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ABSTRACT

From Stocks to Flows – Evidence for the Climate-Migration-Nexus

Slow onset climate change has the potential to cause significant migration flows. Scientists have recently made considerable efforts to quantify these flows based on empirical methods. However, the literature on international migration has failed to come to a clear conclusion as many studies found no significant effects of climate, while others did. In this paper, we aim to uncover a factor which likely contributes to the mixed picture in the literature: how migration flow data is obtained from migrant stock data. Using the influential study of Cattaneo and Peri (2016) as a workhorse, we demonstrate that the derived empirical results depend heavily on the applied method to derive migration flows. Therefore, our study reveals the necessity for future research on international migration to test the sensitivity of estimated effects to changes in the construction of migration flows.

JEL Classification: F22, J61, O15, Q54, Q56

Keywords: climate change, emigration, economic development, migration data

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1. Introduction

Humans follow various strategies to adapt to climate change. Possibly the most extreme form of adaptation is to emigrate from negatively affected regions (Reid, 2014) and move temporarily or permanently to less affected regions in the same country (internal migration) or abroad (international migration). As early as 1990, the Intergovernmental Panel on Climate Change (IPCC) predicted that human migration will be the single greatest impact of climate change with millions of people displaced. Early estimates of the number of climate refugees range in from 10–25 million and 150–300 million by 2050 (Ionesco et al., 2016). More recently, the Groundswell Report (Rigaud et al., 2018) predicted that up to 143 million people could be forced to migrate within their own countries to escape the slow onset impacts of climate change in Sub-Saharan Africa, South Asia, and Latin America between 2020 and 2050.

Over the last two decades, an increasing number of studies have attempted to quantify climate-induced internal and international migration based on scientific methods. Somewhat surprisingly, these studies have not resulted in a coherent picture, leading to diverging results (Berlemann and Steinhardt, 2017; Cattaneo et al., 2019). Although there is empirical evidence in favor of the hypothesis that climate change induces internal migration, it is far more controversial whether climate change causes large-scale international migration flows.[1] While some studies find that climate plays a role in international migration decisions (e.g. Cattaneo and Peri, 2016; Coniglio and Pesce, 2015; Yavçan, 2021), others do not find evidence of effects in favor of international climate migration (e.g. Ruyssen and Rayp, 2014; Beine and Parsons, 2015).

It is an intriguing question which factors contribute to the conflicting picture in the climate-international migration literature. Berlemann and Steinhardt (2017) discuss a number of methodological differences between the extant studies, such as the measurement of migration and slow onset climate change, the chosen estimation strategies, as well as the choice of control variables. However, two recent meta-analyses by Beine and Jeusette (2019) and Hoffmann et al. (2020) conclude that when focusing more on South-South migration, e.g., in samples consisting of middle income and developing countries with a high dependency of agriculture, studies tend to find a significant effect of climate change on migration. Beine et al. (2019) note that this finding is largely due to the higher exposure of many of these countries to adverse climate impacts and a lower capacity to cope with them.

In this paper, we concentrate on a different, but somewhat related issue: the choice of migration data. As discussed in Berlemann and Steinhardt (2017), international migration studies differ considerably in the employed datasets (and thus

[1] Interestingly enough, the meta-analysis by Beine and Jeusette (2019) does not find that studies focusing on internal migration deliver systematically more effects than those focusing on international displacements.

also in their country samples). Due to the nature of the migration phenomenon, arguably the most natural choice of migration data is bilateral flow data. Numerous studies employ flow data supplied by the Organization for Economic Co-operation and Development (OECD)[2] or the United Nations (UN).[3] However, these datasets do not allow for study of migration within the Global South as they only cover migration targets in developed countries. Thus, when studying international migration patterns within developing countries, alternative data sources must be employed. The typically used alternative to generic flow data is to generate migration flows from migrant stock data, which are part of census data. As census data are generally available only in 5- or 10-year intervals, they reflect medium-run trends rather than short-term fluctuations. However, when slow onset climate change is in the center of interest, the lower frequency of observations is not necessarily a disadvantage in comparison to flow data.

While the empirical literature on the effects of climate change on international migration largely uses migration data derived from migrant stock data, existing studies vary significantly in the way bilateral flow data are obtained. Following Abel and Cohen (2019), these methods can be subdivided into three groups: stock differentiation, migration rates, and demographic accounting. Moreover, within these three groups, variation in generating flow data is common. In this paper, we look at whether the choice of method to derive migration flows from stock data has an effect on the results of an empirical analysis of the impact of slow onset climate change on international migration. In order to do so, we use the estimation approach of one of the most influential studies in the field, the study of the impact of temperature and precipitation on international migration by Cattaneo and Peri (2016). Based on the same raw migrant stock data, we apply six different methods to construct migration flow data, all of which have been used in earlier related work. As a result, we obtain six different datasets of bilateral migration flows. We then apply Cattaneo and Peri's (2016) core estimation approach to the six different datasets and compare the estimation results. We find that the central estimation results depend heavily on the respective method to generate migration flow data from migrant stocks. Thus, the method of deriving migration flows from migrant stock data is likely contributing to the mixed picture on the effects of slow onset climate change on international migration in the literature. Our findings also have implications for other fields of research which analyze international migration flows based on stock data, including the selection of migrants (Grogger and Hanson, 2011), the role of diasporas in explaining emigration (Beine et al., 2011), the impact of emigration on home country institutions (Docquier et al., 2016), and the brain drain of developing countries (Beine et al., 2008).

[2]The OECD provides the International Migration Database (IMD). Data is available at `https://stats.oecd.org/Index.aspx?DataSetCode=MIG`.

[3]Bilateral Migration flows by the UN is available at `https://www.un.org/en/development/desa/population/migration/data/empirical2/migrationflows.asp`.

This paper is organized as follows. Section 2 introduces the various methods to derive flow data from migrant stock data. Section 3 discusses the empirical approach, while Section 4 presents information on the employed data as well as summary statistics. The empirical results are presented and discussed in Section 5, and Section 6 summarizes and draws conclusions.

2. Construction of Bilateral Migration Flows

Various methods have been used to derive migration flows from migrant stock data. Recently, Abel and Cohen (2019) summarized and compared the six methods most often employed and validated them against alternative flow measures. In our subsequent empirical analysis, we consider the same six methods.[4] Following Abel and Cohen (2019), we categorize these six methods into three groups, which are similar in their assumptions and procedures. The first group is referred to as *Stock Differentiation*, the second as *Migration Rates*, and the third as *Demographic Accounting* (see Figure 1 for an overview). We adopt this classification throughout this paper.

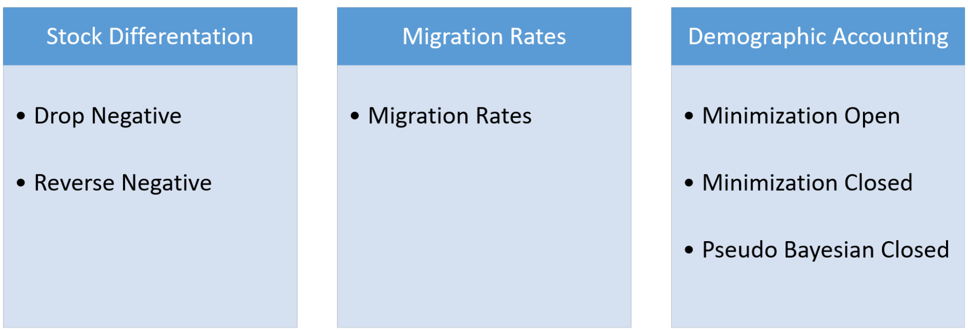

Figure 1: Classification of methods

A commonality among all six methods is that they require information on the stock of persons living within a country at a certain point in time, disaggregated by country of origin. The country of origin is usually defined as the place of birth.[5] Different datasets of migrant stock data are available, varying in both frequency and coverage. The stock data most often employed are from the United Nations and the World Bank. The United Nations database contains data since 1990 in 5-year intervals and is updated biannually.[6] The World Bank provides data on migrant

[4] We use the R package "migest" (version 1.8.2) to calculate all migration flows. This package is available at `https://cran.r-project.org/web/packages/migest/index.html`.

[5] If information on place of birth is not available, country of origin is often approximated by citizenship or ethnicity. See e.g., Özden et al. (2011).

[6] The most recent data revision is available at `https://www.un.org/en/development/desa/population/migration/data/estimates2/estimates19.asp`.

stocks from 1960–2000 in 10-year intervals.[7] Both data sources have highly similar country coverage.

Stock Differentiation methods have the advantage of requiring no data input other than stock information. The overall idea is to calculate flows by differentiating stock information at two distinct points in time. As a result, bilateral net migration flows are obtained. A common issue of this methodological approach is that flows can become negative due to mortality, return and circular migration, definition of citizenship, or naturalization. One solution is to set negative values to zero, as is done in e.g., in Cattaneo and Peri (2016). In line with Abel and Cohen (2019), we refer to this method as *Stock Difference Drop Negative* throughout this paper. The *Stock Difference Reverse Negative* method (applied e.g. in Beine and Parsons, 2015) represents another solution by interpreting negative stock differences as reverse migration flows. Thus, negative flows from country A to country B are added to the derived flows from country B to country A.

The second methodological approach of constructing bilateral migration flow data from migrant stocks (*Migration Rates*) is based on the work of Dennett (2016). Rather than using differences in migrant stocks, this method disaggregates the global migration flows into country pairs.[8] Dennett (2016) argues that the migration flow from origin country A to target country B is highly correlated with the existing migrant stocks for these two countries. Consequently, the author proposes to disaggregate the global migration flow into country pairs based on migration rates, i.e., the share of country-level migrant stock counts in the global foreign-born population.

The third methodological approach, *Demographic Accounting*, assesses changes in population stocks between two points in time within an accounting system. In this system, changes in population stocks only occur through births, deaths, or migration. The same holds true for migrant stocks. However, even after correcting for births and deaths, changes in migrant stocks between two points in time can be the result of a multitude of differing migration patterns with alternative levels of circular and return migration. As both circular and return migration are non-observable, there are challenges in identifying the most likely combination of migration flows that is consistent with the observable stocks. Abel (2013) proposed to derive flow data from a quasi-independent log-linear model using an iterative proportional fitting procedure, with an additional restriction to maximize the number of individuals remaining in their previous country of residence. As a result, this procedure leads to a system of non-negative flows which precisely coincides with migrant stocks.

Due in part to different ways of dealing with non-quadratic migrant stock tables,

[7]The original dataset is based on the work of Özden et al. (2011). The data is available at `https://datacatalog.worldbank.org/dataset/global-bilateral-migration-database`.

[8]Typically, global migration flows are approximated by the absolut sum of net migration flows which are published by e.g., the United Nations.

there are several variations of the *Demographic Accounting* approach. Given that not all countries collect data on immigrants' place of birth, the number of countries of origin is generally larger than the number of countries of residence. Thus, when applying the *Demographic Accounting* approach, a decision must be made on how to deal with this type of asymmetry. Abel (2013) proposes an open demographic accounting system, which allows for moves to or from countries for which bilateral data is available in migrant stock tables. We refer to this method as *Demographic Account Minimization Open* throughout the paper. As an alternative, Abel and Sander (2014) suggest a rescaling of the input data, leading to a closed system in which flows into or out of the accounting system are not possible. We refer to this method as *Demographic Account Minimization Closed*.

Both the *Demographic Account Minimization Open* and the *Demographic Account Minimization Closed* methods use the restriction to maximize the number of individuals remaining in their former country of residence. Therefore, the resulting migration flows reflect the lower bound of the factual occurring migration patterns. In order to allow for greater flexibility, Azose and Raftery (2019) proposed a pseudo-Bayesian alternative which uses a weighted average of a constrained and unconstrained estimate of the *Demographic Account Minimization Closed* method. The unconstrained estimate does not impose any restrictions on the number of those who remain and the number of migrants. The optimal weighting factor for the restricted estimate (0.87) was derived by Azose and Raftery (2019) by minimizing a cost function of the logged differences. European migration flows between 2002 and 2008 from the Integrated Modelling of European Migration (IMEM)[9] project were used to validate the data.

3. Empirical Design

The aim of our empirical analysis is to study whether the employed method of deriving flow data from migrant stock data has an impact on the results of empirical analyses of the climate-migration relationship. We study this question using the example of one of the most influential and methodologically advanced papers in the related literature, the empirical analysis of the impact of climate on migration by Cattaneo and Peri (2016) (CP in the following). In order to capture South-South migration, CP use migrant stock data to calculate bilateral flows. Our empirical analysis consists of using the same migrant stock data as CP (e.g., the same data source and the same sample period) and to construct migration flows from the data using the six methods described in the previous section. Using the resulting six datasets, we then apply the same estimation methodology as CP and compare the estimation results. Before we turn to our empirical analysis, we summarize CP's methodological approach and the major findings of their analysis in the following.

[9]See Raymer et al. (2013) for a detailed description of the data.

One of the main contributions of CP is to analyze the mediating role of income level and the agricultural sector on the long-run relationship between climate variables and migration. While CP study the effect of climate variables on both internal and international migration, we concentrate our brief review on the international dimension of their analysis.

CP base their analysis on stock data from Özden et al. (2011) over the period of 1960-2000 and then use the *Stock Difference Drop Negative* method to calculate bilateral flows in 10-year frequencies. Next, the migration flows are aggregated by country of origin and divided by the population of the country of origin at the beginning of each decade. CP focus their analysis on low- and middle-income countries and therefore exclude OECD countries from their sample. As a result, they end up with a sample of 115 countries for their empirical analysis.

CP use different variants of OLS panel regressions to uncover the effect of temperature and precipitation on emigration rates. The estimated baseline model is

$$Y_{j,t} = \alpha_j + \beta \cdot ln(T_{j,t}) + \gamma \cdot ln(P_{j,t}) + \delta_{r,t} + \phi_{p,t} + \epsilon_{j,t}$$

with $Y_{j,t}$ being the natural logarithm of the emigration rate for country j in decade t. The regression equation contains two climate variables: average temperature ($T_{j,t}$) and average precipitation ($P_{j,t}$). Additional control variables do not enter the regression equation to prevent the well-known overcontrolling problem, which occurs when control variables are themselves endogenous toward the climate variables.[10] To control for country-specific unobservables, the model includes country-fixed effects (α_j). Moreover, CP include decade-region-specific effects[11] ($\delta_{r,t}$) and decade-specific effects for the group of poor countries[12] ($\phi_{p,t}$).

In the first variant of the baseline model, CP interact the two climate variables with a dummy variable for the group of poor countries. The second model variant interacts the climate variables with a dummy variable for agricultural-dependent countries[13], and the third model variant includes both forms of interactions.

The main estimation results of CP are shown in Table 1. The baseline model (column (1)) delivers a positive coefficient for temperature and a negative coefficient for precipitation. However, both coefficients turn out to be not significantly different from zero at the 10% significance level. The inclusion of interaction ef-

[10] See Dell et al. (2014), Beine and Parsons (2017), and Berlemann and Steinhardt (2017).

[11] The regions are Middle East/North Africa, sub-Saharan Africa, Latin America and Caribbean, Western Europe, Eastern Europe and Central Asia, and Asia and Pacific Islands.

[12] Countries were classified as poor when GDP per capita in 1990 was in the lowest quartile of the income distribution of the country sample.

[13] The dummy variable for agricultural-dependent countries is similarly constructed as the dummy for poor countries. Based on the empirical distribution of the share of agricultural value added in GDP, the dummy variable takes the value of 1 if a country belongs to the fourth quartile of the distribution. Note that the necessary raw data is not available for the full sample of countries. Therefore, regressions making use of this variable are based on a slightly reduced sample.

fects between a dummy variable for poor countries and the two climate variables reveals a heterogeneous effect of climate variables on emigration (column (2)). The estimated positive coefficient of temperature now becomes significant at the 5% level. Moreover, the coefficient of the interaction effect between temperature and the poor dummy turns out to be negative and significant at the 1% level. No significant effect can be found for precipitation. Thus, people from middle-income countries exhibit a higher probability to emigrate under increasing temperatures, while the opposite holds true for people from poor countries. CP explain the latter by binding liquidity constraints in poor countries. Increasing temperatures decrease agricultural productivity, resulting in lower emigration since people become poorer and less able to pay migration costs. In middle-income countries, worsening climate conditions instead result in larger emigration, as the opportunity costs of staying are reduced and liquidity constraints are not binding.

To explicitly test the influence and importance of the agricultural sector, CP include interactions between the climate variables and a dummy for agricultural-dependent countries in column (3). In doing so, the coefficient of temperature becomes insignificant; however, the interaction effect with agricultural dependence turns out to be negative and significant at the 1% level. When including both sorts of interactions in column (4), the direct effect of temperature turns out to be significantly positive again. Moreover, both interaction effects for temperature deliver negative significant coefficients. This implies that the negative effect of increasing temperatures in poor countries on emigration is amplified if the country is highly dependent on agriculture. In particular, the estimates in column 4 suggest that an increase in average temperature by 1% in poor countries decreases emigration rates roughly by an additional 12% if the economy is dominated by agricultural activities. Lastly, it is noteworthy that CP do not find evidence of an effect of rainfall on emigration in any of their specifications.

Table 1: Baseline Results of Cattaneo and Peri (2016)

	Dependent variable: ln Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	1.931	**3.755****	2.695	**3.836****
	(1.892)	(1.661)	(1.904)	(1.790)
ln T x Poor		**−19.967*****		**−17.546*****
		(6.607)		(5.068)
ln T x Agri			**−23.996*****	**−15.939***
			(8.457)	(8.285)
ln P	−0.309	−0.223	−0.032	−0.113
	(0.352)	(0.325)	(0.396)	(0.395)
ln P x Poor		−1.399		−0.373
		(1.912)		(2.623)
ln P x Agri			−2.246	−1.674
			(1.423)	(1.577)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R^2	0.179	0.201	0.202	0.216

Note: The table is taken from Cattaneo and Peri (2016), Table 3. The dependent variable is the natural logarithm of the emigration rate. The migration flows are based on the *Stock Difference Drop Negative* method. The regressions focus on population-weighted climate variables. Standard errors are clustered by country of origin. *p<0.1; **p<0.05; ***p<0.01

4. Data & Descriptive Statistics

4.1. Migration Data

Our empirical approach essentially requires employing the same raw data as CP, i.e., migrant stock data compiled by Özden et al. (2011) for 226 countries over the period of 1960-2000. As explained in Section 2, migrant stock tables for different points in time are sufficient to apply the two stock differentiation methods (including the *Stock Difference Drop Negative* method employed by CP). For the other methods, data requirements are higher as net migration data (*Migration Rates*) or data on births, deaths, and population are also necessary (*Demographic Accounting*). This data is unavailable for 31 countries in the sample of Özden et al. (2011) used by CP. As a result, we have to reduce the sample countries to those 195 countries for which we have demographic information available.[14]

In order to rule out that our results are driven by the slightly reduced country sample, we first investigate how the exclusion of the 31 countries without demographic information influences the estimation results derived from the *Stock Difference Drop Negative* method. Therefore, we derive the bilateral migration flows based on the reduced country sample, aggregate them by country of origin, and then compare them to the numbers derived by CP. We base this comparison on the country sample of 115 countries of origin,[15] which is ultimately used in the regression of the baseline model in CP. In Figure B.5 in the Appendix, we plot the values of the derived emigration flows by CP against those derived from the restricted sample for each decade. We observe a very high correlation of nearly 0.95.[16] Thus, there is little reason to believe that using the restricted sample leads to distorted results. In fact we show in Section 5 that we find the same empirical results as CP when applying the *Stock Difference Drop Negative* method to the restricted sample.

Both the *Demographic Accounting* and *Migration Rates* methods need to be supplemented with additional demographic data. The necessary population data, births, and deaths were extracted from the United Nations World Population

[14]In the stock data of Özden et al. (2011), Serbia and Montenegro are defined as one country. The same holds true for South Sudan and Sudan.

[15]The difference between the 226 countries for which migrant stock information is available and the 115 countries in the regression sample is due to (i) the exclusion of OECD countries as countries of origin and (ii) missing values for the income variable which is needed to classify countries as poor or not poor.

[16]The two outliers in Figure B.5 emerge from a different treatment of emigration flows between China, Macao, and Hong Kong. CP treat them as one country. Therefore, they first calculate the total outflows for each country and then aggregate them. We follow CP and consider them as one country. However, we do not include flows between these three countries as we consider them as internal flows. When applying the same aggregation method as CP, the correlation further increases to nearly 1.0 (see Figure B.6 in the Appendix). Table 2 shows that the treatment of China is ultimately without material effect on the derived results.

Prospect 2015 revision (WPP2015).[17] While the data is available in 5-year frequencies, we aggregate it over decades to make it compatible with the frequency of our migrant stock data.[18]

For the *Demographic Account Pseudo Bayesian Closed* method, we need additional data. Azose and Raftery (2019) calibrated their derived results using bilateral migration flow data from the International Migration Database of the OECD and the flow data from the IMEM project, respectively. Unfortunately, our bilateral migration data covers the period of 1960-2000 which does not coincide with the OECD data (annual data over the period of 2000-2019)[19] and the IMEM project data (annual data over the period of 2002-2008). To obtain an appropriate weighting factor for the restricted and unrestricted bilateral migration flows, we use UN migrant stock data to calculate 10-year migration flows over the period of 2000-2010 to mimic our data situation. We then use the migration flows toward OECD countries to derive a suitable weighting factor for the restricted case, which turns out to be 0.7565. In our calibration, we do not adjust our estimates for multiple transitions of individuals by a Long-Boertlein index since the value of Azose and Raftery (2019) corresponds to 5-year flows.[20]

In Figure 2, we show the time series of aggregate migration flows generated by the six alternative methods, using only the 115 countries included in our regressions. The left panel illustrates the sum of all migration flows for a given period. The *Demographic Account Pseudo Bayesian Closed* method delivers the highest number of total migration flows for all periods, while the lowest numbers are constantly resulting from the *Stock Difference Drop Negative* method. In the right panel, we show the median emigration rate.

In order to shed light on the relative importance of migration flows between different regions of the world, we show the resulting bilateral migration flows in Figure 3 as chord diagrams.[21] Each graph corresponds to the results of one of the six methods. We show the bilateral migration flows for the last decade of the sample period (1990- 2000). The arrows indicate the direction of the flows. The flow sizes are indicated by the width at the base. The number at the base axis indicates the flow size in millions. The graphs illustrate the importance of migration flows between, but also within, geographic regions. It is evident that focusing solely on South-North migration would neglect a substantial share of movements between

[17] The data is available on `https://population.un.org/wpp/Download/Archive/Standard/`.

[18] We therefore follow CP and treat Serbia and Montenegro as well as Sudan and South Sudan as one country. The *Demographic Account Minimization Open and Closed* methods derive aggregate outflows to be zero for some observations. We add 'one' to these observations to calculate log emigration rate.

[19] Data last checked on April 1, 2021.

[20] We thank Jonathan J. Azose, Adrian E. Raftery, and Nathan Welch for providing information on implementing the *Demographic Account Pseudo Bayesian Closed* method.

[21] The graphs were created with the help of the circlize R package available at `https://cran.r-project.org/web/packages/circlize/index.html`.

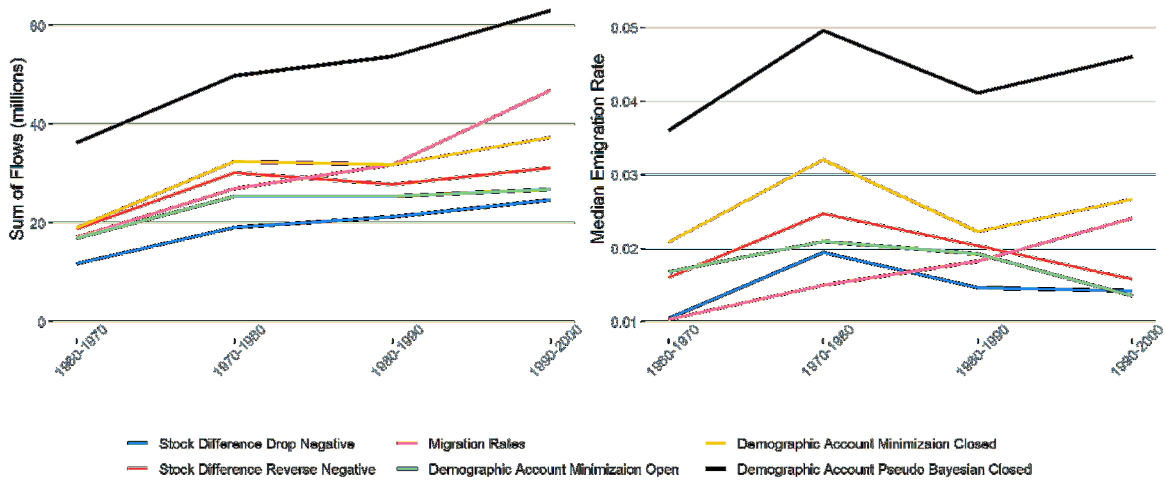

Figure 2: Time series of derived aggregated migration flows (left panel) and median emigration rate (right panel) for 115 countries.

countries that may be particularly important in the context of changing climate conditions.

4.2. Climate Variables

As explained earlier, CP use temperature and precipitation as climate variables in their analysis. The data were taken from the earlier study by Dell et al. (2012) and originate from the Terrestrial Air Temperature and Precipitation dataset of the University of Delaware (see Matsuura and Willmott, 2007).[22] The original data is gridded at a 0.5×0.5 degree resolution[23] and was aggregated using population weights at the country level.[24] For the empirical analysis, precipitation and temperature were averaged over decades. In order to replicate the analysis by CP as best as possible, we rely on precisely the same climate data.

4.3. Per-capita Income and Agricultural Dependence

In order to classify their country sample into low- and middle-income countries[25], CP use GDP per capita as of 1990. The data was extracted from Penn World Table (2009). Countries were classified as poor when GDP per capita in 1990 was in the lowest quartile of the income distribution of the country sample.

The dummy for agricultural-dependent countries is constructed on the basis of the share of the value-added of the agricultural sector in relation to GDP. The data

[22]The authors use version 1.01 of the dataset. The data can be retrieved at: `http://climate.geog.udel.edu/~climate/`.

[23]A degree resolution of 0.5×0.5 corresponds roughly to $56km \times 56km$ at the equator.

[24]Population data for 1990 from CIESIN (2005) is used.

[25]High-income (OECD) countries were excluded from the sample.

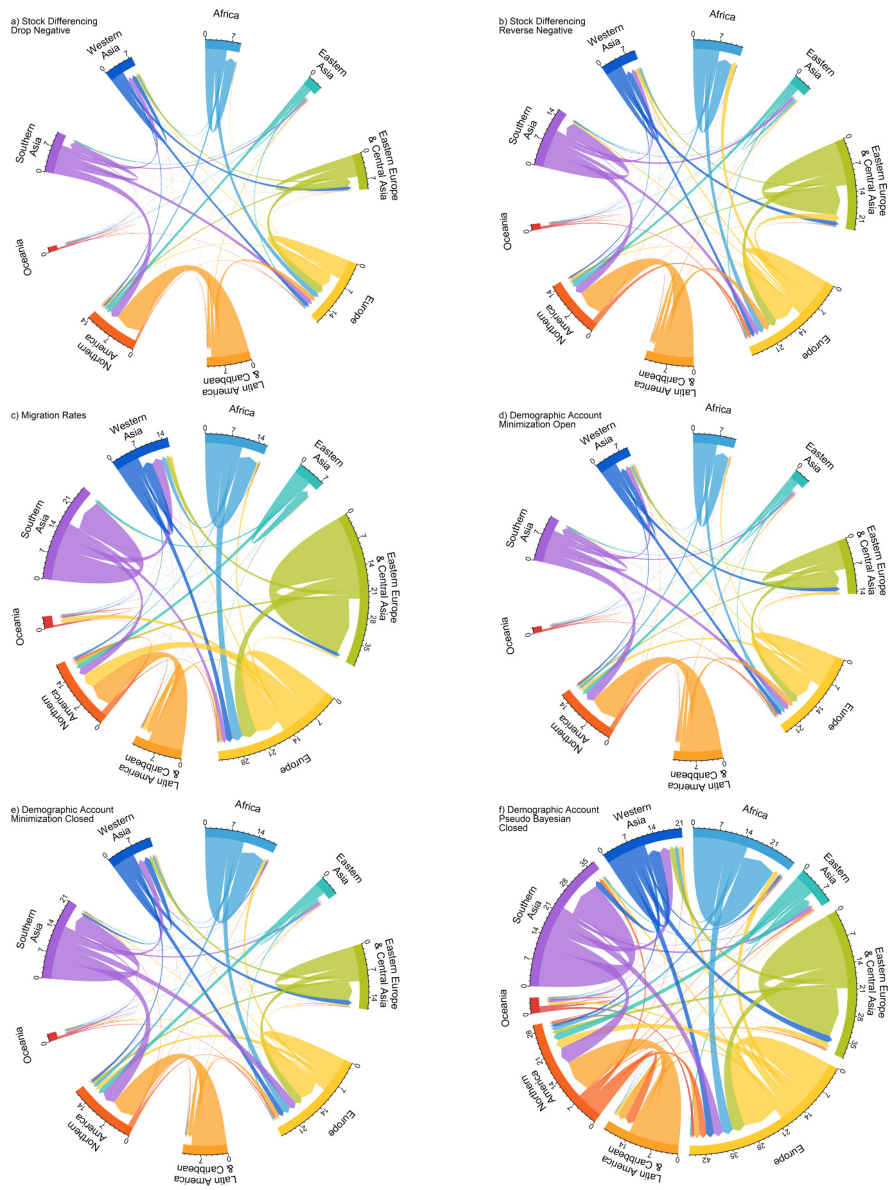

Figure 3: Derived Migration Flows 1990-2000 by Method. The direction of the flows are marked by their arrowheads. The size of the flow is indicated by the width of the arrow at its base. Numbers on the outer section axis, which indicate the size of migration flows, are in millions of individuals per decade.

was taken from the World Development Indicators database (World Bank, 2015). The dummy was coded as 1 for countries in the highest quartile of the sample distribution and 0 otherwise.

5. Empirical Analysis

In this section, we test the sensitivity of the link between climate variables (temperature and precipitation) and international migration to changes in the measure of bilateral migration flows. As outlined earlier, we use CP's estimation approach as a workhorse for this analysis. In this section, we provide the main estimation results for the six different methods to derive bilateral migration flows, explained in Section 3. Furthermore, we deliver additional empirical results using further modified variants of the *Demographic Accounting* approach.

First, we replicate the basic model of CP using the *Stock Difference Drop Negative* method. The only difference is that we use aggregated emigration flows from a restricted sample of 195×195 country pairs instead of the full sample.[26] The corresponding results are reported in Table 2.

In line with the high correlation between the full and restricted sample migration measure shown in Figure B.5, the results are highly similar to the benchmark results of CP, which are reported in Table 1. This holds true both in terms of magnitude and significance. As CP, we find a positive and significant effect of temperature on international migration in middle-income countries (columns 2 and 4). With respect to income, the estimates are also in line with CP, suggesting that increasing temperatures in low-income countries decrease emigration (columns 2 and 4). This poverty trap is amplified in countries with large agriculture sectors (columns 3 and 4). The magnitude of all effects is not distinguishable from those in the benchmark model of CP, which are displayed in Table 1. Thus, we are able to replicate the main results of CP even when using a smaller subset of country pairs for which demographic data is available.

Second, we use the *Stock Difference Reverse Negative* method to derive bilateral migration flows. Compared to the *Stock Difference Drop Negative* method, the only difference is that we treat all negative flow values as return migration and recalculate migration flows by adding the absolute value of negative flows between country A and country B to the observed migration flow between country B and country A. This modification was initially developed by Beine and Parsons (2015) and has since been used in other studies (e.g. Rojas-Romagosa and Bollen, 2018). The corresponding results are reported in Table 3. The first notable difference to the previous results is that we do not find any significant direct effect of temperature any more (columns 2 to 4). Furthermore, the interaction coefficient with poor countries instead remains large in value and highly significant (columns 2 and 4). However, the amplification effect for countries heavily dependent on agriculture turns insignificant as soon as we allow the temperature effect to vary between poor and middle-income countries (column 4). Overall, the estimates in Table 3 demonstrate that the treatment of negative bilateral migration flows is a sensitive issue in the *Stock Differentiation* approaches, which has the potential to affect

[26] See Section 4 for an explanation and justification of the restricted sample.

Table 2: Stock Difference Drop Negative

	Dependent Variable: ln Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	2.866	4.742***	3.781**	4.996***
	(1.804)	(1.405)	(1.770)	(1.503)
ln T x Poor		−20.526***		−18.581***
		(6.646)		(5.000)
ln T x Agri			−24.487***	−16.022*
			(8.462)	(8.288)
ln P	−0.348	−0.263	−0.037	−0.126
	(0.340)	(0.313)	(0.388)	(0.386)
ln P x Poor		−1.406		−0.331
		(1.897)		(2.621)
ln P x Agri			−2.194	−1.622
			(1.416)	(1.571)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.194	0.218	0.219	0.234

Note: Emigration flows are based on the *Stock Difference Drop Negative* method and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

results substantially.

Third, we use the *Migration Rates* method, which derives international bilateral migration flows by combining migrant stock data with total global migration flows (Dennett, 2016). As was evident previously, doing so delivers no significant direct effect of temperature (Table 4, columns 2 to 4). However, we find no significant temperature effect in low-income countries anymore. The estimated coefficient of the corresponding interaction term in column 4 (with a value of -4,06) is more than three times smaller than in the benchmark CP model in the full and restricted sample (Table 1 and Table 2). The interaction term between temperature and the share of value-added in agriculture instead is fairly close to that found by CP, both in terms of magnitude and significance (columns 2 and 4). Nonetheless, the results in Table 4 demonstrate using the example of CP that a clear relationship based on models using *Stock Differentiation* becomes statistically insignificant when bilateral

Table 3: Stock Difference Reverse Negative

	Dependent Variable: ln Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	0.574	2.082	1.198	2.422
	(1.508)	(1.511)	(1.602)	(1.565)
ln T x Poor		-16.313^{**}		-18.632^{***}
		(6.460)		(6.998)
ln T x Agri			-17.766^{**}	-9.330
			(8.093)	(9.271)
ln P	-0.205	-0.230	0.017	-0.074
	(0.331)	(0.338)	(0.416)	(0.418)
ln P x Poor		-0.192		-0.282
		(1.568)		(2.582)
ln P x Agri			-0.873	-0.326
			(1.129)	(1.647)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.17	0.186	0.187	0.203

Note: Emigration flows are based on the *Stock Difference Reverse Negative* method of Beine and Parsons (2015) and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

migration flows are derived via migration rates.

In the following, we apply the *Demographic Accounting* approach, which combine migrant stocks with demographic data to generate bilateral migration systems. This technique became increasingly popular in recent years (e.g. Abel, 2013; Abel and Sander, 2014; Abel, 2018; Azose and Raftery, 2019) as the demand for reliable figures of international migration flows has steadily grown. The main challenge of this methodological approach is to deal with countries outside the sample for which data on demographic variables or migrant stocks is missing.

A simple solution to this issue is the *Demographic Account Minimization Open* method, which allows for flows outside the migration system. The corresponding results are displayed in Table 5. As was done previously, when applying *Stock Difference Drop Negative* and *Migration Rates*, we do not find a significant effect

Table 4: Migration Rates

	Dependent Variable: ln Emigration			
	(1)	(2)	(3)	(4)
ln T	0.568	1.226	1.064	1.204
	(1.076)	(0.887)	(0.849)	(0.844)
ln T x Poor		−7.286		−4.069
		(4.709)		(4.464)
ln T x Agri			−17.158***	−14.054**
			(4.555)	(5.827)
ln P	−0.240	−0.165	−0.200	−0.171
	(0.305)	(0.312)	(0.347)	(0.355)
ln P x Poor		−0.948		−1.260
		(0.877)		(1.221)
ln P x Agri			−0.774	−0.023
			(0.850)	(1.080)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.464	0.469	0.46	0.462

Note: Emigration flows are based on the *Migration Rates* method of Dennett (2016) and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

of temperatures in middle-income countries. Moreover, we do not find any effect of temperatures in poor countries and the interaction term with agriculture is far from significance. These substantial differences relative to the main results of CP are driven by large increases in standard errors, while the estimated coefficients are close to those of CP.

This changes when we use the *Demographic Account Minimization Closed* method, which creates a closed demographic accounting system. In this system, all individuals are born and die in the same set of countries and can only migrate only between these countries (if at all). In this case, see Table 6, both standard errors and point estimates differ substantially from the results using the *Stock Difference Drop Negative* method. As was the case previously, we do not find evidence of temperature affecting international migration in poor and middle-income countries. It is noteworthy that we find a significant precipitation effect as long as we do not

Table 5: Demographic Account Minimization Open

	Dependent Variable: ln Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	2.893	4.891	5.559	6.739
	(3.716)	(4.078)	(4.251)	(4.272)
ln T x Poor		−22.240		−19.234
		(20.012)		(27.397)
ln T x Agri			−27.077	−17.552
			(23.919)	(27.482)
ln P	−1.090	−0.807	−0.218	−0.280
	(0.837)	(0.753)	(0.853)	(0.873)
ln P x Poor		−3.438		−1.067
		(4.058)		(6.510)
ln P x Agri			−3.740	−2.767
			(3.494)	(5.478)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.088	0.095	0.104	0.107

Note: Emigration flows are based on the *Demographic Account Minimization Open* method of Abel (2013) and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

allow climate variables to vary with the size of the agricultural sector (columns 1 and 2).

Lastly, we apply the *Demographic Account Pseudo Bayesian Closed* method, which was initally developed by Azose and Raftery (2019). It extends the *Demographic Account Minimization Closed* method by using pseudo-Bayesian techniques to derive missing migration flows between countries. The corresponding results, reported in Table 7, are highly similar to those using the *Demographic Account Minimization Closed* method. All temperature coefficients, including interactions, are far from significance and differ strongly both in terms of standard errors and magnitude from those using the simple differentiation approach, which drops all negative bilateral flows. If anything, there is weak evidence for precipitation negatively affecting migration in middle-income countries (column 2).

Table 6: Demographic Account Minimization Closed

	Dependent Variable: Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	−0.634	−0.669	0.062	0.555
	(3.927)	(3.791)	(4.781)	(4.681)
ln T x Poor		0.356		−3.511
		(24.868)		(20.223)
ln T x Agri			−19.334	−20.331
			(25.093)	(25.991)
ln P	−2.123*	−2.106*	−1.975	−2.093
	(1.198)	(1.213)	(1.465)	(1.434)
ln P x Poor		−0.163		2.403
		(4.832)		(5.774)
ln P x Agri			−2.747	−3.937
			(3.716)	(3.984)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.085	0.085	0.09	0.091

Note: Emigration flows are based on the *Demographic Account Minimization Closed* method of Abel and Sander (2014) and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

Thus far, all results for the *Demographic Accounting* methods have been based on emigration rates derived from bilateral gross flows as it is often done in the related literature. This may reduce comparability with the results of CP, as they use net bilateral flows. However, the *Demographic Accounting* methods allow us to calculate net bilateral flows, as flows can be decomposed by place of birth. We therefore modify the methods and calculate birth-specific net bilateral flows from country A to country B by considering only persons born in country A. If net flows become negative, we set them to zero. Thus, we do not include return migrants, transnational migration, or circular migration anymore. As a result, the magnitude of bilateral migration flows decreases substantially (see Figure A.4 in the Appendix). The corresponding regression results are displayed in Table A.8 to A.10 in the Appendix. They demonstrate that *Demographic Accounting* methods also deliver estimates which significantly differ from those of CP when focusing on net migration.

Table 7: Demographic Account Pseudo Bayesian Closed

	Dependent Variable: ln Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	0.703	1.294	0.888	1.512
	(1.620)	(1.467)	(1.957)	(1.755)
ln T x Poor		−6.383		−8.840
		(10.517)		(7.479)
ln T x Agri			−10.570	−6.997
			(7.723)	(8.828)
ln P	−0.586	−0.601*	−0.534	−0.594
	(0.380)	(0.360)	(0.452)	(0.437)
ln P x Poor		−0.022		0.274
		(2.006)		(1.820)
ln P x Agri			−1.421	−1.376
			(1.324)	(1.306)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.09	0.093	0.142	0.148

Note: Emigration flows are based on the *Demographic Account Pseudo Bayesian Closed* method of Azose and Raftery (2019) and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

Overall, our estimates in Tables 3 to 7 demonstrate using the contribution of CP that results on the link between international migration and climate change are highly sensitive to the choice of the dependent variable. Depending on the approach to derive bilateral migration flows, the same empirical model and data delivers notably different results.

6. Summary and Conclusions

While the impact of slow onset climate change on international migration has often been studied, the empirical evidence is mixed. This paper does not explicitly aim to contribute to finding a final answer as to whether climate change causes international migration flows. Rather, our aim is to raise awareness that the methodological approach of constructing bilateral migration flows from migrant stock data might be highly relevant for the derived results. As generic bilateral flow data is generally only available for highly developed target countries yet climate migration likely occurs primarily between countries of the Global South, the majority of related empirical studies rely on migrant stock data as source of constructing migration flow data. Therefore, this issue is highly relevant for the empirical literature on the impact of climate on international migration.

In this paper, we demonstrate the impact of the chosen method of deriving flow data from migrant stocks using the the influential and methodologically sound analysis by Cattaneo and Peri (2016). In their analysis, the authors find rising temperatures increase emigration in medium-income countries, while the opposite holds true in poor and agricultural-dependent countries. Furthermore, they do not find an effect of precipitation on emigration. In contrast, we show that when using the *Stock Difference Reverse Negative* rather than the *Stock Difference Drop Negative* method, there is no longer an effect of temperature on emigration in medium-income countries. The same holds true for agricultural-dependent countries. The only remaining effect is the negative effect of temperature on emigration in poor countries. Using the *Migration Rates* method, only temperature in agricultural-dependent countries has a significant and negative effect on emigration. As soon as we employ one of the *Demographic Accounting* methods, neither temperature nor precipitation has any significant effect on emigration. The picture becomes even more heterogeneous when using the *Demographic Accounting* methods to derive net emigration flows.

Our paper has a number of implications for current and future research. First, the large heterogeneity of empirical results suggest that the diverging results in the climate-international-migration literature at least to some extent are due to methodological differences in deriving migration flows from migrant stock data. Second, to increase comparability across studies, it would be beneficial to agree on a common standard to clarify which method has been used to derive flows from stock data. Since the literature has not reached a consensus as to which of the six discussed methods is superior and each have distinct advantages and drawbacks, e.g., in terms of data requirements, consistency, and complexity of calculation, we explicitly refrain from advocating a certain method in this paper. Third, it seems reasonable to test the sensitivity of estimated results to changes in the way migrant stocks are transformed into flow data. The second and third implication also apply to fields of research outside of climate economics, particularly those which focus on the economic and political drivers and determinants of international migration (e.g. Beine et al., 2011, 2008; Docquier et al., 2016; Grogger and Hanson, 2011) and rely on stock-based migration measures.

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Appendix A. Further Estimation Results III: Net Migration Flows Demographic Accounting

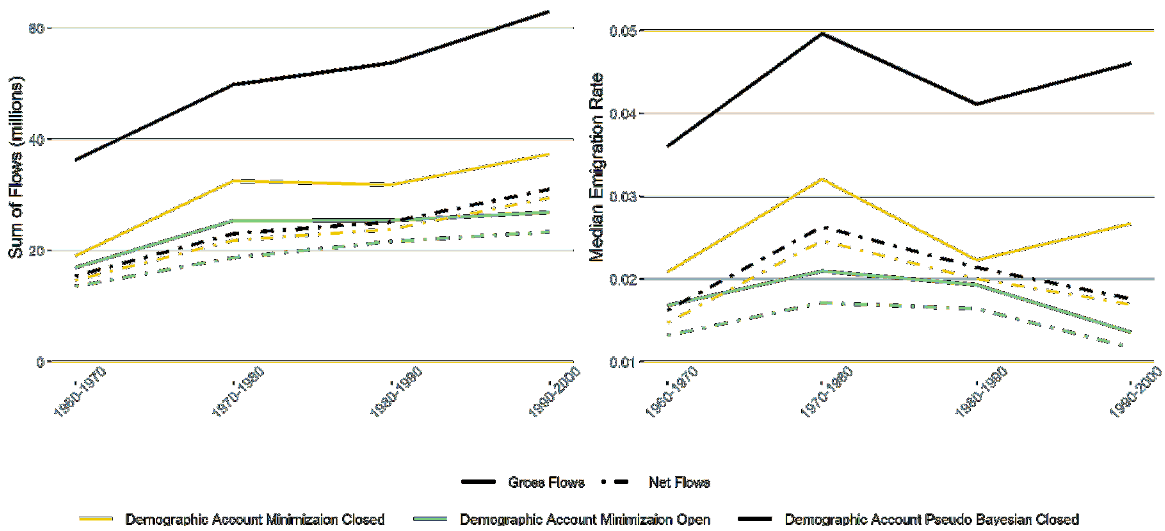

Figure A.4: Time series of derived aggregated migration flows (left panel) and median emigration rate (right panel) for 115 countries using bilateral gross and net flows.

Table A.8: Demographic Account Minimization Open Net Flows

	Ln Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	18.341*	21.940**	22.424**	23.663**
	(11.066)	(10.076)	(10.768)	(10.747)
ln T x Poor		−39.266		−19.320
		(38.617)		(46.687)
ln T x Agri			−48.381	−39.336
			(39.966)	(41.355)
ln P	−0.568	−0.458	−0.132	−0.215
	(1.711)	(1.815)	(2.299)	(2.367)
ln P x Poor		−2.156		−0.575
		(6.424)		(10.627)
ln P x Agri			−4.508	−3.791
			(4.983)	(8.285)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.124	0.13	0.139	0.14

Note: Emigration flows are based on the *Demographic Account Minimization Open* method of Abel (2013) and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

Table A.9: Demographic Account Minimization Closed Net Flows

	Ln Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	16.408	23.278**	19.342	25.156**
	(13.303)	(10.618)	(15.058)	(12.688)
ln T x Poor		−74.053**		−73.003**
		(37.188)		(36.845)
ln T x Agri			−46.109	−23.100
			(43.200)	(48.075)
ln P	−3.793*	−4.049*	−3.624	−4.373*
	(2.129)	(2.126)	(2.765)	(2.616)
ln P x Poor		0.579		8.433
		(6.248)		(7.567)
ln P x Agri			−5.710	−8.588
			(5.501)	(6.159)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.092	0.105	0.093	0.11

Note: Emigration flows are based on the *Demographic Account Minimization Closed* method of Abel and Sander (2014) and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

Table A.10: Demographic Account Pseudo Bayesian Closed

	Ln Emigration Rate			
	(1)	(2)	(3)	(4)
ln T	3.742	5.412*	5.034	6.121*
	(3.373)	(2.930)	(3.935)	(3.597)
ln T x Poor		−18.170		−11.799
		(17.966)		(12.745)
ln T x Agri			−23.369	−21.101
			(14.545)	(15.270)
ln P	−0.970	−0.947	−0.729	−0.907
	(0.756)	(0.685)	(0.841)	(0.783)
ln P x Poor		−0.712		2.742
		(3.496)		(3.080)
ln P x Agri			−4.451**	−5.642**
			(2.121)	(2.595)
Country of origin fixed effects	Yes	Yes	Yes	Yes
Decade Region effects	Yes	Yes	Yes	Yes
Decade Poor effects	Yes	Yes	Yes	Yes
Observations	458	458	414	414
Number of Countries	115	115	104	104
R-squared	0.128	0.133	0.186	0.193

Note: Emigration flows are based on the Demographic Account Pseudo Bayesian Closed method of Azose and Raftery (2019) and a restricted sample of 195x195 bilateral country pairs. Standard errors are clustered by country of origin. Climate variables are based on population weights. *p<0.1; **p<0.05; ***p<0.01

Appendix B. Data Adjustments

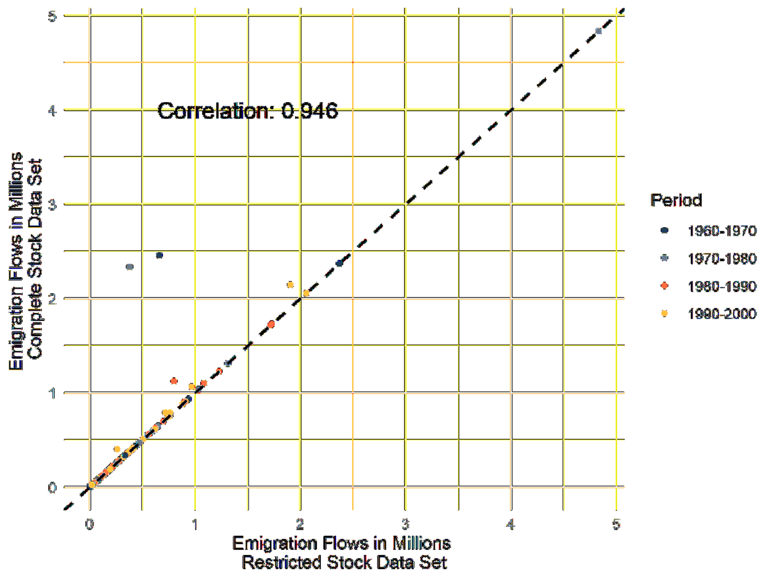

Figure B.5: Correlation of emigration flows. The dashed black line corresponds to the 45-degree line. The figure compares aggregated emigration flows for 115 countries derived by CP (unrestricted case) and our derived emigration flows (restricted case) using the *Stock Difference Drop Negative* method. Migration flows by CP use data for all 226 countries. In contrast, we rely on a restricted country set of 195 countries and apply a different aggregation scheme with respect to China, Hong Kong, and Macao.

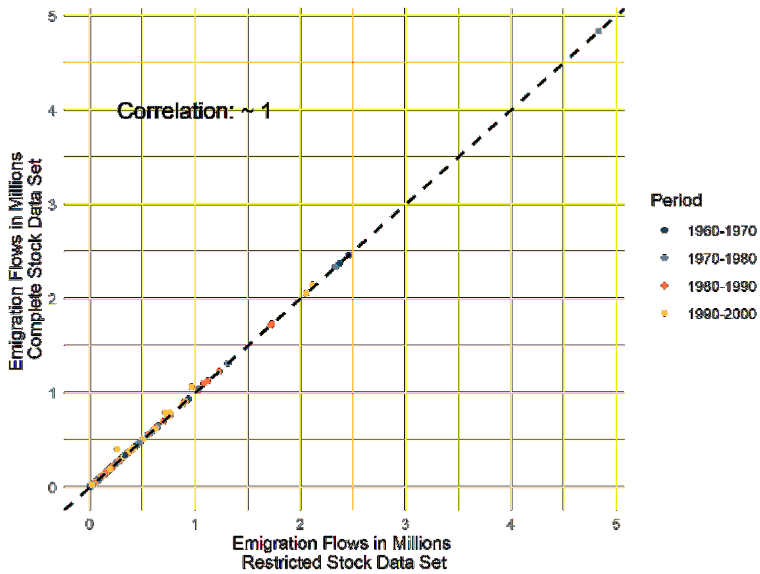

Figure B.6: Correlation of emigration flows. For this graph, we apply the same aggregation scheme as CP with respect to China, Hong Kong, and Macao. The dashed black line corresponds to the 45-degree line. The figure compares aggregated emigration flows for 115 countries derived by CP (unrestricted case) and our derived emigration flows (restricted case) using the *Stock Difference Drop Negative* method. Migration flows by CP use data for all 226 countries. In contrast, we rely on a restricted country set of 195 countries.

Appendix C. Country List

Poor Countries: Afghanistan, Benin, Burkina Faso, Burundi, Cambodia, Central African Republic, Democratic Republic of Congo, the Equatorial Guinea, Ethiopia, Gambia, Ghana, Guinea-Bissau, Lao People's Democratic Republic, Lesotho, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Nigeria, Rwanda, Somalia, Sudan, United Republic of Tanzania, Togo, Uganda, Yemen and Zambia

Middle-Income Countries: Albania, Algeria, Angola, Argentina, Bahamas, Bangladesh, Belize, Bhutan, Bolivia, Botswana, Brazil, Brunei Darussalam, Bulgaria, Cameroon, Cape Verde, Chad, China, Colombia, Comoros, Congo, Costa Rica, Côte d'Ivoire, Cuba, Cyprus, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Gabon, Guatemala, Guinea, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kenya, Kuwait, Lebanon, Libya, Malaysia, Mauritania, Mauritius, Morocco, Namibia, Nicaragua, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Puerto Rico, Qatar, Romania, Russia, Saint Vincent and the Grenadines, Samoa, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia and Montenegro, Sierra Leone, Solomon Islands, South Africa, Sri Lanka, Suriname, Swaziland, Syrian Arab Republic, Thailand, Trinidad and Tobago, Tunisia, United Arab Emirates, Uruguay, Vanuatu, Venezuela, Vietnam, and Zimbabwe