

# Working Papers

## RESEARCH DEPARTMENT

WP 19-33

August 2019

<https://doi.org/10.21799/frbp.wp.2019.33>

# The Well-Being of Nations: Estimating Welfare from International Migration

**Sanghoon Lee**

University of British Columbia

**Seung Hoon Lee**

Georgia Institute of Technology

**Jeffrey Lin**

Federal Reserve Bank of Philadelphia Research Department

---

**ISSN:** 1962-5361

**Disclaimer:** This Philadelphia Fed working paper represents preliminary research that is being circulated for discussion purposes. The views expressed in these papers are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. Philadelphia Fed working papers are free to download at: <https://philadelphiafed.org/research-and-data/publications/working-papers>.

# The Well-Being of Nations: Estimating Welfare from International Migration\*

Sanghoon Lee<sup>†</sup>      Seung Hoon Lee<sup>‡</sup>      Jeffrey Lin<sup>§</sup>

August 27, 2019

## 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 economic 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

*JEL classification:* D63, I31, F22, J61

---

\*We thank Rebecca Diamond, Tom Holmes, Kyle Mangum, and participants at the Asian Real Estate Society annual conference, the North American meetings of the Urban Economics Association, the University of British Columbia, and the Summer Conference in Urban Economics and Real Estate.

<sup>†</sup>Sauder School of Business, University of British Columbia, sanghoon.lee@sauder.ubc.ca.

<sup>‡</sup>School of Economics, Georgia Institute of Technology, seunghoon@econ.gatech.edu.

<sup>§</sup>Research Department, Federal Reserve Bank of Philadelphia, jeff.lin@phil.frb.org.

**Disclaimer:** This Philadelphia Fed working paper represents preliminary research that is being circulated for discussion purposes. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. Philadelphia Fed working papers are free to download at <https://www.philadelphiafed.org/research-and-data/publications/working-papers>.

# 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.

In this paper, 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 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. 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 virtue of our choice model is to provide a micro-foundation for gravity in international 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.

Our estimates, by relying on revealed preference, complement previous estimates of country well-being. 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 instead relies on a discrete-choice framework that allows for the incorporation of a number of factors. Thus, we are not required to take a strong *ex ante* stand on what factors best predict welfare. 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. Thus, our estimates of country well-being rely on different assumptions and data compared with other work. The main distinction of our approach is that we rely on people’s migration or staying choices to infer what countries—and what welfare factors—they prefer.

We deal with a number of important challenges. First, 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. Second, there may be unobserved migration restrictions preventing entry or exit. For example, emigration restrictions increase the number of stayers, inflating our estimates of country welfare, since our model interprets this as revealed preference. To address this, we project our estimates in a second stage on a number of observable country factors. Under certain conditions, these second-stage welfare estimates are invariant to the presence of unobserved factors. We also emphasize that we are interested in *predicting* the welfare of countries, rather than performing causal inference on the effect of factors on welfare.

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 contribution is to estimate quality of life for countries as a whole. Our welfare estimates are distinct from within-country quality of life estimates in that we incorporate housing costs and income. Unlike work estimating within-country variation in quality of life, we do not assume spatial equilibrium. In contrast, within-country quality of life estimates explicitly exclude housing costs and incomes as these prices vary across space in order to equalize utility across regions.<sup>1</sup>

A large literature tries to understand the determinants of migration flows (Grogger and Hanson 2011; Pacheco et al. 2013). Much of this literature emphasizes migration as 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.

## 2 Model

There are  $J$  countries of varying size, with *initial* populations  $\{N_j\}$ . Each person  $i$  living in an origin country  $o \in J$  maximizes utility  $U$  by choosing a destination country of residence  $d \in J$ .

$$\max_{d \in J} U_{od}^i \equiv u_d - c_{od} + \xi_d + \epsilon_{od}^i \quad (1)$$

The choice to stay,  $d = o$ , is permitted. Everyone in the world faces the same choice set, though moving costs  $c_{od}$  vary across origin–destination pairs. Destination country  $d$  offers utility  $u_d \in \mathbb{R}$  to its residents. Destination utility  $u_d \equiv Z_d' \alpha$  can be represented as a linear combination of destination-country factors  $Z_d$ . The cost of moving between origin  $o$  and destination  $d$  is described by  $c_{od} \equiv X_{od}' \beta$ , where  $X_{od}$  is a vector of factors consisting of

---

<sup>1</sup>Our method is similar to work in other contexts; e.g., Sorkin (2018) uses revealed preference of workers to estimate utility across jobs.

characteristics of the origin–destination country pair (e.g., distance between countries  $o$  and  $d$  or country  $d$ ’s immigration policy towards residents of  $o$ ). We normalize  $c_{od}$  so that  $c_{od} = 0$  if  $d = o$ . A random effect  $\xi_d$  captures unobserved destination-country migration policies or any other unobserved destination-specific factor.

A person-level idiosyncratic shock  $\epsilon_{od}^i$  follows a Gumbel (type-I extreme value) distribution with location parameter  $\gamma \ln N_d$  and shape parameter 1. This structure formalizes the intuition that larger countries offer more possible opportunities for potential migrants. Since the location parameter assumption adds  $\gamma \ln N_d$  to the standard Gumbel, the probability that a person in country  $o$  chooses country  $d$  is

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

This setup is equivalent to a model where each person receives  $N_d^\gamma$  number of draws following the *standard* Gumbel distribution commonly used in the literature (with location 0 and shape 1). ( $\gamma$  governs the sensitivity of choice to country size.) To see this, note that equation 2 is equivalent to

$$\frac{N_d^\gamma \exp(u_d - c_{od} + \xi_d)}{\sum_j N_j^\gamma \exp(u_j - c_{oj} + \xi_j)}, \quad (3)$$

or the standard logit probability weighted by destination country size. These assumptions allow us to account for larger gross flows into larger destination countries.

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  $\frac{1}{3}$  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  $(\frac{2}{3}, \frac{1}{3})$ , but the standard logit setup yields choice probabilities  $(\frac{1}{2}, \frac{1}{2})$ . In contrast, our setup with  $\gamma = 1$  yields the intuitive choice probabilities because country AB offers twice as many opportunities. In practice, we allow  $\gamma$  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 which 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.<sup>2</sup>

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  $\pi_{od}$  now increases with destination size  $N_d$  (equation 3). Therefore flows increase with destination size, consistent with gravity.<sup>3</sup>

Anderson (2011) describes a discrete choice model of migration that generates 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. Our model is distinct in that it does not require utility to increase with country size.<sup>4</sup>

## 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

---

<sup>2</sup>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  $\pi_{od}$  of migrating from  $o$  to  $d$ :

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

<sup>3</sup>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  $G_d \equiv \frac{\exp(u_d - \xi_d)}{\sum_j N_j \exp(u_j - c_{oj} + \xi_j)}$ .

<sup>4</sup>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.

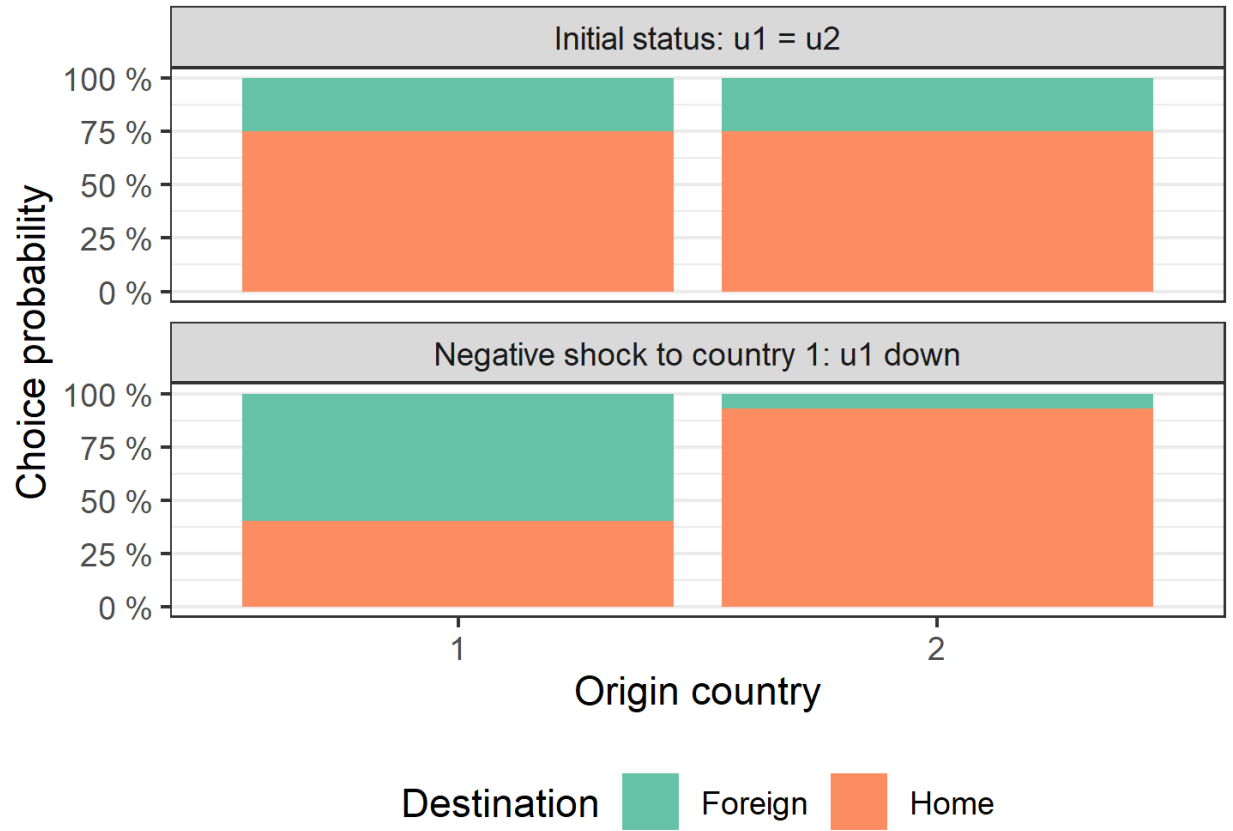


Figure 1: Lower welfare increases outflows and decreases inflows

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 (the other countries 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.

### 3 Estimation

We estimate our model in two stages. First, we rewrite equation (1) as:

$$\max_{d \in J} U_{od}^i \equiv \delta_d - X'_{od}\beta + \nu_{od}^i, \quad (4)$$

where

$$\delta_d \equiv Z'_d\alpha + \gamma \log N_d + \xi_d \quad (5)$$

and  $\nu_{od}^i$  follows the standard Gumbel distribution. In the first stage, we estimate  $\delta_d$ . In the second stage, we regress  $\hat{\delta}_d$  onto welfare factors  $Z_d$  and  $\log N_d$ .

We estimate the first stage of the model (equation 4) 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. To correct for this inflation, we cluster standard errors by origin country.

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  $\pi_{od}$  and invert the model to obtain  $\delta_{od}$ . We do not use this method because our object of interest is  $\delta_d$ , which varies at the destination level instead of at the origin–destination pair level.<sup>5</sup> 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  $\delta_{o,d}$  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 not  $-\infty$ . Thus, zero shares do not pose a problem for our estimates unless a country de-populates entirely.<sup>6</sup>

---

<sup>5</sup>BLP require  $\delta$  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.

<sup>6</sup>A property commonly discussed in discrete choice models is whether model predictions are restricted by the Independence of Irrelevant Alternatives (IIA). But IIA is less important here because we are not interested in estimating choices when a new country emerges or an existing country disappears. In our model, IIA is binding at the level of each origin country but not at the global level. To see this, suppose that the world consists of two countries A and B of the same size. Country A workers choose A and B with 66.6% and 33.3% probabilities (i.e., 2 to 1 ratio) and country B workers choose A and B with 33.3% and 66.6% probabilities. Now suppose that we add country C to the choice set, where country C is identical to country B. Country A workers choose A, B, and C with 50%, 25%, and 25%. Country B workers choose A, B, and C with 20%, 40%, and 40%. Note that the IIA holds at an origin country level; the probability ratios



Our first-stage estimate of  $\hat{\delta}_d$  includes destination utility  $u_d$ , log population  $\gamma \ln N_d$ , and unobserved destination factors  $\xi_d$ . 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  $\xi_d$ . 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 (e.g., immigration policy). 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 directly affect welfare, beyond the welfare factors we include in the second-stage regression. For example, country size may increase national pride. If this is true (and we omit it from our second-stage regression), then we will under-estimate welfare for larger countries. We assume that country welfare is orthogonal to country size conditioned on the welfare factors we include in our second-stage regression. Given our inclusion of many welfare factors including income, inequality, etc., we view this assumption as reasonable.

Second, 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.

Third, unobserved migration policy factors may be correlated with our included welfare

---

of choosing countries A and B remain 2 to 1 for country A or 1 to 2 for country B. However, at a global level the ratio of people choosing countries A and B changes from 1 to 1 (33.3%+66.6% vs. 66.6% + 33.3%) to 1 to 0.92 (33.3 + 50%).

factors  $Z_d$ .<sup>7</sup> For example, if countries with higher per-capita GDP tend to have stricter immigration policies, then our projected welfare estimates will be biased. However, if the strictness of immigration policy is related to a country’s *overall* utility, then the country welfare rankings will be preserved in our estimates.<sup>8</sup>

Fourth, 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  $\delta_d$ . 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.

## 4 Results

### 4.1 First-stage estimates

To estimate equation 4 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

---

<sup>7</sup>There is limited data on migration policies around the world. Even if we could measure migration policy exactly, there are many non-policy migration costs that are difficult to measure, e.g., the social costs of leaving family and friend networks may vary by sending or destination country. One possibility is to use measures of destination-level immigration policy as control variables. These data are from the UN World Population Policies Database. This survey asks member and non-member states about government policies with respect to population. There are two challenges. One is that nearly all of the survey questions elicit preferences about changes in policy, rather than policy levels themselves. The second that there is a large number of questions, which is a challenge given our limited degrees of freedom.

<sup>8</sup>Suppose the strictness of immigration policy increases only with the number of immigrant inflows. As long as these policies do not reverse the rank order of immigration flows, they will not reverse our estimated country ranks.

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

$1_{Diff}$	-3.337 <sup>c</sup> (1.262)
$1_{Diff} \times \text{Log distance}$	-0.962 <sup>c</sup> (0.194)
$1_{Diff} \times \text{Shared border}$	1.518 <sup>c</sup> (0.282)
$1_{Diff} \times \text{Common language}$	0.700 <sup>c</sup> (0.128)
$1_{Diff} \times \text{Colonial link}$	1.415 <sup>c</sup> (0.183)
$N$	1.14e+12

First-stage estimates of equation 4. Standard errors robust to clustering by origin country reported in parentheses. <sup>a</sup>— $p < 0.10$ ; <sup>b</sup>— $p < 0.05$ ; <sup>c</sup>— $p < 0.01$ .

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 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 of migrants (e.g. Beine et al. 2011.)<sup>9</sup>

Table 1 shows first-stage estimates, omitting the estimated country fixed effects  $\hat{\delta}_d$ . We include six 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. They are clustered by origin country, to allow for within-country correlation in destination choice.

The signs of the coefficients are as expected and precisely estimated. Country pairs that share a border, a language, or a colonial link have higher migration flows. Countries that are

<sup>9</sup>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 ( $1_{Diff} = 1$ ).

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  $(179 \times 6.39 \text{ billion} \approx ) 1.14 \text{ trillion}$ .

As a robustness check, we also estimate a specification of equation 4 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. For example, North Korea’s strict emigration controls reduce outflows, which our baseline model may attribute to superior quality of life. 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  $\delta_d$ . Instead, only gross flows from other countries *to* country  $d$  identify  $\delta_d$ . In our judgment, the loss of identifying variation from stayers exceeds the benefits of absorbing origin-country factors. We report these results in Appendix B.

## 4.2 Second-stage estimates

To estimate our second stage (equation 5), 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 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. (In particular, missing data on welfare factors seems likely to be correlated with welfare itself.) 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.

Therefore, we begin with a judgmental list of factors drawn from the World Bank and other sources. Then, we use LASSO to select factors that best predict welfare. We begin with the following eight factors, in addition to controlling for 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 diameter; (vii) a measure of contractibility that captures perceptions of the extent to which agents have confidence in the rule of law; (viii) and infant mortality, or the number of infants dying before reaching one year of age, per 1,000 live births.<sup>10</sup>

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, 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 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.

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 0.48. 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 0.59.

Column 4 shows estimates including all eight factors plus population size. Estimated coefficients on population and GDP per capita are nearly identical to column 1. Other coefficient signs are as expected. Inequality predicts lower welfare, and is precisely estimated. More public expenditures as a share of total expenditures on health care predict higher welfare. Control of corruption increases welfare but is not significantly different from zero. Leisure increases welfare, but this is also imprecise. Pollution lowers welfare but is imprecisely estimated. The estimated coefficients on contractibility and infant mortality have unexpected signs, but they are imprecisely estimated and are likely collinear with the other included

---

<sup>10</sup>These data and their sources are described in Appendix A. Appendix Table A2 provides summary statistics for destination country factors.

Table 2: Destination-country factors predict welfare

	(1) GDP	(2) $\lambda.1se$	(3) $\lambda.min$	(4) All
Log(Population)	0.484 <sup>c</sup> (0.038)	0.478 <sup>c</sup> (0.064)	0.488 <sup>c</sup> (0.065)	0.485 <sup>c</sup> (0.065)
Log(GDP per capita)	0.492 <sup>c</sup> (0.044)	0.376 <sup>c</sup> (0.118)	0.351 <sup>c</sup> (0.121)	0.483 <sup>c</sup> (0.178)
Gini coefficient		-4.306 <sup>c</sup> (1.374)	-4.297 <sup>c</sup> (1.375)	-5.129 <sup>c</sup> (1.543)
Public share of health exp.		2.306 <sup>c</sup> (0.866)	2.302 <sup>c</sup> (0.866)	2.298 <sup>b</sup> (0.874)
Control of corruption		-0.074 (0.214)	-0.104 (0.217)	0.054 (0.427)
Log(Mean work hours)		-1.418 (1.056)	-1.126 (1.099)	-1.040 (1.108)
Log(PM25)			-0.213 (0.223)	-0.278 (0.234)
Contractibility				-0.198 (0.415)
Infant mortality				0.253 (0.265)
Constant	-9.737 <sup>c</sup> (0.744)	-3.339 (4.019)	-3.726 (4.042)	-5.233 (4.305)
Observations	174	85	85	85
Adjusted R <sup>2</sup>	0.589	0.637	0.637	0.634

Second-stage estimates of equation 5. Standard errors in parentheses. <sup>a</sup>— $p < 0.10$ ; <sup>b</sup>— $p < 0.05$ ; <sup>c</sup>— $p < 0.01$ .

factors.

We use the LASSO estimator to improve our predictions. We use 10-fold cross-validation to compute root mean squared errors (RMSE). In cross-validation, the model is estimated with a training sample while the RMSE is calculated on test sample. A larger number of predictors does not necessarily lead to a lower RMSE. In our case, the model achieves the minimum RMSE when contractibility and infant mortality are dropped and the penalty parameter  $\lambda$  is set at 0.048. This is shown in column 3. We also report the recommended practice of selecting the highest  $\lambda$  within one standard error of the  $\lambda$ -minimizing RMSE. This leads to a more parsimonious model with fewer predictors. This model drops air pollution, as shown in column 2. Once a model is selected with cross-validation, we estimate the model with the full sample to obtain the coefficient estimates reported in columns 2 and 3.

Overall, we prefer the  $\lambda_{1se}$  estimates reported in column 2. This is the more parsimonious model selected by LASSO within one standard error of the  $\lambda$ -minimizing RMSE. The fact that measures of air quality, institutions, and mortality are excluded in this model does not imply that these are not important welfare factors. Instead, our interpretation is that, conditioned on the other five factors, these measures do not improve predictions of country welfare.

An important pattern in our results is that the coefficient on population is stable and precisely estimated across specifications. This is important because our unprojected estimates of country welfare are  $\hat{u}_d = \hat{\delta}_d - \hat{\gamma} \log N_d$ . The stable estimates of  $\hat{\gamma}$  suggest that our unprojected estimates of welfare are robust. We choose  $\gamma = 0.48$  for our unprojected estimates of welfare.

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 regression. Five factors (plus population) have negligible missing values—GDP, control of corruption, PM25, contractibility, and infant mortality. (We exclude just 7 countries with missing values for any of these five factors.) Then, we use these five factors 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

We compare our country welfare estimates to other estimates of country welfare. Our estimates are correlated with other estimates of welfare. Figure 2 shows the largest countries with more than 30 million inhabitants ranked by our estimates of country welfare compared

	(1) lambda.1se	(2) lambda.min	(3) full	(4) unprojected	(5) GDP per capita	(6) Jones Klenow	(7) Cantril ladder
1	United Kingdom	Italy	France	United States	United States	United States	Canada
2	Italy	France	Japan	Italy	United Kingdom	France	United States
3	Canada	United States	United States	Canada	Japan	United Kingdom	Spain
4	United States	Germany	Canada	Spain	Canada	Japan	United Kingdom
5	Germany	Canada	United Kingdom	S. Africa	France	Canada	France
6	Japan	Japan	Poland	Germany	Germany	Italy	Italy
7	S. Korea	United Kingdom	Germany	United Kingdom	Italy	Spain	Mexico
8	France	S. Korea	Italy	France	Spain	Germany	Germany
9	Mexico	Mexico	S. Korea	Russia	S. Korea	S. Korea	Brazil
10	Spain	Spain	Spain	Poland	Poland	Poland	Japan
11	Poland	Russia	Turkey	Japan	Mexico	Mexico	Argentina
12	Turkey	Poland	China	Ukraine	Turkey	Turkey	Colombia
13	Thailand	China	Russia	Thailand	Russia	Argentina	Thailand
14	Indonesia	Brazil	Argentina	Turkey	S. Africa	Russia	Poland
15	Brazil	Turkey	Mexico	Kenya	Argentina	Iran	S. Korea
16	S. Africa	Iran	Colombia	Nigeria	Brazil	Ukraine	Pakistan
17	Russia	Colombia	Brazil	Iran	Colombia	Brazil	Egypt
18	Argentina	Philippines	Thailand	Egypt	Iran	Thailand	Vietnam
19	India	S. Africa	Iran	Ethiopia	Thailand	Colombia	Iran
20	Ukraine	Thailand	Philippines	S. Korea	Morocco	Egypt	Turkey
21	Iran	Argentina	S. Africa	Colombia	Ukraine	China	India
22	China	Ukraine	Pakistan	Tanzania	China	Indonesia	S. Africa
23	Morocco	Pakistan	India	Argentina	Indonesia	Morocco	Russia
24	Philippines	Egypt	Bangladesh	Morocco	Philippines	Philippines	Morocco
25	Colombia	Morocco	Tanzania	Brazil	Egypt	S. Africa	Ukraine
26	Tanzania	Vietnam	Vietnam	China	Nigeria	Pakistan	Indonesia
27	Pakistan	Kenya	Nigeria	Vietnam	Pakistan	Vietnam	Philippines
28	Bangladesh	Indonesia	Kenya	India	India	India	Nigeria
29	Egypt	Nigeria	Ethiopia	Mexico	Vietnam	Bangladesh	China
30	Nigeria	Bangladesh	Indonesia	Philippines	Kenya	Nigeria	Bangladesh
31	Kenya	Ethiopia	Ukraine	Pakistan	Bangladesh	Kenya	Kenya
32	Vietnam	India	Egypt	Indonesia	Tanzania	Tanzania	Ethiopia
33	Ethiopia	Tanzania	Morocco	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 due to missing values in the Cantril ladder measure. Country names are colored according to region. Red—Africa; Orange—Americas; Green—Asia; Blue—Europe.

with other estimates of country welfare.<sup>11</sup>

Figure 2, column 1 shows welfare estimates using estimates from our  $\lambda.1se$  model reported in Table 2, column 2. Using those estimates of  $\hat{\alpha}$ , we form estimates of country welfare as  $\hat{u}_d = Z'_d \hat{\alpha}$ . Among large countries, the U.K., Italy, Canada, the U.S., and Germany top the list. Among all countries, Norway, Luxembourg, the U.K., Italy, Canada, the U.S., Switzerland, Australia, Qatar, and Austria make up the top ten. Haiti, Cape Verde, and the Central African Republic have the lowest quality of life according to our  $\lambda.1se$  model. Among all 172 countries, Mexico (39) is similarly ranked compared with Croatia (40); India (85) is slightly ahead of China (97); and Chile (65) ranks a little higher compared with Brazil (69).

Columns 2 and 3 in Figure 2 show the welfare rank of countries according to estimates from our  $\lambda.min$  model and the model including the full vector of factors reported in Table 2, columns 3 and 4, respectively. Overall, our estimates of country welfare are robust to includ-

<sup>11</sup>Appendix Figure D1 shows the welfare rank of a larger group of 172 countries. We drop 7 countries with missing data. See Appendix C for details.



ing more or fewer factors in Table 2. The pairwise correlation coefficients of our projected welfare estimates  $\hat{u}_d = Z_d' \hat{\alpha}$  across the specifications reported in Table 2 range from 0.78 to 0.80.<sup>12</sup> But smaller differences across these rankings are predicted by differences in included or excluded factors. For example, South Korea ranks 23rd according to our  $\lambda$ .1se estimate (and seventh among large countries.) Our  $\lambda$ .min and full models add additional welfare factors, including air pollution. As a result, South Korea drops to 31st according to our  $\lambda$ .min estimate and 44th in our all-factor estimate. Northern European nations with superior air quality increase in rank. When the model includes the full vector of factors, France rises to the top ranking among large countries and 4th among all countries. Thus, despite the overall similarity between the country welfare rankings using different second-stage models reported in Table 2, there is some churning in rank depending on the inclusion or exclusion of specific factors.

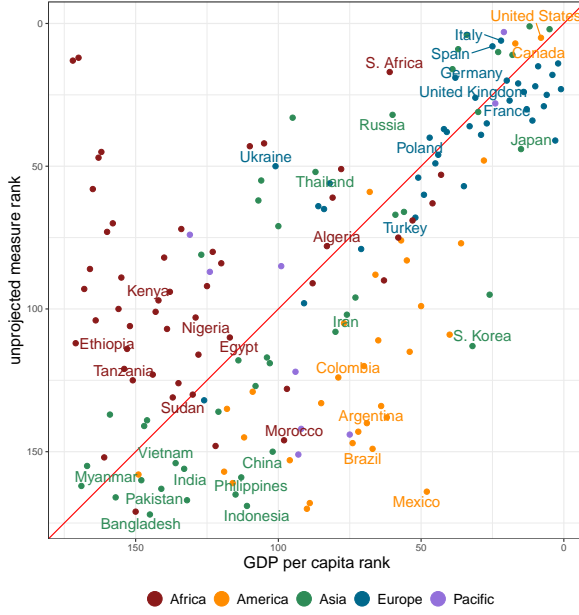
Next, we compare these ranks to our unprojected welfare estimates,  $\hat{u}_d = \hat{\delta}_d - \hat{\gamma} \log N_d$ . These are shown in Figure 2, column 4. In general, there is a positive but more modest correlation (0.62) between our unprojected estimates of welfare and our projected estimates of welfare. 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 well on both our projected and unprojected measures.

Figure 3 compares our unprojected and projected ( $\lambda$ .1se) welfare estimates with GDP per capita. Overall, our projected estimates (Figure 3b) are much more tightly correlated with GDP per capita compared with our unprojected estimates (Figure 3a). 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 conceptual limitations.

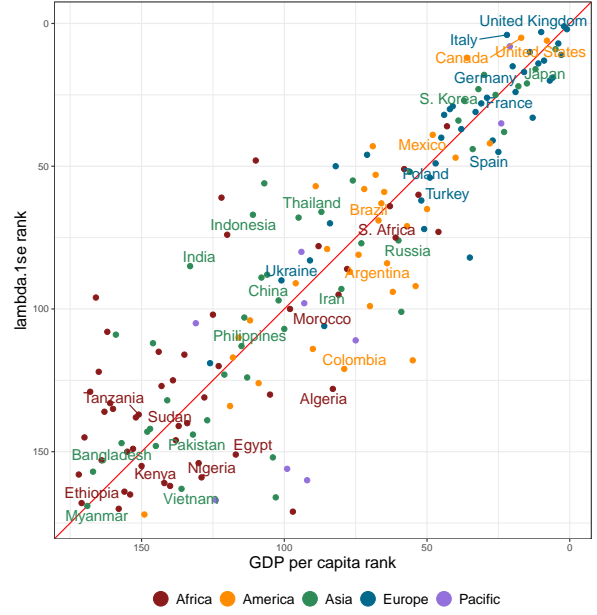
There are some interesting regional patterns. Figure 3a shows that Asian countries (in green) have inferior ranks according to our unprojected welfare estimates compared with GDP per capita. This indicates that they have relatively few inflows relative to their income.

---

<sup>12</sup>See Figure D5.



(a) Unprojected vs. GDP per capita



(b) Projected vs. GDP per capita

Figure 3: Comparison of welfare estimates

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 strongly related to GDP per capita, with a correlation coefficient of 0.88. This is expected, since GDP per capita is an important factor in the construction of our projected welfare estimate. Our projected estimates are also highly correlated with the Jones-Klenow estimates of country welfare, with correlation coefficients ranging around 0.84. 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 range from 0.71–0.76. This is comparable to the correlation between the Cantril ladder and GDP per capita of 0.83.

## 5 Conclusion

This paper proposes 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.

## References

- Abel, Guy J, and Nikola Sander. 2014. “Quantifying global international migration flows”. *Science* 343 (6178): 1520–1522. ISSN: 0036-8075.
- Anderson, James E. 2011. “The gravity model”. *Annual Review of Economics* 3 (1): 133–160. ISSN: 1941-1383.
- Beine, Michel, Frédéric Docquier, and Çağlar Özden. 2011. “Diasporas”. *Journal of Development Economics* 95 (1): 30–41. <https://EconPapers.repec.org/RePEc:eee:deveco:v:95:y:2011:i:1:p:30-41>.

- Bernard, Andrew B, Stephen J Redding, and Peter K Schott. 2011. “Multiproduct firms and trade liberalization”. *Quarterly Journal of Economics* 126 (3): 1271–1318. ISSN: 0033-5533.
- Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. “Automobile prices in market equilibrium”. *Econometrica: Journal of the Econometric Society* 63 (4): 841–890. ISSN: 0012-9682.
- Bodvarsson, Örn B, Nicole B Simpson, and Chad Sparber. 2015. “Migration theory”. In *Handbook of the Economics of International Migration*, 1:3–51. Elsevier. ISBN: 2212-0092.
- Desmet, Klaus, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg. 2018. “The geography of development”. *Journal of Political Economy* 126 (3): 903–983. ISSN: 0022-3808.
- Diamond, Rebecca. 2016. “The determinants and welfare implications of US workers’ diverging location choices by skill: 1980-2000”. *American Economic Review* 106 (3): 479–524. ISSN: 0002-8282.
- Easterlin, Richard A. 1974. “Does economic growth improve the human lot? Some empirical evidence”. In *Nations and Households in Economic Growth*, 89–125. Elsevier.
- Grogger, Jeffrey, and Gordon H Hanson. 2011. “Income maximization and the selection and sorting of international migrants”. *Journal of Development Economics* 95 (1): 42–57. ISSN: 0304-3878.
- Head, Keith, and John Ries. 2008. “FDI as an Outcome of the Market for Corporate Control: Theory and Evidence”. *Journal of International Economics* 74 (1): 2–20. ISSN: 0022-1996.
- International Labour Organization. *ILOSTAT*. Type: dataset. <https://ilostat.ilo.org/>.
- Jones, Charles I, and Peter J Klenow. 2016. “Beyond GDP? Welfare across countries and time”. *American Economic Review* 106 (9): 2426–57. ISSN: 0002-8282.
- Kahn, Matthew E. 1995. “A revealed preference approach to ranking city quality of life”. *Journal of Urban Economics* 38 (2): 221–235. ISSN: 0094-1190.
- Kaufmann, Daniel, Aart Kraay, and Massimo Mastruzzi. 2011. “The worldwide governance indicators: Methodology and analytical issues”. *Hague Journal on the Rule of Law* 3 (2): 220–246. ISSN: 1876-4053.
- Krueger, Alan B, Daniel Kahneman, Claude Fischler, David Schkade, Norbert Schwarz, and Arthur A Stone. 2009. “Time use and subjective well-being in France and the US”. *Social Indicators Research* 93 (1): 7–18. ISSN: 0303-8300.
- Manova, Kalina. 2012. “Credit constraints, heterogeneous firms, and international trade”. *Review of Economic Studies* 80 (2): 711–744. ISSN: 1467-937X.

- Mayer, Thierry, and Soledad Zignago. 2011. “Notes on CEPII’s distances measures: The GeoDist database”. *CEPII working paper* No. 2011-25.
- McFadden, Daniel. 1973. “Conditional logit analysis of qualitative choice behavior”. In *Frontiers in Econometrics*, 105–142. Academic Press: New York.
- Pacheco, Gail Anne, Stephanie Rossouw, and Joshua Lewer. 2013. “Do non-economic quality of life factors drive immigration?” *Social Indicators Research* 110 (1): 1–15. ISSN: 0303-8300.
- Ram, Rati. 1982. “Composite indices of physical quality of life, basic needs fulfilment, and income: A ‘principal component’ representation”. *Journal of Development Economics* 11 (2): 227–247. ISSN: 0304-3878.
- Roback, Jennifer. 1982. “Wages, rents, and the quality of life”. *Journal of Political Economy* 90 (6): 1257–1278. ISSN: 0022-3808.
- Slottje, Daniel J. 1991. “Measuring the quality of life across countries”. *Review of Economics and Statistics* 73 (4): 684–693. ISSN: 0034-6535.
- Sorkin, Isaac. 2018. “Ranking firms using revealed preference”. *Quarterly Journal of Economics* 133 (3): 1331–1393. ISSN: 0033-5533.
- United Nations. 2018. *WIID – World Income Inequality Database*. Type: dataset. <https://www.wider.unu.edu/project/wiid-world-income-inequality-database>.
- Wooldridge, Jeffrey M. 2003. “Cluster-sample methods in applied econometrics”. *American Economic Review* 93 (2): 133–138. ISSN: 0002-8282.
- World Bank. *World Bank Open Data*. Type: dataset. <https://data.worldbank.org/>.

FOR ONLINE PUBLICATION

# 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  $1(\text{Shared border})$ , (ii) an indicator for whether a country pairs shares a common official primary language  $1(\text{Common language})$ , and (iii) an indicator for whether the two countries have ever been linked through a colonial relationship  $1(\text{Colonial link})$ . 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, 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

Table A1: Summary statistics for origin–destination pairs

	mean (s.d.)
$1_{Diff}$	0.994 (0.075)
$1_{Diff} \times \ln(\text{Distance})$	8.703 (1.010)
$1_{Diff} \times 1(\text{Shared border})$	0.017 (0.130)
$1_{Diff} \times 1(\text{Common language})$	0.148 (0.355)
$1_{Diff} \times 1(\text{Colonial link})$	0.011 (0.106)
$N$ of country pairs	32,041

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.

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 expenditures not financed by private households' out of pocket payments, taken from 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 provided by the World Bank and refers to the population-weighted exposure to ambient pollution of suspended particles measuring less than 2.5 microns in diameter. 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.

Table A2: Summary statistics for destination countries

	<i>N</i>	Mean	St. Dev.
Log(Population)	178	15.740	1.854
Log(GDP per capita)	174	8.039	1.624
Gini coefficient	143	0.394	0.080
Public share of health exp.	124	0.667	0.180
Control of corruption	176	-0.078	1.020
Log(Mean work hr)	90	3.697	0.115
Log(PM25)	175	3.162	0.642
Contractibility	176	-0.107	1.013
Infant mortality	174	3.030	1.067

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

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. For example, North Korea’s strict emigration controls reduce outflows, which our baseline model may attribute to superior quality of life. 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  $\delta_d$ . Instead, only gross flows from other countries *to* country  $d$  identify  $\delta_d$ .

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  $\hat{\gamma} = 0.58$  to construct our projected estimates of welfare. Figure B1 shows the welfare rank of countries according to our projected  $\lambda.1se$  estimates. Several features are worth noting. First, 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

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

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

First-stage estimates. Estimates of interactions of  $1_{Diff}$  with origin fixed effects omitted. Standard errors robust to clustering by origin country reported in parentheses. <sup>a</sup>— $p < 0.10$ ; <sup>b</sup>— $p < 0.05$ ; <sup>c</sup>— $p < 0.01$ .

Table B2: Destination-country factors predict welfare

	(1) GDP	(2) $\lambda.1se$	(3) $\lambda.min$	(4) All
Log(Population)	0.423 <sup>c</sup> (0.075)	0.584 <sup>c</sup> (0.098)	0.688 <sup>c</sup> (0.093)	0.687 <sup>c</sup> (0.094)
Log(GDP per capita)	0.586 <sup>c</sup> (0.063)	0.542 <sup>c</sup> (0.166)	0.343 <sup>b</sup> (0.158)	0.358 (0.233)
Gini coefficient		0.014 (0.017)	0.021 (0.016)	0.020 (0.018)
Public share of health exp.		0.587 (1.207)	−0.095 (1.111)	−0.093 (1.131)
Control of corruption		0.084 (0.267)	0.044 (0.243)	0.077 (0.596)
Log(Mean work hours)		−1.832 (1.304)	−1.052 (1.201)	−1.019 (1.252)
Log(PM25)			−1.209 <sup>c</sup> (0.297)	−1.207 <sup>c</sup> (0.312)
Contractibility				−0.037 (0.614)
Infant mortality				0.026 (0.326)
Constant	−8.811 <sup>c</sup> (1.396)	−5.416 (4.940)	−4.569 (4.499)	−4.839 (5.247)
Observations	144	82	82	82
Adjusted R <sup>2</sup>	0.432	0.546	0.624	0.614

Second-stage estimates of equation 5. Standard errors in parentheses. <sup>a</sup>— $p < 0.10$ ; <sup>b</sup>— $p < 0.05$ ; <sup>c</sup>— $p < 0.01$ .

flows. Without this variation we are only able to estimate  $\hat{\delta}_d$  for 142 countries. Second, there is notable churning in our estimates. Overall, these estimates are positively correlated with our main projected estimates, with a correlation coefficient of 0.62. However, these estimates vary in interesting ways. The U.S. drops from 6th to 14th, suggesting that U.S. stayers are an important source of variation raising our estimates of welfare of the U.S. In contrast, Honduras rises from 104th to 15th, suggesting that outflows from Honduras play a big role in lowering our estimates of welfare for Honduras. In our judgment, the loss of identifying variation from stayers exceeds the benefits of absorbing origin-country factors.

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

Figure B1: The welfare rank of countries according to  $\lambda$ .lse 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 large number of missing values for 3 variables: (i) the Gini coefficient, (ii) the public share of health expenditure, and (iii) mean work hours. We impute these missing values with their conditional means using regression. The other 6 variables are observed for nearly every country (at least 174 of 179 countries). We use these 6 variables as predictors to impute missing values for the remaining three variables. First, we exclude 7 countries with missing values on the 6 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 6 predictor factors, we can construct projected welfare estimates for 172 countries.

Table C1: Summary statistics for imputed country factors

Statistic	$N$	Mean	St. Dev.
Gini coefficient	173	0.396	0.074
Public share of health exp.	172	0.654	0.162
Log(Mean work hours)	173	3.710	0.092

## D The welfare rank of countries

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

Figure D1: The welfare rank of countries according to  $\lambda.1se$

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

Figure D2: The welfare rank of countries according to  $\lambda_{\min}$

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

Figure D3: The welfare rank of countries according to full

These are welfare rankings for countries according to estimates from our full model reported in Table 2, column 4. Country names are colored according to region. Red—Africa; Orange—Americas; Green—Asia; Blue—Europe; Purple—Pacific.

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

Figure D4: 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.

	lambda.1se	lambda.min	full	unprojected	GDPc	Jones Klenow	Cantril ladder
lambda.1se	1	0.78	0.8	0.62	0.88	0.84	0.76
lambda.min		1	0.78	0.56	0.87	0.84	0.74
full			1	0.59	0.86	0.84	0.71
unprojected				1	0.6	0.6	0.47
GDPc					1	0.95	0.83
Jones Klenow						1	0.83
Cantril ladder							1

Figure D5: Correlation among the welfare measures