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Modeling Migration Dynamics in Stochastic Labor Supply Forecasting

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Abstract

Population size and structure in conjunction with the participation behavior are the determinants of labor supply. Thereby, among the demographic components, migration is the one shaping both the size and the structure of a population the strongest in the short to medium term while simultaneously exhibiting high uncertainty, with migration patterns varying between origin-destination-pairs depending on a range of economic and other determinants. Yet, existing stochastic forecasting approaches that jointly address population and labor force participation are sparse and do neither account for differences in future immigration flows across origin countries nor for the interdependencies of immigration and emigration in the destination country. Addressing this shortcoming, we propose an augmentation of an integrated stochastic population and labor force participation forecasting framework by a gravity-equation component to model future immigration and emigration, their interaction, and their determinants more appropriately. By conducting a stochastic forecast, we find that until 2060 the potential labor supply in Germany is declining by 11.7 percent, strongly driven by the even more distinct decline of the working-age population and only partially cushioned by rising participation rates. Thereby, increasing immigration to Germany is highly probable, yet its net effect is limited due to simultaneously rising emigration figures.

Zusammenfassung

Die Bevölkerungsgröße und -struktur im Zusammenspiel mit dem Erwerbsverhalten sind die Determinanten des Arbeitsangebots. Dabei ist Migration nicht nur diejenige demografische Komponente, die eine Bevölkerung mit Blick auf Größe wie auch Struktur kurz- bis mittelfristig am stärksten prägt, sondern sie weist auch vergleichsweise hohe Unsicherheit auf, da Migrationsbewegungen zwischen Herkunfts- und Zielländern von einer Reihe ökonomischer und anderer Faktoren beeinflusst werden. Bestehende stochastische Prognoseansätze, die Bevölkerungs- und Erwerbsbeteiligung gemeinsam modellieren, sind jedoch rar gesät und berücksichtigen weder Unterschiede in den Migrationsbewegungen über Herkunftsländer hinweg noch den Zusammenhang von Einwanderung und Auswanderung im Zielland. Dieses Papier zeigt, wie ein bestehender integrierter, stochastischer Ansatz zur gleichzeitigen Prognose von Bevölkerung und Erwerbsbeteiligung durch Gravitationsmodelle ergänzt werden kann, um so die künftige Zu- und Abwanderung, ihre Interaktion sowie ihre Determinanten angemessener zu modellieren. Die Anwendung dieses Ansatzes auf deutsche Daten zeigt, dass das Erwerbspersonenpotenzial Deutschlands bis 2060 um 11,7 Prozent abnimmt, stark getrieben durch den noch deutlicheren Rückgang der Bevölkerung im erwerbsfähigen Alter und nur teilweise abgefedert mittels steigender Erwerbsquoten. Dabei sind steigende Zuwanderungszahlen nach Deutschland zwar wahrscheinlich, ihr Nettoeffekt ist jedoch aufgrund gleichzeitig wachsenden Abwanderungszahlen begrenzt.

JEL classification

J11, J21, F22

Keywords

Labor supply, hidden unemployment, international migration, population decline, stochastic forecasting

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1 Introduction

A number of countries across Europe, including Germany, are either already experiencing population decline or are likely to do so in the near future. The latest United Nations population prospect (UN 2022, medium variant) projects the aggregate population of the EU-27 to decline from 2024 onwards, with 18 countries expected to have a smaller population in 2060 compared to 2022. More recent data by Eurostat (2022) even demonstrates that, given the Covid-19 pandemic slowing down immigration (Bodnár and O'Brien 2022), the aggregate EU-27 population has already decreased in 2020 and 2021.

Notably, this population decline is expected to exhibit a distinct age-pattern. With high-births cohorts (*baby boomers*) approaching retirement age, if not reached by now, and enduring low fertility since decades, working-age populations of European countries are likely to face a disproportional strong decrease, and so does Germany, despite experiencing high net migration during the past years (documented, among others, by Fuchs et al. 2019). In the baseline scenario, the EUROPOP2019 projection expects for Germany a decline of the working-age population by more than 13 percent until 2060 while the population aged 65 and above is expected to increase by more than 30 percent over the same period. Consequently, the old-age dependency ratio increases from 33.2 to 49.6 persons aged 65 and above relative to those in working-age (Eurostat 2021). National projections by the Federal Statistical Office (FSO), depending on the scenario under consideration, resemble these figures (e.g. FSO 2022a).

Clearly, such hitherto unseen demographic changes raise questions of corresponding implications, such as the stability of social security or health systems, but, above all, in the labor market, as the size of the labor force, by definition, strongly depends on the size of the working-age population, along with participation behavior (for a discussion on effects of population ageing and decline from a macroeconomic perspective see, among others, Bloom et al. 2015 or Hellwagner and Weber 2021). Consequently, population projections may be accompanied by corresponding projections of labor force participation rates (e.g. FSO 2020; see survey in chapter 2).

Yet, existing population and participation projections frequently face critique from two angles. On one hand, corresponding figures such as those from examples cited above, usually stem from deterministic rather than stochastic models, as the former are more common in the literature (Vanella et al. 2020). However, deterministic approaches, although typically relying on pre-defined parameters that are likely based on well-founded assumptions, are not able to quantify the uncertainty inherent to the corresponding scenario but rather exhibit a statistical probability of actual occurrence close to zero (Keilman et al. 2002; Vanella et al. 2020). Stochastic approaches overcome this limitation. While there is a growing series of existing stochastic population models (e.g. Azose et al. 2016; Raftery et al. 2014a), the disbalance of deterministic and stochastic approaches is even more pronounced for projections of labor force participation. Here, only a very limited body of literature exists (e.g. Frees 2003). On the other hand, many approaches rely on projecting net migration rather than gross migration and do not model its determinants explicitly, both of which has been subject to critical discussions (e.g. Fuchs et al. 2021 respectively Cappelen et al. 2015). Appropriately modeling (gross) migration is of key importance given its crucial role for the demographic change in a wide range of countries in the more recent past. Put differently, contrarily to low-frequency long-term trends in natural population change, the interplay of fertility and mortality, recent high migration figures continue to fuel (working-age) population growth for many countries that, otherwise, would have faced the onset of population decline way earlier. Additionally, the age-structure of migration tends lower old-age dependency ratios in destination countries, i.e., tends to counteract population ageing (Wilson et al. 2013; see Craveiro et al. 2019 for a recent discussion on "replacement migration" among European countries).

Addressing these issues, we set up an integrated stochastic model to forecast both the population and the labor force in Germany until 2060 based upon Fuchs et al. (2017) and extend the modeling approach therein by explicitly incorporating determinants of migration. As a case study, Germany is of particular interest, given high net migration coupled with rising participation rates, although with persisting differences across demographic groups, have resulted in steadily rising labor force figures in the past (Fuchs et al. 2019) – despite being among the countries with the lowest fertility rates across the globe for decades (Bujard 2020).

More specifically, using a cohort-component framework, we forecast the population by age, sex, and citizenship and link the results to a forecast of participation rates, including hidden unemployment (see Agbola 2005 or Armstrong 1999, among others), i.e., the potential labor force, again disaggregated by age, sex, and citizenship. Throughout the paper, we primarily rely on principal components analysis (PCA), as common in stochastic demographic forecasts (e.g. Vanella 2018), in order to reduce dimensionality and account for high correlation between the age-, sex-, and citizenship-specific demographic time series. Moreover, substantially extending earlier approaches like Fuchs et al. (2017), we augment the common cohort-component framework by accounting for both the determinants of immigration, inspired by gravity models (e.g. Mayda 2010), as well as the interdependencies of immigration and emigration (see Fuchs et al. 2021), linking the former to the latter, in detail.

Thus, our contribution to the literature is twofold: In a general perspective, we extend the outlined, still rather sparse body of stochastic forecasting models that integrate both population and labor force participation. More specifically, we introduce a detailed migration modeling strategy to our forecast in order to account for the determinants of migration and, consequently, its impact on the potential labor force in Germany more appropriately compared to most of the existing literature.

The resulting forecast suggests the population in Germany to decline from 83.2 million in 2020 to 72.6 million in 2060, with the working-age population facing a proportionally more distinct decline from 62.3 to 52.2 million. Importantly, the new migration modeling approach forecasts an overall increase in immigration, yet with changing patterns compared to the more recent past. For European countries, we find declining future immigration figures, but they are likely to remain the main sending countries for Germany. Consequently, the rise of future immigration figures is more likely to be driven by inflows from Asia and Africa. However, despite overall rising immigration, net migration is expected to decline. The time-series estimate of the number of emigrants shows an increase as the non-German population grows, which is not offset by the growing immigration.

As a consequence, in conjunction with the integrated forecast of labor force participation rates, we find that the potential labor force forecast for 2060 is 40.4 million, an 11.7 percent decline compared to 2020.

While these findings are, concerning direction and magnitude of the expected changes, in line with other, mostly deterministic projections in Germany (e.g. FSO 2020), the quantification of the potential labor force decline probability clearly demonstrates a decrease to be the most likely future development, calling for corresponding action from a policy perspective.

The remainder of the paper is structured as follows. In section 2, a brief overview of the relevant literature, that is, migration modeling as well as (deterministic and stochastic) demographic projections and forecasts, is given. In section 3, we introduce our general estimation framework and used data sources. Then, section 4 offers a detailed outline of the migration modeling approach, being the core contribution of our paper. Section 5 presents the results. The last section concludes.

2 Literature review

With the intention of modeling and forecasting gross migration flows to and from Germany as well as labor force participation within a stochastic framework, this paper connects to at least three different but intertwined strands of the literature: (1) modeling the determinants of current and future migration flows rather than relying on deterministic assumptions, (2) closely connected, population projections and forecasting in general, accompanied by questions of suitable methods to deal with high dimensional data and incorporate uncertainty, and (3) accounting for changing labor force participation patterns across demographic groups over time, i.e., again appropriately incorporating its determinants into a (stochastic) forecasting approach.

2.1 Modeling migration and its determinants

Identifying and analyzing the determinants of migration has a long tradition across disciplines (e.g. Brettell et al. 2022 or Pisaresvskaya et al. 2020, among others). The literature discusses a variety of factors – and economic determinants are typically assigned a crucial role. Bertoli et al. (2013) demonstrate that earnings significantly impact individual migration decisions. Similarly, Ortega and Peri (2013) document that migration flows are strongly dependent on income per capita in destination countries. Closely connected to economic issues, educational factors are well-known to impact migration decision and patterns. Thereby, empirical findings suggest positive selection, i.e. that more educated individuals are more likely to migrate (e.g. Lutz and KC 2011). Grogger and Hanson (2011) show that not only positive selection but also positive sorting, i.e. migration targeted to countries with larger skill-related wage differences, can be formalized in an income maximization model. Other empirical results demonstrate a distinct role of institutions for migration decisions. The findings of Mayda (2010), among others, support the role of spatial proximity, i.e. distance of origin and destination, to strongly impact migration dynamics. Ortega and Peri (2013) show that for countries within the European Union, the elasticity to income per capita is twice as high; similarly, migration regulation strongly impacts migration flows. Geis et al. (2013) find that the institutional framework in the labor market, such as union coverage and unemployment benefits, significantly influence location decisions among migrants. Moreover, studies suggest that network effects are crucial in explaining migration flows (Beine et al. 2011; Pedersen et al. 2008), in particular in case of migration patterns on a more disaggregated spatial level. Similarly, linguistic proximity (Adsera and Pytlikova 2015) has been shown to impact migration dynamics.

Now, incorporating migration into forecasting approaches faces two central questions: First, how to appropriately model these determinants? Second, how to incorporate migration into the (demographic) forecasting model?

First, in the economic literature, the former has frequently been operationalized by applying differing versions of *gravity models* (e.g. Alesina et al. 2016; Clark et al. 2007; Gallardo-Sejas et al. 2006; Hanson and McIntosh 2016; Karemera et al. 2000; Kim and Cohen 2010; Mayda 2010; Ortega and Peri 2013; Ramos and Suriñach 2017). Gravity equations have a long and well-established tradition in trade economics (e.g. Anderson 1979; Tinbergen 1962). In the case of migration analysis, as Beine et al. (2016) argue, the rise in applications of gravity models has appeared more recently, closely connected to the availability of migration data and corresponding time series[1]. Thereby, migration flows from a given origin country to a given destination country are usually regressed on a set of independent variables reflecting migration determinants as outlined above. Thus, a corresponding model may be written as

$$\frac{M_{ijt}}{P_{it}} = \frac{W_i}{W_j} + D \tag{1}$$

with M_{ijt} being the migration flow from (origin) country i to (destination) country j at time t; P_{it} being the population of the country i at time t; W_i being one or several (economic) variables of country i and W_j being the same variables in country j, the ratios of which are assumed to exert influence on the migration intensity between both countries; and D being a vector of deterministics, such as distance, a common border, common language, or migration regulations.

In the literature, the inclusion of (economic) determinants, W_i/W_j, is often motivated by a random utility maximization (RUM) model (e.g. Beine et al. 2016; Ortega and Peri 2013). Following Beine et al. (2016), the RUM assumes that the utility for individual k from moving from country i to country j at time t, U_{kijt}, consists of a deterministic component, w_{ijt}, an individual-specific component, e_{kijt}, and is connected to costs, c_{ijt}:

$$U_{kijt} = w_{ijt} - c_{ijt} + e_{kijt} \tag{2}$$

By drawing on a suitable variable W, and correspondingly the ratio of this variable in both countries, W_i/W_j, we may approximate the expected profits that stem from equation (2) and

[1] For a discussion on the history of gravity models and the application in the context of migration analysis, interested readers may refer to Anderson (2011).

which govern the migration intensity between two given countries. For a more detailed discussion on the properties and implications underlying the RUM and its empirical application, see Beine et al. (2016).

Second, the latter question addresses decisions on the appropriate target variable as well as on the incorporation of risk and uncertainty. As a target variable, migration may be modelled as either (gross or net) flows or rates, with the former being used in a variety of projection approaches (e.g. FSO 2022a). Yet, a number of authors, such as Bijak (2011) or Fuchs et al. (2021), notice drawbacks of relying on flows rather than rates. Importantly, rates, being calculated based on the population at risk of migrating, exhibit, on the one hand, stable age-patterns (Rogers and Castro 1981) and thus, on the other hand, appropriately account for changes in the structure of the population. This is of particular importance given the age- and sex-specific patterns in international migration (see, among others, Raymer et al. 2011 or Van Mol and de Valk 2016) in combination with demographic changes, i.e. population ageing, across countries. Moreover, among the three demographic components, migration forecasting is associated with disproportionally strong risk (e.g. Azose et al. 2016), calling for an appropriate modeling strategy to account for this inherent uncertainty. Yet, observing the role of determinants as well as documenting substantial uncertainty in migration dynamics does not, straightforwardly, suggest a best-practice implementation of any empirical strategy in migration forecasting, but crucially also depends on the overall population projection and forecasting model.

2.2 Population forecasting: a brief overview of methods

Typically, population forecasts are conducted using the cohort-component framework. Now being the demographic workhorse, it has been popularized, among others, by the seminal contribution of Lee and Carter (1992). Corresponding models start from an initial population disaggregated by categories such as sex, age, or citizenship. Then, using forecasted values for demographic components like fertility, mortality, and migration, the future trajectories of all cohorts are derived. Notably, approaches differ in the way future values of components are calculated, in particular with regard to the incorporation of risk and uncertainty, and are thus often divided into deterministic and stochastic frameworks.

Deterministic approaches are characterized by pre-defining relevant values, such as future fertility and mortality rates as well as migration rates or flows, and calculating, based upon these values and an initial population, the future trajectories. Deterministic approaches are frequently applied by statistical offices (e.g. FSO 2022a) and are often used to compare different scenarios and the corresponding implications to each other (e.g. Bijak et al. 2007; Lomax et al. 2020; Lutz et al. 2019).

Yet, despite their popularity, deterministic approaches have faced substantial critique (e.g. Lee and Tuljapurkar 1994). By pre-defining the relevant values of the projection, such as the annual net migration or fertility and mortality rates, deterministic approaches may capture intuitively realistic scenarios – however, these scenarios exhibit a statistical probability to actually unfold that is close to zero (Keilman et al. 2002). Contrarily, stochastic approaches are able to quantify the uncertainty inherent to population projections by relying on adequate statistical methods. Corresponding approaches, either concerned with one or with several demographic components, are applied both in frequentist and Bayesian traditions (Alders et al. 2007; Alkema et al. 2011; Azose et al. 2016; Bijak 2011; Bijak and Wiśniowski 2010; Lee 1998; Lee and Tuljapurkar 1994; Raftery et al. 2013; Raftery et al. 2014a; Raftery et al. 2014b; Sanderson et al. 2004; Vanella and Deschermeier 2020; Wiśniowski et al. 2015).

Moreover, population forecasting approaches, given the high collinearity in age- and sex-specific time series of demographic components like mortality, often draw on principal components analysis (PCA) (e.g. Bell and Monsell 1991; Booth and Tickle 2008; Bozik and Bell 1987). Notably, PCA-based approaches can be easily combined with an overall stochastic framework as recent examples demonstrate (e.g. Vanella and Deschermeier 2020). Similarly, also gravity equations have already been combined with forecasting exercises in the literature (Hanson and McIntosh 2016; Kim and Cohen 2010; among others).

2.3 Analyzing and forecasting (potential) labor supply

In conjunction with the overall population, the size of the labor supply crucially depends on the participation behavior. Participation rates do not only vary by age and sex (e.g. Juhn and Potter 2006; Killingsworth and Heckman 1986; Psacharopoulos and Tzannatos 1989), but also by further categorizations such as educational attainment (e.g. Jefferson 2008; Krueger 2017) or citizenship respectively migration history (e.g. Anectol 2000; Donato et al. 2014). A large body of literature has developed around these observations, with the corresponding analyses and discussions addressing various determinants.

In the short to medium term, business cycle effects are attributed a key role in driving labor force participation (e.g. Cajner et al. 2021). Cajner et al. (2017) document ethnic differences in both labor force participation and unemployment in the U.S. that are amplified by business cycle dynamics. Similarly, Hoynes et al. (2012) document substantial differences of business cycle effects on employment and unemployment rates between sexes, ethnic groups, age, and education. In analyzing changing participation patterns in a long-term perspective, Krueger (2017) emphasizes, among other things, the effect of increasing school enrollments on the decline in participation rates among young persons. In a similar vein, Pilkauskas et al. (2016) show that both the extent and the timing of maternal labor force participation varies substantially by education. Targeting institutional determinants of labor force participation, a recent contribution by Alon et al. (2021), analyzing employment patterns in the U.S. during the Covid-19 pandemic, shows that, along other causes, the increased need for childcare as consequence of school and daycare closures contributed to larger employment declines of women compared to men. Cipollone et al. (2014) show that a substantial amount of the increase in young women labor force participation across European countries can be attributed to labor market institutions and family-oriented policies, and this evidence is amplified by education. Similarly, Blau and Kahn (2013) conclude that implementation of family-oriented policies in other OECD countries explains a substantial amount of the relative decline in U.S. female participation rates. Thus, a wide range of factors, from business cycle effects to educational attainment and institutional frameworks, also often conceptualized as “added worker” and “discouragement” effects (see Fuchs and Weber 2017 for a discussion), determine labor force participation rates across age-, sex-, and citizenship-groups. Recent, more comprehensive overviews of determinants driving long-term trends in employment rates are given by Aaronson et al. (2014) and Abraham and Kearney (2020).

Notably, labor force participation rates as delivered by surveys and official statistics document the observable participation in the labor market. However, relying on these rates underestimates the *potential labor supply* available to a country's labor market. In the literature, this part of labor supply, which is or may be available additionally to the labor supply that is observed by participation rates, is often labelled as *hidden unemployment* or *hidden labor force*. The concept is well established since decades (e.g. Dernburg and Strand 1966) and is strongly resembled by more recent debates on the business cycle effects on labor force participation, as outlined above. Consequently, while unemployment definitions usually encompass people within the labor force, i.e. those without employment but actively searching for some, definitions of hidden unemployment (hidden labor force) often refer to people "who are not now in the labour force but who would be in the labour force if the conditions characteristic of full employment existed" (Stricker and Sheehan 1981: 3, cf. Agbola 2005: 94). Yet, as the discussion on determinants of participation behavior above has shown, exclusively relying on full employment, i.e. the state business cycle as the central determinant of hidden unemployment, falls short of other structural factors explaining non-participation, such as child care (see also Baum and Mitchell 2010).

An accurate forecast of future labor supply necessarily also depends on the future developments of the determinants of the hidden labor force – but some of which are, as for instance in case of future business cycle dynamics, difficult to predict in the long-term. As a consequence, estimating hidden unemployment for past observations, i.e. in-sample *potential labor force participation rates*, conducting forecasts based upon these rates, and linking the results to those from an appropriate population forecast delivers much more consistent figures of the (upper bound of) labor supply available to the labor market in the future.

However, there is still uncertainty, both with respect to the future trajectories of potential participation rates as concerning future demographic developments. While there exists a variety of stochastic demographic forecasts, as outlined above, similar approaches to participation forecasting are much sparser. Selected examples encompass Frees (2003), Frees (2006), and Lanza-Queiroz et al. (2021).

Moreover, existing integrated approaches that combine projections of future population and future (potential) labor supply are often at least partially conducted in deterministic settings, as selected examples indicate (e.g. Aaronson et al. 2006; Hornstein and Kudlyak 2019; Loichinger 2015; Marois et al. 2020; Montes 2018; Tossi 2011). Loichinger (2015), for instance, projects future population and labor force participation among 26 countries until 2053, decomposed by age, sex- , and education in three deterministic scenarios. Similarly, Marios et al. (2020) compare six scenarios, with varying assumptions on labor force participation and other parameters. Montes (2018), using U.S. data, conducts a projection of (potential) labor force participation rates for a variety of subgroups over a 10-year-horizon and combines this projection with a corresponding deterministic CBO population projection. A similar approach is presented by Tossi (2011). Also, Aaronson et al. (2006), using a comprehensive econometric approach, or Hornstein and Kudlyak (2019), who estimate a state space model of age-, sex-, and cohort-specific participation and unemployment rates as well as educational shares, combine their resulting forecasts with deterministic population projections. But in deterministic projections, as outlined, migration usually follows the pre-specified future trajectory.

By contrast, fully stochastic accounts are sparse. Fuchs et al. (2017) provide a corresponding example. They forecast age-, sex-, and citizenship-specific immigration and emigration rates, and forecast the total size of immigration separately. Vanella et al. (2022), as a more recent example, combine stochastic population and labor force participation rate forecasts in estimating prevalence and costs of absenteeism in the face of population aging, and forecast (pseudo) net migration rates. Thus, despite careful and comprehensive approaches to jointly model future dynamics of labor force participation and population, most examples fall short of appropriately modeling migration dynamics, that is, its determinants and incorporate its inherent uncertainty as outlined in the literature review, calling for further methodological developments in forecasting models.

3 Integrated stochastic forecasting model: an overview

The overall framework presented in this section resembles the integrated forecasting approach outlined in Fuchs et al. (2017). Therefore, this section discusses those components that we adopt in the present paper only briefly. This encompasses (1) the estimation of age- and sex-specific potential labor force participation rates and (2) the estimation and forecast of principal components (PCs) for rates of fertility, mortality, naturalizations, as well as immigration and emigration rates. Eventually, relying on the framework presented in this as well as in the upcoming section, we obtain a joint stochastic forecast of the demographic components and the labor force participation rates by drawing 5,000 times from the residuals with replacement. By using quantiles of the resulting 5,000 trajectories, we are able to derive confidence intervals.

Importantly, immigration rates as used in our model are part of a *top-down approach* – that is, we calculate and forecast the age-, sex- and citizenship-specific shares of aggregate immigration flows to Germany rather than the disaggregate immigration rates directly. We outline the forecast of aggregate immigration flows, using a gravity-type migration modeling approach, separately and in detail in the upcoming chapter as it constitutes a key extension compared to Fuchs et al. (2017). We obtain future age-, sex-, and citizenship-specific immigration flows by multiplying the forecasted aggregate immigration flows with the forecasted structural rates. By contrast, we model emigration rates using the commonly applied *bottom-up approach* – that is, we calculate age-, sex- and citizenship-specific emigration rates by dividing outflows by the corresponding population stock in Germany. Vice versa, we derive future emigration flows by multiplying the forecasted emigration rates with the corresponding forecasted population stock.

3.1 Potential labor force participation rates

We use LFPRs from the labor force survey in Germany, disaggregated by five-year age groups (15-74 years), sex, and citizenship (Germans and non-Germans), for the years 1990-2019. In general, the LFPRs used in this paper correspond to those published by the Federal Statistical Office (e.g. FSO 2022a), but, however, offer more detailed disaggregation along demographic categories and were provided by the FSO on request. We additionally adjust these participation rates by marginal employment that is not captured in the underlying survey. The information on marginal employment is provided by the Federal Employment Agency. For further information on the adjustment for marginal employment, see Fuchs and Weber (2005). For a discussion on the undercoverage of marginal employment in the LFS, see Körner and Maderer-Puch (2015).

Now, let a_{jt} denote the participation rate of a demographic group j at time t. Then, the estimated participation rate, $\hat{a}_{jt}$,may be written as

$$\hat{a}_{jt} = \alpha + \beta U_t + \gamma X_t \tag{3}$$

where α is the intercept, U_t is a scalar containing relevant labor market indicators as discussed above, and X_t is a vector of further control variables, with β and γ holding the corresponding coefficients. As outlined in the literature review, suitable determinants indicate the size of hidden unemployment. Thus, by plugging in full-employment values, U_t^f, into the estimated equation allows to obtain $\hat{a}_{jt}^f$, i.e., the estimated participation rate of a demographic group j at time t under full-employment conditions:

$$\hat{a}_{jt}^f = \alpha + \beta U_t^f + \gamma X_t \tag{4}$$

Now, since the estimated values $\hat{a}_{jt}$ and $\hat{a}_{jt}^f$ only vary with respect to the values of the labor market indicators, we can use the difference of both, $a_{jt}^h = \hat{a}_{jt}^f - \hat{a}_{jt}$, to obtain the hidden unemployment rate, a_{jt}^h, of a demographic group j at time t, and derive, straightforwardly, the *potential labor force participation rate*, a_{jt}^p, as

$$a_{jt}^p = a_{jt} + a_{jt}^h \tag{5}$$

The selection of both a suitable labor market indicator U_t and additional regressors X_t varies across demographic groups. In the appendix, Table A-1 offers a detailed overview of included variables and the corresponding data sources. Notably, in the estimation presented in equations (3), (4), and (5) as well as in the forecast procedure presented below, we include the participation rates as logits to ensure that rates never exceed 100 percent[2].

[2] Thus, more formally, we transform a_{jt} into $ln\left(\frac{a_{jt}}{(1-a_{jt})}\right)$ to estimate $\hat{a}_{jt}$ and $\hat{a}_{jt}^f$ as well as to derive a_{jt}^h, which we then transform back into rates by applying $\left(\frac{1}{\left(1+exp\left(a_{jt}^h\right)\right)}\right)$.

3.2 Estimation and stochastic prediction of demographic components

Compared to five-year age groups for labor force participation rates, the data availability for fertility, mortality, naturalization, immigration and emigration rates (compare Table A-2), allows an even more detailed disaggregation into single-year groups by sex and citizenship, and thus, as discussed in the literature review, calls for a dimensionality-reduction technique like PC analysis.

By applying PCA, we obtain linear combinations of the original variables that are orthogonal, i.e. uncorrelated, to each other. In the case of age-specific fertility rates among German women aged 15 to 49 years, the i^{th} PC in year t may be written as

$$P_{it} = \sum_{j=1}^{35} \lambda_{ij} b_{jt} \tag{6}$$

where λ_{ij} is the loading of the fertility rate b of age group j on the i^{th} PC and is derived by singular value decomposition (see Vanella 2018 for further discussion).

Notably, PCs contribute to decreasing extents to the explanation of the underlying variation in given variables. For highly correlated series, such as mortality rates, the first and second PC often explain a sufficient amount of variation. For less collinear series, the literature has developed criteria to determine the number of PCs required to sufficiently explain the underlying variation, usually targeting a certain threshold of the *eigenvalue*. In the present paper, we rely on the familiar *Kaiser-Guttmann criterion*, suggesting to retain those PCs exhibiting an eigenvalue greater than or equal to 1. As we apply PCA for each demographic component individually, the number of corresponding included PCs varies. Below, Table 3-1 gives an overview for fertility, mortality, and naturalization rates, encompassing information on years, disaggregation by age groups as well as on the number of PCs required according to the Kaiser-Guttmann criterion and the corresponding explained variance.

Table 3-1: Forecasted number of PCs for each variable and corresponding explained variance

v	Variable	No. of PCs	Variance explained (%)
1	Mortality, males	2	98
2	Mortality, females	2	98
3	Fertility, German	3	98
4	Fertility, non-German	3	94
5	Naturalizations, males	6	96
6	Naturalizations, females	6	97
7	Immigration, German, males	12	94
8	Immigration, German, females	9	94
9	Immigration, non-German, males	13	95
10	Immigration, non-German, females	8	94
11	Emigration, German, males	8	95
12	Emigration, German, females	6	94
13	Emigration, non-German, males	7	95
14	Emigration, non-German, females	7	95

Source: Author's own computation. Data used as explained in the text. © IAB

We forecast i PCs of each variable v in Table 3-1 using individual autoregressive (AR) and moving-average (MA) structures, A_{vi}, ranging from AR(1) or MA(1) to ARMA(3,3), and rely on those minimizing both the Schwarz and the Hannan-Quinn information criterion. Table A-3 in the appendix exemplarily presents the results from applying a corresponding suitable structure to the second PC of the crude fertility rates of German women.

Notably, the first PC of the demographic components typically exhibits a sharp upward or downward sloping behavior, and forecasting strongly trending variables possibly leads to implausible results. To avoid this, a logistic transformation with a saturation level s_{v1} was chosen. Thus, for a given first principal component PC, pc_{v1}, we estimate

$$\ln\left(\frac{s_{v1}}{pc_{v1}} - 1\right) = (\varphi + t + A_{v1}) \qquad (7)$$

which can be written as

$$pc_{v1} = \frac{s_{v1}}{(1 + \exp(\varphi + t + A_{v1}))} \tag{8}$$

where φ is a constant, t is a linear time trend, and the error term has been dropped for simplicity.

4 Modeling migration dynamics

As in Fuchs et al. (2017), the model distinguishes between immigration and emigration rather than estimating net migration. Moreover, while Fuchs et al. (2017) already decompose immigration and emigration rates into a large number of PCs and forecast those components, alongside of a forecast of total immigration, to derive future migration flows, the approach fails to account for both the determinants of immigration as well as its interdependencies with emigration. The present approach addresses that shortcoming by advancing the estimation strategy of Fuchs et al. (2017) in two dimensions: First, we estimate and forecast immigration, separated by pools of sending countries, thereby testing and incorporating a series of explanatory variables in a gravity framework in accordance with the literature. Second, we forecast PCs of emigration rates, however, we augment the earlier approach by incorporating information on immigration in the previous year as an additional important predictor. Below, these modeling steps are described in detail.

4.1 Immigration

4.1.1 Estimation strategy

As indicated above and shown in the literature review, we model immigration to Germany using a gravity-type approach. Formally, we regress the immigration of persons with citizenship c to Germany, in_c, relative to the respective population in the origin country[3], pop_c, on a constant, μ; on a weight variable, W; as well as on a vector of additional controls, B_{ct}. Formally, the equation can be written as

$$\frac{in_{ct}}{pop_{ct}} = \mu + \theta \frac{W_{ct}}{W_{gt}} + \Theta B_{ct} + \varepsilon_{ct} \tag{9}$$

where θ is the coefficient of the weight variable, Θ is a vector of coefficients corresponding to the vector of the additional regressors B_{ct}, and ε_{ct} is the error term. B_{ct} holds AR-terms and additional variables such as EU membership or individual fixed-effects, the latter capturing effects of time-invariant variables that are often included in gravity equations, e.g. the distance between two countries, whenever appropriate, as indicated in the table below.

[3] In doing so, we assume that citizenship-specific immigration flows represent directional flows between other countries and Germany. This assumption is an inevitable limitation due to lacking data on actual directional flows.

Estimating this kind of model allows to do so drawing on either slope homogeneity or heterogeneity in θ, with the latter ranging from country-specific coefficients to coefficients for groups of countries (*pools*). Notably, in a case in which migration flows to a destination country and their determinants are similar within groups of origin countries but distinct between these groups, a pool-wise estimation strategy is more appropriate and efficient, and has already been discussed in the literature (e.g. Peeters 2012).

Consequently, in the present paper, we adopt this pool-wise estimation strategy. To form pools of the inflow data for European countries that are as homogeneous as possible, we conduct hierarchical agglomerative cluster analyses (Murtagh and Legendre 2014) and apply a set of well-established dissimilarity measures, including dynamic time warping (DTW). DTW is particularly useful for detecting patterns in our case as it can handle series of different lengths or detect similar, possibly time-shifted patterns across several series, and considers the shape of time series more accurately than, for example, Euclidean distance (Montero and Vilar 2014).

Based on the cluster analyses, on the one hand, we model return migration of German citizens separately and, on the other hand, arrive at seven pools of sending countries and six additional individual models. Below, Table 4-1 lists each in detail, indicating both included countries and included regressors. We estimate equation (9) for each of these 13 specifications.

Table 4-1: Pools of countries and corresponding regressors used in the gravity-equation estimation

Pool	Name	Countries (ISO codes)	W	B
1	Northern Europe	DK, FI, IS, NL, NO, SE, GB	$GDP(t)$	$AR(1)$
2	Southern Europe	AT, ES, GR, IT, PT, SI	$GDP(t)$	$AR(1), AR(2)$
3	Central Europe and smaller countries	BE, CH, CY & MT, FR, IE, LU	$GDP(t)$	$AR(1)$
4	Eastern Europe (EU)	EE & LT & LV, CZ & SK, HU	$UR(t)$	$EU, AR(1), AR(2)$
5	DE main immigration countries	BG, PL, RO, RS & ME	$GDP(t-1)$	$EU, AR(1), AR(2)$
6	South-Eastern Europe	AL, BA, HR, MK	$UR(t)$	$EU, AR(1)$
7	Eastern Europe (Non-EU)	BY, RU, UA	$GDP(t)$	$AR(1)$
ROW	Rest of the World	Africa	-	$AR(1), d_{15t18}, \ln(trend)$
		Asia	-	$AR(1), d_{15t18}, trend$
		Australia/Oceania	$GDP(t)$	$AR(1)$
		North America	$GDP(t)$	$AR(1), AR(2)$
		Turkey	$UR(t)$	$AR(1), AR(2)$
		South America	$UR(t)$	$AR(1)$

Notes: Combination of countries such as "CY & MT" indicate aggregation, e.g. due to low immigration figures. W indicates the weight variable used in equation of the corresponding pool. B indicates the additional regressors, where EU is a dummy variable that indicates EU membership; d_{15t18} is a dummy variable equal to one for the years 2015 to 2018 and zero else; $trend$ indicates a time trend, logarithmized if applicable; models for pools of countries contain individual-fixed effects. For each continent/country as listed in "ROW", a separate model is estimated.

Sources: Data used as explained in the text. © IAB

The selection of appropriate weight variables W for each equation are based upon the literature review presented in section 2. In addition to economic characteristics (gross domestic product, unemployment rate), we also test demographic characteristics (population, median age, total fertility rate, education) and educational variables (e.g. government expenditure on education as a percentage of GDP or mean years of schooling (ISCED 1 or higher)). Yet, eventually, only the unemployment rate and gross domestic product turned out to be significant predictors of pool-wise immigration flows. Additionally, Table A-4: Variables tested but not included in gravity-equation framework and corresponding data sources in the appendix provides a detailed overview of tested (and not included) explanatory variables and the corresponding data sources. To conduct the forecast of immigration flows until 2060, we condition on existing projections of unemployment, GDP, and population.

4.1.2 Data sources

The data stem from a wide variety of sources. We use immigration by citizenship from 1962 to 2020 from the migration statistics of the FSO. We distribute immigration from the smallest countries, such as San Marino, Vatican City or Andorra, as well as the inflows labelled "Other, stateless and undeclared" proportionally across the other countries. We use population figures from the World Population Prospects (2019) portal of the United Nations (Department of Economic and Social Affairs Population Division), providing annual population data and indicators with estimates (1950 to 2020) and standard projection variants (2021 to 2100) for nearly 300 regions, subregions, and countries.

The GDP data stem from UNCTADSTAT (2022) (GDP per capita in 2015 US Dollars). However, since the UNCTADSTAT data ends in 2020 but the projection requires future values to condition on, as noted above, we use relative changes from the OECD (2018) to extend the UNCTADSTAT series up to 2060. Whenever it was necessary to combine states, e.g. due to aggregation in the immigration flows above as in the case of the Baltic states of Estonia, Latvia and Lithuania, we weight by population size. By contrast, only very limited data on unemployment forecasts are available. The International Monetary Fund's World Economic Outlook Database (2022) provides unemployment rates for 196 countries as a percentage of the total labor force from 1980 to 2027. If necessary, the projections were again weighted by the population size. We fit models that closely mirror these existing projections of unemployment and GDP, e.g. by using appropriate trends or AR- and MA-terms, and project future values across all sending countries up to 2060 in each bootstrapping iteration.

4.1.3 Evaluation of in-sample accuracy

Although the suitability of gravity-type approaches for immigration forecasting is, in principle, well-established in the literature, the justification of its incorporation still depends on a better performance compared to the previously applied approach in Fuchs et al. (2017). To this end, and as conducted throughout the population projection and forecasting literature (e.g. Ahlburg 1995), we evaluate the in-sample accuracy for the period 1998 to 2020 using a series of appropriate measures. For better classification, we also compare the model to a naïve projection, which in this case is the mean value from the ten preceding years.

Figure 4-1: Comparison of forecast accuracy using the MAPE over rolling windows

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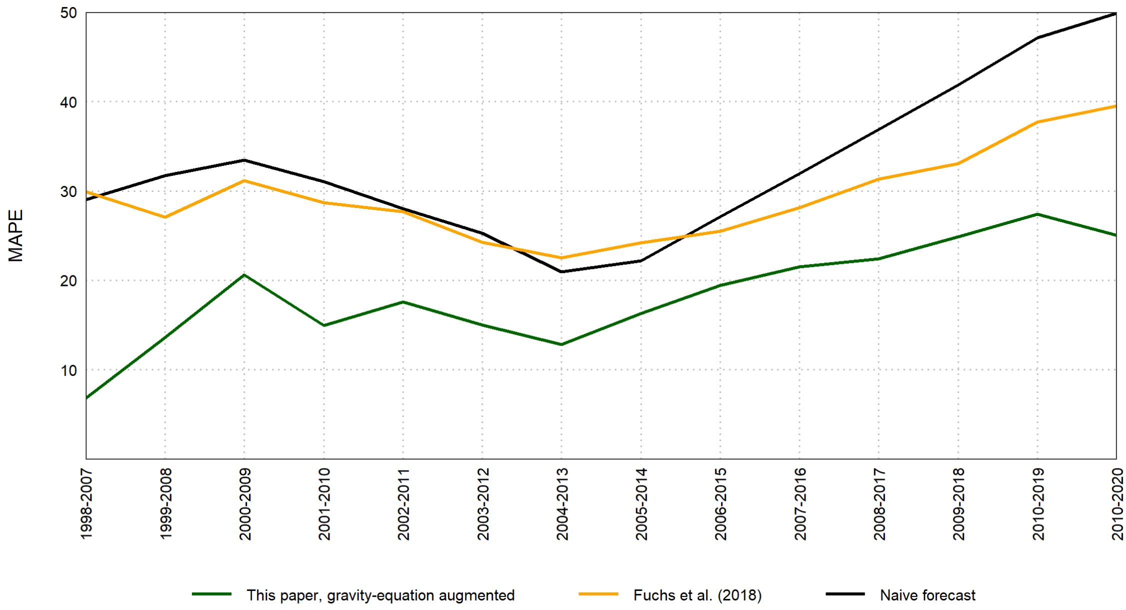

Source: Author's own computation. © IAB

Initially, the estimation results may be compared by the deviations from the true values, quantified by the Mean Absolute Percentage Error (MAPE). The MAPE is presumably the most commonly used forecast accuracy measure and has been proven, despite critique, to deliver a solid basis for evaluation (see, e.g., Rayer 2007). Figure 4-1 provides a visual comparison of the MAPE of the model presented in this paper and the MAPEs of the naïve approach as well as of the approach by Fuchs et al. (2017), evaluated for rolling windows of several sub-periods. In the appendix, Table A-5 compares the values of the additional accuracy measures alongside the MAPE – the Mean Absolute Error (MAE), the Mean Percentage Error (MPE), and the Root Mean Square Error (RMSE). As can be seen in Figure 4-1 and in Table A-5, the gravity-type approach outperforms both Fuchs et al. (2017) and the naïve forecast.

Yet, the accuracy differences may also be tested formally. The most commonly used tool to assess the significance of differences in prediction accuracy is probably the Diebold-Mariano (DM) test (Diebold and Mariano 1995), but it tends to reject the null hypothesis too often for small samples. A more well-suited test is the Harvey-Leybourne-Newbold (HLN) test (Harvey et al. 1997). Using the HLN test, we find that for nearly all of the time intervals shown in Figure 4-1, the accuracy differences are statistically significant, i.e. the accuracy of the predicted values is significantly better with the gravity-type approach presented in this paper compared to Fuchs et al. (2017). In the appendix, Table A-6 provides the results of the HLN test.

4.2 Emigration

The remaining demographic component to be estimated and forecasted is emigration. As in Fuchs et al. (2017) and as outlined above, we estimate age-, sex-, and citizenship[4]-specific emigration rates by applying PCA, again retrieving and forecasting those PCs with an eigenvalue greater than one (see Table 3-1). Then, the resulting rates are multiplied by the corresponding demographic stratum (age, sex, citizenship), yielding stratum-specific emigration flows.

However, there is empirical evidence that emigration is strongly correlated with lagged recent immigration (e.g. Vanella et al. forth.). While existing migration and population forecasting approaches usually lack this interdependency – also Vanella et al. (forth.) account for this interdependency only implicitly – we propose an explicit modeling step. To this end, we create an additional explanatory variable, z_{vit}, representing the inflows from abroad in the previous year of the respective age- and sex-specific group, and add this variable to the estimation and forecast of the i sex-specific PCs of emigration rates, v. As this interdependency of lagged immigration and subsequent emigration is particularly evident in the context of migration flows of non-Germans, we calculate z_{vit} only for $v = \{13{,}14\}$, i.e. only for the sex-specific emigration rates of non-Germans as given by Table 3-1. We create this variable z_{vit} as a linear combination of the inflow rates of the age-specific groups, a[5], from age 1 to 100 in the previous year[6] and the loadings of the respective age-specific group on the i^{th} PC of the sex-specific emigration rates v. The rates are calculated analogously to the emigration rates. More formally, this is

$$z_{vit} = \sum_{a=1}^{100} \frac{in_{a-1,t-1}}{pop_{a-1,t-1}} * \lambda_{vi,a+1} \tag{10}$$

where $in_{a-1,t-1}$ is the immigration of age-specific group a in the previous year, $pop_{a-1,t-1}$ is the corresponding population, and $\lambda_{vi,a+1}$ is the loading of the age-specific group a on the i^{th} PC of the emigration rates v. A more intuitive explanation: In the case of the first PC of emigration rates among non-German males, i.e. $v = \{13\}$ and $i = \{1\}$, we find the weighted value for males aged 25 years, i.e. $a = \{25\}$, by multiplying the immigration rate of the same cohort in the previous year, i.e. of $a - 1 = \{24\}$ in $t - 1$, with the loading of males aged 25 years on the first PC of the emigration rates v.

Thus, following the notation of equations (7) and (8), the estimation equation of corresponding emigration PCs may then be written as

$$pc_{vit} = \varphi + z_{vit} + A_{vit} + \zeta_{vit} \tag{11}$$

[4] In this case, we only distinguish between Germans and non-Germans, as indicated by Table 3-1.

[5] Notably, as we are calculating the additional explanatory variable for principal components sex-specific emigration rates among non-Germans, the subscript a in each case refers to inflows in a given age- *and* sex- *and* citizenship-specific group. We refrained from introducing a more complex notation in order to improve the comprehension of the model description.

[6] Therefore, the age group of 0-year-olds is missing.

where pc_{vit} is the ith PC of the emigration rates, v, φ is a constant, A_{vit} is the regressor structure as outlined above, and ζ_{vit} is the error term.

Notably, in order to reduce dimensionality and ensure efficient estimation, we include this newly created variable z_{vit} only in some of the estimated and forecasted PCs according to Table 3-1, depending on statistical significance. This is the case for the first two of seven PCs of the emigration rates for men and for the first three of seven PCs for women. Importantly, these are precisely the PCs that have the greatest explanatory power. We model all other relevant emigration PCs as in Fuchs et al. (2017), i.e. we estimate equation (11) without the additional explanatory variable z_{vit}. Notably, the bottom-up approach from previous forecasts was retained here: The total number of moves is the sum of the individual subgroups.

5 Results

In this section, we report the main results of our stochastic model, organized in two blocks. First, we present the population forecast, both for total and for working-age population, alongside of the estimated future migration, fertility, and mortality figures. We compare our findings to existing, widely used projections and discuss differences. Second, we present results of the potential labor force forecast, that is, the size as well as the composition of future potential labor force. As noted above, the plotted confidence intervals are based on a stochastic simulation with 5,000 draws from the residuals (bootstrap).

Forecasted population and its components in Germany until 2060

According to our forecast, Germany will experience a secular population decline in the years and decades to come. There will be nearly 10 million people less living in Germany in 2060 compared to 2020, a drop from over 83.2 million to about 72.6 million. This corresponds to a decrease of about 13.5 percent. With a probability of 66 percent, given the estimated confidence intervals, the size of the total population in 2060 will be between 70.6 and 74.6 million people.

This finding slightly deviates from total population figures in commonly used scenarios of existing deterministic projections, such as the first variant ("G2L2W1") of the 15th coordinated population projection of the FSO (2022b) and the medium variant of the World Population Prospect (2019). In order to compare the corresponding future trajectories of those projections to our results, and since all models depart from different baseline years and population levels, we chain-link the figures to the last in-sample observation of total population in 2020 (for the UN series) respectively to our forecasted value for 2022 (for the FSO series). We visualize this comparison in Figure 5-1, displayed by the solid (this paper), dashed (UN projection, medium variant), and dotted (FSO projection, G2L2W1 variant) orange lines, with the orange area indicating the confidence interval and the grey area indicating the forecast period. According to our model, the population decline will be more distinct than existing projections assume, with 2.94 million people less in 2060 compared to the chain-linked FSO projection, and 3.15 million people less compared to the chain-linked UN projection.

Notably, according to our model, the working-age population (here, those aged 15 to under 75 years) will drop from 62.3 million to 52.2 million persons by 2060. This corresponds to a decline of 16 percent compared with the baseline year 2020 - i.e., the decline will be even more distinct compared to the total population. Here, however, the downward trend will weaken starting from around 2035 when the last *baby boomers* leave working-age. Contrarily to the forecast of total population, as the solid (this paper), dashed (UN), and dotted (FSO) purple lines and the corresponding light purple area in Figure 5-1 indicate, our model forecasts working-age dynamics until 2060 that are much more similar to the UN and FSO projections.

These forecasted future total and working-age population trajectories in general as well as the differences and similarities to existing projections can be explained by examining the forecasted dynamics among the individual demographic components, i.e. migration, fertility, and mortality. Table 5-1 lists all corresponding results of our model in detail.

Figure 5-1: Past and forecasted total and working-age population

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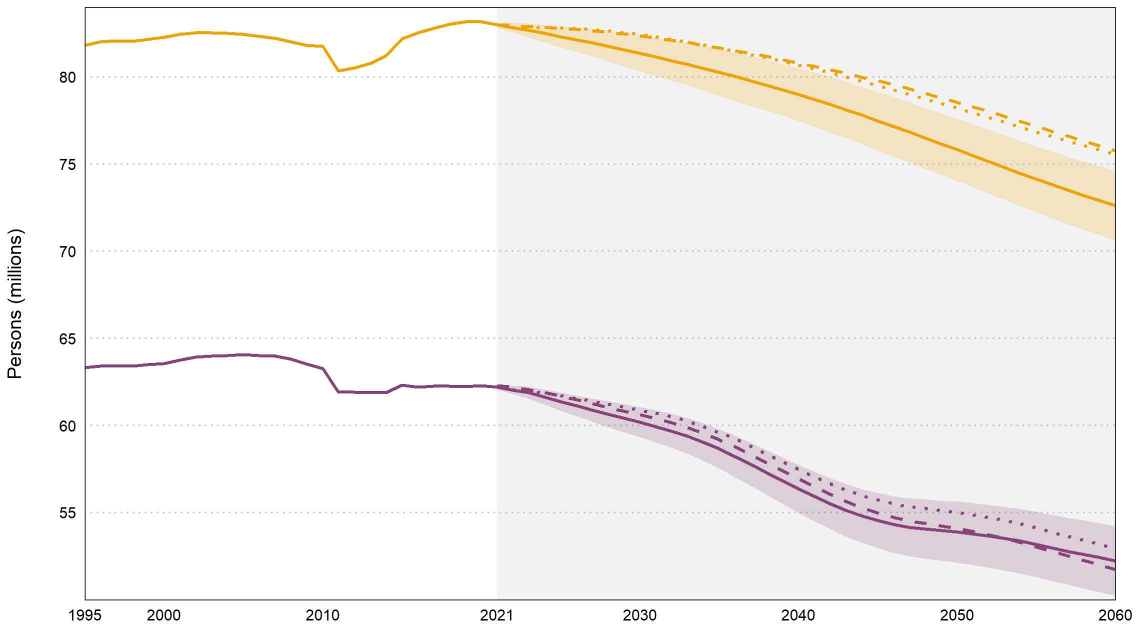


Note: Solid (this paper), dashed (UN), and dotted (FSO) lines indicate forecast and projection results. The orange lines indicate results for the total population. The purple lines indicate results for the working-age population. The orange- and purple-shaded areas indicate 66% confidence intervals. The grey-shaded area indicates the forecast horizon.

Sources: Author's computation and sources mentioned in the text. © IAB

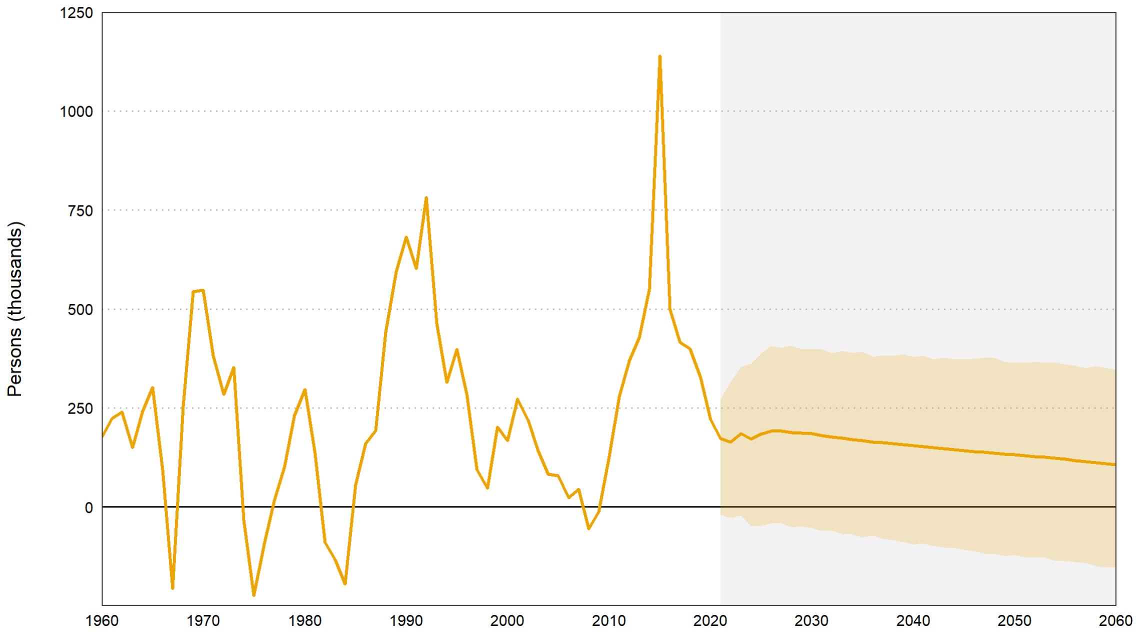
First, our newly introduced migration modeling approach forecasts an average migration surplus of around 150,000 persons between 2021 and 2060, whereby net migration will be halving over the forecast horizon from 220,000 persons in 2020 to 106,000 persons in 2060. Past and forecasted figures alongside the corresponding confidence interval are displayed in Figure 5-2. The migration projections of the UN (about 155,000 on average) and of the FSO (about 170,000 on average)[7] are close to our forecast average but assume different trajectories. While our model forecasts a smooth decline of net migration over the upcoming four decades, the World Population Prospect assumes a largely stable net migration throughout the projection horizon, the FSO from 2033 onwards.

While more differentiated data – beyond net migration – are not available for the World Population Prospect (2019) and FSO (2022b) projections, our model allows to further disentangle future net migration figures and explain the forecasted more distinct decline in net migration in 2060. Most importantly, the findings are strongly driven by flows of non-Germans. Our migration modeling is based on an increase of the corresponding immigration figures from 0.99 million in 2020 to 1.09 million people towards the end of the forecasting period, whereby the immigration of European citizens - over the past 10 years on average 900,000 persons - will decrease to about 600,000 persons. The main countries of origin are likely to remain Poland, Bulgaria, Romania, Serbia, and Turkey. By contrast, the immigration of Non-Europeans will increase from 240,000 to 500,000 persons. This finding, a high level of immigration from the EU as a rather temporary than permanent phenomenon, is also reached by other analyses (e.g. Bertoli et al. 2016). Possible reasons for this are, on the one hand, the high immigration flows from European countries were characterized by various enlargement processes of the EU (Fuchs et al. 2019). In addition, the persistently low birth rate in Eastern European countries, which are the main sending countries for Germany, has been and will be further reducing the population at risk of migrating, in particular among the younger age group with a disproportionally high propensity to migrate. Furthermore, the main sending countries in Eastern Europe, such as Poland, have already caught up in terms of economic performance and will probably continue to do so. On the other hand, the demographic developments in non-European territories in particular offers the possibility that immigration from there will increase - even if war- and crisis-induced migration is excluded. However, the forecasted immigration flows for non-Germans are offset by emigration flows increasing from 750,000 to 1 million people. Rising in-migration and the resulting increase in the population of non-Germans also induce stronger out-migration.

The migration flows of non-German citizens strongly dominate current and future migration dynamics, whereas the immigration and emigration of German citizens plays a subordinated role. Their migration balance is initially negative, averaging less than 15,000 persons per year between 2021 and 2060. Below, Figure 3 visualizes the course of forecasted net migration (German and non-German citizens) over the forecast horizon.

[7] Figures refer to averages from 2023 onwards as the FSO value for 2022 contains the refugee migration flows from the Ukraine, which is, in turn, neither contained in our forecast nor in the UN projection.

Figure 5-2: Past and forecasted net migration for Germany



Note: The orange-shaded area indicates the 66% confidence interval. The grey-shaded area indicates the forecast horizon.
Source: Author's own computation. Data used as explained in the text. © IAB

Second, the model forecasts a further decline of mortality respectively an increase of life expectancy. For the life expectancy of newborns, the model shows an increase for men from 78.6 years (according to the 2018/2020 life table) to 80.9 years and for women from 83.4 years to 84.7 years in 2060. These results for the development of life expectancy are below those of other projections. The FSO (2022a) – here, for the cited variant ("G2L2W1"), only the assumptions for 2070 are available – assumes 84.6 years for men and 88.2 years for women. Similarly, our results also differ from those of the UN's World Population Prospect (2019) for 2060, with 85 years for men and 88.4 for women. Notably, the gap between our results and those of existing projections varies over time. For example, our findings for 2035 are similar to those from the first medium-term population projection published by the Federal Statistical Office in 2021 (FSO 2021): According to the FSO (2021), life expectancy in 2035 is 80.2 years for men and 84.3 years for women. For the same year, our model yields life expectancy values of 79.9 and 84.1 years, respectively.

Third, the difference in fertility between German and foreign women decreases over the forecast horizon. According to our results, the total fertility rate (TFR) of foreign women will drop only slightly from the currently high level of 2.0 children per woman in 2020 to 1.9 in 2060. For German women, by contrast, the model forecasts an increase from 1.4 children in 2020 to 1.6 in 2060. Overall, the birth rate in Germany increases from 1.5 to 1.7 in 2060. This finding is in line with the medium variant of the UN World Population Prospect (projecting a TFR of 1.7 in 2060), but higher than the FSO G2 assumptions (projecting a TFR of 1.55 in 2060).

Thus, the population stock results delivered by our modeling approach, and the differences to established projections, can be disentangled along the individual demographic components: Our approach forecasts mortality patterns that are substantially higher in 2060 compared to the FSO and the UN, explaining stronger differences in the total population results compared to the results for the working-age population. Moreover, our findings for fertility are higher compared to the FSO, but similar to the UN. In turn, for cumulated net migration until 2060, the figures delivered by our model are similar to the UN projection but lower than the FSO assumptions – as the latter already incorporates migration flows from Ukraine in 2022, with still comparatively high levels in subsequent years. Thus, as exemplarily noted above, our results do not only differ to the FSO and UN assumptions in 2060 but our model also forecasts different trajectories over time.

As a consequence of the interaction of three components, and of particular importance in a labor market perspective, the population in Germany is not only decreasing but will also face further aging, at least in the medium-term. The median age of 44.1 years for men and 47.7 years for women in 2020 will initially rise and reach its peak between 2035 and 2040, at 44.7 and 48.3 years for men and women, respectively. Notably, thereafter, it will decline again. In 2060, 50 percent of all women will be at most 46.1 years old and 50 percent of all men at most 43.5 years old, and thus younger than in the starting year 2020. This development is driven by two factors: On the one hand, there is a persistent "rejuvenating effect" of immigrants. On the other hand, the baby boomers will enter age groups with high mortality. As outlined, the combination of both results in the initial aging and subsequent rejuvenating of the population.

Commonly, possible effects of a given age structure are quantified by support or dependency ratios, which are computed as the ratio of people who are not yet or no longer of working age to the number of people in working age. To a certain extent, these ratios provide insights concerning the future burden on social security systems, whereby the absolute number is less important than the progression. In Table 5-1, the (total) dependency ratio is defined as those under 15 years of age and persons 67 years of age and older divided by the population between 15 and 66. Consequently, this measure is a combination the old-age dependency ratio (67-year-olds divided by 15- to 66-year-olds) and the youth dependency ratio (under-15s divided by 15-to-66-year-olds). Here, too, we observe an initial increase from 50 at present to 60 by around 2040, which is mainly determined by the increase in the old-age dependency ratio (from 29.3 in 2020 to 40.6 in 2038). After that, both the total and old-age dependency ratios fall (to 59.9 and 36.3 in 2060, respectively). The increase in the youth dependency ratio, although smaller, is consistent and increases from 20.7 in 2020 to 23.6 in 2060.

Table 5-1: Central results of the population forecast

Year	Population (total, 1000s)			Population (working age, 1000s)			Migration (net, total, 1000s)		
	Point	Upper	Lower	P	U	L	P	U	L
2020	83,155			62,273			220		
2030	81,350	82,414	80,312	60,163	61,030	59,302	185	398	-53
2040	78,979	80,499	77,455	56,350	57,723	54,981	155	380	-95
2050	75,808	77,601	74,008	53,869	55,616	52,126	132	364	-121
2060	72,598	74,560	70,610	52,212	54,209	50,211	106	346	-152

Year	Total fertility rate						Life expectancy at birth (years)						Median age (years)					
	German			Non-German			Female			Male			Female			Male		
	P	U	L	P	U	L	P	U	L	P	U	L	P	U	L	P	U	L
2020	1.43			2.00			83.4			78.6			47.7			44.1		
2030	1.57	1.64	1.49	1.93	2.12	1.74	83.9	84.3	83.4	79.6	79.8	79.4	47.7	48.1	47.3	44.3	45.0	43.7
2040	1.59	1.67	1.52	1.92	2.11	1.72	84.3	84.9	83.6	80.2	80.3	80.0	48.3	48.9	47.7	44.5	45.5	43.7
2050	1.60	1.68	1.52	1.91	2.10	1.72	84.5	85.2	83.8	80.6	80.7	80.4	47.4	48.0	46.8	43.9	44.9	43.0
2060	1.60	1.68	1.53	1.91	2.11	1.72	84.7	85.5	84.0	80.9	81.0	80.7	46.1	46.7	45.5	43.5	44.3	42.8

Year	Youth ratio (< 15 years)			Old-age ratio (> 66 years)			Total dependency ratio		
	P	U	L	P	U	L	P	U	L
2020	20.70			29.27			49.97		
2030	22.55	22.96	22.10	35.47	35.79	35.14	58.01	58.11	57.89
2040	22.70	23.23	22.12	40.20	40.76	39.67	62.90	62.91	62.87
2050	22.90	23.36	22.43	37.37	37.97	36.81	60.27	60.40	60.17
2060	23.55	23.98	23.08	36.33	37.04	35.68	59.88	60.12	59.65

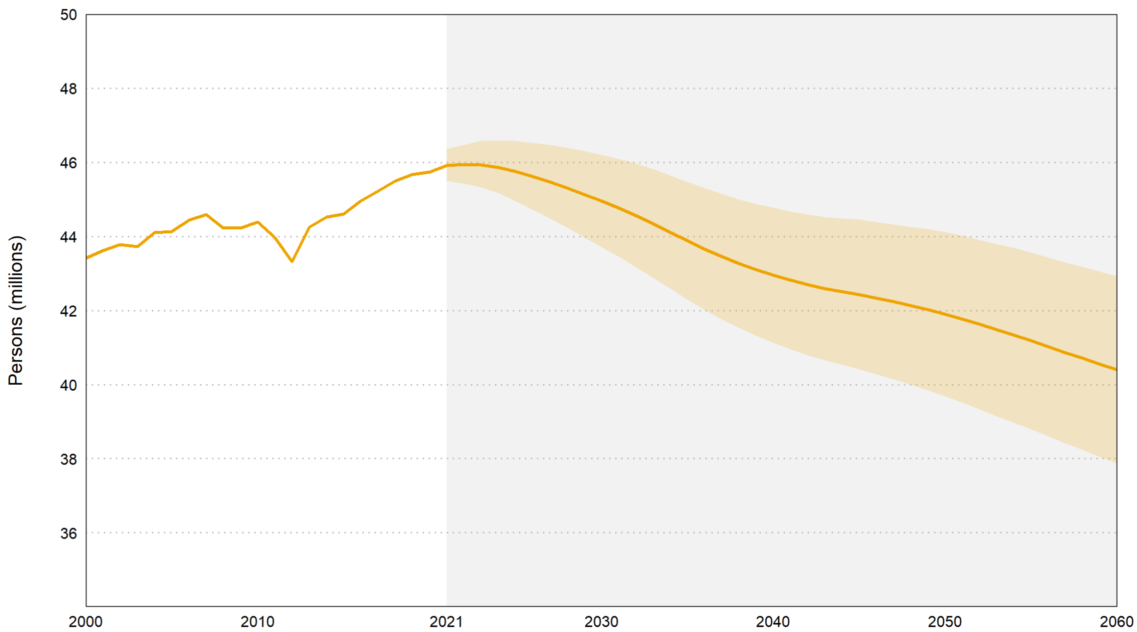
Sources: Author's own computation. Data used as explained in the text. © IAB

Forecast of the potential labor force in Germany until 2060

In addition to the population in working-age, its participation patterns are the second crucial component that determine labor supply, and our integrated modeling approach jointly forecasts both. Notably, all forecasted figures presented in this subsection are based on the corrected potential labor force participation rates (see Chapter 3.1), i.e. the observable participation rates as documented by the labor force survey plus the estimated hidden labor force, introduced by Fuchs and Weber (2021).

As Figure 5-3 demonstrates, the secular decline of the (working-age) population is mirrored by the future trajectory of the potential labor force. Until 2060, the potential labor force will decline by 11.7 percent, from 45.7 million to 40.4 million. Importantly, the relative decline of the potential labor force is less distinct than both of the total population (nearly 13 percent) and of the working-age population (about 16 percent). This divergence is explained by rising participation rates in the upcoming decades. Thus, while the first crucial component of the potential labor force, the population, faces a pronounced decline, the second crucial component, participation rates, are expected to increase in the future, perpetuating the long-term rise observed during past decades. Yet, as stated, rising participation rates will not offset the large demographic decline of labor supply in Germany until 2060, but only provide a mitigating effect. However, a close look on the results presented in Table 5-2 reveal age-, sex- and citizenship-specific differences driving this mitigating effect.

Figure 5-3: Estimated past and forecasted potential labor force



Note: The orange-shaded area indicates the 66% confidence interval. The grey-shaded area indicates the forecast horizon.
Source: Author's own computation. Data used as explained in the text. © IAB

First, among persons in prime-age (25-54 years), increases are nearly exclusively driven by rising participation of women. The participation rates of German women are forecasted to increase by four percentage points from 89 percent in 2020 to 93 percent in 2060. The participation rates of non-German women are forecasted to rise even more strongly, from 67 percent in 2020 to 77 percent in 2060. On the contrary, both German and non-German males in prime-age already exhibit high participation rates in 2020 and face only slight increases over the next four decades. Put differently, our model forecasts a convergence of participation rates between males and females over the upcoming four decades, yet the participation of non-German women is still expected to remain substantially lower.

Table 5-2: Central results of the potential labor force participation rates forecast

Year	Labor Force Participation, aged 25-54 years											
	Non-German, Women			Non-German, Men			German, Women			German, Men		
	P	U	L	P	U	L	P	U	L	P	U	L
2020	67.2%			90.8%			88.7%			95.0%		
2030	71.4%	73.1%	69.5%	92.2%	93.9%	90.3%	91.6%	92.6%	90.6%	95.7%	96.6%	94.7%
2040	73.7%	76.4%	70.8%	92.1%	93.9%	90.2%	92.6%	94.0%	91.2%	95.6%	96.9%	94.3%
2050	75.4%	78.5%	72.0%	92.1%	92.8%	91.4%	93.0%	94.6%	91.2%	95.6%	96.9%	94.3%
2060	77.2%	80.4%	73.8%	92.1%	92.6%	91.6%	93.3%	95.5%	91.1%	95.7%	97.0%	94.3%
Year	**Labor Force Participation, aged 55-74 years**											
	Non-German, Women			**Non-German, Men**			**German, Women**			**German, Men**		
	P	**U**	**L**	**P**	**U**	**L**	**P**	**U**	**L**	**P**	**U**	**L**
2020	36.1%			51.3%			43.5%			52.1%		
2030	43.4%	43.5%	43.3%	57.9%	59.6%	56.0%	42.4%	43.4%	41.4%	56.7%	57.7%	55.8%
2040	42.6%	42.8%	42.4%	54.5%	56.2%	52.6%	41.2%	42.6%	39.8%	54.3%	55.6%	53.0%
2050	42.1%	42.4%	41.8%	54.5%	55.1%	53.7%	47.6%	49.2%	45.8%	62.1%	63.4%	60.7%
2060	42.7%	42.9%	42.5%	54.3%	54.7%	53.7%	45.4%	47.6%	43.1%	59.4%	60.7%	58.0%

Sources: Author’s own computation. Data used as explained in the text. © IAB

Second, among elderly persons (55-74 years), participation rates are forecasted to rise for both males and females and among Germans and non-Germans. The most distinct increases until 2060 are expected to happen among non-German women (43 percent in 2060) and German men (59 percent in 2060), both with a rise of seven percentage points. Increases of participation rates among non-German men (51 percent to 54 percent) and German women (44 percent to 45 percent) are forecasted to be somewhat less strong. Importantly, as the decadal values for 2030, 2040, and 2050 indicate, the overall participation rates of the elderly do not increase in a steadily manner, likely reflecting compositional effects. By 2030, a substantial share of the baby boom generation is still within age-groups subject to high participation rates[8], while elderly cohorts among those aged 55-74 years are not only smaller but also subject to lower participation rates. By 2040, tides turn and the effect of the baby boomers reverses. Subsequently, until 2050 and 2060, participation rates are on the rise again. Notably, this pattern is particularly evident among German men and women, but not among non-German persons as only the former have been subject to the baby boom phenomenon.

6 Conclusion

Similar to other advanced economies, Germany is expecting a distinct and enduring demographic decline in the decades to come, in particular among those in working-age, being the core quantity that determines labor supply. Among the three demographic components, migration shapes a population the strongest in the short- to medium-term. Yet, despite its crucial role, existing population projections and forecasts – and even less so integrated approaches that jointly project population figures and labor force participation rates, both of deterministic and stochastic nature – hardly model the determinants of migration, although well documented across disciplines.

Addressing this shortcoming, we propose an augmentation to the integrated stochastic approach to forecast both population and labor supply proposed by Fuchs et al. (2017) that allows to adequately model migration dynamics, and apply this framework to German data. Thereby, we draw on a series of econometric models established in the demographic and economic literature. By applying PCA, we address the high-dimensionality and multicollinearity of fine-grained demographic data, such as births and death rates or naturalizations. Using ARMA models, we forecast both these demographic PCs as well as participation rates. Moreover, we estimate gravity-type equations for pools of sending countries and account for the empirically observed correlation of immigration and emigration, that is, the correlation of (lagged) immigration figures and emigration figures. By applying residual resampling (bootstrapping) to our system of equations, we are able to derive confidence intervals and, thus, quantify the uncertainty inherent to our forecast.

Our results suggest that until 2060, the total population will decrease by 12.7 percent and the working-age population (15-74 years) will decline even more strongly (-16 percent). This forecasted population decline, for the total population and even more distinct for the working-age population, is the result of the interplay of the individual demographic components. For more than 50 years, the birth rate in Germany has been below replacement level. Consequently, now and in the near future, the baby boom generation is gradually leaving working age – and subsequent cohorts are smaller in size. And this downward trend induced by natural population change will likely persist: According to our estimates, the total fertility rate will increase only slightly by 2060, from currently 1.5 children per woman to roughly 1.7.

[8] In the appendix, we provide more detailed results for 5-years age groups (Table A-7 and Table A-8).

Importantly, the fertility-driven decline will not be offset by high immigration to Germany. Even though our model forecasts rising immigration, the net migration effect is limited due to simultaneously increasing emigration figures of non-Germans. According to our estimations, overall net migration will fall to 106,000 persons per year by 2060. Moreover, rising aggregated immigration figures mask composition changes. While the annual inflows of European citizens are forecasted to decrease to 600,000 persons in 2060 (from current ten-year average of 900,000), the annual immigration of Non-Europeans is likely to increase substantially, from 240,000 in 2020 to 500,000 persons in 2060. Importantly, these estimates are subject to high uncertainty: For example, the derived 66 percent confidence interval of total net migration covers a range from over 350,000 persons per year (net inflow) to less than -150,000 (net outflow) in 2060.

Eventually, the forecast of the potential labor force, i.e. combining the population forecast with the forecast of participation rates, yields a decline of 5.3 million persons, from around 45.7 million at present to about 40.4 million in 2060. Notably, with a forecasted decrease of 11.7 percent according to our model, the decline in the potential labor force is substantially smaller compared to the total and the working-age population. Thus, while population, the first core component of labor supply, is declining in size, the second core component, participation rates, will continue to rise. As our modeling strategy allows to disentangle the results by age, sex, and citizenship, we are able to trace these mitigating effects back to demographic sub-groups. The results suggest to expect a further increase in group-specific potential participation rates, particularly among the elderly and among women. For example, the labor force participation rate of women in the 5-year-age groups between 40 and 50 will rise from the current 87 percent and 88 percent to 93 percent and 95 percent, respectively, and will thus be only slightly lower than that of men. However, as outlined, the increasing labor force participation cannot compensate for the decline induced by natural population change.

The results and the modeling strategy presented in this paper entail implications for both the general, more methodological discussions on population, in particular migration, and labor supply forecasting as well as for policy makers. On one hand, we have proposed a novel stochastic framework to jointly forecast labor force participation rates and the population, with the latter explicitly modeling migration determinants and the interdependencies of immigration and subsequent emigration. On the other hand, our results indicate that, despite a distinct and enduring decline in the population, there are mitigation potentials to cushion its effects on overall labor supply. As we have shown, along the lines of sex- and citizenship-specific categories, there is still room for increases in participation rates, in particular among women. However, as documented by the literature, increasing female participation rates requires corresponding policy actions (e.g. Andresen and Havnes 2019; Bick and Fuchs-Schündlein 2017; Christiansen et al. 2016). Moreover, as our results show, immigration figures to Germany are likely to see a further increase, but so do emigration figures. Thus, a policy aiming to cushion adverse labor supply effects of population by increasing net migration might also start by counteracting the willingness or necessity to emigrate shortly after immigration.

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A Appendix

Table A-1: Variables included in the estimation of the potential labor force participation rates

Variable	Description	Source
Unemployment	Unemployment rate of the dependent labor force	Federal Employment Agency
	Unemployment rate of females	Federal Employment Agency
	Unemployment rate of foreigners	Federal Employment Agency
	Hidden labor force schemes related to employees subject to social security contributions	Federal Employment Agency, own calculations
Vacancies	Number of jobs subject to social security contributions reported related to dependent civilian labor force	Federal Employment Agency, Federal Statistical Office, own calculations
Wages	Net wages employees (consumer price index deflator, 2015=100%)	Federal Statistical Office: Federal government national accounts - compensation of employees, wages and salaries
Education	Student ratio females, 20-24	Federal Statistical Office, own calculations
Population	TFR, non-German women	Federal Statistical Office
	Ratio of women aged 30-34 to children under 6 (non-Germans)	Federal Statistical Office, own calculations
	Ratio of women aged 35-39 to children under 6 (non-Germans)	Federal Statistical Office, own calculations
	Ratio of women aged 40-44 to children under 6 (non-Germans)	Federal Statistical Office, own calculations
Retirement	Average retirement age, females	German Federal Pension Insurance
	Average retirement age, males	German Federal Pension Insurance

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Table A-2: Dimensions and sources of the variables used in the PCA

Variable	Data points	Age groups	Source
Mortality, males	62	101/111	FSO (2021) and HMD (2018)
Mortality, females	62	101/111	FSO (2021) and HMD (2018)
Fertility, German	30	35	FSO (2021)
Fertility, non-German	30	35	FSO (2021)
Naturalizations, males	23	96	FSO (2021)
Naturalizations, females	23	96	FSO (2021)
Immigration, German, males	30	96	FSO (2021)
Immigration, German, females	30	96	FSO (2021)
Immigration, non-German, males	30	96	FSO (2021)
Immigration, non-German, females	30	96	FSO (2021)
Emigration, German, males	30	96	FSO (2021)
Emigration, German, females	30	96	FSO (2021)
Emigration, non-German, males	30	96	FSO (2021)
Emigration, non-German, females	30	96	FSO (2021)

Note: All variables are used as rates. FSO denotes the Federal Statistical Office, HMD refers to the Human Mortality Database. As the FSO data offers mortality rates only up to 101 years, we augment this collection by HMD data up to 111 years.

Table A-3: Example of PC equation, here the second PC of the birth rates for German women

	Coefficient	Std. Error	t-Statistic	p
AR(1)	0.6498	0.2071	3.1383	0.0046
AR(2)	0.5499	0.1927	2.8532	0.0090
AR(3)	-0.3458	0.1713	-2.0195	0.0552
MA(1)	0.9541	0.0774	12.3234	0.0000
R-squared	0.9234	Mean dependent var	0.1935	
Adjusted R-squared	0.9134	S.D. dependent var	1.4775	
SE of regression	0.4347	Akaike info criterion	1.3076	
Sum squared resid	4.3461	Schwarz criterion	1.4996	
Log likelihood	-13.6528	Hannan-Quinn criter	1.3647	
		Durbin-Watson stat	2.0213	
Inverted AR Roots	0.79	0.59	-0.74	
Inverted MA Roots	-0.95			

Sources: Author's own computation. Data used as explained in the text. © IAB

Table A-4: Variables tested but not included in gravity-equation framework and corresponding data sources

Field	Variable	Source
Education	Mean years of schooling (ISCED 1 or higher), population 25+ years, both sexes	UNESCO (2021)
Education	Government expenditure on education in relation to the population of compulsory school age	UNESCO (2021)
Education	Gross graduation ratio from first degree programmes (ISCED 6 and 7) in tertiary education	UNESCO (2021)
Education	Government expenditure on education as a percentage of GDP (%)	UNESCO (2021)
Demography	Annual total dep. ratio [(0-14 & 65+) / 15-64] (%)	UN (2019)
Demography	Median age	UN (2019)
Demography	Life expectancy at birth, both sexes combined (years)	UN (2019)
Demography	Total fertility (live births per woman)	UN (2019)

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Table A-5: Values of accuracy measures for comparisons with Fuchs et al. (2017) and a naïve approach

Window	This paper, gravity-equation				Fuchs et al. (2017)				Naïve approach			
	MPE	MAPE	RMSE	MAE	MPE	MAPE	RMSE	MAE	MPE	MAPE	RMSE	MAE
1998-2007	0.04	6.84	48,618	41,091	0.30	29.91	192,739	180,728	0.29	29.02	180,902	175,907
1999-2008	0.13	13.62	94,808	79,918	0.27	27.04	177,480	160,613	0.32	31.72	196,234	191,181
2000-2009	0.21	20.59	130,519	122,066	0.31	31.15	197,603	184,777	0.33	33.45	204,242	200,331
2001-2010	0.14	14.96	98,669	88,251	0.29	28.70	185,773	170,467	0.31	31.07	191,406	186,204
2002-2011	0.16	17.58	112,722	105,878	0.27	27.66	178,029	164,532	0.27	28.04	176,238	168,243
2003-2012	0.09	15.00	105,510	97,737	0.21	24.26	161,287	149,044	0.19	25.27	164,926	159,124
2004-2013	-0.01	12.85	143,349	103,224	0.12	22.52	173,676	155,531	0.05	20.98	184,776	155,815
2005-2014	0.04	16.28	177,907	135,136	0.06	24.22	234,783	194,555	-0.06	22.21	283,645	204,908
2006-2015	-0.04	19.45	385,795	230,875	-0.07	25.50	455,214	295,886	-0.17	27.12	520,068	334,073
2007-2016	-0.12	21.50	462,559	298,445	-0.17	28.12	545,247	376,066	-0.27	31.93	632,921	439,955
2008-2017	-0.19	22.41	483,505	330,867	-0.23	31.34	585,049	433,908	-0.35	36.85	684,931	516,967
2009-2018	-0.24	24.87	508,775	374,996	-0.33	33.03	628,076	485,565	-0.42	41.84	729,312	592,015
2010-2019	-0.27	27.39	518,269	409,565	-0.38	37.73	658,740	548,209	-0.47	47.13	765,017	664,212
2011-2020	-0.25	25.04	490,232	379,870	-0.40	39.52	661,675	567,291	-0.50	49.87	773,303	694,463

Sources: Author’s own computation. Data used as explained in the text. © IAB

Table A-6: Results of the HLN test for comparisons Fuchs et al. (2017)

Window	Test statistic	H: Models have different levels of accuracy	H: Fuchs et al. (2017) is less accurate	H: Fuchs et al. (2017) is more accurate
1998-2007	-2.7819	***	***	-
1999-2008	-2.8282	***	***	-
2000-2009	-2.9490	***	***	-
2001-2010	-2.9358	***	***	-
2002-2011	-2.8526	***	***	-
2003-2012	-2.2038	**	**	-
2004-2013	-1.2423	-	-	-
2005-2014	-1.6844	*	**	-
2006-2015	-1.5616	-	*	-
2007-2016	-1.9197	*	**	-
2008-2017	-2.1888	**	**	-
2009-2018	-2.3810	**	***	-
2010-2019	-2.5442	**	***	-
2011-2020	-2.6275	**	***	-

Note: Notation for significance levels: *** < 0.01 / ** < 0.05 / * < 0.1 / - >= 0.1

Sources: Author’s own computation. Data used as explained in the text. © IAB

Table A-7: Results of the potential labor force participation rates forecast for males by age

Year	Labor Force Participation, males											
	20-24 years			25-29 years			30-34 years			35-39 years		
	P	U	L	P	U	L	P	U	L	P	U	L
2020	77.0%			89.2%			95.3%			95.8%		
2030	83.8%	84.5%	83.0%	89.6%	89.6%	89.5%	96.2%	96.2%	96.2%	96.3%	96.2%	96.3%
2040	84.8%	85.4%	84.1%	89.5%	89.6%	89.5%	96.2%	96.2%	96.2%	96.2%	96.2%	96.3%
2050	85.4%	85.9%	84.9%	89.5%	89.6%	89.4%	96.2%	96.2%	96.2%	96.2%	96.1%	96.3%
2060	85.6%	86.0%	85.1%	89.5%	89.5%	89.4%	96.2%	96.2%	96.2%	96.1%	96.1%	96.2%
	40-44 years			45-49 years			50-54 years			55-59 years		
	P	U	L	P	U	L	P	U	L	P	U	L
2020	95.8%			95.3%			94.1%			90.3%		
2030	96.7%	96.7%	96.7%	95.5%	95.6%	95.5%	94.8%	95.0%	94.7%	94.2%	94.5%	93.7%
2040	96.6%	96.7%	96.5%	95.5%	95.5%	95.4%	94.9%	94.9%	94.8%	95.2%	95.4%	95.1%
2050	96.6%	96.6%	96.5%	95.4%	95.5%	95.4%	94.8%	94.9%	94.8%	95.2%	95.2%	95.1%
2060	96.6%	96.7%	96.6%	95.4%	95.4%	95.4%	94.8%	94.8%	94.8%	95.1%	95.1%	95.1%
	60-64 years			65 years and above								
	P	U	L	P	U	L						
2020	75.3%			17.8%								
2030	93.7%	94.4%	93.0%	27.8%	29.1%	26.4%						
2040	94.8%	95.4%	94.2%	26.9%	29.0%	24.8%						
2050	95.1%	95.3%	94.9%	33.2%	35.7%	30.7%						
2060	94.8%	94.9%	94.6%	32.8%	35.3%	30.3%						

Sources: Author’s own computation. Data used as explained in the text. © IAB

Table A-8: Results of the potential labor force participation rates forecast for females by age

Year	Labor Force Participation, females											
	20-24 years			25-29 years			30-34 years			35-39 years		
	P	U	L	P	U	L	P	U	L	P	U	L
2020	70.9%			80.9%			82.8%			84.1%		
2030	71.1%	71.3%	70.9%	80.7%	80.5%	80.9%	83.0%	83.0%	83.0%	86.8%	86.9%	86.6%
2040	71.0%	71.1%	70.9%	80.3%	80.1%	80.6%	82.4%	82.2%	82.6%	87.7%	87.6%	87.8%
2050	70.4%	70.3%	70.4%	79.8%	79.6%	80.0%	82.5%	82.4%	82.7%	88.3%	88.2%	88.4%
2060	70.2%	70.1%	70.2%	79.5%	79.3%	79.7%	81.9%	81.7%	82.1%	88.9%	88.8%	88.9%
	40-44 years			45-49 years			50-54 years			55-59 years		
	P	U	L	P	U	L	P	U	L	P	U	L
2020	87.4%			87.9%			86.4%			83.3%		
2030	90.7%	91.3%	90.1%	90.9%	91.1%	90.7%	91.4%	91.7%	91.1%	88.0%	88.2%	87.7%
2040	91.7%	92.1%	91.3%	92.4%	92.5%	92.4%	94.6%	94.7%	94.5%	91.8%	91.9%	91.8%
2050	92.3%	92.5%	92.0%	93.8%	93.7%	93.7%	96.1%	96.1%	96.1%	94.1%	94.1%	94.1%
2060	93.0%	93.2%	92.7%	94.9%	95.0%	94.9%	97.2%	97.2%	97.1%	95.7%	95.7%	95.7%
	60-64 years			65 years and above								
	P	U	L	P	U	L						
2020	66.7%			12.0%								
2030	72.2%	73.2%	71.3%	17.7%	19.1%	16.3%						
2040	74.3%	75.5%	73.2%	17.4%	19.8%	15.1%						
2050	74.2%	75.2%	73.4%	21.8%	24.9%	18.7%						
2060	74.5%	75.3%	73.8%	21.8%	25.5%	18.0%						

Sources: Author's own computation. Data used as explained in the text. © IAB

Figures

Tables

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