DRAFT PAPER

Macroeconomic implications of demographic changes in Bulgaria

Ventsislav Ivanov, Desislava Cvetkova, Andrey Vassilev

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Abstract: This study examines the macroeconomic implications of demographic changes in Bulgaria, focusing on their effects on potential output, inflation, and fiscal sustainability. Using a human capital-augmented production function and a Bayesian Vector Autoregression (BVAR) model, we assess how demographic trends—particularly population ageing and labour force decline—affect economic growth, consumption, and wage dynamics in Bulgaria. We estimate the evolution of human capital using an approach that incorporates demographic projections and labour market characteristics. Our findings indicate that Bulgaria's declining working-age population will continue to constrain potential growth, primarily through reduced labour input and to a much lower extent through slower human capital accumulation. While demographic changes exert upward pressure on wages due to labour shortages, their overall accumulated impact on inflation after a prolonged period of time is deflationary, as lower aggregate demand outweighs wage-driven cost increases, assuming the structure of the economy remains unchanged from its current state. Furthermore, we project a significant increase in government debt under an ageing scenario compared to a scenario without ageing effects, driven by lower tax revenues and increased public spending on healthcare. These results highlight the urgent need for policies that enhance labour market participation, improve productivity, and ensure fiscal sustainability in the face of demographic headwinds.

Keywords: *demographic change, potential output, ageing population, inflation, fiscal sustainability, human capital, Bayesian VAR, machine learning*

JEL Classification: E27, J11, J24, H68, O47

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1. Introduction

Demographic changes observed in most countries nowadays have important macroeconomic implications. Economic development and subsequent healthcare advances led to a decrease in mortality rates and an increase in life expectancy. At the same time, economic growth resulted in rising urbanization, increasing levels of education and higher female participation in the labour market, which resulted in declining fertility rates. All these factors contributed to the declining and ageing of the population.

The ongoing unfavourable demographic trends pose significant challenges for long-term economic development both on the supply side - by affecting the production factors - and on the demand side - through changes in the households' consumption and saving behaviour. They are also expected to influence the price formation processes within a country and the sustainability of public finances in the long-term.

A declining and ageing population affects negatively potential growth mainly through a shrinking labour force. In addition, it is also supposed to result in decreasing labour quality as the relationship between age and individual productivity is typically hump-shaped. At the same time, the rising share of the population with supposedly better qualifications, proxied by the observed higher educational attainment levels, and improved health conditions may constrain the negative impact of ageing on labour productivity (Bodnar and Nerlich, 2022). Furthermore, demographic changes are expected to lead to lower household savings in the long term and to limit the accumulation of physical capital, as well as to affect negatively technological progress as older people are supposed to be less eager to take risks and to accept innovations.

Demographic transition also affects the inflation dynamics within a country through its impact on the relative prices of production factors, consumption patterns of households and the effects on potential growth and fiscal and monetary policies (Anderson et al., 2014). The effects of demographics on the inflation via the supply side and the demand side channels are opposing, so the net effect will vary and will depend on the particular structural characteristics of the economy. The empirical studies suggest that shrinking working-age population exerts upward pressure on wage inflation due to the supply side constraints on the labour component. However, ageing is also supposed to reflect in lower aggregate demand due to shifts in consumer preferences.

Furthermore, negative demographic trends pose risks for the sustainability of public finances in the long term, affecting both the revenue and the expenditure sides of the state budget. A declining and ageing population is considered to lead to a lower tax and social security base of the budget and to simultaneously increase the ageing-related public spending on pensions and healthcare. Consequently, demographic transition may be expected to result in a deterioration of the budget balance and an increase in public debt (Aguila, 2011, Elmeskov, 2004, Tosun, 2003).

Bulgaria is among the countries substantially impacted by the above developments. For several decades the country has faced serious demographic challenges driven by various economic, political and social factors that result in low fertility, high mortality rate and emigration. As a result, its population is steadily decreasing and ageing, a trend that is expected to continue in the future according to national and international demographic projections. Bulgaria's population decreased by 25.7%[1] over the period 1990-2023 compared to an increase of 7.1% in the EU-27 countries in the same period, while the median age[2] of the population reached 47.1 years in 2023 compared to the average of 44.7 years for the EU. Thus, Bulgaria is ranked as one of the EU countries with the fastest shrinking and ageing population.

The objective of this study is to examine the macroeconomic implications of demographic transition in Bulgaria, namely the effects of decreasing and ageing population on potential growth, price setting processes and the long-term sustainability of public finances.

We examine the impact of demographic changes on potential output, considering both the decline in working-age population and the effects of ageing labour force on productivity, applying a version of Bulgarian National Banks's main macroeconometric model for the estimation of potential output. In order to assess the effects of ageing on potential output, an approach that includes the construction of a human capital index is used where the labour force is disaggregated into groups based on sex, age, and educational status of the individuals. These groups are adjusted for the "quality" of the labour they supply, using relative wages as a proxy for their relative productivity. Our findings point to a steady slowdown of the accumulation of human capital in Bulgaria since 2000, while the contribution of human capital to potential output is projected to be close to zero during the forecast horizon. The decreasing working-age population is also projected to remain a drag on potential output and to continue to result in negative contributions of labour component to potential growth until 2060. Thereafter, the decline of the working-age population is envisaged to come to a standstill. However, the ageing labour force is expected to result in a decreasing participation rate, keeping the contribution of labour to potential growth slightly negative.

In order to assess the impact of the demographic transition on inflation, we estimate its effects on real wages and consumption under two scenarios - with a constant labour force ("no ageing scenario") and with the effects of demographic changes ("ageing scenario"). Furthermore, we apply a Bayesian Vector Autoregression (BVAR) model for the estimation of the relationships among core inflation, real wages, and real private consumption. Real wage growth is higher in the ageing scenario over most of the forecast horizon due to rising labour shortages. Meanwhile, consumption growth is found to be lower in the ageing scenario driven by the shift in consumer preferences and income differences across different age cohorts. A key assumption behind the estimation is that the structure of the Bulgarian economy in the forecast period remains similar to its current state, which, given the long-time spans considered in the analysis, could be argued is a limiting and stringent assumption. As regards the impact on inflation, the results indicate that demographic processes will lead to lower inflation in Bulgaria due to their stronger impact on aggregate demand than the inflationary effect on wage dynamics. The estimated impact suggest that in the ageing scenario inflation in Bulgaria will be around 0.2–0.4 percentage points lower per year compared to the non-ageing scenario.

The impact of demographic processes on the sustainability of public finance is assessed by estimating the dynamics of public debt in two scenarios - with and without ageing effects. Our findings indicate that government debt is consistently higher and increases more rapidly throughout the projection period under the ageing scenario compared to the non-ageing

[1] Population data as of 31 December of the reference year.

[2] The median age divides population into two equal parts: half of the country's population is under this age and the other half is older.

scenario, ultimately reaching a difference of 35 percentage points of GDP by the end of the period. This increase in debt is primarily driven by lower expected direct and indirect tax revenues, stemming from a shrinking labour force and subdued inflation in the ageing scenario.

The rest of the paper is structured as follows. Section 2 contains a review of the existing literature on the impact of demographic changes on potential output, price developments, and the sustainability of public finances. Section 3 presents the methodology and results for the effects of demographic transition on potential output. Section 4 describes the chosen approach for the assessment of the impact of demographic processes on wages, consumption and inflation and presents the results. Section 5 reveals the preferred methodology and the obtained results, concerning the effects of demographic changes on public finances. Section 6 summarizes the findings and concludes the paper.

2. Literature Review

The overall economic impact of demographic changes is a complicated process, which includes interrelated relationships between diverse macroeconomic indicators. The graph below tries to summarize and simplify the main transmission channels identified by the literature through which demographic transition affects the economy.

Main transmission channels

Source: Authors' representation

The subsequent sections present previous theoretical and empirical studies that examine the influence of demographic changes on the three areas of interest, namely potential output, price developments, and the sustainability of public finances.

2.1. Effects on Potential Output

Demographic changes affects directly economic growth by decreasing labour supply due to the smaller size of the cohorts that enter the labour force compared to the ones that exit it (Carone et al., 2005). The negative effect arising through that channel could be temporarily reduced by increasing female participation and pension reforms which have the objective to increase the retirement age in line with rising life expectancy (Bodnar and Nerlich, 2022) or by migration inflows in the country. The size of that negative impact is usually estimated by the standard labour input variable in the production function approach, based on data about hours worked and the number of employees (e.g. European Commission, 2020, Ganev, 2005).

Another channel through which demographic transition affects directly economic growth includes the change in labour quality. According to the literature, individual labour productivity starts to decline after the age of 50, especially for jobs where problem solving and speed of learning are crucial (Skirbekk, 2003). In an attempt to assess the impact of the change in age-specific labour productivity on economic growth, the concept of human capital is broadly used in the theoretical and empirical studies. Human capital theory was formulated by T. Schultz, G. Becker and J. Mincer in the beginning of 1960s. The theory has the objective to explain individuals' decisions to invest in education and training and the effects of these decisions on productivity and lifetime earnings. The concept for human capital includes assets such as inherited knowledge, education, on-the job training, healthcare and experience.

According to the theoretical framework, people invest in themselves because they expect to receive higher earnings in the future. Schultz (1961) compares the incentive for investment in human capital with those for physical capital, which represents the rate of return or the yield on the investment measured by individual earnings. Schultz emphasizes the rising significance of foregone earnings during education and estimated that if they are taken into account, the rate of return on human capital investment could reach the one on physical capital. He points out that young people are more eager to invest in themselves as they have more years to benefit from their investment. He also considers migration as a form of investment in human capital and concluded that young people easily move to live in another city or country because of the expected higher return.

Becker (1964) underscores the key role of education for future incomes. He finds a positive correlation between education and other forms of investment in human capital and claims that earnings increase with age at a decreasing rate as their rate of growth depends on the accumulated skills. Becker also discusses the social rates of return on investment in human capital. As social benefits are more difficult to capture, Becker develops lower and upper limits to social rates of return on college education measured by national income and found that lower limits are similar to private rates of return on college education. Mincer (1980) includes in social returns assets such as communication skills, healthy population and responsible society and concluded that the benefits of such kind of investment are underestimated. He considers bad health and erosion of skills as a depreciation of human capital. Mincer finds an inverse relationship between female education and fertility rates, which is explained by rising foregone earnings because of the time spent for childcare. He points out that these foregone earnings are greater for educated women.

Although the theory is micro founded, it has important macroeconomic implications as it outlines the positive relationship between investment in human capital and economic growth.

Mincer (1980) states that human capital accumulation is a condition and a consequence of economic growth as it is interrelated with physical capital and in addition is a source of technological progress. Thus, investment in human capital turns out to be an essential factor for the reduction of the negative effects of ageing on economic growth.

Various theoretical and empirical studies are dedicated to the relationship between the investment in human capital and economic growth. Initially, Lucas (1988) introduces human capital as an additional factor in the neoclassical Solow growth model. According to Lucas, the addition of human capital results in constant rates of return to overall capital (physical and human capital), although rates of return on physical capital alone are decreasing. Mankiw, Romer and Weil (1992) augment the Solow model by including secondary school enrolment as a percentage of the working-age population as a proxy for human capital and test the model using cross-country data for the period 1960-1985. By modifying the Solow model, they manage to explain about 80% of differences in income per capita across the countries.

Fernandez and Mauro (2000) estimate the impact of human capital on economic growth in Spain using an augmented Solow growth model where labour is adjusted for quality by weighting workers according to their productivity. Fernandez and Mauro (2000) construct a human capital index for the 1977-1997 period and projected its development during the 1998-2003 period based on individuals' demographic characteristics. Their methodology for the construction of human capital takes into account not only educational attainment but also the accumulated experience and the interactions between the formal education and learning by doing. For that purpose, Fernandez and Mauro group Spanish workers according to individual characteristics such as age, gender and educational level, which are supposed to result in significant differences in wages. Thus, relative wages are used as a proxy for relative productivity among Spanish labour force. Fernandez and Mauro find that the contribution of human capital to economic growth in Spain steadily increased during the 1977-1997 period.

Ganeva (2006) examines the impact of human capital on economic growth in Bulgaria over the period 1949-2005 based on quantitative data about education. Ganeva divides the sample into two periods. The first one includes the years of socialism from 1949 to 1989, while the second one encompasses the period of transition to a market-oriented economy (1990-2005). The study finds that the rise in average years of education resulted in increasing income per capita in Bulgaria over the period 1949-1989, while the stock of human capital affected indirectly economic growth over the period 1990-2005 by its impact on total factor productivity.

Despite the broad consensus on the importance of human capital accumulation for economic growth, its measurement has remained challenging over the years. Difficulties in measuring human capital stem from its qualitative nature, which cannot be captured easily by quantitative indicators. As a result, a variety of different approaches has been applied in the literature. Boarini et al. (2012) provide a comprehensive overview of the existing approaches. They define two major categories, namely indicators-based and monetary-based approaches. The first category is further divided into quantity-based measures such as the average years of schooling and quality-based measures, including indicators like test scores. The monetary-based approaches include indirect (residual) and direct measures. The World Bank (2011) uses an indirect approach, measuring human capital as a residual coming from the difference between national wealth (estimated by the discounted value of future consumption) and produced capital, natural endowments, and net foreign assets. The direct measures encompass the cost-based approach, which relies on data about the expenditures related to the accumulation of human capital such as costs for education and training, and income-based approach, which uses data about individuals' income by level of education. The latter two approaches are the most common ones in the literature (Boarini et al., 2012). One of their advantages is that they allow a comparison of the importance of different indicators for human capital accumulation by combining these indicators into one variable. For example, the income-based approach could compare the importance of the demography and the level of education for the accumulation of human capital. On the other hand, these approaches are not able to capture the non-market benefits of investment in human capital, thus they underestimate its overall importance for economic growth. In addition, the cost-based approach suffers from the limitations of distinguishing between expenditures on investment in human capital and consumption expenditures. It also faces difficulties in measuring the depreciation rate while the income-based approach depends on subjective estimations of future earnings. Thus, there is no consensus as to what is the most appropriate approach for measuring the accumulation of human capital.

Demographic changes also affect economic growth through the other production factors – physical capital and total factor productivity. According to Carone et al. (2005), ageing leads to substitution from labour towards physical capital in the medium-term. However, economic growth and household savings are expected to decline in the long-term, thus leading to lower investment activity. In addition, ageing is supposed to affect negatively technological progress, as older people are considered less eager to accept innovations and to take risks.

2.2. Effects on Savings Rate and Household Consumption

Declining and ageing population affects economic growth, inflation and fiscal sustainability by changing consumption and saving patterns of the individuals over their lifetime.

According to the life cycle hypothesis, developed by F. Modigliani and R. Brumberg in the early 1950s, people try to smooth their consumption over their lifetime by saving when their income is high in order to secure their consumption during retirement (e.g. Deaton, 2005, Modigliani, 1966). The theory suggests that young and old people save less, as their income is usually low. That hypothesis corresponds to the so-called hump-shaped labour income profile by age groups, described by Mincer (1974). According to it, earnings increase rapidly at the start of a person`s career and their growth rate starts to decrease slowly at the age of 40-50 years due to factors such as lower productivity, switching to part-time employment and lower activity in the labour market. As a result, the aggregate savings rate tends to decrease in ageing societies. At the macro level, lower saving results in lower investment, thus affecting negatively the accumulation of physical capital within a country.

A number of studies tested empirically the reliability of the life-cycle hypothesis. Higgins and Williamson (1997) examine the impact of demographic transition on saving and investment behaviour in some Asian countries over the period 1950-1992 and find that aggregate savings rates tend to be smaller in countries with high young and old-dependency ratios. Based on an unweighted average of a number of cross-section studies covering OECD countries, time-series analyses for Japan during 1950s–1980s and panel data for several industrial countries, Meredith (1995) estimates that an increase of 1 pps in the old-age dependency ratio leads to a decrease of 0.86 pps in the savings rate. In another empirical study for Japan, Faruqee (2001), suggests that with the ageing of the population, savings rates should decline but other aspects of demographic changes, such as fewer young adults and increased longevity, could counterbalance the negative effects on saving rates. Bloom et al. (2007) confirm the negative relationship between dependency ratio and savings but argue that depending on the characteristics of the social security system, longer life expectancy could lead to higher savings rates. Bequest motives for savings are another factor that is considered to prevent the savings rate of the elderly from decreasing (see e.g. Meredith, 1995). As a result, the literature does not provide unambiguous empirical evidence whether the saving rates differ significantly with the change of the age profile of the population.

The results about the effects of ageing on consumption patterns of households are also controversial. Lee and Mason (2007) point out that the increase in the elderly population will reduce the per capita income of all generations and will lead to a net decrease in total household consumption. According to Kotlikoff and Summers (1981), households with children postpone the accumulation of funds for retirement which leads to lower consumption later on in life. Furthermore, bequest motives for saving of the elderly reduce additionally their consumption. However, some authors emphasize that ageing will to some extent change overall preferences of households and their consumption structure, but not the level of the aggregate consumption (Walder and Doring, 2012, Velarde and Hermann, 2014). For example, Merette and Georges (2009) claim that population ageing is likely to cause sectoral shifts in demand – demand for health services will increase disproportionately while demand for housing services is likely to decline as the rate of household formation slows, resulting in smaller and fewer houses being constructed. In a study for Germany, Stöver (2012) finds that population ageing did not have a large impact on aggregate consumption, but had a significant effect on its components. Stöver claimed that ageing leads to higher healthcare expenditures, however, they are offset by lower expenditures on food and non-alcoholic beverages.

2.3. Effects on Inflation

Demographic transition is considered to affect inflation dynamics through its impact on the relative prices of production factors, consumption patterns of households and the effects on potential growth and fiscal and monetary policies, among others (see e.g. Anderson et al., 2014). However, there are contradictory results in the literature as regards the direction of that impact.

One of the streams supports the statement that ageing leads to lower inflation. According to the studies belonging to that stream, ageing population results in lower aggregate demand as it changes consumer preferences. They argued that older cohorts spend more in relative terms than younger cohorts on services such as healthcare and long-term care, while the expenditures related to transport, durable goods and clothing are becoming more limited (Bodnar and Nerlich, 2022). The prices of the services predominantly consumed by older cohorts are largely regulated, making them more rigid vis-à-vis higher demand. As a result, the ageing population could lead to disinflation (Bodnar and Nerlich, 2022). Ageing is also considered to exert downward pressure on asset prices, especially, house prices, thus also affecting inflation dynamics (Takats, 2010; Bodnar and Nerlich, 2022). That statement is based on the life-cycle hypothesis, which suggests that individuals in their middle age save part of their income by buying assets, such as houses, in order to secure their consumption during retirement. When the working-age population decreases and that trend is accompanied by rising elderly cohort, asset prices tend to decline. Although these findings are not supported by recent trends, probably as a result of factors such as credit availability, higher living standards, preferences of the older people for living in single households, as well as better healthy conditions of the elderly compared to the past (Bodnar and Nerlich, 2022), shrinking and ageing population is supposed to lead to lower house prices in the long-term due to the oversupply of houses.

Anderson et al. (2014) finds a negative correlation between ageing and inflation mainly due to lower GDP growth compared to its potential because of the rising fiscal expenditures related to population ageing, which increase the necessity of fiscal consolidation. Bobeica, Lis, Nickel, and Sun (2017) also confirm empirically the negative relationship between ageing and inflation based on a cointegrated VAR model using data for Germany, the US and the euro area as a whole over the period 1975-2016. Their findings are in line with the secular stagnation hypothesis, which suggests that population ageing leads to a relatively higher increase in aggregate savings than investment, which results in low or negative equilibrium real interest rates. Bullard et al. (2012) provide another explanation based on political factors. They argue that the rising share of older cohorts makes them the main group of voters. As older cohorts rely primarily on their savings for consumption, they prefer higher rates of return on their savings and low inflation rates. According to Bullard et al. (2012) the preferences of the dominant voter group influence the redistributive policy of the governments and may result in lower inflation, which serves as a tool for the redistribution of the limited resources. In addition, according to the human capital theory, ageing is expected to lead to lower wage inflation because of the inverted U-shape age-wage profile of the individuals due to declining productivity of the elderly (Mincer, 1974). Papadopoulos, Patria, and Triest (2017) test the hypothesis that increased share of older cohorts exert downward pressure on wages for that working-age group relative to the younger cohorts. In a study based on US data for the period 1964-2016, they find that large cohorts receive lower wages within a given educational attainment group compared to smaller cohorts.

The other stream in the literature emphasizes the idea that ageing is inflationary. Studies belonging to that stream (e.g. Juselius and Takats, 2015) suggest that the elderly population relies more on accumulated savings in order to finance consumption than on direct participation in the production process. Because of the discrepancy between aggregate demand and supply, population ageing could create inflationary pressure. Furthermore, declining labour supply may lead to additional pressure on inflation through the wage channel. Wage dynamics could be also affected because of the introduction of seniority-based wage systems, which link wage rate with length of service. Juselius and Takats (2015) confirmed empirically the positive impact of ageing on inflation. In a study based on panel data for 22 countries over the period 1955-2010, they found that the higher share of dependents (both young and old) is inflationary while higher share of working-age population is associated with lower inflation. In addition, a number of empirical studies reject the hypothesis that ageing leads to a decrease in aggregate wages. They argue that conclusions based on cross-sectional data could be misleading as they compare wages of different persons at a specific year rather than how individual earnings change over the life cycle (e.g. Luong and Hebert, 2009). Based on data for Britain and Germany, Myck (2007) found that the inverted U-shape profile of aggregate wages is due to the fact that better paid elderly are more prone to leave the labour market earlier than low-paid workers and because of the transition to part-time jobs of some older workers while individual earnings are not falling with age.

According to Katagiri et al. (2014), the impact of ageing on inflation depends on the causes of ageing. They found that ageing is inflationary when it is caused by a decline in birth rates, but it creates deflationary pressure in cases of an increase in longevity. The difference in outcomes can be explained by political factors. Thus, inflationary pressures come from a shrinking tax base and rising government expenditures while deflation is a result of rising share of older voters, which influences government decisions. Katagiri et al. (2014) estimate that ageing generated deflation of about 0.6 pps per year in Japan since 1976 onwards. Hartl and Leite (2019) use an overlapping-generations (OLG) model to decompose the impact of demographic change on inflation into two components: size effects, which reflect changes in the overall population size, and structure effects, which capture shifts in the population's age composition. They found that the change in population size exerts inflationary pressure while the direction of the impact of the age structure component depends on which age group plays a key role in shaping aggregate consumption and saving patterns, which could lead to both inflationary and deflationary pressures. Bodnar and Nerlich (2022) suggest that changes in the population age structure may be a driver of trend inflation. They stated that if the ageing process is driven by low birth rates and decreasing share of young cohorts in combination with rising or stable labour supply, which is the case in the euro area over the past two decades, ageing is disinflationary. On the contrary, an increasing share of older cohorts accompanied by a shrinking labour force is considered to exert inflationary pressure. As a result, outcomes differ across countries due to differences in consumption and saving patterns induced by varying demographic structures.

2.4. Effects on Fiscal Sustainability

A shrinking and ageing population directly reduces the tax and social security base of the state budget while it contributes to increasing expenditures on pensions, healthcare, and long-term care. The resulting combination of lower tax revenues and higher social spending leads to a deterioration in the budget balance and rising public debt, posing a risk to the sustainability of public finances (Aguila, 2011; Elmeskov, 2004; Tosun, 2003; Eskesen, 2002). These challenges are particularly pronounced in countries with predominantly pay-as-you-go pension systems, as is the case in Bulgaria. Higher government spending due to population ageing may necessitate deficit financing through debt issuance or tax increases, ultimately reducing disposable income, constraining potential growth, and potentially exacerbating fertility declines (Hock and Weil, 2012).

However, this assumption rests on the premise that governments and households do not adjust their behaviour, which is not entirely realistic. Some researchers (e.g., Eiras and Niepelt, 2012; Lisenkova, Merette, and Wright, 2013) argue that governments may reallocate expenditures, prioritizing ageing-related costs at the expense of education and infrastructure investment. Such redistribution, however, is expected to have a net negative effect on long-term economic growth. Other scholars, such as Blake and Mayhew (2006), suggest that steady immigration flows could offset labour shortages caused by an ageing domestic population, thereby mitigating the adverse impact on growth. Yet, this argument primarily applies to wealthier countries that attract sustained economic immigration and is less relevant for economies undergoing ageing transformation before achieving high-income status (Lee, Mason, and Cotlear, 2010). Furthermore, as argued by an OECD paper (2013), the fiscal impact of immigration depends on several factors, such as the composition of the immigrant population in terms of age, employment status, education as well as on the design of the tax and benefit system in the host country.

An alternative policy response is raising the retirement age in line with increasing life expectancy, as noted by Finch (2014). While economically rational, this measure is often politically unpopular. Empirical evidence suggests that such adjustments may not fully counteract the negative economic effects of demographic decline. For instance, Bloom et al. (2011) examined 43 countries and found a weak correlation between rising life expectancy and retirement age. In an overlapping generations (OLG) model for Bulgaria, Karagyozova-Markova (2015) demonstrated that the planned retirement age increases under the 2015 pension reform would not fully offset the negative effects of population decline on long-term economic growth but would significantly alleviate budgetary pressures associated with ageing.

Another concern is that rising pension costs will not only stem from demographic shifts but also from the retirement of higher-earning, more educated individuals (Diaz-Gimenez and Diaz-Saavedra, 2009). Additionally, high educational attainment has been linked to earlier retirement, placing additional strain on public finances. Countries where older households rely heavily on public pensions to sustain their living standards will face heightened fiscal pressures, while those where private asset accumulation plays a greater role will be particularly vulnerable in a low-return economic environment.

3. The Impact of Demographic Transition on Economic Growth

Demographic changes affect negatively potential output through both the decline in the working-age population and via the ageing labour force, which is typically perceived as less productive. The effect of the second channel could be assessed quantitatively by a variable that tries to measure the accumulation of human capital in the economy.

3.1. **Methodology**

In this section we will first introduce our approach for the construction of human capital index and then we will describe the model for the estimation of potential output.

- Human Capital Index

For the construction of the human capital index, we use the income-based approach, following the procedure used by Fernandez and Mauro (2000) where the labour force is disaggregated into groups cross-classified by sex, age, and education and these groups are further adjusted for their quality of labour using relative wages as a proxy for the relative productivity among the individuals.

The average human capital for a given year could be represented as follows:

$$\mathbf{h_t = \sum_{s,\,i,\,j} w_{s,\,i,\,j}\ \ n_{s,\,i,\,j}(t)}$$

where $\mathbf{w_{s,\,i,\,j}}$ is the wage ratio between individual groups classified by sex (s), education (i), and age (j) based on 2018 income data, with each individual group‘s wage level scaled relative to the lowest earning individual group’s wage level in terms of the characteristics sex, education and age (we elaborate further on how this calculation is done on the next pages), while $\mathbf{n_{s,\,i,\,j}(t)}$ represents the proportion of the labour force of sex (s), education (i), and age group (j) at time (t). The details of the calculation are provided below.

Meanwhile, the human capital of economically inactive persons is considered to be zero in line with other studies on that topic (see for example Jones and Chiripanhura, 2010).

The method to measure workers' productivity using their wage levels is widely used in the literature. In addition, age, gender, and education are considered to be reflected in differences in wages (see for example Willis, 1986; Fernandez and Mauro, 2000). Thus, by breaking down employees into age, gender and educational groups according to their income, we can evaluate if there are significant differences in the productivity levels among these groups for Bulgaria. This could shed light on how changes in the population structure due to ageing influence the overall level of human capital in the country.

In what follows, we provide an estimation of the human capital index for Bulgaria for the 2000-2070 period in line with the described methodology. We do not cover the effects of the COVID-19 pandemic on the accumulation of human capital, which are supposed to be significant, given the impact of the pandemic on individuals' health status and educational outcomes (Gee et al., 2023, Gewalt et al., 2022). However, these effects are indirectly captured by demographic statistics such as population size and life expectancy data.

Our approach to measure relative wages is based on the employees' cash or near cash income[3] classified by sex, age groups and education, using available anonymized EU-SILC micro data for 2018, while for the disaggregation of the labour force by economic activity status we rely on anonymized EU-LFS micro data for the 2000-2019 period.

Data from both micro data sets were classified based on sex, age groups and education ensuring comparability between the two data sources within these groups. We focus on the assessment of the accumulation of human capital for the working-age population between 15-69 years, the age group that is used later on for the estimation of potential output. Meanwhile, the educational attainment level is provided in three broad categories – low, medium and high, based on the highest ISCED level attained[4].

We use EU-SILC data to categorize the different population cohorts based on their respective income and to obtain the wage ratio between the individual groups. To identify the activity status of persons at a given year we rely on EU-LFS data. A detailed description of the data used in the analysis is provided in Appendix 1.

In order to measure the relative wages between different groups we use the group with the lowest income (that group refers to women aged between 16 and 24 years with low level of education) as a base unit (equal to one). All other groups are compared relative to that benchmark. Table 1 reveals that there is substantial variation in income levels across age, education and gender. Considering workers' age profile, a hump-shaped distribution is observed, where the income of employed individuals reaches its peak around the age of 50. After that, it starts to decline which could be related to factors such as reduced productivity or the shift to part-time employment. The most pronounced income disparities are seen across educational levels: as educational attainment rises, so does individual income. There are also subtle gender-based differences in income, with men's earnings generally surpassing those of women in nearly all observed groups. Factors from the literature, such as caregiving

[3] According to the EU-SILC methodological guidelines the employee cash or near cash net income refers to the monetary component of the compensation of employees in cash payable by an employer to an employee after the deduction of the tax at source and the social insurance contributions. For more information see DOCSILC065 operation 2018_V5.pdf (europa.eu)

[4] The International Standard Classification of Education (ISCED) classifies the educational attainment of persons based on standard concepts, definitions and classifications. Both EU-LFS and EU-SILC use ISCED for gathering information on the education of interviewed persons, ensuring comparability across the two surveys. For more information on ISCED and the formation of the three categories used in our analysis, see Appendix 1.

responsibilities and sector-specific roles attributed to each gender, are usually given as an explanation for those gender-related income discrepancies (for more information on that topic, see Blau and Kahn, 2017).

Table1: Wage ratios by age, sex and education

Age group	16-24	25-34	35-44	45-54	55-64	65-74
Female						
Low	1.0	1.4	1.8	1.8	1.8	1.7
Medium	1.9	2.4	2.5	2.7	2.6	2.3
High	2.5	3.8	5.5	5.8	5.3	3.1
Male						
Female						
Low	1.4	2.1	2.1	2.4	2.1	2.0
Medium	2.1	3.1	3.8	3.5	2.9	2.3
High	2.6	5.8	9.2	8.1	6.1	6.7

Source: Own estimates based on EU-SILC micro data for 2018.

- Human capital index estimation steps

The human capital index is estimated in two steps. Using the approach and data described above, we first construct a human capital index for the period 2000-2019 and then we project its development over the next 50 years. The assessment of human capital for the 2000-2019 period is relatively straightforward due to the availability of the necessary data, provided by anonymized EU-LFS micro data. We assume that the wage ratios, as computed on the basis of the 2018 EU SILC data, remain constant, both during the historical period and over the forecast horizon, in line with the approach developed by Fernandez and Mauro (2000) in their study on the topic. We check how robust this assumption is as compared to the wage ratios derived from EU-SILC income data for several years in the data sample. Although the ratios vary over the sample, the main conclusions regarding income distribution among different groups based on age, gender and education remain in place.

The evolution of the human capital index over the 2020-2070 period is based on the projected demographic characteristics of the population, assuming constant wage ratios. Data on demographic developments are sourced from NSI's demographic statistics, both historical data for the 2020-2023 period and five-year projections for 2025-2070 horizon, which are interpolated on an annual frequency for the Bulgarian population by age and sex. Usually, national and international demographic forecasts provide information about the population divided only by age and sex while for the estimation of the human capital index, we also need data about the population breakdown by educational level. Furthermore, we are also interested in the activity status of the working age population over the forecast horizon. In order to forecast the educational level and the activity status of the population by 2070, we develop a model based on machine-learning techniques.

- Modelling approach for forecasting educational attainment and labour force participation over the long-term horizon

Machine learning has become a key analytical tool in social sciences. As modern datasets grow in size and complexity, there is a clear need for methods that can identify intricate patterns in the data. Machine learning methods often exhibit high predictive power and can identify non-linear relationships. For clear-cut decisions, such as entering the labour market or attaining a certain educational level, these models yield comprehensive insights that can drive strategic decisions, as demonstrated by Mullainathan and Spiess (2017) and Athey (2019).

We have chosen a mix of five classification techniques for our study: Logistic Regression, Random Forest, Gradient Boosting, KNeighbors, and Linear SVC. Instead of using only one model we opted for the ensemble weighted average approach, which has been shown to lead to better predictive performance in numerous studies (Dietterich (2000); Polikar (2006)). The main idea behind the ensemble learning method is that by aggregating the predictions from different classifiers we reduce total errors as each model makes different types of errors. More information on the specific characteristics and features of each of those models is presented in Appendix 2.

Our choice of the above five methods is motivated by the following considerations:

• Diversity of Techniques: These models represent different facets of machine learning – ensemble methods, traditional statistical modelling, instance-based learning, and support vector classification.

• Performance: Historically, models like Random Forest, Gradient Boosting, and Linear SVC have demonstrated high predictive accuracy for complex datasets, as noted by Friedman (2001) and Breiman (2001). This makes them appropriate choices for nuanced human capital analysis.

• Interpretability: While ensemble methods like Random Forest and Gradient Boosting offer high predictive power, Logistic Regression stands out for its simplicity and clarity. Its ability to provide interpretable coefficients for each variable can be invaluable when explaining results for policy implications. (Hosmer, Lemeshow, and Sturdivant (2013)).

• Flexibility & Scalability: These models are adaptable to various data sizes and complexities, ensuring that as our dataset grows or changes, we can continue to rely on them without significant modifications, as highlighted by James et al. (2013).

We employ micro data on educational attainment and labour force participation status from the EU- LFS to train the five machine learning models we previously described. We use 80% of our dataset to train the models and the remaining 20% to test their performance, in line with conventions established in the literature. Finally, we average the results obtained by the five machine learning models, giving weights to the models according to their accuracy scores. For that purpose, we multiply the model prediction by its weight (its accuracy score) and then divide the obtained value by the sum of all models' weights, in order to receive the same scale for all models.

- Education composition forecasting

We use the previously described five machine-learning models in order to obtain the educational level of the Bulgarian working-age population over the 2020-2070 period as Eurostat and NSI provide projections about the population divided only by age and sex. The main objective is to estimate the probability that individuals attain a certain educational level based on their age and gender – variables that are commonly studied in the literature and are assumed to significantly influence an individual's educational level. Furthermore, we include life expectancy[5] as an additional variable that proxies the longer planning horizons of individuals, which incentivise investments in education. Although household characteristics are also considered to have an impact on individual's decision to attain a specific educational level, we are not able to include such information due to lack of data for the entire time horizon we are interested in.

The probability distributions obtained from the different models are weighted, according to the accuracy scores of the models and averaged out. They are interpreted as the probability that a certain age group of a specific gender has low, medium, or high educational level (with total probability summing up to one). As Linear SVC model does not provide probability distributions, we use probability calibration methods in order to convert the output to probabilities, namely we rely on Calibrated Classifier CV method that is incorporated in the scikit-learn library in Python. Based on these probabilities, we adjust the NSI's demographic projections for Bulgaria to ascertain the educational distribution across age groups and genders.

- Activity composition forecasting

As a next step, we require a forecast for the labour force status of the population during the 2020-2070 horizon. In our study, the economically active population consists of individuals between 15 and 69 years who participate in the labour market. We calculate the probability of individuals being active, using the same machine learning techniques previously used for educational level estimation. The key explanatory variables include age, gender, education, and the output gap (to capture business cycle impacts on activity), while the age-dependency ratio[6] serves as a proxy for other time-varying factors impacting activity, including the need for a sufficient percentage of people to work in order to support financially households. Data about the age and gender distribution of the population is sourced from the NSI's demographic forecast and this data is also used for the calculation of the age-dependency ratio. The educational breakdown forecast is derived from the previous estimation step, while the output gap is sourced from the BNB's long-term forecast for potential economic growth (see the next section). Age, gender, and education are frequently cited in the literature as being among the main determinants of labour market participation. In addition, the phase of the business cycle is also supposed to play a role for labour market participation as the expansionary phase is considered to be positively linked with the probability of a person being economically active (see Ivanov et al., 2022, for a previous study on Bulgaria). In order to capture the effects of the cyclical position of the economy on the activity of the labour force, we include the output gap as an explanatory variable.

The outcomes are presented as probabilities of individuals being part of the labour force. These probabilities are then used to adjust Bulgaria's demographic forecast, resulting in a detailed picture of the active population's composition.

[5] According to the Eurostat definition, life expectancy at a specific age represents the average number of additional years a person of that age can be expected to live, based on the current age-specific death rates. We use Eurostat's life expectancy data for individuals less the one year for both the historic period and the forecast horizon.

[6] According to the Eurostat definition, the age-dependency ratio indicates the proportion of the population that is likely dependent on others for their daily living (the young under 15 and the elderly aged 65 and over) to the working-age population (15-64 years). It measures the age structure of the population in terms of economic activity and dependency. For the purpose of our study, we calculate the age-dependency ratio as the proportion of the dependent people (under 15 years and elderly above 69 years) to the working-age population (15-69 years).

Finally, we construct a human capital index for the 2000-2070 period by combining our historical estimates and projections. We smooth the whole series in order to remove the effect of cyclical developments, which have especially strong impact on the activity of low skilled workers. The first year of the sample is taken as a benchmark (2000=100) for tracing the evolution of human capital over time.

❖ Potential output method description

In order to estimate the impact of demographic transition on economic growth, we base our analysis on the Bulgarian National Bank's (BNB) multivariate model for the assessment of potential output, modifying it to include the estimated human capital index. That model combines a Cobb-Douglas production function with constant returns to scale with behavioural equations of the Phillips curve and Okun's law. The production function approach has the objective to assess the contribution of individual production factors (labour input, physical capital and total factor productivity) to potential growth in the long-term, while the behavioural equations aim to evaluate the relationship between the output gap and inflation and the output gap and unemployment gap. The modelling process involves creating a system of equations, estimating model parameters, and determining the path of unobservable variables using the Kalman filter.[7] Structural models of this type offer two main benefits: they provide better identification of unobserved components using more economic information compared to traditional production function models, and the long-term trends derived from them align closely with concepts defined in literature, such as potential output and natural unemployment rate.

The production function, which describes potential output in the long run, has the following form:

$$\boldsymbol{Y_t = A_t K_t^{1-\alpha} L_t^{\alpha}}$$

where:

$\boldsymbol{Y_t}$ is potential output at time t

$\boldsymbol{A_t}$ is total factor productivity at time t

$\boldsymbol{K_t}$ is the stock of capital at time t

$\boldsymbol{L_t}$ is labour input at time t

The parameter α is the labour share, set at 0.6. Both parameters α and 1- α are calibrated on the basis of national accounts data for the compensation of employees, gross operating surplus and gross value added over the 2010-2023 period. Thus, the labour share α represents the share of the compensation of employed people in gross value added[8].

The labour input is decomposed into working age population, labour force participation rate, employment rate, hours worked and human capital. The working age population represents the population between 15 and 69 years, based on NSI's demographic projections. The age group 65-69 is included in the labour input because of the expected further activisation of that group

[7] For more details about the estimation steps of the BNB model, see the research topic "Methods for estimating the cyclical position of the economy", *BNB Economic Review, issue 1/2019.*

[8] The estimation of the compensation of employed is based on the assumption that the compensation per employee and the compensation per self-employed are equal.

as a result of implemented pension reform in 2015[9]. The calculation of the participation rate is based on our estimations about the labour force status of the population, described in the previous section. Unemployment is expected to decline gradually and reach our estimate of the NAIRU (3.3%) by 2030, supported by rising economic activity and adverse demographic trends. Until then, this development contributes slightly positively to potential output. After 2030, a technical assumption is applied whereby the unemployment rate stabilises at the NAIRU, making its contribution to potential output broadly neutral. Meanwhile, hours worked per employee are assumed to remain constant over the whole forecast horizon at the last observed levels and thus, to have zero contribution to potential growth. In the original BNB model, used to estimate the potential output of the economy, the contribution of human capital to potential output is imbedded in the TFP variable, which includes all other factors (besides labour input and physical capital) that influence potential growth (human capital, technological progress, institutional framework, etc.). In our study, we extend the original model by explicitly identifying human capital as part of the labour input variable. That approach allows us to account for that portion of total factor productivity attributed to the knowledge and experience of workers. The augmented labour input has the following form:

$$\mathbf{L_t = HW_t\ (1\text{-}UR_t)\ PR_t\ WAP_t\ HC_t}$$

where:

L_t is labour input at time t

HW_t is the number of hours worked per employee at time t

UR_t is the unemployment rate at time t

PR_t is the participation rate at time t

WAP_t is the working age population at time t

HC_t is human capital index at time t

The stock of capital is constructed using the perpetual inventory method. For the projection horizon, the annual depreciation rate is set at 6.5% in line with the average share of consumption of fixed capital during the historical period.

TFP growth is assumed to converge gradually to the average EU TFP growth rate projections of 1% in the long-term horizon (since 2039 onwards) (European Commission, 2020).

3.2. Results

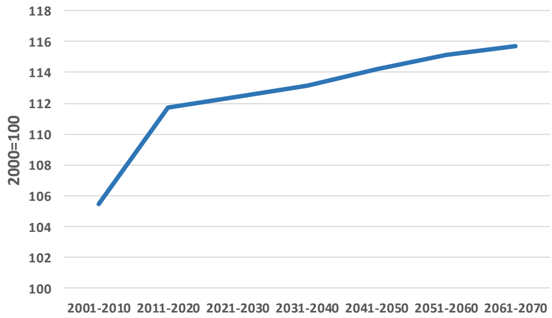
❖ Human capital estimation

According to our estimations, the accumulation of human capital in Bulgaria has increased since 2000. However, its rate of growth steadily slowed down from 0.8% on average during the 2001-2010 period to 0.3% over the period 2011-2020. Our calculations indicate that the growth rate of the accumulation of human capital will continue to decrease to 0.1% during the 2021-2030

[9] The 2015 pension reform introduced a gradual increase in the retirement age and the required contributory period, with the retirement age for men rising from 63 years and 10 months to 65 years by 2029, and for women from 60 years and 10 months to 65 years by 2037; at the same time, the minimum contributory period will increase to 40 years for men and 37 years for women. After 2037, the retirement age will be adjusted automatically in line with increases in average life expectancy.

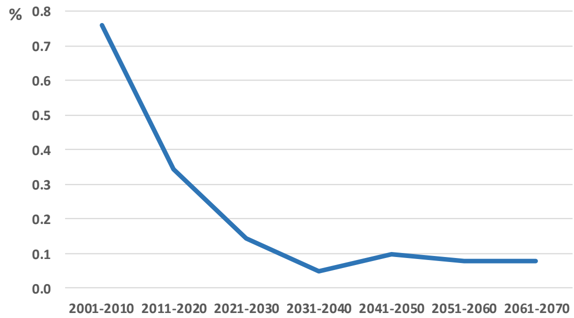
period and will be almost neutral in the 2031-2040 period. The accumulation of human capital is projected to remain very subdued over the rest of the projected horizon with a growth rate around 0.1%.

Figure 1. Human capital index (2000=100)



Source: Own estimates

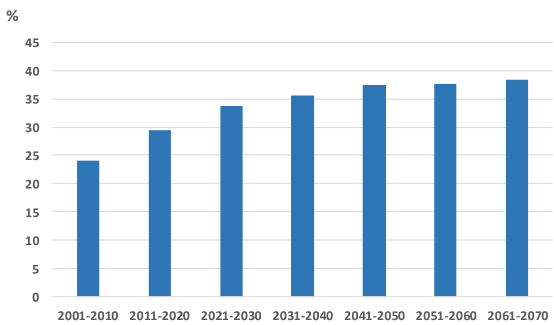
Figure 2. Human capital index (% change)



Source: Own estimates

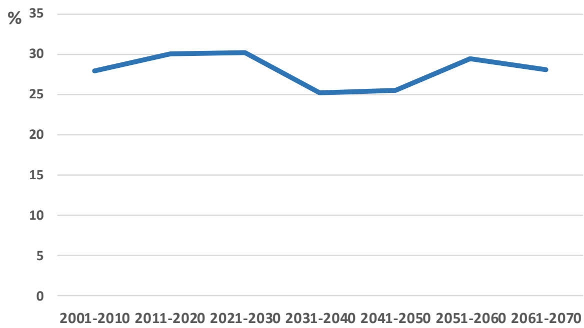
Factors that have most significantly contributed to the accumulation of human capital over the 2001-2020 period include the rising share of the working-age population with high educational attainment level (Figure 3) as well as robust share of the most productive age groups between 35 and 49 years (Figure 4). The high level of productivity of people between 35 and 49 years as measured by their wages is assumed to reflect not only the attained educational level but also the accumulated knowledge and experience through learning by doing. Meanwhile, the ageing labour force could be identified as one of the main factors for the decreasing growth of the accumulation of human capital, with the share of people above 60 years in the working-age population (15-69 years) rising on average from 15.7% in 2001-2010 to 19.9% during 2011-2020 period. Those developments are in line with findings in the literature that ageing leads to lower labour productivity.

Figure 3. Active people with high educational attainment level (% of total active people)



Source: NSI, BNB estimates

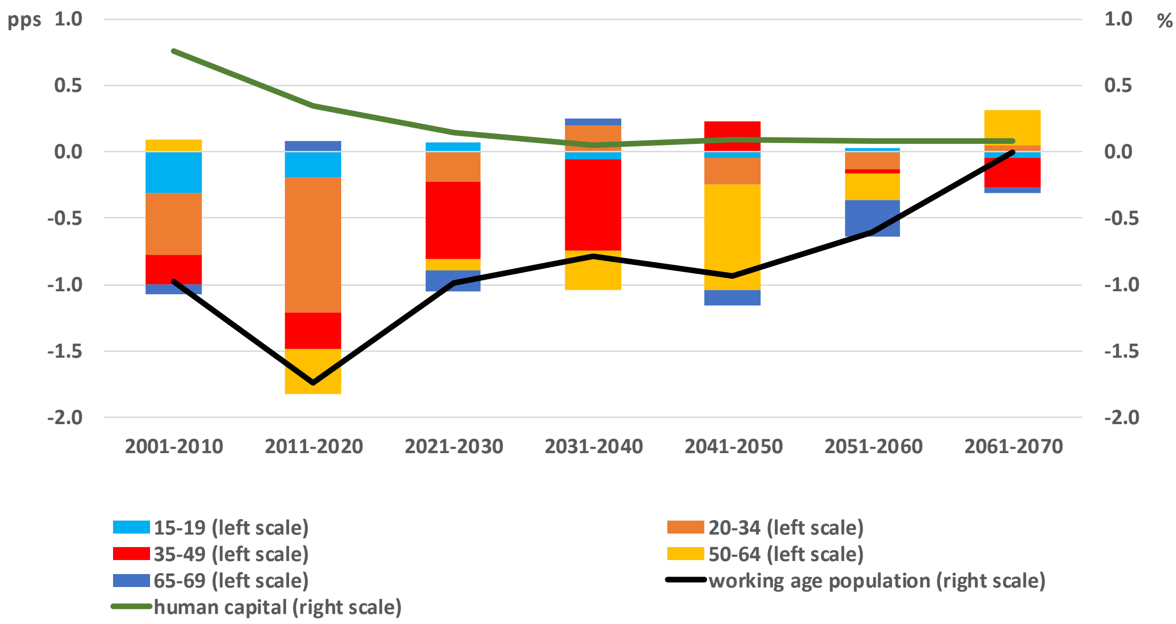
Figure 4. Population aged 35-49 years (% of total)



Source: NSI

Based on NSI's demographic statistics, we expect that the ageing population and the subsequent shift in the age composition of the labour force will continue to be a drag on the accumulation of human capital in Bulgaria over the forecast horizon. Figure 5 below represents the contribution of each age cohort to the decline in the working-age population and links that shift in the age structure with the slowdown in the accumulation of human capital. The changes in the age profile of the working-age population appear to be more important for the dynamics of human capital than the pace of decline of the population as it is illustrated in the figure. The most unfavourable development in human capital is anticipated to take place over the period 2031-2040 when the decrease in the working-age population will be mainly driven by the decline in the age group 35-49 years, which encompasses the most productive workers. At the same time, the projected increase in the share of persons with higher education in the labour force and the expected growth in activity rates will support human capital developments. As a result, the low growth of the accumulation of human capital is expected to persist till the end of the forecast horizon.

Figure 5. Demographic transition and its impact on human capital



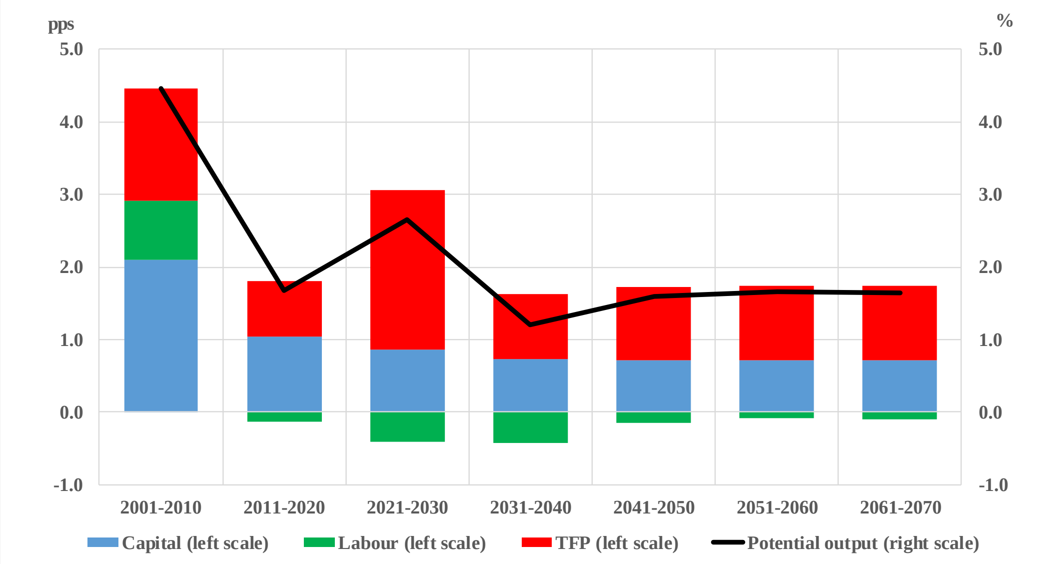
Note: The contribution by age cohorts to the decline in the working-age population is represented on the left scale, while the annual change in the working-age population and the accumulation of human capital is shown on the right scale. Data is averaged for consecutive ten-year horizons.

Source: NSI, Own estimates

❖ Potential output estimation

Our estimations reveal a substantial slowdown of potential growth in Bulgaria from 4.5% on average for the 2001-2010 period to 1.7% during the 2011-2020 horizon. The slowdown was driven by all production factors which were adversely affected by various challenges such as the fallout from the global financial crisis, the European debt crisis as well as the spread of the COVID-19 pandemic (Figure 6). Over that decade both public and private investment activity weakened significantly, as private investment growth dropped from an average of 10.0% in 2001-2010 to 1.6% in 2011-2020 period, including because of lower FDI inflows to the country. Thus, physical capital and TFP accumulations plateaued, while labour input decreased.

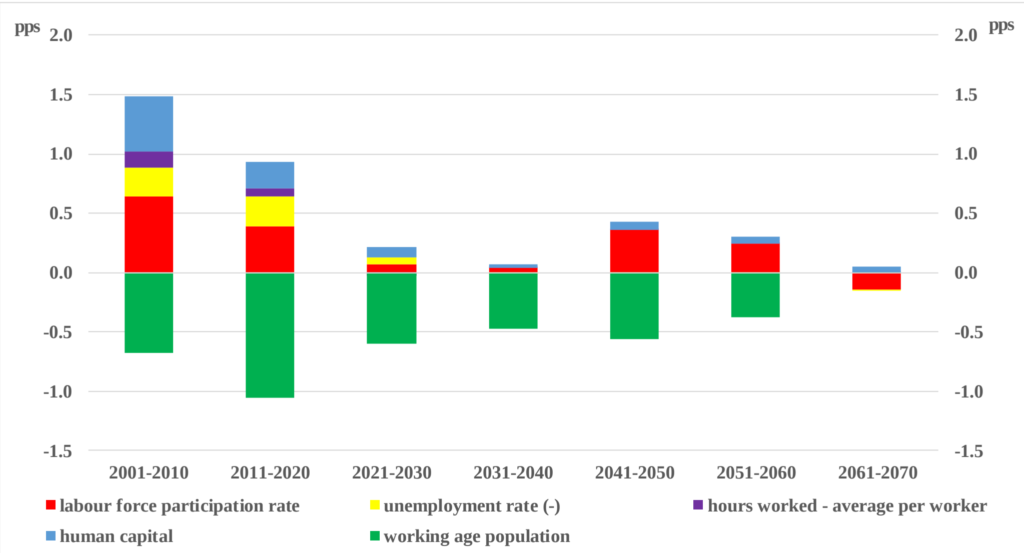
Figure 6. Average contributions to potential output growth



Source: Own estimations

Besides the above mentioned challenges which reflected in lower participation rate, labour input was severely affected by the unfavourable demographic developments in the country that resulted in declining labour force and weaker accumulation of human capital (Figure 7). Consequently, labour input turned out to have negative contribution to potential output over the 2011-2020 period, a trend that is expected to continue during the whole forecast horizon.

Figure 7. Breakdown of labour contribution to potential output growth



Source: Own estimations

Potential output growth is projected to remain well below its average value estimated for 2001-2010 period, with growth rates close to 1.7% over the long term. The most adverse impact of labour on potential growth is supposed to take place during the 2021-2040 period with a negative contribution estimated at -0.4pps (Figure 6). This development will be primarily driven by projected strong decrease in the most productive age group of the population (as illustrated in Figure 5), which is supposed to lead to lower activity rate and weaker accumulation of human capital. As a result, the overall impact of ageing on potential output might be stronger than the one outlined by the slowdown of the accumulation of human capital, with the positive contribution of the above mentioned two factors projecting to decrease from 0.6pps during the 2011-2020 period to 0.1pps over the 2021-2040 horizon. In addition, ageing could lead to lower hours worked per worker, while in our forecast we assume that those component is neutral in the long-term. Although shrinking labour force will continue to be the major drag on potential output growth, its negative contribution is expected to decrease compared to the previous decades. The decline of the working-age population is envisaged to continue to moderate and to reverse towards the very end of the forecast horizon, a trend that is outlined by the NSI demographic projections. At the same time, ageing is expected to continue to result in the subdued accumulation of human capital over the 2041-2070 period and to reflect in declining participation rate at the end of the forecast horizon. According to our estimates, human capital will have a modest positive contribution of around 0.1 pps to potential growth for the 2041-2070 period, supported mainly by projected increasing share of persons with higher education in the labour force. Meanwhile, the average hours worked per person and the unemployment rate are supposed to have a broadly neutral contribution to potential growth over the long term. As a result, the labour input is estimated to have a slight negative contribution of around 0.1 pps to potential growth over the 2041-2070 period. The other production factors are taken to evolve according to the assumptions outlined above. The contribution of physical capital will decelerate compared to past trends, stabilizing at around 0.7 pps, while the contribution of total factor productivity is envisaged to be close to 1pps in the long term, standing well below the values, estimating for the 2001-2010 time span.

4. The Impact of Demographic Processes on Wages, Consumption and Inflation

Demographic changes, particularly population ageing, may exert significant influences on inflation dynamics through both demand- and supply-side channels. On the one hand, population ageing and decline can dampen inflationary pressures by reducing aggregate demand, as older cohorts tend to consume less. On the other hand, these processes can create upward pressure on inflation by driving up wages due to labour shortages. These contrasting effects have been widely discussed in the literature, with some studies emphasizing the deflationary impact of weaker demand, while others highlight inflationary pressures stemming from tightening labour markets. The effects of demographic changes on the inflation via the supply side and the demand side channels are opposing, so the net effect will vary and will depend on the particular structural characteristics of the economy.

4.1. Methodology

The analysis aims to identify which of these opposing forces is likely to dominate in the case of the Bulgarian economy. To achieve this, we examine the effects of demographic processes on real wages and consumption and how these, in turn, influence inflation.

1) Supply-Side Effects: Wage Dynamics

The supply-side analysis focuses on constructing scenarios for real wage growth under two assumptions: one with a constant labour force ("no ageing scenario") and another incorporating the effects of demographic changes ("ageing scenario"). Under the “no-ageing scenario” the labour input in the production function is fixed at its 2023 level over the whole forecast horizon, while the ageing scenario is based on the results about the labour input provided in the previous section.

Economic theory suggests that real wages are proportional to the marginal productivity of labour, which is influenced by both the size of the labour force and its structure. By applying assumptions derived from potential growth analyses, we estimate real wages under the two scenarios. This allows us to assess how labour market tightening from declining and ageing population translates into wage pressures, as described by the following relationship:

$$w_t = \frac{\partial Y_t}{\partial L_t}$$

$$= \frac{\partial (A_t K_t^{1-\alpha} L_t^{\alpha})}{\partial L_t}$$

$$w_t = (1-\alpha)\ A_t K_t^{1-\alpha} L_t^{\alpha}$$

where L accounts for both the effects of shrinking and ageing population.

2) Demand-Side Effects: Consumption Patterns

On the demand side, we estimate consumption levels under the assumption of a constant population structure and compare them with consumption levels projected under an ageing population scenario. The deviation between the two scenarios quantifies the impact of demographic shifts on aggregate demand. The estimation relies on population data by age groups from the National Statistical Institute (NSI), historical consumption propensities by age cohorts obtained from Labour Force Survey (LFS) experimental statistics, and income data from the European Union Statistics on Income and Living Conditions (EU-SILC). To ensure consistency, aggregate propensities to consume are calculated as the average of available observations for 2010, 2015, and 2020, and are assumed to remain constant throughout the projection period. Income forecasts are derived by applying the wage-determination equation to income levels under both the ageing and no-ageing scenarios. This approach allows for an assessment of how demographic composition influences consumption patterns. The consumption levels are estimated using the following equation:

$$C_t = \sum_a (P_a \times W_{a,t} \times N_{a,t})$$

where:

C_t represents total consumption at time *t*.

P_a is the average propensity to consume for age group *a*.

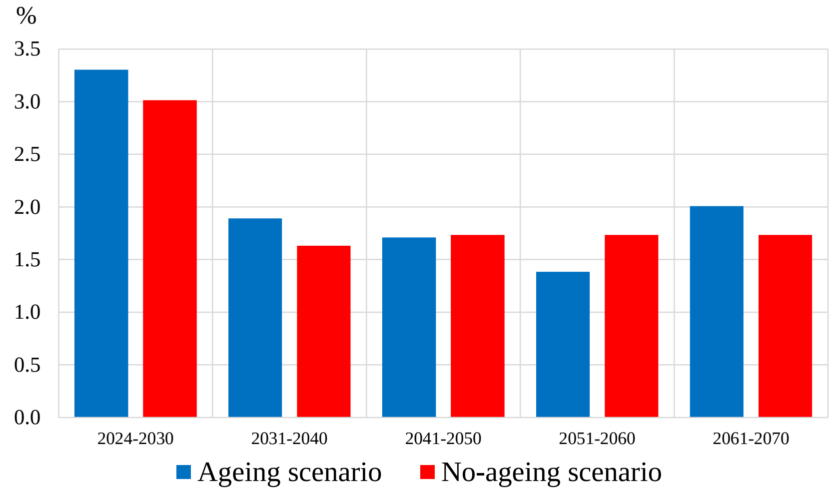
$W_{a,t}$ is the average wage of individuals in age group *a* at time t.

$N_{a,t}$ is the population size of age group *a* at time t.

The analysis reveals that real annual average wage growth steadily slows down in both scenarios, with the growth of real wages under ageing scenario reaching its lowest rate over the

2051-2060 period (see Figure 8). Comparing the two scenarios, wages are estimated to be higher in the ageing one over most of the simulation horizon, driven by tight labour market conditions as a result of shrinking labour pool and rising labour shortages. Such dynamics are consistent with the literature, which highlights that labour shortages typically lead to increased wage pressures. Between 2041 and 2060, real annual average wage growth in the ageing scenario is expected to be subdued relative to the one in the no-ageing scenario, as the projected temporary and modest expansion in the labour force during this period contributes to dampening upward wage pressures that would otherwise arise from demographic ageing.

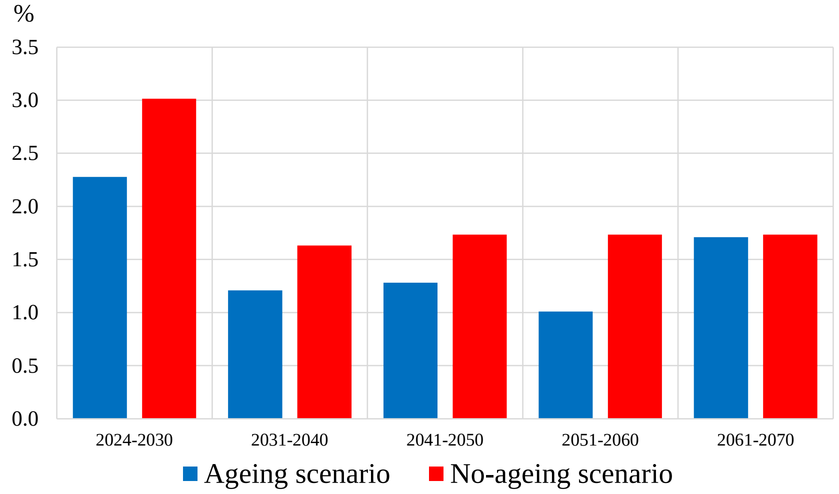
Figure 8: Real annual wage growth forecast (averaged for the period)



Source: Own estimations.

In contrast, the data indicate that real annual average consumption growth is comparatively lower in the ageing scenario, as illustrated in Figure 9 below. Here, the consumption levels under the ageing scenario fall short by an average of 0.5 percentage points per year relative to estimated consumption levels under the no-ageing scenario. This discrepancy highlights the more substantial influence of population composition changes, where an ageing demographic tends to curtail overall consumption, despite the rise in individual wages. As older cohorts experience slower income growth and lower labour market participation, their contribution to aggregate consumption declines.. This shift in population structure constrains aggregate consumption growth, which is particularly pronounced in the 2051-2060 period. Thus, while rising wages may suggest a robust economic environment, the demographic transition poses significant challenges that could dampen consumption growth, potentially offsetting inflationary pressures.

Figure 9: Real annual consumption growth forecast (averaged for the period)



Source: Own estimations.

3) Empirical analysis of the effects of demographic changes on inflation based on a Bayesian VAR model

To analyze the macroeconomic implications of ageing on inflation, wages, and consumption, we employ a Bayesian Vector Autoregression (BVAR) model. This approach allows us to investigate the dynamic interrelationships among core inflation, real wages, real private consumption, and oil prices while addressing the limitations of traditional VAR models in small sample settings or with high-dimensional datasets. We use core inflation as a measure of price change because it excludes the typically highly volatile food and energy prices. The inclusion of consumption and wages in the model is well-grounded in economic theory and supported by empirical evidence, while the oil price is included as an exogenous variable to capture international conditions. Moreover, the oil price is particularly relevant for the prices of services and industrial goods, which are components of core inflation

VAR models, introduced by Sims (1980), are widely used in econometrics to capture the dynamic relationships between multiple time series. Each variable is modelled as a function of its own lagged values and the lagged values of other variables, making VAR a powerful tool for empirical macroeconomic analysis. However, as the number of variables and lags increases, VAR models often suffer from overparameterization, leading to imprecise estimates and reduced forecasting accuracy, particularly with limited data.

BVAR models address these issues by incorporating Bayesian priors, which impose restrictions on parameter estimates based on prior knowledge or assumptions. This helps stabilize the estimates and improves their interpretability. Priors allow researchers to incorporate beliefs about plausible parameter values, regularizing the estimation process and mitigating the risk of overfitting. The resulting estimates are a blend of the information from the data (the likelihood) and the prior assumptions.

For this study, we utilize a Normal-Wishart prior, which provides a flexible framework for jointly estimating the VAR coefficients β and the error covariance matrix Σ. This prior combines:

- A Normal prior for β, reflecting expectations about the size and direction of the coefficients.
- A Wishart prior for Σ, which constrains the covariance structure of residuals, ensuring stability in the presence of small sample sizes.

The Normal-Wishart prior offers greater flexibility compared to alternatives such as the Minnesota prior by allowing independent treatment of β and Σ (for more information on that topic see Heidari (2011) and Blake and Mumtaz (2012). This is particularly important for models where structural identification and theoretical consistency are critical, as in the case for the estimation of effects of demographic changes on inflation.

The BVAR model is estimated using the Bayesian Estimation, Analysis, and Regression (BEAR) toolbox, developed by Dieppe et al. (2016). The dataset includes quarterly observations for core inflation, real wages per employee, real private consumption, and oil prices (the latter is being treated as exogenous). The sample period spans Q1 2000 to Q4 2023, with all variables used in levels and normalized for consistency. Formal model selection criteria, including the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), indicate that six lags provide the optimal fit for the model. On the next step we set hyperparameters, similar to Ivanov et al. (2018)[10].

To identify structural shocks, we employ the Cholesky decomposition, a widely used recursive identification approach. The ordering of variables in the Cholesky decomposition is critical, as it determines how shocks are transmitted across variables. For this analysis, the variables are ordered as follows: real wages → real private consumption → core inflation, with oil prices treated as exogenous.

This ordering implies:

- Real wage shocks can affect private consumption and core inflation but are not influenced by them contemporaneously.
- Private consumption shocks influence core inflation but do not affect wages within the same period.
- Core inflation does not contemporaneously affect wages or consumption.

4.2. Results

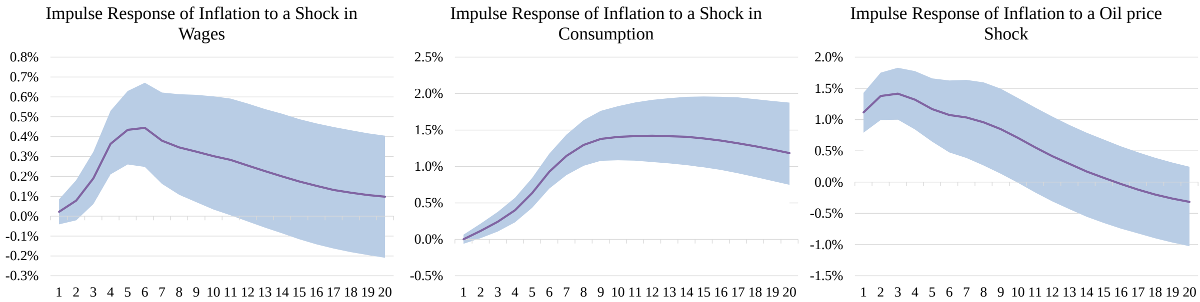
The impulse response functions (IRFs) derived from the BVAR model capture the dynamic effects of shocks to real wages, consumption, and oil prices on core inflation. These IRFs allow us to quantify the magnitude, direction, and persistence of each shock's impact over time.

The results from the impulse response functions indicate that in Bulgaria, oil price shocks have a significant and persistent impact on core inflation. This aligns with findings in the literature on commodity price shocks in small open economies and supports our initial expectations.

[10] We set the hyperparameters for the Normal-Wishart prior to ensure theoretical consistency, such that impulse response functions align with established economic theory; temporal stability, so that shocks dissipate over time in line with realistic macroeconomic dynamics; and decomposition clarity, avoiding excessive attribution of variability to the dependent variable's own lag structure. More information on the exact values of the hyperparameters is provided in Appendix 3.

For household consumption, the results reveal a slower impact on core inflation. An increase in real consumption generates an effect that builds gradually, reaching its peak around the second year, and shows no signs of fading thereafter. This finding highlights the medium-term role of consumption dynamics as a key driver of inflation, particularly through sustained demand pressures.

Figure 10: Impulse Response graph



Source: Own estimations.

The impact of real wages on core inflation appears more limited in comparison. A likely explanation lies in the way wage shocks influence inflation indirectly through household consumption. When wages rise, a significant portion of the additional income is typically spent on goods and services, boosting consumption. This increase in demand contributes to inflation, but as the effects are channelled through consumption rather than directly impacting prices, the overall response of inflation to wage shocks may seem less pronounced. Additionally, the timing of these effects could further explain the muted direct response. Wage increases may take time to translate into meaningful changes in consumption patterns, and the resulting inflationary pressures might overlap with those already attributed to consumption dynamics in the model. This layered transmission could dampen the direct observed impact of wages on inflation while reinforcing the role of consumption as the primary driver.

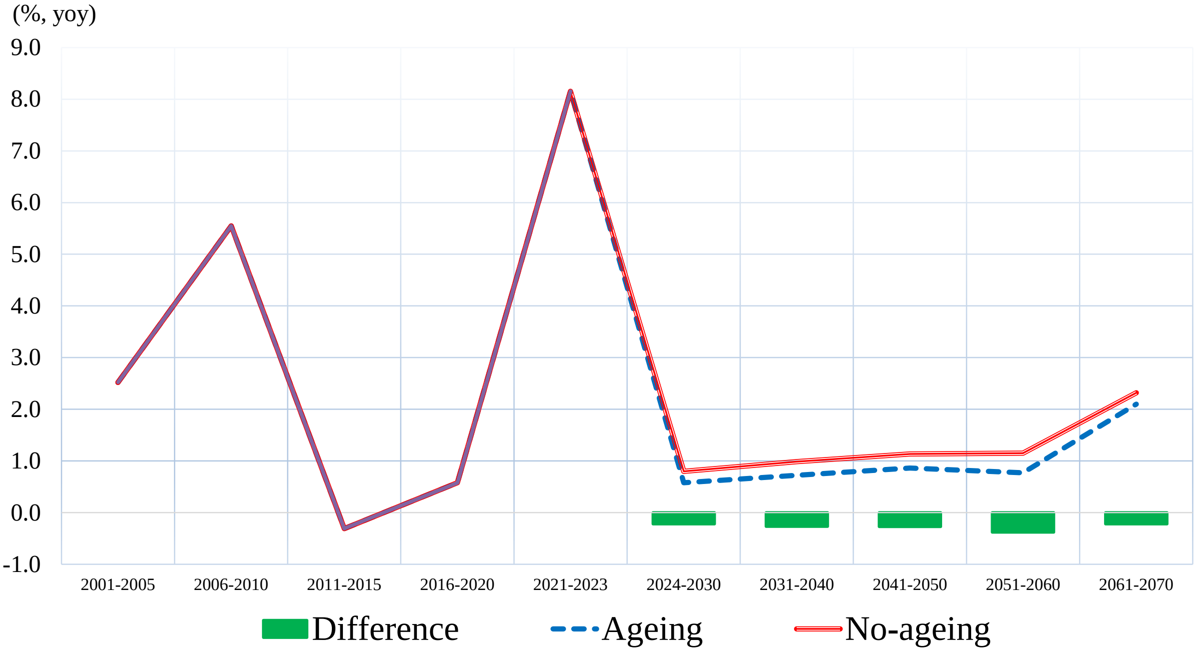
To estimate the trajectory of core inflation under the ageing and no-ageing scenarios we construct conditional forecasts. Forecasts for real wages and real consumption, derived from the earlier analysis[11], are used as inputs to the BVAR model. These projections allow us to assess how demographic changes influence inflationary dynamics through wage growth and consumption shifts. We assume that the price of oil, treated as an exogenous variable, remains constant throughout the forecast horizon. This is a standard, neutral assumption for exogenous time series, avoiding speculative projections.

This approach enables us to capture the interplay between wage-driven inflationary pressures and the demand-side disinflationary effects of ageing, providing a clear view of how demographic trends may shape Bulgaria's inflation dynamics.

The results show that core inflation remains permanently lower in the ageing scenario, suggesting that the impact of reduced aggregate consumption outweighs the effects of a declining labour supply and the resulting increase in wages. The effect is estimated to range between 0.2-0.4 pps. over the forecast horizon, with the strongest impact expected to take place in the 2051-2060 period when ageing is projected to have the most adverse effects on consumption and wages.

[11] We transform annual consumption and wage data to a quarterly frequency using a standard interpolation procedure in Eviews.

Figure 12: Conditional forecast of core inflation



Source: Own estimations.

5. The Impact of Demographic Changes on Fiscal Sustainability

Negative demographic developments related to a declining and ageing population may pose serious challenges to public finances. As the population shrinks and its composition shifts toward higher age groups with different spending patterns, budget revenue capacity is eroded. Simultaneously, an ageing population drives up public expenditure due to factors such as increased demand for healthcare and higher spending on pensions. The combination of these developments puts pressure on the state budget and ultimately causes its deterioration.

The widening of budget deficits results in accelerated accumulation of public debt. Over time, this trend can lead to unsustainable debt dynamics, especially if interest rates rise or if economic growth fails to keep pace with debt servicing costs. It is therefore essential to analyse debt sustainability under different demographic scenarios. By projecting how different population trajectories affect public finances, policymakers can better understand long-term fiscal risks and design proactive strategies to preserve debt sustainability in the face of demographic headwinds.

5.1. Methodology

The trajectory of public debt can be expressed as:

$$D_t = \left[\frac{1 + i_t}{1 + g_t}\right] D_{t-1} - PB_t + SF_t$$

where:

- D_t is public debt as a percentage of GDP,
- i_t is the real effective interest rate,
- g_t is the real GDP growth rate, and

- PB_t is the primary budget balance as a percentage of GDP.
- SF_t is stock-flow adjustment term, due to intra-year exchange rate fluctuations / financing mix change

According to the equation, the debt level at time t depends on its level in period t−1, the primary budget balance, and the interest rate-growth differential. All else being equal, when the real effective interest rate on government debt exceeds real GDP growth, debt increases. In our forecast, we assume a zero interest rate-growth differential, zero stock-flow adjustment term and focus solely on the impact of primary balance dynamics on debt.

Demographic changes can influence both revenues and expenditures, altering the budget balance needed to ensure sustainability. By isolating the role of the primary balance, we assess the extent to which fiscal policy adjustments may be required to maintain stable debt levels in the long run. We employ a bottom-up approach in which projected macroeconomic variables are treated as exogenous in the fiscal forecasting process. First, the future values of the key fiscal variables are determined on the basis of the expected macroeconomic and price developments, elasticities of budget components to macroeconomic variables and exogenous technical assumptions. Second, the main fiscal ratios and aggregates are generated using accounting identities.

We focus only on budget revenues and expenditures directly affected by ageing, such as taxes on labour income and consumption, pension and healthcare expenditures, and public sector wages. All other revenues and expenditures are assumed to remain constant as a share of GDP, based on their historical averages from 2007 to 2019[12]. We have chosen the period after 2007, when Bulgaria joined the EU, due to changes in the structure of budget revenues and expenditures, particularly the increased share of grants from the EU, the expenditures of implementing EU programs, and Bulgaria's contribution to the EU budget. At the same time the period considered is limited to 2019 to exclude the effects of the COVID-19 pandemic and the aftermath of the war in Ukraine, as both periods involved the introduction of numerous discretionary measures with significant impacts, some of which remained permanent, such as COVID-19-related pension supplements.

Following the methodology outlined in the previous sections, our estimations are conducted under two scenarios:

- **Baseline scenario (ageing scenario):** Incorporates the demographic projections and macroeconomic variables from the previous sections to assess their impact on major revenue and expenditure components of budget balance.
- **Alternative scenario (no-ageing scenario):** As in the previous sections, we assume that the level and composition of the population remain unchanged over time in the alternative scenario, along with employment and pension data. The only effects arise from the macroeconomic variables estimated under the alternative scenario.

Budget Revenues

Since tax revenues are modelled as endogenous to changes in relevant macroeconomic variables (chosen as proxies for the respective tax bases), budget revenue forecast uses as an input the forecast of nominal private consumption, nominal compensation of employees and

[12] We use annual cash data on the execution of the Consolidated Fiscal Program.

employment, as described above. Second, we determine the tax revenue elasticities. They indicate what the percentage change of certain tax revenue is after a 1% increase of the tax base. Empirical studies indicate that tax revenue elasticities fluctuate in the short and medium term due to the business cycle but tend to stabilize around 1 in the long run (Wolswijk, 2009). Under our framework, value-added tax and personal income tax revenues are assumed to follow this pattern, as Bulgaria's flat income tax system eliminates additional benefits from bracket creep and we also assume no fiscal policy changes in both the ageing and non-ageing scenarios. Regarding budget revenues from social security and health contributions paid by employees and employers, we assume an elasticity of 0.75 with respect to nominal compensation of employees. This value corresponds to the estimated elasticity of social security contributions with respect to compensation of employees, as used in BNB's main macroeconometric forecasting model[13]. The elasticity is estimated to be below 1, which reflects the statutory maximum social insurance income, beyond which no further contributions are required.[14] Additionally, contributions for the self-employed are based on a minimum insurance threshold. Both minimum and maximum insurance threshold are assumed to increase in line with nominal wages for the projection period. Furthermore, we take into account healthcare contributions for individuals under 18 years old, students, and pensioners which are fully covered by the state budget, determined based on the minimum social security income and pension amounts. Consequently, demographic trends, particularly the number of students[15] and pensioners, play role in shaping social security revenue.

Table 2. Tax bases and elasticities

Budget component	**Macro base**	**Elasticity**	**Other considerations**
Personal income tax	Compensation of employees	1	
Value added tax	Private consumption	1	
Social security contributions	Compensation of employees	0.75	Self-employed, Pensioners and Students contributions

Source: Own estimations

Budget Expenditures

The long-term spending projections are primarily driven by price developments and demographic factors. The projections are broadly based on the assumption of unchanged fiscal policy and they factor in only the already legislated policy changes (such as increasing the retirement age as part of the 2015 pension reform).

Public wages

The forecast for compensation of employees in the government sector is derived as the product of the number of employees and the average compensation per employee. The number of public

[13] The coefficient reflects the estimated long-run relationship between social security revenues and compensation of employees over the period 1999Q1–2024Q4, as captured in the long-run equation of the error correction model.
[14] The maximum insurable income has been in place in Bulgaria since 2000, which may explain why the elasticity estimated in the econometric model is below one.
[15] The number of students is a function of the projected levels of persons aged 18–25 and the ratio of students in tertiary education by age group, which converges to the EU average over the projection horizon.

employees is assumed to follow the decline in the total labour force for the economy over the projection horizon. The average compensation per employee is also assumed to grow in line with compensation per employee for the economy.

Social Payments

Social payments are decomposed into pensions, unemployment benefits, healthcare expenditures and other cash benefits. All these payments are related to the dynamics of certain labour market variables and price indices, following the relevant legislation.

Pensions

We only model the effects of population ageing on the pay-as-you-go pension system or the so-called first pillar of the social security system, since it is the only one that matters for the sustainability of public finances. The forecast of pensions is derived as the product of the number of pensions and the average monthly entitlement, as described below.

Number of pensions

To a large extent the number of pensions is based on the estimations published in the Actuarial Report of the National Social Security Institute (NSSI) from 2024. In the NSSI report, pensioners are categorized into three groups: those receiving earning-related pensions, disability pensions, and survivor's pensions. We further break down pensioners into those born before 1 January 1960 and respectively those born after 31 December 1959, as well as those retiring under Article 69 of the Social Security Code[16]. Pensioners born before 1 January 1960 were insured solely under the first pillar of the pension system and receive their pensions exclusively from it. In contrast, those born after 31 December 1959 are required to contribute to the second pillar, managed by pension insurance companies, and have the option of additional voluntary contributions to the third pillar. As a result, their insurance contributions are distributed across all three pillars, meaning that only part of their future pensions will be paid by the state (the first pillar). This shift reduces the future fiscal impact of pension costs for those born before 1960, as assessed through a mechanical exercise incorporating population forecasts by cohort and mortality rates by age group. Another important NSSI assumption we consider is the significant increase in disability pensions expected after the 2023 amendments to the Regulation on Medical Expertise.

[16] These are military personnel, civil servants under the Ministry of Internal Affairs Act, etc.

Table 3. Number of Pensions (thousands)

Year	2023	2030	2040	2050	2060	2070
Total pensions	**2030**	**2040**	**1898**	**1890**	**1837**	**1729**
Personal pensions	**1923**	**1900**	**1764**	**1781**	**1750**	**1652**
Earning-related pensions	1414	1317	1180	1214	1229	1180
Pensions for people born before 1 January 1960	1169	667	175	17	1	0
Pensions for people born after 31 December 1959	245	650	1005	1197	1228	1180
Art. 69 pensions	82	80	78	75	73	70
Pensions for people born before 1 January 1960	48	27	7	0	0	0
Pensions for people born after 31 December 1959	34	53	71	75	73	70
Sickness pensions	367	445	452	437	395	351
Other pensions	59	58	54	55	54	51
Survivor`s pensions	**108**	**140**	**135**	**110**	**87**	**76**

Source: National Social Security Institute, own estimations.

Average Pension

The path of the average pension is calculated using the Swiss indexation formula, which is based on the average increase in the harmonized consumer index and in the insurance income from the previous year. Nominal compensation per employee growth is used as a proxy for insurance income growth. Additionally, according to the Social Security Code, there is a pension cap of BGN 3,400 per pensioner, which we assume will also increase in line with the Swiss rule. Finally, we use an external NSSI assumption regarding the reduction of pensions for pensioners insured in the second and third pillars of the pension system (see Table 4).

Table 4. Pension reduction (average for both sexes) %

Year	Reduction in the amount of pension
2023	9.6%
2030	13.8%
2040	20.1%
2050	24.1%
2060	25.3%
2070	25.3%

Source: National Social Security Institute.

Unemployment benefits

Unemployment benefits are modelled as a function of the number of unemployed and the compensation per employee. The dynamics of the number of unemployed is used as a proxy for the dynamics of the number of people entitled to receive unemployment benefits.

Healthcare expenditures

Healthcare expenditures are projected to grow at the same rate as revenues from health insurance contributions. However, ageing populations typically leads to faster increases in healthcare costs, requiring adjustments based on age-specific expenditure patterns. To account for this, we use 2024 data on the distribution of healthcare expenditures by age group and assume that this distribution remains unchanged over the forecast horizon. Total healthcare expenditures are then projected to grow in line with the growth rate of compensation per employee, adjusted for the demographic dynamics of each age group from the NSI population projections.

Other transfers in cash

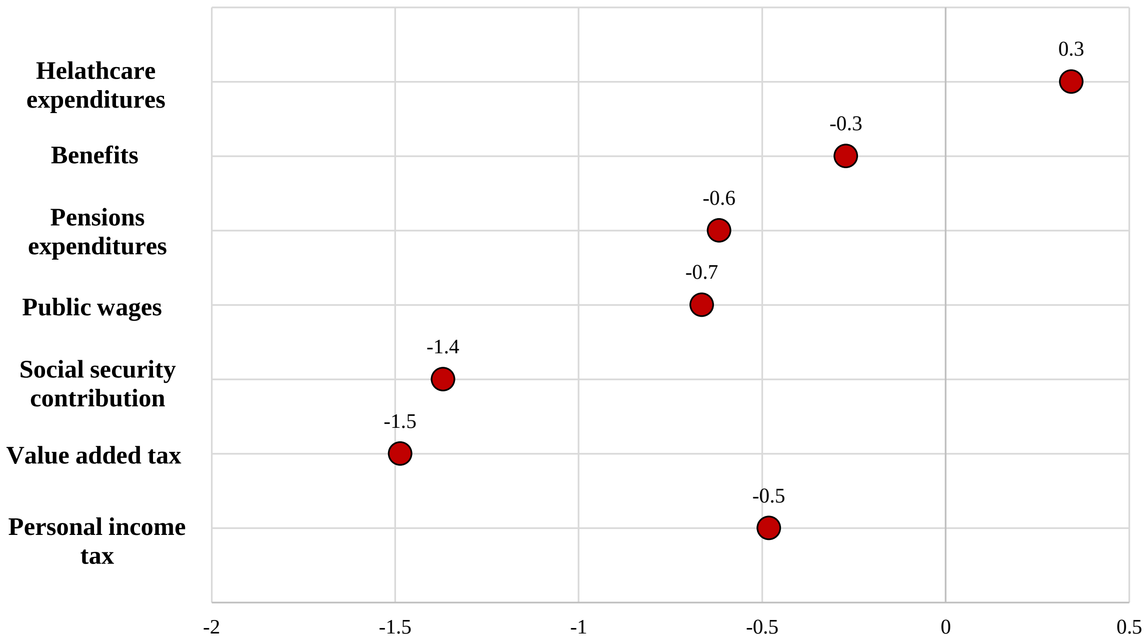
Other transfers in cash include sick and maternity leave entitlements and other various social payments, which are assumed to grow broadly in line with nominal compensation of employees.

5.2. Results

The projected ageing of the population would lead to significantly lower budget revenues as a percentage of GDP in the baseline scenario compared to the alternative scenario at the end of the projection horizon. This difference is particularly pronounced for revenues from social and health insurance contributions (1.4 p.p. of GDP) due to the shrinking labour force in the baseline scenario, which also affects personal income tax revenues (the latter are estimated to be lower by 0.5 p.p. of GDP in the baseline in 2070 relative to the alternative scenario). Additionally, VAT revenues are negatively impacted by lower household consumption, as calculated in the previous section, resulting in a budget shortfall of 0.6 p.p. of GDP.

At the same time, ageing also leads to lower total budget expenditures in the baseline scenario. The largest reduction is in public-sector personnel costs (0.7 p.p. of GDP), reflecting the projected decrease in the number of employees in line with the overall forecast. Pension expenditures follow closely, being 0.6 p.p. of GDP lower in 2070 under the ageing scenario compared to the non-ageing scenario. This is due, on the one hand, to the assumption of a stable number of pensioners in the alternative scenario, and on the other, to higher projected inflation in the alternative scenario, which outweighs the effects of higher real wages in the baseline scenario. However, healthcare costs are projected to be higher (0.3 p.p. of GDP) in the baseline scenario due to the rising share of the population over 55, requiring greater healthcare spending.

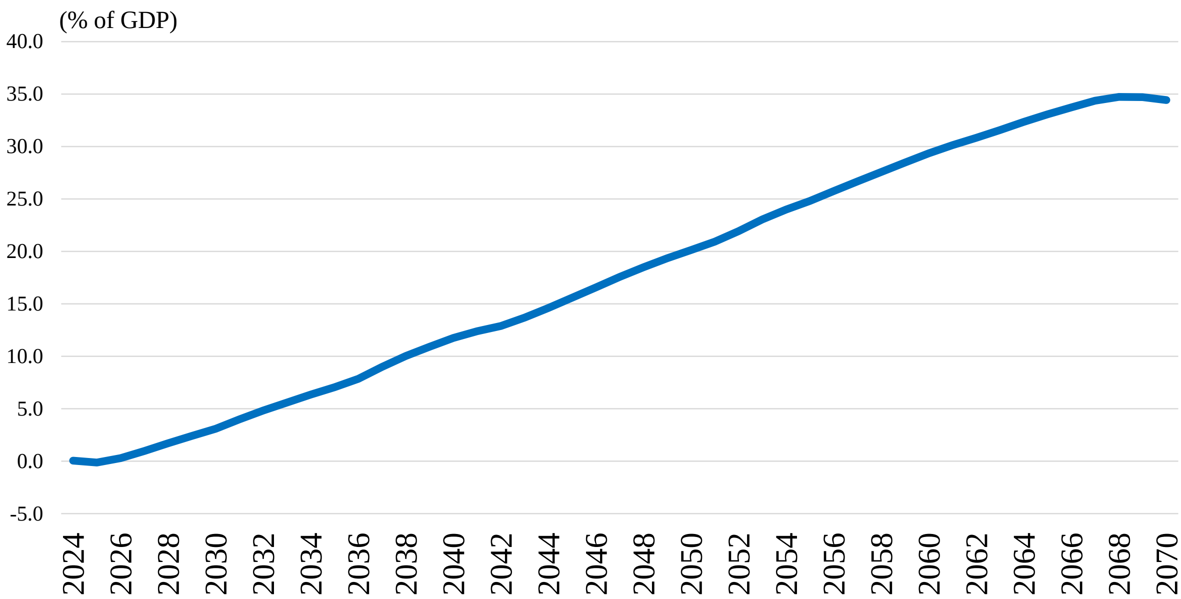
Figure 13. Selected budget revenues and expenditures in 2070: Ageing scenario –Non-ageing scenario (as % of GDP)



Source: Own estimations.

As a result of the projected lower budget revenues in the baseline scenario in comparison to the alternative scenario, which outweigh the reduction in total budget expenditures, public debt is expected to increase and remain higher than in the alternative scenario throughout the projection horizon. The debt gap reaches 35p.p. of GDP in 2068, after which it stabilizes at this elevated level.

Figure 14: Debt Gap between scenarios: Ageing scenario –Non-ageing scenario



Source: Own estimations.

A debt increase driven by demographic changes constrains the government's policy options for its reduction. On the one hand, raising tax rates may exacerbate the expansion of the shadow economy, unregistered employment or disincentivise productive workers. On the other hand, limiting the growth of ageing-related expenditures is often politically unpopular. Therefore, the government should prioritize and incentivize investments that enhance the country's long-term economic potential, both in physical and human capital.

The approach for estimating the effects of demographic changes on fiscal sustainability, presented above, was selected as a first approximation to roughly assess the impact of the deterioration of the primary budget deficit on the public debt level. However, the approach has certain important limitations. First, the approach is based on the assumption of unchanged fiscal policy, which may be considered unrealistic as under the ageing scenario it is mechanically assumed that increasing budget expenditures and lower budget revenues will lead to an explosive increase in government debt, which in practice will likely induce a reaction in financial markets. Compliance with the government's intertemporal budget constraint requires stabilization of government's debt over the long-term horizon, which is not ensured in the estimates presented above. Second, the approach does not account for the increase in interest costs arising from differences in the level of accumulated debt between the two scenarios. Third, it is unrealistic to assume that fiscal policy has no effects on macroeconomic activity over the projection horizon irrespective of whether there is a sharp increase in government debt as a result of ageing effects on the budget balance (with no changes in tax rates introduced) or whether the government increases both tax rates and also ensures debt financing of the budget.

Conclusion

The demographic transition in Bulgaria presents significant macroeconomic challenges that will shape the country's long-term economic trajectory. We employ several approaches, including machine learning techniques and a Bayesian VAR model, to assess the impact of demographic changes on potential output, inflation, and fiscal sustainability. Our analysis uses a comparative framework that considers scenarios reflecting population ageing and decline, based on the NSI's main demographic forecast, as well as non-ageing scenario in which the size and structure of the population remain at their 2023 levels.

Our analysis highlights that the declining and ageing population impacts negatively potential output, primarily through a shrinking labour force and to a much smaller extent through a slowdown in human capital accumulation. While the projected increase in the educational attainment of the workforce, which in this paper is assumed to enhance the qualification of the workforce, partially offsets these effects, its contribution is insufficient to counteract the broader demographic headwinds.

The study also finds that demographic changes influence inflation dynamics, albeit in a complex manner. While a shrinking labour supply exerts upward pressure on wages, the shift in consumption patterns associated with an ageing population leads to weaker aggregate demand, ultimately resulting in lower inflationary pressures over the long run. The empirical results from our Bayesian VAR analysis indicate that the demand-side effects of demographic changes dominate, leading to a projected decline in inflation of 0.2-0.4 percentage points over the forecast horizon compared to a scenario without ageing effects.

Furthermore, demographic trends pose risks to fiscal sustainability. The projected increase in government debt, which is 35 percentage points of GDP higher in 2070 under the ageing scenario compared to a no-ageing scenario, underscores the strain on public finances that can be expected. This deterioration of the budget balance is driven by lower tax revenues due to a shrinking workforce and rising age-related expenditures on healthcare, while pension expenditures are estimated to be relatively lower in the ageing scenario.

In light of these findings, policies aimed at mitigating the negative effects of demographic transition should focus on increasing labour force participation, promoting skill development, and ensuring the sustainability of public finances. Structural reforms that encourage higher productivity, improve human capital accumulation, and enhance fiscal discipline will be crucial in addressing the long-term macroeconomic implications of demographic change in Bulgaria.

Despite the robustness of the analysis, certain limitations should be acknowledged. The study relies on historical relationships between demographic variables and macroeconomic outcomes, which may not fully capture the potential effects of future technological advancements or policy shifts. Additionally, the assumptions underlying the projections—such as labour force participation rates and productivity growth—introduce uncertainty into the long-term forecasts. Future research could extend this work by incorporating general equilibrium models to assess the broader economic feedback effects of demographic trends, fiscal policy reaction function (which is not analysed in this paper) or by integrating micro-level data to better understand individual labour market and consumption behaviours. Exploring the role of migration, automation, the quality of education, and health-related productivity changes would further enrich the policy implications of demographic shifts in Bulgaria.

Appendices

Appendix 1. Data description

In the “Estimation” section of the main text, we outlined our methodology for calculating the human capital index, highlighting the data sources used for both the historical (2000-2019) and projection (2020-2070) periods. This section contains detailed information on the data sources, variables and data cleaning procedures employed in our quantitative analysis.

Data sources

❖ Labor Force survey (EU-LFS)

The LFS is a large sample survey among private households that measures the labour status of individuals aged 15 and over and provides information on other characteristics of the target population. The survey is conducted by the National Statistical Institute following the methodology established by Eurostat for all member states, ensuring comparability across countries and time. In our study, we make use of LFS micro data on the economic status of the population grouped by other personal characteristics, namely sex, age and education.

LFS micro dataset includes a “grossing factor” variable which can be used to reweight the data to ensure that they are representative of the population as a whole. The weight is constructed with reference to the official demographic statistics at the end of the year (31 December) prior to the interview. The grossing factor, as the name suggests, can also be used to “gross up” results to the population level. This allows us to easily estimate from the data how many people fall into certain groups across the country (e.g. how many people are employed).

The LFS dataset that we have used in our study contains anonymized microdata for the period 2000-2019 for Bulgaria. This pooled dataset consists of slightly over 1 million observations.

❖ Statistics on income and living conditions (EU-SILC)

The EU-SILC aims to collect timely and comparable cross-sectional and longitudinal multidimensional microdata on income, poverty, social exclusion, and living conditions. In the context of our study EU-SILC has the advantage of providing individual data on the income received as an employee.

The EU-SILC micro dataset includes a "cross-sectional personal weight" variable which is used to reweight the data to ensure they are representative of the broader population (persons aged 16 and over). This weight is constructed based on various considerations, including the design of the survey, the probability of selection, and adjustments for non-response. The data is also calibrated against demographic benchmarks, typically derived from official statistics available at the end of the year (31 December) preceding the year of the interview. This cross-sectional personal weight, in line with its purpose, can be applied to "gross up" or scale the survey results to the target population level. By using this weight, it becomes straightforward to derive estimates from the sample data about broader population characteristics. For example, when analyzing income disparities between different sexes, age groups, or educational levels, the weighted data provides a more realistic overview of the actual income differences in the entire population. This means that the conclusions drawn about the mean income levels of male versus female employees or the earnings of those with tertiary education versus the earnings of those with primary education will be indicative of the wider population dynamics, rather than just the sampled individuals.

The EU-SILC dataset available for our study contains anonymized microdata from 2007 to 2018 specific to Bulgaria. This dataset comprises approximately 155 thousand observations.

The EU-LFS and EU-SILC are sample surveys conducted in accordance with EC regulations and provide comparable data across countries and time on specific topics. While both focus on socio-economic indicators, each of the two surveys has a unique scope.

❖ NSI demographic projection

The study uses the first variant of the NSI's demographic projections, which is defined as the realistic scenario and is prepared according to the EU regulations on the demographic and socio-economic development of the Member States. The projections were updated in 2023 and include the period up to 2090. The starting point of the projection is the population as of 07.09.2021.

The population and its structure are presented as of 31 December of the respective year. Data is presented as five-year age groups. In line with the objective of our study, we have used data on the age and sex structure distribution of the population until 2070, which is further interpolated on annual frequency.

Variables used

This section offers a detailed overview of the variables selected from the various datasets for the human capital index calculation, as well as the adjustments made to ensure consistent results from the EU-LFS and EU-SILC microdata.

❖ Age

Both EU-LFS and EU-SILC datasets include a variable or a combination of variables that identify the age of each individual observed.

In EU-LFS the variable AGE is provided as a derived variable calculated as a difference between the year of the survey (variable REFYEAR) and the year of birth (YEARBIR). Due to confidentiality concerns, the variables REFYEAR and YEARBIR are not made available. Additionally, rather than providing the exact age of an individual, the dataset specifies the age group (in 5-year age bands) to which the individual belongs.

In the EU-SILC dataset, the age of the individual can be determined using two provided variables: the year of the interview (PB010) and the individual's year of birth (PB140). The age of each interviewed individual was calculated as the difference between the year of the interview and the year of birth. Subsequently, these ages were grouped into distinct categories, with each individual assigned to the appropriate age group. The age groups were set in 10-year intervals (16-25, 26-35,…, 66-75) for use in the computation of relative wages.

❖ Sex

The identification of individuals by sex is directly provided in the micro datasets of both EU-LFS and EU-SILC.

The weighted population distribution by sex from both surveys showed complete coherence for 2018 (see table 1), a year we selected for the comparison due to its significance in calculating the wage ratios for our study.

Table 1: Comparison of the distribution of the population by sex within EU-LFS and EU-SILC, 2018, weighted data.

	EU-LFS		**EU-SILC**	
	Persons, in thousands	% of Total	Persons, in thousands	% of Total
Male	2885.3	**48.0**	2874.2	**48.0**
Female	3126.7	**52.0**	3109.9	**52.0**
Total	6012.0		5984.0	

❖ Education

Both EU-LFS and EU-SILC use the International Standard Classification of Education (ISCED) to record the highest educational level attained of all individuals. The ISCED, developed by UNESCO, is based on standard concepts, definitions and classifications. Its primary goal is to provide a tool suitable for assembling, compiling and presenting comparable statistics on education both within countries (across different sample surveys) and internationally.

There have been two key versions of the ISCED over the years that are relevant for our study: ISCED 1997 and ISCED 2011.

The ISCED 1997 was the second iteration of this classification system. It was designed to serve as an instrument suitable for statistics on education systems in various countries. It classified education into seven levels (from 0 to 6), with each level defined by the type of education and the duration. Key elements of this classification included:

0 Pre-primary education (level 0)

1 Primary or first stage of basic education (level 1)

2 Lower secondary or second stage of basic education (level 2)

3 Upper secondary education (level 3)

4 Post-secondary non-tertiary education (level 4)

5 First stage of tertiary education (level 5)

6 Second stage of tertiary education (level 6)

Each level had specific criteria based on the content of the programs, the age of students, and the qualifications awarded.

ISCED 2011 emerged from realizing the need for a more detailed classification due to global educational reforms. This newer version introduced changes to improve the comparability of education statistics. It expanded the levels of education to nine (from 0 to 8), reflecting a more nuanced classification of tertiary education:

000 Early childhood education (level 0)

100 Primary education (level 1)

200 Lower secondary education (level 2)

300 Upper secondary education (level 3)

400 Post-secondary non-tertiary education (level 4)

500 Short-cycle tertiary education (level 5)

600 Bachelor's equivalent level (level 6)

700 Master's equivalent level (level 7)

800 Doctoral or equivalent level (level 8)

Both EU-LFS and EU-SILC adopted ISCED 2011 in their methodologies starting from 2014. Prior to this integration, the surveys were based on the ISCED 1997 version. To maintain data consistency and comparability across the transition from ISCED 1997 to ISCED 2011, we grouped educational attainment levels into three broad categories: low, medium and high. This approach ensures coherent analysis of trends spanning before and after the 2014 classification shift. Table 2 outlines this categorization in relation to each ISCED version.

Table 2: Educational attainment level groups according to ISCED 1997 and ISCED 2011

	Educational attainment level		
	Low	**Medium**	**High**
ISCED 1997	0-2	3-4	5-6
ISCED 2011	000-100	200-500	600-800

Table 3 presents a comparison of the population distribution by educational attainment level according to EU-LFS and EU-SILC for 2018, the year we used as the reference point for calculating the wage ratios in our study.

Table 3: Comparison of the distribution of the population by educational attainment level within EU-LFS and EU-SILC, 2018, weighted data.

	EU-LFS		**EU-SILC**	
	Persons, in thousands	% of Total	Persons, in thousands	% of Total
Low	1521.5	**25.3**	1634.7	**27.3**
Medium	3085.7	**51.3**	3002.1	**50.2**
High	1404.9	**23.4**	1347.3	**22.5**
Total	6012.0		5984.0	

The results in table 3 suggest that the two surveys show strong coherence in terms of educational attainment level of persons, with any minor discrepancies potentially arising from the different age groups targeted in each survey.

❖ Economic activity

The economic activity of individuals is central to our study, playing a key role in the construction of the human capital index. However, a notable discrepancy arises when comparing the EU-LFS and EU-SILC microdata in how they define the economic activity status of the individuals. This disparity originates from the distinct objectives of each survey, with LFS focusing on labour market and SILC focusing on income, leading to different approaches of defining the working status of persons.

From the EU-LFS microdata we relied on the ILOSTAT variable to determine the economic activity of individuals. This variable aligns with the working status definitions set by the International Labor Organization (ILO) and identifies persons as one of four distinct categories based on a number of questions being asked: employed, unemployed, inactive and in compulsory military service.

EU-SILC, on the other hand, adopts a distinct approach. Given its primary emphasis on income and living conditions, it does not adhere to the ILO's strict definitions for the economic activity status of individuals. To address this, we turned to an alternative variable within the EU-SILC micro dataset that serves as a proxy of the economic activity of the individuals – PL031: "self-defined current economic status". This variable captures individuals' self-declared economic activity and is categorized into 11 distinct groups: employed full-time and part-time, self-employed full-time and part-time, unemployed, student, in retirement, permanently disabled and/or unfit to work, in compulsory military service, fulfilling domestic tasks and other inactive person. Given that within our study EU-SILC data was primarily used to calculate relative wages for persons based on their demographic characteristics (sex, age group and education) we filtered variable PL031 to take only persons that declared to be employed. Additionally, the self-employed group was excluded due to inconsistencies like income outliers and their relatively small representation within the overall population.

Table 4 presents a comparison between the economic activity status of the population according to EU-LFS and EU-SILC for 2018. We specifically highlighted this year as it was the reference point for calculating the wage ratios in our study. The table presents persons in three broad categories – employed, unemployed and inactive where the "inactive" category includes all individuals who do not fall under the employed or unemployed classifications in both datasets.

The table shows that the standard EU-SILC self-defined definition reasonably captures employment, but compared to the EU-LFS it overestimates the unemployed relative to the inactive. Nevertheless, the EU-LFS is used throughout our study to identify individuals by their activity status while EU-SILC data is used to provide a detailed view of their income.

Table 4: Comparison of the distribution of the population by the economic activity status of persons within EU-LFS and EU-SILC, 2018, weighted data.

	EU-LFS (ILO definition)		**EU-SILC (self-declared)**	
	Persons, in thousands	% of Total	Persons, in thousands	% of Total
Employed	3152.7	**52.4**	3136.8	**52.4**
Unemployed	173.3	**2.9**	489.8	**8.2**
Inactive	2686.0	**44.7**	2357.4	**39.4**
Total	6012.0		5984.0	

❖ Individual income

To calculate the wage ratio between the individual groups – population categorized by sex, age group and education, we used net "employee cash or near cash income" variable (PY010N) from the EU-SILC micro dataset. We opted for the EU-SILC over the EU-LFS because the latter only provides data on the income decile group an individual falls into. As an income decile group divides the population into ten equal parts based on income, with each group representing 10% of the population, this categorization offers limited information on exact income levels, making it insufficient for the purposes of our study.

The net "employee cash or near cash income" variable is one of the target variables of EU-SILC and according to the survey methodological guidelines it represents the gross monetary compensation payable by an employer to an employee, including regular wages, bonuses, allowances, and various supplementary payments, but excluding taxes and/or social insurance contributions.

To get only the income of employed individuals, we filtered the dataset based on the economic activity variable we had earlier defined. The income for each demographic cohort of employed individuals was determined by calculating the mean income of all members within that specific group using weighted data.

Appendix 2. Overview of the ML models used in the analysis

Logistic regression is a fundamental machine learning technique commonly used for binary classification tasks. It models the relationship between a dependent binary variable and one or more independent variables by estimating the probabilities of the outcome belonging to a specific class. The method applies the logistic function, also known as the sigmoid function, to transform the linear regression output into a probability score (Cox (1958)). Logistic regression remains widely used in fields, such as medical diagnosis, marketing, and social sciences for its interpretability and simplicity.

Random Forest is a powerful ensemble learning method used for both classification and regression tasks. Breiman (2001) introduced Random Forest, which constructs multiple decision trees during the training process and combines their predictions to produce a more robust and accurate result. Each decision tree is built using a random subset of the data and features, which helps reduce overfitting and improves generalization. The final prediction in a random forest is typically determined by aggregating the individual predictions from each tree, either by majority voting (for classification) or averaging (for regression). The model's robustness against overfitting and ability to handle high-dimensional data have made it a popular choice in domains such as image recognition and recommendation systems.

Gradient Boosting, developed and formalized by Friedman (2001), is another ensemble technique that builds predictive models sequentially to minimize errors. It has gained widespread adoption for its superior accuracy and flexibility, making it particularly suitable for capturing non-linear relationships in complex datasets.

KNeighbors (K-Nearest Neighbours) is a simple yet powerful instance-based learning algorithm that classifies instances based on a majority vote of their neighbours. For a given input, it looks at the 'K' closest training examples and assigns a classification based on the majority class among them. Distances, such as Euclidean, are typically used to identify these neighbours. KNeighbors is especially useful in scenarios with irregular decision boundaries, as explained by Cover and Hard (1967).

Linear SVC (Support Vector Classification) is a type of Support Vector Machine (SVM) that is used for classification tasks. It aims to find the hyperplane that best separates the classes of data. The hyperplane is selected based on the maximum margin from the nearest data points of all the classes. Cortes and Vapnik (1995) highlight its efficiency in high-dimensional spaces, making it an excellent candidate for datasets with complex structures.

The efficiency of machine learning models can often be gauged by their accuracy score, which reflects the proportion of correct predictions made. In the context of Logistic Regression, the score measures the model's proficiency in predicting different outcomes based on linear relationships, but it may not fully capture complexities in non-linear data or imbalanced classes. Random Forest's accuracy gives insight into the combined capability of multiple decision trees formulated from diverse data subsets, although it may be sensitive to noise or class disparities. The accuracy of Gradient Boosting reveals the additive prediction prowess of trees constructed sequentially, but the model may occasionally overfit if there is an abundance of trees or when faced with skewed datasets. KNeighbors bases its accuracy on the predominant class among the 'K' closest data points, but this can be skewed by variations in data scale or by extraneous features. Meanwhile, Linear SVC's accuracy score represents its efficacy in classifying based on an ideal separating hyperplane, working under the assumption of linear separability in the data. While each model has its nuances, the aggregation of the selected models is assumed to reduce their potential pitfalls, resulting in higher classification accuracy.

Appendix 3. BVAR specification

Bayesian VAR: prior specification

prior distribution:	Normal-Wishart (sigma as univariate AR)
auto-regressive coefficient:	1
overall tightness λ_1:	0.8
cross-variable weighting λ_2:	0.6
lag decay λ_3:	1
exogenous variable tightness λ_4:	100
block exogeneity shrinkage λ_5:	0.001
Sum-of-coefficients tightness λ_6:	1
Dummy initial observation tightness λ_7:	0.5
total number of iterations:	20000
burn-in iterations:	10000
grid search:	no
block exogeneity:	no
sum-of-coefficients extension:	no
dummy initial observation extension:	yes

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