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Applying Concepts and Tools in Demography for Estimating, Analyzing, and Forecasting Forced Migration

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Executive Summary

Among demographic events (birth, death, and migration), migration is notably the most volatile component to forecast accurately. Accounting for forced migration is even more challenging given the difficulty in collecting forced migration data. Knowledge of trends and patterns of forced migration and its future trajectory is, however, highly relevant for policy planning for migrant sending and receiving areas. This paper aims to review existing methodological tools to estimate and forecast migration in demography and explore how they can be applied to the study of forced migration. It presents steps towards estimation of forced migration and future assessments, which comprise: (1) migration flows estimation methods using both traditional and nontraditional data; (2) empirical analysis of drivers of migration and migration patterns; and (3) forecasting migration based on multidimensional population projections and scenarios approach. The paper then discusses how these demographic methods and tools can be applied to estimate and forecast forced migration.

Keywords

drivers of migration, forecast, forced migration, migration estimate, population projections, shared socioeconomic pathways (SSPs)

Introduction

Forced displacement has been increasing in the past two decades from ~40 million forcibly displaced persons worldwide in 1990 to 82.4 million in 2020 (UNHCR 2021). Especially since 2010, the number of forcibly displaced rose rapidly except for the year 2020 when the COVID-19 pandemic resulted in travel restrictions within and across borders. The increase in the number of people forcibly displaced in the past decade coincides with the increasing intensity of violent conflicts and frequency of extreme climate events (Abel et al. 2019; Conte and Migali 2019). Therefore, knowing how different drivers contribute to forced migration as well as where displaced persons come from and where they end up is fundamental for policy planning. For host communities, for instance, the scale of the influx of displaced persons can put pressure on societal and environmental systems leading to conflict (Reuveny 2007). It is thus crucial to monitor the impacts of forced migration and monitor its dynamics over time.

Obtaining precise statistics on the number of the forcibly displaced, let alone their origin and destination, is difficult. There are two main agencies that provide statistics on refugees and forced migrant populations, the United Nations High Commissioner for

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Refugees (UNHCR) and the Internal Displacement Monitoring Centre (IDMC). The data are mainly sourced from national governments' records and estimates as well as from registration in camps, local governments, local and international relief agencies, UN agencies and other international organizations, foreign military authorities, civil society organizations, news media outlets, and other entities (Reed, Haaga and Keely 1998; IDMC 2018).

The data from these sources however may not always be reliable because of unstable situations that put forcibly displaced persons constantly on the move. Therefore, in the case of humanitarian emergencies such as natural disasters and wars, various alternative techniques such as aerial photography are introduced for rapid assessments of populations in need. In the past two decades, advancement in the field of Geographical Information Systems has contributed to a better understanding of forced migration (Avtar et al. 2021). Recently earth observation comprising remotely sensed data and ground measurements have been applied to map and monitor refugee/internally displaced persons camps and their surroundings (Kemper and Heinzel 2014; Lang et al. 2010, 2020). High-resolution optical satellite imagery is used for population estimation based on manually or automated dwelling counting or measurement areas of different land-use types. Although this type of earth observation data is particularly useful in the humanitarian domain where rapid interventions are needed, the volume, complexity and "noisiness" of the data require a high degree of computational complexity in data analysis (IOM 2018). Furthermore, data continuity can be an issue both in terms of absence of data and the nonrepeatability of the physical objects and processes observed which are unique in space and time.

In medium- to long-term policy planning for refugee settlement and integration, estimates of forced migrant stocks and flows are required. Given that demography has long been dealing with the development of migration estimates and forecasts, demographic concepts and methodological tools can also potentially be applicable to the study of forced migration. This paper aims to discuss how existing methods can be applied to estimate and assess future forced migration. This involves three steps: (1) estimates of baseline migration data; (2) empirical analysis of drivers of migration and migration patterns; and (3) migration forecasts based on population projections and scenarios approach. It is important to note here that this paper does not aim to provide a comprehensive review of existing methods to estimate and forecast migration but rather to explore possibilities of applying them to forced migration study.

Steps Towards Estimation of Forced Migration and Future Assessments

Among the key demographic behaviors (i.e., fertility, mortality, and migration) underlying population dynamics, migration is considered to be the most volatile. Not only is it difficult to predict future migration trends given changing push and pull factors at the origin and destination (van Nimwegen and van der Erf 2010), but even estimating the current level of migration is challenging. The multiple moves migrants typically make, inconsistency in the definitions of a migrant, and the lack of migration registration data, especially on the origin side, are major reasons why studying and tracking migration movements are particularly difficult (Raymer 2017). A similar challenge applies to the study of forced migration, which is often determined by unpredictable environmental and political drivers such as conflicts, political upheavals, and disasters. Here we explore demographic methods that can potentially be relevant to forced migration study and present the potential applications in three steps.

Estimates of Migration Flows

To understand migration patterns and trends and migrant behaviors, bilateral flow data are more relevant than net migration or migration stock data (Abel 2013). Net migration data do not reveal the number of movements from the place of origin or to the place of destination. Meanwhile, although migrant population stocks data allow us to gauge the number of foreign-born residents in each country, they do not reveal the number of migrants entering and leaving a country. Since stock data collect the information on the number of people living in a country based on, for instance, place of birth at a given point in time, they are not suitable for providing an indication of contemporary migration flows. Especially in countries where return migration or mortality among foreign populations is high, using stock data to represent the current migration system can be misleading.

Flow data, on the other hand, capture movements of populations from origin to destination over a period of time and can capture the overall volume of global migration and changes in spatial patterns (Abel and Sander 2014). Nevertheless, estimating bilateral migration flows and patterns, both internal and international migration, is a challenging task owing to both the lack of data and discrepancies in the definition and measurement of migration data (Bell et al. 2002; Willekens et al. 2016). Forecasting future migration flows thus is even more difficult not only because of the lack of data but also due to the complexity of the migration process and high predictive uncertainty (Bijak and Wiśniowski 2010). In recent years, new approaches have been developed to estimate bilateral migration flows. These approaches can be broadly divided into migration estimates based on: (1) traditional data sources and (2) nontraditional data sources.

Methods recently developed to synthetically estimate bilateral migration flows between countries are based on bilateral migration stock data (Abel 2013, 2018b; Abel and Sander 2014; Dennett 2016; Azose and Raftery 2019), which are typically obtained from traditional data sources including population census, population registry, and administrative data. Abel and Cohen (2019) present a comprehensive overview of existing methods and validation of each method. The methods, which can be broadly divided into three groups according to calculation measures, are described in Table 1. The variation for each measure depends on how specific features, for example, stock difference or missing bilateral migration flows, are treated in the model. A detailed description of each method can be found in Abel and Cohen (2019).

In order to provide systematic comparisons of estimates from different methods, Abel and Cohen (2019) estimate migration flows from changes in migrant stocks based on the six methods presented in Table 1 using the same migrant stock data. Estimated bilateral migration flows obtained from each method are then validated with reported bilateral and total migration flows data for 45 countries as well as net migration flows data for all countries. For the first time, different migration flow estimate measures are directly compared based on the correlation between the estimated migration flows and available reported data. Indeed, it is found that the correlations between the reported data and the migration flows estimates vary across migration measures with estimates obtained from closed demographic accounting methods and the pseudo-Bayesian method, displaying the highest correlations. These findings suggest that in the absence of bilateral migration flows data, it is plausible to derive flows from stock tables using the methods presented in Table 1.

While the indirect methods for estimating bilateral migration flows are promising to apply to forced migration, they still rely on availability of bilateral migrant stock data, which are not always available, especially in the case of internal migration (Bell and Charles-Edwards 2013; Bell *et al.* 2015). The past decade has observed a substantial increase in studies using nontraditional data sources including mobile phone records, e-mail messages, social media data, and internet search data to estimate migration. Examples and summaries of the use of nontraditional data sources or "big data" to study migration, including discussions about strengths and challenges, can be found in Laczko and Rango (2014), Hughes *et al.* (2016), IOM (2018), Spyratos *et al.* (2018), IOM's GMDAC (2021), and Sîrbu *et al.* (2021).

With respect to internet-based data, IP addresses of repeated website logins and email-sending have been used to infer migration trends and patterns. For example, Zagheni and Weber (2012) estimate age and gender-specific migration rates using data extracted from Yahoo! E-mail messages. Migration flows are captured based on the geographic locations where e-mail messages are sent over the period 2009 to 2011. If most emails are regularly sent from country A for 6 months and then for another period most e-mails are sent regularly from country B for 6 months, it is consequently inferred that the user has migrated from country A to country B over the course of the year. When compared with administrative data from national statistical agencies, the estimates of age profiles of migration are shown to be consistent. A similar analysis can be done using geo-referenced social media data such as Twitter tweets (Zagheni and Weber 2012; Hawelka et al. 2014; Fiorio et al. 2017), LinkedIn profiles (State, Weber and Zagheni

Table 1. Summary of Migration Flows Estimation Methods.

Approach	Description	Methods	Literature
Stock differencing	Use the differences in the size of migrant stocks for a given pair of countries at the beginning and end of a given period	Stock difference, drop negative (all negative differences set to zero)	(Beine, Docquier, and Özden 2011; Bertoli and Fernández-Huertas Moraga 2015)
		Stock difference, reverse negative (decreases in bilateral migrant stocks treated as a reverse migration flow)	(Beine and Parsons 2015)
Migration rates	Use migration stock rates at a single time point to estimate migration flow rates over a specific period, multiplied by a population at risk	Migration rates	(Dennett 2016)
Demographic accounting	Use sequential stock tables to estimate migration flows that are constrained to meet the stock tables accounting for natural population change from births and deaths	Open demographic accounting system, minimization (persons can move to or from countries beyond those in the input bilateral migrant stock tables)	(Abel 2013)
		Closed demographic accounting system, minimization (all persons either move, do not move, are born or die in the same set of countries)	(Abel and Sander 2014)
		Demographic accounting, use pseudo-Bayesian model to estimate migration flows as a weighted average of the estimates of minimum migration flows	(Azose and Raftery 2019)

Source: Adapted from Abel and Cohen (2019).

2013; State et al. 2014), and Facebook (Zagheni, Weber and Gummadi 2017). The timely nature, wide coverage, and relatively limited cost in data access make geo-located digital records attractive alternative data sources to estimate mobility and migration.

Despite their great potential, one major challenge of relying on social media or e-mail data sources is sample selection bias because the user base is comprised of people with different demographic, socioeconomic, and cultural backgrounds. Consequently, migration estimates from these sources are not representative of general migration patterns in a population. A few methods have been proposed to correct for the over- or under-representativeness of social media users. For example, to address the sample selection bias of Twitter users, Yildiz et al. (2017) perform a post-stratification by estimating log-linear models in order to weight the Twitter sample by demographic characteristics such as age, sex, and location, allowing for matching the auxiliary marginal totals from the ground truth data source. Spyratos et al. (2018) apply Facebook penetration rates by age and gender in a country of origin and country of destination of a Facebook expat to correct for the representativeness bias. The corrected number of Facebook Network expats obtained appears to be well-correlated with the number of migrants obtained from Eurostat migration statistics.

Google search data, on the other hand, is more representative than other digital data platforms, given the use of the Google search engine by more than one billion users. Böhme, Gröger and Stöhr (2020) exploit Google search data to predict migration. Based on an empirical evidence that people who are intending to migrate would acquire relevant information about migration prior to departure (Maitland and Xu 2015), Böhme, Gröger and Stöhr (2020) measure migration intentions by monitoring online search intensities for migration-related search terms in Google Trends Index. It is found that geo-referenced online search data for migration-related search terms yield substantial predictive power for international migration flows. In fact, in an unpublished work, Connor (2017) has demonstrated that online search activity obtained from Google Trends can be used to forecast forced migration in the case of recent Syrian and Iraqi refugees entering Europe. Note however that this applies only to migrant populations with access to technology and internet. The predictive power does not apply to the case of migrants from sub-Saharan Africa traveling through Libya into Italy, for instance. It is thus important to crosscheck Web-based data with actual migration data if possible.

Recent efforts have sought to address some of the issues regarding the limitations and challenges of both traditional and nontraditional migration data. With respect to sample selection bias, a probabilistic statistical framework has been applied to combine social media data from Facebook with traditional survey or administrative data to produce timely "nowcast" of migrant stocks (Yildiz *et al.* 2019; Alexander, Polimis and Zagheni 2020). A Bayesian hierarchical model has been used to adjust for bias of social media data, to account for both historical past trends and spatial heterogeneity (e.g., in age structure of migrants) and to allow for different sources of uncertainty around the different data used. Through validation of the performance of the proposed model, Alexander, Polimis and Zagheni (2020) show that the Bayesian model which combines both social media and survey data provides the substantial gain in accuracy in the prediction of short-term migration trends. This study offers an innovative approach to address time lag issue and the undercount of the level of migration in official migration statistics.

Empirical Analysis of Drivers of Migration and Migration Patterns

When it comes to predicting future migration trends, understanding the drivers of migration allows for estimating the *likelihood* of migration before people start to move. Typically, the impact of "push" and "pull" factors driving migration can be quantified and estimated using econometric models, especially gravity models, with bilateral migration as an outcome of interest. The explanatory factors used in the models are commonly derived from migration theories accounting for the complexity of migration decisions that are determined by a series of factors that sometimes interact with each other. The empirical models typically include the determinants of migration which are related to characteristics of the origin or destination such as environmental and economic conditions or immigration policies as well as dyadic variables representing the relationships between origin and destination such as physical and linguistic proximity (Ramos 2016).

Here I present an example of the application of econometric techniques to model a climate driver of migration. Climate change has recently gained major media and public attention as a potential driver of outmigration. However, it is improper to address the linkage between climatic change and migration in a simple, linear manner. Black et al. (2011a, 2011b, 5) propose a conceptual framework to present the direct and indirect impacts of environmental change on migration decisions. The framework puts emphasis on key drivers of migration, namely, economic, political, social, and demographic factors and how environmental change interacts with these drivers in influencing migration decisions. Owing to its evidence base design, it is possible to apply the framework to assess migration processes empirically, accounting for different drivers and the interactions between them.

To empirically capture the direct and indirect impacts of climate change on migration require both sound theoretical background and empirical set up. Abel et al. (2019) applies a simplified version of Black et al.'s (2011a, 2011b, 5) framework to empirically investigate the relationships between climate change, conflict and forced migration. Figure 1 presents the potential pathway (red arrows) through which climate change can affect migration which runs through conflict. Climate change-induced repeated drought events, for instance, can lead to conflict over scarce resources in a country with poor governance. Due to climate-induced conflict, people

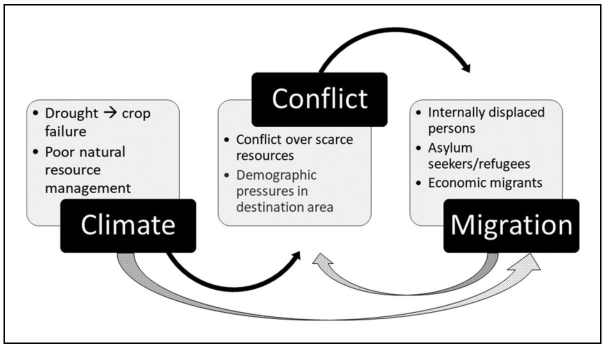

Figure 1. A conceptualization of the pathways through which climate change may impact upon conflict and migration as presented by Abel *et al.* (2019, 242).
Source: Reprinted from Abel, Guy J., Michael Brottrager, Jesus Crespo Cuaresma, and Raya Muttarak. 2019. "Climate, Conflict and Forced Migration". *Global Environmental Change* 54 (January): 239–49., Copyright (2019), with permission from Elsevier.

are forcibly displaced.[1] Based on empirical data on climatic conditions, conflict outbreaks and bilateral flows of asylum seekers, it is possible to empirically model for the relationships described in Figure 1.

Abel et al. (2019) employ advanced econometric techniques, using three-stage selection equations to assess the causal link between climate and refugee flows mediated through an increase in conflict caused by climatic shocks. This methodological framework initially assesses the determinants of the probability of conflict, analyses how the probability of country *i* sending asylum-seekers to country *j* depends on conflict occurrence, and estimates the size of asylum-seeking applications given country characteristics. The first equation deals with the selection of countries into conflict, the second with the selection to bilateral asylum-seeking applications between two countries, and the third equation assesses the size of the flow given conflict occurrence. Asylum flows also vary with the type and magnitude of the conflict. Ibáñez and Vélez (2008) show that in Colombia, conflict which involves the presence of illegal armed groups, that is, paramilitary or guerrilla, is more likely to result in displacement. Likewise, Conte and Migali (2019) find that the intensity of conflict measured by the number of battle-related deaths is positively correlated with asylum flows. It is therefore possible to estimate the volume of asylum-seeking applications if we know the type and magnitude of the conflict. This application provides an example of how drivers of migration which determine migration patterns can be better understood and empirically presented.

Technically, the estimated coefficients can be used to predict how changes in climatic conditions would translate into the corresponding number of migrants. The work of Missirian and Schlenker (2017) provides an example of such application. They first run a panel regression analysis to examine whether weather anomalies (i.e., hotter-than-normal temperatures) will result in an increase or decrease in asylum applications from 103 source countries outside the Organization for Economic Co-operation and Development (OECD) to any member state in the European Union (EU). It is found that asylum applications increase when temperatures deviate from the moderate optimum of ~20 °C. Using the predicted temperature changes under the global climate models, the coefficients estimated from the regression models are extrapolated into future number of asylum applications under different climate change scenarios.

Although this approach can potentially be applied for migration estimates and prediction of future migration, the results from the econometric models depend on the choice of explanatory factors and consequently may fail to capture the diversity of global migration phenomena. In fact, the study by Missirian and Schlenker (2017) was criticized for failing to address the complexity of migration, for example, the role of migration policy (Briggs 2017). Furthermore, when the results from the econometric models are applied to predict migration, it is based on the assumption that the estimated relationship between migration drivers and observed migration from historical data (or data from other geographical areas) also hold for the future (or other contexts) (Sohst and Tjaden 2020). Policy implications drawn from such analysis thus needs to be aware of the complexity and uncertainty inherent in prediction of migration processes.

[1]Note that there is also a possibility of reverse causation as presented by the dark blue arrows in Figure 1. In fact, in the field of peace and conflict studies, it is often considered that conflict is an outcome of environmental migration whereby migration-induced population pressure in receiving areas lead to competition over natural and economic resources and tensions (Reuveny 2007, 2008; Raleigh 2010). The empirical evidence in this direction however is not well established.

Forecasting Migration Based on Multidimensional Population Projections and Scenarios

In population projections, demographic projections of migration are produced as part of the demographic components of population change. The key differences between migration projections and predictions are the forecasting method where the former relies on the future development of migration (along with mortality and fertility) under different assumptions, while the latter usually rely on econometric models to estimate future migration (Sohst et al. 2020). This paper does not aim to review existing methods used for forecasting migration which can be found, for example, in Bijak (2011), Disney et al. (2015), and Sohst et al. (2020). The paper rather aims to explore how population projections, especially multidimensional population projections method and scenario-based approach can be applied to migration forecasts.

Given that the propensity to migrate varies with personal attributes, changes in demographic characteristics within a population, for example, through the cohort replacement mechanism, can affect migration trends and patterns. Accordingly, Willekens (2018) incorporates the process of demographic metabolism which characterizes "how societies change as a consequence of the changing composition of their members" (Lutz 2013, 283) to his proposal of mechanism-based migration forecasting. Because younger generations differ from older generations in terms of exposure to new technologies, values and living environment, the entry of new cohorts replacing the older ones is a potential driver of social transformation. Not only are younger cohorts more mobile-minded and tolerant towards immigration (Striessnig and Lutz 2016; Umansky, Lutz and Weber 2019), changes in personal attributes such as higher levels of educational attainment can also influence the propensity to migrate.

For personal characteristics underlying migration which remain stable throughout the life course, social change occurs through cohort effects. In this case, a prediction of social change can be done using the cohort-component model (Willekens 2018). In practice, one can first start with establishing an empirical relationship between demographic characteristics (e.g., by age, sex, and education) and forced migration, and in a second step forecast how future migration will look under different demographic scenarios. The latter assumes that the trajectories of forced migration patterns in the future are driven by cohort replacement, that is, changes in population composition. In this case, ideally demographic attributes that are relevant for migration should be accounted for in demographic modelling. Conventionally, only age and sex structures are considered in population projections. However, there are other population characteristics that are relevant for population dynamics such as place of residence, education, and ethnicity. The Wittgenstein Centre for Demography and Global Human Capital and the International Institute for Applied Systems Analysis employ a multidimensional approach adding new relevant dimensions such as educational attainment (KC et al. 2010; Lutz, Butz and KC 2014), labor force participation (Loichinger 2015; Loichinger, KC and Lutz 2016), and rural/urban place of residence (KC et al. 2018) to population projections.

Considering different dimensions of population heterogeneity beyond age and sex can result in stark differences in projected population. For instance, using a Bayesian probabilistic population projection method, the United Nations (UN) concludes that the world population will increase to between 9.6 and 12.3 billion by the end of the century (Gerland et al. 2014). However, Lutz et al. (2014) point out that the UN assumption of constant fertility is unrealistic. For instance, a changing education structure in Nigeria with younger women being more educated than the older generations means that fertility will be lower in the future. By considering education-specific total fertility rate, the population projection for Nigeria in the middle-of-the-road scenario for 2100 is lower than 600 million as compared to 914 million in the 2012 assessment in the UN model (Abel et al. 2016). Hence, with respect to assumptions about migration, factoring in educational attainment and other relevant demographic characteristics would also yield different migration patterns.

Recently in the climate change research community, the shared socioeconomic pathways (SSPs) have been introduced as qualitative narratives of five scenarios of future societal development which pose different challenges to mitigation and adaption (O'Neill et al. 2017). The SSPs have been quantified into different dimensions that are relevant for climate change mitigation and adaptation such as population and education

(KC and Lutz 2017), urbanization (Jiang and O'Neill 2017), income (Leimbach et al. 2015; Crespo Cuaresma 2017), human development (Crespo Cuaresma and Lutz 2016), inequality (Rao et al. 2019), and governance (Andrijevic et al. 2020). Recently, there have been attempts to forecast how migration patterns will look like under five SSPs scenarios (Abel 2018a) and how different migration scenarios result in varying trajectories of income inequality (Benveniste et al. 2021). It is therefore potentially possible to derive different forced migration scenarios from the SSPs narratives as has been done for other dimensions like civil conflict (Hegre et al. 2016).

While the cohort-component model is relevant for describing macro-level change, it cannot account for the dynamics in personal attributes which change over the individual life course. Certain events such as leaving the parental home, leaving school, getting married and divorce are associated with age and have implications on migration. This means that it is also important to account for the change in personal attributes determining migration when attempting to forecast migration. Unlike population-based models such as the cohort-component model, individual-based models such as agent-based models and micro-simulation models can capture demographic events and other life transitions that occur throughout the life course at the individual level. Willekens (2005) proposes that it is possible to project the life course of an individual (individual biographies) while aggregating them to produce the cohort biography through bridging the micro-macro models. This method allows for the interaction between migration and other demographic events throughout the life course and can also potentially incorporate other drivers of migration such as individual and institutional factors. Although Willekens (2018) has sketched in detail how a causal forecasting model of migration, which accounts for the mechanisms underlying migration, can be implemented, so far this approach has not been fully implemented.

Discussion: Potential Applications to Forced Migration

The approaches and methods described above are potentially useful for estimating and forecasting forced migration. To select which method to use depends on the purpose of the study. Some research questions require knowledge of how many people involuntarily move from a place of origin and where they end up in each time interval. This requires bilateral migration flows data. In the absence of the baseline bilateral forced migration flows data, there are several indirect ways of deriving flows data from stocks data (Abel and Cohen 2019). However, these methods require stocks data as input data to calculate migration flows.

Nontraditional data sources can potentially fill gaps in the absence of forced migration data. To that end, the international community including the Eurostat and the UN have established various task forces and working groups to explore potential applications of big data sources such as monitoring of the sustainable development goals to inform policy (United Nations 2016). Specifically for migration, a global initiative — the Big Data for Migration Alliance (BD4M) — was initiated in 2018 by the International Organization for Migration's Global Migration Data Analysis Centre and the European Commission's Joint Research Centre. The BD4M network is specially dedicated to facilitate the responsible and ethical use of new data sources and innovative methodologies to improve the evidence base on migration and human mobility (BD4M 2018). This initiative presents a promising alternative platform to estimate forced migration.

Likewise, policy planning of infrastructure and social services requires an instrument to forecast future trends and patterns of forced migration both at the sending and receiving areas/countries. Predicting migration, specifically forced migration, however, is very difficult due to the lack of quality baseline data, the complex interplays between individual and macro-level factors in shaping migration, and potential fluctuations within a short period of time. Based on econometric analysis of drivers of forced migration coupled with scenario-based population projections, it is possible to combine different approaches to forecast forced migration.

As a first step, baseline forced migration flows data are required. This would enable an empirical model to be set up to estimate the relationships between drivers (e.g., economic, political, social, and environmental) and forced migration. The estimated coefficients can be used to predict forced migration that corresponds to the change in each migration driver. The models from Missirian and Schlenker (2017), for instance, predict the change in the percentage of asylum applications in the EU which corresponds to the change in temperature under different warming scenarios (representative concentration pathway (RCP)). The established empirical knowledge of the relationships between migration drivers and forced migration can be used to forecast how forced migration will look given the changes in the drivers, which can be quantified based on scenarios such as the RCP and the SSPs. The SSP dimensions relevant to forced migration such as conflict (Hegre et al. 2016), governance (Andrijevic et al. 2020), and inequality (Rao et al. 2019) have already been quantified and forecasted until 2100 and can readily be used. This can be coupled with population projections which provide information on future population size, composition, and distribution. Changes in future population attributes influencing the propensity to migrate and trajectories for population changes have also been quantified by the SSPs scenarios (KC and Lutz 2017). Knowing the changes in the drivers of forced migration and population dynamics can, thus, be applied to forecasting the trends and patterns of future forced migration.

Implications of Forced Migration Estimation and Forecasting for Policy Use

The increase in migration across the Mediterranean to Europe in recent years has illustrated that migration management policies need to be grounded in evidence (Baldwin-Edwards, Blitz and Crawley 2019). Knowing the number of forced migrants and their respective characteristics (e.g., age, gender, education, country of origins) is crucial to governing migration across borders, with tools that can range from temporary protection, to ensuring access to suitable accommodations, to social benefits and education. Likewise, predictions and forecasting of future forced migration are fundamental for proactively preparing for future challenges.

Given the diversity of methods available for migration forecasting, Sohst and Tjaden (2020) present a guideline on how to select the "best" approach to support decision making. They suggest first asking questions about how the forecasts will be used in practice and the tasks they will need to support. Accordingly, Bijak et al. (2019) propose a risk management matrix which uses a traffic-lights color coding system to identify the importance of policy interventions according to the levels of uncertainty of migration forecasts and impact on social and policy areas. Asylum-related migration is considered to have the highest impact and uncertainty and, therefore, short-term forecast horizons are more appropriate (Bijak et al. 2019; Sohst and Tjaden 2020). In this case, models that allow for early warning, such as the gravity models, can detect the signs of structural changes in migration trends given the changes in the drivers of forced migration.

On the other hand, for longer time horizons, a foresight or scenarios approach which involves qualitative narrative storylines about possible future migration in the form of what-if scenarios are relevant for strategic policy planning. Using multidimensional microsimulation projection model, Marois, Bélanger and Lutz (2020), for instance, present a wide range of future migration scenarios which vary by educational composition of migrants and labor market integration efforts. Instead of using the conventional age-dependency ratio, they calculate productivity-weighted labor-force dependency ratio (PWLFDR) which gives higher weight to the active population with higher levels of education since education is positively associated with productivity. As presented in Figure 2, the scenario (iv. Canadian/Swedish_LF) which assumes high labor force participation for both men and women (Swedish_LF) coupled with the Canadian migration model (high immigration of well-educated migrants combined with intermediate integration into the labor force), PWLFDR is the lowest in this scenario.

Such exercise does not aim to present realities but rather requires experts and policy makers to think outside the box and look beyond current expectations. By developing multiple stories about plausible future developments, it can help to draw implications for policy in the present. In this context, the multidimensional population projections using a scenario-based approach are appropriate for this purpose. Due to high uncertainties, Sohst and Tjaden (2020)

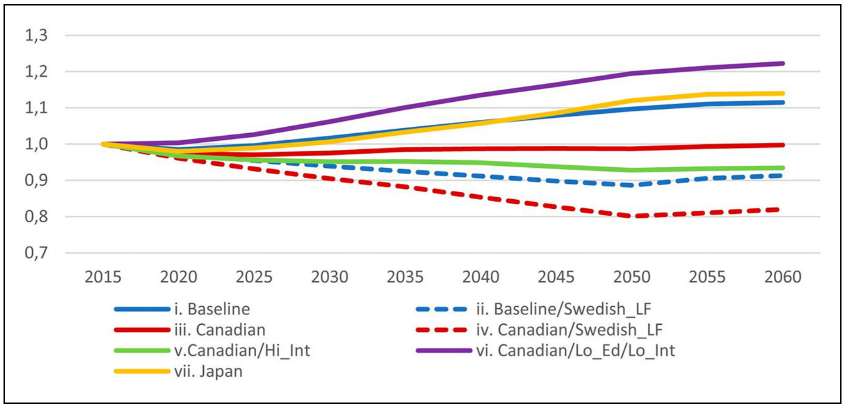

Figure 2. Projection of the productivity-weighted labor-force dependency ratio for the EU-28 under different scenarios, 2015–2060 as presented by Marois, Bélanger and Lutz (2020, 7693).
Source: Reprinted from Marois, G., A. Bélanger, and W. Lutz. 2020. "Population Aging, Migration, and Productivity in Europe". *Proceedings of the National Academy of Sciences*, e201918988, Copyright (2020), with permission from National Academy of Sciences.

recommend use of various methods when applicable in order to cross-validate the results from different forecasting approaches.

Conclusion

Among demographic events (birth, death, and migration), migration is notably the most volatile component to forecast accurately. Accounting for forced migration is even more challenging given the difficulty in collecting accurate forced migration data. By reviewing current methods and tools to estimate and forecast migration, this paper explores the possibility of applying existing methodological tools in demography to the study of forced migration. The paper does not aim to provide a comprehensive and systematic review but rather to explore current methods and to sketch steps towards making forced migration estimates and forecasts. It, thus, provides a starting point for methodological and empirical advancement in the field of forced migration from a demographic perspective.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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