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Parsimonious stochastic forecasting of international and internal migration on the NUTS-3 level – an outlook of regional depopulation trends in Germany

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Abstract

Substantiated knowledge of future demographic changes that is derived from sound statistical and mathematical methods is a crucial determinant of regional planning. Of the components of demographic developments, migration shapes regional demographics the most over the short term. However, despite its importance, existing approaches model future regional migration based on deterministic assumptions that do not sufficiently account for its highly probabilistic nature. In response to this shortcoming in the literature, our paper uses age- and gender-specific migration data for German NUTS-3 regions over the 1995–2019 period and compares the performance of a variety of forecasting models in backtests. Using the best-performing model specification and drawing on Monte Carlo simulations, we present a stochastic forecast of regional migration dynamics across German regions until 2040 and analyze their role in regional depopulation. The results provide evidence that well-known age-specific migration patterns across the urban-rural continuum of regions, such as the education-induced migration of young adults, are very likely to persist, and to continue to shape future regional (de)population dynamics.

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1 Introduction

Regional differences in demographic trends related to population size and structure are well documented across countries (see, for example, BiB, 2021; De Beer et al., 2010; OECD, 2018, among others). Having precise knowledge of the quality and the quantity of those developments is crucial for regional infrastructure planning, such as for estimating the supply of childcare and schools needed, or for labor market planning (Wilson, 2015a; Zhang and Bryant, 2020). Similarly, the future demand for healthcare due to population aging (Vanella et al., 2020b) or for housing depends on the future population size and structure (Gløersen et al., 2016; Vanella et al., 2020a). Therefore, both governments and enterprises have a strong interest in regional population forecasts that can provide them with a quantitative basis for decision-making (Wilson et al., 2021).

Notably, of the three components of demographic change – fertility, mortality and migration – migration shapes regional populations the most over the short term (Deschermeier, 2011), while fertility and mortality trends are more important over the long term (Vanella et al., 2020a). Migration dynamics can have substantial effects on a region's population, and particularly in smaller areas, where outflows can have a large impact on both the size and the structure of the population (Deschermeier, 2011; Zhang and Bryant, 2020).

The causes and the consequences of migration are multi-faceted, and have been studied using a wide range of approaches across disciplines.[1] However, a pivotal distinction can be made between its two different but nonetheless contiguous components: internal and international flows.[2]

Discussions of internal migration frequently address issues such as persistent net out-migration from economically weaker regions, particularly among younger, more educated and skilled sub-populations, which is likely to be driven by varying regional opportunities (Fratesi and Percoco, 2013; Sander, 2014). Regional heterogeneity in mobility, health services, shopping opportunities, housing, labor market opportunities and education (Zhang and Bryant, 2020), or in attractiveness (Skirbekk et al., 2007) based on factors such as architecture and landscape, may drive

[1] Given the scope of this paper, we do not provide a comprehensive cross-disciplinary review of approaches to (regional) migration. However, suitable starting points for corresponding investigations may be recent contributions across disciplinary boundaries, such as in King (2011) or Pisarevskaya et al. (2020), among others.

[2] In this paper, the term *flow* generally refers to any migratory movement of people. Normally, the flows are documented as directional data, i.e., as migrations from certain origin regions to certain target regions.

internal migration, and can ultimately lead to the emergence of regional demographic disparities in larger countries (Eberhardt et al., 2014). Importantly, when a significant share of the younger population leaves a region, an echo effect can occur: i.e., as the population of reproductive age decreases, birth numbers decline, which, in turn, further accelerates depopulation trends.

By contrast, a wide range of factors, from crises and macroeconomic conditions (Vanella and Deschermeier, 2018) to environmental change (Black et al., 2011), can heavily affect international migration flows. In host countries, international flows are likely to affect different regions to varying degrees (see, for example, Heider et al., 2020, for the case of German regions). Moreover, there is evidence that the two components are closely intertwined (see King and Skeldon, 2010 for a comprehensive discussion): i.e., high levels of international immigration lead to further internal migration flows. For instance, the correlation coefficient between annual international immigration to Germany for the years 1994 to 2018 and the one-year delayed out-migration of the German districts (i.e., migration over district borders in 1995–2019) is 94.8% (own computation based on GENESIS-Online, 2021; Statistische Ämter des Bundes und der Länder, 2021a).

Given the fundamental complexity of migration and its importance for regional demographic changes, and thus for regional planning in general, gaining a better understanding of future developments in regional migration is key to developing policies aimed at either counteracting regional depopulation and aging or mitigating the expected developments by, for example, adjusting infrastructure supply based on diminishing or changing regional demand (Iwanow and Gutting, 2020; Krüger, 2020). However, the existing approaches do not account for uncertainty in regional migration projections (e.g., Maretzke et al., 2021). By relying on deterministic assumptions, these projections are generally unable to quantify the probability that specific migration scenarios will occur, or the resulting migration flows. Given the importance of migration for regional population dynamics, these approaches clearly have significant shortcomings. At the same time, modeling migration is demanding, as it has a high degree of stochasticity; that is, migration tends to be volatile and sensitive to acute events (Vanella and Deschermeier, 2018). In the present paper, we evaluate potential approaches to incorporating stochasticity into small area migration forecasting, while simultaneously accounting for varying patterns and correlations across different age groups and regions. By incorporating both international and internal migration into a joint framework, we propose a novel, parsimonious stochastic forecasting approach.

The remainder of the paper is structured as follows. In the next section, we give a short overview of the state of research on migration projections with an emphasis on regional migration and discuss the features and limitations of existing (deterministic) approaches. In the third section, we introduce the data sources used and the properties of the best-performing model among a variety of models compared based on a backtest. Then, based on this model, we provide in the fourth section a stochastic forecast of age-specific future migration among German regions until 2040, indicating both the extent and the probabilities of migration-induced population declines. In the last section, we present our conclusions and a discussion of the results and the limitations of the study, while pointing out the need for more detailed data and further methodological advances.

2 (Regional) migration projections: An illustrative overview

Typically, population projections take into account three demographic components of population change: fertility, mortality and migration. Those projections draw on a variety of methodological procedures at both the national[3] and the regional level.[4] Notably, of the three major components, migration is the most challenging to forecast (UN DESA, 2022), largely due to data limitations caused by the under-detection of actual migrations in the reported data (Rogers et al., 2010), and to inconsistencies between different datasets and territorial changes, which can complicate the construction of consistent time series (Vanella and Deschermeier, 2018). Moreover, the sensitivity of migratory movements to political, social, economic and environmental trends and events implies that such movements are characterized by high stochasticity and inherently limited predictability. This is because the phenomena underlying migration may themselves be difficult to predict (Vanella and Deschermeier, 2018, 2020), and can appear rather abruptly, as demonstrated by the war-related refugee flows from Syria and Iraq between 2014 and 2016 (Vanella et al., 2022), or, more recently, the refugee flows from Afghanistan (Heidelberg Institute for International Conflict Research, 2022) and Ukraine (UNHCR, 2022).

Given the wide range of challenges associated with migration forecasting, there is no consensus on "best practices." Approaches differ regarding *what* and *how* to forecast; that is, regarding which target variables should be used, e.g., what modeling flows or rates should be employed and what degree of detail they should have. Moreover, there is no consensus on the overall modeling framework that should be used. The latter raises questions that are inevitably related to the incorporation of risk and uncertainty in the model, including questions ranging from what estimation strategy and what determinants should be used, to what cross- and autocorrelations should be considered, to what underlying assumptions about future migration should be included.

2.1 Flows, rates and the degree of detail: Target variables

Initially, migration forecasts depend primarily on the target variables to be modeled. While the approaches used by the statistical offices generally target gross or net

[3] For a general overview, see Vanella et al. (2020a).

[4] A recent comprehensive survey is given by Wilson et al. (2021).

migration flows, many authors, such as Bijak (2011) or Fuchs et al. (2021), have argued against forecasting migration flows. Fuchs et al. (2021) pointed to the "philosophical advantages" of forecasting migration rates instead of flows. Migration rates show relatively robust age patterns (Rogers and Castro, 1981), which implies that rates should be less volatile than flows. Migration rates are computed based on the population at risk of migrating. Consequently, forecasting rates rather than flows accounts for structural changes in the size and the age structure of the population, which can, in turn, significantly influence migration flows. Moreover, forecasts of migration flows using very small baseline populations, such as the oldest-old or the populations of sparsely populated regions, may lead to negative simulations for the end-of-period population. This combination may, in absolute values, result in net out-migration estimations that exceed the initial population base – which is, obviously, impossible (Fuchs et al., 2021). Thus, particularly, albeit not exclusively, in regional forecasting contexts, estimating rates appears to have advantages compared to estimating flows.

Indeed, regional migration rate forecasts have a long tradition (see, e.g., Rogers and Castro, 1981 or Rogers et al., 2010). However, one clear limitation of forecasting regional migration rates is that in-migration rates are difficult to define. Whereas out-migration rates from one region can be easily computed, at least in countries with adequate regional population and migration data, computing in-migration rates is not as straightforward, since the baseline population is not well-defined. Calculating migration rates based on the regions of origin of the migrants is not feasible in many contexts, and especially in the case of international migration from countries with less reliable statistical documentation. While computing rates based on the corresponding population of the target region for the purposes of projection is an alternative approach, it is philosophically questionable, as we do not use the population at risk in the denominator, but instead approximate the gravity of more populous regions in lieu of computing migration rates (Fuchs et al., 2021).

In addition to the question of whether to model flows or rates, the question of what degree of detail is appropriate can arise when deciding whether to incorporate the target variable disaggregated by categories such as age, gender or citizenship, as substantial differences in these categories have been documented. Raymer et al. (2011) estimated migrations by origin, destination, age and gender for European countries, and found age- and gender-specific patterns across countries. Similarly, Van Mol and de Valk (2016) demonstrated that the age and gender structure of migrants differs depending on both their citizenship and their destination country.

2.2 Consistency in forecasts of internal and international migration

On the regional level, migration comprises both international and internal flows. These flows affect and shape regions within a country quantitatively and qualitatively, and to different degrees (Fratesi and Percoco, 2013). In Germany, for example, distinct internal migration patterns have been observed in recent decades, as, following reunification, the number of people migrating from East Germany to West Germany greatly exceeded the number of people migrating in the opposite direction (see, as a recent example, Rosenbaum-Feldbrügge et al., 2022). While this demonstrates that both components should be included in projections, it also suggests that the target variables should be further distinguished for this category as well. The latter point is again supported by empirical evidence. For example, in the case of Germany, scholars have shown that out-migration from East Germany is selective in terms of age and gender (Kröhnert and Vollmer, 2012; Leibert, 2016).

However, relying on highly disaggregated target variables along all these dimensions faces two limitations in empirical applications. First, detailed regional migration data[5] are usually sparse (Rowe et al., 2019; Wilson et al., 2021). Second, even when these data are available, the dimensionality increases drastically, particularly for approaches that include region-to-region flows, which may even be disaggregated by gender, age and citizenship, as outlined above.

Migration projections that focus on the national level, such as those by UN DESA (2022), do not cover the regional perspective, and are, therefore, not necessarily compatible with regional projections for the same country. For the case of Germany, Maretzke et al. (2021) followed a hierarchical procedure that, first, assumed one of the variants suggested by Destatis (2019) for international migration between Germany and other countries, and, second, assumed internal migration rates in Germany based on a qualitative assessment and past data. While this approach has merit, it cannot capture changes in internal migration patterns after immigration shocks.[6] Moreover, due to its complex model structure, which is based on bi-directional internal migration, it is not feasible to sufficiently incorporate uncertainty into the projection, particularly given the high stochasticity in international migration (for more on that problem, see Section 2.4).

2.3 Modeling migration processes and determinants

Closely connected to questions of which target variables should be selected is the decision about which general modeling framework should be used, e.g., which migration determinants should be included. A large body of literature has emphasized the importance of including determinants in analyses of migration patterns. Among the potential drivers of migration that have been discussed in the literature are economic reasons (e.g., Bertoli et al., 2013; Grogger and Hanson, 2011; Mayda, 2010), the impact of education (e.g., Bernard and Bell, 2018; Lutz and KC, 2011;

[5] Bell et al. (2014) present a comprehensive overview of internal migration data for the 193 UN member states.

[6] Even after internal and international migrations have been separated, there is still a variety of possible approaches to incorporating these flows. Interested readers may consult Rees et al. (2015), who discussed a variety of approaches to modeling international migration streams in subnational population projections.

Lutz, 2021), network effects (e.g., Beine et al., 2011; Pedersen et al., 2008), the institutional framework (e.g., Geis et al., 2013; Ortega and Peri, 2013), personal preferences (Mulliner et al., 2020; also *amenity migration*, e.g., Steinicke et al., 2012) and environmental causes (e.g., Beine and Parsons, 2015; Black et al., 2011; Cai et al., 2016).[7]

Notably, these scholars found that the observed migration patterns are usually explained by more than one of those drivers, or by interactions between them. For example, Leibert (2016) attributed the abovementioned internal migration in Germany, in which gender-selective out-migration plays a large role, to a combination of economic and context-specific institutional factors, including the labor market situation in East Germany after reunification combined with high levels of labor force participation among East German women. Heider et al. (2020) found that the locational choices of international migrants across German regions are strongly driven by network effects as well as by individual-level factors, such as educational considerations. Prenzel (2021), using German data, showed that regional population aging fueled by the selective out-migration of younger individuals may itself reinforce out-migration, and thus that polarization dynamics, in addition to the other discussed reasons, may be another explanatory factor in regional migration patterns.[8]

Just as a variety of migration determinants have been discussed across disciplines, a wide range of approaches have been used to forecast migration. While statistical offices (e.g., UN DESA, 2022) tend to rely on rather simple models for migration computations, more sophisticated alternatives have been applied in the literature. For instance, Kubis and Schneider (2020) used an econometric panel model that predicted immigration and emigration by EU citizens in Germany, and included labor market and freedom-of-movement variables as predictors. Lipps and Betz (2005) suggested forecasting cumulative net migration to Germany using an ARIMA model. Vanella and Deschermeier (2018) proposed ARIMA forecasting of principal components derived from age-, gender- and nationality-specific net migration to Germany. Moreover, migration forecasts between certain regions can also be performed based on directional models. Examples of studies that used this approach include Abel and Cohen (2019) and the sources cited therein. An example for forecasting bi-directional flows between Germany and Poland was provided by Bijak (2011).

Importantly, the methodological approach to migration forecasting may also vary depending on the extent to which cross-correlations between in-migration and out-migration, age and gender groups (which also model family migration indirectly), and different regions are included in the model.

[7] For further discussions, see, among others, Simpson (2022) or Van Hear et al. (2018). Interested readers may also refer to collections of interdisciplinary perspectives on migration, such as Brettell and Hollifield (2022).

[8] For a more detailed discussion of the drivers of migration between East and West Germany, see Rosenbaum-Feldbrügge et al. (2022).

Vanella and Deschermeier (2018), for example, covered these correlations on the national level by employing the abovementioned approach. From a regional perspective, simple (top-down) models do not sufficiently account for correlations in migration between regions. An illustrative example is that large inflows to a major city like Berlin will be highly correlated with migration flows to or from neighboring regions; in this case, Brandenburg. These correlations might be negative in the case of movements between Berlin and Brandenburg, or they may be positive if large inflows to Berlin are associated with large inflows to the neighboring regions because, for example, migrants are unable to find accommodation in Berlin due to a lack of available housing (Henger and Oberst, 2019a). At the same time, co-movement, such as family migration, will be observable in the data due to high positive correlations between corresponding age groups. This is a well-known phenomenon that has been investigated by Rogers and Castro (1981), and in later studies on the age schedule of migration.

2.4 Incorporating risk and uncertainty

Finally, migration projections, like demographic projections in general, differ in how they include risk and uncertainty. Migration projections are often categorized as either deterministic or stochastic approaches. While deterministic population projections were frequently employed in the past, as they were widely used by statistical agencies (Deschermeier, 2011; Vanella and Deschermeier, 2020), stochastic approaches have become increasingly popular in recent decades, at least on the national level.[9]

Deterministic approaches, which are often scenario-based (see, e.g., UN DESA, 2022), seek to identify several realistic outcomes. Some authors use rather naïve assumptions: i.e., that the most recent observations form the basis for the most probable future scenarios. For instance, the United Nations Population Division relies on such an assumption in its projections of international non-refugee migration in the medium scenario of its World Population Prospects (UN DESA, 2022). In cases in which the assumption that recent migration flows will continue in the future is not realistic, alternative values may be proposed, either for the near future (specifying a level) or for the medium to long term (specifying a full future trajectory). For instance, the national population projections for Germany proposed by Destatis (2019) assume that net migration will, in sum, converge to levels computed as the historical means over three varying periods. In this example, net migration to Germany is assumed to reach a level of between 111,000 and 300,000 in 2030.

Among the reasons why deterministic approaches have been popular are that they can be computed quickly, and they can be easily used to compare a range of different policy scenarios and the corresponding effects (Vanella et al., 2020a).

[9] For a survey on Germany, see Vanella and Deschermeier (2020).

For example, Lomax et al. (2020) recently discussed a series of Brexit-dependent migration scenarios and presented corresponding deterministic projections for each scenario. Lutz et al. (2019), developed several demographic scenarios for the European Union in which they analyzed the impacts of fertility, mortality, migration, education and labor force participation. They showed that projections of how many people, stratified by skill level, will be living and working in the European Union in 2060 differed depending on which assumptions were applied. Similarly, Marois et al. (2020) compared six scenarios for the EU-28 that differed depending on which assumptions regarding immigration volumes, the educational selectivity of migrants, and labor force integration and participation were used, and analyzed the corresponding impacts on various dependency ratios. De Beer et al. (2010), taking a smaller-scale perspective, compared four policy scenarios based on different assumptions for reducing socioeconomic inequalities and moderating climate change across European regions, and assessed the impact of these policies on demographic developments such as (working-age) population growth and population aging.

However, despite being popular, deterministic approaches have major limitations, as they rely on scenario assumptions; that is, on fixing the relevant parameters at predefined values, and then making a straightforward calculation of the corresponding future developments. As these approaches are unable to quantify the probability that the respective scenarios will occur (Vanella et al., 2020a), they do not reflect future uncertainty, but instead only present a rather small number of realistic scenarios. While these scenarios may be informative, the statistical probability that they will actually take place is close to zero (Keilman et al., 2002). By contrast, stochastic (population) projections overcome these limitations, as they quantify the probability that future trajectories will occur by relying on statistical information and methods for both frequentist (e.g., Fuchs et al., 2018 or Vanella and Deschermeier, 2020) and Bayesian (e.g., Azose et al., 2016) frameworks.

Despite having these favorable properties, the stochastic modeling of (international) migration has previously been performed for only a few individual countries (Azose et al., 2016), such as Germany (Vanella and Deschermeier, 2018), or for migration between countries, such as between Germany and Poland (Bijak, 2011). However, as was noted above, the quantification of prediction intervals instead of point forecasts is preferable, since it allows researchers to assign probabilities to the outcomes of the respective future migration trajectories (Vanella and Deschermeier, 2018). Nonetheless, given its volatile nature, migration is particularly difficult to forecast, even when a stochastic framework is applied.[10]

Notably, in addition to stochastic approaches, there is also a series of approaches that combine both (scenario) assumptions and policy comparisons. For example, Lutz et al. (1998) suggested randomizing expert-based scenarios to derive stochastic

[10] Which additionally lowers the predictive value of selective (i.e., deterministic) scenarios, as the probability of an outcome is lower than it is for processes that are easier to predict, such as mortality improvements.

expert-based forecasts. Abel et al. (2016) incorporated future education pathways based upon the Sustainable Development Goals in a Bayesian framework. Marois et al. (2021) used a stochastic microsimulation model for China with pre-defined parameter values, e.g., for the total fertility rate, to project adjusted old-age dependency ratios that factored in both educational attainment and labor force participation. Similarly, Bijak (2011) and Azose et al. (2016), among others, have recently suggested using Bayesian approaches to combine the information derived from the data with qualitative knowledge or assumptions regarding future migration. The use of such approaches is conceivable if the necessary data are not available or are erroneous, or if we believe that the past data are unlikely to reflect future developments in migration.

2.5 Migration forecasts for German regions

For the reasons outlined above, the approaches to modeling regional migration are, in practice, quite heterogeneous. However, deterministic approaches are used even more frequently for regional projections than for projections on the national level. This is illustrated by looking at various recent population projections for German regions, some of which have already been addressed. For example, Maretzke et al. (2021) provided comprehensive population estimates for German NUTS-3 regions until 2040. They modeled internal migration using high dimensional region-to-region migration data from 2011–2017 and assuming constant mean outflow rates in the future, disaggregated by age and gender. Similarly, they modeled net international migration by applying a series of deterministic assumptions based on regional data from the observation period and assumptions about the overall levels of migration to Germany in the future. Reinhold and Thomsen (2015) provided population projection results for NUTS-3 regions of the German federal state of Lower Saxony using an average of different projection techniques. While they relied on several deterministic assumptions about regional migration dynamics, such as constant inward to outward migration ratios or zero net migration, they did not differentiate between internal and international migration. Breidenbach et al. (2018) provided much more fine-grained estimates, projecting the total population in Germany until 2050 using a 1×1-km grid. They did not take internal migration dynamics into account. Moreover, they assumed that net international migration to Germany will remain at constant levels, and will be distributed across regions proportionally to the total population. Regional projections using the subnational data of other countries often relied on deterministic modeling as well (e.g., Eurostat, 2021; Raymer et al., 2006; Wilson, 2015a).

By contrast, fewer regional migration projections have taken uncertainty into account. Ballas et al. (2005) estimated the internal migration probabilities for regions in Ireland over the 1991–2002 period by using Monte Carlo sampling from individual census records. However, they excluded international migration from their analysis due to a lack of data. Bryant and Zhang (2016) estimated regional emigration rates disaggregated by sex and age in New Zealand over the 2014–2038 time interval using a complex Bayesian approach. Similarly, Zhang and Bryant (2020) used a sophisticated Bayesian model to project migration between Icelandic regions.

Thus, even though migration dynamics play a crucial role in the demographic development – and, consequently, in the overall economic and social development – of regions, most regional projection approaches do not rely on a consistent (including both international and internal migration) and accurate (stochastic) modeling strategy. Investigating either international or internal migration, but not both, fails to account for the interdependencies or regionally differing effects of these two migration components. Furthermore, as Fuchs et al. (2021) demonstrated, in addition to relying on the sensitivity to the assumed parameter values, modeling migration deterministically implies a heavy dependence on a detailed approach for modeling in-migration and out-migration dynamics. This issue is of particular importance on the regional level, as Wilson and Bell (2004) showed for internal migration. In the same vein, Wilson et al. (2021) underlined the need for stochastic modeling of regional population changes in future research.

Therefore, given the state of the research and the respective implications and limitations of the prevailing deterministic methods outlined above, we propose in the upcoming section a comprehensive and parsimonious stochastic framework for forecasting migration on the regional level in Germany.

3 Data and methods

Based on the literature, we can identify a series of potentially relevant characteristics of a model for forecasting migration between German regions. However, the incorporation of these factors is constrained by data availability, which we discuss below. Moreover, *ex-ante*, there is ambiguity about which modeling approach performs the best. Therefore, the comparison of different specifications may be necessary.

Previous studies have evaluated a series of candidate models to find out which one performs the best. Reinhold and Thomsen (2015), using data for selected German regions, compared the accuracy of individual and model averaging forecasting techniques. Rayer (2008) compared the forecast error levels of different population forecasting techniques using data on U.S. counties. Wilson (2015b), building upon the findings of Rayer (2008) and others, compared the forecast accuracy of more than 200,000 simple to more complex averaged and composite model specifications for regions in Australia, England and Wales and New Zealand.

In line with these examples, and based on both the relevant factors discussed in the review above and the available data for German regions, we identified eight models to be tested and compared to each other:

- a prediction of gross migration flows using naïve status quo assumptions,
- a prediction of gross migration flows using observed mean and median values,
- a prediction of net migration flows using principal component analysis,

- a prediction of log-gross migration flows using principal component analysis,
- a prediction of gross migration rates using naïve status quo assumptions,
- a prediction of gross migration rates using observed mean and median values,
- a prediction of net migration rates using principal component analysis and
- a prediction of log-gross migration rates using principal component analysis.

Thus, our empirical strategy consisted of two major building blocks. *First*, we determined which of those eight competing models is most accurate by conducting a sequence of deterministic backtests (see, for instance, Vanella and Deschermeier, 2019). In doing so, we applied each model to each of the six available gender-age groups[11] by taking data for the years 1995–2014 as a baseline, while assuming no knowledge of the migration trends after that period. We then created in-sample forecasts for the years 2015–2019, and compared the corresponding *ex-post* errors. Interested readers can find details on the models that were tested, the measure of accuracy that was used (the symmetric mean absolute percentage error, see Chen et al., 2017), and the results for all other models in Appendix A. *Second*, the best-performing model was used to conduct a stochastic NUTS-3-level migration forecast until 2040. By applying this two-step procedure, we addressed the discussions outlined in the literature review about which target variables (net versus gross, flows versus rates) and empirical strategies should be used (from naïve models to principal components analysis), and how uncertainty should be incorporated.

3.1 Data: Sources and preparation

We used publicly available small-area data on migration from and to NUTS-3 regions in Germany (*Kreise/Districts*) for the 1995–2019 period from the German federal statistical office and the statistical offices of the federal states (Statistische Ämter des Bundes und der Länder, 2022). As there were various changes in administrative territories over the baseline period, we redistributed the past migration flows[12] to districts based on their boundaries as of December 31, 2019. For the data of districts in which the boundaries changed[13] over time, and for which obtaining consistent time series was therefore not feasible, we created pseudo-districts. Appendix B gives an overview of the territorial reforms since 1995, and of how we converted data with incompatible boundaries into consistent time series.

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11 0–17; 18–24; 25–29; 30–49; 50–64; 65+ years.

12 In contrast to the general definition of migration flows as presented in Section 1, our model refers to the sum of either inflows or outflows during one-year periods from the perspective of a certain district. For instance, we consider each out-migration from Berlin as an outflow and each in-migration to Berlin as an inflow. Thus, our definition of flows is non-directional. For example, a person moving from Berlin to Wolfsburg in the year 2020 will appear as an outflow in the data for Berlin and as an inflow in the data for Wolfsburg.

13 For instance, after reunification, some districts in East Germany were dissolved and redistributed to three or four new districts.

Although it would have been preferable to do so, as we discussed above, the available data did not allow us to distinguish between internal and international flows or citizenships. Furthermore, in 15 of the 16 federal states, the district-level data did not distinguish migrants by gender before 2002. We obtained gender-differenced time series for those 15 federal states by performing a backcast of the rates for males among all migrants across all age groups and districts. For this purpose, we computed the age-specific shares of males among all migrants for 2002–2019, and then performed PCA on the resulting 4,596 time series (in- and out-migration, six age groups, 383 districts). The obtained PCs were backcasted until 1995, and were then retransformed to male shares for all age groups and districts, and multiplied by the total migration data to obtain gender-specific flows.[14]

3.2 Forecast model

The highest forecast accuracy was achieved by the PCA model for log-gross migration flows. Using this model for our forecast, we first performed PCA on the covariance matrix of annual age- (six groups), gender- (binary) and district-specific (396 districts and pseudo-districts) log-migration flow time series for 1995–2019, which corresponds to a 25 (years) $\times$ 9,504 (variables) matrix. PCA performed singular value decomposition on this matrix, thereby transforming the original and highly correlated data into linear combinations of the original variables that were uncorrelated, so-called principal components. This allowed us to efficiently cover cross-correlations between the original variables in our forecast (Vanella, 2018). More technical details on the PCA model used for the specific case in this paper are given in Appendix A.

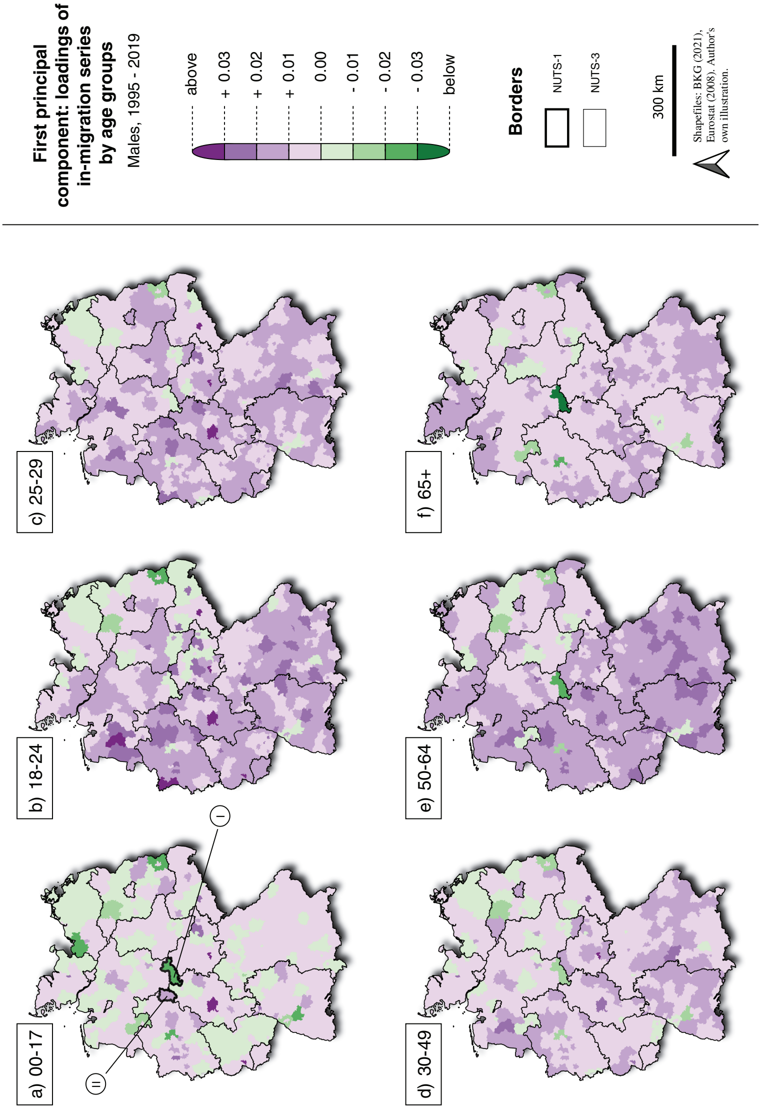
The inversed loadings (coefficients) of the district-, age- and gender-specific log-migration on Principal Component 1 (PC1)[15] are illustrated in Figures 1–4, whereby Figures 1 and 2 indicate loadings of age- and gender-specific in-migration and Figures 3 and 4 indicate loadings of age- and gender-specific out-migration. Darker colors are associated with higher correlations between PC1 and the respective log-migrations. Shades of green indicate negative loadings of the respective flows on PC1, while shades of purple indicate a positive connection.

For instance, the district of Göttingen (I) has a dark green color in Figure 1(a), which means that a decrease in PC1's inverse is, on average and *ceteris paribus* (c.p.), associated with relatively large *increases* in in-migration to Göttingen among males aged 0–17 years. Simultaneously, the dark purple of the district of Höxter (II) indicates that for the same age-gender stratum, an increase in PC1's inverse is, on average and c.p., associated with rather large *increases* in in-migration to Höxter. Moreover, the district of Göttingen (I) has a dark green color in Figure 4(f) as well.

[14] We purposely keep the description of the backcast method rather short. For interested readers, more details are offered in Appendix C.

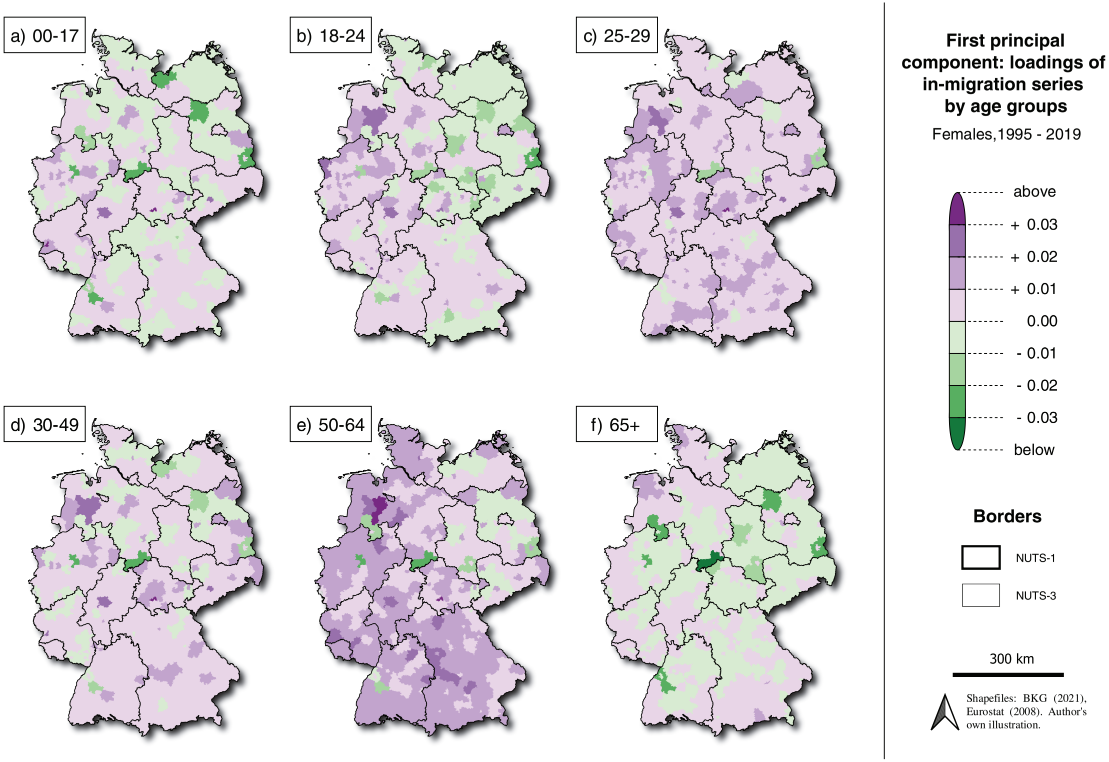
[15] For ease of interpretation, the sign of the PC1 time series (and, thereby, its loadings) was inverted in Figures 1–5, such that an increase in PC1 is associated with c.p. increases in migration.

Figure 1:
Loadings of the first principal component for log-inflows by males



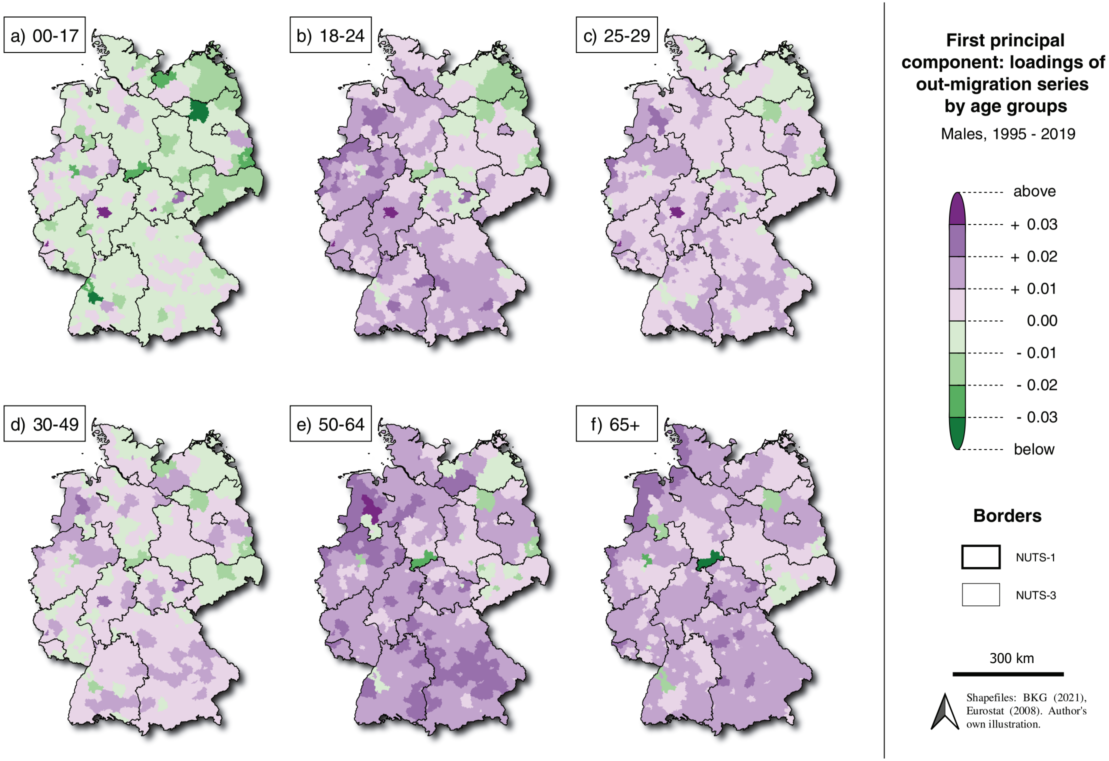
Source: Authors' computation and illustration.

Figure 2:
Loadings of the first principal component for log-inflows by females



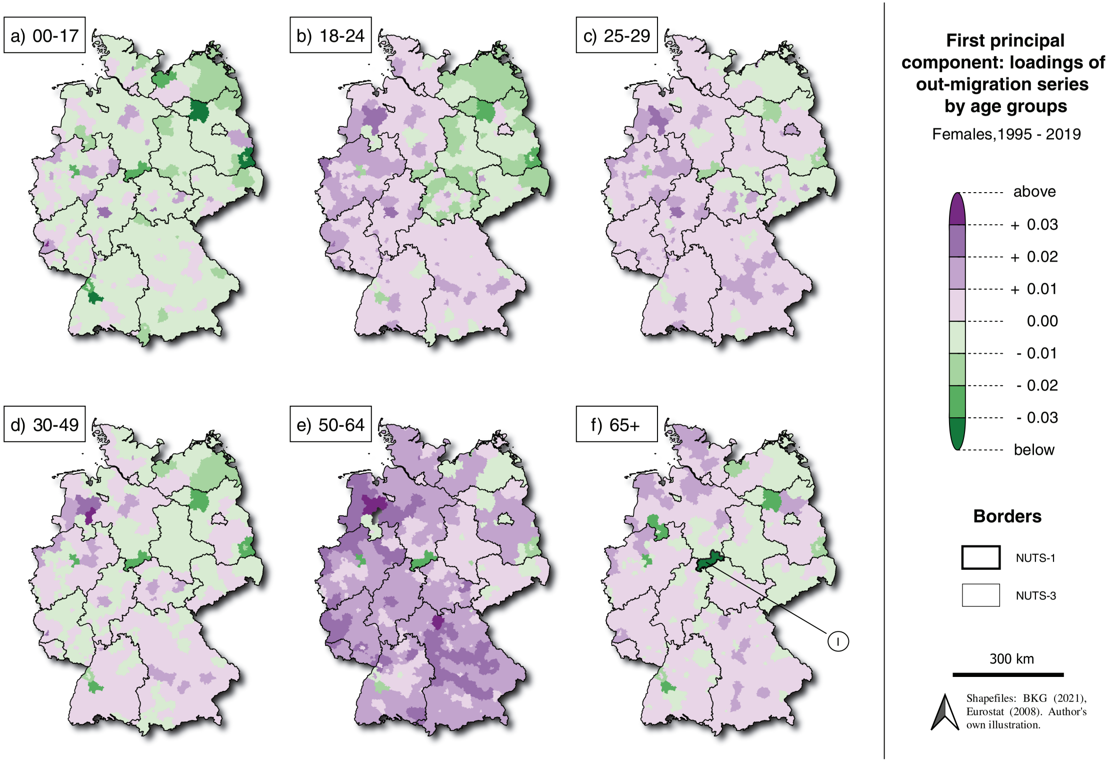
Source: Authors' computation and illustration.

Figure 3:
Loadings of the first principal component for log-outflows by males



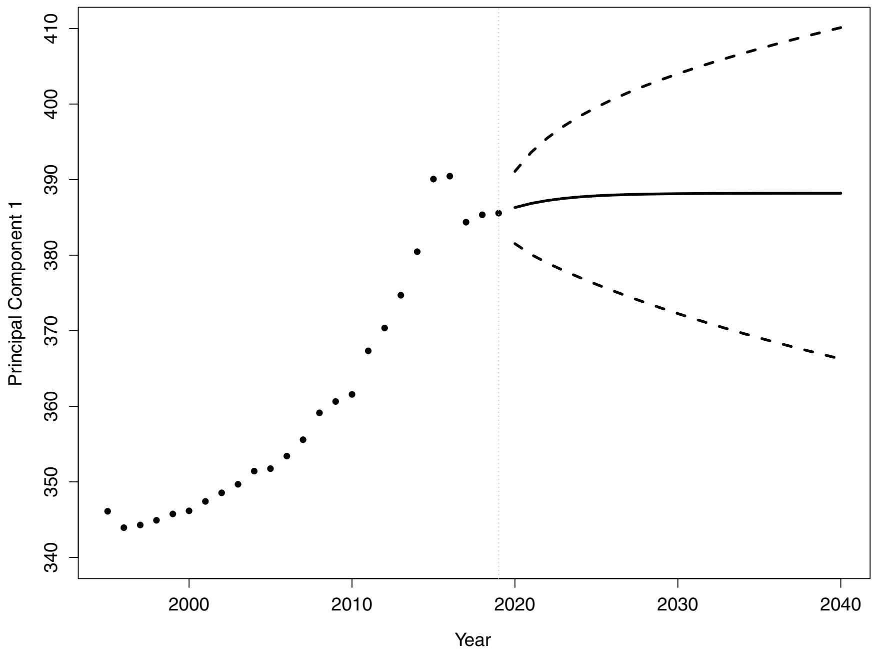
Source: Authors' computation and illustration.

Figure 4:
Loadings of the first principal component for log-outflows by females



Source: Authors' computation and illustration.

Figure 5:
Time series of Principal Component 1 (with inversed sign) with forecast



Source: Authors' computation and illustration.

This implies that a decrease in PC1's inverse is associated not only with increases in *in-migration* to Göttingen among young people, but also with increases in *out-migration* from Göttingen among females aged 65+ (c.p.). These selected examples demonstrate that trends in PC1 cover migration dynamics that occur simultaneously across districts, age groups and genders. Thus, as indicated by the literature review, we found that results relying on estimation by PCA accounted for the correlations and the interdependencies between regions and demographic groups reported in the historical data, such as the displacement of age groups due to overburdened local real estate markets.

Overall, PC1 explained more than 52% of the variance in the 9,504 variables throughout the 25-year period. Figure 5 illustrates its inversed course over time, alongside a forecast that was derived using an approach explained in Appendix A (see description of Model 4), including 95% prediction intervals (PIs) for illustrative purposes. Apart from the years 2015 and 2016, which were outliers due to the significant international refugee inflows and internal migration flows that occurred during that period (see Fuchs et al., 2021 and Vanella et al., 2022), PC1 followed a mostly monotonous course: migration was increasing steadily, then slowed down in the late 2000s, and accelerated again in the wake of the so-called Arab Spring in 2011 (Vanella and Deschermeier, 2018). After the large inflow of refugees ended in 2016, a deceleration of the curve can be observed.

Therefore, the long-term trend of PC1 can be emulated quite well by fitting an inverse logistic trend function to the time series. The model's inflection point (the year 2011) was chosen such that the fit maximized the model's likelihood. Then, the model coefficients were estimated by ordinary least squares (OLS). The model generating the prediction in Figure 5 is given in (1).

$$E[P_{1,y}|P_{1,2019}] \approx -345.675 - 45.998 \frac{\exp\left(\frac{y-2011}{2.856}\right)}{1+\exp\left(\frac{y-2011}{2.856}\right)} + r_{2019} \tag{1}$$

with

- $P_{1,y}$: value of PC1 in year y,
- y taking the values $2020, 2021, \ldots, 2040$,
- $r_{2019} \approx 3.478$: the residual between the observation for PC1 in 2019 and the trend function's prediction for 2019.

After visual inspection of the residuals' time series and their autocorrelation function (ACF) and partial autocorrelation function (PACF) (see, e.g., Shumway and Stoffer, 2017), we concluded that they were appropriately modeled by a random walk process.

3.3 Stochastic forecast of regional migration flows until 2040

Having estimated in-sample regional migration using the best-performing specification, we attempted to forecast future regional migration among German regions until 2040. However, as was outlined above, uncertainty about future migration was a major concern. To account for this uncertainty, we set up a stochastic version of (1), which is given in (2).

$$P_{1,y} \approx -345.675 - 45.998 \frac{\exp\left(\frac{y-2011}{2.856}\right)}{1+\exp\left(\frac{y-2011}{2.856}\right)} + r_y, \tag{2}$$

with r_y being a random walk process that can be written as:

$$r_y = r_{y-1} + \varepsilon_y = r_{y-2} + \varepsilon_{y-1} + \varepsilon_y = \cdots, \tag{3}$$

with ε_y being a stochastic white noise process:

$$\varepsilon_y \sim \mathcal{NIID}(0, 0.149^2) \quad \forall y. \tag{4}$$

Table 1:
Explained share of variance by principal component

Principal component	Individual share of explained variance [as %]	Cumulative share of explained variance [as %]
1	52.4	52.4
2	25.7	78.1
3	4.9	83.0
4	3.9	86.9
5	2.1	89.0
6	1.8	90.7
7	1.1	91.8
8	1.0	92.8
9–9,504	<1.0	100.0

By drawing 1,000 times for each year over the forecast horizon from (4), plugged into (3), and thus also in (2), we computed 1,000 trajectories for PC1 until 2040. The remaining PCs jointly explained less than half of the variance in all log-migration time series (see Table 1 below). Since they did not show clear trending behavior, we assumed that those PCs followed random walk processes as in (3) and simulated 1,000 trajectories for each, which allowed us to consider the associated risk and to construct more realistic PIs, as suggested by Vanella and Deschermeier (2020). Using this approach, we obtained annual simulation matrices for all PCs that could be easily retransformed into annual simulation matrices of the log-migration, and by exponentiation, of migration flows, as given in (5):

$$\Gamma_y = \exp(\Pi_y \Lambda^{-1}), \tag{5}$$

with Π_y (1,000 × 9,504) being the simulation matrix of the PCs for year y, Λ^{-1} being the inverse of the loadings matrix (9,504^2), and Γ_y being the simulation matrix of the migration flows for year y (1,000 × 9,504). Based on the quantiles of the 1,000 simulated trajectories, we derived PIs for each district-, age-, gender- and direction-specific time series.

Subsequently, we aggregated each individual trajectory over the forecast horizon, resulting in cumulative migration flows until 2040:

$$\Gamma_{.} = \sum_{y=2020}^{2040} \Gamma_y. \tag{6}$$

Having obtained migration flows over the forecast horizon, we were able to derive measures of migration-associated depopulation for each district, age and gender. To this end, we subtracted, for each of the 1,000 trajectories, the forecasted outflows from the respective forecasted inflows. This yielded cumulative district-, age- and gender-specific net migration distributions through 2040. More formally, let $\gamma_{d,a,g,i,.,t}$ be the cumulative inflows to district d by individuals in age group a and of gender g in trajectory t for 2020–2040 and $\gamma_{d,a,g,o,.,t}$ be the corresponding outflow. Then, the net cumulative flow for the said district, age group, gender and trajectory is

$$\gamma_{d,a,g,n,.,t} = \gamma_{d,a,g,i,.,t} - \gamma_{d,a,g,o,.,t}. \tag{7}$$

Thus, $\gamma_{d,a,g,n,.,t}$ indicates whether a district faces an increase or a decrease in the corresponding demographic stratum because of migration flows over the forecast horizon – importantly, in absolute numbers.

However, German districts differ in population size, which alters the relevance of flows as absolute numbers. For example, a population decline of 10,000 is more severe in a district of 50,000 inhabitants than in a district of 1,000,000 inhabitants. To obtain a more realistic picture of the significance for each district of population decline due to negative net migration or population growth due to positive net migration, we computed the quotient of the cumulative net migration and the official population estimate as of December 31, 2019 ($B_{d,a,g,2019}$) for each stratum:

$$\frac{\gamma_{d,a,g,n,.,t}}{B_{d,a,g,2019}}. \tag{8}$$

Finally, we used our stochastic results to estimate the probability of migration-induced depopulation for each stratum. For instance, let $\Delta_{d,a,g,.}$ be a binary variable that takes the value of one if the cumulative net migration to d among individuals in age group a and of gender g during 2020–2040 is negative, and the value of zero otherwise:

$$\Delta_{d,a,g,t} := \mathbb{1}(\gamma_{d,a,g,n,.,t} < 0). \tag{9}$$

Then, the estimated probability of migration-induced depopulation based on our Monte Carlo simulation with 1,000 trajectories for the said district, age group and gender, is

$$\hat{P}(D) = \frac{\sum_{t=1}^{1,000} \Delta_{d,a,g,t}}{1,000}. \tag{10}$$

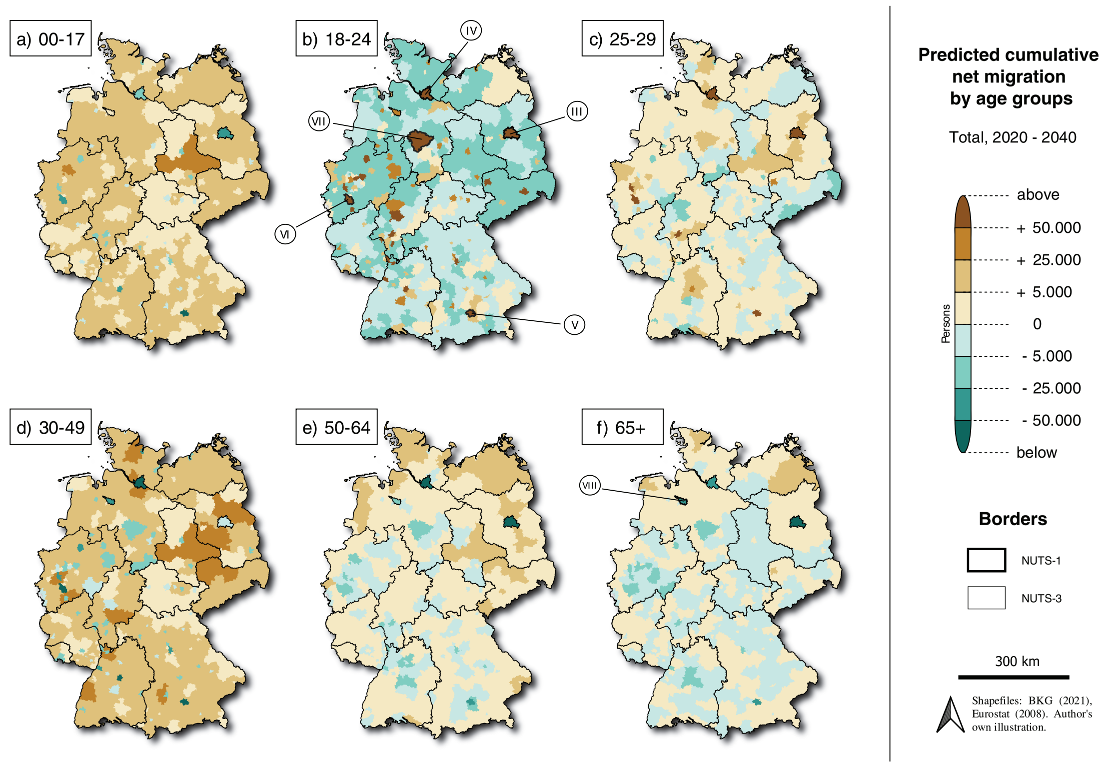
We will present the results generated from (6), (8) and (10) by district and age in Section 4. Gender-specific results can be found in Online Supplementary File 1 (available at https://doi.org/10.1553/p-5pn2-fmn8). We discuss the limitations of our approach in Section 5.

4 Results

4.1 Future migration flows among German regions

As the initial output of the model, given by (6), delivers migration flows, we visualize and compare the corresponding median of the forecasted flows in Figure 6. In this context, four distinct future migration patterns become visible.

Figure 6:
Median cumulative net migration in 2020–2040 by NUTS-3 region and age group



Source: Authors' computation and illustration.

First, there is strong evidence that for the 18–24 age group, migration-induced depopulation will occur in the majority of German regions by 2040, as indicated by the dark turquoise colors in Figure 6(b). Simultaneously, we observe scattered, brown-colored districts on the map representing major cities, which indicates that high levels of positive net migration to these cities among this age group will occur over the forecast horizon. For instance, Berlin (III), Hamburg (IV), München (V), Köln (VI) and Hannover region (VII) are easily distinguishable from their respective neighboring regions. These results are very much in line with the observed internal migration patterns in the recent past, which were characterized by educational migration by young adults from rural areas to nearby cities with universities and more occupational training opportunities (Siedentop et al., 2014 and the sources cited in the literature review).

Second, as illustrated by Figure 6(c), the forecast indicates that for the 25–29 age group, there will be positive net migration in most German regions, particularly in large cities, and only slight decreases in others. A key explanatory factor in this result is that overall positive net international migration is predicted for this age group due to both labor migration and, as implicitly included in the data, refugee migration (Vanella and Deschermeier, 2018; Vanella et al., 2022). The major cities and some of their surrounding areas will experience larger inflows since international migrants traditionally move to larger cities that are internationally known, and that frequently offer migrants a better network of co-patriates (Henger and Oberst, 2019b; Saa et al., 2020; Sharma and Das, 2018 and the sources cited in the literature review) who can facilitate their orientation after they arrive in the destination country (Gans and Ritzinger, 2014; Martén et al., 2019). However, by construction, Figure 6(c) displays internal movements as well. Here, migration patterns may be explained by the overall regional economic situation; that is, by labor market opportunities. Wage differentials between West Germany and East Germany have persisted since reunification (Smolny and Kirbach, 2011). Moreover, employment growth remains higher in West Germany, and this trend is expected to continue (Heining et al., 2021). For instance, the district of Göttingen shows positive net migration for the 18–24 age group (Figure 6(b)), but negative net migration for the 25–29 age group. This can be explained by Göttingen having a highly respected university that attracts students from other regions, but also a relatively small labor market that does not offer enough qualified jobs to keep graduates from leaving the city after they have finished their studies (Buch et al., 2011).[16]

Third, Figures 6(a) (0–17 years) and 6(d) (30–49 years) show quite different patterns of regional migration flows, apart from the overall positive net international

[16] Readers should, however, keep in mind that Figure 6 visualizes absolute net migration. Therefore, the color shades are naturally darker for larger districts. This somewhat explains the shades of the pseudo-district 150018285868991, which is merged from multiple rather rural districts in the federal state of Sachsen-Anhalt (see Appendix A for more details). Simultaneously, the 25–29 age group is the smallest of the six included age groups; thus, by construction, it tends to yield smaller absolute numbers.

migration. According to the median forecast, there will be negative net migration to major cities among the 30–49 age group. Figure 6(a) echoes these trends, as it shows migration among children, who typically migrate with their parents, most of whom are in the 30–49 age group. This echo in the migration age schedule has been investigated for decades, and was already observed by Rogers and Castro (1981), as was discussed above. The observed migration patterns can also be attributed to other factors identified in the literature, such as increased personal preferences for living in a quieter and more rural environment, and financial constraints that make it difficult to afford to live in a city (Günther, 2013). Young families are especially likely to search for housing on the outskirts of cities (Peter et al., 2022), as these areas tend to offer more safety and quiet and more affordable housing (Voigtländer and Sagner, 2020). Notably, as was discussed earlier, young families who leave cities often migrate to neighboring regions, as these areas typically offer good infrastructure and allow them to reach the city center relatively quickly (Peter et al., 2022). Moreover, the abovementioned gravity of major cities for internal and international migrants results in additional pressure on real estate markets, which can, in turn, lead to high levels of out-migration (e.g., Henger and Oberst, 2019a).

Fourth, Figures 6(e) and 6(f) illustrate that despite the large numbers of people in both groups, migration intensities generally decrease with age, as indicated by the lighter shades. A notable exception to these decreasing dynamics is the finding that deurbanization trends accelerate with increasing age, and will continue to do so in the future, according to the forecast. In Figures 6(e) and 6(f), the dark turquoise colors in Berlin, Hamburg, Bremen (VIII) and München indicate that levels of net out-migration among older people are high in these regions. Simultaneously, migration gains among older age groups are expected to occur in some areas surrounding these major cities, and in some northern regions of Germany, particularly those bordering the North Sea and the Baltic Sea. Recalling the literature review, this finding can be attributed to amenity migration. It is well known that retirement is associated with local migration peaks (Rogers and Castro, 1981), as significant numbers of individuals migrate to regions or countries they find more attractive (Vanella and Deschermeier, 2018). In our forecast, the seaside regions are expected to experience net inflows of older age groups in the future.

4.2 Migration flows along the urban-rural continuum

The analysis of migration flows across regions according to the median forecast has shown that in-migration and out-migration exhibit distinct age-specific patterns that can be linked to a series of explanatory factors discussed in the literature. Those factors often result in migration along the urban-rural-continuum, as was outlined. However, relying on district-level data may blur this finding, given that districts do not have a uniform residential structure; that is, each district may contain both rural and urban areas. To substantiate the finding that future migration will run along the

Table 2:
Median cumulative net migration 2020–2040 by age group and type of region [in thousands]

RegioStaR category	Age group 0–17	18–24	25–29	30–49	50–64	65+	Cumulative
71: metropolis in urban region	−198	+1,814	+999	−400	−236	−271	**+1,708**
72: regiopolis and large city in urban region	+58	+1,486	−36	−393	−52	−80	**+981**
73: medium-sized city, urban area in urban region	+888	−221	+202	+1,304	−69	−48	**+2,057**
74: small town area, village area in urban region	+369	−193	+63	+554	+57	+16	**+865**
75: central city in rural region	+106	+131	−32	+104	+39	+18	**+366**
76: medium-sized city, urban area in rural region	+520	−241	+40	+664	+170	+20	**+1,172**
77: small town area, village area in rural region	+373	−259	+54	+535	+187	+48	**+938**

Source: Authors' computation and illustration.

urban-rural continuum, we analyzed the forecasted migration figures with respect to the residential structure of a district.

An established classification for German regions is the *RegioStaR typology* by the Federal Ministry for Digital and Transport (BMVI). In a recent example, Heinsohn et al. (2022) suggested using the RegioStaR 7 specification to characterize regions in a study on regional COVID-19 infection dynamics in schools, as it provides a reasonable trade-off between enabling a sufficient differentiation of regions (seven) while still ensuring that the analysis is comprehensible. Since RegioStaR uses LAU nomenclature, Heinsohn et al. (2022) calculated the median category among all LAUs in each NUTS-3 region, with each LAU weighted by the corresponding populations on December 31, 2019. The resulting figure is used as the representative RegioStaR category of the NUTS-3 region (district). We borrowed their approach in the present paper. The RegioStaR typology is provided online by the BMVI (2021), alongside population estimates. Based on the outlined procedure, we derived net migration forecasts by age group and type of region. The median values in thousand individuals, cumulated over the forecast horizon, are given in Table 2. In the median, the model forecasted no overall migration-induced depopulation for any RegioStaR *category* due to positive international net migration. There was, however, support for the finding of age-specific regional depopulation due to age-specific migration patterns.

Heavily urban areas (71, 72) are expected to gain more than three million net migrants in the young adult age group (aged 18–24). Conversely, more rural areas to medium-sized cities (73, 74, 76, 77) are expected to face substantial declines in the population aged 18–24. This confirms the finding that internal migration from more rural to urban areas will occur among young people, most of whom are moving to pursue educational opportunities.

Simultaneously, these urban areas will face migration-induced declines among the 0–17 and 30–49 age groups. Again, more rural areas and medium-sized cities will experience the opposite trend: i.e., strong inflows of these age groups. This substantiates the finding that families are expected to migrate from heavily urban areas to smaller-sized cities or the countryside.

Similarly, cities are expected to lose population in the age groups close to or beyond retirement age, while more rural areas experience corresponding inflows. Again, this underlines the finding that amenity migration from urban areas to more rural regions will occur among people aged 50 and older.

4.3 Migration flows relative to district population size

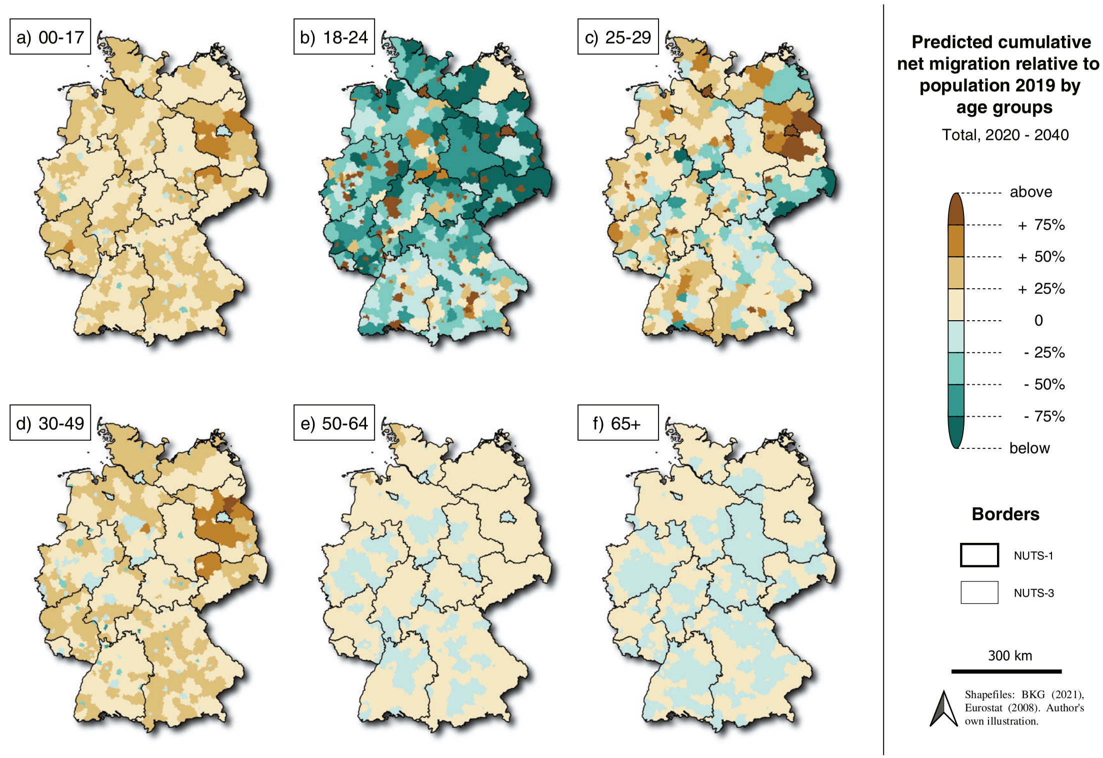
All of the results presented up to this point rely on levels. On the one hand, this allows us to compare the districts and to track migration patterns across region types. On the other hand, absolute numbers may not capture the district-specific significance of migration, as the population sizes of districts vary greatly. Therefore, we computed the cumulative net migration over the forecast horizon relative to the 2019 end-of-year population, as given in (8). However, readers should keep in mind that this is a synthetic measure that should not be confused with a rate or a share. Again, Figure 7 illustrates the median results.

The displayed patterns demonstrate that focusing on levels of migration flows can blur the significance of migration flows for particular regions. For instance, Berlin and its neighboring regions are disproportionally affected by family migration, as shown by these regions having darker color shades compared to other regions across Germany in Figures 7(a) and 7(d). Moreover, as Figure 7(b) illustrates, the out-migration by young adults from more rural areas to cities is, proportional to the number of persons in this age group, even more pronounced than the results in terms of levels suggest. Particularly in the eastern part of Germany, Berlin and other university cities appear to attract significant shares of individuals aged 18–24 who are migrating for educational reasons. However, our results also suggest that this trend is at least partially offset by remigration after the completion of education. Finally, Figures 7(e) and 7(f) demonstrate that migration patterns among people aged 50 and older are less intense proportional to the age group size than the observed net flows in Figures 6(e) and 6(f) indicate.

4.4 Probabilities of migration-induced regional depopulation

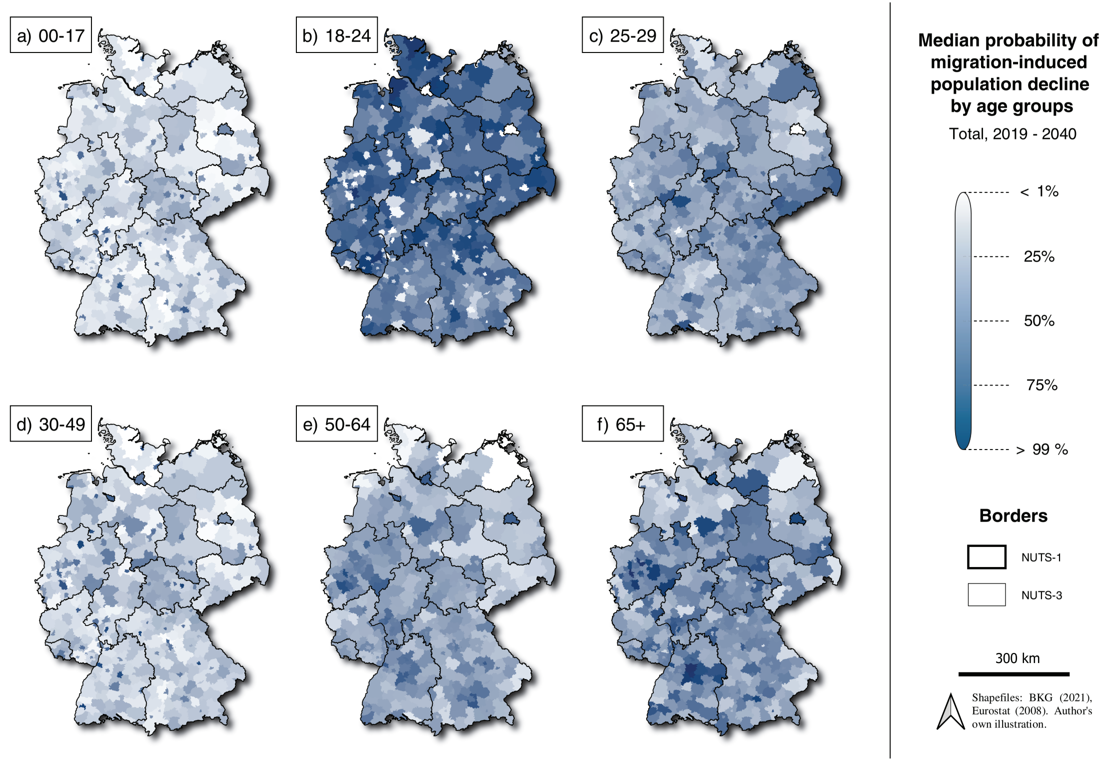
The results presented above have demonstrated that until 2040, distinct age-specific migration patterns are likely to shape population dynamics across German regions.

Figure 7:
Median cumulative net migration in 2020–2040 by NUTS-3 region and age group divided by the corresponding population on December 31, 2019



Source: Statistische Ämter des Bundes und der Länder (2021b); authors' computation and illustration.

Figure 8:
Probability of migration-induced depopulation between 2019 and 2040 by district and age group



Source: Authors' computation and illustration.

However, migration patterns, and thus our findings, are subject to substantial uncertainty. To account for this uncertainty in our forecast, we present the probability of migration-induced depopulation, as derived via (9) and (10) through our Monte Carlo simulation, in Figure 8. Again, we cumulated the results over the forecast horizon, and present total rather than gender-specific findings. The latter can be found in Online Supplementary File 1.

First, among children, migration-induced depopulation[17] is highly unlikely to occur over the forecast horizon in the vast majority of German districts. We observe that only some major cities face an increased probability of migration-driven decreases in the youngest age group. This finding is substantiated by the model results for the 30–49 age group, for whom the decline probabilities, as well as the forecasted median flows, closely mirror those of the youngest age group.

Second, in most German districts, the probability that the population aged 18–24 will shrink due to net out-migration is high. At the same time, we see that large cities, depicted by white dots surrounded by dark blue areas in Figure 8, have very low probabilities of losing population in this age group. Thus, the forecasted median migration flows indicate not only that substantial migration-induced declines of the population aged 18–24 will take place in rural areas in both absolute and proportional terms, but also that these declines are highly likely to actually occur.

Third, for the 25–29 age group, no clear patterns in terms of decline probabilities can be derived. It is likely that the composite, mutually offsetting effects of different migration flows, such as international migration, remigration after education or labor market-related migration, and the accompanying uncertainty, cause wide prediction intervals. Consequently, based upon the forecast presented in this paper, no clear statement regarding the probability of a migration-induced decline in the population aged 25–29, even in the regions exhibiting negative developments in the median forecast in Figures 6 and 7, can be made.

Fourth, median population changes due to migration among the population aged 50 and older will be quantitatively rather small, but are highly likely to take place in some districts. In other words, the model results shown in Figure 8 suggest that large cities are likely face a decline in the population close to or beyond retirement age due to net outflows of people in this age group.

5 Discussion and conclusion

This article presented a novel approach for joint stochastic forecasting of both international and internal migration on the NUTS-3 level in Germany. Relying on backtests, we found that a principal component-based approach to estimating log-migration flows gave the best prediction. This approach simultaneously computed future trajectories of in-migration and out-migration flows by age group and gender, while accounting for correlations among in-migration and out-migration

17 Which does not rule out depopulation because of low fertility.

across districts, age groups and genders. Moreover, time trends in migration and autocorrelations were captured via time series analysis. Including stochasticity by using Monte Carlo simulation, we derived both the regional depopulation probabilities and the median net migration by age group and type of region for the 2020–2040 period. Thus, given the state of research in regional migration projections and forecasts, our modeling effort adds a novel approach to the existing literature.

Our findings provide evidence of strong heterogeneity in migration-induced regional depopulation patterns across German regions. This heterogeneity encompasses differences in both the quality and the quantity of migration by age group, gender and region. The results indicate that among parents (aged 30–49) and their children (aged 0–17), the probability of migrating and the migration flows are increased only for migration from large cities to the countryside. By contrast, the model results point to a high probability of migrating and large migration flows of young adults (aged 18–24) migrating from more rural regions to cities, presumably for reasons such as education. Similarly, the findings suggest that among people of early working ages (aged 25–29), the probability of migrating to economically stronger regions is high, which demonstrates the role labor market opportunities play in migration decisions. In contrast to the patterns observed among younger age groups, the results for people close to or beyond retirement age (aged 50 and older) indicate that they are more likely to migrate from urban areas and industrial centers, and that while these migration patterns are quantitatively less distinct, they are still highly probable.

Compared to the official German regional population projection performed by Maretzke et al. (2021), our median forecast has qualitative similarities but quantitative differences. The latter stem from significant differences in the predicted net international migration levels. Whereas Maretzke et al. (2021) assumed that net migration to Germany will converge to a level of 200,000 by 2026 and will remain at that level thereafter, our model predicts a cumulative net migration level of over eight million between 2020 and 2040, i.e., an annual average of 385,000 over that period. While this estimate is within the range of scenarios deemed realistic by Destatis (2019), it is close to their high migration assumption. Notably, an advantage of our approach is that it is fully stochastic and covers all scenarios described by Destatis (2019), while quantifying their individual probabilities. However, our structural results are remarkably similar to those of Maretzke et al. (2021). Whereas both studies predicted positive net international migration for all types of regions, they also predicted that cities and their neighboring regions will gain population in the younger age groups, whereas the rural areas will lose population in these age groups due to internal migration to urban centers. Thus, the migration-induced increases in rural areas are attributable to in-migration by the older age groups, leading to the aging of the overall regional population. Therefore, both studies predicted that the increase in the heterogeneity of regional age structures, particularly between urban and rural areas, will continue in the future.

Nonetheless, the approach presented in this paper is subject to several limitations. *First*, due to data availability, the analysis was restricted to six pre-defined age groups. This may be a drawback for future research, since the inclusion of our findings into annual population forecasts will likely require migration forecasts for one-year age groups. We did not impose assumptions on the age structure of the migrants to circumvent this limitation, but instead relied on the information available in the raw data. Fitting age schedules to the data, which is a common practice in migration modeling, would lead to smooth curves, and, when plugged into a forecast model, narrower prediction intervals that underestimate the future risk (Vanella and Deschermeier, 2020). Our model can, however, be seen as a building block that may feed into hierarchical migration forecasts. For instance, we could use auxiliary data, such as information on the age structure at a higher level of geographical aggregation, such as federal states, to construct forecasts of within-age group distributions of migrants, and multiply them by our age group-specific forecasts, which would result in one-year age group trajectories. Similarly, the availability of gender-specific migration data at this level of geographical disaggregation was restricted to the period from 2002 onward. Therefore, we needed to approximate the gender-specific time series before that point in time by predicting the gender shares through backcasting. Thus, having sufficiently detailed demographic input data would lead to more accurate age- and gender-specific migration forecasts.

Second, closely connected to the preceding limitation, the best-performing model in the backtests, which was used to perform the forecasting exercise, relied on migration flows. As was outlined in Section 2, several authors (Bijak, 2011; Fuchs et al., 2021) noted the advantages of using migration rates rather than flows. However, as was also discussed in Section 2, calculating in-migration rates at the regional level is not straightforward. Thus, the reliance on pseudo-in-migration rates, with their accompanying disadvantages, in the model comparison procedure likely explains the underperformance of the models using migration rates compared to those using flows.

Third, given the volatile nature of migration dynamics in general, migration data are associated with high levels of uncertainty. In particular, international refugee migration is hardly predictable, since it is sensitive to unforeseeable shocks (Vanella et al., 2022). For prediction purposes, it is important to have a sound estimation of future international flows, including of refugee migration, as these processes also shape internal migration. This is a point that should be addressed in future research.

Fourth, the forecast can only be as good as the input data. Thus, trends not included in the historical data also cannot be predicted over the long term by an adequate stochastic approach.[18] *Fifth*, closely connected to the preceding point, migration

[18] For example, the model is restricted to real estate market developments, as reflected in the past data. Regions, and especially cities, can only increase to the extent that the supply of housing and infrastructure (e.g., childcare, schools or mobility infrastructure) allows them to do so. Similarly, migration is only possible if the receiving region's real estate market offers the migrants room to live. A city that has received a large number of migrants in the past, but does not have living space available and is not building new housing projects, will not be able to generate further positive net migration in the future. However, this limitation appears to be mitigated by our model, as many of those trends – for instance, the trends for Berlin – are already included in the data for past periods, and are, therefore, implicitly included in the model.

is influenced by a variety of factors, which, for illustrative purposes, and while acknowledging the vast diversity among underlying reasons for migration decisions across individuals and households, may be identified as either *push* or *pull* factors, with the first being those that induce out-migration from some region, and the latter being those that draw in-migration to some region (Lee, 1966). Both push and pull factors can be of an economic,[19] a political,[20] a social[21] or an environmental nature.[22] A truly holistic approach would forecast migration based on the future development of those predictors. Importantly, the latter would need to be predicted themselves, which would be far from straightforward, and would greatly exceed the scope of this paper.

To conclude, our model addresses a significant shortcoming in the regional migration projection literature by comparing the performance of different modeling approaches and suggesting a stochastic strategy, thereby stimulating the improvement of the projection approaches commonly used by both researchers and statistical offices. In the bigger picture, by contributing to the accuracy of regional population projections in general, this paper also enhances the quality of the demographic base upon which decisions and actions in local and regional planning are taken.

Authors' contributions

Conceptualization: PV; Methodology: PV; Software: PV and TH; Validation: PD and TH; Formal Analysis: PV; Investigation: PV and TH; Resources: PV and TH; Data Curation: PV; Writing – Original Draft: PV and TH; Writing – Review & Editing: PV and TH; Visualization: TH and PV; Supervision: PV; Project Administration: PV.

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19 For example, income (differences) or unemployment rates (Kubis and Schneider, 2020).

20 Such as forced migration because of armed conflicts (Heidelberg Institute for International Conflict Research, 2022) or migration induced by restrictions to freedom of speech in the country of origin (EASO, 2016).

21 Such as migration to a more family-friendly region after the birth of a child, as shown in the paper.

22 For instance, nutritional problems caused by droughts and associated crop failures (UNHCR, 2020).

Data availability

The data used for the study or generated by the authors are available from the corresponding author upon reasonable request.

Supplementary material

Available online at https://doi.org/10.1553/p-5pn2-fmn8

Supplementary file 1. Forecast results by age group, gender and district.
Supplementary file 2. Annual migration flows for the years 1995–2019 by age, gender, direction and district.
Supplementary file 3. Annual (pseudo) migration rates through 1996–2019 by age, gender, direction and district.

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Appendix A. Model selection

Model 1: Gross migration flows, naïve model

As a baseline, we assumed a naïve model that holds migration flows constant to their last observed levels, i.e., for each district, age group and gender, the expected annual migration flows $M_{d,a,g,y}$ for the years 2015–2019 were assumed to equal the corresponding observation for 2014:

$$E[M_{d,a,g,y}] = M_{d,a,g,2014}, \quad y = 2015, 2016, \ldots, 2019. \tag{A.1}$$

Models 2A and 2B: Gross migration flows, observed mean and median values

As was discussed, several of the contemporaneous approaches in migration forecasting assume the convergence of migration flows to a prespecified level. Therefore, we tested two variants of models with target levels. *Model 2A* was inspired by the international migration assumption in Destatis (2019). Thus, we assumed that the migration flows for all strata will equal their respective historical means over the whole baseline period, i.e.,

$$E[M_{d,a,g,y}] = \bar{M}_{d,a,g}, \quad y = 2015, 2016, \ldots, 2019, \tag{A.2}$$

with $\bar{M}_{d,a,g}$ being the annual mean of migration to or from district d for age group a and gender g for 1995–2014. As a second variant, *Model 2B* imposed the expected median, since Vanella and Deschermeier (2020) suggested assuming that crisis-induced migration converges toward its long-term median rather than the mean, as the mean is more sensitive to extreme migration, which may, for example, be caused by extraordinary refugee flows. Then, the expected annual migration flow from or to some district by some age group of a certain gender is

$$E[M_{d,a,g,y}] = \tilde{M}_{d,a,g}, \quad y = 2015, 2016, \ldots, 2019, \tag{A.3}$$

with $\tilde{M}_{d,a,g}$ being the median migration flow from or to district d for age group a and gender g for 1995–2014.

Model 3: Net migration flows, principal component analysis

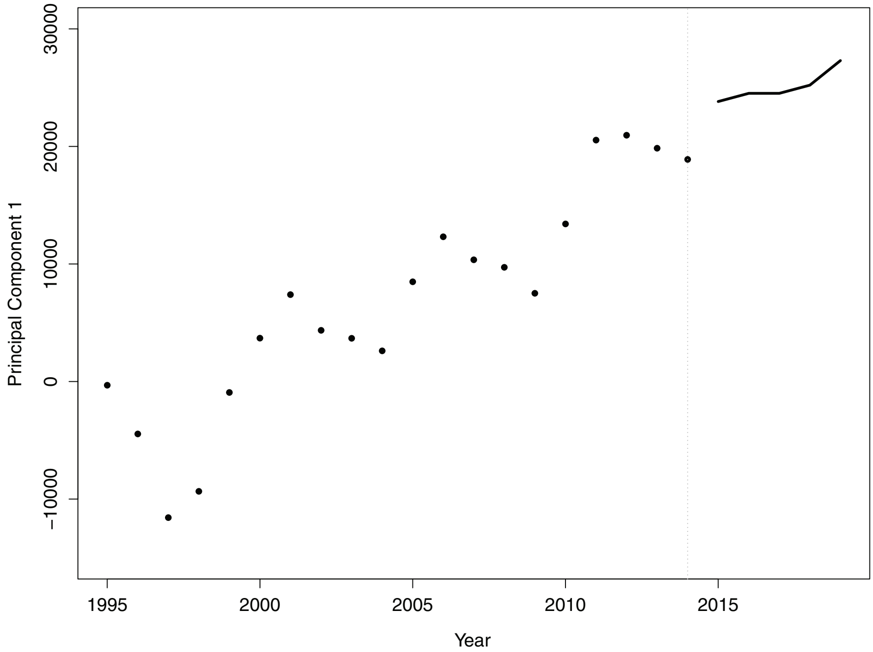
Model 3 is based on Vanella and Deschermeier (2018), applying PCA to the time series matrix of district-, age- and gender-specific net migration flows, a $20 \times 4{,}752$ matrix.[23] As was outlined, PCA transforms the original variables into linear combinations that are correlated to all original variables, yet are uncorrelated among themselves. For the case of net migration flows, for instance, the value of the jth PC in year y can be written as:

$$P_{j,y} = \sum_{d=1}^{396} \sum_{a=1}^{6} \sum_{g=1}^{2} \lambda_{j,d,a,g} N_{d,a,g,y}, \tag{A.4}$$

with $\lambda_{j,d,a,g}$ being called the *loading* (or coefficient) of net migration in district d, in age group a, and of gender g on PC j, and $N_{d,a,g,y}$ being the observed net migration in the said district of the said age group and gender in the said year. The loadings

23 20 years of observations (1995–2014) in the rows, 2 genders × 6 age groups (≤17; 18–24; 25–29; 30–49; 50–64; ≥65) × 396 (pseudo) districts in the columns.

Figure A.1:
Time series (with inversed sign) of Principal Component 1 of net migration model with forecast



Source: Authors' computation and illustration.

are computed by singular value decomposition.[24] Based on graphical analysis of the time series, the ACF, the PACF and maximum likelihood estimation, we fit a trend function with a linear and cosine trend to the time series of the first PC (which explained close to 55% of the variance in the 4,752 time series). The nuisance parameter was emulated by a random walk process:

$$E[P^3_{1,y}|P^3_{1,2014}] \approx 3{,}588 - 1{,}393(y - 1997) + 4{,}276 \cos\left(\frac{(y-1997)\pi}{3}\right) + r^3_{2014},$$
$$y = 2015, 2016, \ldots, 2019, \qquad \text{(A.5)}$$

with r_{2014} being the residual between the value of the first PC and the predicted value by the trend function in 2014. The cosine had a periodicity of six years and was fit as suggested by Vanella et al. (2021) for forecasting weekly mortality rates. The past values are illustrated with the predictions for 2015–2019 in Figure A.1, again with an inversed sign as in the main text to facilitate interpretation.

24 See, e.g., Vanella (2018) for more details on applied PCA in demographic forecasting.

The remaining 4,751 PCs were assumed to be constant for 2015–2019, similarly to (A.1). The matrix of predicted PCs was then transformed back into predictions of net migrations for each district, age group and gender by inverting (A.4) over the set of PC predictions. In matrix notation, the predicted annual net migrations 2015–2019 are

$$\hat{N} = \hat{P} \times \Lambda^{-1}, \tag{A.6}$$

with $\hat{P}$ ($5 \times 4{,}752$) being the predicted PCs for 2015–2019 and Λ^{-1} being the inverted loading matrix ($4{,}752^2$).

Model 4: Log-gross migration flows, principal component analysis

For *Model 4*, the best-performing model used for the stochastic forecast in the main text, we pursued an estimation approach similar to that for Model 3. However, instead of using net migration flows, we applied PCA to a $20 \times 9{,}504$ matrix of the district-, age- and gender-specific migration log-inflows and log-outflows:

$$Q_{j,y} = \sum_{d=1}^{396} \sum_{a=1}^{6} \sum_{g=1}^{2} \sum_{z=1}^{2} \lambda_{j,d,a,g,z} L_{d,a,g,z,y}, \tag{A.7}$$

with $L_{d,a,g,z,y}$ being the log-migration in or from district d, among age group a, of gender g, and of type z ($z = 1$: inflows; $z = 2$: outflows) in year y.

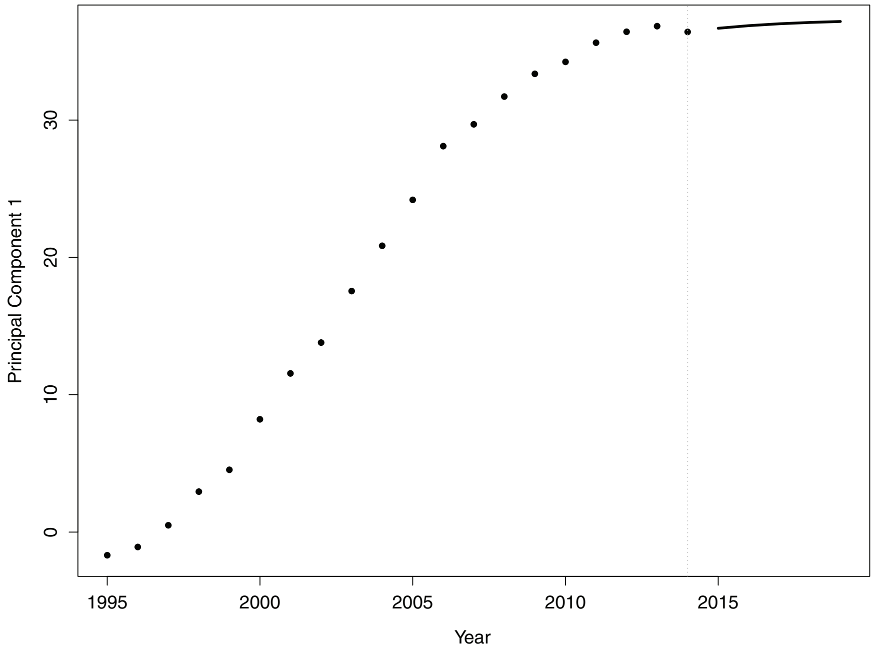
In doing so, we were able to cover trends of both in-migration and out-migration while simultaneously accounting for interdependencies between the two; a phenomenon that was also observed by, for example, Fuchs et al. (2021). By construction, migration flows cannot take negative values. Thus, we included the natural logarithms of migration flows in the PCA. Here again, the first PC (which covered almost 57% of the variance in the 9,504 variables) was predicted in detail by fitting a trend function (in this case, an inverse logistic trend) to the data and modeling the nuisance as a random walk. The resulting forecast function was:

$$E[P^4_{1,y} | P^4_{1,2014}] \approx 3.646 - 41{,}803 \frac{\exp\left(\frac{y-2003}{2.908}\right)}{1 + \exp\left(\frac{y-2003}{2.908}\right)} + r^4_{2014},$$
$$y = 2015, 2016, \ldots, 2019. \tag{A.8}$$

Figure A.2 shows the inversed course of the first PC with its prediction for 2015–2019.

The remaining 9,503 PCs were assumed constant, as they did not exhibit clear trending behavior. Thus, the prediction of the PC matrix can be easily performed in a similar fashion as given in (A.6).

Figure A.2:
Time series (with inversed sign) of Principal Component 1 of the log-migration model with forecast



Source: Authors' computation and illustration.

Model 5: Gross migration rates, naïve model

Many authors have suggested forecasting migration rates instead of migration flows, as was discussed in the literature review. Fuchs et al. (2021), for instance, showed for international migration in Germany that emigration rates are less volatile than emigration flows. Therefore, we tested models that were, in essence, similar to those already tested, but used migration rates instead of flows.

For instance, the out-migration rate of age group a of gender g from district d in year y is defined as the quotient of out-migration flows from that stratum divided by the end-of-year population estimate of the said stratum at the end of the previous year:

$$e_{d,a,g,y} := \frac{E_{d,a,g,y}}{B_{d,a,g,y-1}}. \tag{A.9}$$

Since it is not possible to derive immigration rates due to data restrictions (see Fuchs et al., 2021 and the discussion in Section 2), we defined the notion of *pseudo-in-migration rates*, which relates the inflow to some districts to the population of the target region instead of the origin region:

$$i_{d,a,g,y} := \frac{I_{d,a,g,y}}{B_{d,a,g,y-1}}. \tag{A.10}$$

Although this is a highly hypothetical measure, it allowed for a standardization of in-migration according to out-migration that enabled us to consider the previously discussed correlations between in-migration and out-migration flows in our statistical analysis. Moreover, we indirectly included a higher gravity of migration by larger districts, and thus implicitly accounted for spatial dependence. *Model 5* took a naïve prediction approach similar to that in Model 1, but with migration rates, which were held constant at their 2014 level:

$$E[m_{d,a,g,y}] = m_{d,a,g,2014}, \quad y = 2015, 2016, \ldots, 2019. \tag{A.11}$$

Models 6A and 6B: Gross migration rates, observed mean and median values

Like in Models 2A and 2B, in these models we tested two scenarios for the migration rates, with *Model 6A* assuming the long-term means and *Model 6B* taking the long-term medians as asymptotes. Accordingly, Model 6A assumed

$$E[m_{d,a,g,y}] = \bar{m}_{d,a,g}, \quad y = 2015, 2016, \ldots, 2019, \tag{A.12}$$

with $\bar{m}_{d,a,g}$ being the mean of the district-, age- and gender-specific migration rate over the 1996–2019 period.[25] Accordingly, Model 6B assumed

$$E[m_{d,a,g,y}] = \tilde{m}_{d,a,g}, \quad y = 2015, 2016, \ldots, 2019, \tag{A.13}$$

with $\tilde{m}_{d,a,g}$ being the median of the district-, age- and gender-specific migration rate over the 1996–2019 period.

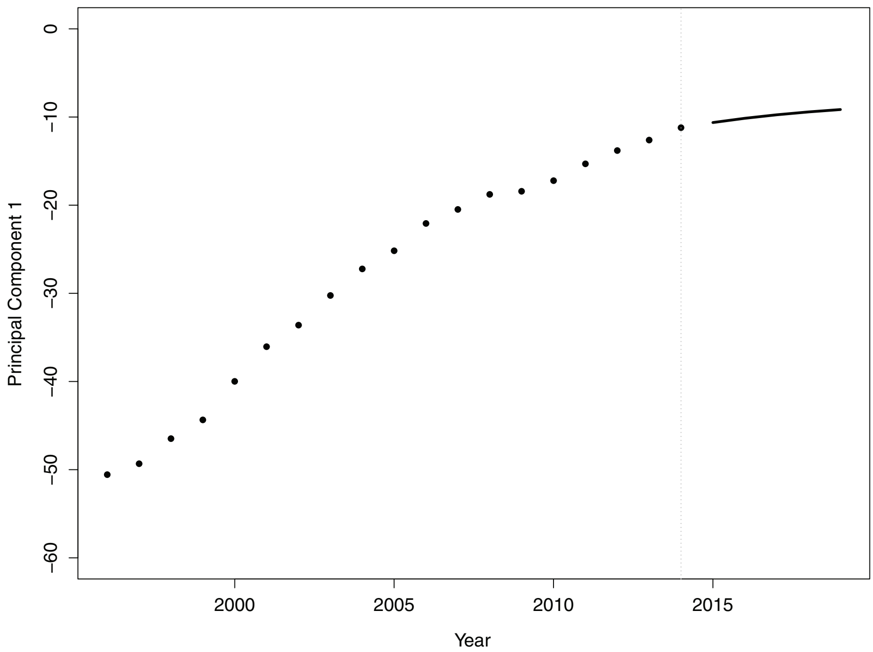
Model 7: Net migration rates, principal component analysis

Corresponding to Model 3, we performed PCA on pseudo net migration rates for all strata. We defined the pseudo net migration rate in district d for age group a, and gender g in year y as the difference between (A.10) and (A.9), given that migration projections based on net growth rates are the current standard in regional population projections in Germany (see Maretzke et al., 2021):

$$n_{d,a,g,y} := i_{d,a,g,y} - e_{d,a,g,y}. \tag{A.14}$$

[25] Note that there is no observation for 1995 because the population data are not available in the needed format before December 31, 1995.

Figure A.3:
Time series (with inversed sign) of Principal Component 1 of the log-migration rate model with forecast



Source: Authors' computation and illustration

However, in this case, PCA did not produce trending functions, and thus did not give insights useful for forecasting. As a result, the prediction of the PCs led to the same problem that arose when using the raw data: i.e., determining which target values should be pre-defined. Therefore, Model 7 was discarded.

Model 8: Log-gross migration rates, principal component analysis

Finally, we performed PCA on the compilation matrix of all log-pseudo in-migration and out-migration rate time series.[26] Like for the approaches explained earlier, a forecast model was fit to the time series of the first PC (which explained over 54% of the variance in the 9,504 variables over the 1996–2014 period). The past course and forecast are illustrated in Figure A.3.

26 Again, we ensured non-negativity among eventual simulations in this way.

The prediction was computed by the following forecast function:

$$E[P^8_{1,y}|P^8_{1,2014}] \approx 70.554 - 61.548 \frac{\exp\left(\frac{y-2000}{4.854}\right)}{1+\exp\left(\frac{y-2000}{4.854}\right)} + r^8_{2014},$$
$$y = 2015, 2016, \ldots, 2019. \tag{A.15}$$

The parameters are similar to the previously presented PC-based approaches. Here again, the remaining PCs do not exhibit clear trending behavior, and are therefore expected to remain constant at their 2014 levels over the forecast horizon.

Comparison of the forecast performance of the candidate models

Since units and dimensions of the predictions depend on the underlying model (net versus gross migration or flows versus rates), we applied a relative measure of forecast accuracy. Additionally, the dataset covered zero values of gross migration. To account for these specifics of the data, we compared the models via their *ex-post symmetric mean absolute percentage error* (SMAPE). Chen et al. (2017) defined the SMAPE as

$$SMAPE := \frac{1}{n}\sum_t \frac{2|e_t|}{|Y_t|+|F_t|}, \tag{A.16}$$

with Y_t being the observation for some variable Y at time t, F_t being its forecast based on some model for the same period, and e_t being the difference between Y_t and F_t. Using the SMAPE not only provides the desired properties, i.e., a relative measure that allows for zero values; it also avoids a high level of asymmetry among the forecast errors, which could appear for denominators close to zero (Chen et al., 2017).

Table A.1 gives a short presentation of the model approaches with their respective SMAPEs. The results of our backtests indicated a poor predictive performance of Model 3, which extrapolated past trends in net migration flows. PCA of pseudo net migration rates did not give additional insights compared to the rather simple models (1, 2A, 2B, 5, 6A, 6B) that were based on pre-stated assumptions about the development of migration. Notably, Models 2A, 2B, 6A and 6B performed significantly worse than the naïve Models 1 and 5, with the rate model having a slightly lower SMAPE than the flow model. According to our measure, the PC-based models that distinguished between in- and out-migration were superior, with Model 4 having the best forecast performance overall. Thus, Model 4 was used for the following forecast in the present study.

Table A.1:
Model summaries with forecast accuracies

Model	Input variables	Dimensions	Target variables	Method	SMAPE
1	Gross migration	396 Districts 6 Age groups 2 Genders In- and out-migration	Gross migration	Naïve prediction of all district-, age- and gender-specific migration flows	7.63%
2A	Gross migration	396 Districts 6 Age groups 2 Genders In- and out-migration	Gross migration	All district-, age- and gender-specific migration flows assumed to take their respective annual means from 1995–2019 in the forecast	14.23%
2B	Gross migration	396 Districts 6 Age groups 2 Genders In- and out-migration	Gross migration	All district-, age- and gender-specific migration flows assumed to take their respective annual medians from 1995–2019 in the forecast	15.16%
3	Net migration	396 Districts 6 Age groups 2 Genders Net migration	Principal components of net migration	PCA on covariance matrix of district-, age- and gender-specific net migration flow time series matrix Forecast function fit for first PC; naïve prediction of remaining PCs	44.88%
4	Log-gross migration	396 Districts 6 Age groups 2 Genders In- and out-migration	Principal components of log-gross migration	PCA on covariance matrix of logarithmized district-, age- and gender-specific gross migration flow time series matrix Forecast function fit for first PC; naïve prediction of remaining PCs	1.27%
5	Gross migration rates	396 Districts 6 Age groups 2 Genders Pseudo in-migration rates and out-migration rates	Gross migration rates	Naïve prediction of all district-, age- and gender-specific (pseudo) migration rates	7.4%

Continued

Table A.1: Continued

Model	Input variables	Dimensions	Target variables	Method	SMAPE
6A	Gross migration rates	396 Districts 6 Age groups 2 Genders Pseudo in-migration rates and out-migration rates	Gross migration rates	All district-, age-, and gender-specific (pseudo) migration rates assumed to take their respective annual means from 1995–2019 in the forecast	14.06%
6B	Gross migration rates	396 Districts 6 Age groups 2 Genders Pseudo in-migration rates and out-migration rates	Gross migration rates	All district-, age- and gender-specific (pseudo) migration rates assumed to take their respective annual medians from 1995–2019 in the forecast	14.73%
7	Pseudo net migration rates	396 Districts 6 Age groups 2 Genders Pseudo net migration rates	Principal components of pseudo-net migration rates	PCA on covariance matrix of district-, age- and gender-specific pseudo net migration rate time series matrix Naïve prediction of all PCs	Discarded due to lack of trends identified by PCA
8	Log-gross migration rates	396 Districts 6 Age groups 2 Genders Pseudo in-migration rates and out-migration rates	Principal components of log-gross migration rates	PCA on covariance matrix of logarithmized district-, age- and gender-specific pseudo migration rate time series matrix Forecast function fit for first PC; naïve prediction of remaining PCs	2.96%

Appendix B. Inclusion of territorial reforms and lack of data in Germany since 1995 in the model

Time	Change in raw data	Data preparation
1998	No data before 1998 available for Eisenach city (16056)	Computation of data before 1998 as differences between inter-district migration data for all Thüringen districts from totals for Thüringen
1998	Kreisreform Sachsen: • Merging of various districts • Renaming of statistical regions: ∘ Chemnitz: 141 → 145 ∘ Dresden: 142 → 146 ∘ Leipzig: 143 → 147	All old district definitions discarded; district definitions since 1998 available for whole period in the raw data
2007	Redefinitions of Sachsen-Anhalt districts: • Halle city: 15202 → 15002 • Magdeburg city: 15303 → 15003 • Altmarkkreis Salzwedel: 15370 → 15081 • Landkreis Stendal: 15363 → 15090	Old definitions changed to new ones before 2007
2007	Mergers of Sachsen-Anhalt districts: • Bördekreis (15355) and Ohrekreis (15362) → Landkreis Börde (15083) • Kreis Mansfelder Land (15260) and Kreis Sangerhausen (15266) → Landkreis Mansfeld-Südharz (15087) • Kreis Merseburg-Querfurt (15261) and Saalkreis (15265) → Saalekreis (15088)	Aggregation of data before 2007 to new definitions
2007	• Redefinition of Burgenlandkreis: 15256 → 15084 • Integration of Landkreis Weißenfels (15268) into 15084	Aggregation of 15256 and 15268 before 2007 into 15084
2007	Mergers and separations of Sachsen-Anhalt districts: • Merger of Landkreis Bitterfeld (15154) and Landkreis Köthen (15159) → Landkreis Anhalt-Bitterfeld (15082) • Merger of Landkreis Halberstadt (15357), Landkreis Quedlinburg (15364), and Landkreis Wernigerode (15369) → Landkreis Harz (15085) • Merger of Kreis Bernburg (15153) and Kreis Schönebeck (15367) → Salzlandkreis (15089) • Landkreis Anhalt-Zerbst (15151) divided into Dessau-Roßlau city (15001), Landkreis Anhalt-Bitterfeld (15082), Landkreis Jerichower Land (15086), and Landkreis Wittenberg (15091) • Landkreis Aschersleben-Staßfurt (15352) divided into Landkreis Harz (15085) and Salzlandkreis (15089)	No one-to-one distribution to new borders possible; thus, aggregation of all districts to pseudo-district 150018285868991

Continued

Appendix B. Continued

Time	Change in raw data	Data preparation
2008	Separate reporting of data of city of Hannover and Hannover region without Hannover city	Separate time series before 2008 cannot be constructed; thus, data since 2008 cumulated to total Hannover region, according to old definition
2009	Merger of Aachen city (05334002) and Kreis Aachen (05354) to Städteregion Aachen (05334)	Computation of data since 2009 to old definitions by subtracting 05334002 from 05334
2011	Mergers of Mecklenburg-Vorpommern districts: • Landkreis Bad Doberan (13051) and Landkreis Güstrow (13053) → Landkreis Rostock (13072) • Hansestadt Stralsund (13005), Landkreis Nordvorpommern (13057), and Landkreis Rügen (13061) → Landkreis Vorpommern-Rügen (13073) • Landkreis Ludwigslust (13054) and Landkreis Parchim (13060) → Landkreis Ludwigslist-Parchim (13076)	Aggregation of data before 2011 to new definitions
2011	• Redefinition of Landkreis Nordwestmecklenburg: 13058 → 13074 • Integration of Hansestadt Wismar (13006) into 13074	Aggregation of 13058 and 13074 before 2011 into 13074
2011	Mergers and separations of Mecklenburg-Vorpommern districts: • Hansestadt Greifswald (13001), partially Landkreis Demmin (13052), Landkreis Ostvorpommern (13059), and Landkreis Uecker-Randow (13062) → Landkreis Vorpommern-Greifswald (13075) • Neubrandenburg city (13002), partially Landkreis Demmin (13052), Landkreis Mecklenburg-Strelitz (13055), and Landkreis Müritz (13056) → Landkreis Mecklenburgische Seenplatte (13071)	No one-to-one distribution to new border possible; thus, aggregation of all districts to pseudo-district 1307175
2016	• Redefinition of Landkreis Göttingen: 03152 → 03159 • Integration of Landkreis Osterode am Harz (03156) into 03159	Aggregation of 03152 and 03156 before 2016 into 03159

Approaches to boundary change incorporation

The table above gives a comprehensive overview of the boundary changes underlying the dataset used for the empirical analysis. We applied a rather simple method that sought to obtain consistent time series throughout the period under consideration (1995–2019) by either relying on outdated boundaries or merging districts. We acknowledge that there is an established literature offering a variety of approaches to obtaining missing year-district (or another level of geographical disaggregation) observations, which strongly depends on the corresponding use case. Interested readers may start with examples such as Martin et al. (2002), Norman et al. (2003) or Logan et al. (2021).

Appendix C. Estimation of age- and sex-specific migration before 2002

As indicated in Section 3, for districts in 15 of the 16 federal states, age-specific but no gender-specific migration data are available in the pre-2002 data. To address this gap, we took annual age- and gender-specific data on district-level gross migration flows (Statistische Ämter des Bundes und der Länder, 2022) for 2002–2019. Based on these data, we constructed time series for migration flows by age group and gender for each district for in- and out-migration. To account for differences in the migration patterns between the genders and to retrieve the maximum of information from the data, we computed the annual shares of males among all migrants for each age-district stratum for 2002–2019:

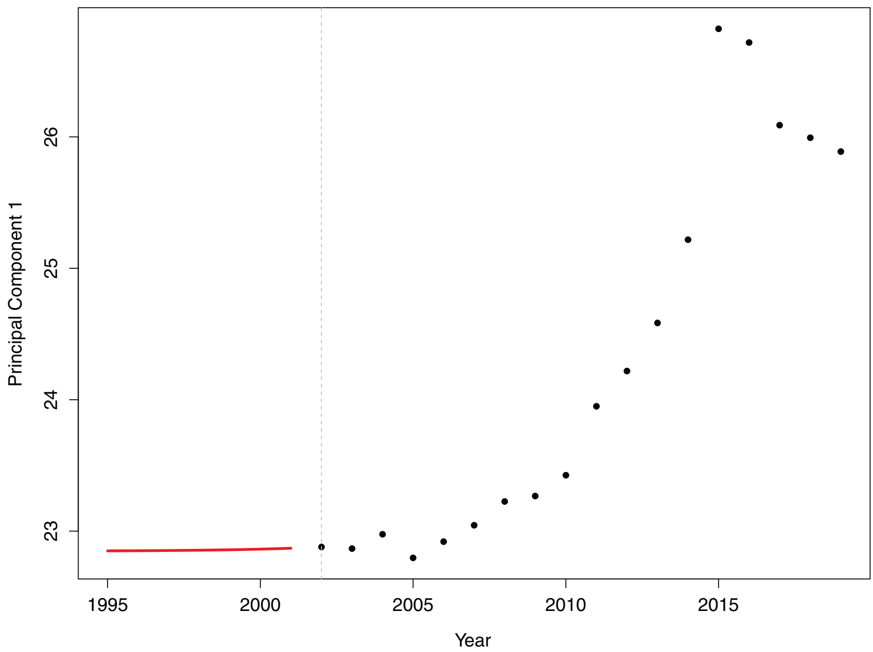
$$s_{d,a,z,y} := \frac{M_{d,a,m,z,y}}{M_{d,a,z,y}}, \tag{A.17}$$

With $M_{d,a,m,z,y}$ being the number of male migrations from or to district d in age group a for migration type z in year y, and $M_{d,a,z,y}$ being the corresponding total migration number for both genders.

The data were highly dimensional (4,596 time series), and the time series were highly correlated. Again, we applied PCA to deal with both problems. Figures C.1 and C.2 show the time series of the first two PCs. Those time series explained 55.7% of the total variance in the male share time series.

The red lines show the backcasts derived from time series models that were constructed as linear combinations of a mathematical trend function (exponential trend between 2002 and 2015 for the first principal component and the logistic trend between 2002 and 2010 for the second principal component) and a random walk model each. The remaining PCs did not show clear trending behavior, and were therefore assumed to be random walks. The backcasts of the PCs were then retransformed into backcasts of the male migration shares for each age group and district. We derived the shares of men and women among all migrants per age-district

Figure C.1:
Time series of Principal Component 1 of male shares in district migration with backcast

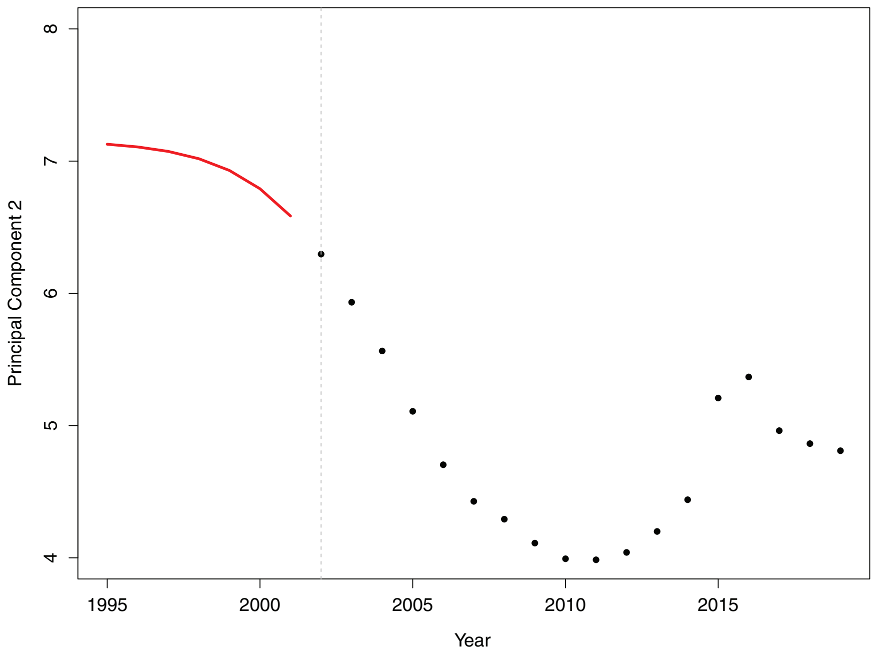


Source: Authors' computation and illustration.

stratum and year by multiplying the corresponding backcast of the male share, and its inverse, by the total migration for the given age-district stratum.

Supplementary Files S2 and S3 (available at https://doi.org/10.1553/p-5pn2-fmn8) offer the annual migration flows for the years 1995–2019 and the corresponding (pseudo) migration rates through 1996–2019, by age, gender, direction and district, respectively, in matrix form for further use. The data before 2002 are our backcast estimates as described above.

Figure C.2:
Time series of Principal Component 2 of male shares in district migration with backcast



Source: Authors' computation and illustration.