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The Future of Migration to Germany

Assessing Methods in Migration Forecasting

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EXECUTIVE SUMMARY

Since the influx of migrants to Europe, many politicians and policymakers have called for improved foresight and preparedness when it comes to future migration flows. The demand for migration forecasts has increased substantially over the last years and efforts to meet this demand have been mounting. This report assesses three major methods in quantitative migration forecasts in the medium and long run, highlighting the uncertainties, opportunities, as well as methodologic and theoretical dissimilarities across the different approaches. Germany serves as an illustrative case study. In cooperation with leading authors in the field of migration forecasting, this report produces three distinct estimates for net migration flows to Germany over the next 20 years.

In a first step, this report critically discusses the demand for migration forecasts, clarifies the terminology and maps the various stakeholders, ranging from national statistical offices, to research institutes and international organisations. A large part of this report is dedicated to uncertainties in migration forecasting. In particular, it addresses in how far the complexity of migration determinants, insufficient data, lack of a unifying theory and the inherent unpredictability of political, economic or environmental shocks challenge the accuracy of such forecasts. With a focus on quantitative methods in demography and economics, this report sheds light on three major forecasting tools: Bayesian Statistical Modelling, Gravity Models, and Structural Equation Models. The report highlights their main features, as well as advantages and disadvantages of the three models and explains their peculiarity vis a vis qualitative and hybrid models in migration forecasting.

One of the core elements of this report is the extraction of Germany-specific forecasts. In a comparative approach, the report emphasises methodologic differences and describes how these translate into substantial divergence across estimates. Despite the fact that these methods are highly sophisticated, expertly executed and internally coherent, they can produce vastly different outcomes. The empirical analysis shows that the gap across the model estimates (for net migration flows to Germany in 2040) lies in the millions. In a separate exercise, the report demonstrates that even within a certain model, the predictions can vary substantially, depending on the underlying data. A comparison of the Bayesian Model with and without post 2015 immigration data for Germany reveals that forecasts are highly sensitive to short-term shocks.

Overall, this report stresses the importance of migration forecasting as a staple of migration research simultaneously cautioning the users of these forecasts to not take isolated estimates at face value. The report concludes with proposal for more transparency from both producers (in terms of methods and uncertainty) and consumers of migration forecasts (in terms of choice and purpose of forecasts).

METHODOLOGY

This report provides an overview of quantitative forecasting models with a focus on demographic and economic perspectives. Quantitative models, in this context, are defined as those forecasting methods that do not use expert-opinions or other qualitative tools in estimating future migration. They are considered purely data-driven models with theoretical underpinnings that are either used for the statistical estimation strategy or provide a mathematically modelled basis for the estimation.

The main and long-standing approach to migration forecasts in demography is Bayesian Statistic Modelling, which is one of the three quantitative methods highlighted in this report. More recently, economists have faced the task of predicting future migration flows with two main methodologies: Gravity Models of Migration and Structural Equation models, both of which have only been applied by very few researchers in the field.

Estimates for Germany have been provided by the leading researchers in the respective fields. Jonathan Azose, Jakub Bijak, and Adrian Raftery with contributions from Hana Sevcikova and Nathan Welch have provided estimates for Germany within the Bayesian Framework. The economists and (to the best of my knowledge) only researchers that have applied the vastly established Gravity Model of Migration to Migration Forecasts, Gordon Hanson and Craig McIntosh (2016), have made their forecasts freely accessible. Lastly, Frédéric Docquier with two sets of co-authors were (again, to the best of my knowledge) the first to use Structural Equation Models to estimate future migration flows. Christoph Deuster, Michal Burzynski and Frédéric Docquier (2019) have kindly provided their estimates for Germany.

The report does not produce original estimates but collects and visualises estimates developed by the leading experts in the field. It follows a comparative approach that allows highlighting strengths and weaknesses of various estimation techniques. This report also serves as a map of stakeholders as well as a literature and methods review. The assessment and comparison of methods results in suggestions for improved transparency in migration forecasting.

The Future of Migration to Germany
Assessing Methods in Migration Forecasting

I. The Demand for Migration Forecasts

Forecasts are a rare but popular commodity among governments, companies and individuals alike. Experts in various fields devote a considerable amount of their research effort to predicting economic, demographic or climatic developments in the short-, medium- and long-term future. This ranges from forecasting GDP growth in the next months, fertility and mortality in the next decades and goes as far as making predictions on climate change over the next century. Forecasts can support the design of effective policies for the future and appropriate policy planning and thus lay the groundwork to a path of stability. However, most forecasts are subject to major uncertainties and come with important caveats. At the same time, policymakers are particularly interested in predictions in areas that face the biggest uncertainties.

Since the influx of migrants to Europe, many politicians and policymakers have called for a more structured and unified approach to migration policies across the EU. A full array of reforms to European migration policies have been initiated since 2015, including the European Agenda on Migration, the Common European Asylum System or the EU Blue Card. Operationalising some of these reforms in a charged political environment has proven to be difficult. In the aftermath of the so-called 'refugee crisis' EU institutions and member states have begun to critically reflect on migration management and processes (Collett and Camille Le Coz 2018). One dimension that has been addressed frequently over the past year and has gained public traction is the development of an early warning system and adequate crisis response mechanisms and early warning system for future migration flows. For instance, in February of 2019, Annegret Kramp-Karrenbauer, the head of the Christian Democrats (CDU) and successor to Angela Merkel, stressed that 'we have learned our lesson and called for an 'early warning system' to better prepare for future crises[1].

On the level of the European Union, Article 33 of the Dublin Regulation III envisages exactly that: 'a mechanism for early warning preparedness and management of asylum crises'. The European Asylum Support Office (EASO) is part of the Early warning and Preparedness System (EPS), gathering data on asylum flows, acting as a clearing house for information from origin countries as well as conducting its own research on migration. The EPS has already been in place since 2013. However, it was not able to centralise and transmit the fragmented information on the impending refugee inflow to the relevant EU bodies in time. As a consequence, indications from individual experts, NGOs or national governments did not receive the attention necessary to trigger a coordinated policy response. Instead, in 2015 the Luxembourg Presidency activated the Integrated Political Crisis Response (IPCR), the European Council's crisis management mechanism[2]. The IPCR includes a weekly reporting mechanism, the so-called Integrated Situational Awareness and Analysis report, which gathers information from major EU bodies, international organisations and member states. Since its activation, it has been used to look for solutions to the refugee crisis at the European Council level. The IPCR was initially designed as a crisis response tool in the case of earth quakes or the bird flu. Its appropriation as a refugee management tool is telling. The European Union is looking for tools that render future refugee and migration flows more predictable and therefore more manageable.

1 Quoted from her speech at the 'Werkstattgespräch – Migration, Sicherheit und Integration' on the 10th and 11th of February 2019.
2 Council of the EU, press release 30.10.2015 'Migratory crisis: EU Council Presidency steps up information sharing between member states by activating IPCR'.

There have been efforts on the European level to develop early warning systems for the short-run. The European Asylum Support Office (EASO) has prepared a report in 2018 that analyses the current use of early-warning systems for asylum-related migration across EU member states and neighbouring countries. Based on the Ad-Hoc Query on Forecasting and Contingency Planning Arrangements for International Protection Applicants of the European Migration Network (2014), the report reviews potential criteria that an EU-wide early warning system would have to fulfil (Bijak, Forster, and Hilton 2017). According to the authors, the benefit of an EU-wide early warning system would be to change the decision-making from a reactive to a pro-active manner, which in turn eases contingency planning. The authors stress that it is key that the model suits the needs of the user, that limitations and underlying uncertainty are clearly communicated and that models are updated on a regular basis.

The authors show that the approaches are rather simple in statistical terms, mostly producing forecasts up to a year. However, they differ in the degree of sophistication – some are based on simple extrapolation of trends (e.g. Ireland) whereas, for instance, Sweden and Switzerland put in place more complex quantitative models. Others only use qualitative rather than quantitative approaches (e.g. Poland). The most sophisticated models incorporate different types of information, combining quantitative data on asylum trends with insights from experts, border intelligence and migration routes. The main strength of these models is the consideration of qualitative information by experts basically in real time. The collection, processing and dissemination of data takes time and is therefore usually not available as quickly as assessments by experts on the ground. The authors stress the quality of a model crucially depends on its regular review, evaluation and adjustment, which is rarely done in practice. An EU-wide early warning system should predict changes in the asylum flow based on EASO data and be supplemented by expert knowledge, formal conflict intensity indices as well as stakeholders' subjective opinion on sensitivity. The scope of the model is to generate warnings, if asylum-flows are predicted to rise beyond a certain threshold, which are defined by stakeholders upfront. In statistical terms, it is designed as a two-stage model, following a Bayesian framework.

In general, early warning systems borrow concepts from both qualitative and quantitative migration forecasting methods. However, they do not aim to say anything about how fundamental changes on a global scale will affect migration patterns to Europe or Germany. Rather, they aim to anticipate 'shocks' to asylum-related migration. This includes the anticipation of civil war and but also comprises the collection and analysis of data on migratory flows at the gates to Europe and before. These short-term changes or 'shocks' to migration are typically the factors that will be excluded from long-term migration forecasts. There may be assumptions about the average size and frequency of those shocks but in the end, they are only noise in the data (unless forecasters are willing to make assumptions about how and where civil conflict is likely to happen in the next 50 years). It is important to draw this distinction because it has meaningful implications for how these forecasts can and should be interpreted.

Table 1 Difference between Early Warning Systems and Migration Forecasting

early warnung systems	migration forecasting
• short term frame • asylum-related migration • focus on shocks to migration • depend more expert opinions	• long term frame • overall migration • averaging out shocks to migration • depend more on data

The above mentioned early warning systems are aimed at making short-term predictions. This report, instead, deals with migration forecasts in the medium and long run, that is, migration flows over the next 10 to 80 years. It does not focus on forced asylum related migration forecasts (although they may be one component in overall migration). Predicting civil conflict or other asylum-relevant events over more than one or two years, yet 20, 30 or even 50 years into the future and quantifying its effect on the number of asylum seekers to a specific destination country is fairly challenging, if not nearly impossible. Migration forecasts can only rely on larger and more fundamental dynamics of human development such as population change, economic development, climate change, etc. Therefore, policymakers need to distinguish between so called 'early warning systems' addressing short-term political risks and instabilities across major source countries and migration forecasts, which typically cover a longer time-frame and focus on the fundamental dynamics of migration.

There are many overlapping concepts and terminologies in the migration forecasting sphere. Policymakers call for migration scenarios, projections, forecasts or estimations oftentimes using those terms synonymously. Table 2 gives a description of how this report will use these terms based on their typical application in demography. Migration scenarios are theoretical explorations by experts of future changes and their effect on migration. They are typically of qualitative nature. Section 3 will describe in more detail how qualitative and quantitative models differ but migration scenarios are usually the departure point for quantitative models of migration. Particularly when it comes to the underlying assumptions in quantitative modelling, scenarios develop answers to the question: What are reasonable assumptions to make? The difference between projections and forecasts is not as clear cut. There are significant overlaps in the definitions and use within demography but also other fields, such as business finance. This report will only provide a working definition for this analysis, based on various statistics boards and national statistics offices. The Australian Bureau of Statistics describes the difference as follows: 'While both involve analysis of data, the key difference between a forecast and a projection is the nature of the assertion in relation to the assumption occurring'. In other words, projections are simply inferring a future value (for migration) based on a set of assumptions. Forecasts predict a future value for an expected set of future events based on a likely set of assumptions. The former asks What is the outcome if certain assumptions were true? The latter asks What is the range of possible outcomes for expected future events? Forecasts also provide an estimate and an associated confidence interval.

Table 2 Terminology in Migration Forecasting [3]

Type	Description	Guiding Questions
Scenarios	Scenarios are narratives that describe future changes (potential future political, economic, social, technological and environmental changes) and their consequences for migration, and have no predictive objective. They are typically of qualitative nature and serve as a basis for assumptions used in quantitative methods.	What are possible/reasonable assumptions to make?
Projection	Computation of future changes in population numbers, given certain assumptions about future trends in the rates of fertility, mortality and migration. Demographers often issue low, mediam and high projections of the same population, based on different assumptions of how these rates will change the future.	What is the outcome if certain assumptions were true?

[3] Based on the Population Reference Bureau's Glossary of Demographic Terms, the Glossary of the International Migration Institute, and the Statistical Language Tool of the Australian Bureau of Statistics.

continuation of Table 2

Type	Description	Guiding Questions
Forecast	Forecasts speculate future values for a population of possible values with a level of confidence (usually indicated as confidence intervals), based on the current and past values as an expectation (prediction) of what will happen.	What is the range of possible outcomes for expected future events?
Estimation	Forecasts include an estimation. An Estimate is a value (not a range of values) inferred for a population of values based on data collected from a sample of data from that population. The estimate can also be produces parametrically or through a model simulation.	

Overall, the demand for migration forecasts is large and many stakeholders are catering to it. Figure 1 presents a crude mapping of research institutes (in red), EU bodies (in yellow) and international organisations (in green) that are currently running migration forecasts. The map includes statistics offices such as UN DESA or Eurostat that factor in their demographic forecasting, a migration component. For a long time, population projections did not include migratory flows (closed population projections) or assumed net zero migration (Bouvier, Poston, and Zhai 1997). Today, the United Nations Population Division uses simplified assumptions about migration, for instance, that recent levels of migration remain stable, or that refugees will return to their countries of origin within 5 to 10 years (UN DESA 2017b). However, the UN is now working on more sophisticated models of migration (Azose and Raftery 2015). Other international organisations, such as the International Organization for Migration (IOM) have revised their skeptical view towards migration forecasts (Bijak 2016) and are now exploring new ways to model future migration flows.

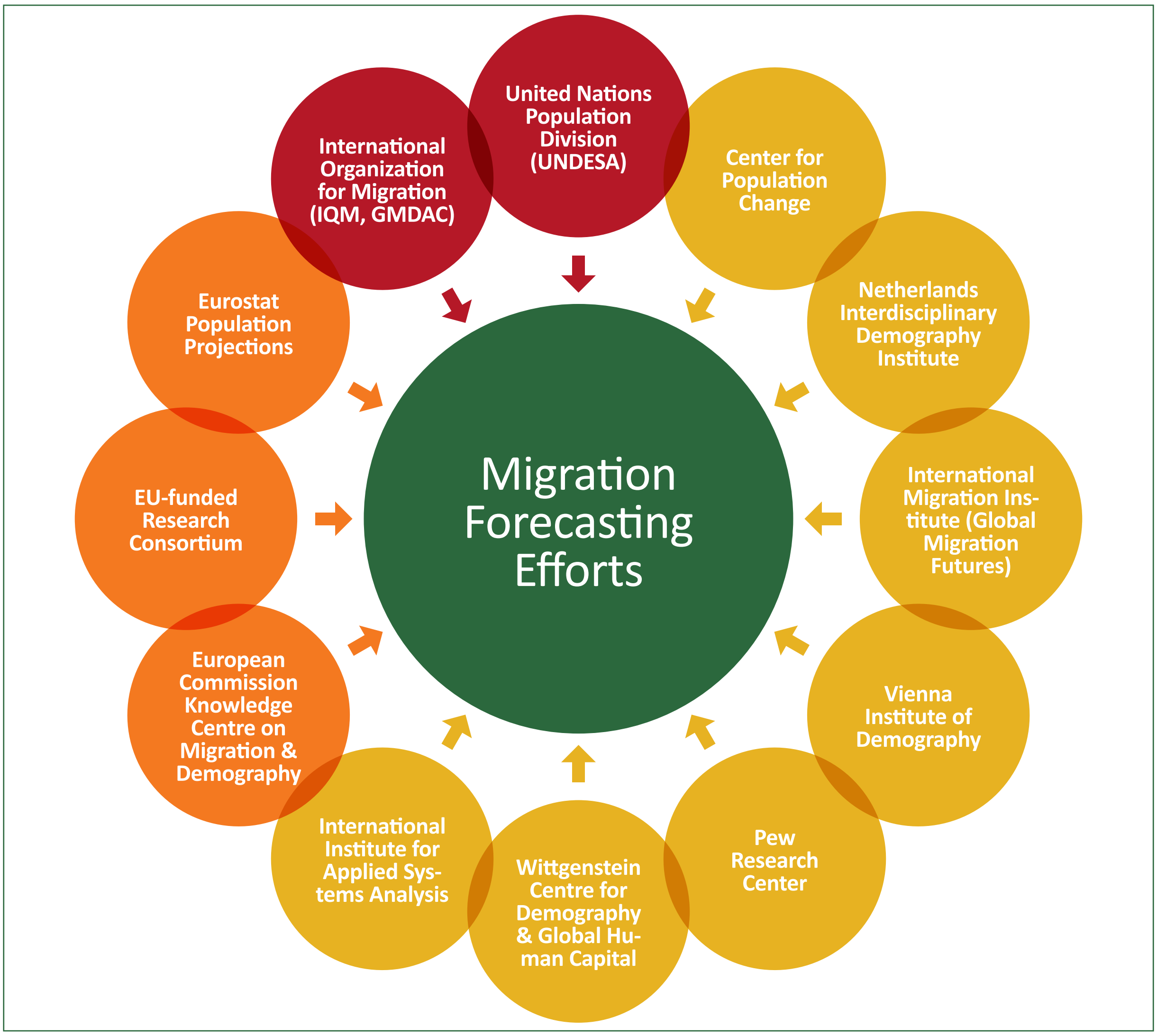
More sophisticated approaches have been introduced by demographers at various research institutes, such as the Wittgenstein Centre or the Pew Research Center. Early on in 2009, the International Migration Institute brought together prominent researchers in migration to launch the 'Global Migration Futures' project. The project applies a migration scenario methodology that is expert-driven and primarily exploratory and of qualitative nature. In 2016, the International Institute for Applied Systems Analysis in cooperation with the European Commission's Joint Research Centre has created CEPAM, the Centre of Expertise on Population and Migration, which provides science-based knowledge on migration to support EU policies, including migration projections. Similarly, the Centre for Population Change (a joint partnership between three universities in the UK) is home to some of the leading demographers on migration forecasting. Additionally, the European Union encourages the creation of even broader research consortiums on the topic. In 2015, the International Organization for Migration has launched the Global Migration Data Analysis Centre (GMDAC). GMDAC together with the Netherlands Interdisciplinary Demography Institute are currently developing expert-based migration scenarios for the year 2030[4]. Funding economists, demographers, sociologists and other social scientists through major grants, the EU prioritises the development of mid- and long-term migration scenarios in the academic sphere[5].

In order for all of these efforts to result in informed policy making, two things must hold true: migration forecasts are a) informative and b) understood and applied appropriately. Let's start with the first requirement: migration forecasts are predictive of actual migration flows. All of the stakeholders that produce migration forecasts preface their work with one important caveat: uncertainty. This report will dedicate a large part to the analysis of various factors of uncertainty in migration forecasting. This ranges from ambiguities in migra-

4 The methodology will be discussed in Chapter 3. For more details see Acostamadiedo et al. (forthcoming).
5 A recent Horizon 2020 Call entitled 'Understanding migration mobility patterns: elaborating mid and long-term migration scenarios' includes the objective to develop 'projections and scenarios that are essential for appropriate planning and effective policymaking'.

tion theory, to the quality of migration data, to the unpredictability of important future events. In his Data Brief to the IOM's Global Migration Data Analysis Centre (GMDAC), Jakub Bijak, one of the leading researchers in migration forecasts, warned that the 'belief in the possibility of producing precise migration forecasts is not only naïve, but also can backfire if reality does not conform to the expectations'[6]. Policymakers can only prepare for the future if migration forecasters predict it accurately. If expectations fall short of reality, then migration forecasts can even be counterproductive as they might trigger inappropriate policy responses. The second requirement, namely that migration forecasts will serve as a basis for good policies, is a political one and therefore lies outside of the domain of the forecaster. A political consensus on migration policy is difficult to achieve. In a highly charged environment, it is hard to foresee how estimates on future migration flows to Europe (which can vary substantially) will be interpreted and/or exploited. Forecasts are sensitive to their underlying assumptions, they bring with them important uncertainties and should be interpreted with great care. If nuanced interpretation flounders, migration forecasts may heat up the political climate rather than provide a basis for constructive policy making.

Figure 1 Stakeholders in producing qualitative and quantitative migration scenarios and projections (EU focus)



6 IOM, Global Migration Data Analysis Centre (2016) Migration forecasting: Beyond the limits of uncertainty, Data Briefing Series ISSN 2415-1653, Issue No. 6, page 6

While this report will not make any major claims on the normative component, it still cautions users of migration forecasts. Section 2 of this report will highlight the various sources of uncertainty in migration forecasting, discussing the complexity of migration determinants, the strong underlying (and often invisible) assumptions in quantitative models, as well as the various inaccuracies introduced through other forecasts and imperfect data. In Section 3, the report sheds light on the major forecasting methods, briefly reviewing qualitative models and migration scenarios before moving to a description and critical assessment of quantitative methods. Section 4 zooms into the German context, extracting migration forecasts from recent research papers, comparing and assessing them. This section will also look at Germany-specific, socio-economic uncertainties. The last section will discuss the usefulness of migration forecasts and provide recommended uses and interpretation.

II. Uncertainty in Migration Forecasting

There is always an element of uncertainty when making claims about the future. However, migration forecasts are particularly vulnerable to various forms of uncertainty. This paper establishes five sources of uncertainty in migration forecasting. First, it starts with a discussion of the complexity of migration determinants and the lack of a unified and generalised migration theory across disciplines, which makes a consensus on the best forecasting strategy difficult (agreeing on actual numbers is almost impossible). Second, it outlines that this complexity can typically not be fully reflected in empirical research. Therefore, most forecasts use strongly simplified assumptions that run in the background of the quantitative models. Outcomes are highly sensitive to small changes in those assumptions[7]. Third, migration forecasts are themselves often based on forecasts, for instance about fertility, climate, GDP growth, etc. Each of these forecasts carries a level of uncertainty that is introduced into the migration forecast. Fourth, it presents some of the major data sources used in migration, emphasising that migration data is notoriously bad (low frequency, low geographic resolution, low accuracy). Basing forecasts on imprecise data will introduce an additional source of inaccuracy and uncertainty. Lastly, it discusses several types of future shocks (technological, political, environmental) that are not foreseeable but ultimately some of the most important drivers of migration in the future. Overall, this section serves as a critical reflection on the abilities and limits of migration forecasting.

2.1 Complexity of Migration Determinants

Migration determinants are highly complex. Behavioural, social, cultural, political, economic and many other factors are at play, interacting with one another in multifarious ways. Because migration touches so many aspects of life, different fields examine the topic from different angles. Table 2 describes, in a highly simplified manner, how different social sciences approach migration theory.

There are many overlapping concepts and ideas, for instance between sociology and demography, sociology and economics, political science and law, history and anthropology, and so on. However, migration research does not yet feed off of a unified migration theory, though there are trends towards an integration of the different micro-, meso- and macro-level theories. As a result, migration forecasts are not footed on such overarching concepts or theories. Forecasts depart from very different theoretical foundations and can therefore produce very different results, within and across disciplines.

Demographers, for instance, consider migration (together with fertility and mortality) as one main determinant of population change (Zelinsky 1971; Courgeau and Franck 2007). The so-called 'demographic transition' is a combination of the 'vital transition' (birth and death rates) and the 'mobility transition' (spatial mobility, including migration). Zelinsky, who was a trained geographer, coined many of these terms, bringing a spatial component to demography. Migration – in demography – draws its relevance from its effect on population change and is analysed as such.

Anthropological and sociological concepts of migration share many similarities. Their qualitative scholars focus more on specific case studies and use those to develop broader concepts on migration. Especially the idea that migrants belong to a social space that is dynamic, hybrid, ever-changing and spans across the globe as a transnational sphere is a core concept of many sociological analyses. In order to assess the volume and type of future migration flows, these analyses develop qualitative migration scenarios that try

[7] For more details on the major assumptions as well as their strengths and weaknesses, see Section 3.

to incorporate these complex and dynamic processes. I will discuss the differences between qualitative and quantitative approaches in more detail in Section 3. However, in principle, quantitative models would not be able to measure and incorporate all of the dimensions deemed important by qualitative sociologists and anthropologists.

Political scientists and scholars of the law (as well as philosophers) have an interest in the effects of migration on the nation state, institutions and the legal structure, especially when it comes to state power, citizenship and enforcement.

Economists typically consider a representative agent who faces a trade-off between the costs and benefits of migration. Some factors, such as existing migrant networks, would decrease migration costs and therefore increase migration. Other factors, such as language or cultural barriers, would decrease gains from migration and therefore decrease migration. Usually, the representative agent's behaviour will be aggregated to represent and explain migration patterns on a macro-level.

Overall, migration is a topic that is examined by various fields from very different perspectives. This is owed to the complexity of migration processes but it is also the reason why it is difficult to base forecasting on a strong theoretical footing. This complexity makes migration very different from other dimensions for which forecasts are typically (and more reliably) created. For instance, fertility is a concept used and examined not only in demography but also in economics, sociology or history (Leridon 2015). Theoretical concepts such as the three or four stage demographic transition models have also been adopted in economics (Becker and Barro 1988; Willis 1973) and other fields and are used as a basis for forecasting models in fertility. Fertility forecasts are rather reliable in comparison to other forecasts, not only because data on fertility is better (longer time-frame and higher accuracy) and fertility moves more slowly (which makes it more predictable) but also because a generalised theory is very helpful for developing quantitative models.

The lack of theoretical underpinnings is largely owed to the complexity of migration determinants. On a macro-level, the main determinants of migration include geographic distance, common language, whether countries have former colonial links (which are non-time-varying determinants) as well as economic wealth at destination, unemployment rate, income and age structure at origin, immigration policies, climatic factors and conflict (Mayda 2010; Flahaux and Haas 2016; Beine and Parsons 2017; Kim and Cohen 2010). At a meso-level, transnational networks (Haug 2008; McKenzie and Rapoport 2010) and migration infrastructure are major determinants of migration (Xiang and Lindquist 2014). And finally, at a micro or individual level, there are determinants such as age, family status, risk aversion, perceptions, imaginations, local amenities, personal wealth and credit constraints etc. (Jaeger et al. 2010). All of these components interact in various ways; the mechanics of migration patterns remain opaque and we only observe aggregate bilateral migration flows and stocks.

Table 3 Simplified overview of Migration Theories in Social Sciences

	Demography	Geography	History	Anthropology	Sociology	Economics	Political Science	Law
Research Question	How does migration affect population change?	What explains the spatial patterns of migration?	How do we understand the immigrant experience?	How does migration affect societal change and ethnic identity?	What explains incorporation and exclusion?	What explains the propensity to migrate and what are the effects of migration?	What is the role of the state in controlling migration?	How does the law affect migration?
Concepts	• Demographic transition model • Vital transition • Mobility hump & transition	• Gravity theory • Entropy • Catastrophe theory & bifurcations	• History of human mobility • Historical-structural approach	• Transnationalism & ethnicity • Identity & hybridity • Social change	• Push & pull factors • Transnational social spaces • World systems theory	• Neo-classical (macro & micro) • Dual labor market theory • New economics of migration	• State power, sovereignty • Citizenship • Migration governance	• Forms, processes, institutions of immigration law • Enforcement

Source: based on Brettell and Hollifield (2013), Bijak (2006), Kupiszewski (2002), Zlotnik (1998)

Additionally, no single migration decision is alike. Climate migrants are different from economic migrants, who are different from the politically persecuted, and so on. Research on the importance of different determinants by migration category is still in its infancy. Depending on whether we think future migration may be driven more by climate change or even technological change not only means that we have to have a clear vision of how these dimensions change individually but have a concept of how these changes interact with other determinants of migration. These interaction effects are immensely complex and cannot be all incorporated into a quantitative model, even if we had a clear theoretical concept of how these dimensions interact in reality.

It may be possible to use artificial intelligence, neural networks and deep learning to understand migration patterns in the future. These systems would be able to identify patterns in highly complex settings. However, they need to be 'fed' with enormous data sets with millions of observations in order to train their pattern recognition. Section 2.4 discusses the fact that migration data of high accuracy, high frequency and high resolution is not yet available and also not harmonised across most countries. Even sophisticated AI techniques would not be able to overcome the lack of data availability.

2.2 Implicit Assumptions

The complexity of migration determinants cannot be fully incorporated into the existing quantitative models and tools. Therefore, forecasts use strong and simplifying assumptions about the world. Let's take the so-called time series models as an example. Main forecasting models and their assumptions will be discussed in Section 3, but time series models are a good example of how strong some underlying assumptions can be. Time-series models are fully agnostic in terms of the determinants of migration, they do not include any covariates that may influence migration in the future. Rather, they are data-driven processes that use past observations to model future flows. The so-called Random Walk with drift or 'autoregressive model' belongs to the group of time series models (Random Walk is a special case of AR(1) models, where the parameter for past migration φ equals 1). It predicts migration in the next period as a function of a constant base rate, the migration flow in the previous period with a certain parameter, and a normally distributed error term (it takes the following functional form: $m_{t+1} = c + \varphi m_t + \varepsilon_t$). There are also more sophisticated versions of this, adding different error terms (autoregressive with moving average) or integrate linear trends[8].

One can argue that relying purely on stochastic models in migration forecasting is the least restrictive since we do not have to make any assumptions about the influence of covariates on migration and how they will develop in the future. On the other hand, one could also argue that the lack of assumptions and exclusion of important co-variates (like demographic change, climate change, world income or technological disruptions) is in itself a strong claim about the future of migration. Furthermore, the simplicity of the approach masks some important statistical assumptions in the model, such as requiring normally distributed error terms or linear trends in some cases.

There is an important trade-off in this type of forecasting. The fewer assumptions about the stochastic behaviour of migration, the larger the range of possible outcomes further into the future. Long-term upper and lower bound predictions about migration can diverge substantially and may not be of practical use. More 'precise' (not accurate) forecasts comprise a lot of assumptions and implicit models about migration. This creates a tension between the interests of producers and users of migration forecasts. Forecasters would like to make as few restrictive assumptions about migration as possible (in the end many of those assumptions involve value judgements), which results in a large range of possible outcomes. Conversely, users of forecasts expect a reasonable range of outcomes to which they can tailor policies. In order to get to these reasonable ranges, forecasters develop more sophisticated models such as gravity models of migration or structural models. These models, which I will discuss in detail in Section 3, carry various assumptions about the functional form of migration and its relevant co-determinants. They may be able to narrow down the range of expected migration flows but changing some of the underlying assumptions would change the outcomes substantially. This is important to note when interpreting these forecasts. Cautious users of forecasts should ask themselves: what are the underlying assumptions and am I willing to accept them?

Overall, simple time-series models do not make any claims about what other factors will impact migration in the future. This also means that potentially relevant determinants of migration are set aside. However, we know that many factors are crucial for our understanding of migration. For instance, the age and educational structure of a society is one of the most important predictors of migration. Economic growth, climate change, migration policies and political stability are crucial to the future development of migration as well. Multivariate models of migration try to incorporate all of these dimensions to predict migration.

Let's assume that we have a simple model that explains migration with demographic change (with a functional form similar to: $m_t = \alpha + \beta * D_t + \varepsilon_t$, where m_t is migration at time t and D_t is a measure of the demographic structure at time t, β is the elasticity of migration to changes in demographic structure). Let's also assume we have used data on migration and age structure in the past and know that an increase in the age cohort between 15 and 35 by 10% is associated with an increase in migration by 1%. If we want to make predictions about migration in the future, we have to make predictions about demographic changes in the future. In this case, we would like to estimate $m_{t+1} = \alpha + \beta * D_{t+1} + \varepsilon_{t+1}$. This means we have to have a forecast for D_{t+1} to say something about m_{t+1}. Predictions on future demographic changes in themselves incorporate various assumptions and forecasting errors. If we add more co-variates on economic growth or unemployment for instance (such that $m_{t+1} = \alpha+\beta * D_{t+1}+ \partial * E_{t+1} + \gamma * U_{t+1} + \varepsilon_{t+1}$), we will be adding more implicit assumptions and margins of error that are ultimately reflected in the migration forecast. These forecasts are based on forecasts themselves, and will consequently introduce more uncertainty into the estimation. The analysis and assessment of forecast should therefore also depend on the assessment on the underlying assumptions, both stochastically as well as in terms of the underlying forecasting methods used to determine covariates of migration in the future.

8 Bijak (2015) gives the most comprehensive overview on the major assumptions used in different types of forecasting models.

2.3 Insufficient Data

The first step in forecasting migration is the analysis of data on past migration. Past patterns are the basis for explaining future patterns. This is true for simple time-series models of migration as well as more complex, multivariate models. However, the quality of migration data is oftentimes insufficient. This has been recognised by the international community. The High-Level Dialogues on International Migration and Development of 2006 and 2013 have highlighted 'the need for reliable statistical data on international migration'. In 2017, the Global Migration Group (within the World Bank's KNOMAD initiative framework) has published a 'Handbook for Improving the Production and Use of Migration Data for Development', outlining the gaps and room for progress in the coverage of all forms of human mobility (such as labour migration, asylum-related migration, commuters, expats, students, irregular migrants etc.).

There are three main types of data sources on migration, as illustrated in Table 4. One major type of migration data is administrative data, which is collected by national, regional or local authorities in official records. These records do not necessarily have the primary goal of documenting migration but they are used for administrative purposes and can include information on place of birth, citizenship or residency status. For instance, migration data can be extracted indirectly from tax records or work permits if they include markers for citizenship or migration status. There are also more direct proxies for migration in the records on issued visas or data collection at the border. While these data sources have many advantages in terms of coverage (theoretically the whole working population of a country should be included in the tax records) and time frame (people can be followed over a long period of time), there are a few major drawbacks. Double counting or under-coverage is a common problem in administrative data, since records are not always persons (but cases) and some individuals may never be registered (for instance, in the case of informal labour). Additionally, this type of data may only cover little information on socio-demographics, living situation, or economic wealth, which then makes it difficult to uncover heterogeneity across individuals.

Table 4 Advantages and Disadvantages of Main Data Types on Migration

	Advantages	Disadvantages
Administrative: Border Collection; Work & Tax Records; Visa Permits	• Large data sets, potentially • covering the whole population • Tracking over time • High frequency and geographic resolution	• „Records not people“: multiple issuing or registration (within and across countries) • Rarely cover exits • No socio-demographic information
Survey: House hold Surveys; Census	• Wealth of information on respondents • Likely to capture groups of interest (including harder to reach populations)	• Small sample size, often too smal to make claims abaout sub-groups • Suffering from typical survey blases • Low frequency
Big Data: Social Media; Mobile Phones; Google Search	• Real time movement of people: velocity • Available in countries with low administrative or survey coverage • Large coverage, including „irregular“ migrants	• Highly self-selected • Phones + SM accounts, not people • Opacity about what is actually measured • Inaccuracy of IP address + phone location

More detailed information on individuals can be extracted from survey data. This includes socio-demographic and economic information on the respondents as well as more detailed questions on the different types of migration status. Many surveys have designated sections that specifically target the determinants of migration and ask about reasons for migration, intended length of stay, or migration aspirations[9]. In some cases, survey sampling methods allow reaching the population of interest, which may not be captured in administrative data (for instance, in the case of irregular migration). Nevertheless, most surveys are limited in sample size. Detailed analyses of migrants from different origin countries, with different lengths of stay, employment status or other subgroup analyses are difficult in small samples. Naturally, the national census does not suffer from this problem. It is the survey with the largest coverage but it is also a survey of low frequency (typically every ten years), which can impede timely analyses and often masks important changes and developments between survey years. In contrast to administrative data, surveys may also suffer from the usual biases that may lead to inaccurate conclusions.

In the last few years, alternative data sources have emerged that may have the potential to address the issue of coverage, frequency and biased response. The potential of big data for migration research is large. The European Commission Knowledge Centre on Migration and Demography (KCMD) and the International Organization for Migration (IOM) with the Global Migration Data Analysis Centre (GMDAC) have launched a workshop and drafted a data policy brief to inform the Global Compact on Migration about the importance of Big Data[10]. Big Data refers to information in high volume (large amounts of data, usually not computable by standard statistical software), velocity (high frequency) and variety (different types of data, such as networks, preferences, textual, imagery, etc.). This data can come from mobile phone call detail records (CDR), Google searches, geo-locations in social media or IP addresses. In a recent technical report, the European Commission's Joint Research Centre has used Facebook Network Data to estimate the number of 'expats' in 17 EU countries. One major drawback of the analysis is the selection bias into social networks. While Facebook covers vast parts of the world population (it has about 2.4 billion monthly active users worldwide), its users are not a representative sample of the whole population. In order to make claims about how migration captured in social media data reflects actual migration, researchers have to make strong assumptions about how migrants select into social media platforms by age, gender, origin, etc.

Typically, the analysis of selection into social media (including giving more weight or discounting certain observations) rests on existing data on migration from surveys and administrative sources. In other words: checking whether migration estimates from big data are plausible means comparing them to traditional data sources. This makes big data prone to similar problems as traditional data sources. While it is difficult to infer overall migration rates, it is possible to detect changes in migration flows in certain sub-groups. A few researchers have looked at geo-located data from Twitter to analyse movement within and across countries (Zagheni et al. 2014). The authors use a difference-in-differences approach to infer out-migration rates and account for selection into the social network. This means that they compare changes in migration for Twitter users to overall migration numbers and analyse the differing patterns to make claims about how the selected sample relates to the whole population.

Despite increasing efforts to improve the quality of migration data, the data basis for migration forecasts remains unsatisfactory. An important impediment to comparable and detailed migration statistics is the lack of information exchange within and across countries. In comparison to data on international trade, where UN Comtrade publishes quarterly data on the trade in goods and services worldwide with detailed codes for product and service categories, migration data is much harder to monitor and countries rarely harmonise their immigration and emigration data.

[9] See for instance the Gallup World Poll, the European Labour Force Survey, the Mediterranean Household International Migration Survey (MED-HIMS) and many others that have migration components in their questionnaires.
[10] See 'Data Bulletin: Informing a Global Compact for Migration' IOM GMDAC, Issue No. 5 (2018)

In a large consolidation effort, the World Bank and migration researchers have combined more than one thousand census and population register records to construct decennial matrices (bilateral migrant stocks for about 200 countries) spanning 1960 to 2000 (Özden et al. 2011). The data-set uses the foreign-born definition of migrants. More recently, the OECD has developed a bilateral migration matrix for the years 2000 and 2010 together with the World Bank, which includes information on demographic characteristics (age and gender), duration of stay, labour market outcomes (labour market status, occupations, sectors of activity), fields of study, educational attainment and place of birth. Despite the large efforts behind the consolidation of various data sources across countries, the resulting data set suffers from important biases, as Özden et al. (2011), the researchers behind the World Bank Migration Data Set, summarise:

'In constructing global bilateral migration matrices, several challenges arise. First, destination countries typically classify migrants in different ways—by place of birth, citizenship, duration of stay, or type of visa. Using different criteria for a global dataset generates discrepancies in the data. Second, many geopolitical changes occurred between 1960 and 2000, with many international borders redrawn as new countries emerged and others disappeared. In addition to creating millions of migrants overnight—as when the Soviet Union collapsed—these events complicate the tracking of migrants over time. Third, even when national censuses of destination countries include data on international migrant stocks, the data are presented along aggregate geographic categories rather than by country of origin. Data therefore need to be disaggregated to the country level. Finally, the greatest hurdle is dealing with omitted or missing census data. Very few destination countries—especially developing countries—have conducted rigorous censuses or population registers during every census round over the second half of the twentieth century. Wars, civil strife, lack of funding, and political intransigence are but a few reasons why records may be discontinuous.'

These drawbacks in the data are a serious impediment to quantitative migration research which oftentimes relies on these global migration matrices (especially the so-called gravity models, which will be discussed in Section 3). The challenges are particularly severe in the migration forecasting sphere. An analysis of the movement of people across the globe over a long period of time requires comprehensive data, which not only covers the final destination country but also all intermediate steps, including transitory migration within the Global South (for which there is even less reliable data). However, the lack of alternatives binds migration forecasters to this type of data. Current data collection and consolidation efforts will bear fruit in the future but in interpreting migration forecasts for now, one has to account for potential gaps, inconsistencies and biases introduced by the data.

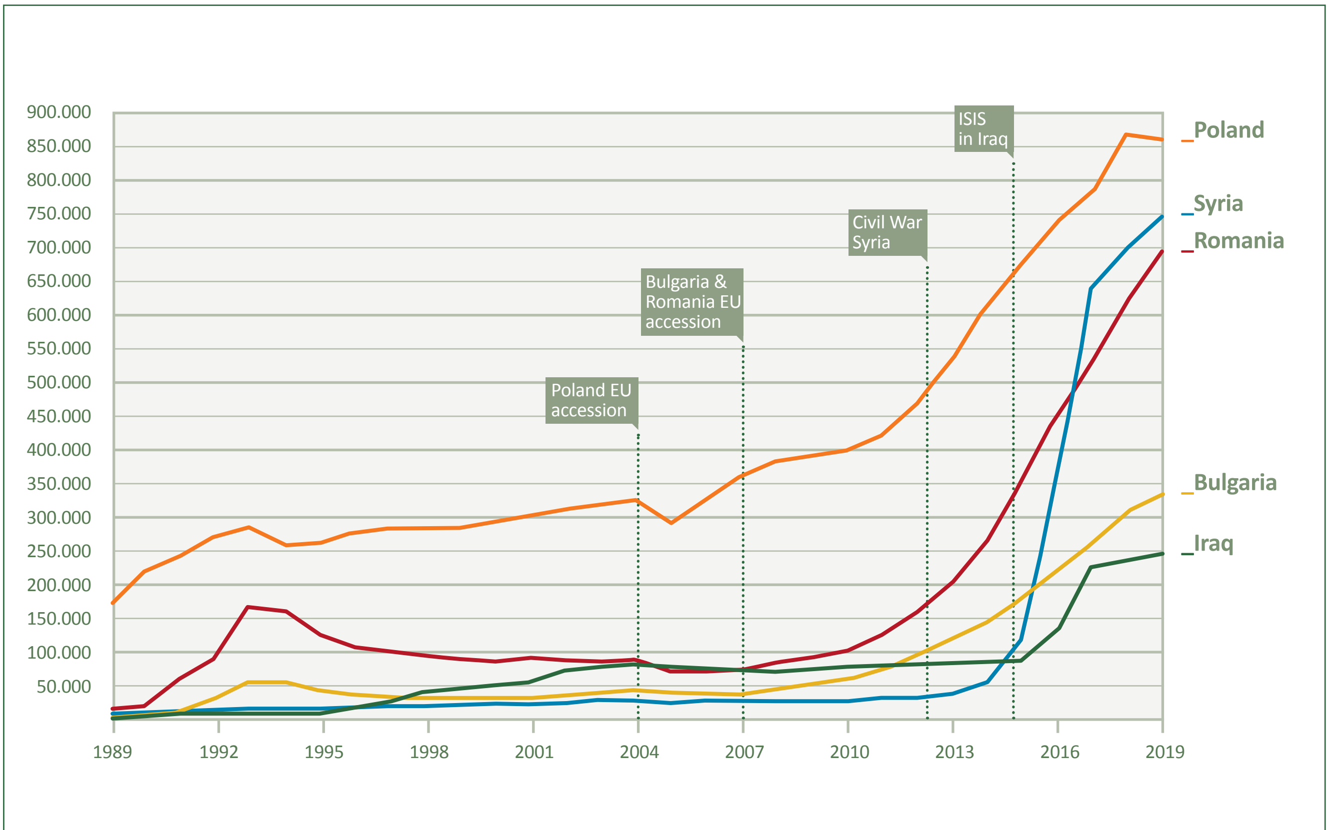
2.4 Future Shocks

The strongest impediment to accurate migration forecasts is the inherent inability to foresee or predict important events or major shifts in economics, politics, technology, climate or other major drivers of migration. Figure 2 shows the number of individuals with a foreign citizenship living in Germany between 1989 and 2019 for a selected number of source countries (as recorded in the German Central Register for Foreigners, the 'Ausländerzentralregister'). The figure shows how bumps in the number of foreigners relate to a few relevant political events[11]. The accession of Poland (2004), Romania and Bulgaria (2007) to the European Union was associated with an increase in the number of foreigners from those countries. Additionally, incidents of war and conflict like in Syria and Iraq are equally associated with substantial increases in the migrant population. All of these events are major drivers of migration and these groups make up a substantial share of the migrant population living in Germany.

[11] It is worth noting that the graph shows migrant stocks (the total number of migrants present in Germany) and is thus a cumulative representation that incorporates deaths, fertility and exists in addition to new entries.

It is very difficult to predict political change, especially in the long run. Consequently, migration forecasts usually ignore potential incidents of conflict or changes in migration policy in the future. However, even small initial deviations can lead to substantial long-run change. For instance, existing migrant networks are a strong factor for migration from the same source country. Networks decrease informational barriers, lead to better job outcomes at destination and decrease the overall cost of migration (Haug 2008; Liu 2013; McKenzie and Rapoport 2010; Munshi 2003). This means that changes in the size of a migrant network due to an unforeseen event (for instance, the war in Syria and the subsequent migration to Germany) might affect migration from Syria to Germany for decades to come. There are substantial ripple effects that can stem from events that are typically not captured in migration forecasts.

Figure 2 Number of Migrants to Germany by Source Country over Time



Source: DeStatis & own elaborations

Another example of an important driver of migration is climate change. We know that regional and international migration is determined by vulnerability, exposure to risk and adaptive capacity in the face of climate change (McLeman and Smit 2006; Feng, Krueger, and Oppenheimer 2010; Black et al. 2011). Even if it were possible to quantify how migration patterns evolve with climate change (volume, regional versus international, favored destination countries) and even if it were possible to perfectly predict changes in temperature, rainfall and weather volatility, some major uncertainties would remain. Even if climate change is factored into migration forecasts, it is so under the 'ceteris paribus' assumption, that is, under the assumption that 'all else remains equal'. This means that potential policy changes that counteract or reinforce climate change would be set aside. The same holds for technological progress (some disruptive technological changes may significantly alter the course and patterns of migration), economic growth, demographic changes, etc. Since these dimensions interact with one another in complex ways and migration policy responses may in turn respond to these changes (for instance, increased climate change may increase migration but therefore trigger a restrictive migration policy that may ultimately reduce migration in response to climate change), it is very difficult to predict their consequences in a credible way.

In sum, uncertainty in migration forecasting covers multiple dimensions: the complexity of migration determinants, the lack of data of high velocity, volume and accuracy, implicit assumptions used to derive forecasts of a reasonable range, forecasts based on forecasts that already carry a level of uncertainty and a set of assumptions with them, and finally, all of the economic, political, technological or climate uncertainties which present some of the most important drivers of migration but cannot be foreseen, especially not over a long period of time. It is important to note these caveats when policymakers use these forecasts to get 'a rough estimate' of migration to Germany (or any other country) in the future. It is more likely than not that even these rough estimates deviate substantially from what the future of migration looks like.

III. Forecasting Methods

There are various ways to conduct migration forecasting exercises. Methods vary substantially within and across fields. While the focus of this report is the assessment of quantitative approaches, it is important to conceptualise how qualitative and quantitative methods interact and can inform one another. The main goal of this section is to sketch the logic behind three of the most important quantitative forecasting methods, namely Bayesian Statistical Modelling, Gravity Models of Migration and Structural Models, highlighting the results of some of the central academic papers. At the end of this chapter, there will be an overview over some of the qualitative migration forecasting methods and how they can be integrated with quantitative forecasting methods. This chapter will also serve as the methodological basis for selected migration forecasts presented in the following chapter.

3.1 Bayesian Statistical Modelling

Bayesian models can be thought of as an extension of univariate time series models, modified by using probabilistic methods as input. The only influencing factor of future migration is past migration; hence, this method is considered as a purely data driven approach[12]. This gives additional flexibility and tools to overcome some problems of migration data, as put in Bijak et al. (2019), uncertainty in migration forecasting can be divided into three components: inherent uncertainty of future events, uncertainty coming from migration data (as discussed in Chapter 2) and uncertainty induced by the model. All aforementioned types of uncertainty can be accessed by Bayesian models. However, this comes at the price of further statistical assumptions and exclusion of covariates potentially containing additional information.

Different time-series models can be used for Bayesian forecasting. For the sake of simplicity, let's consider an AR (1) model where future migration depends on migration in the last period and the future error term yielding, $m_{ij,t+1} = c + \varphi\, m_{ij,t} + \varepsilon_{t+1}$. The most intuitive way to think about Bayesian forecasts is to contrast them against linear regression. In a linear framework we would estimate φ parameter by a linear regression from past data $m_{ijt} = c + \varphi\, m_{ij,t-1} + \varepsilon_{t-1}$ additionally assuming normal distribution of the error term. Once we have estimated $\varphi \epsilon$ (0,1) for instance 0.7, meaning that migration in period t linearly depends on migration in t-1 by factor 0.7. For a migration flow of the size of 100 in period t, our model hence would predict a migration flow of 70 in $t+1$, assuming normal distributed errors with zero mean. Migration data mostly comes in decadal frequency. Let's assume we base our forecast on the most recent DIOC-E data (which is widely used in literature), our forecast from the year 2019 onwards would be based on five data points from 1960–2010. The precision of estimated parameters increases with the number of observations in linear regression models. Relying only on a few data points means that the estimate is noisier and less precise.

The strength of the Bayesian framework is that it takes a probabilistic rather than deterministic approach in the estimation of the model parameters (φ in the Bayesian estimation is a full distribution, not just one parameter). Within the Bayesian framework, parameters are treated as randomly distributed variables, which are drawn from a certain distribution. The type of distribution is chosen as an input variable additional to the observed data. Using the distribution, we can simulate data, following a random, stochastic process and drawing possible values of φ from the assumed distributions by using data generative process such as Markov Chain Monte Carlo[13] (MCMC) methods (Barnett, Kohn, and Sheather 1996). Combining our observations (likelihood

[12] In this section, the report focuses on purely quantitative Bayesian models. Section 3.4 will show how Bayesian models can be extended to incorporate expert opinion and other qualitative dimensions.

[13] A process which randomly stimulates data from a distribution, with new draws depending on the current draw, not influenced by past draws. See Gilks (1995).

function) and prior distribution yields a posterior distribution – which to some extent, increases the validity of observations by our simulated process. The reported results are taken from the posterior distribution, e.g. our parameter φ_{Bayes} is usually the median from the posterior distribution (Bijak 2006) in contrast to φ_{OLS} reflecting the least squares estimator of observations. More explicitly, uncertainty can be shown by reporting credible intervals (confidence intervals) where the true parameter lies in with a probability of e.g. 80%.

Bayesian applications can flexibly include different time series models[14], as ARIMA models, depending on lagged values of the independent variable and the error term. The order of the model usually does not go beyond ARIMA (1,1,1) (Keilman 2001). But there are other determinants of the functional form resulting from the data properties which influence the choice of the model, in particular stationarity, which is a commonly assumed feature of time-series data, stating that data has constant mean and variance over time. With an increasing time horizon, the assumption becomes less likely to hold. However, the functional form can be adjusted to include such features as well (Abel et al. 2013). Moreover, the model choice depends on the characteristics of the migration flow and is not universally applicable in other contexts. Migration of students to the UK are, for instance, rather stable (Disney et al. 2015). Long-term Bayesian forecasts of particular migration flows on a world level seldom exist[15].

Additional information better matching reality can be included as well in the choice of the prior distributions. Not only the distribution of parameters, but also maximum/minimum for univariate distributions or mean/variance of the underlying distribution (for instance the normal distribution) can be estimated, leading to a 'multi-level' or hierarchical Bayesian structure (Berliner 1996). The choice of priors and these multi-level priors (hyper priors) can be made from statistical, but as well from qualitative perspectives (Bijak and Bryant 2016). Expert knowledge can improve forecasting performance, in particular with low data availability (Wiśniowski and Bijak 2009), or if structural breaks can be anticipated, with no similar existing information from the past (Disney et al. 2015).

The goal of Azose and Raftery (2015) is to improve on the UN Population Division's population projections by accounting for uncertainty in international migration. International migration (specifically net migration), fertility and mortality are the key determinants of population change. While UN population projections account for uncertainty in fertility and mortality, they take migration as deterministic, e.g. current migration rates will continue into the future. As outlined in the previous chapter, migration is hardly predictable and uncertainty is large. Therefore, the authors develop a model that can quantitatively scope uncertainty in migration[16].

Azose and Raftery (2015) use a Bayesian hierarchical first-order autoregressive model to fit migration rate data for all countries worldwide. The authors predict migration for 197 countries from 2010 to 2100 in five-year intervals, differentiated by age and sex. Their model takes the form $(r_{c,t} - \mu_c = \varphi_c\,(r_{c,t-1} - \mu_c\,) + \varepsilon_{c,t},$ where the left hand side variable is the difference between the migration rate in country c at time t $(r_{c,t})$ and the country's theoretical long-term average migration rate (μ_c). The right hand side variable (or explanatory variable) is the difference between realised and average migration rate in the previous period, where φ_c is the autoregressive parameter (that lies between 0 and 1 to ensure stationarity). It is important to note that the authors use a hierarchical model, which means that the model parameters are country-specific and are not only informed by their own past migration experience but the migration experience of all other countries (using UN World Population Prospects between 1960 and 2010). This is not the case for non-hierarchical probabilistic models which calibrate the model parameters independently, not taking into account all countries simultaneously.

14 For an extensive overview consider Disney et al. (2015).
15 Except for Azose and Raftery (2015) which will be discussed in greater detail in the following chapters.
16 The authors emphasise that they 'produce both point and interval estimates, providing a natural quantification of uncertainty' (Azose & Raftery, 2015)

In addition to purely quantitative Bayesian models, Bijak and Wiśniowski (2010) include expert-based scenarios derived by a two-round Delphi-survey[17] and converted into probability distributions in their forecast, thus predicting total immigration separately for seven European countries with data from national statistical offices, as well as from international organisations, from 2010 to 2025. Bijak and Wiśniowski (2010) conclude that forecasting migration when horizons are too is useless, in particular with non-stationarity characteristics caused by shocks, such as the EU enlargement. The authors choose a Random-Walk model and state that errors become too large to draw inference upon, suggesting limiting the predictive horizon to 5–10 years. Expert knowledge, however, helps in estimating model parameters and improves short-run predictions, but has no influence on the choice of the underlying model.

3.2 Gravity Models of Migration

The gravity model is a popular and commonly used framework, adapted from Newton's law of gravity, generalised and applied across disciplines, for instance, in international trade, regional science or migration. Research in this area started with Tinbergen (1962) as an application of social physics, and became more interesting to migration related issues, with an increasing data availability (Beine, Bertoli, and Fernández-Huertas Moraga 2016). The intuition is that masses attract one another, with a force proportional to the sum of their masses – and repel one another with increasing distance. In trade, the gravity relationship was found for GDP, showing that the higher the GDP of two countries, the more they trade. Distance, in turn, decreases trade flows (Head and Mayer 2018). For migration, the data reveal similar patterns. Countries which are more attractive for migrants, for instance, measured by GDP, experience higher migration flows. Physical distance, on the other hand, is associated with lower migration flows.

Putting this into the gravity equation $E(m_{ij}) = S_i D_j \phi_{ij}$ represents the expected number of migrants moving from country i to country j. S_i represents the ability of i for sending migrants, ϕ_{ij} expresses bilateral accessibility, to think of as cost of moving between country i and j. Lastly, $D_j = \frac{y_j}{\Omega_i}$ represents the relative attractiveness of destination j, depending on potential earnings (wages or GDP) in country j (y_j), and relative cost of migrating to other destinations then j (Ω_i). The latter term is referred to as multilateral resistance, including attractiveness of alternative destinations is crucial to unbiased estimation (Bertoli and Fernández-Huertas Moraga 2013). In other words, the migration decision multiplicatively depends on relative earnings at the destination, cost of moving, country specific characteristics and the relative attractiveness of other destinations.

In gravity models, attraction points are typically conceptualised as the economic attractiveness of a specific destination country as compared to others[18]. Since expected life-time earnings are difficult to measure, economists use proxies such as the current levels of purchasing-power-parity adjusted GDP (Hanson and McIntosh 2016) or an index constructed with 10-year bond yields on a secondary market combined with consumers expectation of the future (Bertoli, Brücker, and Fernández-Huertas Moraga 2016). When thinking about costs of moving, one could think of a variety of factors inter alia: moving cost, cost for absence from the labour market, psychological cost, the effort of learning a new language (Sjaastad 1962). However, in the 'baseline' gravity model, distance is encompassing all the factors mentioned above, an increase in distance between two countries thus leads to an increase in migration costs. To that, fixed-effects which influence the migration decision similarly across countries are included as dummy variables. For instance, Mayer and Zignago (2011) include the following variables: being a former colony, common first language, common second language, sharing a common border, being landlocked, being a small island.

[17] Survey anonymously asking experts to quantify their expectations on future migration scenarios. For more detail, see Wiśniowski and Bijak (2009).
[18] This goes back to the concept of dual labour market theory of migration described in the previous chapter.

Empirically gravity models are taken to data using multivariate regression. For the aforementioned scenario think of $m_{ij,t} = \beta_0 + \beta_1 \ln(GDP_{i,t}) + \beta_2 \ln(GDP_{j,t}) + \beta_3 \ln(distance_{ij,t}) + \beta_4\, dummies_{ij,t} + \varepsilon_{ij,t}$ describing migration flows at time t. All coefficients linearly influence the migration flow, say an increase in log of GDP_j by 10% is associated with an increase of bilateral migration by 1%. Hence, in this simple model there is no interaction between the variables.

For forecasting, the estimated parameters are used to extrapolate migration well into the future. In other words, past data reveals how the right-hand side variable relates to outcome variable (for instance, how GDP at destination relates to migration to that destination country) and this relationship is assumed to continue in the future (e.g. changes in GDP in the future correlate with changes in migration flows in the future by the size of the estimated parameter). To that, one needs input of future GDP data, which is based on assumptions and forecasts, as well as assumptions on the future error term. Assuming normal distribution with a zero mean and constant variance comes at the price of neglecting influence of shocks or structural changes. In this model of future migration, linearly depends on parameters from the past and assumed growth patterns of the input variables.

Despite the straightforward nature of this theoretical mechanism, several statistical challenges come with these estimations. Distributional assumptions have to match individual characteristics, considering, for instance, the varying pay regarding gender. Also, utility across countries might differ depending on individual characteristics (Ortega and Peri 2013). Functional form and approximations have to be well-specified and multilateral resistance has to be measured appropriately[19].

Gravity models can incorporate a wide array of information across disciplines, as long as they are metric. To get an overview of the literature, let's take a look at recent studies. Backhaus, Martinez-Zarzoso, and Muris (2015) measure the effect of climate changes on bilateral migration, by including average temperature and precipitation in country of origin, additional to the 'basic' framework. Friebel et al. (2018) examine changes in smuggling routes and thus migration cost on migration intentions. Naghsh Nejad and Young (2012) examine the effect of discrimination by gender in looking at the migration decision of high skilled women, by computing a womens' right index, including economic, social and political rights from the CIRI human rights dataset (Cingranelli and Richards 2010) and looking at the differences between the origin and destination country. The authors find a non-linear relationship between the women's rights gap and migration. Women are more likely to migrate (compared to men), when women's rights in the destination country are higher, unless the current level of women's rights in the origin country is at a very low level.

At a macroeconomic level, Bertoli, Brücker, and Fernández-Huertas Moraga (2016) examine monthly EU migration to Germany from 2006 to 2014 including the sequential nature of migration decisions, allowing the individual to assess the discounted utility of migrating in t+1 (V_{t+1}). So the individual utility is defined as $U_{ijkt} \equiv w_{kt} - c_{jk} + bV_{t+1}(k) + \varepsilon_{ikt}$. Here, in addition to the basic framework, expectations on future economic conditions in home and destination countries are assumed to be the driving factors of migration. These are measured by 10-year bond yields on the secondary market and consumers´ confidence. An increase of 10-year bond yields (equal to a worsening of economic outlook) or an increase in unemployment at the home country is associated with more migration, the magnitude, however, differs with regard to the empirical specification.

As outlined above, gravity models can incorporate an array of determining variables, depending on the interpretation of attraction and distance. Models can include, for instance, environmental, political, sociological, micro/macro-economic, geographical data and test corresponding theories on what drives migration.

[19] For an extensive overview on econometric issues, consider Beine, Bertoli, and Fernández-Huertas Moraga (2016).

Empirically, options are much more strongly limited by data availability and quality, which is going to be further discussed in this chapter. So far, only descriptive ex-post gravity papers have been discussed. The data requirements for forecasts however are even higher. Predicting future changes ideally has to be based either on variables which are stable in the long-run or, if existing, on migration theories observed in the past. Economic variables, for example, GDP or unemployment, can be significantly affected by shocks, e.g. financial crises, wars, climate change or technological progress, which cannot be foreseen. When including such variables, assumptions about future developments have to be made which might seem somewhat arbitrary.

The scope of the gravity models is to build a framework which can represent the migration decision of a 'representative migrant' in a gravity framework. The narrowness of the definition, however, is limited by data availability and quality. Looking at the majority of the studies with a broad geographical scope, most commonly used is the Database on Immigrants in OECD countries (DIOC) and Database on Immigrants in OECD and non-OECD Countries (DIOC-E), which makes it worth looking into in more detail. Data is drawn from national statistical offices, and in few cases, extrapolated from country-specific surveys. It offers bilateral-stock data, defined as 'a static measure of the number of persons that can be identified as international migrants at a given time' (UN DESA 2017a), in decadal frequency from 1950–2010, including variables such as sex, age, education, nationality, and country of birth. However, the categories are not always directly measured, but based on estimations as well. To that, using DIOC-E phases several impediments as outlined in Chapter 2.3 including: geopolitical changes, different definitions of national statistical offices, and varying data quality across countries[20]. In spite of that, decadal stock data offers a fairly unsatisfactory basis for analysis. In/out- migration is netted and basing analysis on 10-year snapshots might neglect significant movements in between. Yet, the DIOC-E Database remains the most comprehensive migration data source, and in spite of all drawbacks, it is indispensable for gravity model analysis.

Alternatively, gravity models can be built on survey data. However, in the majority of studies, the geographical coverage is limited. To analyse global migration, the Gallup World Poll (GWP), offers a wide geographic coverage and granularity and is conducted every year for a sample-size of 1,000 individuals per country older than 15 years. GWP covers more than 150 countries, and deals with various topics, such as personal health, financial well-being, food and shelter and several questions concerning migration intentions (inter alia: desired destination of migration, migration intention during the next 12 months, migration preparations). As the data is not publicly available, consider Gubert and Senne (2016) for descriptive statistics on migration intentions to the EU or Esipova, Ray, and Pugliese (2011)for migration intentions on the world level. In spite of the richness of information in the survey data, only migration intentions can be measured, which differ substantially compared to actual migration (Dustmann and Okatenko 2014). Hence having more information comes at the price of losing predictive power on actual migration.

Hanson and McIntosh (2016) are among the first to apply gravity models to migration forecasting. Compared to the previous outlined studies, this one relies on fundamental, demographical factors, such as the fertility rate, which is thought to be more stable over time. Hanson and McIntosh (2016) aim to analyse how exposed the EU is to migration pressures stemming from different fertility rates, and comparing it to US immigration. They argue that for US-Mexican migration, differences in labour supply (caused by differences in fertility rates) were the reason for sustained and high migration rates in the past. The US exhibited relatively low birth-rates, whereas Mexico faced higher birth-rates, and these demographic factors might be used to infer differences in labour-supply 15 to 20 years ahead, when newborns reach the working age. Based on Lutz, Sanderson, and Scherbov (2001), the authors argue and assume, that fertility rates remain fairly stable and can be used to forecast population growth up to two or three generations ahead. Looking at the EU,

[20] For an overview on 'special cases', consider the technical appendix of the DIOC-E database → **http://www.oecd.org/els/mig/DIOC-E-2010-11-methodology.pdf**

Hanson and McIntosh (2016) argue that declining fertility rates in the EU and increasing rates in Sub-Sahara Africa and the Middle-East-Asia could lead to an increase in migration pressure, similar to the US in the past. In their empirical analysis, built on a standard gravity framework including GDP, distance and a set of dummy variables, the focus lies on two additional explanatory variables. First, migration networks, which measure the present number of migrants from the same country of origin in the destination country, decrease migration cost. Second, differences in age-cohort birth size are considered to infer differences in future labour supply. Two regressions are conducted: the first without networks, the second including networks.

Taking bilateral migrant stock data from 1960–2010, the authors compute migrant stocks in receiving countries and calibrate the parameters for 175 sending and 25 receiving countries. They use the projections on population growth from the UN World Population Projections from 2017 and GDP growth from the IMF forecast for as inputs. Based on their empirical analysis and forecast, the authors conclude that immigration from Sub-Saharan Africa will rise from 2010 to 2050 from 4.6 to 13.4 million, whilst at the same time, the number of working-age adults in the region will rise from 500 million to 1.3 billion. Overall, the authors focus on the demographic component of migration, illustrating how changes in population growth (particularly in the North African region and in Sub-Saharan Africa) will result in changes in migration pressures. They conclude that the United States will largely be insulated from population-growth driven migration since it is far away from the motors of population growth. On the other hand, in the eyes of the authors, Europe will 'face strong population pressures for immigration for decades to come'. Nonetheless, as will be detailed in the next chapter, the authors predict decreasing migration flows to Germany over the next decades.

3.3 Structural Equation Models

The best way to understand structural equation models is in a comparative exercise to standard regression models (or Ordinary Least Squares Estimation, OLS). As explained in the previous section, gravity models in migration are taken to the data in the form of a multivariate regression analysis. These regression analyses estimate the effect of a few (presumably exogenous or independent) explanatory variables on the main variable of interest, in this case migration. The size of the effect is captured in the coefficient of the explanatory variable (denoted as β below). Imagine a simple regression with migration networks at destination as an explanatory variable for migration to that country, which takes the following form: $migration_{ijt} = \alpha + \beta * networks_{ijt} + \varepsilon_{ijt}$. Imagine we find that a 10% increase in migration networks from source country j, living at destination country i, at time t increases migration by 1%. In this simple regression, we have assumed that there is a linear relationship between networks and migration, that no other (omitted) variable influences migration. We also assume that migration in itself has no effect on migrant networks (which is clearly not the case) and other assumptions that ultimately relate to the distribution of the error term.

Regression analysis is a data driven approach, structural equation models (SEMs), on the other hand, are theory driven empirics[21]. At the beginning of a structural estimation, there is a theoretical model that determines how and whether certain variables are related to one another (so-called 'weak assumptions'). For instance, migrant networks determine migration but we can also stipulate in a SEM that migration in itself, as well as a vector of other explanatory variables (described below as Z_ijt) affect migration networks. In this case, we would additionally write that $networks_{ijt} = \alpha + \beta * migration_{ijt} + \gamma * Z'_{ijt} + \varepsilon_{ijt}$ This means that we do not have to assume a unidirectional or causal relationship between the exogenous (networks) and the endogenous (migration) variable, but we can incorporate the possibility of a reverse relationship between them. However, the theoretical model has to determine how these variables relate to one another. Additionally, SEMs have to make so-called 'strong assumptions' on which variables are independent from one another. In our example, this means that the theoretical model should identify a variable within the vector Z that has an effect on net-

[21] This explanation largely follows Hoyle (2015); Heckman and Vytlacil (2005) and Alan C. Acock (2013).

works but not on migration itself. By rearranging multiple equations, an SEM should be able to express each dependent variable with at least one exogenous variable. In this way, SEMs partially reflect the logic of an Instrumental Variable Estimation.

The coefficient of an OLS estimation represents the slope of a fitted line that minimises the difference between predicted and actual data points. The parameters of an SEMs minimise the difference between the predicted and actual variance-covariance matrix (typically with a Maximum Likelihood Method). While the coefficient of an OLS (denoted as β) would suggest how – all else remaining equal – one variable influences the other, the parameter of a structural equation reflects the effect of multiple, interacting variables on a variable of interest.

Since SEMs incorporate multiple relationships (as opposed to regression models that are based on one relationship between a dependent variable and a set of predictors), they are useful in analysing complex systems with many interdependencies. SEMs are also particularly suited to address constructs that are measured with error (since SEMs make explicit assumptions on how errors relate to one another) and they are useful in analysing indirect or mediated effects between variables (since SEMs conceptualise indirect relationships). Overall, SEMs try to get at the causal mechanism between variables. While simple regression analysis depends on the research design to make causal claims, SEMs depend on the underlying model and its assumptions. The credibility of the causal claim therefore depends on the structure of the model (as it would rely on the research design for a simple regression analysis).

The ability to accommodate complex systems makes SEMs a useful tool in migration forecasting. However, the more complex the phenomenon, the more difficult it is to construct an appropriate theoretical framework around it. This also relates to the previous section on uncertainties in migration forecasting. One issue is the lack of a unified theoretical framework for international migration (that does not exist within the economics disciplines, let alone across disciplines) that could inform such SEMs. Instead, some recent papers, notably Dao, Docquier, Maurel and Schaus (2018) and Burzynski, Deuster and Docquier (2019) present their own theoretical frameworks to estimate international migration through an SEM.

In their paper 'Global Migration in the 20th and 21st Centuries: The Unstoppable Force of Demography' Dao et al. develop a model of migration that is determined by wage disparities between countries, differences in amenities and migration costs. The authors also assume that there are two skills levels among individuals, which have different returns to their labour across countries. At the same time, the authors model the economy in the form of firms with a certain production technology that produces these wage disparities. Wage disparities in themselves are dependent on the allocation of labour across countries, which is affected by international migration. All these factors jointly determine the world distribution of income and the allocation of the world population.

In a simple regression model, migration would only depend on differences in wages and amenities, as well as migration costs. We would estimate the effect of all of these factors on migration in an OLS. The SEM now allows us to incorporate the fact that wage differences are affected by migration as well. If more people move to a place where wages are higher, those wages will in turn decrease as labour supply increases. This will in turn affect the incentives to migrate due to changes in wages. This loop of causation can be incorporated in an SEM, which wouldn't be the case in a simple OLS. However, one may argue that the theoretical model is still too simple and does not include other important factors, such as socio-cultural determinants. If we were to make the model more complex, we would have to specify how exactly other variables affect one another.

Additionally, all the variables in the model have to be captured in data sets. Even if we think that some dimensions are important to a model in theory, we have to be able to measure them in practice (and ideally with a large sample size to increase the accuracy of the estimated parameters) (Bollen 1990; Bearden, Sharma, and

Teel 1982). This is particularly true when it comes to using structural models in forecasting. As mentioned in the section on imprecise data, the challenge is not to only measure variables in the past but to reasonably predict how they will develop in the future. To go back to the previous example, if we believe migration is determined by migration networks, we will have to be able to predict future migration networks to say anything about future migration. This caveat also holds for SEMs.

In their paper, Dao et al. (2018) calibrate their model to match the economic and socio-demographic characteristics of 180 countries and the bilateral migration stocks of 180 times 180 country pairs (by skill level) for the year 2010. The authors use data on the size and the structure of the labour force from the Wittgenstein Centre for Demography and Global Human Capital, they use the wage ration between skilled and less skilled workers from Hendricks (2004), GDP data from the Maddison's project[22], and data on migration from the OECD[23]. In a second step, the authors check the plausibility of their calibrated model in a backcasting exercise, where they retrospectively predict bilateral migration given past data and compare them with the actual migration figures from the past. The authors find a very good match between modelled and actual migration figures.

In order to predict bilateral migration stocks well into the future (in this case until the year 2100), the authors have to turn to predictions on the variables they used for the calibration and backcasting exercise. They use socio-demographic scenarios from Lutz, Butz, and Samir (2014) , who provide projections by age, sex, and education levels for all countries of the world. Therefore, they are able to use these predictions for all relevant variables and make estimates about future migration stocks (of the working age population, age 25 to 64) between all country pairs worldwide until the year 2100. The authors use different scenarios in the population predictions and show predictions for different assumptions about the substitutability of low and high skilled labour, as well as different migration policies (reflected in migration costs). They predict that the share of migrants over the world population increases from 3.6% in 2010 to 4.5% in 2050 and to 6.0% in 2100, which equals an absolute increase of about 111 million people between today and 2100. In OECD countries the proportion of working age immigrants will increase from 11.9% to 27.5% in the next 80 years.

In a similar attempt, Burzynski, Deuster, and Docquier (2019) develop an SEM that has a similar basic model structure but extends it substantially. The theoretical framework additionally incorporates different sectors, accounts for in-country migration, technological change and individual decisions about education and fertility. The goal of the paper is to 'quantitatively analyse the root drivers underlying the long-term trend in the worldwide distribution of skills (i.e., domestic access to education, sector allocation of workers, and international migration) and highlight the implications of these root drivers for economic convergence and global inequality'. One of the ways in which skill is distributed across countries is migration and therefore migration can foster or dampen economic inequality in their framework. Since the authors model how migration reacts to changes to demographic and technological change, they are able to predict future migration stocks (again, for the working age population).

The authors of the latter paper have kindly provided us with their migration simulations for Germany over the next 80 years. We will present and compare their results with other predictions in the next chapter.

3.4 Qualitative versus Quantitative Modelling

Many of the caveats to quantitative forecasts outlined in the previous chapter also apply to qualitative forecasts. The lack of a guiding and unified theory of migration and the complexity of its determinants are independent of any methodologic approach; the anticipation of future shocks remains difficult for qualitative and quantitative researchers alike. In contrast to quantitative models, qualitative scenarios

[22] Described in Bolt and van Zanden (2014).
[23] Described in Arslan et al. (2016).

are expert-based rather than data-driven. Plausibility checks along the way help to avoid typical data-driven inaccuracies that stem from erroneous extrapolation of past (and often imperfectly measured) data or over-interpreting statistical artefacts (considering, for instance, that the increase in the number of recorded migrants after the collapse of the Soviet Union is a statistical artefact, rather than the mass movement of people after 1990[24]). While quantitative models rely on methodologic assumptions, rooted in statistical analysis (the next sections will explain a few of those assumptions), qualitative scenarios demand that experts postulate certain assumptions from which future scenarios are then derived. These are individual or consensus assessments about the determinants of migration, potential shocks to migration, including political or social change in the future. Usually, experts develop a variety of scenarios, where they explore different set-ups and their potential consequences. Often, qualitative scenarios are informed by existing data on migration and quantitative assessments of socio-economic and demographic developments in the future.

The International Migration Institute (IMI) in cooperation with the Amsterdam Institute for Social Science Research (AISSR) has developed a Migration Scenario Methodology which is an exploratory, qualitative migration projection or forecasting tool that seeks to identify possible future sources of structural change at the global level and their consequences for migration. Instead of coming up with forecast and projections in the form of numbers and giving concrete time-frames for different scenarios, the tool aims to develop narratives about the future of migration driven and developed by migration experts. Interactions between migration experts in the form of workshops aim to foster a vivid debate among researchers and policymakers alike.

The project was comprised of four main phases rolled out between 2009 and 2013. In the first phase, the researchers reviewed the literature on the main drivers of migration and adapted scenario methodologies from business and military to the migration context[25]. The authors elaborated a theoretical framework of the social, political, cultural, economic, demographic and environmental factors in sending and receiving countries that drive migration and set the framework through which experts would develop different scenarios. In the second phase, 25 experts and stakeholders from different backgrounds (geographically, academically, etc.) were invited to a workshop with the aim of developing ‘first-generation’ scenarios for migration to Europe. Experts developed 16 scenarios and identified future relative certainties and uncertainties. A subset of 8 scenarios were selected in the third phase of the project to be reiterated and deepened. An online survey among 50 migration experts was conducted in order to critique underlying assumptions and check plausibility. Respondents assessed the effects of technology and international networks on mobility; the effect of social norms and values on the composition of migrant populations; the interaction between xenophobia and migration policies, as well as the consequences of climate change, all within the context of migration from North Africa to Europe. In the fourth and last stage of the project, more experts gathered in various workshops to identify other emerging trends and uncertainties and apply the scenario methodology to concrete contexts and case studies.

One of the many outputs of the exercise is the identification of global ‘megatrends’ for future international migration. The experts have identified nine main factors: climate change, increasing networks & globalisation, ageing populations and shifting demographics, changing technology, declining population fertility, diversifying societies, increasing education, increasing longevity and urbanising developing countries. Other outputs included case studies on migration in the Pacific or the Horn of Africa and Yemen as well as policy briefs that contextualised and explained the scenario methodology to various stakeholders and policymakers.

[24] Özden et al. (2011).
[25] See Paoletti, Hein, and Carlos (2010) and Haas, Carlos, and Simona (2010) for a conceptual and methodological review

In a more recent qualitative exercise in 2017, the International Organization for Migration together with Friedrich-Ebert Foundation and Global Future developed four scenarios for the future of international migration and mobility with the help of a group of 50 individuals, comprised of migrants, policymakers, academics, opinion-makers and individuals from the private sector, think tanks, and international organisations. Similar to the Migration Scenario Methodology of the IMI and AISSR, these experts (although not only academic experts) gathered and exchanged their knowledge during several workshops. First, a scoping workshop served as a tool to identify the overarching principles of the migration scenario building; then a survey among the experts was conducted to narrow down the most important factors shaping the future of migration; lastly, two scenario building workshops and one webinar were held to design and flesh out the consequences of potential outcomes. As with most qualitative migration scenarios, the project was not designed to develop and propose concrete numbers on future migration flows but to illustrate how political decisions today may lead to different outcomes in the future (visualising the year 2030 as the cut-off point). Participants outlined the consequences of various scenarios for poverty, demography, inequality between and within countries, as well as the nexus between conflicts, failed states, and bad governance.

Both of these projects are illustrative of the exploratory approach behind qualitative migration scenarios. Experts from various backgrounds engage and exchange with one another to develop plausible scenarios for the future, critically assessing various dimensions that determine and are determined by migration. Most of these efforts do not aim to quantify, project or forecast migration but to contextualise the debate and point to potential consequences of policy decisions and changes on the macro-level.

There are some efforts to combine qualitative and quantitative approaches in migration forecasting. Sander, Abel, and Riosmena (2013) use a so-called multiregional flow model[26] and combine it with expert-based what-if scenarios to develop a set of projections until the year 2060. The authors first establish the main forces of migration through a review of the literature: I) geography and timing of international migration flows, II) the continuation of migration flows (state dependence and network effects of migration), III) economic forces, development and emigration IV) climate and environmental change V) shocks, violence, political upheaval, displacement, VI) migration policies and VII) socio-demographic factors.

In a second step, they use global estimates of international migration flow data between 1990 and 2010 for 196 countries (estimated from sequential stock data) to create a picture of current emigration and immigration rates. Departing from the main determinants of migration from the literature and data on current migration, expert views on the future of migration were collected in the form of an online survey. The survey was sent to all members of international population association to obtain expert opinions on the impact of various factors on future migration to and from a country of the expert's choice. Respondents were given various arguments. The arguments were divided across five broad thematic categories, along the lines of the determinants established in the literature review (such as economic development, climate change, demographic factors, cost of migration, migration regimes and policy). Within each of these categories, the researchers identified five to seven arguments or statements.

Overall experts had to make an assessment on a scale from -1 to +1 about whether a certain argument would have a negative or positive effect on net migration and give a validity score to that argument. For instance, one argument was 'Remittances will become more important for the economic development of migrant-sending countries' and respondents had to rate how valid this argument was and how strong of an effect it would have on emigration/immigration. Based on these scores, the authors were able to numerically weight different arguments for the development of migration scenarios. The results from the online survey were combined with an expert group meeting. Similar to purely qualitative scenario-building

[26] See Abel and Sander (2014) for an overview on the estimation of migration flow data.

workshops, experts from different geographic regions, scientific disciplines and areas of expertise (so called 'meta-experts' in total) exchanged their expertise and expressed their views on the importance of some migration determinants in the future. In contrast to conventional scenario-workshops, these experts had to quantify their assessments (on a scale, the same as in the online survey). In the end, combining the online survey with the meta-expert assessment, the researchers could develop 'net impact factors' for all arguments. These act as some form of 'weights' that not only determine the likelihood of the argument occurring (plausibility) but also how important it is for future migration flows (impact). Based on all of these assessments, the authors then developed three different scenarios.

The first scenario (the 'medium scenario') followed the meta-experts' suggestion to assume constant migration rates (not absolute numbers, in order to account for population change) throughout the projection horizon in 2060. In other words, existing emigration and immigration rates between 2005 and 2010 were assumed to continue linearly until 2060. For 25 countries, the expert group made adjustments to the baseline rate of 2005 to 2010 since these countries were confronted with an 'unusual' migration pattern during that time. In this very basic model, the authors estimate the world migrant population in 2060 to be at 350 million and the net migration (immigrants minus emigrants) to Europe and North America to be at about 6 million each in 2060. Emigration from South Asia and Africa is projected to increase over the next 40 years.

In addition to the medium scenario, the authors and experts developed two other scenarios, one named 'Rise of the East' (RE) and the other 'Intensifying Global Competition' (IGC). These alternative scenarios were built based on the assumptions and arguments developed by the meta-experts. The meta experts identified seven arguments as being the most relevant to shaping future trajectories of migration. The RE scenario is based on the argument 'Major economic recessions/stagnation in industrialized countries will lead to less demand for migrants' within the economic development category. It assumes stagnating economies in the West, resulting in restrictive migration policies, and the rise of South-East Asia as a main destination region. IGC assumes increased economic growth worldwide with an increase in competition for labour and other resources, resulting in liberal immigration policies and increased mobility. Assumptions in the IGC scenario are based on the net impact factor for five different arguments, namely labour and skill shortages, water conflicts, youth bulge, established networks and political instability.

The authors estimate that in 2060, IGC produces over 500 million migrants, RES less than 300 million. Depending on the scenario, the geographic distribution of migrants varies substantially. The fundamental feature of RE is that Western countries become less attractive to migrants due to their stagnant economies; at the same time, Western governments become more restrictive in terms of migration policy, which leads to a decline in migration to Western countries (cut by two thirds in Europe between 2010 and 2060). IGC, on the other hand, presents an alternative scenario with a flourishing economy in the West. Combined with demographic changes in the developing world and climatic and political shocks, migration to Europe is projected to increase by over 50% until 2060, it may even almost double for North America.

Overall, Sander, Abel, and Riosmena (2013) combine expert opinions with quantitative modelling to develop different scenarios for the future. However, their analysis shows that expert opinion on what is a crucial factor for the future of migration can vary substantially. In contrast to purely qualitative studies, the authors aim to attribute probabilities and weights to expert opinions by letting them grade the respective importance, which is important if we want to systematically integrate qualitative assessments into quantitative studies. Nevertheless, the selection of experts and their personal biases make it hard to consider those assessments as universal or common wisdom in the field.

Building on a similar strategy, Acostamadiedo et al. (forthcoming) studied future immigration to Europe in 2030 using a two-step approach. In the first step, the authors reviewed migration scenarios and forecasting studies from academic and grey literature, including the European Asylum Support Office, the Joint Research Centre from the EU, OECD, IOM, among others. Based on the review, they synthesised the most impactful and uncertain migration drivers to Europe in 2030, and summarised four migration scenarios. In the second step, using a Delphi survey to show the degree of expert agreement, the research team asked migration experts to rate the probability of each of the four scenarios becoming real, and the implications for total labour, irregular, and humanitarian inflows to Europe according to each scenario. Following this, they can provide a quantitative estimate of future inflows to Europe in 2030 within a range of plausible future scenarios. In contrast to Sander et al. (2013), the researchers provide the possibility for experts to incorporate changes in the size and direction of migration drivers in the future. However, their quantitative assessments purely rely on the experts' predictions and do not follow a quantitative modelling method. That is, experts suggest a specific number for migration flows for the year 2030 and are able to incorporate uncertainty and changes in migration determinants dynamically. However, these expert suggestions are not framed within or anchored in a quantitative model (like in Sander et al., 2013).

As mentioned in the introductory paragraph, both quantitative and qualitative migration forecasting methods have important caveats. The uncertainties described in Chapter 2 almost universally apply to attempts to predict the future of migration around the world. The question is how different approaches are able to mitigate these uncertainties. Table 5 compares how qualitative and quantitative models can address the different dimensions of uncertainty. In general, qualitative and quantitative models are quite complementary in the way they deal with different sources of uncertainty. The complexity of determinants and the lack of a unifying theory on migration can be accounted for, in part, through an exchange of expertise across fields and can include experiences of non-academic experts and other stakeholders. Quantitative models are usually highly simplified (for many reasons, as described in Chapter 2) and focus on one methodology that is then fed with data. Hybrid models across disciplines are rare in migration forecasting. On the other hand, the methodologic rigor of quantitative models allows (to an extent) transparency about the assumptions required to run the quantitative model (both statistic assumptions and model assumptions, as in gravity or structural models). These assumptions often operate in the background but are universally agreed on in the field, different assumptions create different quantitative methods. Therefore, the choice of model clearly reflects and signals the choice of implicit assumptions (for the expert, not necessarily for the layman). Qualitative models are more opaque in the set of assumptions that feed the experts' assessments. As in Sander et al.'s (2013) model, experts rate the accuracy and importance of the arguments without making explicit which assumptions led them to a specific assessment. Additionally, the scope of qualitative workshops is limited. The choice of experts and workshop formats may crucially influence the outcomes of qualitative scenarios. Which assumptions led to a specific workshop design? Why were these experts selected and not others? What is the optimal size of workshops? What are the participants' biases and how are they accounted for? If diverging opinions exist, how is this resolved? All of these questions are instrumental in understanding how a specific forecast was created. Unfortunately, many of these assumptions remain in the background of many qualitative analyses.

Table 5 Comparison between Uncertainties in Qualitative and Quantitative Modelling

	Qualitative Models	Quantitative Models
Complexity of Determinants	Can be partially accounted for through expert opinions & exchange	Depending on model, complexity can only be reflected in a limited way.
Implicit Assumptions	Difficult to make transparent how assumptions are formed and how they are weighted. „Trust“ in experts and compromise between divergign opinions required.	Assumptions are structurally clear (statistic assumptions are part of the model, theoretical assumptions are explicitly stated). Assumption tend to be strong. Models are very sensitive to changes in assumptions.
Imprecise Data	If data used: plausibility checks for observed data as a basis for future projections. Assessment on whether this is „out of the ordinary“ or expected to continue.	Data-driven approach makes predictions vulnerable to imprecise data.
Future Shocks	Short-run expert predictions may be possible. Long-rund uncertainty remains.	„One-Off“ shocks in short- and long-run difficult to incorporate in models.

For cases in which qualitative approaches use some data to inform their scenarios (even if the output is not numerical, qualitative methods may also consult existing data sets on main migration corridors, migration determinants or surveys), they tend to be less sensitive to imprecise data. A 'glib' in the data, migration caused by unique contexts, statistical or measurement artefacts can be reviewed and reappraised more effectively (especially if the model does not require data as input but only as context). Quantitative models, by nature, extrapolate in different ways from existing data and are therefore more vulnerable to their inaccuracies. However, it is imaginable that quantitative migration forecasters could construct migration data sets from past migration that treat these inaccuracies more carefully and may even remove that fraction of migration that is 'contextual' and separate a basic trend from 'noise'. Still, this can only be done through the introduction of many more assumptions that may be somewhat arbitrary (and introduce an additional source of uncertainty). Lastly, future shocks to the economy, technology, climate change or political stability can substantially alter the course of migration in the future. Both qualitative and quantitative models are prone to this source of uncertainty, especially in the long-run. Quantitative models follow a pre-determined metric which makes it difficult to incorporate 'one-off' shocks, even if they could be foreseen by experts. Qualitative models would, in theory, be able to account for potential shocks that announce themselves well in advance. Unfortunately, political escalation, economic recession or other shocks are difficult to predict, even in the short-run.

3.5 Strengths and Weaknesses of Quantitative Models

There is not only complementarity between qualitative and quantitative models. Different approaches within quantitative modelling should be considered jointly to get a more nuanced picture of likely scenarios in the future. Table 6 provides an overview of a few of the main papers for each of the methods presented in the previous sections, including hybrid models (e.g. mix between quantitative and qualitative approach). The table presents the main mechanisms behind the theory, which is particularly strong for structural models as they depend on explicit relationships between variables. In order to estimate future migration flows, structural models have to provide a guiding theory that determines which variables influence one another and which do not. In the papers on structural models described above, migration is driven by a few main factors, including wage disparities, differences in amenities, migration costs, education. Gravity models follow the basic mechanism that describes gravity as a trade-off between size and distance, which is re-interpreted in migration economics as pull factors (size, for instance, GDP) and migration costs (distance, for instance, geographic distance or language barriers). How the model is specified in an estimating equation and which variables are included depends on the underlying theory of the researcher. Bayesian models are not tied to a specific mechanism. Past migration determines (with various deviations) future migration without making strong assumptions about channels and mechanisms.

Table 6 Overview Quantitative Papers by Method

Model Type	Study		Mechanism	Inputs	Time Horizon	Coverage
Structual Models	Dao et al. (2018)	Global Migration in the 20th and 21st Centuries: the Unstoppable Force of Demography	Migration due to differences in wage and amenities	Socio-Demographic Projections by Lutz et al. (2014)	2020 - 2100 (10 year rhythm)	180 countries
	Burzynski et al. (2019)	Geography of Skills and global Inequality	Migration due to differences in wages, consumption and schooling cost	UN WPP & WDI Educational Attianment Data Theil Index	2010 - 2100 (30 year rhythm)	145 developing 34 OECD-countries
Gravity Models	Hanson & McIntosh (2016)	Is the Mediterranean the New Rio Grande? US and EU Immigration Pressures in the Long Run	Migration due to differences in labor supply, resulting from changes in fertility	UN WPP 2017 IMF GDP forecast	2010 - 2050 (10 year rhythm)	175 sending/ 25 receiving-countries
Bayesian Models	Azose & Raftery (2015)	Bayesian Probabilistic Projection of International Migration	Future migration depends on past migration and long-term migration	UN WPP 2010	2010 - 2100 (5 year rhythm)	197 countries
	Bijak & Wiśniowski (2010)	Bayesian forecasting of immigration by using expert knowledge	No theorethical implications	National Data Experts opinion on migration flows	2010 - 2025 (yearly rhythm)	7 EU countries
Hybrid Models	Sander et al. (2013)	The future of international migration: Developing expert-based assumptions for global population projections	Casual Forecasting Lutz (2012) Experts opinions on likelihood of certain scenarios	UN WPP 2010 Experts opinion (Members of 2011 WP council)	2010 - 2060 (5 year rhythm)	10 regions

Most forecasting efforts are directed towards very long-run predictions that may reach until 2100. Quantitative methods are not necessarily limited in the span they can cover. Theoretically, under a given set of assumptions, past data could be extrapolated indefinitely. However, over longer time horizons, confidence intervals of these forecasts increase substantially, such that the uncertainty and range of possible outcomes becomes so large that it is difficult to make any dependable claims on the future of migration. Most quantitative forecasters warn about the exponentially increasing uncertainty and caution the users of forecasts to discount claims made far into the future.

Geographic coverage mostly depends on the availability of data and is quite large for most quantitative forecasts. Mostly, migration forecasts are made on the receiving country level, e.g. how many migrants can a certain country expect over the course of a few decades. Breaking estimates down by source country becomes increasingly challenging. In particular, structural models rely on a large number of observations to be able to calibrate the parameters of various variables and predict future migration. On the bilateral level (e.g. between sending and receiving countries), there are only very few observations available (for instance, the World Bank bilateral migration matrix would only include six observations for each country pair). Consequently, estimates will be less accurate on the bilateral level and become more reliable as the aggregation level increases (country, region, continent). A higher aggregation level, however, limits the ability to make claims about the structure of future migration flows (main future corridors etc.) and consequently weakens policymakers' ability to design targeted migration policies.

This report assesses the strengths and weaknesses of different quantitative forecasting models as well as potential complementarities between them. Table 7 provides an assessment of Structural Models, Gravity Models and Bayesian Models along four dimensions: theoretical foundation, transparency of assumptions, data requirements and predictiveness of the model. Strengths are highlighted in green, weaknesses in red, mediocre performance along the dimension is marked in yellow.

- **Theoretical Foundation:** this dimension assesses in how far the model makes explicit through which channels future migration will be affected and how different factors interact with one another. A strong theoretical foundation requires a guiding theory about migration and its functioning.

- **Transparency of Assumptions:** this dimension assesses how the guiding theory is translated into a quantitative estimation of future migration flows. A high level of transparency presents the underlying assumptions of the model in an open and comprehensive manner.

- **Data Requirements:** this dimension assesses the scope and level of granularity required for the estimation strategy. High data requirements can pose a hurdle to a precise forecast of future migration flows, as only high volumes of data allow for decreasing errors and confidence intervals.

- **Predictiveness:** this dimension assesses whether the model is predictive, explanatory or descriptive in the design. High predictiveness models include time series models which are designed to extrapolate into the future rather than describe or explain current or past migration.

As already outlined in Table 6 for concrete research papers, the various quantitative methods approach migration forecasting from different angles. While Structural Models are theory-intensive and make explicit how different variables interact with one another, Gravity Models are guided by the principle of size and distance (as described in the previous sections). Bayesian Models do not make any claims about the determining factors of migration. This is also why many of the papers using Bayesian or Gravity Models do not make the key underlying assumptions of their models very explicit. This may be explained by the fact that, in many cases, once the quantitative approach is chosen, the underpinning statistics are assumed to be understood. But rarely do these models carefully develop and explain the choice of models or variables used in the estimation and the sensitivity of the estimation to changes in the choice of model or variables.

Table 7 Strengths and Weaknesses of Quantitative Migration Forecasting Models

Model Type	Theoretical Foundation	Transparency of Assumptions	Data Requirements	Predictiveness
Structural Models	strong	high	high	medium
Gravity Models	medium	medium	medium	low
Bayesian Models	weak	medium	low	high

There is an important trade-off between a strong theoretical foundation and low data requirements. While complexity of the theory (and the number of relevant factors and variables associated with it) is not necessarily a good proxy for the quality or strength of the theoretical model, it is obvious that a multitude of factors influence migration today and in the future. Incorporating only a sub-sample of the most important variables is data intensive. While Bayesian models can infer future trends from past data only, explanatory or descriptive models need an array of explanatory variables to make predictions about the future. Additionally, structural models require many observations to increase precision of the parameter calibration. Consequently, both the estimation method and the underlying theory of structural models require a substantial amount of data. These data requirements can introduce various biases and inaccuracies and may sometimes not even be available as forecasts (as described in Section 2.3).

Each forecasting method has its advantages and pitfalls. Overall, the methods are complementary and should be considered jointly by users of quantitative forecasts. Depending on the preferences regarding theoretical foundations, the transparency of assumptions, data requirements or the predictive structure of the model, different methods may be more suitable in certain contexts. However, all methods come with substantial uncertainty and should be interpreted with this caveat.

IV. Migration to Germany

This chapter presents Germany-specific forecasts from different methods and compares them. The goal is to make transparent how uncertainties and methodologic differences manifest themselves in quantitative migration forecasts. With the support of the authors of the main studies in the respective forecasting fields, this report extracts forecasts for Germany, visualises and compares them. The selected forecasts will be assessed along the four dimensions presented in Table 7 and differences will be highlighted. In light of these forecasts, the last section of this chapter outlines the particularities of the German migration context and describes their potential consequences for the accuracy of these forecasts.

4.1 Selected Forecasts for Germany – Assessment and Plausibility

The different forecasts for Germany were provided by the leading researchers in the field of migration forecasting. One to two forecasts were selected for each quantitative migration forecasting model presented in the previous chapter as a way of illustrating the wide methodological option space. The numbers are presented as net migration flows to Germany, e.g. the difference between the number of people who will immigrate to Germany minus the number of people who will emigrate from Germany (in millions). Depending on the data provided by the authors, we are able to also present confidence intervals as a measures of uncertainty for the respective predictions (we do so for the Bayesian models). This does not mean that other quantitative models do not produce these confidence intervals; they are just not represented in the graphs for the gravity and structural approach. In general, it holds true that for all models, the uncertainty will increase substantially over time.

Additionally, time-horizons of the forecasts differ. In principle, all models could yield predictions for any time-horizon and for any time-intervals (yearly, 5-year, 10-year or 30-year intervals). For gravity models and structural models, which need forecasts for the determinants of migration, the time horizon covered for migration will depend on the time-horizons covered in forecasts for their input variables (such as demographic change or productivity). Choosing the time intervals between reported estimates lie at the discretion of the researchers. Producing and comparing estimates for future migration flows to Germany bears the risk of concealing important differences in methodology, theory, and data used. Even if researchers produce similar estimates, that in itself would not suffice to validate a certain number.

The following chapter will present outcomes of different quantitative forecasting methods for Germany. Forecasts for each model should be interpreted with caveats and uncertainties presented in the Chapters 2 and 3. All forecasts have been developed using methods at the frontier of their respective fields with high internal validity. With regard to comparisons between methods, this report does not take a stance on which model is preferable but rather highlights the differences in the approaches and thus results. The report will briefly compare and contextualize the outcsmes of these forecasts, highlighting the sources of divergence in the respective estimates.

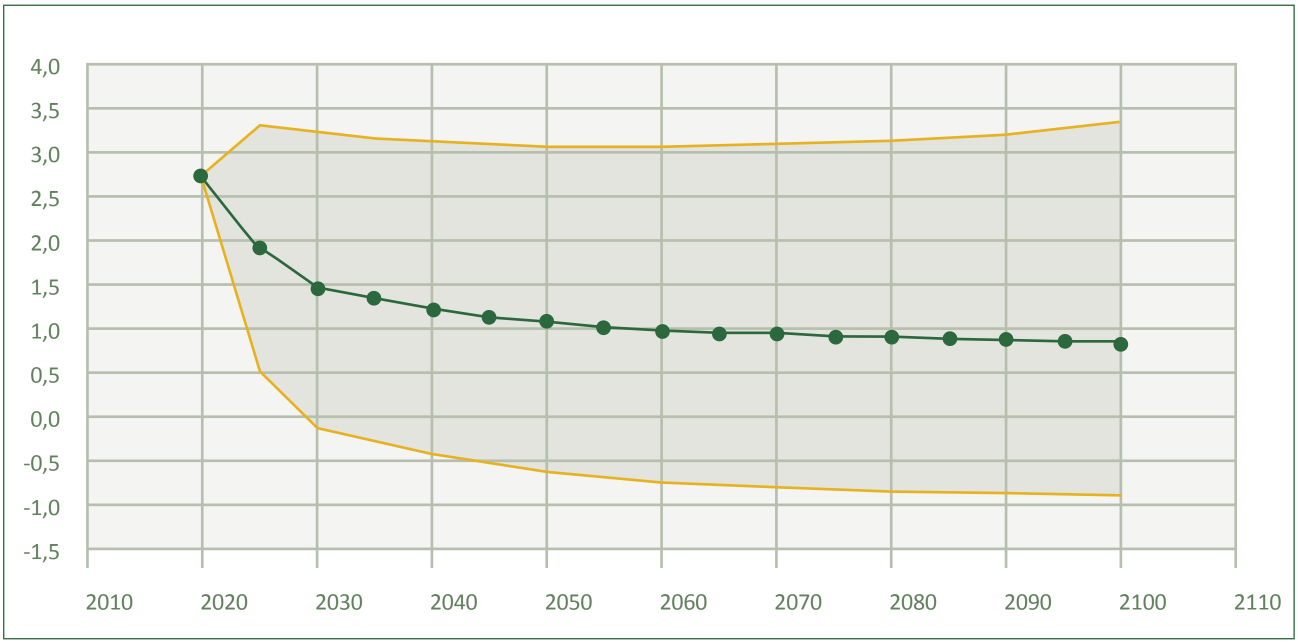
Example from Bayesian Models: Azose, Sevcikova & Raftery (2016)

Based on a Bayesian hierarchical model on net migration rates used in Azose and Raftery (2015) described in Chapter 3, Azose, Sevcikova & Raftery (2016) provide population projections for all countries, developing probabilistic projections for mortality, fertility, and migration. They argue that UN population projections vastly understate uncertainty because they do not take into account the uncertainty in migration projections, one major factor in population change. In order to adequately reflect uncertainty in population forecast, Azose et al. (2016) forecasts migration and include the uncertainty arising from it to the overall uncertainty in population projections.

For this report, Azose, Sevcikova and Raftery have shared updated migration forecasts for Germany until 2100, using migration data from the United Nations World Population Prospects 2019. As with all time series models, there are no assumptions about the determining factors of migration. Future migration is simply inferred from past migration patterns (again in hierarchical form, e.g. taking into account the particular country and the world), as described in more detail in Chapter 3. The red line in Figure 3 depicts net migration flows to Germany, the shaded lines show the 80% probability interval. Migration flows are expected to decrease sharply over the next 15 years and then stabilise at around 1 million starting in 2040. Confidence intervals remain roughly constant and very large after 2040, ranging from approximately -1 to approx. 3 million.

Inferring from past data, the post-2015 influx is considered as a one-time shock to net migration flows and the forecast shows that migration will revert back to a lower level. However, the overall level of net migration compared to the 1950 to 2015 period is estimated to be higher on average. In other words, the post-2015 influx is factored in as a onetime shock but one that i) adjusts expected net migration flows upwards and ii) increases the range of uncertainty in projections for Germany.

Figure 3 **Net Migration Flow to Germany (in million) from Azose et al. (2016)**



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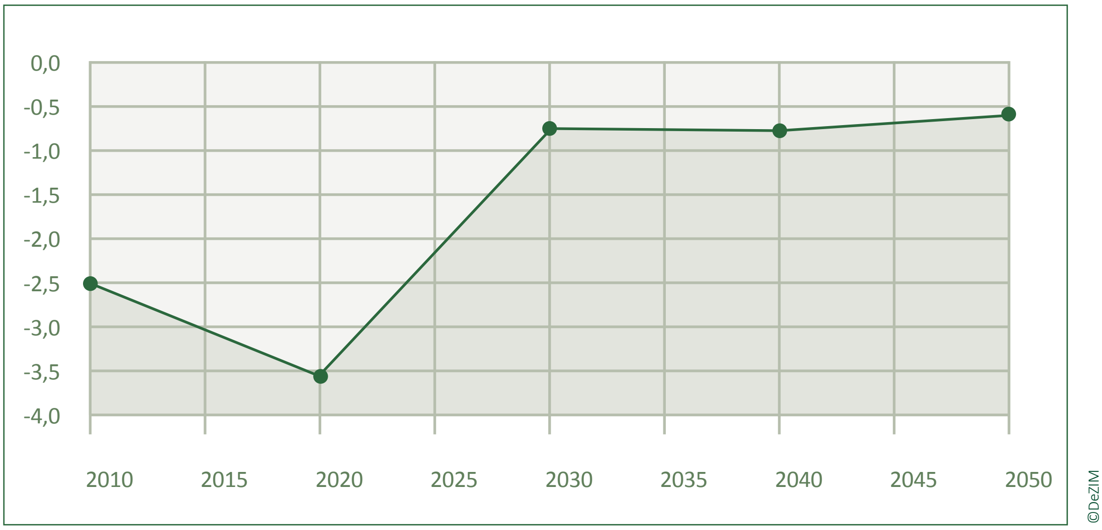
Example from Gravity Models: Hanson and McIntosh (2016)

In the Gravity framework, migration is driven by differences in labour supply resulting from differences in fertility rates, which is a demographic factor and is ought to be more stable over time. The authors argue that one can infer differences in labour-supply from fertility rates at least 15–20 years ahead. Furthermore, they include migration networks in their analysis and ascribe a driving role in predicting migration to it. Only with the interaction with existing migration networks in the destination country do changes in fertility rates translate into more migration.

Using the UN world population prospects from 2017, the DIOC data base and an extrapolation of the IMF GDP forecast of 2018, Hanson & McIntosh predict migration to Germany, measured by first-generation migrants, in the age group of 15 to 64. Relying on 2010 data, the migrant network in Germany seems to be not sufficiently high to foster migration into the country, conversely predicting a net outflow starting after 2020. In fact, the authors even predict ‘negative migration stocks’ for Germany, which in reality are not possible. The graph below converts negative stocks into net migration flows by subtracting estimated stocks over time.

Gravity models by their construction ascribe a large share of effect to GDP and distance, combined with predicted declining fertility rates of countries in close proximity, which leads to a decline in migration from close-by countries. Hanson & McIntosh take increasing fertility rates, for Sub-Saharan Africa as given. However, the moving costs are significantly higher, with no first common language, and few past colonial relationships. Migration networks are not big enough to reduce the cost of moving and lead to increasing migration. The gravity model linearly depicts the relation between the dependent and independent variables. In spite of including interaction terms and dummy variables, some interaction amongst the variables might be neglected. Using a structural model could give a more nuanced prediction.

Figure 4 Net Migration Flow to Germany (in million) from Hanson & McIntosh (2016)



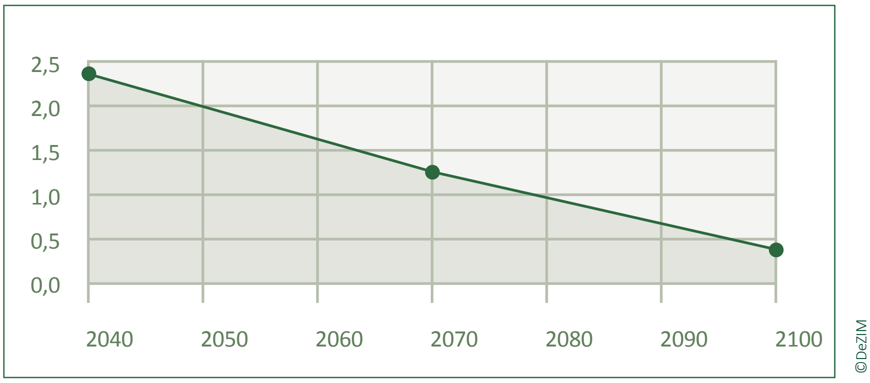
Example from Structural Models: Burzynski, Deuster and Docquier (2019)

In the class of structural models, Burzynski, Deuster and Docquier (2019) develop a complex econometrical model with high data requirements, where migration depends on differences in wages, consumption and schooling cost. The factors are modelled endogenously and depend on individual decisions about education and fertility. These choices further depend on the sector (high- vs. low-skilled) and the region (urban vs. rural) where the potential migrants live.

Using the UN World Population Projections and WDI data on educational attainment (the Theil Index for inequality is endogenous to their model), the authors predict the total migration stock for Germany, which is converted to flow variables for better comparison. They differentiate between home country, skill-level and region of origin (urban vs. rural). The graph below shows the net migration to Germany. Calculated for every 30-years, the model predicts net migration of 2.4 million to Germany in 2040. This number reflects the net migration in the past 30 years from 2010–2040. The authors predict a drop of net migration to less than 500,000 in the year 2100. While the stock of migrants slowly increases, the number of net migrants decreases. The authors estimate migrant stocks for the working age population in Germany, which are converted into flows for the below graph. The decrease in forecasted migration flow size comes directly from the underlying assumptions within the model of the input data. In particular, the authors assume a stagnation of the share of college educated workers and a marked slowdown in population growth for the OECD countries, whilst access to education and mobility restrictions in developing remain at a similar level.

Although the model gives detailed predictions on country and skill level, these have to be treated with caution. For the particular case of Germany, for instance, the stock of Mexican migrants is highly over-predicted with approximately 950,000 migrants in 2010, which does not reflect reality. Furthermore, the authors use the DIOC data base for calibration which does not include migration data for Germany from 2015 onwards. Consequently, the substantial increase in the immigrant stock over the recent year has not been taken into account.

Figure 5 **Net Migration Flow to Germany (in million) from Burzynski et al. (2019)**



All of the methods presented are highly sophisticated and executed by the leading researchers in the respective fields. Nevertheless, they make different predictions on the volume and direction of net migration flows to Germany. It is difficult to find an adequate comparison point for the three main reference papers Azose et al. (2016), Hanson and McIntosh (2016) and Burzynski et al. (2019). All of the papers provide a distinct prediction for the year 2040. However, the interpretation of those point estimates are different. A first glance, the numbers reveal that the estimates vary substantially across the models, ranging from a negative inflow (more people leave Germany than move to Germany) of -0.75 million in the gravity model to +2.34 million in the structural model (and +1.23 million in the Bayesian model). The range of predicted outcomes across models lies at 3 million. This first glance even underestimates the differences across models.

In fact, the differences in time-intervals have an effect on the interpretation on the point estimate. The data points illustrated for Azose et al. (2016), for instance, predict the net migration flow to Germany over the previous 5 years, while the data point in Burzynski et al. (2019) shows net migration flows over the past 30 years, that is, from 2010 to 2040. If we compared the 20-year span between 2020 and 2040 for all three papers, Azose et al. predict a 5.8 million[27] net migration flow, Hanson and McIntosh predict approximately -1.5 million (a net decrease in migration flows) and Burzynski et al. predict 1.5 million[28]. All of the estimations reveal largely diverging patterns for the next two decades.

The stark differences across these forecasts demonstrates the uncertainty involved in making predictions about the future. As outlined in the previous chapters, the differences in estimates arise from differences in estimation methods, data use and theoretical underpinnings. Therefore, it is crucial to understand the underlying concepts of these estimates before taking any number at face value. In Chapter 5, the report will outline how forecasts should be contextualised in order to make them a useful tool for policymakers, highlighting the role of both consumers and producers in the migration forecast ecosystem.

[27] This number is cumulatively added from the 5-year median estimates between 2025 and 2040; for full comparability one would have to add the migration flows of 2010 to 2020, since Burzynski et al. (2019) as well as Hanson and McIntosh (2016) use the World Bank migration data and thus 2010 as reference point. Azose et al. use 2014 as a reference point.

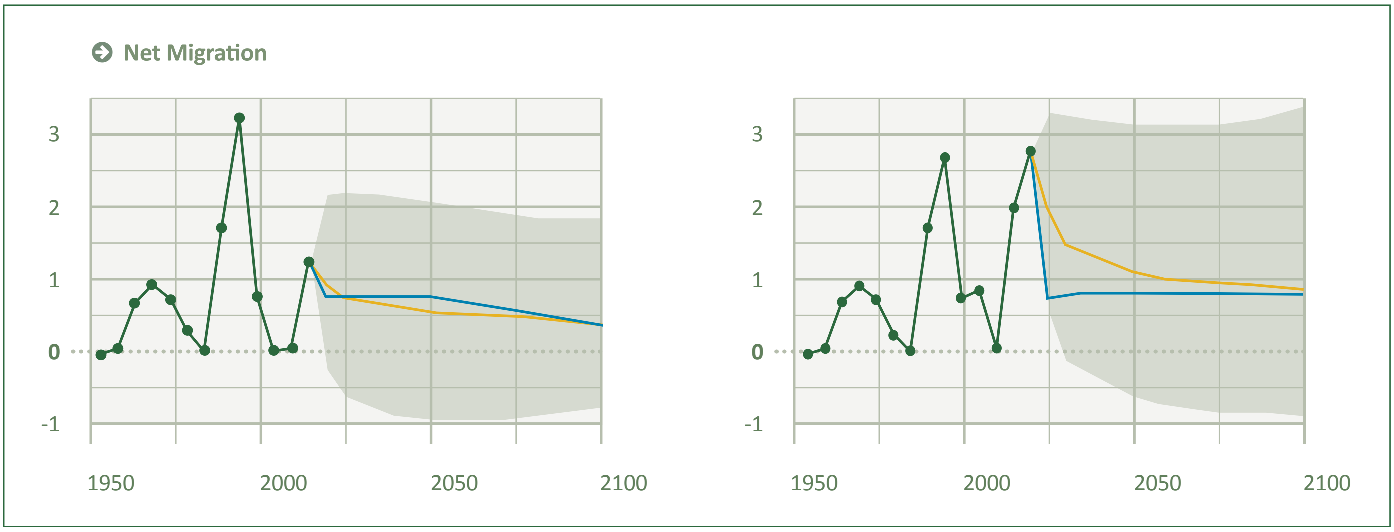
[28] Burzynski et al. (2019) do not provide a point estimate for 2020. The 20-year span net flow is linearly extrapolated from the net flow predicti on between 2010 and 2040.

4.2 Germany-specific Uncertainty

The first part of this chapter illustrates that forecasts for Germany can vary substantially. One of the main sources of variation (even within methods) can be traced back to whether the refugee influx of 2015 is already included in the data used for the forecasts. Particularly when it comes to network effects (one of the main determinants of future migration is the existing migrant stock from a specific source country), small shocks can alter future trajectories significantly. For instance, Burzynski, Deuster, and Docquier (2019) only include bilateral migration data from 2010 for their calibration, which reflects a very different migrant composition than only five years later. Decomposing the aggregate migration forecast for Germany by source countries reveals that the model produces very low immigration rates from Syria. In their model, out of an estimated 9.3 million immigrants in Germany by 2040, only about 25,000 come from Syria. In fact, this is only a fraction of the current Syrian migrant stock in Germany.

Gravity and Bayesian models suffer from the same issue. Azose and Raftery (2015) provided a comparison between migration forecasts to Germany, using the United Nations World Population Prospects (WPP) of 2015, which did not include the recent influx to Germany, with a forecast using the WPP of 2019 (see Figure 3). The red line presents the median forecasts under the Azose, Ševčíková, and Raftery (2016) model, the blue line is the United Nations projection (with deterministic migration). Not only do the UN and Azose et al. diverge (difference lies in how migration is modelled) but the same model produces substantially different migration predictions, depending on whether the 2019 data is used or not. Median net migration to Germany in 2100 goes from 400,000 to almost 900,000[29] and the probability bounds of 80% (highlighted in red) expand substantially.

Figure 6 Comparison between Migration Forecasts to Germany (left WPP 2015, right WPP 2019)



Source: Memo Sevcikova & Raftery (2019)

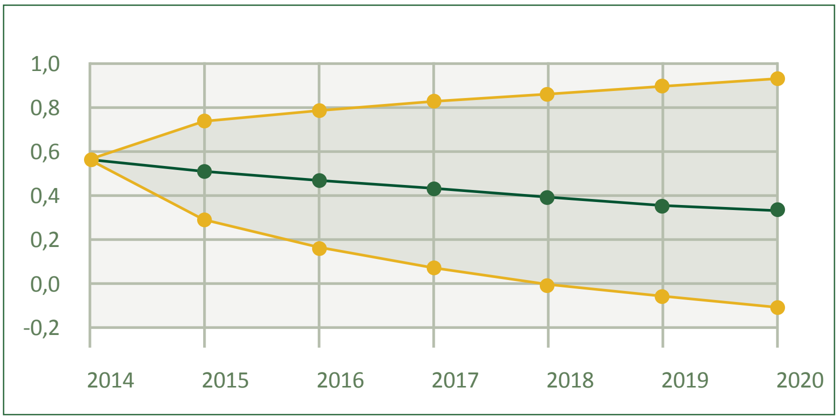
A similar example comes from the Global Migration Data Analysis Centre (GMDAC), for which Bijak has authored a policy brief under the IOM Data Briefing Series[30] emphasising uncertainty in migration forecasting. For this forecast, Bijak follows a fully Bayesian approach similar to the example in Chapter 3.1, choosing an AR(1) model, in the form $m_{ij,t+1} = c + \varphi\, m_{ij,t} + \varepsilon_{t+1}$. Hence, migration in period t+1 solely depends on migration in t and the choice of the model parameters. As an input variable, no expert opinions are included (Bijak & Wisniowski 2010 extend simple Bayesian forecasts with expert knowledge), parameters hence are

[29] The values should be interpreted as the net median number of migrants per five-year period
[30] The Global Migration Data Analysis Centre Data Briefing Series is available here: → **https://publications.iom.int/system/files/gmdac_data_briefing_series_issue_6.pdf**

determined by the choice of priors, their limits and distributions. Using these parameters, data is simulated, possible values from the distribution are drawn and combined and jointly determine the posterior distribution. The parameter values from the posterior distribution are then used for forecasting.

The middle line depicts the median prediction (upper and lower confidence bounds marked in orange). The estimation process follows a simple AR(1) , the authors predict a slow decay of net migration to Germany[31]. With normally distributed errors, the authors' most likely scenario (mean forecast) expected shocks to migration equal zero. Migration is predicted to decline from 580,000 per year in 2015 to approximately 320,000 in 2020, with a declining influence of past migration. This development follows strictly from the calibrated parameter value. The confidence interval shows the uncertainty coming with the forecast; if any shocks to migration occur (for whatever reason), the migration rate is likely to lie within the confidence interval from minimum -110,000 to 900,000 per year. The degree of uncertainty increases quickly: within five years the Delta is already one million migrants per year. In contrast to the structural equation model, we cannot ascribe the changes to underlying variables or development of fundamental variables which determine migration, but rather to model calibrations.

Figure 7 Net Migration Flow to Germany (in million) from Bijak (2016)



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The model was estimated using data on past migration flows for Germany between 1990 and 2014. Again, the 2015 influx has not been included in the estimation. Even though the uncertainty bounds are large and range from approximately 475,000 in 2015 to almost one million in 2020, the actual migrant inflow of 2015 lies well outside of the estimated uncertainty bounds (within the shaded lines). It follows that even if forecasts give space to uncertainty, unforeseen shocks can be so large that even the indicated range of uncertainty is not enough to cover all potential outcomes in the future.

While it is possible to continuously feed the models with the most recent data, shocks to the structure of migration are almost impossible to foresee well in advance. The sensitivity of quantitative models to these shocks is immense and most methods cannot distinguish between a unique event or a change in trends of migration patterns. If and to what extent these shocks should be included in the forecasting models is at the discretion of the forecasters. Typically, they take an agnostic approach and include the data at face value without making any assumptions on the nature of the shock and its probability to continue in a certain pattern. This is where hybrid models, e.g. a combined approach of expert-based judgement and quantitative methods, can become a valid alternative. Understanding the sensitivity of quantitative

[31] Bijak does not use the stationarity assumption in this model. The author points to the fact that the non-stationarity of this AR(1) process is quite high, namely at 10% for immigration and almost 25% for emigration.

models to fluctuations in the data and adapting the input accordingly, based on plausibility and qualitative assessment of the data structure, may help attenuate these sources of uncertainty in quantitative models. However, the usual caveats to expert-based assumptions outlined in the previous chapter still apply and should be taken into account when interpreting hybrid models.

In addition to particularities in Germany's recent change in migration structure, there are also other economic, political and social dimensions that quantitative models (especially if they are anchored in theory) cannot integrate sufficiently. Structural models, for instance, can incorporate meta-level trends that affect migration, such as population growth, technological change or assumptions about the restrictiveness of migration policies. These models are designed to reflect transformations at the global level, usually because they are fed with global migration data. These trends may not apply to the German context and can distort forecasts at the national level. For instance, the structural model in Dao et al. (2018) incorporates the effects of global wage inequalities on migration and the effect of migration on wage inequality. In comparison to purely descriptive models, this is a sophisticated approach of approximating the two-way interaction between wage differences and migration in a forecasting model. However, this interaction effect is assumed to be homogenous across countries (depending on the existing inequalities and population growth). In other words, the mechanisms through which income inequality affects migration and how migration affects inequality is assumed to be identical for all countries, controlling for baseline characteristics. This is questionable since rigidities in the labour market (for instance, the existence of a minimum wage or the bargaining power of unions) can vary substantially even within high income countries. The model parameters will be calibrated based on an average effect, combining the overall interaction effect between inequality and migration worldwide. An application to the German context, using the calibrated parameters from a global analysis, is therefore imprecise by construction. This is also why structural models are performing well in back-casting exercises at the global level but decrease in accuracy at the disaggregate level (when retrofitting the model at the regional or national level).

When assessing uncertainty of forecast at the country level, economic and societal challenges of the future need to be accounted for. The attractiveness of a certain destination country is constantly re-evaluated. One overarching development in Germany is the changing income structure, particularly the decreasing middle class. Recent data from the SOEP confirms that income inequality is increasing in Germany. While the highest incomes increased over the last years, middle net house hold income stagnated. The lowest deciles even face declining real income, stagnating real wages, and increasing share of part-time employment (Grabka and Goebel 2018). While Germany today is perceived as an attractive destination country, recent studies paint a more nuanced picture. Germany appeals mainly to students and entrepreneurs, but is of only average attractiveness for high-qualified workers as compared to other OECD countries (OECD/Bertelsmann Stiftung 2019)[32]. Hence, income opportunities, economic inequality and the structure of the job-market are major determinants of migration and have been in flux over the last decade. An economy in flux changes the attractiveness of a certain destination country. At the same time, changes in the economic make-up of a country influences migration policies, which in turn affect subsequent migration. For instance, Germany has recently passed the Skilled Immigration Act with the aim to facilitate high-skilled migration from countries outside of the European Union. This is a reaction to a steadily increasing demand for high-skilled labour that is not met with domestic or EU workers.

Another particularity of Germany is its membership in the Schengen area. Forecasting models consider each country separately and general equilibrium effects are usually not taken into account (except for hierarchical Bayesian models – but quite crudely – or for assumptions of zero total migration, e.g. emigration has to be the same as immigration at the global level). For instance, migration from Ukraine to Poland (a Schengen member) under a special visa agreement between the two countries will also affect all other Schengen countries, including Germany, because of free mobility of persons in the Schengen space. There are substantial spill-overs in migration flows across countries that belong to the same mobility space. These interaction effects are typically not considered in forecasting models, which conceptualise migration from and to another country as a bilateral rather than a multilateral process. Germany's position in the Schengen area pulls together all of the uncertainties described in Chapter 2.

The complexity of migration determinants goes beyond national or global trends to include regional interactions and policy spaces, which are even less theorised than 'traditional' migration processes. Implicit assumptions in these models include the fact that Germany and all other countries are considered to be independent or insulated in their migration policies. In the structural model presented in the previous chapter, for instance, Germany's migration policy response is independent of other EU or Schengen countries, which is not the case. While EU countries are free to legislate migration laws, policies such as the European Blue Card, a EU working permit similar to the Green Card in the United States, are the result of negotiations among many countries. Even if these complexities were incorporated in the models, the data on mobility within the Schengen zone is even weaker than data on migration from third-countries into the EU. In the absence of border controls and lax enforcement of mandatory registration at local population registers, data of high velocity and volume are even harder to find in this setting.

V. Conclusion and Policy Implications

The goal of this report is to critically assess the increasing demand and the supply of quantitative (and qualitative) migration forecasts in migration research and policy making in recent years. Especially in Germany, the influx of refugees in 2015 was – among many things – also a crisis of preparedness and foresight, and the lack thereof. As outlined in Chapter 1, many legislators and policymakers consider the political and financial investment in forecasting efforts as a necessary step to remedy past mistakes and prepare for the future. However, over-confidence in migration forecasting tools, particularly in the very long run, can lead to adverse outcomes. The greatest risk is that instead of preparing for uncertainty, decision-makers prepare for a false certainty.

It is important to note the distinction between early warning systems, or short-run forecasts, and forecasting methods that span several decades. Early warning systems can use expert opinions and 'real time' data to make a judgement on how many people are expected to migrate in response to an event or overall (political, technological, climatic) development in certain source regions. Monitoring migration from source countries to their neighbouring countries, information provided by embassies, development agencies, NGOs, or ad-hoc interviews with migrants in the field can give insights into the magnitude and likelihood of onward migration. This is a decentralised information gathering effort that results in an assessment of migration flows in the coming years. A forecast draws its predictions from a pre-defined method. The approaches can overlap in part but follow different methods and have different goals. While short-term forecasts have the capacity to inform and guide policy decisions, migration forecasts serve as an overarching framework that helps to understand basic mechanisms of migration and marries theory with data in an attempt to build scenarios for the future of migration.

Forecasting is an indispensable part of basic research on demography and migration. Developing scenarios for the future means understanding migration today, the underlying theory, the strengths and fallbacks of data, and their vulnerability to shocks. Paradoxically, research in migration forecasting serves as a remedy to the problems from which it suffers. More than any deterministic or explanatory quantitative model, forecasting models confront us with the limits of what we know, or can know, about migration today. Migration forecasting is (especially when it comes to gravity or structural forecasting models) still in its infancy. However, efforts to improve them have been fruitful, even over a short time span. Continued research can and should be encouraged, as many of the limits of forecasting can be overcome in the next decades. Improved data gathering and sharing (as called for in the Global Compact for Migration[33]) may help to draw from more accurate data of higher volume and velocity and more sophisticated machine learning tools help to facilitate the processing of complex migration determinants. These are important developments that will continue to improve migration forecasting. However, the results of these forecasts, at least for the moment, should be interpreted with great care if they are used to inform migration policy.

As presented throughout the report, there are substantial uncertainties in migration forecasts. Predictions vary substantially depending on the underlying models and the data used. Even small changes in assumptions or additional data points can result in large deviations within and across forecasting methods. Consequently, it is important to interpret forecasts with caution and become familiar with the fundamental structure of the models in order to contextualise any specific number that the forecasting method produces. Rather than focusing on the absolute predicted number of migration inflows in the future, the

[33] The Global Compact for Safe, Orderly and Regular Migration, a resolution adopted by the United Nations General Assembly on December 19th 2018, agreed on 23 objectives. The first objective is to 'Collect and utilise accurate and disaggregated data as a basis for evidence-based policies'.

careful user of migration forecasts will direct his or her attention to how changes in assumptions result in changes in predictions. In other words, how will a change in the income structure (in the form of higher wage inequality in industrialised countries, for instance) affect migration from the Global South to the Global North? What do different models conclude? Is it positive, negative? Is the expected effect large in magnitude? Focusing solely on a predicted, absolute outcome, or even a range of outcomes, will obscure the ground on which the forecast is resting and make it hard to assess its plausibility.

As the demand and supply of migration forecasts has increased over the last years, policymakers have to navigate an ever increasing maze of methods and predictions. A comparative analysis of different methods becomes more difficult and forecasters can help to increase transparency. Diverging predictions may cause confusion. In order to contextualise migration forecasts for policymakers, researchers and experts can preface their analyses with a sheet that makes the analysis more transparent and can serve as user's guide. If forecasters use a short and concise summary along the similar guiding questions (explained below), policymakers can make more informed inferences from the respective forecasts and are enabled to use them as an impulse for discussions rather than taking any specific number at face value.

The guide could cover seven dimensions (see box below), which are necessary to understand, interpret and compare the respective model: model type, theory and assumptions, determinants and mechanisms, data, time horizon and frequency, prediction and uncertainty, scenarios and sensitivity. The guiding questions address the main sources of uncertainty (assumptions, data etc.) and make explicit what theory and mechanisms are at play. Note that only one of the seven dimensions, 'predictions and uncertainty', is concerned with producing a specific number and the number is not divorced from the uncertainty associated with it. Additionally, different scenarios should be provided and the quantitative prediction should be reexamined using different assumptions, different data time frames or definitions, etc. This may help to understand how sensitive (in magnitude and sign) models are to these changes.

At the same time, users of migration forecasts should formulate clear expectations of such forecasts. First, is there an interest in long-run forecasts or are primarily early warning systems the source of attention for this topic? Encouraging and developing forecasting models may be very different from short-run forecasts and that should be made transparent from the beginning. In a second step, the user of these forecasts should consider whether theory based models or purely data driven (often time-series) models are more appropriate. If theory based models are more attractive, then it is time to investigate whether the model assumptions, the determining variables used and the mechanisms are convincing. Additionally, uncertainty and different scenarios should be considered, knowing that the forecast is more likely to provide inaccurate rather than accurate results. Lastly, users should interpret these forecasts with an eye on the policies or strategies that will be informed by these forecasts; are they compatible with the large uncertainties involved in making these predictions?

Transparency in Migration Forecasting

- **Model Type:**
  to which family of forecasting models does your approach belong to?

- **Theory and Assumptions:**
  what are the theoretical foundations of the model that affect future migration? Which are the assumptions underlying the method (statistical assumptions) and which are the assumptions introduced by the researchers (theory assumptions)?

- **Determinants and Mechanisms:**
  what are the main determining variables used in the model and what are the mechanisms through which the determinants affect future migration?

- **Data:**
  which data sources are being consulted for all variables included in the model?

- **Time Horizon and Frequency:**
  what is the time horizon of the forecast and why was a specific time span and time intervals chosen for the forecast?

- **Predictions and Uncertainty:**
  what is the estimated stock or flow of migrants and how large are the uncertainties? If forecasts are based on other forecasts, how are the respective uncertainties incorporated?

- **Scenarios and Sensitivity:**
  can you provide forecasts for different scenarios? How does the model react to tweaking assumptions and theory? How does the model react to different use of data? How does the model compare to other forecasts and why do they differ?

Migration forecasts are an important policy tool. However, research efforts and policy perspectives have yet to come together in a comprehensive manner. This report gives an overview on the most important forecasting methods in migration and uses Germany as an illustration of how these methods – while being highly sophisticated and internally coherent – can produce different outcomes. This report is also a call for more transparency from both producers (in terms of methods and uncertainty) and consumers of migration forecasts (in terms of choice and purpose of forecasts). As mentioned before, migration forecasts have become and will remain a main staple of basic migration research and new data and statistical tools promise great improvements in forecasting in the future. For the moment, however, they should be regarded as a window to understanding the overarching concepts and trends, dynamics and mechanisms of migration, rather than a window to the future.

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