The Well-Being of Nations: Estimating Welfare from International Migration[*][†]

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Abstract

The limitations of GDP as a measure of welfare are well known. We propose a new method of estimating the well-being of nations. Using gross bilateral international migration flows and a discrete choice model in which everyone in the world chooses a country in which to live, we estimate each country's overall quality of life. Our estimates, by relying on revealed preference, complement previous estimates of well-being that consider only income or a small number of factors, or rely on structural assumptions about how these factors contribute to well-being.

Keywords: International migration, quality of life, GDP

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1 Introduction

The limitations of GDP as a measure of welfare are well known. Standard GDP accounts omit welfare factors such as home production. And some factors that do increase GDP, such as war expenditures, may not increase well-being.

We propose a new method of estimating the well-being of nations based on the revealed preference of every resident of the world. We combine estimates of gross bilateral migration flows across countries with a choice model to estimate each country's quality of life. In our model, every person chooses a country of residence (including the option of staying), given the welfare of each country and bilateral moving costs. The key idea is that, conditioned on moving costs, people tend to move from a low-utility country to a high-utility one. We then use these migration flows to estimate the well-being of nations. Overall, international migration flows suggest that per capita GDP is a good measure of welfare, despite its limitations. However, other factors appear to matter too.

A number of methods have been proposed to estimate country well-being, including principal component analysis of a large vector of factors (Ram 1982; Slottje 1991). Others have proposed estimating welfare using surveys of subjective well-being (Easterlin 1974) or evaluated time use (Krueger et al. 2009). Recently, Jones and Klenow (2016) proposed a method of estimating country well-being using household microdata on consumption and leisure and a calibrated utility model.

Our approach is new and complements existing estimates of country welfare. We rely on a simple revealed preference approach. In using gross migration flows and a discrete choice model, we are not required to take a strong *ex ante* stand on what factors matter for welfare nor how they enter into utility. Our approach is also distinct from previous work in its data requirements. Instead of relying on household surveys or censuses to measure welfare factors, our estimates of country welfare require estimates of gross population flows and country aggregates. Our contribution is to emphasize that people's migration or staying choices can improve our understanding about which countries—and what welfare factors—

they prefer. Surprisingly, despite relying on different assumptions and data compared with other work, our estimates of country well-being affirm the relevance of GDP for welfare.

We deal with a number of important challenges. A first challenge is that there may be many country pairs with zero observed migration flows. Our approach is robust to zeroes. This is because our estimates are in part identified by potential migrants who decide to stay in their origin country, and same-country flows are never nonzero.

A second challenge is that there may be unobserved migration restrictions unrelated to welfare preventing entry or exit. For example, immigration restrictions decrease the number of people choosing the destination country, deflating our estimates of country welfare. The costs of leaving home may vary across origin countries because of their incomes, emigration policies, or other origin-specific factors (Rotte and Vogler, 2000).

We address this concern in three ways. One, we incorporate survey measures of migration policy as control variables. We also allow the cost of leaving an origin country to vary across countries in a robustness check. Two, we project our estimates in a second stage on a vector of observed country factors. These projected estimates may alleviate the bias from unobserved migration policy. To see this, suppose a country's welfare depends only on observed GDP. If a country with high GDP has few immigrants because of its tough immigration policies, this will bias down our estimates of its welfare. In contrast, the country's *rank* in the GDP-projected measure depends only on GDP, not on unobservable immigration policies. In practice, we consider a number of other welfare factors beyond GDP. Three, we focus on estimates of the ordinal rankings of country welfare. This is a useful restriction if the (unobserved) strictness of immigration policy increases with a country's overall welfare. If so, then the estimated *cardinal* welfare levels will be underestimated for high-welfare countries, since they will have fewer inflows than expected. However, the estimated *ordinal* welfare rankings will still be preserved. Overall, while each of these strategies may be imperfect, we view them as first steps in improving our understanding about the link between migration flows and welfare.

We contribute to a recent literature using discrete choice models of labor mobility across locations or sectors (e.g., Bryan and Morten, 2019; Caliendo et al., 2018; Redding, 2016). In these models, people choose locations to maximize utility net of moving costs. Thus, higher-utility destinations attract more people. However, a destination may attract more people simply because it is larger. For example, in our data, more people migrate to China than to Switzerland. In standard models, the explanation is that China offers superior well-being. In our model, China attracts more migrants in part because it offers more opportunities commensurate with its size. We account for this effect by assuming that a person receives a number of idiosyncratic utility draws that is increasing with destination size. Thus, models that do not control for population size may overestimate coefficients on factors positively correlated with size.[1]

A related virtue of our model is to provide a micro-foundation for gravity in migration flows. It is well known that migration flows tend to decrease with distance, increase with origin country size, and increase with destination country size. While the first two features are standard results of choice models with costly migration, there are fewer micro-founded models that generate increasing migration flows with destination country size. Our approach accomplishes this by formalizing the intuition that the number of opportunities rises with destination country size.[2]

A large literature tries to understand the determinants of migration flows (Grogger and Hanson 2011; Pacheco et al. 2013). Much of this literature emphasizes that migration is a human capital investment and that migrants respond to labor market opportunities (Bodvarsson et al. 2015). Instead, our estimates emphasize that migrants may also be responding to other factors, including amenities, consumption, and political freedom.

We extend a large literature in regional economics that estimates variation in quality of life within a country (Roback 1982; Kahn 1995; Diamond 2016). Our approach differs in

1. This critique does not apply to models that use variation over time with destination country fixed effects.

2. We thank Thomas Holmes for the idea of increasing opportunities with location size.

two ways. First, our welfare estimates capture overall utility levels, including housing costs and incomes, whereas Roback estimates local amenity levels, excluding housing costs and incomes. In Roback (1982), workers are indifferent across locations, implying that overall utility levels are equal across locations. Our approach does not assume that workers are indifferent across locations, which allows welfare estimates that vary by country.[3] Second, our welfare estimates are based on the location choices of all people, including non-migrants, and therefore reflect the preferences of both groups. In contrast, in Roback (1982), local amenities and productivities are identified by marginal migrants who are indifferent between locations. If workers are heterogeneous, these marginal migrants may not be representative of the entire population. In contrast, we explicitly model heterogeneity among people, and our welfare estimates exclude these idiosyncratic shocks driving person heterogeneity.

2 Model

There are J countries of varying size, with *initial* populations $\{N_j\}$. Each country j offers multiple opportunities to a person, with the number of opportunities K_j increasing with N_j. We interpret "opportunities" as roughly corresponding to the number of houses, jobs, neighborhoods, or other situations within destination country j that potential migrants might consider in their location choice. Each person i living in an origin country $o \in J$ maximizes utility U by choosing an opportunity $k \in K(\equiv \sum_j K_j)$ from the set of all opportunities in the world.

$$(1) \qquad \max_{k\in K} U^i_{odk} \equiv u_d - c_{od} + \xi_d + \epsilon^i_{odk}.$$

Since opportunities are country-specific, the choice of opportunity k implies choosing the destination country $d(k)$ that contains it. The choice to stay, $d(k) = o$, is permitted.

3. Our method is similar to work in other contexts; e.g., Sorkin (2018) uses revealed preference of workers to estimate utility across jobs.

Everyone in the world faces the same choice set, though moving costs c_{od} vary across origin–destination pairs. Destination country d offers utility u_d to its resident i. c_{od} denotes moving cost between origin o and destination d. A random effect ξ_d captures unobserved destination-country migration policies or any other unobserved destination-specific factor. A person-level idiosyncratic shock ϵ^i_{odk} follows the standard Gumbel (type-I extreme value) distribution.

The choice probability of choosing country d is

$$\pi_{od} = \frac{N_d^\gamma \exp(u_d - c_{od} + \xi_d)}{\sum_j N_j^\gamma \exp(u_j - c_{oj} + \xi_j)}, \tag{2}$$

where N_d^γ is the number of opportunities country d offers. The parameter γ governs the curvature between country size and the number of opportunities.

Why should larger countries offer more opportunities? The following example motivates our setup. Consider three identical countries A, B, and C with zero migration costs. Each person then chooses each country with 1/3 probability. Next, suppose countries A and B combine to form country AB and C remains its own country. Intuitively, the new choice probabilities should be $(2/3, 1/3)$, but the standard logit setup yields choice probabilities $(1/2, 1/2)$. In contrast, our setup with $\gamma = 1$ yields the intuitive choice probabilities because country AB offers twice as many opportunities. In practice, we allow γ to take a value other than 1, because other factors may affect the relationship between opportunities and destination size. For example, country C may gain more visibility in the two-country world. Or, there may be congestion in migration flows that limits opportunities in large country AB.

Accounting for country size is important for two related reasons. First, if we omit this feature of the model and in fact opportunities *do* increase with destination size, then this will bias our estimates toward larger countries and factors that are correlated with country size. Second, allowing multiple draws according to destination size generates a gravity relationship between migration flows and destination size.

2.1 Gravity

Our setup provides micro-foundations for gravity in migration flows. It is well known that there is *gravity* in international migration flows. That is, migration flows m_{od} (i) decrease with distance d_{od}, (ii) increase with origin size N_o, and (iii) increase with destination size N_d, following $m_{od} = \frac{N_o N_d}{d_{od}} \times G_d$. A standard choice model, with migration costs that depend on distance, easily rationalizes declining flows with distance and increasing flows with origin size.[4]

In contrast, few choice models successfully replicate increasing gross flows with destination size. This is important because without this property, our method might attribute increasing flows with destination size to superior well-being in larger countries. By assuming that each person is offered multiple draws for each destination, with the number of draws increasing in destination country size, the choice probability π_{od} now increases with destination size N_d (equation 2). Therefore, flows increase with destination size, consistent with gravity.[5]

Anderson (2011), Bryan and Morten (2019), Caliendo et al. (2018), and Redding (2016) develop discrete choice models of migration in general equilibrium that are consistent with gravity. The key mechanism is a labor market clearing condition: The sum of all migrants to a destination, including self flows, must equal destination size. This condition ensures that bilateral migration flows to a destination country increase with its population size. By itself, this assumption seems innocuous, but combined with the choice structure of the model, it implies the strong prediction that wages, and thus utility, must increase with country size.

4. To see this, note that gross flows from o to d can be expressed as the population size of o multiplied by the logit probability π_{od} of migrating from o to d:

$$m_{od} = N_o \pi_{od} = N_o \frac{\exp(u_d - \log(d_{o,d}))}{\sum_d \exp(u_d - \log(d_{o,d}))} = \frac{N_o}{d_{o,d}} \frac{\exp(u_d)}{\sum_d \exp(u_d - \log(d_{o,d}))}.$$

5. Suppose that $c_{od} \equiv \log(d_{o,d})$ and $\gamma = 1$. Then bilateral migration flows are $m_{od} = \frac{N_o N_d}{d_{o,d}} \times G_d$ where $G_d \equiv \frac{\exp(u_d - \xi_d)}{\sum_j N_j \exp(u_j - c_{oj} + \xi_j)}$.

Our model is distinct in that it does not require utility to increase with country size.[6]

Our model is in partial equilibrium. The implicit assumption we make by using a partial equilibrium model is that migration choices in the 5-year window we use in our empirical analysis do not significantly affect aggregate welfare levels across countries. This assumption is consistent with net flows that are small relative to population stocks as well as evidence of small effects of migration on local labor markets (e.g., Card, 1990.)

2.2 Example

To build intuition about how the model works and how its parameters are identified, consider the following simple simulation. There are two identical countries with symmetric bilateral moving costs. The first panel of Figure 1 shows that the initial choice probabilities are symmetric. For each country, the probability of remaining in one's home country is about 75% and that of moving to the other is 25%.

Next, consider a negative shock to country 1's welfare. When country 1's utility decreases, people in country 1 are more likely to leave the country and people in country 2 (and countries other than country 1 in general) are less likely to choose country 1. The welfare of country 1, u_1, is identified by the small share of country 1 residents that choose country 1 *and* the small share of country 2 residents that choose country 1. In other words, both the large outflows from country 1 and the small inflows to country 1 identify u_1.

Note that more people choose country 2 in the second simulation, even though country 2's utility level is unchanged. In the data, if a country receives many refugees from a neighboring country in crisis, our model will not necessarily interpret that as an increase in u_2. Instead, the estimated utility of country 2 will also be determined by the choice probabilities of residents of country 2 *and* the choice probabilities of residents of every other country in the world.

6. Our approach is similar to earlier work in other contexts. Head and Ries (2008) model foreign direct investment flows that depend on the number of potential acquisition targets in a destination country.

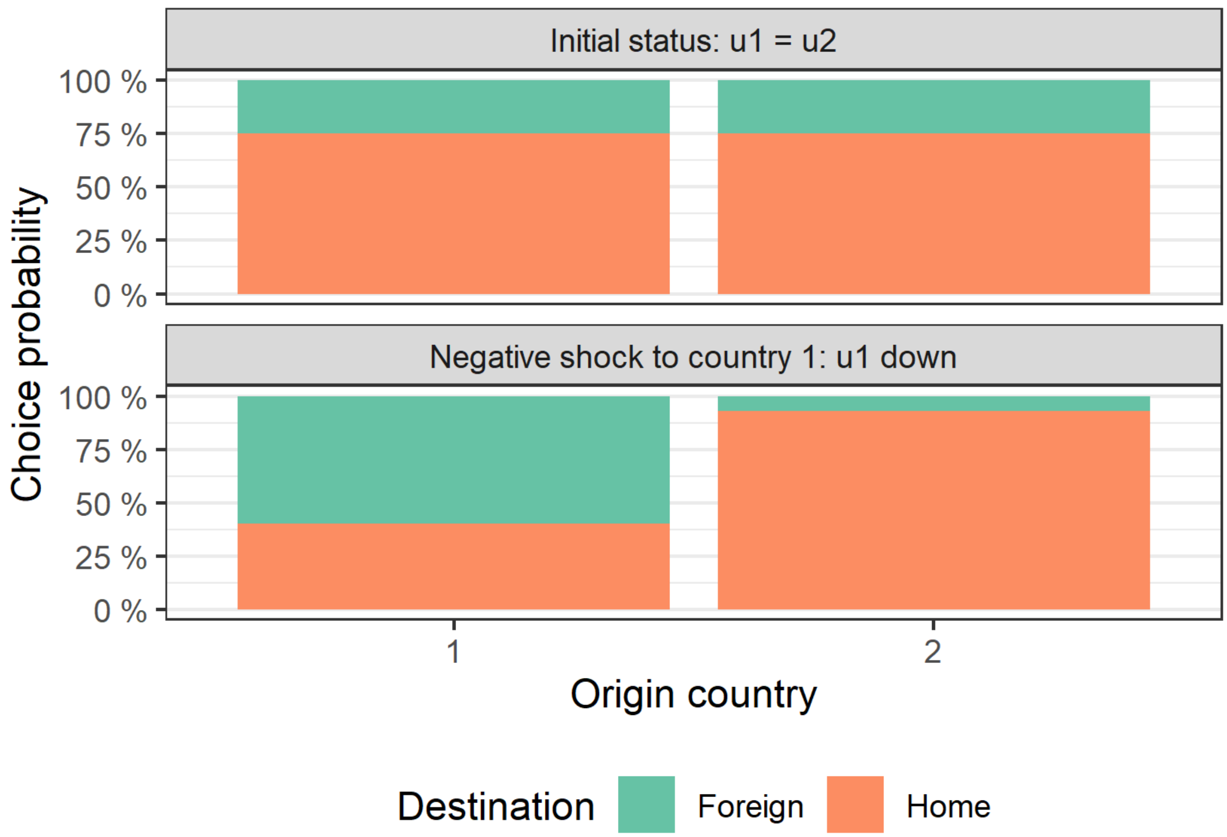


Figure 1: Lower welfare increases outflows and decreases inflows

3 Estimation

We assume that destination utility u_d can be represented as a linear combination of destination-country factors $Z_d'\alpha$ and that the cost of moving between origin o and destination d c_{od} is parameterized as $X_{od}'\beta$, where X_{od} is a vector of factors consisting of characteristics of the origin–destination country pair (e.g., distance between countries o and d or country d's immigration policy toward residents of o). We normalize c_{od} so that $c_{od} = 0$ if $d = o$.

We estimate our model in two stages. We rewrite equation 2 as

$$\pi_{od} = \frac{\exp(\delta_d - X_{od}'\beta)}{\sum_j \exp(\delta_j - X_{oj}'\beta)}, \tag{3}$$

where

$$\delta_d \equiv Z_d'\alpha + \gamma \ln N_d + \xi_d. \tag{4}$$

In the first stage, we estimate δ_d. In the second stage, we project $\hat{\delta}_d$ onto welfare factors Z_d and population size $\ln N_d$.

We estimate the first stage of the model (equation 3) using McFadden's (1973) conditional logit. We expand the matrix of bilateral flows to person-level data to estimate the conditional logit at the individual level (even though bilateral flows are reported at the country-pair level). For example, if the aggregate database has a row showing that 1,000 people migrate from a country o to d, we treat them as 1,000 observations making the same choices.

A common estimation method with aggregate choice data following Berry et al. (1995) (BLP) is to substitute observed choice shares s_{od} for the choice probabilities π_{od} and invert the model to obtain δ_{od}. We do not use this method because our object of interest is δ_d, which varies at the destination level instead of at the origin–destination pair level.[7] A benefit of our setting is that we avoid the zero-share problem. That is, bilateral migration flow data feature zeroes for many origin–destination pairs. The standard concern is that a choice probability of 0 may imply a maximum likelihood estimate for mean utility δ_d of $-\infty$. This is problematic because zero shares may happen by chance, even when the true choice probability is positive. In contrast, in our setting all countries have at least some nonzero "inflows." The fact that at least *some* people in the world always choose to *migrate to* or *remain in* a particular country ensures that our utility estimate for that country $\hat{\delta}_d$ is finite. Thus, zero shares do not pose a problem for our estimates unless a country depopulates entirely.

A concern with conditional logit estimates is the validity of independence from irrelevant alternatives (IIA). We choose to rely on the conditional logit model for the following reasons.

7. BLP require δ and covariates (e.g., prices) to vary at market–product level to estimate the price elasticities of demand. Since our goal is to predict the welfare of each destination country, it is not as important to identify parameters at the origin–destination level.

First, our goal is to estimate the welfare of countries, rather than estimating the effects of counterfactual experiments where a new country emerges or an existing country disappears. IIA is relatively less important in our context. Second, our results are robust to using a nested logit model with countries nested in continents. Our estimated welfare rankings are virtually identical, with a rank correlation more than 0.99. The conditional logit estimator is also much faster, by a factor of more than 150. For these reasons, we focus on the conditional logit model.

Our first-stage estimate of $\hat{\delta}_d$ includes destination utility u_d, log population $\gamma \ln N_d$, and unobserved destination factors ξ_d. In a second-stage regression, we project the first-stage estimates of $\hat{\delta}_d$ onto a vector including $\ln N_d$ and observed welfare factors Z_d. (We weight observations by the inverse of variance for $\hat{\delta}_d$ estimated in stage 1, following Wooldridge (2003).)

We construct two estimates of country welfare. First, our main estimates of country welfare are the *projected* values $\hat{u_d} = Z_d'\hat{\alpha}$. In other words, we use the estimated second-stage coefficients $\hat{\alpha}$ and observed welfare factors Z_d to predict country welfare. These projected estimates make progress on some issues of omitted variables outlined below.

Second, we also construct an *unprojected* welfare estimate of $\hat{u}_d = \hat{\delta}_d - \hat{\gamma} \log N_d$. This estimate does *not* use the estimated welfare factor coefficients $\hat{\alpha}$ but instead takes the first-stage country fixed effect estimates and corrects for the relationship between opportunities and country size implied by our model. Compared with our projected estimates, the unprojected estimates also include unobserved destination factors ξ_d. Thus, the unprojected measure is more comprehensive than the projected one but is more likely to be influenced by unobserved destination factors that are not related with welfare. On the other hand, our unprojected estimates do not require assumptions about the structure of unobserved migration policy factors. Overall, we prefer the projected estimate of welfare, but a comparison between the projected and unprojected estimate is informative about the strengths and weaknesses of each.

Next, we discuss several potential identification concerns. First, population size may indirectly affect welfare via match quality. One potential concern is that more opportunities in larger countries may lead to better match quality. A standard result in discrete choice models is that more choices lead to better utility, all else equal. This is not the case here. In our model, everyone in the world faces the same choice set K regardless of origin country (see equation 1). In other words, people are choosing among the set of potential *opportunities*, not countries. In this interpretation, it is not the case that person's realized utility level is a function of the maximum utility in the country.[8] Thus, the standard result does not apply.[9]

Second, population size may indirectly affect welfare via increasing returns to scale and trade costs. For example, in Krugman (1980), larger countries may have lower consumption costs and superior consumption variety. We attempt to account for this channel by including weighted population density in our second-stage regression.

Third, higher-utility countries may attract more migrants, increasing population size and the number of opportunities. In our setting, we view population size as predetermined at the beginning of our sample period. We assume that net flows over 2005–2010 do not affect population size and therefore the number of opportunities. This is consistent with the fact that net flows tend to be small relative to population stocks.

Fourth, unobserved migration policy factors may be correlated with our included welfare factors Z_d. For example, if immigration policy tends to be stricter for higher-welfare countries, we will underestimate the welfare levels of higher-welfare countries. We address this issue in two ways. One, we control for survey measures of destination country immigration policies in the second stage regression and exclude them in the welfare calculation. Two,

8. To see this, suppose that there are two countries A and B. Country A has two cities and B has one. All cities are identical and offer the same level of utility up to the idiosyncratic preference shock. Thus, *ex ante* expected utilities are equal across cities. Further, people living in country A or B have the same average utility even though country A is larger.

9. This still may be an issue in the presence of moving costs. We address this in the second stage regression where we project $\hat{\delta}$ on a vector of observed welfare factors. $\hat{\delta}$, which is estimated from country-level choice probabilities, includes all factors affecting migration, *including* match quality. To the extent that the second-stage regression includes all relevant welfare factors, it will also capture match quality.

if the strictness of immigration policy increases with a country's overall welfare, then the (cardinal) estimated welfare levels will be underestimated for high-welfare countries but the (ordinal) rankings of countries will still be preserved. Therefore, we focus on ordinal rankings of countries, not on cardinal welfare estimates.

Fifth, one might also be concerned about the endogeneity of the country factors Z_d. For example, per capita GDP (in Z_d) may be correlated with unobservable factors related to δ_d. We are not interpreting the estimates $\hat{\alpha}_d$ as causal effects. Instead, we are solely interested in predicted welfare levels. Our interpretation of the second-stage regression is that $Z_d'\hat{\alpha}$ forms the best linear unbiased *prediction* of u_d. This interpretation is robust to endogenous unobserved factors.

A final concern is that migrants may be very different from stayers, in a way that makes their choices uninformative about country welfare. For example, migrants may have more limited information about their destination countries compared with stayers in those destinations. Or, migrants may generally prefer different factors compared with non-migrants. Our framework already incorporates some heterogeneity. A useful comparison is to the standard Roback (1982) model. In the Roback model, consumption and production amenity levels for each city are identified by marginal migrants who are indifferent between cities. If workers are heterogeneous, these marginal workers may not represent the whole population. In contrast, we explicitly model heterogeneity among workers with ϵ^i_{odk} in equation (1). We remove these idiosyncratic shocks when we compute our welfare estimates. People with sufficiently high realizations of ϵ^i_{odk} choose to migrate to country d, but their high realizations of ϵ^i_{odk} are excluded from our welfare estimates. Moreover, our model includes everyone in the world, not just potential migrants.

That said, migrants may differ from non-migrants in a more fundamental way. A full examination of this issue is beyond the scope of our study. Fortunately, however, there is some existing evidence on this question. Helliwell et al. (2018) report survey estimates from the Gallup World Polls, a set of standardized surveys conducted in more than 160 countries. They compare the subjective well-being of immigrants with the subjective well-being of respondents who are native to immigrants' host countries. Their findings suggest that the subjective well-being reported by foreign-born residents of a country closely matches the subjective well-being reported by respondents born in that country. Across countries, the correlation in ranking by subjective well-being reported by foreign-born and native-born residents is very high: 0.96. These results add to our confidence that migrants' choices are informative about welfare.

4 Results

4.1 First-stage estimates

To estimate equation 3, we use estimates of gross bilateral international migration flows from Abel and Sander (2014). They estimate bilateral migration flows between 196 countries from 2005 to 2010. Their estimates use sequential tabular data on the stock of immigrants by origin and destination country in 2005 and 2010. These stock data are primarily based on place-of-birth responses to national censuses. Thus, successive stock tables report the number of people for every country of residence–country of birth pair, in 2005 and 2010.

Abel and Sander then estimate bilateral flows that are consistent with the observed stock tables. (They also account for changes in immigrant stocks from data on births and deaths and refugee movements.) They set the number of stayers in each country to the maximum possible value—thus, if 1 million people are observed in t as having been born in, and residing in, country A, and 0.9 million such people are observed in $t+1$, then (abstracting from natural increase or decrease) Abel and Sander assume that 0.9 million stayed in country A between t and $t+1$. Thus, the remaining flows represent the minimum number of gross flows required to rationalize the evolution of migrant stocks.

We also use data on bilateral factors X_{od} affecting migration costs from the GeoDist database from CEPII (Mayer and Zignago, 2011). After merging the CEPII data with the

Table 1: Origin-destination country pair factors predict migration flows

1_{Diff}	-3.337^c
	(0.002)
$1_{Diff} \times$ Log distance	-0.962^c
	(0.000)
$1_{Diff} \times$ Shared border	1.518^c
	(0.001)
$1_{Diff} \times$ Common language	0.700^c
	(0.000)
$1_{Diff} \times$ Colonial Link	1.415^c
	(0.001)
N	1.14e+12

First-stage estimates of equation 3. 1_{Diff} is an indicator variable taking a value of 1 if the origin and destination countries are different. Standard errors in parentheses. ^{a}—$p < 0.10$; ^{b}—$p < 0.05$; ^{c}—$p < 0.01$.

Abel and Sander estimates, we are left with pairwise combinations of 179 countries. These data describe for each country pair the presence of a shared border, any shared languages, any past or present colonial relationship, or a number of distance measures. These are standard measures for the transportation costs of physical products (e.g., Bernard et al., 2011) and the moving costs of migrants (e.g., Beine et al., 2011.)[10]

Table 1 shows first-stage estimates of equation 3, omitting the estimated country fixed effects $\hat{\hat{\delta}}_d$. We include five bilateral factors capturing moving costs: (1) whether the destination country is the same as the origin country, i.e., a choice to stay (1_{Diff}); (2) the log of the distance between the pair; (3) whether the pair share a border; (4) whether the pair share a common language; (5) whether the pair share a (past or present) colonial relationship. Factors (2)–(5) enter as interactions with the different-country indicator. Estimated standard errors are reported in parentheses.

The signs of the coefficients are as expected and precisely estimated. Country pairs that

10. For more details on the data and summary statistics, see Appendix A. Appendix Table A1 provides summary statistics for bilateral factors for ($179^2 =$) 32,041 origin-destination pairs. We report means and standard deviations for bilateral factors conditioned on the origin and destination country being different ($1_{Diff} = 1$).

share a border, a language, or a colonial link have higher migration flows. Countries that are more distant have lower migration flows. Same-country gross flows are significantly larger compared with different-country gross flows.

Note the large number of observations reported in the first-stage regression. The unit of observation is each potential destination (179 countries) for each person in the world (6.39 billion), yielding a sample size of (179×6.39 billion $\approx$) 1.14 trillion.

As a robustness check, we also estimate a specification of equation 3 where we interact the indicator for whether the origin and destination countries are different 1_{Diff} with origin-country fixed effects. This has the effect of allowing the cost of leaving a country to vary across countries. It absorbs any origin-country factors that might affect outmigration from that origin. The costs of leaving home may vary across origin countries because of their incomes, emigration policies, or other origin-specific factors (Rotte and Vogler, 2000).

With included interactions with origin fixed effects, unobserved origin factors such as emigration policies no longer affect our estimates. However, these origin-country fixed effects also absorb an important source of identifying variation coming from same-country flows. Outflows from fewer stayers in country d no longer inform our estimates of δ_d. Instead, only gross flows from other countries *to* country d identify δ_d. We report these results in Appendix B.

4.2 Second-stage estimates

To estimate our second stage (equation 4), we use data on country welfare factors from standard sources. Population and GDP are from the World Bank. Other data on country factors, such as inequality, government expenditures, leisure time, and air quality, are drawn from data provided by other international institutions including the United Nations and the International Labour Organization. These are described in Appendix A.

We select factors according to several criteria. First, the factors should be related to welfare. Second, included factors should be observed for many countries, so that we can predict welfare for as many countries as possible without excessive imputation of missing values. Finally, we should not include too many factors. There are potentially many factors that affect welfare. However, we are limited to a sample size of 179 countries, and many potential welfare factors are likely to be highly collinear.

Based on these criteria, we use the following judgmental list of factors drawn from the World Bank and other sources in addition to population size: (i) log GDP per capita; (ii) the Gini coefficient of income; (iii) the public share of total health expenditure not financed by private out-of-pocket expenses; (iv) a measure of control of corruption that captures perceptions of the extent to which public power is exercised for private gain; (v) average weekly work hours; (vi) the population-weighted exposure to ambient pollution of suspended particles measuring less than 2.5 microns in diamenter; (vii) a measure of contractibility that captures perceptions of the extent to which agents have confidence in the rule of law; (viii) infant mortality, or the number of infants dying before reaching one year of age, per 1,000 live births; (ix) average population density weighted by population size of each location; (x) and household consumption share of GDP.[11]

By comparison, Jones and Klenow's (2016) model includes four welfare factors: consumption, leisure, life expectancy, and uncertainty with respect to consumption and leisure (the latter proxied by income inequality). These factors correspond to our included measures of GDP per capita, the consumption share, average weekly work hours, infant mortality, and the Gini coefficient of income. We also include several additional factors. The share of total health expenditures not financed by private out-of-pocket expenses is a measure of the social safety net. Thus it is perhaps another measure of uncertainty with respect to consumption and leisure. Control of corruption and contractibility measure institutional quality and thus to some extent uncertainty but also fairness and opportunity. Particulate matter may contribute to both quality of life and life expectancy.

11. These data and their sources are described in Appendix A. Appendix Table A2 provides summary statistics for destination country factors.

We also include population-weighted average population density using data from the *Gridded Population of the World*. (Each grid cell is weighted by population size so that unpopulated areas within a country receive low weight. The resulting measure is closer to population density as experienced by the average person, rather than the average land area unit.) In the presence of increasing returns to scale and trade costs, denser regions may have lower consumption costs and higher consumption variety (Krugman, 1980). This factor is intended to capture this channel.

Table 2 shows our second-stage estimates. Column 1 shows estimates including only log population and log GDP per capita as predictors. The coefficient estimate on log population is less than 1, consistent with the number of draws increasing less than one-for-one with population. Under the assumption that welfare is orthogonal to country size and conditioned on per capita GDP, the semi-elasticity of draws to population is 0.45. This is precisely estimated. GDP per capita is also strong predictor of welfare. This is precisely estimated. Overall, per capita GDP and population explain a large fraction of the variance in $\hat{\delta}_d$—the adjusted R-squared is 0.53.

Subsequent columns report estimates including all 10 welfare factors, controls for immigration policy, and population size. We use data from the World Population Policies Database (United Nations, 2015). This UN survey asks member and non-member states about the existence or degree of nine policies that may encourage immigration into the countries.[12] We convert answers to these questions into 43 indicator variables to flexibly capture the survey responses. The indicator variables also include missing responses, since missing values may convey some information.

We use LASSO to improve our predictions while keeping the number of included immigration policy variables in a reasonable range. We use 10-fold cross-validation to compute

12. These nine proxies include policies about integration of non-nationals, measures on integration of immigrants, policy on naturalization, level of concern about irregular migration, measures on irregular immigration, programs to facilitate return of migrants to their home countries, policy to encourage the return of citizens, acceptance of dual citizenship, and measures to attract investment by diaspora.

Table 2: Destination-country factors predict welfare

	(1)	(2)	(3)
Log(Population)	0.447^c	0.473^c	0.480^c
	(0.043)	(0.045)	(0.044)
Log(GDP per capita)	0.476^c	0.473^c	0.424^c
	(0.046)	(0.104)	(0.100)
Public share of health spending		1.755^c	1.901^c
		(0.608)	(0.567)
Control of corruption		0.387	0.327
		(0.243)	(0.229)
Gini coefficients		-4.013^c	-3.207^c
		(1.041)	(0.988)
Log(PM25)		−0.125	−0.155
		(0.227)	(0.218)
Log(Mean work hours)		0.022	0.065
		(0.077)	(0.072)
Contractibility		−0.134	0.233
		(0.478)	(0.458)
Infant mortality per 1000		0.017^c	0.014^c
		(0.004)	(0.004)
Log(Weighted population density)		0.191	−0.363
		(0.952)	(0.903)
Consumption share		0.247	0.230
		(0.155)	(0.154)
Immigration policy			
Selection algorithm	None	Lasso, λ.1se	Lasso, λ.min
Number of included policy variables	0	0	8
Observations	172	172	172
Adjusted R^2	0.526	0.628	0.686

Second-stage estimates of equation 4. Standard errors in parentheses. ^{a}—$p < 0.10$; ^{b}—$p < 0.05$; ^{c}—$p < 0.01$.

root mean squared errors (RMSE). In cross-validation, the model is estimated with a randomly chosen training sample and compute the RMSE on the remaining (test) sample. A larger number of predictors does not necessarily lead to a lower RMSE.[13]

We report two models with different choices for the penalty parameter λ. The first, "λ.min" in column 3, is the λ yielding the lowest RMSE. The second, "λ.1se", corresponds to the highest λ within one standard error of the λ-minimizing RMSE. This leads to a more parsimonious model with fewer predictors. In column 3, λ.min selects 8 out 43 immigration variables. In column 2, the more parsimonious λ.1se does not select any immigration control variable.

The coefficients in Table 2 should be interpreted as partial correlations, not as causal effects. The purpose of running the second stage regression is to predict the welfare levels while minimizing bias from unobservable factors affecting bilateral migration flows that are not related to welfare.

The signs on many of the estimated coefficients are as expected. GDP strongly predicts welfare. Other predictors of welfare include higher public expenditures as a share of total expenditures on health care, superior control of corruption, less inequality, and superior air quality, though many of these are imprecisely estimated. Greater leisure seems negatively correlated with welfare, but this is imprecisely estimated. Infant mortality appears to predict welfare, but this is likely collinear with the other included factors. Conditioned on income, higher consumption is positively correlated with welfare.

The estimated coefficient on GDP per capita is smaller in column (3). The selected immigration policy variables appear to be correlated with GDP per capita.

We form our main estimates of welfare as $\hat{u}_d = Z_d'\hat{\alpha}$. Some factors are missing for some countries. To increase the number of estimates of country welfare, we impute missing values using OLS. Six factors (plus population) have few missing values—GDP, control of

13. Because of the randomness in cross-validation, LASSO may select a different set of immigration policy variables each time. We run LASSO 10,000 times and choose the most often selected set of variables.

corruption, PM25, contractibility, infant mortality, and weighted average population density. (We exclude seven countries with missing values for any of these six factors.) Then, we use these six factors and population to predict the missing values of the other three factors. Thus, imputed values represent conditional means. See Appendix C for more details on this procedure.

4.3 Welfare estimates

The first three columns of Figure 2 show our welfare rankings of the largest countries with a population larger than 30 million. We also show other rankings from the literature in the next three columns for comparison. We report the full rankings of 172 countries in online Appendix.

Columns 1 and 2 show the welfare rankings from our λ.1se and λ.min models. Using the estimates of $\hat{\alpha}$ in Table 2, we calculate country welfare as $\hat{u_d} = Z_d'\hat{\alpha}$. Column 3 shows our unprojected ranking: $\hat{\delta} - \hat{\gamma} \log N_d$. Column 4 shows the rankings of GDP per capita, column 5 shows the rankings from Jones and Klenow (2016), and column 6 shows the rankings of survey-based Cantril ladder from the Gallup World Poll in 2007.

Our projected ranks of all 172 countries are highly correlated, with a correlation coefficient of 0.71. These estimates are also correlated with our unprojected estimates rankings (0.60 and 0.61, respectively). Recall that our unprojected estimates are more comprehensive—they more reflect bilateral flows and are not constructed using destination welfare factors. But they may be contaminated by unobserved destination factors that affect migration flows. For example, many of the Persian Gulf countries—the U.A.E., Qatar, Bahrain, and Saudi Arabia—rank highly, according to our unprojected estimates. These superior ranks reflect large inflows of migrant workers, and in many cases, special guest worker programs designed to attract immigrants. However, when we project these large gross flows on welfare factors in our second-stage regressions, the ranks of these countries fall, reflecting inferior welfare factors. On the other hand, traditional immigrant magnets such as the U.S. and Canada do

	(1) λ.1se	(2) λ.min	(3) unprojected	(4) GDP per capita	(5) Jones Klenow	(6) Cantril ladder
1	Japan	Canada	United States	United States	United States	Canada
2	Germany	Japan	Italy	United Kingdom	France	United States
3	United States	United Kingdom	Canada	Japan	United Kingdom	Spain
4	France	Germany	Spain	Canada	Japan	United Kingdom
5	Canada	France	S. Africa	France	Canada	France
6	United Kingdom	United States	Germany	Germany	Italy	Italy
7	Spain	Italy	United Kingdom	Italy	Spain	Mexico
8	Italy	Spain	France	Spain	Germany	Germany
9	S. Korea	S. Korea	Russia	South Korea	South Korea	Brazil
10	Russia	Poland	Poland	Poland	Poland	Japan
11	S. Africa	Turkey	Japan	Mexico	Mexico	Argentina
12	Mexico	Russia	Ukraine	Turkey	Turkey	Colombia
13	Philippines	Mexico	Thailand	Russia	Argentina	Thailand
14	China	Morocco	Turkey	South Africa	Russia	Poland
15	Ukraine	Colombia	Kenya	Argentina	Iran	South Korea
16	Egypt	Ukraine	Nigeria	Brazil	Ukraine	Pakistan
17	Kenya	Vietnam	Iran	Colombia	Brazil	Egypt
18	Thailand	Argentina	Egypt	Iran	Thailand	Vietnam
19	Iran	Egypt	Ethiopia	Thailand	Colombia	Iran
20	Morocco	Iran	S. Korea	Morocco	Egypt	Turkey
21	India	Ethiopia	Colombia	Ukraine	China	India
22	Turkey	S. Africa	Tanzania	China	Indonesia	South Africa
23	Poland	Tanzania	Argentina	Indonesia	Morocco	Russia
24	Indonesia	China	Morocco	Philippines	Philippines	Morocco
25	Tanzania	Kenya	Brazil	Egypt	South Africa	Ukraine
26	Brazil	Indonesia	China	Nigeria	Pakistan	Indonesia
27	Ethiopia	Thailand	Vietnam	Pakistan	Vietnam	Philippines
28	Colombia	Nigeria	India	India	India	Nigeria
29	Argentina	Brazil	Mexico	Vietnam	Bangladesh	China
30	Bangladesh	Bangladesh	Philippines	Kenya	Nigeria	Bangladesh
31	Vietnam	Philippines	Pakistan	Bangladesh	Kenya	Kenya
32	Pakistan	India	Indonesia	Tanzania	Tanzania	Ethiopia
33	Nigeria	Pakistan	Bangladesh	Ethiopia	Ethiopia	Tanzania

Figure 2: Welfare rankings for large countries

These are welfare rankings for large countries with more than 30 million residents. Algeria, Myanmar and Sudan are omitted because of missing values in the Cantril ladder measure. Country names are colored according to region. Red—Africa; Orange—Americas; Green—Asia; Blue—Europe.

well on both our projected and unprojected measures.

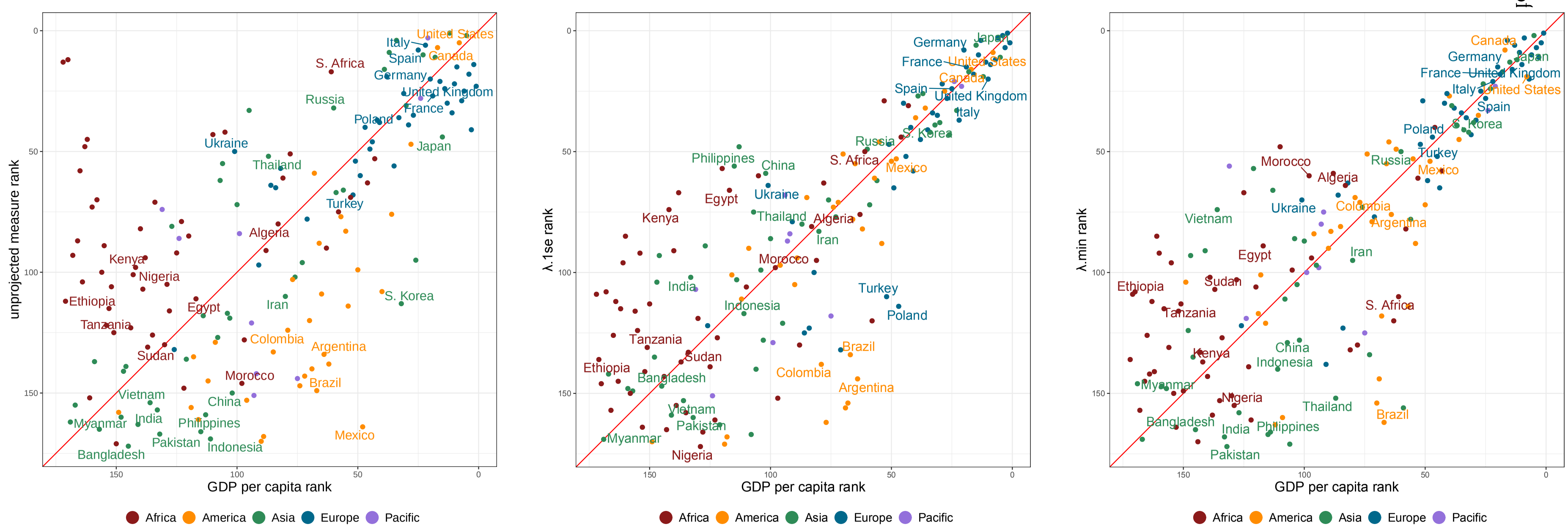
Figure 3 compares our unprojected and projected welfare estimates with GDP per capita. Overall, our projected estimates (Figures 3b and 3c) are more highly correlated with GDP per capita compared with our unprojected estimates (Figure 3a). The rank correlations of GDP per capita with our projected measures are both 0.8, while that with our unprojected measure ranking is 0.6. This is expected, since our projected estimates use as an input GDP per capita to predict welfare. However, it is interesting that even the unprojected measures are highly correlated with per capita GDP. This suggests that per capita GDP is a good measure of welfare, despite its limitations.

There are some interesting regional patterns. Figure 3a shows that Asian countries (in green) have inferior ranks according to our unprojected welfare estimates compared with

GDP per capita. This indicates that they have relatively few inflows relative to their income. On the other hand, African countries (in red) and countries near the Persian Gulf (unlabeled green points in the northeast region of Figure 3a) show the opposite pattern. These are countries with high inflows relative to their income, which results in superior unprojected estimates. This could be because of systematic differences in unmeasured immigration policy, such as the extensive guest worker programs of the Gulf states.

Our projected estimates are also highly correlated with the Jones-Klenow estimates of country welfare, with correlation coefficients of 0.78 and 0.74, respectively. The Jones-Klenow estimates are even more tightly correlated with GDP per capita, with a correlation coefficient of 0.95. Thus, even though our estimates are highly correlated with income, the Jones-Klenow estimates depend even more on GDP per capita. The divergence between our estimates and GDP per capita may reflect the view that other factors matter for welfare. More precisely, our estimates, which depend in part on the revealed preference of migration choices, suggest that people may value many factors beyond GDP.

Finally, we compare our estimates to a measure of subjective well-being. We consider the Cantril ladder measure from the Gallup World Poll in 2007. Respondents in more than 150 countries were asked to evaluate the quality of their lives on an 11-point ladder scale. Desmet et al. (2018) use this as a measure of national utility. Our projected estimates are strongly correlated with the Cantril ladder but somewhat less so than compared with GDP per capita; the correlation coefficients are 0.65 and 0.62, respectively. This is also lower compared with the correlation between the Cantril ladder and GDP per capita of 0.83.



(a) Unprojected vs. GDP per capita

(b) λ.1se vs. GDP per capita

(c) λ.min vs. GDP per capita

Figure 3: Comparison of welfare estimates

5 Conclusion

We propose a new method of estimating the welfare of countries based on international migration patterns. The key idea is that people tend to move from low-utility places to high-utility ones. Our estimates, by relying on the revealed preference of international migrants and stayers, complement previous estimates of country well-being. Our work suggests GDP is a good measure of welfare, despite its limitations. However, international migration flows are responding to additional factors beyond GDP. Our method also provides micro-foundations for gravity in international migration flows by formalizing the idea that opportunities increase with destination country size.

Compared with previous work, our method relaxes some assumptions but imposes others. For example, we place little restriction on how welfare factors enter utility. However, we do need to make assumptions about the structure of unobserved migration factors and the relationship between country size and welfare. Strikingly, despite differences in method, there is great deal of similarity in our country welfare estimates compared with previous work. The limitations of our current study suggest that efforts to better measure bilateral international migration flows and bilateral migration costs would greatly improve our understanding of the well-being of nations.

Appendix

A Data description and imputation

We use estimates of bilateral international migration flows from Abel and Sander (2014). They use migration stock data provided by the United Nations (UN) and impute bilateral flows for 196 countries every 5 years from 1990 through 2010. We choose the most recent data from 2005 to 2010.

Table A1 shows summary statistics for pairwise migration factors X_{od} from CEPII. We use the distance between the most populated cities. We also include several indicator variables: (i) an indicator for contiguity 1(Shared border), (ii) an indicator for whether a country pairs shares a common official primary language 1(Common language), and (iii) an indicator for whether the two countries have ever been linked through a colonial relationship 1(Colonial link). We interact each of these factors with an indicator for whether the origin and destination countries are different, i.e., $1_{Diff} \equiv 1$ if origin $\neq$ destination. We have 32,041 ($= 179^2$) matched country pairs.

Table A2 shows summary statistics for destination factors Z_d. We use 2005 values unless otherwise specified. If a variable is reported by fewer than 100 countries in 2005, we take the average value from 2005 to 2010 to reduce the number of missing values. Population size and GDP per capita are provided by World Bank Open Data. We obtain Gini coefficients from the World Income Inequality Database provided by the United Nations and take average values from 2005 to 2010. (By taking the average, the number of observations increases from 87 to 143.) The public share of health expenditures refers to the percentage of health care

Table A1: Summary statistics for origin–destination pairs

1_{Diff}	0.994
	(0.075)
$1_{Diff} \times$ ln(dist)	8.703
	(1.010)
$1_{Diff} \times$ Sharing Border	0.017
	(0.130)
$1_{Diff} \times$ Common Language	0.148
	(0.355)
$1_{Diff} \times$ Colonial Link	0.011
	(0.106)
N of Country Pairs	32041

This table shows sample means and standard deviations for origin–destination country pair factors. 1_{Diff} is an indicator variable equal to 1 when the origin country is different compared with the destination country. Source: CEPII.

expenditures not financed by private households' out of pocket payments, taken from the International Labour Organization (ILO) database. Control of corruption is one of the six indicators from the Worldwide Governance Indicator (WGI) project run by the World Bank Group (Kaufmann et al. 2011). The WGI provides widely used measures of the institutional quality of countries. Control of corruption captures "perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption." Mean weekly work hours per employee is from the ILO. (By taking average values from 2005 and 2010, the number of observations for this variable increases from 76 to 90.) Contractibility or rule of law is from the WGI. Rule of law is commonly used to measure contractibility in trade (e.g., Manova, 2012). Rule of law captures "perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence."

PM25 is an air quality index distributed by the World Bank and originally collected by the *Global Burden of Disease Study* (GBD, 2017). The GBD defines PM25 as the average level of exposure of a nation's population to concentrations of suspended particles measuring less than 2.5 microns in aerodynamic diameter, which may cause severe health damage by penetrating deep into the respiratory tract. This measure is calculated by weighting mean annual concentrations of PM25 by population. Infant mortality is the number of infants dying before reaching one year of age per 1,000 live births in a given year, also provided by the World Bank.

The population density data comes from the *Gridded Population of the World* (GPW). The GPW partitions the whole world into grid cells of 30 arcseconds by arcseconds and provides population counts for each cell. We compute a weighted population density for each country. The intent of this variable is to capture local density experienced by an average person in a country. We weight the population density of each cell by its total population. By this measure, countries with spatially concentrated populations and large uninhabited areas will feature high average population density.

Table A2: Summary statistics for destination countries

Statistic	N	Mean	St. Dev.
Log(Population)	178	15.740	1.854
Log(GDP per capita)	174	8.039	1.624
Govt. Health Spending	124	0.667	0.180
Control of Corruption	176	−0.078	1.020
Gini Coefficients	143	0.394	0.080
Log(PM25)	175	3.162	0.642
Log(Mean work hr)	90	3.697	0.115
Contractibility	176	−0.107	1.013
Log(Inf mortality per 1000)	174	3.030	1.067
Log(w. Pop. density)	178	6.706	1.050
Consumption share	162	0.623	0.187

This table shows sample means and standard deviations for destination country factors. N is the number of countries with non-missing observations.

B Origin fixed-effects estimates

Migration costs to another country may differ across origin countries because of their incomes, emigration policies, etc. (Rotte and Vogler, 2000). We estimate an alternative model where the first stage includes interactions between the different-country indicator 1_{Diff} and origin-country fixed effects. This has the effect of allowing the cost of leaving a country to vary across countries. It absorbs any origin-country factors that might affect outmigration from that origin.

With included interactions with origin fixed effects, unobserved origin factors such as emigration restrictions no longer bias our estimates. However, these origin-country fixed effects also absorb an important source of identifying variation coming from same-country flows. Outflows from fewer stayers in country d no longer inform our estimates of δ_d. Instead, only gross flows from other countries *to* country d identify δ_d.

Table B1 shows first-stage estimates, omitting origin fixed effect interactions. These estimates are similar to the ones reported in Table 1 for our preferred specification.

The rest of our method remains the same, except for differences in the estimates of $\hat{\delta}_d$ obtained in the altered first stage. Table B2 reports second-stage estimates. The general pattern of estimates is similar compared with the main estimates reported in Table 2 in the main text.

We use $\hat{\gamma} = 0.57$ to construct our projected estimates of welfare. Figures B1 and B2 show the welfare rankings of countries according to our projected λ.1se and λ.min estimates respectively.

Overall, these estimates are positively correlated with our main projected estimates, with correlation coefficients of 0.73 (λ.1se) and 0.72 (λ.min). We are able to rank fewer countries. This is because the origin-country fixed effects absorb an important source of identifying variation coming from same-country flows. Without this variation we are only able to estimate $\hat{\delta}_d$ for 142 countries.

Table B1: Origin-destination country pair factors predict migration flows

$1_{Diff} \times$ ln(dist)	-1.176^c
	(0.000)
$1_{Diff} \times$ Sharing Border	1.135^c
	(0.001)
$1_{Diff} \times$ Common Language	0.464^c
	(0.001)
$1_{Diff} \times$ Colonial Link	1.465^c
	(0.001)
$1_{Diff} \times$ Origin FE	✓
N	9.33e+11

First-stage estimates. Estimates of interactions of 1_{Diff} with origin fixed effects omitted. ^{a}—$p < 0.10$; ^{b}—$p < 0.05$; ^{c}—$p < 0.01$.

Table B2: Destination-country factors predict welfare

	(1)	(2)	(3)
Log(Population)	0.420^{c}	0.498^{c}	0.570^{c}
	(0.076)	(0.083)	(0.084)
Log(GDP per capita)	0.588^{c}	0.673^{c}	0.684^{c}
	(0.064)	(0.178)	(0.182)
Govt. Health Spending		1.597	2.206^{b}
		(1.069)	(1.064)
Control of Corruption		0.591	0.522
		(0.479)	(0.484)
Gini Coefficients		−2.757	-3.025^{a}
		(1.748)	(1.759)
Log(PM25)		−0.529	−0.520
		(0.470)	(0.466)
Log(Mean work hr)		0.007	0.076
		(0.144)	(0.140)
Contractibility		0.190	0.188
		(0.854)	(0.839)
Inf mortality per 1000		0.018^{c}	0.017^{b}
		(0.007)	(0.007)
Log(w. Pop. density)		1.472	3.137^{a}
		(1.349)	(1.852)
Consumption share		−0.106	−0.435
		(0.258)	(0.302)
Immigration policies			
Selection algorithm	None	lasso.1se	lasso.min
N of selected policies	0	0	9
Observations	142	142	142
Adjusted R^2	0.433	0.458	0.511

Second-stage estimates of equation 4. Standard errors in parentheses. ^{a}—$p < 0.10$; ^{b}—$p < 0.05$; ^{c}—$p < 0.01$.

1 Ireland
2 United Kingdom
3 Netherlands
4 Switzerland
5 Canada
6 Denmark
7 Sweden
8 United Arab Emirates
9 Norway
10 United States
11 Austria
12 Kuwait
13 France
14 Belgium
15 Italy
16 Japan
17 Finland
18 Germany
19 Cyprus
20 New Zealand
21 Australia
22 Singapore
23 Israel
24 Mexico
25 Poland
26 Oman
27 Trinidad & Tobago
28 Spain
29 Greece
30 S. Korea
31 Slovakia
32 Slovenia
33 Czech Rep.
34 Libya
35 Croatia
36 Saudi Arabia
37 Venezuela
38 Lebanon
39 Jamaica
40 Uruguay
41 S. Africa
42 Panama
43 Estonia
44 Turkey
45 Guatemala
46 Jordan
47 Portugal
48 Albania
49 Cuba
50 Lithuania
51 Latvia
52 China
53 Mauritius
54 Tunisia
55 Macedonia
56 Kazakhstan
57 Argentina
58 Bulgaria
59 Chile
60 Brazil
61 Indonesia
62 Botswana
63 Russia
64 Namibia
65 Ukraine
66 Gabon
67 Dominican Rep.
68 Bosnia & Herzegovina
69 Cameroon
70 Swaziland
71 Peru
72 Hungary
73 Honduras
74 Morocco
75 Angola
76 Azerbaijan
77 Nigeria
78 Georgia
79 Colombia
80 Nicaragua
81 Bangladesh
82 Algeria
83 Benin
84 Iran
85 Senegal
86 Sudan
87 Cambodia
88 Nepal
89 Malaysia
90 Syria
91 Gambia
92 Uganda
93 C. African Rep.
94 Chad
95 Tanzania
96 Bolivia
97 Costa Rica
98 Rep. of Congo
99 Belarus
100 Sierra Leone
101 Lesotho
102 Armenia
103 Philippines
104 Pakistan
105 Iraq
106 Eritrea
107 Turkmenistan
108 Mali
109 Ethiopia
110 P. N. Guinea
111 El Salvador
112 India
113 Burkina Faso
114 Mozambique
115 Togo
116 Sri Lanka
117 Niger
118 Rwanda
119 Kyrgyzstan
120 Tajikistan
121 Kenya
122 Laos
123 Mauritania
124 Yemen
125 Paraguay
126 Vietnam
127 Thailand
128 Myanmar
129 Moldova
130 Malawi
131 Burundi
132 Mongolia
133 Ecuador
134 Zambia
135 Liberia
136 Uzbekistan
137 Ghana
138 Haiti
139 Madagascar
140 Egypt
141 Guinea
142 Guinea-Bissau

Figure B1: The welfare rank of countries according to λ.1se estimates, absorbing origin-country factors

These are welfare rankings for countries according to estimates of $\hat{u_d} = \hat{\delta}_d - \hat{\gamma} \log N_d$. Country names are colored according to region. Red—Africa; Orange—Americas; Green—Asia; Blue—Europe; Purple—Pacific.

1 United States
2 Austria
3 Sweden
4 Ireland
5 Japan
6 Norway
7 United Kingdom
8 Italy
9 Switzerland
10 Denmark
11 Belgium
12 Netherlands
13 Australia
14 Finland
15 Singapore
16 United Arab Emirates
17 Kuwait
18 Canada
19 New Zealand
20 Cyprus
21 France
22 Germany
23 Trinidad & Tobago
24 Czech Rep.
25 Poland
26 Israel
27 S. Korea
28 Spain
29 Hungary
30 Portugal
31 Turkey
32 Saudi Arabia
33 Estonia
34 Mexico
35 Slovenia
36 Oman
37 Russia
38 Lebanon
39 Bulgaria
40 Argentina
41 S. Africa
42 Jamaica
43 Greece
44 Malaysia
45 Namibia
46 Rep. of Congo
47 Slovakia
48 Kazakhstan
49 Brazil
50 Chile
51 Croatia
52 Albania
53 Botswana
54 Costa Rica
55 Dominican Rep.
56 Uruguay
57 Mauritius
58 Tunisia
59 Libya
60 Cuba
61 Ukraine
62 Venezuela
63 Latvia
64 Ecuador
65 Morocco
66 Lithuania
67 Belarus
68 Swaziland
69 Angola
70 Azerbaijan
71 Iran
72 Gabon
73 Honduras
74 Guatemala
75 Thailand
76 China
77 Mongolia
78 Iraq
79 Bosnia & Herzegovina
80 Paraguay
81 Kyrgyzstan
82 Algeria
83 Nigeria
84 Macedonia
85 Sudan
86 Cameroon
87 Uzbekistan
88 Mali
89 Panama
90 El Salvador
91 Gambia
92 C. African Rep.
93 Guinea-Bissau
94 Pakistan
95 Tanzania
96 Nicaragua
97 Jordan
98 Colombia
99 Georgia
100 Guinea
101 P. N. Guinea
102 Egypt
103 Philippines
104 Yemen
105 Syria
106 Liberia
107 Indonesia
108 Burkina Faso
109 Malawi
110 Cambodia
111 Sri Lanka
112 Kenya
113 Haiti
114 Bangladesh
115 Mozambique
116 India
117 Eritrea
118 Togo
119 Laos
120 Uganda
121 Mauritania
122 Benin
123 Moldova
124 Lesotho
125 Senegal
126 Chad
127 Turkmenistan
128 Niger
129 Zambia
130 Madagascar
131 Burundi
132 Bolivia
133 Armenia
134 Vietnam
135 Myanmar
136 Tajikistan
137 Ghana
138 Sierra Leone
139 Rwanda
140 Peru
141 Ethiopia
142 Nepal

Figure B2: The welfare rank of countries according to λ.min estimates, absorbing origin-country factors

These are welfare rankings for countries according to estimates of $\hat{u}_d = \hat{\delta}_d - \hat{\gamma} \log N_d$. Country names are colored according to region. Red—Africa; Orange—Americas; Green—Asia; Blue—Europe; Purple—Pacific.

C Missing values

Table A2 reports a relatively large number of missing values for 4 variables: (i) the Gini coefficient, (ii) the public share of health expenditure, (iii) mean work hours, and (iv) the consumption share. We impute these missing values with their conditional means using regression. The other 7 variables are observed for nearly every country (at least 174 of 179 countries). We use these 7 variables as predictors to impute missing values for the remaining three variables. First, we exclude 7 countries with missing values on the 7 predictor variables.

Table C1 reports a summary of the imputed characteristics. This table reports slightly greater inequality, less public share of health expenditures, and more work hours compared with the rest of the sample. This suggests that missing values are not at random; for example, countries with low GDP per capita are more likely to fail to report public health spending. Overall, GDP per capita and public health spending are positively correlated (with a correlation coefficient of 0.52).

After dropping 7 countries with missing values in the 7 predictor factors, we can construct projected welfare estimates for 172 countries.

Table C1: Summary statistics for imputed country factors

Statistic	N	Mean	St. Dev.
Govt. health spending	172	0.655	0.161
Gini coefficients	172	0.395	0.074
Log(mean work hr)	172	3.711	0.091
Consumption share	172	0.629	0.185

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FOR ONLINE PUBLICATION ONLY

D The welfare rank of countries

1 Norway
2 Switzerland
3 Ireland
4 Finland
5 Luxembourg
6 Japan
7 Iceland
8 Germany
9 United States
10 Austria
11 Qatar
12 Denmark
13 Netherlands
14 Sweden
15 France
16 Canada
17 Kuwait
18 Belgium
19 United Arab Emirates
20 United Kingdom
21 New Zealand
22 Greece
23 Australia
24 Spain
25 Bahamas
26 Saudi Arabia
27 Oman
28 Cyprus
29 Gabon
30 Croatia
31 Equatorial Guinea
32 Barbados
33 Singapore
34 Slovenia
35 Portugal
36 Trinidad & Tobago
37 Italy
38 Israel
39 S. Korea
40 Hungary
41 Malta
42 Bahrain
43 Brunei
44 Libya
45 Czech Rep.
46 St. Lucia
47 Latvia
48 Sri Lanka
49 Russia
50 S. Africa
51 Belize
52 Estonia
53 Mexico
54 Chile
55 S.V. & Grenadines
56 Philippines
57 Cameroon
58 Slovakia
59 China
60 Rep. of Congo
61 Venezuela
62 Malaysia
63 Namibia
64 Ukraine
65 Lithuania
66 Egypt
67 Chad
68 Micronesia
69 Ecuador
70 Maldives
71 Cuba
72 Lebanon
73 Dominican Rep.
74 Kenya
75 Syria
76 Mauritius
77 Kazakhstan
78 Panama
79 Albania
80 Thailand
81 Algeria
82 Uruguay
83 Iran
84 Tonga
85 Uganda
86 Iraq
87 Samoa
88 Grenada
89 Yemen
90 Paraguay
91 Benin
92 Burkina Faso
93 Kyrgyzstan
94 El Salvador
95 Tunisia
96 Guinea
97 Guatemala
98 Morocco
99 Armenia
100 Belarus
101 Nicaragua
102 India
103 Bhutan
104 Laos
105 Peru
106 Angola
107 P. N. Guinea
108 Niger
109 Burundi
110 Turkey
111 Honduras
112 Malawi
113 Zimbabwe
114 Poland
115 Sierra Leone
116 Mozambique
117 Indonesia
118 Fiji
119 Senegal
120 Botswana
121 Jordan
122 Moldova
123 Macedonia
124 Togo
125 Bosnia & Herzegovina
126 Eritrea
127 Ivory Coast
128 Turkmenistan
129 Vanuatu
130 Swaziland
131 Tanzania
132 Bulgaria
133 Mauritania
134 Brazil
135 Cambodia
136 Ethiopia
137 Sudan
138 Colombia
139 Lesotho
140 Azerbaijan
141 Gambia
142 Afghanistan
143 Mali
144 Argentina
145 Rwanda
146 Liberia
147 Bangladesh
148 Nepal
149 Tajikistan
150 C. African Rep.
151 Solomon Islands
152 Cape Verde
153 Vietnam
154 Costa Rica
155 Comoros
156 Jamaica
157 Madagascar
158 Zambia
159 Uzbekistan
160 Pakistan
161 Djibouti
162 Suriname
163 Mongolia
164 Guinea-Bissau
165 Ghana
166 ST & Principe
167 Georgia
168 Guyana
169 Myanmar
170 Haiti
171 Bolivia
172 Nigeria

Figure D1: The welfare rank of countries according to λ.1se

These are welfare rankings for countries according to estimates from our λ.1se model reported in Table 2, column 2. Country names are colored according to region. Red—Africa; Orange—Americas; Green—Asia; Blue—Europe; Purple—Pacific.

1 Luxembourg
2 Qatar
3 Sweden
4 Belgium
5 Norway
6 Finland
7 Switzerland
8 Canada
9 Netherlands
10 Ireland
11 Iceland
12 United Arab Emirates
13 Japan
14 United Kingdom
15 Germany
16 Austria
17 Kuwait
18 France
19 United States
20 Denmark
21 Italy
22 Brunei
23 Australia
24 Singapore
25 Cyprus
26 Slovakia
27 Trinidad & Tobago
28 Spain
29 Latvia
30 Hungary
31 Oman
32 Czech Rep.
33 New Zealand
34 Malta
35 Bahamas
36 Slovenia
37 Greece
38 Israel
39 Saudi Arabia
40 Libya
41 Bahrain
42 S. Korea
43 Portugal
44 Poland
45 Barbados
46 S.V. & Grenadines
47 Turkey
48 Angola
49 Uruguay
50 Russia
51 Dominican Rep.
52 Croatia
53 St. Lucia
54 Mexico
55 Panama
56 P. N. Guinea
57 Mongolia
58 Equatorial Guinea
59 Swaziland
60 Morocco
61 Gabon
62 Lithuania
63 Belarus
64 Algeria
65 Estonia
66 Sri Lanka
67 Lesotho
68 Bosnia & Herzegovina
69 Colombia
70 Ukraine
71 Suriname
72 Chile
73 Maldives
74 Vietnam
75 Tonga
76 Argentina
77 Bulgaria
78 Malaysia
79 Cuba
80 Samoa
81 Ecuador
82 Botswana
83 El Salvador
84 Guatemala
85 Guinea
86 Armenia
87 Iraq
88 Grenada
89 Egypt
90 Peru
91 Uzbekistan
92 Uganda
93 Laos
94 Cape Verde
95 Iran
96 Togo
97 Jordan
98 Micronesia
99 Rep. of Congo
100 Vanuatu
101 Guyana
102 Comoros
103 ST & Principe
104 Haiti
105 Turkmenistan
106 Cameroon
107 Sudan
108 Liberia
109 Ethiopia
110 S. Africa
111 Georgia
112 Rwanda
113 Tanzania
114 Venezuela
115 C. African Rep.
116 Gambia
117 Bolivia
118 Costa Rica
119 Solomon Islands
120 Mauritius
121 Nicaragua
122 Moldova
123 Macedonia
124 Cambodia
125 Fiji
126 Eritrea
127 Mauritania
128 China
129 Syria
130 Namibia
131 Mozambique
132 Tunisia
133 Ghana
134 Kazakhstan
135 Kyrgyzstan
136 Burundi
137 Kenya
138 Albania
139 Djibouti
140 Indonesia
141 Sierra Leone
142 Malawi
143 Benin
144 Jamaica
145 Madagascar
146 Myanmar
147 Nepal
148 Tajikistan
149 Zimbabwe
150 Burkina Faso
151 Senegal
152 Thailand
153 Zambia
154 Belize
155 Nigeria
156 Lebanon
157 Niger
158 Yemen
159 Chad
160 Paraguay
161 Ivory Coast
162 Brazil
163 Honduras
164 Guinea-Bissau
165 Bangladesh
166 Bhutan
167 Philippines
168 India
169 Afghanistan
170 Mali
171 Azerbaijan
172 Pakistan

Figure D2: The welfare rank of countries according to λ.min

These are welfare rankings for countries according to estimates from our λ.min model reported in Table 2, column 3. Country names are colored according to region. Red—Africa; Orange—Americas; Green—Asia; Blue—Europe; Purple—Pacific.

1 United Arab Emirates
2 Qatar
3 Australia
4 Bahrain
5 United States
6 Italy
7 Canada
8 Spain
9 Saudi Arabia
10 Singapore
11 Kuwait
12 Liberia
13 Burundi
14 Norway
15 Sweden
16 Oman
17 S. Africa
18 Switzerland
19 Czech Rep.
20 Germany
21 Belgium
22 United Kingdom
23 Luxembourg
24 Austria
25 Ireland
26 Portugal
27 France
28 New Zealand
29 Denmark
30 Finland
31 Israel
32 Russia
33 Jordan
34 Netherlands
35 Cyprus
36 Slovenia
37 Hungary
38 Slovakia
39 Greece
40 Poland
41 Iceland
42 Rep. of Congo
43 Angola
44 Japan
45 Sierra Leone
46 Estonia
47 New Caledonia
48 Bahamas
49 Rwanda
50 Croatia
51 Ukraine
52 Namibia
53 Thailand
54 Equatorial Guinea
55 Latvia
56 Azerbaijan
57 Malta
58 Belarus
59 Eritrea
60 Costa Rica
61 Hong Kong
62 Lithuania
63 Tunisia
64 Syria
65 Libya
66 Bosnia & Herzegovina
67 Macedonia
68 Malaysia
69 Lebanon
70 Turkey
71 Gabon
72 C. African Rep.
73 Mauritania
74 Iraq
75 Uganda
76 P. N. Guinea
77 Botswana
78 Barbados
79 Venezuela
80 Bulgaria
81 Djibouti
82 Algeria
83 Yemen
84 Benin
85 St. Lucia
86 Vanuatu
87 Cameroon
88 Solomon Islands
89 Madagascar
90 Panama
91 Togo
92 Mauritius
93 Swaziland
94 French Polynesia
95 Lesotho
96 Niger
97 Chad
98 Brunei
99 Kazakhstan
100 Albania
101 Kenya
102 Chile
103 Mozambique
104 Ghana
105 Maldives
106 Suriname
107 Malawi
108 Nigeria
109 Gambia
110 Comoros
111 Trinidad & Tobago
112 S.V. & Grenadines
113 Iran
114 Egypt
115 Ethiopia
116 S. Korea
117 Grenada
118 Guinea-Bissau
119 Puerto Rico
120 N. Korea
121 ST & Principe
122 Armenia
123 Bhutan
124 Turkmenistan
125 Belize
126 Micronesia
127 Burkina Faso
128 Mali
129 Colombia
130 Tanzania
131 Zambia
132 Georgia
133 Cape Verde
134 Paraguay
135 Senegal
136 Sudan
137 Moldova
138 Ecuador
139 Argentina
140 Guyana
141 Mongolia
142 Nepal
143 Uruguay
144 Kyrgyzstan
145 Jamaica
146 Laos
147 Somalia
148 Tonga
149 Cuba
150 Fiji
151 Honduras
152 Morocco
153 Dominican Rep.
154 Ivory Coast
155 Brazil
156 China
157 Samoa
158 Guinea
159 Guatemala
160 Vietnam
161 Afghanistan
162 Bolivia
163 India
164 Haiti
165 Sri Lanka
166 Cambodia
167 Nicaragua
168 Myanmar
169 Uzbekistan
170 Mexico
171 Tajikistan
172 Philippines
173 Pakistan
174 El Salvador
175 Indonesia
176 Peru
177 Zimbabwe
178 Bangladesh

Figure D3: The welfare rank of countries according to unprojected estimates

These are welfare rankings for countries according to estimates of $\hat{u_d} = \hat{\delta}_d - \hat{\gamma} \log N_d$. Country names are colored according to region. Red—Africa; Orange—Americas; Green—Asia; Blue—Europe; Purple—Pacific.

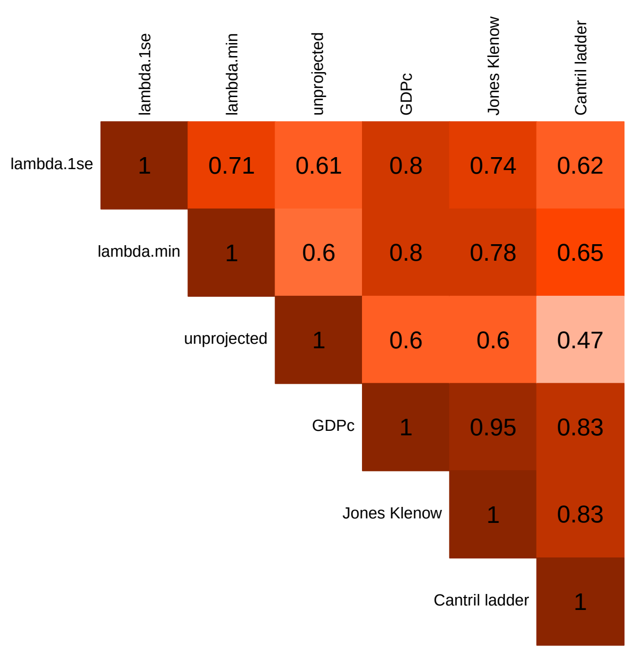

Figure D4: Correlation among the welfare measures