini points	With +5 Gini points
Low income	0.229	0.208	0.278
Lower middle income	0.352	0.328	0.372
Upper middle income	0.340	0.281	0.399

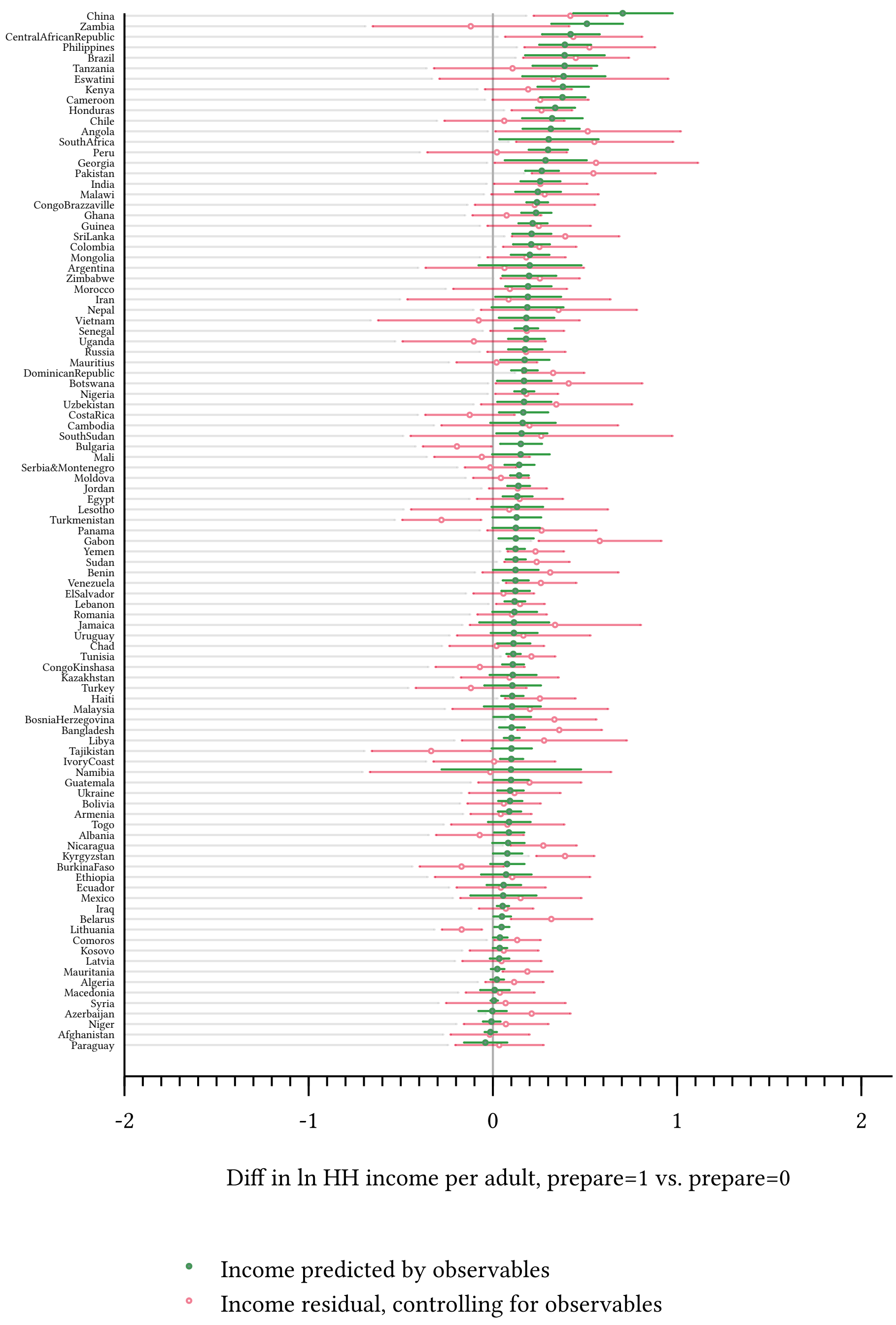
Data for individuals, pooled 2010–2015. Income classes are those used by the World Bank in 2010, according to gross national income per capita (Atlas exchange rate US$): "Low" is ⩽ $1,005; "lower middle" is $1,006–$3,975; "upper middle" is $3,976–$12,275.

Figure 3: Emigrant self-selection on overall determinants of income



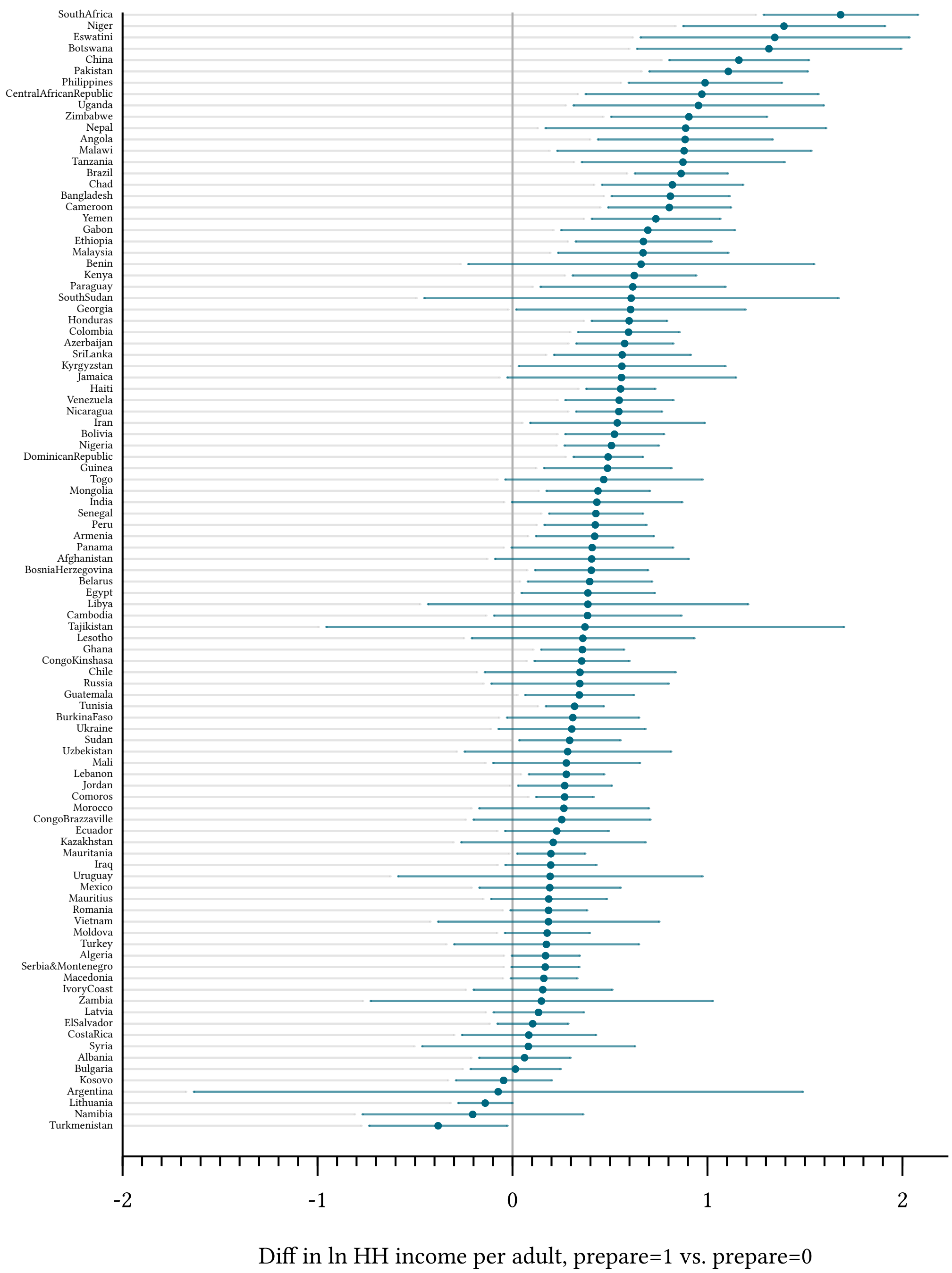
Data for individuals, pooled 2010–2015. Horizontal axis is the coefficient on an indicator for actively preparing to emigrate, where regressand is ln household income per adult, and horizontal line shows 95 percent confidence interval.

Figure 4: Emigrant self-selection on observable versus unobservable income determinants



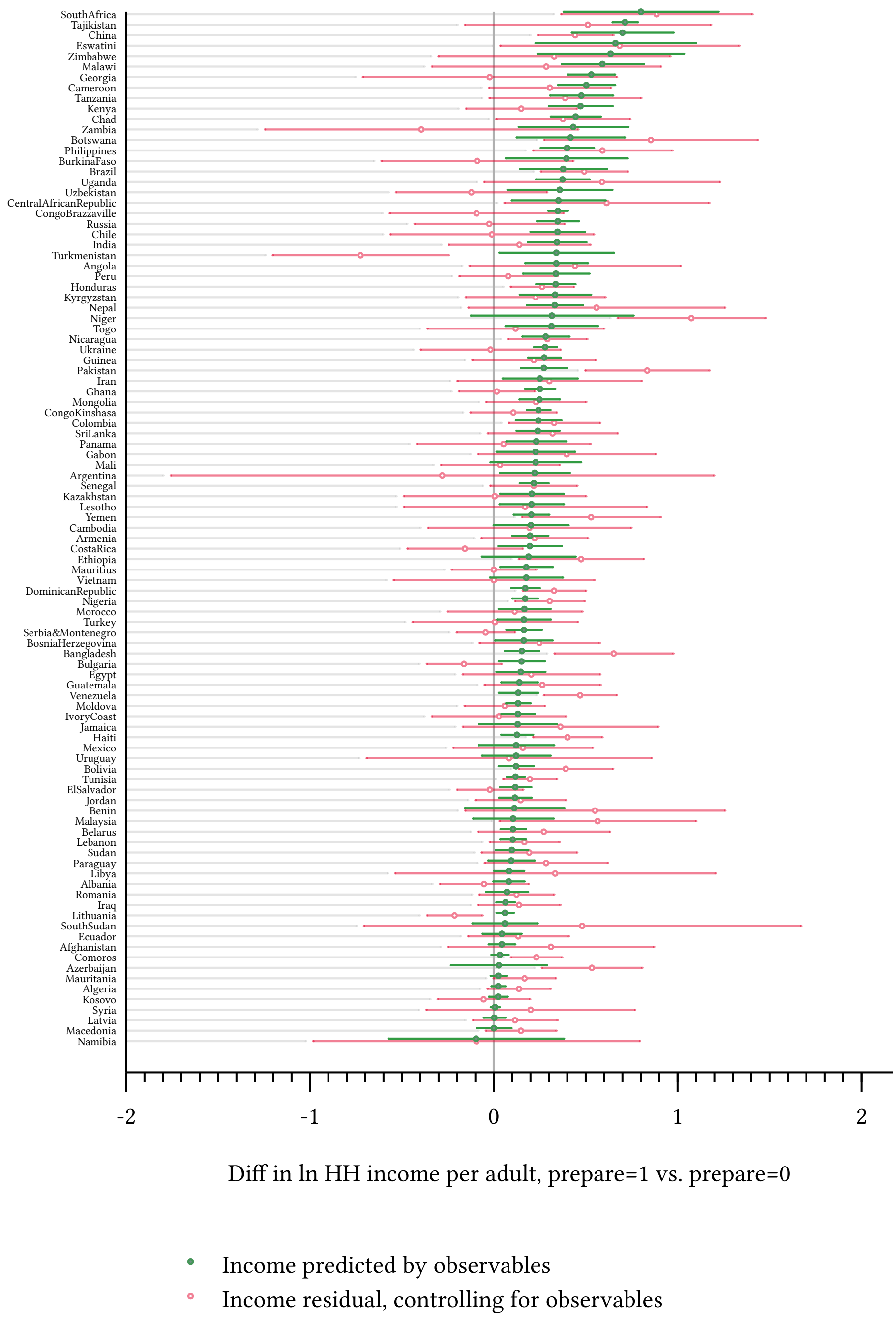
Data for individuals, pooled 2010–2015. Horizontal axis is the coefficient on an indicator for actively preparing to emigrate, where regressand is ln household income per adult. Solid green circles (selection on observables) show coefficient when regressand is income predicted by observable traits: education, age, gender, and rural/urban origin of randomly selected adult respondent. Empty red circles (selection on unobservables) show coefficient when regressand is the income residual after controlling for those observable traits. Horizontal lines show 95 percent confidence interval.

Figure 5: *Rich destinations only*: Emigrant self-selection on overall determinants of income



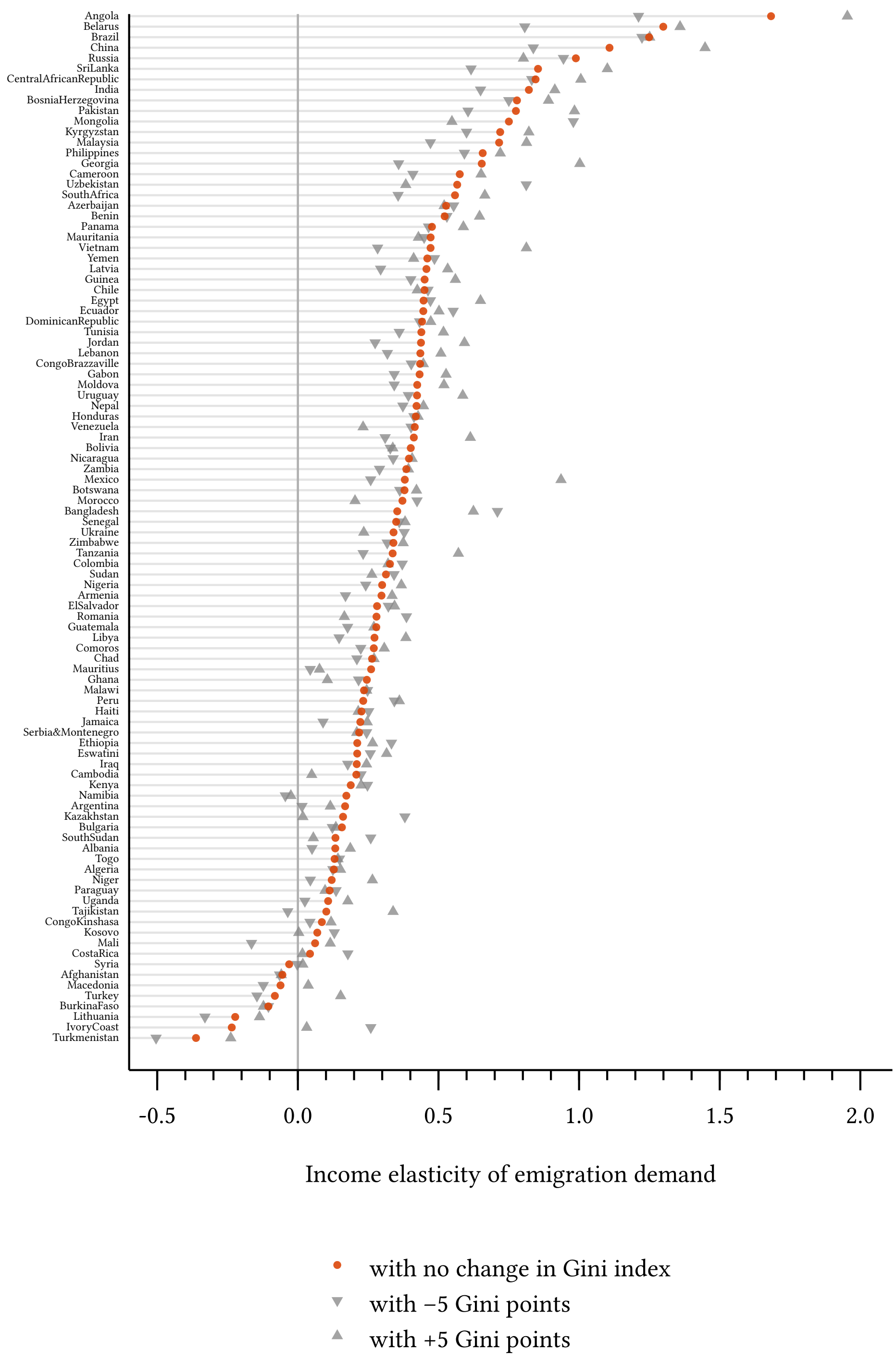
Data for individuals, pooled 2010–2015. Horizontal axis is the coefficient on an indicator for actively preparing to emigrate, where regressand is ln household income per adult, and horizontal line shows 95 percent confidence interval. "Rich destinations" are United States, United Kingdom, France, Germany, the Netherlands, Belgium, Spain, Portugal, Italy, Sweden, Greece, Denmark, Japan, Canada, Australia, New Zealand, and South Korea. (Others, such as Ireland or Norway, were not reported as a planned destination in the sample.)

Figure 6: *Rich destinations only*: Emigrant self-selection on observables versus unobservables



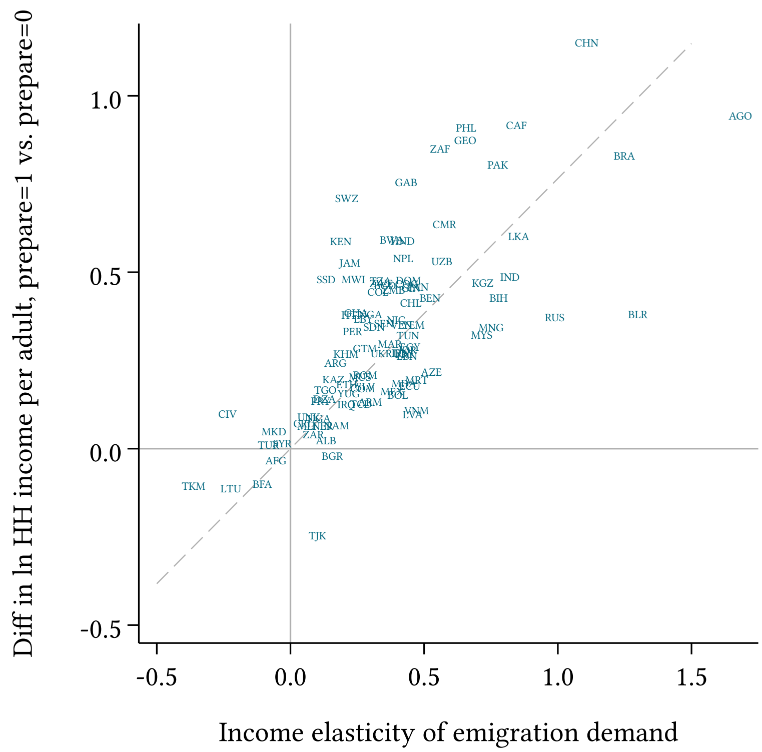
Data for individuals, pooled 2010–2015. Horizontal axis is the coefficient on an indicator for actively preparing to emigrate, where regressand is ln household income per adult. Solid green circles (selection on observables) show coefficient when regressand is income predicted by observable traits: education, age, gender, and rural/urban origin of randomly-selected adult respondent. Empty red circles (selection on unobservables) show coefficient when regressand is the income residual after controlling for those observable traits. Horizontal lines shows 95 percent confidence interval.

Figure 7: Simulation of emigration under rising incomes and changing inequality



Data for individuals, pooled 2010–2015.

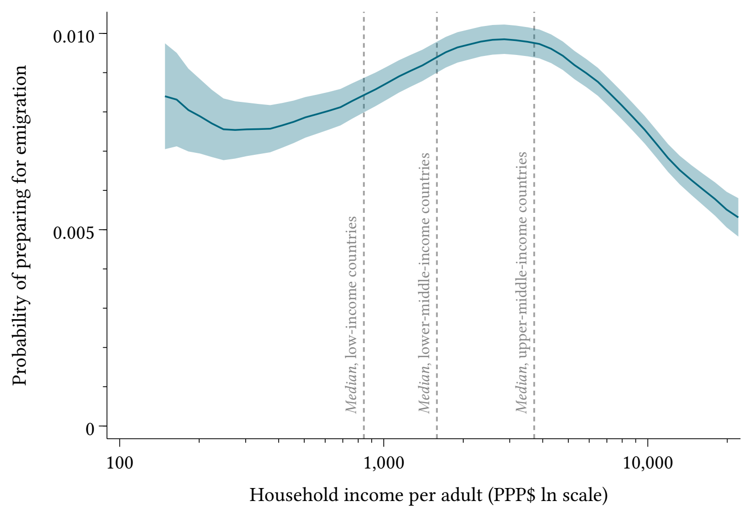
Figure 8: Comparing overall selection and the income elasticity of emigration demand



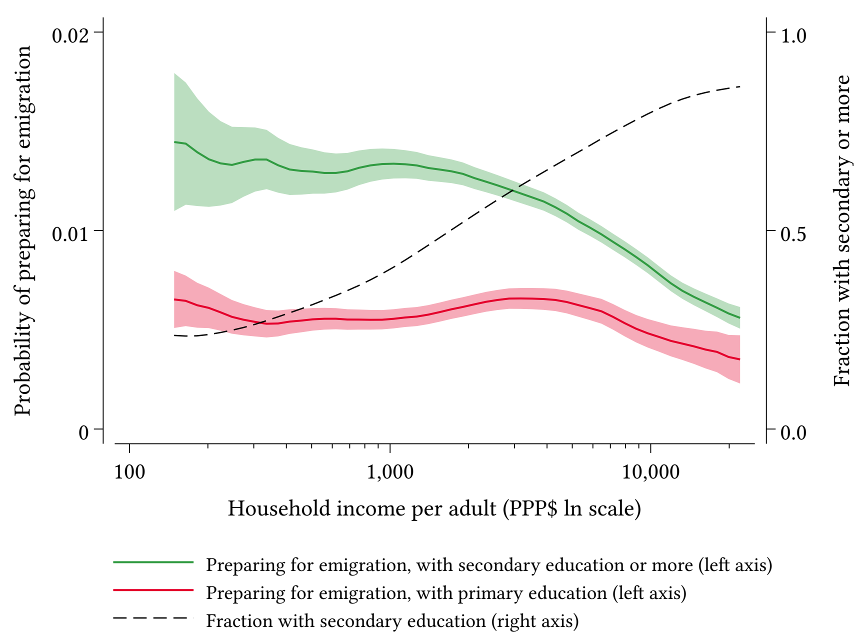
Data for individuals, pooled 2010–2015. Dashed line shows linear regression of the selection measure on income elasticity (with no constant term).

Figure 9: Emigration demand during structural transformation (*Includes both developing countries and high-income countries)*

(a) *Emigration preparation by income, all respondents pooled*



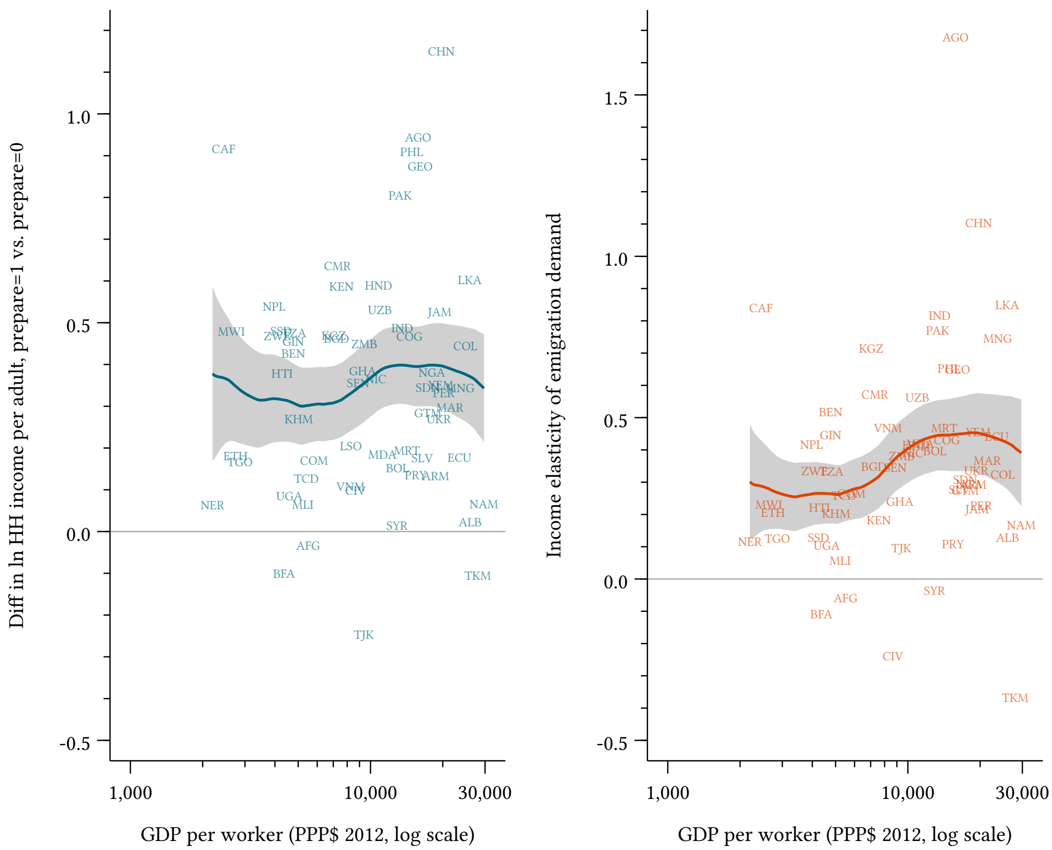
(b) *Separated by education*



Data for individuals, pooled 2010–2015. Sample size in both panels is 814,349 (includes respondents in high-income countries, unlike all preceding analysis). Migration preparation probability shown as Nadaraya-Watson regression, Epanechnikov kernel, bandwidth 0.3 natural log points, weighted by the inverse probability of household sampling within countries, with 95 percent confidence interval on the local mean probability.

Figure 10: Selection and income elasticity of emigration preparation across levels of GDP per worker

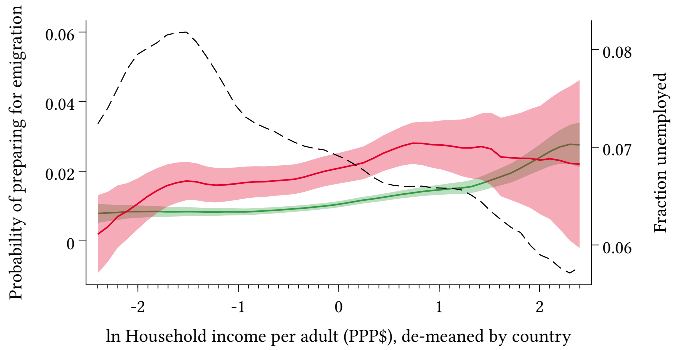
(a) *Overall self-selection* (b) *Income elasticity of emigration demand*



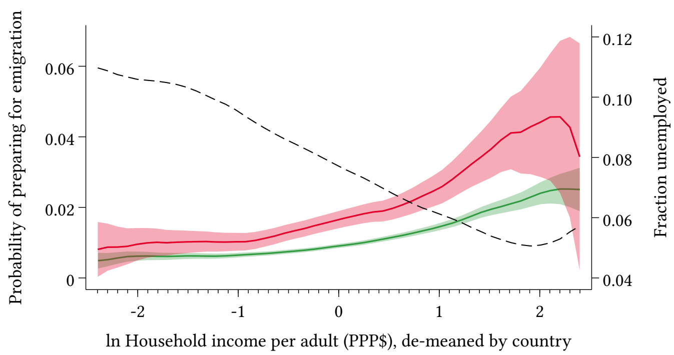
Vertical axes are the coefficient estimates from Figure 3 and Figure 7. Horizontal axis is GDP per worker in 2012 (measured in 2011 US dollars at purchasing power parity) from the World Bank. Lines are Nadaraya-Watson regression across countries, Epanechnikov kernel, bandwidth 0.333, with 95 percent confidence interval.

Figure 11: The role of unemployment

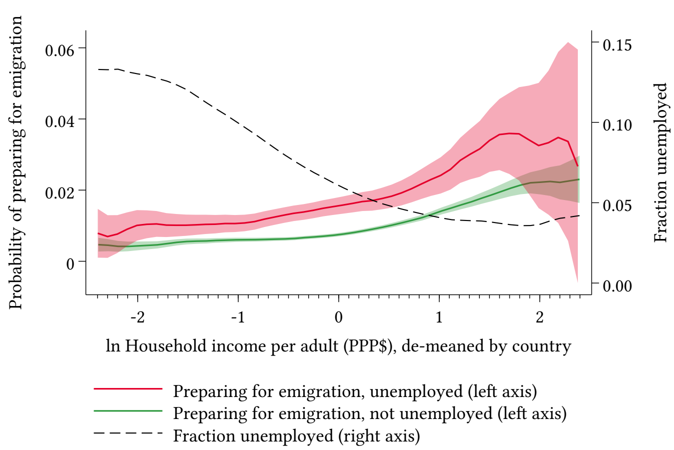
(a) *Low income countries*



(b) *Lower middle income countries*



(c) *Upper middle income countries*



Data for individuals, pooled 2010–2015, sample size 914,411. Migration preparation probability shown as Nadaraya-Watson regression, Epanechnikov kernel, bandwidth 0.3 natural log points, weighted by the inverse probability of household sampling within countries, with 95 percent confidence interval on the local mean probability. Income classes are those used by the World Bank in 2010, according to gross national income per capita (Atlas exchange rate US$): “Low” is ⩽ $1,005; “lower middle” is $1,006–$3,975; “upper middle” is $3,976–$12,275.

Online Appendix

"Migration from Developing Countries: Selection, Income Elasticity, and Simpson's Paradox

Michael A. Clemens and Mariapia Mendola — August 2020

A1 Summary statistics

Table A1 shows summary statistics for the survey dataset. Table A2 tabulates the emigration *preparation* variable for each country separately.

A2 Case selection

Country selection: The raw dataset of pooled responses 2010–2015 contains 1,053,656 respondents in 161 countries. We omit respondents in countries defined as "high income" by the World Bank as of 2010 (greater than $12,275 gross national income per capita in Atlas exchange rate US dollars, leaving 721,004 respondents in 115 developing countries, of whom 7,764 (1.08 percent) reported active preparation to emigrate. We then omit respondents in 5 countries where the data on household income are missing or corrupt (West Bank & Gaza, Liberia, Sierra Leone, Djibouti, and Somalia), leaving 692,836 respondents in 110 developing countries, of whom 7,067 (1.02 percent) reported active preparation to emigrate.

Finally, we omit respondents from 11 countries with very small samples reporting migration preparation, defined by 10 or fewer respondents reporting active preparation to emigrate (Belize, Bhutan, Burundi, Indonesia, Laos, Madagascar, Mozambique, Myanmar, Rwanda, Suriname, Thailand). This leaves 653,613 respondents in 99 different developing countries, of whom 7,013 (1.07 percent) state that they were actively preparing to emigrate. In this group of countries, the average number of respondents per country was 6,604, of whom an average of 70.8 reported active preparation to emigrate. The natural logarithm of household income per adult is 2 percent Winsorized to reduce the influence of extreme incomes in the parametric regressions—though this would not affect the results across most of the support of the nonparametric kernel regressions.

A3 Sensitivity to probability weighting

The kernel regressions in the main text are weighted by the inverse probability of household sampling within countries. Because the sample sizes for almost all countries are the same (1,000 per country per year, thus 6,000 in the pooled 2010–2015 data), this means that the kernel regressions represent the relationship between emigration preparation and income *in the average country.* An alternative approach is to use frequency weights, whereby each respondent is assigned an absolute number of people he or she "represents". A kernel regression thus weighted would represent the emigration preparation-income relationship *for the average person* within a group of countries collectively, this is, it would give higher weight to respondents from more populous countries.

Figure A1 repeats the kernel regressions from the core analysis using frequency weights. The emigration-income profile, $p^*(w)$, remains monotonically increasing across almost the entire income range, in all three country-income classes. There is a small nonmonotonicity for people in low-income countries between 1.0 and 1.3 log points above the country mean of ln household income per adult, and at the extreme high end of the income distribution in upper-middle-income countries.

A4 Sensitivity to small samples

Across countries, the median sample size of respondents reporting active preparation to emigrate is 56. Figure A2 shows the kernel regressions from the core results separated according to whether the sample for each respondent's country includes fewer than 56 people preparing to emigrate (in red) or 56 or more people preparing to emigrate (blue). The migration-income profile, $p^*(w)$, is monotonically increasing regardless of sample size.

A5 Planning versus preparation

Figure A3 compares the responses across the income distribution for migration "planning" and migration "preparation," for all respondents in all 99 countries pooled. The ability to convert planned migration into active, costly preparation for migration is markedly higher for higher-income respondents.

A6 Irregular migration

Figure A4 repeats the core analysis of the emigration demand-income profile, using the survey question on "planning" for migration rather than the question on active "preparation" for migration. The "planning" question has the clear disadvantage of being more distant from actual migration behavior, since answering yes does not require any costly action, but it arguably has the advantage of being more clearly inclusive of both formal and informal migration.

The probability of planning to emigrate generally rises across the country-level income distribution in all three groups of countries, though it falls modestly in low-income countries between 1.8 and 0.7 log points below country-level average income.

As this figure suggests, selection on the overall determinants of income is positive on average in all three groups of countries. Table A3 repeats the core selection regressions from the main text, using the "planning" response instead of the "preparation" response, for all destinations (Table A3a) and for rich destinations only (Table A3b). Selection is positive and highly statistically significant on observed determinants of income, in all three groups of countries and for all destinations. Selection on unobserved determinants of income is intermediate: In most cases we cannot reject the hypothesis of zero, although selection on unobservables is positive and statistically significant at the 5 percent level for "planning" migrants from upper-middle-income countries to all destinations.

A7 Bias test using income predicted by observed traits

Table A4 repeats the bias test from the main text using income predicted by observed traits instead of true income.

A8 Results by country

Tables A5–A7 report the country-level results underlying the figures in the main text.

Appendix Table A1: Summary statistics (unweighted)

(a) *Developing countries of migrant origin (99 countries)*

	count	mean	std. dev.	min	max
Emigration *desire*	618,992	0.228	0.420	0	1
Emigration *plan*	613,056	0.0315	0.175	0	1
Emigration *preparation*	653,613	0.0107	0.103	0	1
Household income/adult	638,238	4,199	9,237	0	1,994,335
ln Household income/adult	623,744	7.74	1.12	0.5655	11.1
Education level	649,957	1.71	0.662	1	3
Age	653,763	38.9	16.9	13	100
Age (categorical)	614,835	32.0	14.8	10	60
Urban	644,304	0.383	0.486	0	1
Female	653,764	0.532	0.499	0	1

(b) *All countries, including high income migrant-origin countries (145 countries)*

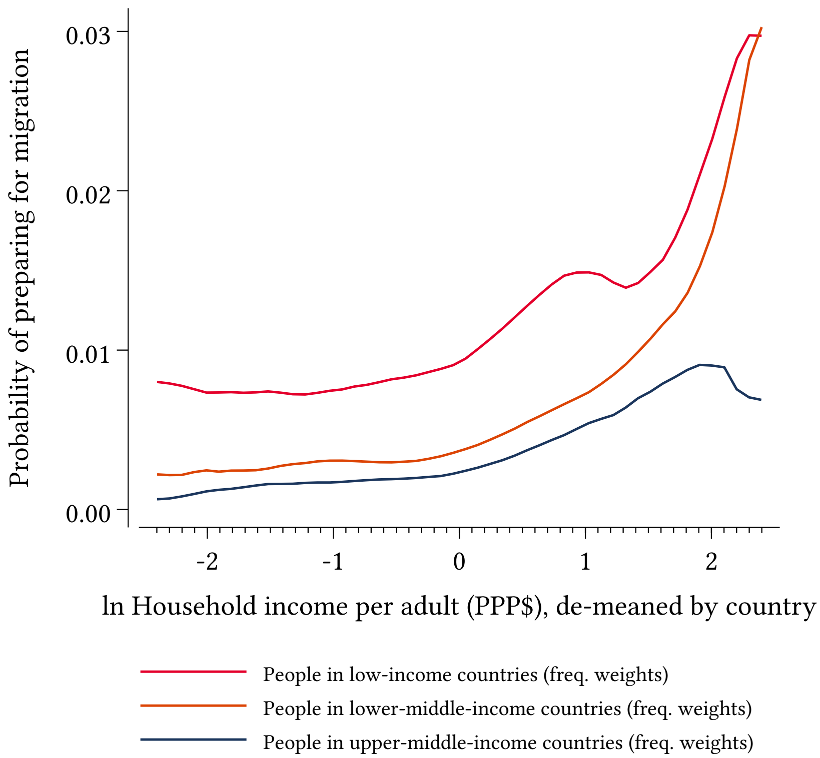
	count	mean	std. dev.	min	max
Emigration *desire*	871,587	0.211	0.408	0	1
Emigration *plan*	864,555	0.0264	0.160	0	1
Emigration *preparation*	986,231	0.00854	0.0920	0	1
Household income/adult	960,715	12,446	659,017	0	4.49×10^8
ln Household income/adult	943,311	8.40	1.381	0.565	13.4
Education level	976,223	1.87	0.682	1	3
Age	986,228	41.8	17.9	13	100
Age (categorical)	903,823	34.1	15.2	10	60
Urban	957,664	0.427	0.495	0	1
Female	986,416	0.532	0.499	0	1

Appendix Table A2: Tabulation of the *prepare* indicator by country (unweighted)

	Prepare	
Country	0	1
Afghanistan	6,911	88
Albania	5,938	130
Algeria	5,904	123
Angola	3,976	24
Argentina	5,984	16
Armenia	5,886	114
Azerbaijan	6,954	45
Bangladesh	7,955	43
Belarus	6,146	26
Benin	4,964	36
Bolivia	5,907	93
Bosnia & Herzegovina	5,965	58
Botswana	5,941	59
Brazil	7,089	14
Bulgaria	5,921	79
Burkina Faso	5,928	80
Cambodia	5,966	34
Cameroon	6,118	82
Central African Rep.	1,975	25
Chad	5,908	92
Chile	6,065	25
China	30,960	29
Colombia	5,911	89
Comoros	4,869	131
Congo Brazzaville	4,889	110
Congo Kinshasa	4,859	141
Côte d'Ivoire	2,961	47
Costa Rica	5,960	46
Dominican Republic	5,808	192
Ecuador	5,965	41
Egypt	14,609	74
El Salvador	5,875	126
Eswatini	971	29
Ethiopia	4,979	25
Gabon	4,933	83
Georgia	5,985	15
Ghana	5,798	210
Guatemala	5,931	82
Guinea	4,941	66
Haiti	2,898	120
Honduras	5,893	105
India	31,086	47
Iran	8,473	47
Iraq	9,809	201
Jamaica	1,467	44
Jordan	8,890	106
Kazakhstan	5,975	24
Kenya	5,927	73
Kosovo	5,986	97
Kyrgyzstan	5,923	76

	Prepare	
Country	0	1
Latvia	4,949	55
Lebanon	8,812	231
Lesotho	982	18
Libya	1,958	49
Lithuania	5,896	103
Macedonia	6,015	68
Malawi	4,920	80
Malaysia	6,969	40
Mali	5,936	63
Mauritania	7,863	144
Mauritius	1,963	37
Mexico	6,990	53
Moldova	5,868	130
Mongolia	5,961	39
Morocco	7,979	84
Namibia	988	12
Nepal	7,083	17
Nicaragua	5,886	117
Niger	5,932	83
Nigeria	6,875	124
Pakistan	7,998	43
Panama	5,933	62
Paraguay	5,958	41
Peru	5,945	54
Philippines	6,956	44
Romania	5,952	54
Russia	14,974	25
Senegal	5,867	131
Serbia & Montenegro	11,966	84
South Africa	6,968	32
South Sudan	1,966	32
Sri Lanka	7,176	39
Sudan	5,617	186
Syria	8,092	41
Tajikistan	5,976	24
Tanzania	5,987	29
Togo	2,935	62
Tunisia	9,112	166
Turkey	7,975	28
Turkmenistan	4,979	21
Uganda	5,916	83
Ukraine	5,961	36
Uruguay	5,974	32
Uzbekistan	5,987	13
Venezuela	5,967	32
Vietnam	6,998	19
Yemen	8,894	106
Zambia	4,958	42
Zimbabwe	5,856	143

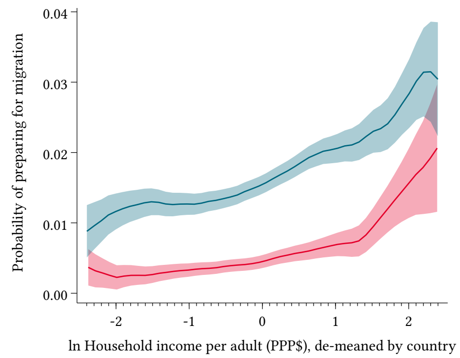
Appendix Figure A1: Alternative weighting (frequency weights), to represent people rather than countries



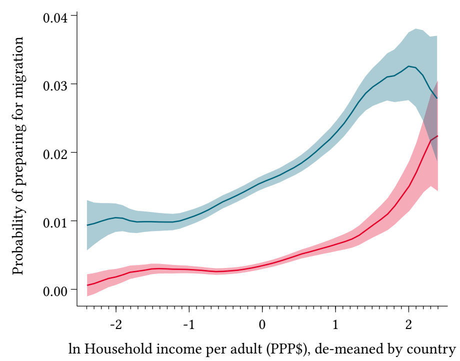
The results in the main text use probability weights reflecting the inverse of the probability of sampling each household *within each country*, so that the results are representative of the average country, with equal weight given to countries regardless of size. This figure uses frequency weights, effectively giving more weight to respondents in larger countries, so that the results are representative of *people* in each country group collectively. Data for individuals, pooled 2010–2015.

Appendix Figure A2: Sensitivity to sample size

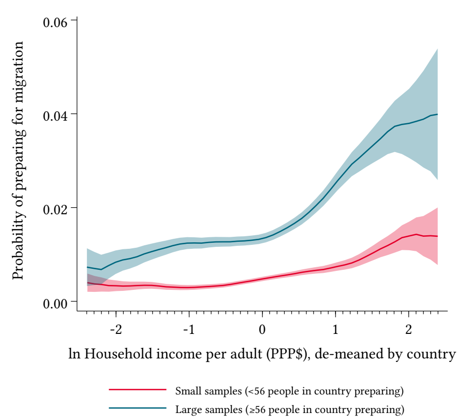
(a) *Low-income countries*



(b) *Lower-middle income countries*

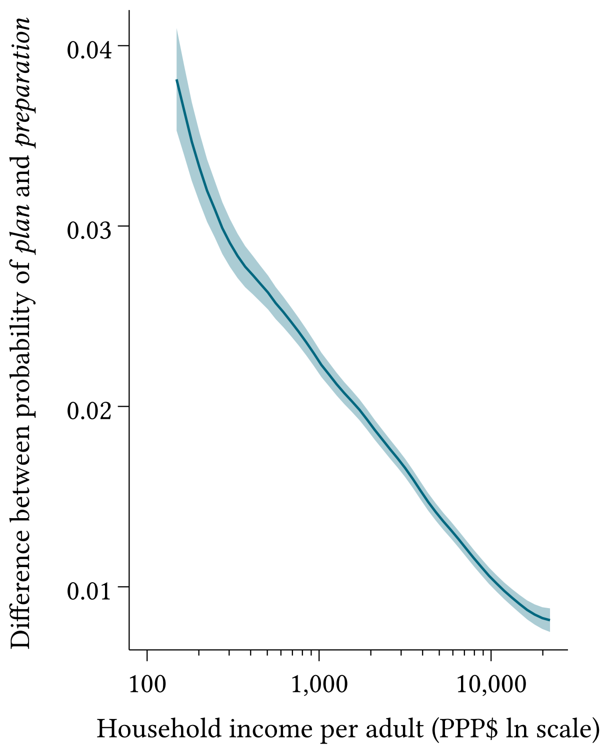


(c) *Upper-middle income countries*



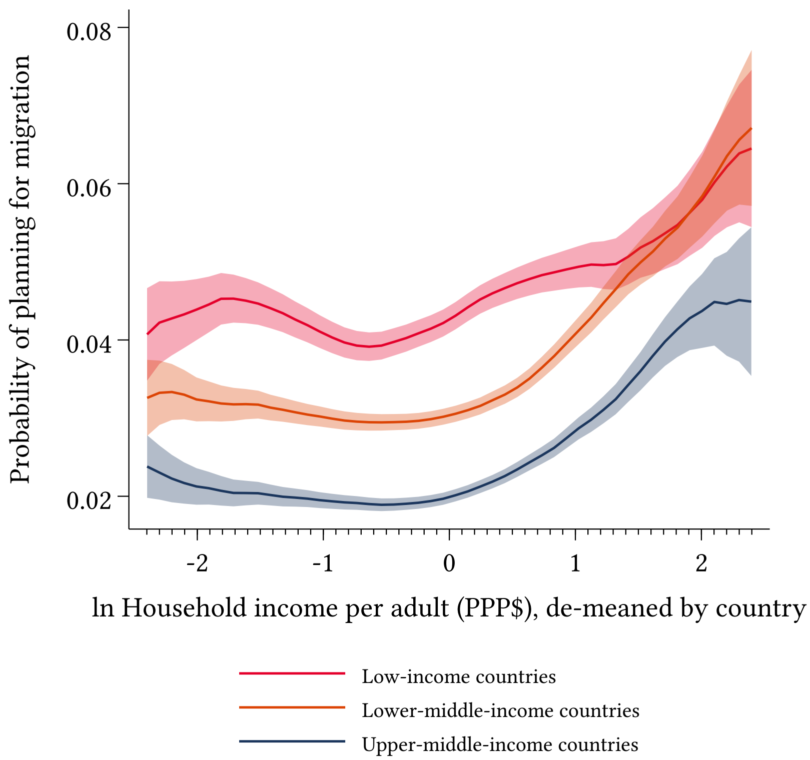
Across country samples, the median number of respondents reporting emigration preparation is 56. Data for individuals, pooled 2010–2015. Migration preparation probability shown as Nadaraya-Watson regression, Epanechnikov kernel, bandwidth 0.3 natural log points, weighted by the inverse probability of household sampling within countries, with 95 percent confidence interval on the local mean probability. Income classes are those used by the World Bank in 2010, according to gross national income per capita (Atlas exchange rate US$): "Low" is ⩽ $1,005; "lower middle" is $1,006–$3,975; "upper middle" is $3,976–$12,275.

Appendix Figure A3: Comparing migration planning and preparation across the individual income distribution, all respondents pooled



Data for individuals in all 99 developing countries, pooled 2010–2015.

Appendix Figure A4: Repeat core analysis using respondents "planning" to emigrate



Data for individuals, pooled 2010–2015.

Appendix Table A3: Selection estimates by country income class, using respondents "planning" to emigrate rather than actively preparing to emigrate

(a) *All destination countries*

	Selection overall		Selection on observables		Selection on unobservables	
	Diff	s.e.	Diff	s.e.	Diff	s.e.
low	0.070	(0.017)	0.077	(0.005)	−0.017	(0.017)
lower middle	0.111	(0.013)	0.086	(0.004)	0.020	(0.013)
upper middle	0.134	(0.015)	0.093	(0.005)	0.034	(0.015)

(b) *Rich destinations only*

	Selection overall		Selection on observables		Selection on unobservables	
	Diff	s.e.	Diff	s.e.	Diff	s.e.
low	0.064	(0.019)	0.080	(0.005)	−0.024	(0.018)
lower middle	0.087	(0.014)	0.080	(0.004)	0.002	(0.014)
upper middle	0.116	(0.017)	0.086	(0.005)	0.023	(0.016)

Estimates of difference in ln income between preparing emigrants and others. Data for individuals, pooled 2010–2015. Robust standard errors in parentheses. "Rich destinations" are United States, United Kingdom, France, Germany, the Netherlands, Belgium, Spain, Portugal, Italy, Sweden, Greece, Denmark, Japan, Canada, Australia, New Zealand, and South Korea. (Others, such as Ireland or Norway, were not reported as a planned destination in the sample.)

Appendix Table A4: Testing for bias from unobserved migration

(a) *All destination countries*

Dep. var.	Gap between *desire* and *plan*		Gap between *plan* and *prepare*	
Included if	Desire	Desire	Plan	Plan
ln Household income/adult predicted by observables	−0.06871	−0.05614	−0.20674	−0.08973
	(0.00358)	(0.00575)	(0.01437)	(0.00984)
N	168,153	160,850	21,718	20,625

(b) *Rich destinations only*

Dep. var.	Gap between *desire* and *plan*		Gap between *plan* and *prepare*	
Included if	Desire	Desire	Plan	Plan
ln Household income/adult predicted by observables	−0.08004	−0.06361	−0.25222	−0.10366
	(0.00457)	(0.00718)	(0.01952)	(0.01033)
N	99,799	95,274	11,813	11,169

"ln Household income/adult predicted by observables" is predicted using education, age, gender, and rural/urban as in the main text. Data for individuals, pooled 2010–2015, weighted by sampling weight. Robust standard errors in parentheses. "Rich destinations" are United States, United Kingdom, France, Germany, the Netherlands, Belgium, Spain, Portugal, Italy, Sweden, Greece, Denmark, Japan, Canada, Australia, New Zealand, and South Korea. (Others, such as Ireland or Norway, were not reported as a planned destination in the sample.)

Appendix Table A5: Selection estimates by group and country

	Selection overall			Selection on observables			Selection on unobservables		
	Diff	s.e.	*p*-val.	Diff	s.e.	*p*-val.	Diff	s.e.	*p*-val.
Low-income countries									
Afghanistan	-0.029	(0.111)	0.790	-0.013	(0.017)	0.436	-0.017	(0.109)	0.879
Bangladesh	0.466	(0.120)	0.000	0.102	(0.035)	0.004	0.361	(0.117)	0.002
Benin	0.431	(0.210)	0.041	0.123	(0.063)	0.050	0.311	(0.188)	0.099
Burkina Faso	-0.097	(0.118)	0.411	0.077	(0.047)	0.100	-0.170	(0.117)	0.145
Cambodia	0.273	(0.201)	0.174	0.162	(0.090)	0.072	0.199	(0.245)	0.417
Central African Republic	0.920	(0.190)	0.000	0.422	(0.079)	0.000	0.437	(0.190)	0.021
Chad	0.131	(0.142)	0.358	0.112	(0.046)	0.014	0.020	(0.131)	0.881
Comoros	0.174	(0.068)	0.011	0.039	(0.020)	0.048	0.132	(0.064)	0.039
Congo Kinshasa	0.044	(0.128)	0.729	0.108	(0.030)	0.000	-0.071	(0.123)	0.567
Ethiopia	0.185	(0.228)	0.417	0.072	(0.069)	0.302	0.105	(0.215)	0.624
Guinea	0.459	(0.135)	0.001	0.216	(0.040)	0.000	0.250	(0.143)	0.081
Haiti	0.383	(0.093)	0.000	0.104	(0.030)	0.001	0.256	(0.098)	0.009
Kenya	0.591	(0.120)	0.000	0.380	(0.071)	0.000	0.192	(0.120)	0.111
Kyrgyzstan	0.473	(0.095)	0.000	0.079	(0.040)	0.050	0.392	(0.080)	0.000
Malawi	0.483	(0.155)	0.002	0.244	(0.063)	0.000	0.282	(0.148)	0.058
Mali	0.068	(0.153)	0.657	0.151	(0.079)	0.057	-0.060	(0.132)	0.649
Nepal	0.543	(0.221)	0.014	0.187	(0.099)	0.059	0.357	(0.216)	0.098
Niger	0.067	(0.112)	0.548	-0.008	(0.024)	0.747	0.071	(0.117)	0.546
South Sudan	0.484	(0.339)	0.153	0.156	(0.070)	0.027	0.263	(0.363)	0.469
Tajikistan	-0.243	(0.186)	0.192	0.101	(0.055)	0.067	-0.335	(0.165)	0.043
Tanzania	0.480	(0.263)	0.069	0.389	(0.089)	0.000	0.107	(0.218)	0.625
Togo	0.170	(0.159)	0.285	0.088	(0.059)	0.134	0.079	(0.157)	0.613
Uganda	0.089	(0.192)	0.643	0.180	(0.050)	0.000	-0.103	(0.198)	0.603
Zimbabwe	0.473	(0.109)	0.000	0.197	(0.074)	0.008	0.255	(0.110)	0.020
Lower-middle-income countries									
Angola	0.947	(0.205)	0.000	0.315	(0.079)	0.000	0.515	(0.257)	0.045
Armenia	0.136	(0.086)	0.114	0.089	(0.032)	0.005	0.043	(0.085)	0.612
Bolivia	0.156	(0.102)	0.127	0.093	(0.033)	0.005	0.059	(0.101)	0.558
Cameroon	0.640	(0.141)	0.000	0.378	(0.062)	0.000	0.257	(0.133)	0.053
Congo Brazzaville	0.471	(0.155)	0.002	0.239	(0.030)	0.000	0.227	(0.166)	0.172
Egypt	0.292	(0.124)	0.019	0.133	(0.041)	0.001	0.146	(0.119)	0.221
El Salvador	0.180	(0.085)	0.035	0.122	(0.039)	0.002	0.057	(0.084)	0.494
Georgia	0.878	(0.235)	0.000	0.286	(0.113)	0.012	0.560	(0.282)	0.047
Ghana	0.388	(0.096)	0.000	0.235	(0.041)	0.000	0.075	(0.095)	0.434
Guatemala	0.287	(0.134)	0.032	0.099	(0.048)	0.040	0.199	(0.143)	0.163
Honduras	0.592	(0.094)	0.000	0.339	(0.054)	0.000	0.264	(0.084)	0.002
India	0.491	(0.129)	0.000	0.257	(0.055)	0.000	0.258	(0.129)	0.046
Iraq	0.128	(0.078)	0.100	0.053	(0.016)	0.001	0.071	(0.075)	0.349
Ivory Coast	0.102	(0.162)	0.529	0.100	(0.032)	0.002	0.007	(0.169)	0.968
Kosovo	0.093	(0.091)	0.308	0.037	(0.020)	0.055	0.060	(0.095)	0.532
Lesotho	0.209	(0.279)	0.455	0.131	(0.071)	0.065	0.089	(0.273)	0.744
Mauritania	0.198	(0.072)	0.006	0.025	(0.018)	0.180	0.187	(0.069)	0.007
Moldova	0.188	(0.077)	0.014	0.143	(0.025)	0.000	0.044	(0.078)	0.575
Mongolia	0.348	(0.105)	0.001	0.201	(0.053)	0.000	0.182	(0.108)	0.093
Morocco	0.301	(0.187)	0.108	0.191	(0.064)	0.003	0.092	(0.158)	0.558
Nicaragua	0.369	(0.108)	0.001	0.083	(0.044)	0.061	0.274	(0.092)	0.003
Nigeria	0.384	(0.097)	0.000	0.169	(0.027)	0.000	0.182	(0.087)	0.036
Pakistan	0.808	(0.195)	0.000	0.266	(0.046)	0.000	0.546	(0.172)	0.001
Paraguay	0.139	(0.155)	0.369	-0.040	(0.059)	0.496	0.035	(0.122)	0.777
Philippines	0.913	(0.191)	0.000	0.391	(0.071)	0.000	0.524	(0.181)	0.004
Senegal	0.359	(0.108)	0.001	0.180	(0.032)	0.000	0.185	(0.102)	0.071
Sri Lanka	0.606	(0.132)	0.000	0.210	(0.054)	0.000	0.393	(0.149)	0.008

Data for individuals, pooled 2010–2015.

Appendix Table A5: Selection estimates by group and country, *continued*

	Selection overall			Selection on observables			Selection on unobservables		
	Diff	s.e.	*p*-val.	Diff	s.e.	*p*-val.	Diff	s.e.	*p*-val.
Lower-middle-income countries, continued									
Sudan	0.349	(0.087)	0.000	0.123	(0.027)	0.000	0.238	(0.090)	0.009
Eswatini	0.713	(0.330)	0.031	0.384	(0.115)	0.001	0.330	(0.317)	0.298
Syria	0.018	(0.159)	0.908	0.006	(0.010)	0.545	0.069	(0.165)	0.676
Turkmenistan	-0.102	(0.101)	0.311	0.129	(0.067)	0.054	-0.279	(0.109)	0.011
Ukraine	0.274	(0.119)	0.021	0.094	(0.036)	0.009	0.118	(0.127)	0.353
Uzbekistan	0.534	(0.182)	0.003	0.169	(0.074)	0.023	0.345	(0.209)	0.100
Vietnam	0.112	(0.290)	0.700	0.182	(0.076)	0.017	-0.077	(0.279)	0.782
Yemen	0.354	(0.073)	0.000	0.123	(0.025)	0.000	0.232	(0.078)	0.003
Zambia	0.453	(0.284)	0.111	0.510	(0.099)	0.000	-0.120	(0.272)	0.659
Upper-middle-income countries									
Albania	0.026	(0.116)	0.822	0.087	(0.041)	0.036	-0.072	(0.122)	0.556
Algeria	0.145	(0.082)	0.078	0.022	(0.018)	0.224	0.116	(0.081)	0.151
Argentina	0.247	(0.246)	0.316	0.200	(0.142)	0.159	0.063	(0.219)	0.773
Azerbaijan	0.222	(0.119)	0.062	-0.003	(0.039)	0.937	0.211	(0.107)	0.049
Belarus	0.385	(0.106)	0.000	0.050	(0.024)	0.037	0.317	(0.113)	0.005
Bosnia-Herzegovina	0.431	(0.097)	0.000	0.104	(0.052)	0.043	0.334	(0.115)	0.004
Botswana	0.596	(0.206)	0.004	0.169	(0.075)	0.024	0.412	(0.203)	0.043
Brazil	0.834	(0.124)	0.000	0.389	(0.110)	0.000	0.450	(0.147)	0.002
Bulgaria	-0.017	(0.110)	0.875	0.152	(0.057)	0.008	-0.195	(0.095)	0.041
Chile	0.417	(0.149)	0.005	0.322	(0.083)	0.000	0.062	(0.166)	0.711
China	1.154	(0.176)	0.000	0.705	(0.137)	0.000	0.421	(0.102)	0.000
Colombia	0.448	(0.106)	0.000	0.208	(0.051)	0.000	0.253	(0.102)	0.013
CostaRica	0.075	(0.136)	0.580	0.165	(0.068)	0.015	-0.126	(0.124)	0.311
Dominican Republic	0.481	(0.089)	0.000	0.170	(0.036)	0.000	0.327	(0.086)	0.000
Ecuador	0.181	(0.118)	0.126	0.058	(0.047)	0.218	0.043	(0.123)	0.725
Gabon	0.758	(0.160)	0.000	0.125	(0.048)	0.010	0.580	(0.170)	0.001
Iran	0.275	(0.304)	0.365	0.190	(0.091)	0.036	0.086	(0.281)	0.760
Jamaica	0.529	(0.264)	0.045	0.114	(0.096)	0.235	0.338	(0.237)	0.154
Jordan	0.283	(0.081)	0.000	0.139	(0.031)	0.000	0.135	(0.080)	0.093
Kazakhstan	0.200	(0.170)	0.239	0.108	(0.065)	0.094	0.090	(0.135)	0.504
Latvia	0.100	(0.110)	0.365	0.035	(0.027)	0.190	0.047	(0.109)	0.665
Lebanon	0.267	(0.068)	0.000	0.118	(0.028)	0.000	0.148	(0.067)	0.028
Libya	0.372	(0.212)	0.080	0.101	(0.021)	0.000	0.278	(0.228)	0.224
Lithuania	-0.109	(0.053)	0.042	0.047	(0.021)	0.021	-0.169	(0.055)	0.002
Macedonia	0.053	(0.094)	0.577	0.010	(0.040)	0.810	0.038	(0.095)	0.688
Malaysia	0.325	(0.203)	0.110	0.104	(0.078)	0.183	0.201	(0.216)	0.351
Mauritius	0.207	(0.144)	0.151	0.172	(0.068)	0.011	0.020	(0.112)	0.857
Mexico	0.165	(0.160)	0.303	0.056	(0.091)	0.539	0.151	(0.168)	0.369
Namibia	0.069	(0.314)	0.826	0.099	(0.193)	0.609	-0.014	(0.334)	0.967
Panama	0.462	(0.138)	0.001	0.125	(0.065)	0.056	0.265	(0.151)	0.080
Peru	0.336	(0.187)	0.073	0.300	(0.054)	0.000	0.022	(0.193)	0.909
Romania	0.213	(0.100)	0.033	0.117	(0.062)	0.057	0.103	(0.096)	0.284
Russia	0.376	(0.106)	0.000	0.175	(0.047)	0.000	0.181	(0.108)	0.095
Serbia & Montenegro	0.160	(0.081)	0.050	0.143	(0.041)	0.000	-0.014	(0.071)	0.847
South Africa	0.853	(0.240)	0.000	0.303	(0.137)	0.027	0.551	(0.217)	0.011
Tunisia	0.324	(0.067)	0.000	0.111	(0.019)	0.000	0.209	(0.065)	0.001
Turkey	0.015	(0.185)	0.937	0.106	(0.078)	0.175	-0.119	(0.153)	0.437
Uruguay	0.273	(0.185)	0.141	0.114	(0.064)	0.076	0.166	(0.185)	0.369
Venezuela	0.355	(0.111)	0.001	0.123	(0.035)	0.001	0.261	(0.098)	0.008

Data for individuals, pooled 2010–2015.

Appendix Table A6: *Rich destinations only*: Selection estimates by group and country

	Selection overall			Selection on observables			Selection on unobservables		
	Diff	s.e.	p-val.	Diff	s.e.	p-val.	Diff	s.e.	p-val.
Low-income countries									
Afghanistan	0.406	(0.253)	0.108	0.044	(0.037)	0.231	0.311	(0.286)	0.277
Bangladesh	0.810	(0.154)	0.000	0.153	(0.047)	0.001	0.653	(0.165)	0.000
Benin	0.659	(0.452)	0.145	0.113	(0.138)	0.414	0.551	(0.361)	0.127
BurkinaFaso	0.309	(0.173)	0.073	0.396	(0.169)	0.019	-0.090	(0.266)	0.735
Cambodia	0.385	(0.245)	0.116	0.202	(0.104)	0.051	0.195	(0.282)	0.491
Central African Republic	0.971	(0.305)	0.001	0.352	(0.130)	0.007	0.614	(0.284)	0.031
Chad	0.820	(0.185)	0.000	0.445	(0.069)	0.000	0.377	(0.186)	0.043
Comoros	0.268	(0.075)	0.000	0.033	(0.023)	0.162	0.232	(0.071)	0.001
Congo Kinshasa	0.355	(0.124)	0.004	0.243	(0.032)	0.000	0.107	(0.120)	0.372
Ethiopia	0.671	(0.178)	0.000	0.189	(0.130)	0.145	0.475	(0.173)	0.006
Guinea	0.487	(0.167)	0.003	0.275	(0.045)	0.000	0.218	(0.171)	0.203
Haiti	0.555	(0.090)	0.000	0.126	(0.044)	0.004	0.401	(0.096)	0.000
Kenya	0.624	(0.162)	0.000	0.472	(0.088)	0.000	0.150	(0.154)	0.330
Kyrgyzstan	0.561	(0.270)	0.038	0.334	(0.099)	0.001	0.227	(0.194)	0.242
Malawi	0.880	(0.332)	0.008	0.592	(0.114)	0.000	0.286	(0.318)	0.369
Mali	0.276	(0.192)	0.149	0.228	(0.126)	0.070	0.035	(0.165)	0.834
Nepal	0.888	(0.367)	0.016	0.332	(0.077)	0.000	0.559	(0.356)	0.116
Niger	1.393	(0.264)	0.000	0.317	(0.226)	0.161	1.076	(0.205)	0.000
South Sudan	0.609	(0.542)	0.261	0.060	(0.090)	0.505	0.482	(0.607)	0.427
Tajikistan	0.372	(0.677)	0.583	0.714	(0.035)	0.000	0.511	(0.342)	0.134
Tanzania	0.874	(0.265)	0.001	0.477	(0.087)	0.000	0.389	(0.211)	0.065
Togo	0.468	(0.258)	0.070	0.314	(0.128)	0.014	0.119	(0.245)	0.627
Uganda	0.954	(0.327)	0.004	0.374	(0.074)	0.000	0.589	(0.327)	0.072
Zimbabwe	0.905	(0.204)	0.000	0.636	(0.203)	0.002	0.329	(0.322)	0.307
Lower-middle-income countries									
Angola	0.885	(0.229)	0.000	0.340	(0.087)	0.000	0.442	(0.293)	0.132
Armenia	0.421	(0.154)	0.006	0.198	(0.050)	0.000	0.222	(0.148)	0.133
Bolivia	0.523	(0.129)	0.000	0.121	(0.049)	0.013	0.391	(0.131)	0.003
Cameroon	0.804	(0.161)	0.000	0.504	(0.079)	0.000	0.305	(0.169)	0.072
Congo Brazzaville	0.253	(0.231)	0.275	0.349	(0.027)	0.000	-0.094	(0.241)	0.697
Egypt	0.387	(0.174)	0.026	0.147	(0.068)	0.030	0.204	(0.191)	0.285
El Salvador	0.104	(0.092)	0.263	0.118	(0.043)	0.006	-0.021	(0.092)	0.822
Georgia	0.606	(0.300)	0.043	0.530	(0.065)	0.000	-0.022	(0.353)	0.951
Ghana	0.359	(0.109)	0.001	0.251	(0.042)	0.000	0.016	(0.105)	0.879
Guatemala	0.343	(0.142)	0.016	0.139	(0.051)	0.006	0.265	(0.161)	0.099
Honduras	0.598	(0.099)	0.000	0.336	(0.054)	0.000	0.264	(0.088)	0.003
India	0.433	(0.223)	0.052	0.344	(0.081)	0.000	0.140	(0.197)	0.477
Iraq	0.196	(0.119)	0.100	0.063	(0.025)	0.013	0.137	(0.114)	0.229
Ivory Coast	0.155	(0.181)	0.392	0.131	(0.046)	0.005	0.028	(0.186)	0.881
Kosovo	-0.045	(0.125)	0.717	0.024	(0.026)	0.358	-0.055	(0.128)	0.670
Lesotho	0.361	(0.291)	0.215	0.205	(0.089)	0.022	0.171	(0.337)	0.612
Mauritania	0.197	(0.089)	0.027	0.025	(0.022)	0.242	0.168	(0.086)	0.052
Moldova	0.178	(0.111)	0.109	0.132	(0.034)	0.000	0.059	(0.112)	0.597
Mongolia	0.438	(0.135)	0.001	0.249	(0.056)	0.000	0.230	(0.139)	0.097
Morocco	0.263	(0.222)	0.235	0.167	(0.072)	0.020	0.114	(0.187)	0.542
Nicaragua	0.545	(0.112)	0.000	0.283	(0.065)	0.000	0.292	(0.110)	0.008
Nigeria	0.508	(0.123)	0.000	0.171	(0.035)	0.000	0.304	(0.097)	0.002
Pakistan	1.107	(0.207)	0.000	0.272	(0.064)	0.000	0.835	(0.172)	0.000
Paraguay	0.617	(0.242)	0.011	0.095	(0.064)	0.138	0.285	(0.171)	0.095
Philippines	0.988	(0.200)	0.000	0.399	(0.074)	0.000	0.592	(0.193)	0.002
Senegal	0.428	(0.123)	0.001	0.219	(0.040)	0.000	0.217	(0.121)	0.072
SriLanka	0.563	(0.179)	0.002	0.239	(0.059)	0.000	0.320	(0.180)	0.076

Data for individuals, pooled 2010–2015. "Rich destinations" are United States, United Kingdom, France, Germany, the Netherlands, Belgium, Spain, Portugal, Italy, Sweden, Greece, Denmark, Japan, Canada, Australia, New Zealand, and South Korea.

Appendix Table A6: *Rich destinations only*: Selection estimates by group and country, *continued*

	Selection overall			Selection on observables			Selection on unobservables		
	Diff	s.e.	*p*-val.	Diff	s.e.	*p*-val.	Diff	s.e.	*p*-val.
Lower-middle-income countries, continued									
Sudan	0.293	(0.132)	0.027	0.098	(0.044)	0.027	0.193	(0.132)	0.145
Eswatini	1.345	(0.352)	0.000	0.662	(0.222)	0.003	0.684	(0.332)	0.039
Syria	0.082	(0.278)	0.769	0.007	(0.012)	0.549	0.200	(0.289)	0.489
Turkmenistan	-0.382	(0.181)	0.035	0.341	(0.159)	0.032	-0.725	(0.244)	0.003
Ukraine	0.304	(0.192)	0.113	0.280	(0.031)	0.000	-0.017	(0.194)	0.929
Uzbekistan	0.283	(0.270)	0.295	0.359	(0.145)	0.014	-0.122	(0.210)	0.562
Vietnam	0.184	(0.289)	0.524	0.177	(0.101)	0.080	0.001	(0.279)	0.998
Yemen	0.735	(0.168)	0.000	0.204	(0.049)	0.000	0.530	(0.193)	0.006
Zambia	0.149	(0.447)	0.740	0.433	(0.152)	0.004	-0.394	(0.435)	0.366
Upper-middle-income countries									
Albania	0.062	(0.119)	0.604	0.082	(0.043)	0.057	-0.053	(0.123)	0.669
Algeria	0.169	(0.089)	0.057	0.025	(0.019)	0.198	0.137	(0.088)	0.117
Argentina	-0.074	(0.797)	0.926	0.222	(0.097)	0.022	-0.280	(0.754)	0.710
Azerbaijan	0.575	(0.127)	0.000	0.027	(0.133)	0.839	0.534	(0.139)	0.000
Belarus	0.396	(0.163)	0.015	0.105	(0.035)	0.003	0.273	(0.183)	0.136
Bosnia-Herzegovina	0.404	(0.148)	0.006	0.163	(0.079)	0.040	0.249	(0.166)	0.135
Botswana	1.315	(0.346)	0.000	0.418	(0.150)	0.005	0.854	(0.297)	0.004
Brazil	0.865	(0.121)	0.000	0.378	(0.120)	0.002	0.493	(0.121)	0.000
Bulgaria	0.015	(0.118)	0.901	0.151	(0.064)	0.018	-0.162	(0.104)	0.119
Chile	0.346	(0.250)	0.166	0.347	(0.075)	0.000	-0.009	(0.283)	0.974
China	1.161	(0.182)	0.000	0.700	(0.141)	0.000	0.444	(0.105)	0.000
Colombia	0.595	(0.133)	0.000	0.243	(0.063)	0.000	0.329	(0.127)	0.009
Costa Rica	0.084	(0.175)	0.633	0.196	(0.088)	0.025	-0.157	(0.160)	0.327
Dominican Republic	0.490	(0.091)	0.000	0.172	(0.039)	0.000	0.329	(0.088)	0.000
Ecuador	0.227	(0.135)	0.094	0.044	(0.054)	0.413	0.133	(0.140)	0.340
Gabon	0.694	(0.227)	0.002	0.228	(0.109)	0.036	0.397	(0.247)	0.108
Iran	0.537	(0.228)	0.019	0.251	(0.104)	0.016	0.303	(0.256)	0.236
Jamaica	0.559	(0.299)	0.062	0.130	(0.108)	0.226	0.363	(0.272)	0.182
Jordan	0.268	(0.123)	0.029	0.116	(0.045)	0.010	0.146	(0.126)	0.246
Kazakhstan	0.209	(0.241)	0.386	0.207	(0.088)	0.019	0.006	(0.253)	0.982
Latvia	0.133	(0.118)	0.258	0.003	(0.030)	0.911	0.115	(0.118)	0.326
Lebanon	0.276	(0.099)	0.005	0.104	(0.036)	0.003	0.167	(0.097)	0.084
Libya	0.387	(0.419)	0.356	0.083	(0.041)	0.045	0.334	(0.445)	0.452
Lithuania	-0.140	(0.071)	0.048	0.061	(0.024)	0.010	-0.213	(0.077)	0.006
Macedonia	0.161	(0.087)	0.065	0.001	(0.048)	0.989	0.148	(0.098)	0.131
Malaysia	0.670	(0.223)	0.003	0.106	(0.112)	0.344	0.565	(0.273)	0.038
Mauritius	0.186	(0.151)	0.219	0.177	(0.073)	0.016	0.000	(0.117)	0.999
Mexico	0.191	(0.185)	0.301	0.122	(0.105)	0.242	0.159	(0.194)	0.412
Namibia	-0.204	(0.289)	0.480	-0.096	(0.243)	0.692	-0.094	(0.453)	0.835
Panama	0.409	(0.211)	0.053	0.231	(0.083)	0.006	0.053	(0.241)	0.827
Peru	0.425	(0.133)	0.001	0.338	(0.092)	0.000	0.079	(0.136)	0.562
Romania	0.185	(0.100)	0.065	0.072	(0.058)	0.215	0.124	(0.104)	0.231
Russia	0.345	(0.232)	0.137	0.348	(0.058)	0.000	-0.024	(0.208)	0.910
Serbia & Montenegro	0.168	(0.089)	0.059	0.164	(0.049)	0.001	-0.044	(0.081)	0.590
South Africa	1.683	(0.202)	0.000	0.801	(0.215)	0.000	0.886	(0.266)	0.001
Tunisia	0.319	(0.076)	0.000	0.119	(0.024)	0.000	0.197	(0.075)	0.008
Turkey	0.174	(0.242)	0.472	0.164	(0.074)	0.027	0.007	(0.229)	0.976
Uruguay	0.193	(0.398)	0.628	0.122	(0.095)	0.200	0.083	(0.396)	0.834
Venezuela	0.547	(0.141)	0.000	0.134	(0.055)	0.015	0.470	(0.101)	0.000

Data for individuals, pooled 2010–2015. "Rich destinations" are United States, United Kingdom, France, Germany, the Netherlands, Belgium, Spain, Portugal, Italy, Sweden, Greece, Denmark, Japan, Canada, Australia, New Zealand, and South Korea.

Appendix Table A7: Simulation: Income elasticity of emigration preparation

	No change in Gini	With −5 Gini points	With +5 Gini points
Low-income countries			
Afghanistan	−0.055	−0.065	−0.059
Bangladesh	0.354	0.710	0.624
Benin	0.522	0.530	0.646
Burkina Faso	−0.105	−0.105	−0.122
Cambodia	0.208	0.225	0.049
Central African Republic	0.845	0.832	1.006
Chad	0.264	0.210	0.271
Comoros	0.270	0.224	0.307
Congo Kinshasa	0.085	0.043	0.118
Ethiopia	0.211	0.333	0.266
Guinea	0.451	0.402	0.560
Haiti	0.226	0.252	0.215
Kenya	0.188	0.248	0.225
Kyrgyzstan	0.720	0.600	0.822
Malawi	0.236	0.248	0.245
Mali	0.061	−0.165	0.115
Nepal	0.422	0.374	0.447
Niger	0.121	0.045	0.265
SouthSudan	0.134	0.259	0.055
Tajikistan	0.101	−0.036	0.339
Tanzania	0.337	0.232	0.571
Togo	0.131	0.148	0.143
Uganda	0.108	0.025	0.178
Zimbabwe	0.340	0.318	0.375
Lower-middle-income countries			
Angola	1.683	1.211	1.954
Armenia	0.298	0.170	0.335
Bolivia	0.402	0.329	0.338
Cameroon	0.576	0.409	0.652
Congo Brazzaville	0.435	0.403	0.446
Egypt	0.447	0.472	0.649
El Salvador	0.282	0.322	0.344
Georgia	0.654	0.358	1.003
Ghana	0.246	0.216	0.105
Guatemala	0.279	0.177	0.270
Honduras	0.420	0.413	0.428
India	0.822	0.650	0.914
Iraq	0.210	0.178	0.244
Ivory Coast	−0.235	0.260	0.031
Kosovo	0.069	0.130	0.003
Mauritania	0.472	0.449	0.429
Moldova	0.425	0.343	0.520
Mongolia	0.751	0.980	0.548
Morocco	0.372	0.424	0.203
Nicaragua	0.395	0.339	0.407
Nigeria	0.300	0.242	0.368
Pakistan	0.775	0.605	0.984
Paraguay	0.113	0.136	0.097
Philippines	0.657	0.592	0.720
Senegal	0.350	0.361	0.381
Sri Lanka	0.854	0.616	1.101

Data for individuals, pooled 2010–2015.

Appendix Table A7: Simulation: Income elasticity of emigration preparation, *continued*

	No change in Gini	With −5 Gini points	With +5 Gini points
Lower-middle-income countries, continued			
Sudan	0.313	0.342	0.263
Eswatini	0.211	0.258	0.316
Syria	−0.031	−0.002	0.018
Turkmenistan	−0.362	−0.504	−0.238
Ukraine	0.340	0.378	0.234
Uzbekistan	0.567	0.812	0.384
Vietnam	0.472	0.284	0.813
Yemen	0.460	0.486	0.412
Zambia	0.386	0.291	0.393
Upper-middle-income countries			
Albania	0.133	0.051	0.187
Algeria	0.128	0.125	0.152
Argentina	0.168	0.015	0.116
Azerbaijan	0.527	0.554	0.520
Belarus	1.300	0.807	1.359
Bosnia-Herzegovina	0.779	0.750	0.891
Botswana	0.379	0.362	0.422
Brazil	1.249	1.224	1.251
Bulgaria	0.157	0.123	0.135
Chile	0.450	0.463	0.425
China	1.108	0.837	1.448
Colombia	0.328	0.371	0.321
Costa Rica	0.043	0.178	0.016
Dominican Republic	0.442	0.433	0.473
Ecuador	0.446	0.552	0.502
Gabon	0.433	0.343	0.527
Iran	0.413	0.310	0.614
Jamaica	0.222	0.090	0.247
Jordan	0.438	0.275	0.592
Kazakhstan	0.161	0.381	0.018
Latvia	0.457	0.294	0.533
Lebanon	0.436	0.319	0.509
Libya	0.273	0.147	0.384
Lithuania	−0.223	−0.330	−0.136
Macedonia	−0.062	−0.123	0.037
Malaysia	0.716	0.472	0.813
Mauritius	0.261	0.044	0.077
Mexico	0.381	0.259	0.936
Namibia	0.173	−0.044	−0.025
Panama	0.477	0.465	0.589
Peru	0.232	0.343	0.361
Romania	0.280	0.386	0.166
Russia	0.989	0.945	0.802
Serbia & Montenegro	0.218	0.245	0.210
South Africa	0.559	0.357	0.665
Tunisia	0.439	0.361	0.518
Turkey	−0.082	−0.145	0.152
Uruguay	0.424	0.393	0.586
Venezuela	0.416	0.403	0.232

Data for individuals, pooled 2010–2015.