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Demographic Microsimulation Model For Türkiye[1]

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Abstract

This paper focuses on the use of microsimulation methodology to generate reliable population estimations for Türkiye. Microsimulation closely mimics life course dynamics and is therefore well-suited for predicting demographic changes. Using data from the 2018 Türkiye Demographic Health Survey, we developed a new microsimulation method that allows for greater customization and accuracy without relying on external patterns or models. The resulting population simulation includes age, education, marital status, usual residence, and labour force status for each individual until 2030. Our study demonstrates the flexibility and adaptability of microsimulation for demography and argues that it provides a coherent and meaningful way to estimate and project population attributes that other tools cannot provide. Ultimately, the dynamic simulation model has the potential to inform important policy decisions related to the population in Türkiye.

Keywords: *Data Matching, Fertility, Household Labour Force Survey, Microsimulation, Türkiye Demographic and Health Survey.*

Öz

Bu makale, Türkiye için güvenilir nüfus projeksiyonları oluşturmak amacıyla mikrosimülasyon metodolojisini kullanmaktadır. Mikrosimülasyon, yaşam seyri dinamiklerini yakından taklit ettiğinden demografik değişiklikleri tahmin etmek için oldukça uygundur. Çalışma kapsamında, 2018 Türkiye Nüfus Sağlığı Araştırması verilerini kullanarak, harici kalıplara veya modellere dayanmadan özelleştirmeye olanak ve doğruluk sağlayan yeni bir mikro simülasyon yöntemi geliştirilmiştir. Çalışmamız, mikrosimülasyonun demografi için esneklik ve uyarlanabilirlik sağladığını, nüfusun özniteliklerini tahmin etmek ve projeksiyon yapabilmek için diğer araçların sağlayamadığı tutarlı ve anlamlı sonuçları sağladığını savunmaktadır. Sonuç olarak, dinamik simülasyon modeli Türkiye'deki nüfusla ilgili önemli politika kararları için güvenilir bilgi sağlama potansiyeline sahiptir.

Anahtar Kelimeler: *Doğurganlık, Hanehalkı İşgücü Araştırması, Mikro simülasyon, Türkiye Nüfus ve Sağlık Araştırması, Veri Eşleştirme.*

[1] *This paper is based on unpublished PhD thesis "An Alternative Approach to Population Projection in Turkey: Reconsidering Population Policies using Dynamic Microsimulation Model".*

Introduction

The study of population has been of great importance since the beginning of human history, as it has been observed that societies that have been able to structure their population in a planned way have tended to dominate other groups (Robinson, 2014). To promote prosperity, development, and growth, societies must plan, organize, and manage their population in a way that takes into account the resources available to them. As a result, predicting the impact of decisions, policies, and plans on the population has become a priority for forward-thinking systems.

Microsimulation is a methodology that allows researchers to mimic the behavior of a real or imaginary population using a model, which is especially useful when the system is complex and difficult to analyze in its real environment (Epstein & Axtell, 1996). By choosing a sample or synthetic population to represent the system, microsimulation can provide detailed information about the future composition of the population to policy makers. This study aims to establish a customized microsimulation with the Turkey Demographic and Health Survey (TDHS) to produce consistent estimation on age, sex, education, labour force, and population.

The origins of microsimulation can be traced back to the inception of dynamic microsimulation, which was influenced by the publication of Orcutt’s (1957) paper. In the early 1970s, Orcutt and other researchers developed the Dynamic Income Simulation Model (DYNASIM), one of the earliest microsimulation models that utilized the dynamic microanalytical simulation approach. Developed nations commonly employ microsimulations as a tool for decision-making. To illustrate, Germany employed a dynamic microsimulation model in the 1970s to assess the demographic impacts and professional activities. Subsequently, this model underwent enhancements and was utilized to analyze household formation and earnings for pension reform purposes (Li & O’Donoghue, Autumn 2013).

In their study, Thomas et al. (2017) concentrates on fertility and introduce FamilyScape 3.0, a microsimulation tool designed for modeling family formation and child well-being. The research demonstrates the model's accurate simulation of sexual activity, contraceptive behavior, pregnancy outcomes, as well as maternal and child results.

Population scientists have used microsimulation for many years to predict and project populations and their characteristics. Microsimulation requires detailed and varied data from multiple sources in order to be accurate and consistent. Macro-level population projections can produce estimates about basic population structures, but for more detailed characteristics such as education, household composition, and labour force, separate estimation studies must be carried out.

Microsimulation can help researchers examine the impact of alternative macro scenarios on individuals and households and can be especially useful when studying diverse and complex populations with reciprocal relationships between variables. In this regard, we aim to provide estimates for various components such as education, fertility, labour force, income, economic activity, marital status, and household type. This microsimulation study is the first for Türkiye which reveals the cross-relationship of previously mentioned components.

Microsimulation models are powerful tools used by researchers to model and predict population dynamics. The dynamic microsimulation model used in this study allows for a more accurate reflection of reality by considering the changing circumstances of an individual's life. This study used a dynamic microsimulation model that takes into account the changing circumstances of an individual's life to provide a more accurate reflection of reality.

Methods

There are two types of microsimulation models in literature, static and dynamic. Static microsimulation is a straightforward approach that models a population at a single point in time, without considering any changes that may occur over time. This type of simulation is useful for estimating the distribution of various characteristics, such as education levels, in a given year. However, static microsimulation cannot account for changes that may occur over time, such as demographic shifts or changes in economic conditions (Merz, 1994).

Dynamic microsimulation is a more complex approach that models the population over time, taking into account changes in demographics, socioeconomic status, and other factors. In dynamic microsimulations, events trigger other events in a cause-and-effect relationship. Dynamic microsimulation uses longitudinal data and can simulate changes in the population over a specified time. This approach is useful for forecasting future trends, such as the projected distribution of income or the impact of demographic changes on a particular population (Dekkers, 2015). These changes are modelled using a stochastic process known as Markov Chains (Kijima, 1997). Based on life course observations, probabilities of an individual transitioning from one state to another are derived, making it an accurate representation of reality.

In this study, the continuous closed microsimulation approach, the closed system framework utilized in our analysis does not incorporate external interventions and excludes the consideration of international migration. This decision was made due to the inherent challenges associated with obtaining precise assumptions and comprehensive data on international migration, particularly within the Türkiye context. The lack of detailed and reliable data on international migration limits our ability to establish consistent estimations and reliable outcomes.

Model used

In this study, a dynamic continuous-time micro-simulation was carried out, using a Markov chain methodology to maintain continuity, which is a process that has a discrete state space (Kijima, 1997). This property, called the Markov property;

$$P\ (X_{t_{n+1}} \in\ A\ |X_{t_0} = x_0, \ldots, X_{t_n} = x_n) = P(X_{t_{n+1}} \in\ A\ |X_{t_n} = x_n)$$

for all times $0 = t0\ \leq t1\ \leq \cdots \leq tn\ \leq tn + 1$ and all $x0, \ldots, xn$ in the state space.

$$p_{st}\ (x, A) := \ P(X_{s+t} \in\ A\ |X_s = x)$$

denotes the likelihood that the model takes a value in A at time t according to its value x at time s (Serfozo, 2009).

The CTMC is stochastic and assumes that the current state, rather than the past trend, influences the probability of possible events. In this case, the stochastic process becomes a CTMC with the following conditions $\{X(t): t \geq 0, t \in \mathbb{Z}\}$;

$$P(X(s+t) = j|X(s) = i, X(r) = i_r, r \in A_s s \subseteq [0, s)) = P(X(s+t) = j|X(s) = i)$$

where i and j denotes states, s and t denotes time. On the left side of the equation, r represents the past time and s represents the present time. As in addition to the value at the "present" time s. The conditional probabilities $P(X(s+t) = j|X(s) = i)$ are called the transition probabilities.

The notation of the CTMC transition probabilities matrix, in which $v_i, for\ i\ \in S,$ the exponential distribution of the exposure rate of a system after entering the i state, and then the probability $m_{ij}, for\ i, j \in S$ of the system to enter the j state, is as follows.

$v_i = \ \sum_{k \neq i} p_{ik} = -q_{ik}$, for all i

$P = [m_{ij}] = \frac{p_{ik}}{\sum_{k \neq i} p_{ik}}$, for all $i \neq j$

The model used in this study is a dynamic model that uses the continuous-time Markov chain. It is necessary for the microsimulation model to be dynamic for time to pass, and there is randomness in the event while passing from one state to another. In this study, life events are anticipated to progress historically. The Monte-Carlo method is used to generate new cases from the probability distribution, where the waiting time is computed using the exponential inverse distribution function of transition rates derived from observation data. The inverse exponential distribution function used in the model for the computation of waiting times for each event and record is denoted as;

$$P(T \leq t) = F(t) = 1 - e^{-\lambda t}$$

where, λ ($\lambda \in U[0,1]$) denotes random value from the uniform distribution (Willekens, 2011).

Unlike discrete-time models, where the duration of events is defined, continuous-time models allow for the modelling of events occurring at any time, adding to the randomness and dynamic nature of the model. To ensure the continuity of the dynamic microsimulation and to maintain randomness, the cross-sectional microdata from the previous year is sequenced with the current year's microdata.

We developed a package in R to implement the model we used in this study. The syntax written in R, contains 970 line, is used to simulate demographic characteristics for a specific population. The required data for the package was designed to be prepared in excel format, including variables such as base year population, death rates, marriage and divorce rates, fertility rates, educational transition rates, labor force transition rates, birth order transition rates, and migration transition rates. For instance, the decision phase of deaths has been shown below, where the deathrates are assigned to the baseline population and the implementation of the decision as presented using the formula (6);

```
POP<-
merge(POP,DEATH_R,by.x=c("YEAR","REGION",
"AGE","SEX"),all.x=TRUE) POP$DEATH_WT<-(-
1)*log((1-runif(nrow(POP),0,1)))/(
log(1POP$RATE))POP$DEATH_DATE<-
ifelse(POP$DEATH_WT<1,i+POP$DEATH_WT,0)
```

Assumptions

There are several assumptions and limitations that need to be considered while interpreting the results. The accuracy of the simulation model relies on the quality of the input data used, which may be subject to sampling errors, confidence intervals, and biases. Household formation and dissolution due to movements were not specifically simulated due to the lack of data apart from marriage and divorce. This means that household changes due to education, work, or other reasons were not taken into account.

To address this limitation, the method simulated household migration instead of individual migration by selecting random households while preserving the age, sex, and size of total migrants.

Fertility rates were assigned according to age and region. The total number of births were distributed in accordance with education level and birth order of women.

Finally, newlyweds were assumed to leave their parental home and form a new family in a new household, due to a lack of data on family formation behavior.

Data

To conduct microsimulation, at a minimum, certain essential data components are typically required. These include baseline data comprising demographic characteristics, as well as longitudinal data concerning educational and labor force status transitions or exposure rates, such as fertility and mortality rates. These data serve as the foundation for calculating the transition rates associated with these characteristics.

To ensure that the dataset used for microsimulation is rich and diverse, two datasets namely TDHS and Household Labour Force Survey (HLFS) datasets were integrated and used.

The main data source of the simulation in this study is the TDHS, which collects data on household characteristics and lists all household members (DHS Program, 2022). The data set is enriched with HLFS (TurkStat, Household Labor Force Survey, 2019) microdata using data integration techniques. The obtained dataset is used as the baseline population, with the household members being used as the representation of all individuals.

The data integration process involves merging datasets into a single, consistent dataset using data matching techniques. Typically, this is done by using a common or similar variable as a key identifier (Gabriella et al., 2014). However, in our case, the data to be matched did not have a common identifier. To achieve more precise and detailed matching, we used more than one field to match the data, harmonizing similar fields to a common denominator.

In the study, we employed an equality-based record matching technique, wherein two records are considered a match if some or all the fields are equal or nearly equal. This matching technique was applied based on individual characteristics.

In order to accurately match the data from TDHS and HLFS, we utilized common variables that represented 5 different attributes of individuals (NUTS-1 region, 5-year age group, sex, marital status, and educational level attained). These variables (Table 1) were adjusted to have the same categories, ensuring that they could be compared. We then compared the distributions of the variables to determine if they measured the same characteristic with similar outputs.

Table 1*. Categories of common variables*

Marital Status	Education Level	Regions	Sex	Age group
Never married	No / Primary school	NUTS-1 12 regions	Male	5-year age group
Married	Middle school		Female	
Divorced	High school			
Widowed	University			

It is important to note that this technique has a limitation as it assumes that individuals with similar characteristics will have similar labor force variables, which may not always hold true in real-life scenarios.

Before performing the matching, the researchers needed to ensure that both datasets revealed similar distributions for Türkiye. In datasets that do not show similar distribution, the matching may occur below the expected level (unassigned records), some categories may not be matched at all, and the distribution obtained according to the matching may present a completely different picture.

In this article, we compared the population distribution of two datasets, TDHS and HLFS, with the Address Based Population Register System (ABPRS) population distribution. ABPRS is a population database that was established by the Turkish government to provide accurate and up-to-date information on the population of Türkiye.

The database is constructed on a national address database, which is updated regularly by the Ministry of Interior using data from local municipalities. Figure 1 presents the comparison, as the output of the microsimulation we conducted will be compared with ABPRS-based indicators. Our analysis revealed that both TDHS and HLFS datasets displayed population distributions similar to the ABPRS population distribution for Türkiye.

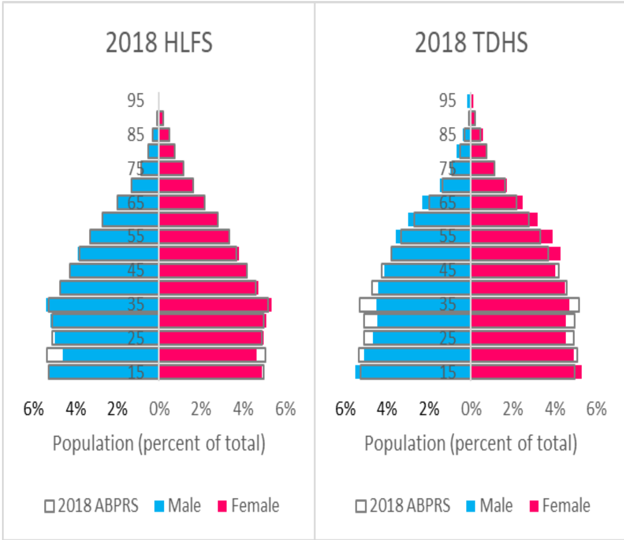

Figure 1. *Population pyramids, 2018 TDHS and 2018 HLFS*

Although differences in certain age groups are obvious between TDHS and HLFS, distributions of variables have been compared to assess if variables measure the same characteristic with similar outputs. To this end, the Hellinger distance function is used to assess the similarity of distributions in TDHS and HLFS, and the score obtained for each variable remains below 5%, which is considered a cut-off line for an indication of good fit (Figure 2).

After finding that the TDHS and HLFS datasets are suitable for matching, the household labour

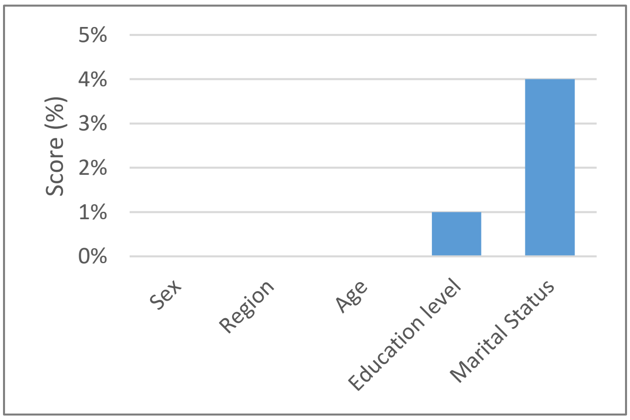

Figure 2. *Hellinger distance of the common variables (%)*

force survey dataset containing 374 thousand records was aggregated by region, age group, sex, education level, marital status, and transition from one state of the labour force to another, containing 9980 rows. From the derived new dataset, the labour force variable was converted into probabilities by considering the labour force status a year ago. Here, the category consists of each singular case of the new dataset's variables excluding labour force status.

By combining these two datasets and using their respective variables, we were able to generate a robust base year population that accurately reflects the demographic and socioeconomic characteristics of the Turkish population. The 2018 TDHS Household Member Data Set provided us with important demographic information on individuals, including their address number, age, sex, education, marital status, region, relation to the head of the household, weight, and number of children. We also used the HLFS micro dataset to obtain information on individuals' employment status, economic activity, and status in employment.

Table 2. Baseline data sources and variables

TDHS-2018: Household Member Data	2017-2019 LBS microdata
Address No	Employment Status
Age	Economic Activity
Sex	Status in Employment
Education	
Marital Status	
Region	
Relation to Head of HH	
Weight	
Number of Child	

Microsimulation requires data on the population's demographic indicators and their status in each variable, as well as transition probabilities to determine how long it takes to switch from one state to another. Therefore, estimating event exposure rates from longitudinal datasets is easier than from cross-sectional data (Zagheni, 2015). Transition rates must be selected and computed rigorously to ensure a consistent and coherent simulation. Figure 3 illustrates the transition rates and their respective sources, accompanied by the reference period.

Fertility rates TDHS 2018	Labour force: 2018 HLFS microdata	Education: TurkStat, Education Statistics, 2018-2019	Mortality: TurkStat, Mortality Statistics, 2018
• Region • Education • Fertility rates • Birth Order	• Employment Status • Economic Activity • Status in Employment	• Age • Sex • Region	• Age • Sex • Region

Figure 3. *Source of transition rates*

Transition probabilities for childbearing were calculated using 2018 TDHS datasets (Table 3), fertility rates by educational level and birth order were produced. From the HLFS dataset, previous year and current employment status were taken into account to calculate transition rates. Mortality data was derived from official records of 2018 deaths stratified by region, age, and sex, which were published by TurkStat (TurkStat, Vital Statistics, 2022) to determine deaths.

The probabilities of transitioning between different education levels were calculated by applying formula (5) to the number of individuals who have transitioned between 2018 and 2019, considering their age, sex, and region. The data used for this calculation is maintained in the National Education Statistics Database and provided by TurkStat upon our formal request.

However, the dataset used in microsimulation contains a limited number of rare events, such as giving birth to a sixth child or widowed women with kids finding a job. To overcome this limitation, the dataset has been expanded by duplicating individual records 10 times with the same attributes but different IDs and addresses.

This replication method ensures that microsimulations can be carried out with a large number of individuals and households without compromising on age, sex, education, marital status, or any other distribution (Dupriez, 2017).

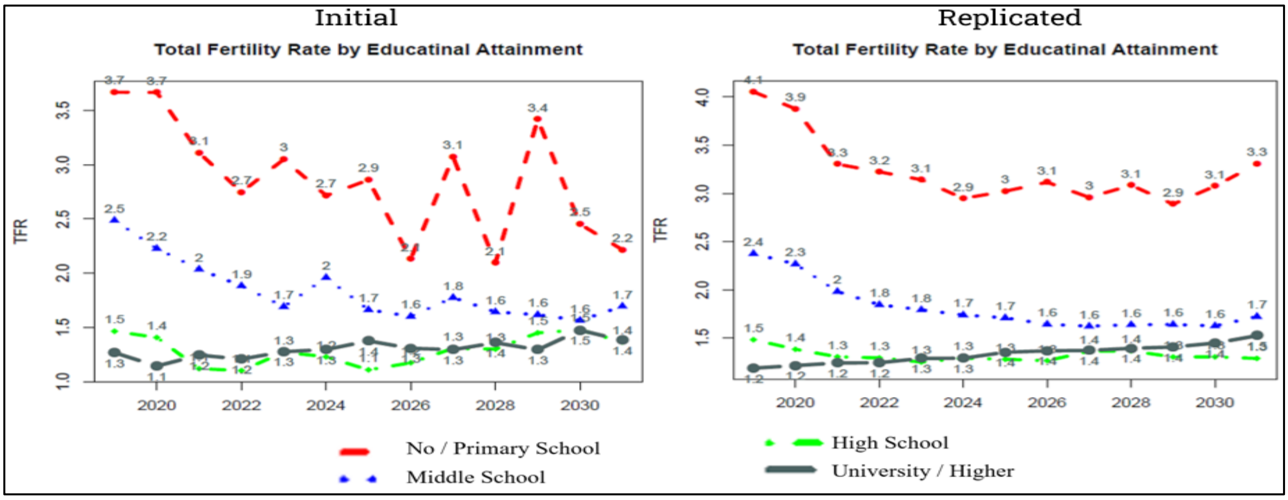

Figure 4. *Results comparison of initial and replicated sample*

The smooth transition and consistency observed (Figure 4) in the trend of the indicators obtained from the simulation result using the duplicated baseline were only possible because the transition probabilities were calculated over the population of Türkiye.

Table 3. *Transition rates of women for Istanbul region*

Age group	Death rate	ASFR (no or primary school graduates)	Labour force status (from unemployed to employed)
0	0.00697		
1-4	0.000318		
5-9	0.000136		
10-14	0.00016		
15-19	0.000187	0.0000	0.232
20-24	0.000209	0.1983	0.225
25-29	0.000217	0.1163	0.071
30-34	0.000322	0.0478	0.070
35-39	0.000442	0.0504	0.079
40-44	0.000677	0.0138	0.053
45-49	0.001145	0.0000	0.026
50-54	0.002065		0.048
55-59	0.00344		0.000
60-64	0.006184		0.000
65-69	0.010501		0.000
70-75	0.018363		0.000
75-79	0.036102		0.000
80-84	0.066046		
85+	0.145297		

If the transition probabilities were also calculated from the DHS data, the breakdowns of indicators would be underrepresented due to the low number of observations. However, by using the statistics that TurkStat calculates taking into account the whole country as observations, each transition probability is derived from more observations, which results in a more accurate simulation. In essence, the duplication of the baseline data increases the number of observations and brings the simulation results closer to real-world distribution. Validation and consistency are crucial for any simulation model, and our study is no exception. Researchers have suggested that the results obtained from the dynamic microsimulation model should be compared with observed data to validate the results (Merz, 1994). However, it is important to note that the results obtained from simulation may differ from statistics to a certain extent due to differences in methodology.

Results

In this study, the simulation method applied assumed a closed migration system and did not take into account the institutional population, which led to a lower estimate of the population size between 2019-2021 compared to data from the ABPRS. A considerable portion of the institutional population comprises students residing in dormitories, and statistical data indicates that this group exhibits a higher growth rate compared to the household population (Ministry of National

Education, 2022). Nevertheless, the population growth rate remained relatively stable at around 5 per thousand. Projections based on the simulation suggest that population is expected to reach 86.6 million by 2030 (Figure 5).

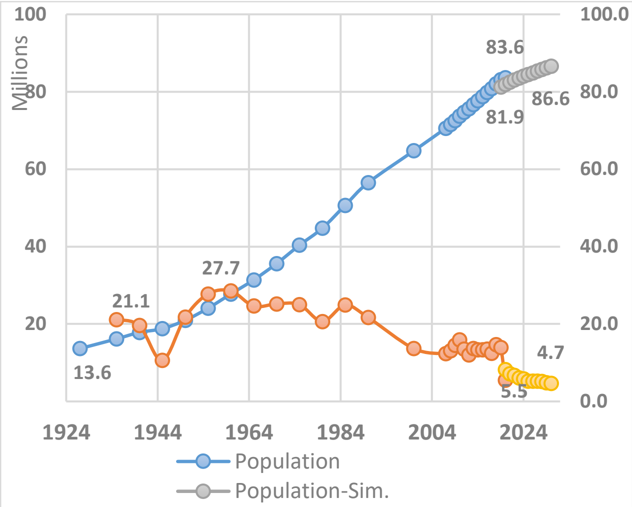

Figure 5. *Population and growth rate, 2007-2021 TurkStat, 2019-2030 Simulation*

In this research, we compared the population size estimated by our simulation to projections made by the United Nations (UN) and the Turkish Statistical Institute (TurkStat) in Figure 6. It's noticeable that our simulation started with a lower population level than the other projections, as it only considered household populations, while the UN and TurkStat projections accounted for both household and institutional populations. However, despite the initial difference in population size, our simulation produced similar trends to those observed in the Address Based Population Registration System (ABPRS) results. This indicates that our simulation methodology was effective in capturing the key demographic trends in Türkiye, despite the limited scope of the simulation.

Table 4 presents the projected changes in population across NUTS1 regions in Türkiye from 2019 to 2030. The table shows a downward trend in the population of Istanbul (TR1), West Marmara (TR2), Aegean (TR3) regions, and upward trend in the other regions with the highest in Southeast Anatolia Region (TRC), which is projected to experience a steady increase in population. The largest decline is expected in Istanbul Region (TR1), which is projected to decrease from 15.4 million in 2019 to 13.9 million in 2030. The main reason for this decrease is that, according to TurkStat migration statistics, Istanbul's net migration has been consistently negative in 2016, 2017 and 2018. In Turkey, the patterns of internal migration are influenced by the timing of parliamentary and local administration elections. The elections held in 2018 for the parliamentary seats and in 2019 for local administration positions have notably disrupted the migration rates, particularly in İstanbul and this is reflected in the model. These findings suggest a concentration of the population in large urban areas, particularly in the western and southern regions of Turkey. The implications of these projections are significant for public policy, particularly for infrastructure planning and resource allocation in the country.

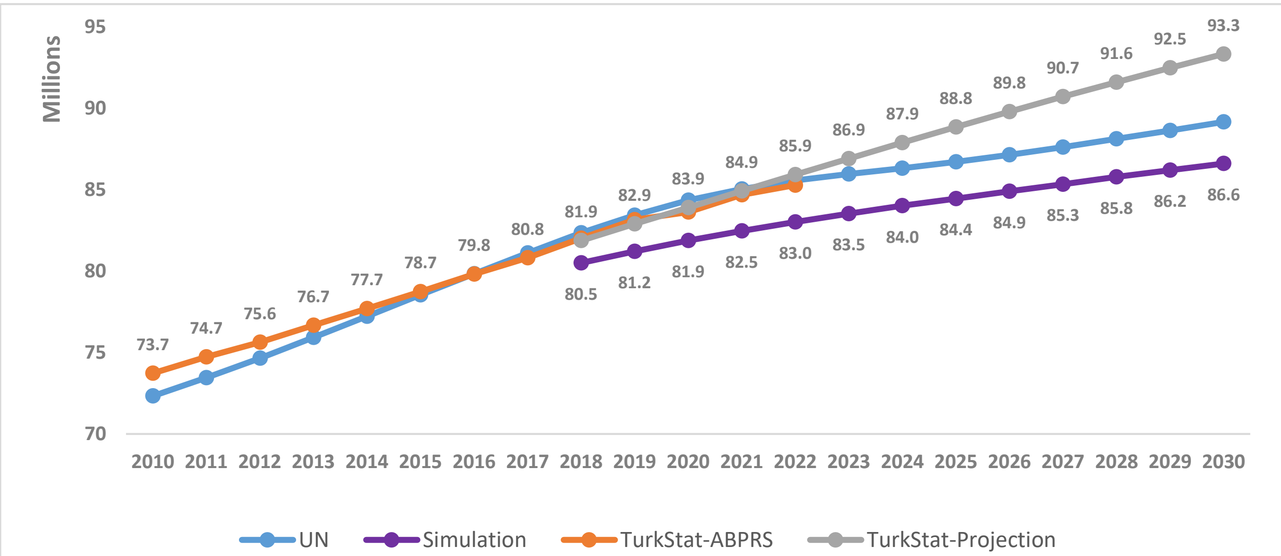

Figure 6*. Population by selected estimations, 2018-2030*

Table 4. Population estimation by NUTS-1 Regions, 2019-2030

	2019	2021	2023	2025	2027	2030
TR1	15,365,821	15,259,591	14,872,185	14,627,642	14,353,750	13,896,713
TR2	3,586,109	3,621,017	3,631,865	3,647,722	3,622,747	3,578,374
TR3	10,301,512	10,224,367	10,152,781	10,060,706	9,922,056	9,756,682
TR4	7,673,240	7,784,874	7,878,615	7,952,589	8,046,727	8,197,683
TR5	7,989,689	8,073,680	8,171,552	8,218,650	8,335,326	8,494,503
TR6	10,346,170	10,533,186	10,739,762	10,895,337	11,064,492	11,317,811
TR7	3,994,400	4,042,454	4,113,012	4,199,480	4,266,754	4,360,403
TR8	4,463,869	4,540,337	4,652,509	4,691,742	4,742,902	4,760,683
TR9	2,202,667	2,297,659	2,393,282	2,456,035	2,474,894	2,489,214
TRA	2,136,340	2,241,542	2,357,373	2,476,722	2,582,468	2,712,564
TRB	4,064,174	4,239,378	4,418,820	4,581,172	4,724,698	4,951,223
TRC	9,121,171	9,620,319	10,144,583	10,620,229	11,142,423	12,007,388

In comparison to the assumptions made by the United Nations (UN) and TurkStat population projections (Figure 7), the total fertility rate (TFR) observed in TurkStat statistics is lower than their predictions. However, in contrast to this trend, the TFR calculated through the simulation estimates the closest value and approaches official statistics over time.

The estimated total fertility rate (TFR) for Türkiye was found to be 2.1 in 2019, indicating a moderate level of fertility. However, our projections reveal a significant decline in the TFR to 1.6 by 2030, indicating a downward trend in fertility rates. Specifically, when analyzing the sub-regions,

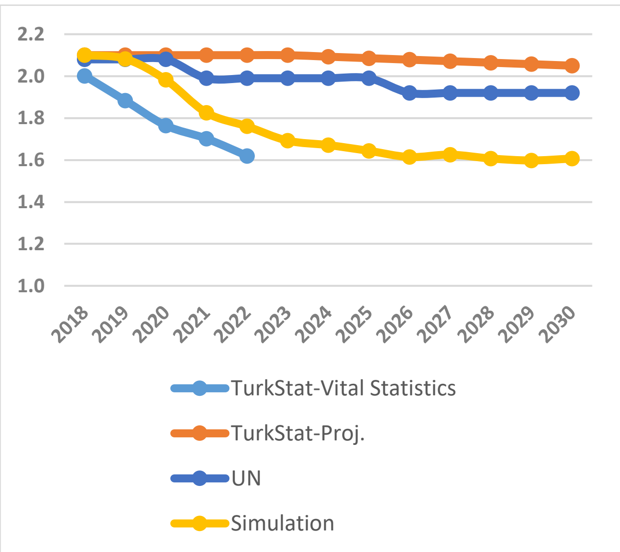

Figure 7. *Total Fertility Rates of selected estimations*

İstanbul displayed a TFR of approximately 2 in 2019 (Figure 8). However, our projections indicate a substantial decline in the TFR, reaching 1 by 2030. This decline suggests a significant reduction in fertility levels within the İstanbul region.

In Southeast Anatolia, the TFR was notably higher at 2.9 in 2019, indicating relatively higher fertility rates compared to other regions. However, our projections indicate a gradual decrease in the TFR, reaching 2.2 by 2030. Despite the decline, the region is expected to maintain a relatively higher in fertility levels within of 1.1 in 2019. However, our projections suggest a noteworthy increase in the TFR, reaching 1.8 by the East Black Sea region.considerably lower TFR 2030. This upward trend indicates a potential rise fertility rate compared to other regions in Türkiye. Conversely, the East Black Sea

Figure 9 reveals that there is a demographic shift influencing the educational composition of the population. The population of individuals with no school or primary school education are ageing and not being replaced by younger generations with similar educational backgrounds. In contrast, the number of individuals with university and higher education degrees is increasing,

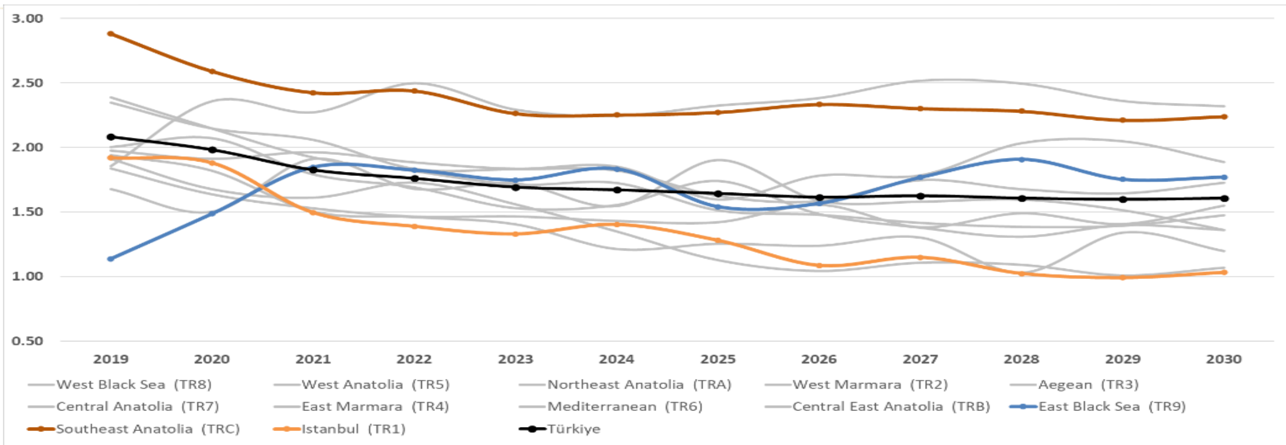

Figure 8. *Total fertility rate by regions, 2019-2030*

particularly among women. This shift in educational levels may have various implications for society. For example, it could influence the types of jobs available, the skillsets required in the workforce, and the overall level of economic development. Additionally, it may affect social and cultural norms and values, as well as the distribution of power and privilege in society.

decade, indicating a sense of predictability and stability for those entering or already in the workforce. At the same time, the predicted increase in women's employment is a positive development and is in line with the global trend of more women participating in the labour force (Elder & Dorothea, 2004).

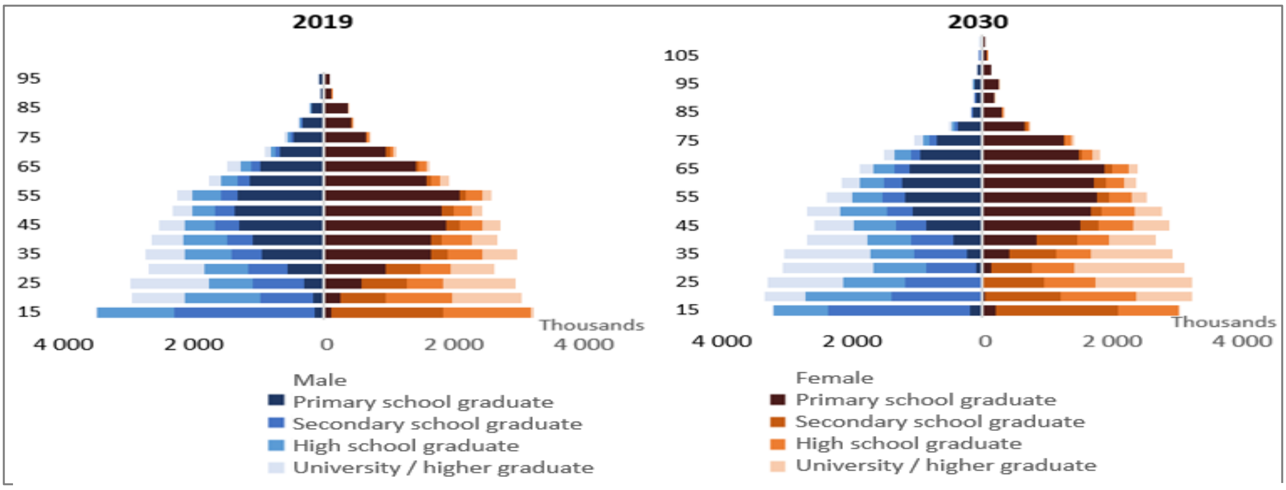

Figure 9. *Population pyramid by completed educational level, 15+ age, 2019, 2030*

It is important to note that these findings may be influenced by a variety of factors, such as government policies, cultural norms, and economic conditions. Further research and analysis would be needed to fully understand the underlying causes and potential consequences of this shift in educational levels.

Results indicate that the labour force market will experience relatively stable conditions without significant changes (Table 5) by 2030. However, it is expected that the employment rate for women will see a slight increase during this period.These findings suggest that the job market will remain relatively consistent over the next

It's important to note that these projections are subject to change and can be influenced by various factors such as technological advancements, shifts in industry demands, and economic policies. Nonetheless, these findings provide some insights into what the labour market could look like in the near future. Overall, our findings demonstrate that the simulation method we used provides a valuable tool for estimating population size and projecting demographic trends, particularly for household populations, and can serve as a beneficial complement to other projection methods.

Table 5. *Employment rate by age group and sex (%), 2019-2030*

	Male		Female	
	2019	**2030**	**2019**	**2030**
15-19	25.4	14.9	15.3	13.9
20-24	59.5	59.8	32.0	26.4
25-29	74.2	73.7	35.6	34.8
30-34	81.1	76.9	37.2	40.0
35-39	83.3	76.6	38.5	41.2
40-44	83.2	73.8	41.9	42.9
45-49	79.3	70.7	40.0	39.5
50-54	64.6	63.4	27.4	32.5
55-59	55.7	54.5	20.2	24.9
60-64	40.4	42.7	13.2	18.4

Conclusions and recommendations

In conclusion, the findings of this study are consistent with the mainstream judgement (Bakar et al., 2017, Levent, 2002, Ergöçmen, 2012, Eryurt, 2018, Eryurt & Koç, 2012), which predicts a decline in fertility and an increase in investment per child, education, and health quality. The microsimulation approach used in this study provides more consistent estimates even for key indicators than macro-level projections.

The simulation approach also generates nuanced information on demographic events, such as age, sex, region, and educational attainment, and labour force status by age, and sex. Future research can integrate more sophisticated models to analyze the full distributive effects of policies and other macro-shocks.

The results highlight the importance of taking regional differences into account in planning to improve employment, income, and education levels. Targeted interventions can be more effective and efficient by covering problematic sub-segments rather than the entire population.

Lastly, while our demographic microsimulation methodology allows detailed and realistic demographic projections, it still faces limitations in terms of data demands and quality. Data accessibility is improving, but the lack of appropriate data can hinder the use of microsimulation models.

It is important to note that our analysis focused exclusively on socioeconomic catachrestic, as the consideration of international migration was excluded due to the challenges associated with obtaining accurate and consistent data and feasible assumptions in this context. The absence of international migration in our analysis represents a limitation. The lack of detailed and reliable data on international migration made it challenging to incorporate this factor into our microsimulation model. Future studies should aim to address this limitation by considering the complexities of international migration within the Türkiye context, thereby providing a more comprehensive understanding of migration dynamics in the country.

In addition, data quality issues, especially in internal migration, data can cause skewed results. To improve the model, it would be ideal to have a socioeconomic population database with administrative records of social and economic characteristics to further understand migration behavior.

The software developed in R has served its purpose, but it should be developed, interfaced, and adapted to standard data sets for use in future population studies. The matching strategy proposed can also be improved by trying different models with more characteristic features. Future research should focus on addressing these limitations to create more realistic demographic projection models.

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