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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 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

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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.

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.[1]

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 $d \in J$.

$$\max_{d \in J} U^i_{od} \equiv u_d - c_{od} + \xi_d + \epsilon^i_{od} \tag{1}$$

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

[1]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 ξ_d captures unobserved destination-country migration policies or any other unobserved destination-specific factor.

A person-level idiosyncratic shock ϵ^i_{od} 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

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

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

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

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 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 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.[2]

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 3). Therefore flows increase with destination size, consistent with gravity.[3]

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.[4]

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

[2] 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:

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

[3] 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 $G_d \equiv \frac{\exp(u_d - \xi_d)}{\sum_j N_j \exp(u_j - c_{oj} + \xi_j)}$.

[4] 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.

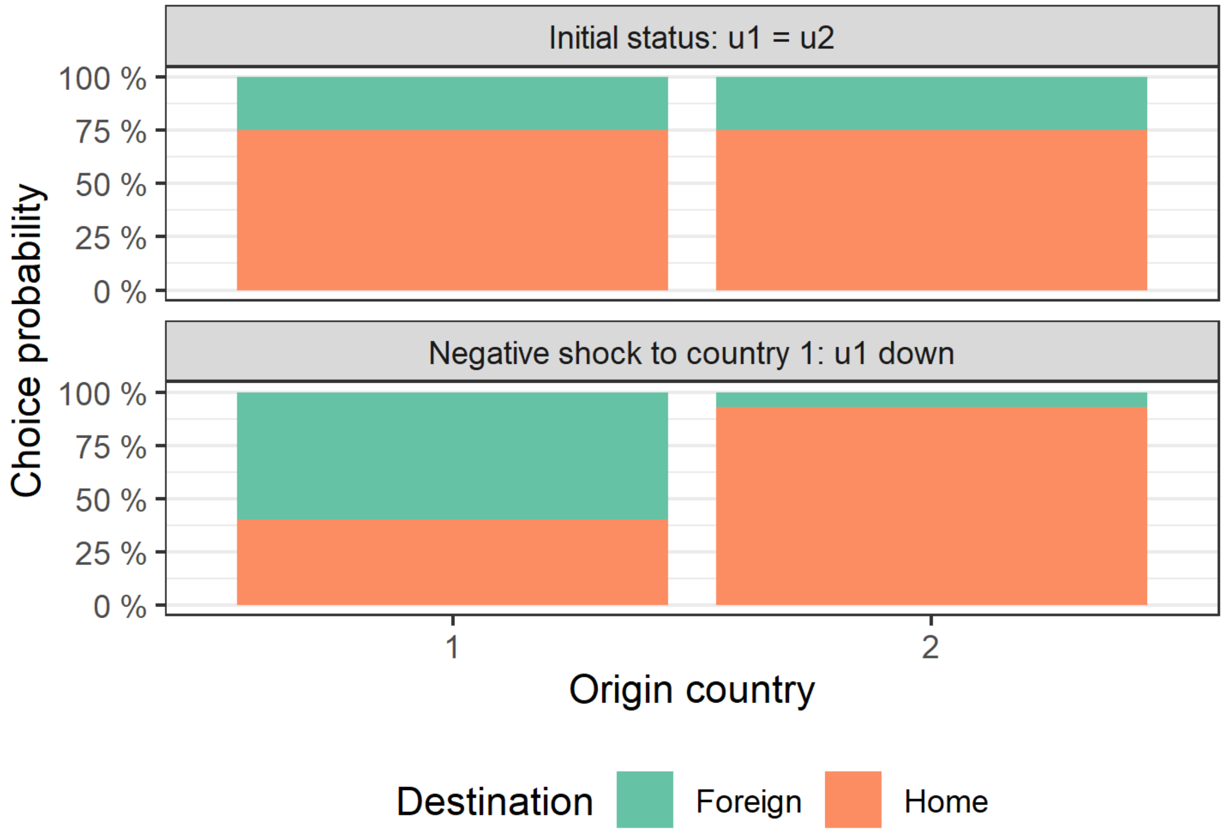


Figure 1: Lower welfare increases outflows and decreases inflows

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:

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

where

$$\delta_d \equiv Z'_d\alpha + \gamma \log N_d + \xi_d \tag{5}$$

and ν_{od}^i follows the standard Gumbel distribution. In the first stage, we estimate δ_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 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.[5] 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.[6]

[5] 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.

[6] 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 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 (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.[7] 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.[8]

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 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.

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

[7] 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.

[8] 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^c
	(1.262)
$1_{Diff}\times$ Log distance	-0.962^c
	(0.194)
$1_{Diff}\times$ Shared border	1.518^c
	(0.282)
$1_{Diff}\times$ Common language	0.700^c
	(0.128)
$1_{Diff}\times$ Colonial link	1.415^c
	(0.183)
N	1.14e+12

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

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.)[9]

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

[9]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 billion $\approx$) 1.14 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 δ_d. Instead, only gross flows from other countries *to* country d identify δ_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 diamenter; (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.[10]

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

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

Second-stage estimates of equation 5. Standard errors in parentheses. ^{a}—$p < 0.10$; ^{b}—$p < 0.05$; ^{c}—$p < 0.01$.

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 λ is set at 0.048. This is shown in column 3. We also report the recommended practice of selecting the highest λ within one standard error of the λ-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 λ.1se estimates reported in column 2. This is the more parsimonious model selected by LASSO within one standard error of the λ-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.[11]

Figure 2, column 1 shows welfare estimates using estimates from our λ.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 λ.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 λ.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-

[11] 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.

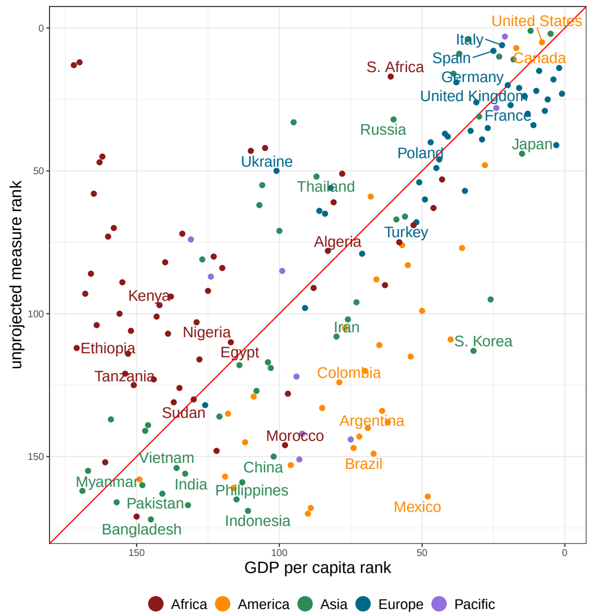
ing more or fewer factors in Table 2. The pairwise correlation coefficients of our projected welfare estimates $\hat{u_d} = Z_d'\hat{\alpha}$ across the specifications reported in Table 2 range from 0.78 to 0.80.[12] But smaller differences across these rankings are predicted by differences in included or excluded factors. For example, South Korea ranks 23rd according to our λ.1se estimate (and seventh among large countries.) Our λ.min and full models add additional welfare factors, including air pollution. As a result, South Korea drops to 31st according to our λ.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.

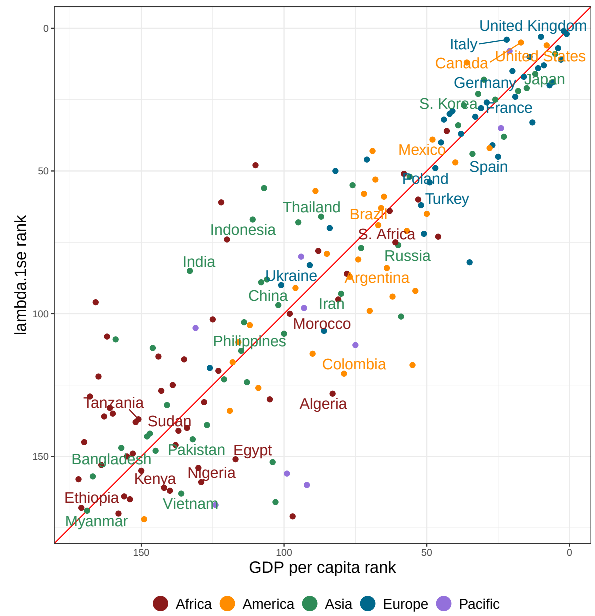
Figure 3 compares our unprojected and projected (λ.1se) welfare estimates with GDP per capita. Overall, our projected estimates (Figure 3b) are much more tightly correlated with GDP per capita compared with our unprojected estimates (Figure 3a). This is expected, since our projected estimates use as 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.

[12]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.

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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, 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(Distance)	8.703
	(1.010)
$1_{Diff} \times$ 1(Shared border)	0.017
	(0.130)
$1_{Diff} \times$ 1(Common language)	0.148
	(0.355)
$1_{Diff} \times$ 1(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

	N	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 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 $\hat{\hat{\delta}}_d$ 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 λ.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(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. Standard errors robust to clustering by origin country reported in parentheses. ^{a}—$p < 0.10$; ^{b}—$p < 0.05$; ^{c}—$p < 0.01$.

Table B2: Destination-country factors predict welfare

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

Second-stage estimates of equation 5. Standard errors in parentheses. ^{a}—$p < 0.10$; ^{b}—$p < 0.05$; ^{c}—$p < 0.01$.

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

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.

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

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

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

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
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 Rwanda
49 Bahamas
50 Croatia
51 Ukraine
52 Namibia
53 Thailand
54 Equatorial Guinea
55 Latvia
56 Azerbaijan
57 Belarus
58 Malta
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 Iraq
74 Mauritania
75 Uganda
76 P. N. Guinea
77 Botswana
78 Venezuela
79 Barbados
80 Algeria
81 Bulgaria
82 Djibouti
83 Yemen
84 Benin
85 St. Lucia
86 Cameroon
87 Vanuatu
88 Madagascar
89 Solomon Islands
90 Panama
91 Togo
92 Mauritius
93 Swaziland
94 French Polynesia
95 Lesotho
96 Niger
97 Chad
98 Brunei
99 Kazakhstan
100 Kenya
101 Albania
102 Chile
103 Mozambique
104 Ghana
105 Maldives
106 Nigeria
107 Malawi
108 Suriname
109 Gambia
110 Comoros
111 Iran
112 Trinidad & Tobago
113 Egypt
114 S.V. & Grenadines
115 Ethiopia
116 S. Korea
117 Guinea-Bissau
118 Grenada
119 Puerto Rico
120 N. Korea
121 ST & Principe
122 Armenia
123 Bhutan
124 Turkmenistan
125 Belize
126 Burkina Faso
127 Micronesia
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 India
163 Bolivia
164 Haiti
165 Sri Lanka
166 Cambodia
167 Nicaragua
168 Myanmar
169 Uzbekistan
170 Mexico
171 Philippines
172 Tajikistan
173 Pakistan
174 El Salvador
175 Indonesia
176 Peru
177 Zimbabwe
178 Bangladesh

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.

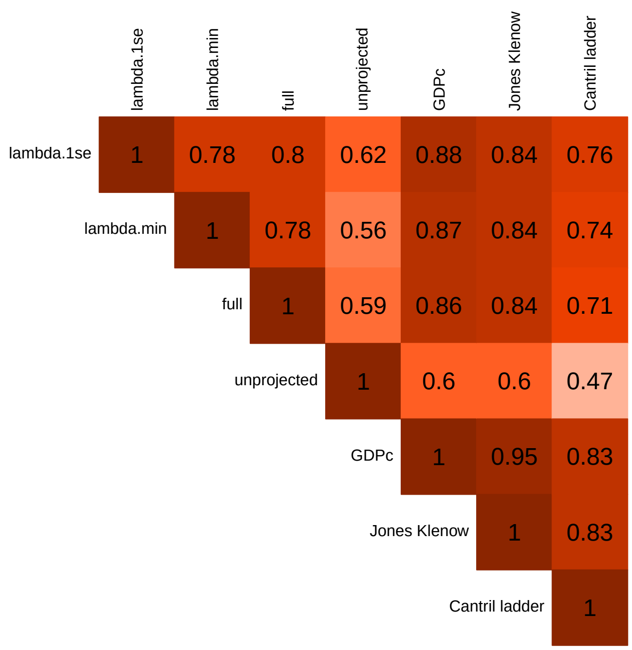

Figure D5: Correlation among the welfare measures