Toward a Sustainable Healthcare; Projection and Evaluation of Norway's Health Workers and Health Spending by Regression Analysis in the Next Two Decades

By Sahand Barati Nardin
Supervisor: Tron Anders Moger

Department of Health Management and Health Economics
The Faculty of Medicine
UNIVERSITY OF OSLO

June 2022

DECLARATION IN LIEU OF OATH

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28.06.2022 	28.06.2022 
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Acknowledgements

This final thesis would not have been possible without the support of many people. I would like to express my deepest gratitude to my supervisor, Prof. Tron Anders Moger, whose guidance from the initial step of research enabled me to develop an understanding of the subject. Prof. Moger has been an inspiration as I hurdled through the path of this final thesis. I am thankful for the extraordinary experiences he arranged for me and for providing opportunities for me to grow professionally.

I am grateful for my parents whose constant love and support keep me motivated and confident. My accomplishments and success are because they believed in me; particularly my mother who is the true definition of a leader and the ultimate role model. My deepest thanks to my brothers, who keep me grounded, remind me of what is important in life, and are always supportive of my adventures. Finally, many thanks to numerous friends who endured this long process with me, always offering support and love.

Abstract

Health workers play a crucial role in performing health system functions. Thus, an effective health care system highly depends on the system being sufficiently scaled in terms of health workers and budget. The main purpose of this study is to predict the number of health workers (e.g. doctors, nurses, and caring personnel) as well as health spending during the projection period 2021-40. The factor considered to affect these outcomes is the demographic change in the population by age and sex, and data were collected from Statistics Norway (SSB). The numbers of health care workers and health spending for the period 2002-2020 were collected from OECD. Data analysis was performed using the time series analysis and multiple linear regression.

The values of R^2 for the models were higher than 99.5% demonstrating all models fit the data up to 2020 well. Consequently, the models were used to project the health workers and health spending for the period 2021-40 and under three scenarios; main, low, and high alternative for population growth.

According to the results, the growth of doctors and health spending during the projection period 2021-40 is significant, 73% and 81% respectively. The projections for the future number of nurses and caring personnel are less significant, 21% for each. However, the growth of each outcome during the entire projection period is not constant through the period.

The results of this study help to achieve a proper decision in both the short and longer term. Furthermore, in this study, we investigate key policies associated with health workers shortage and maldistribution. It is likely that the health care system will face considerable challenges in meeting demand in the near future unless there are changes in technology, treatment, and general health in the elderly population to reduce demand due to demographic changes.

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Introduction

Health care worker supply is the number of people who have the requisite skills and qualifications to provide health care, and are willing to work in the health care sector (Spetz and Given, 2003) (Tulenko et al., 2016). The number of doctors and nurses in a country can be represented by the import or export of these health care professionals, the number of new graduates, deaths, retirements, and/or workforce attrition (Scheffler and Arnold, 2019). Labor economics can predict that increases in wages will increase the number of individuals wanting to enter the health care profession, either through education or migration. However, in many OECD countries such as Norway, such professions are highly regulated – the number of medical student spots is capped by the Norwegian government per year, for instance. Furthermore, despite the freedom of movement provided by participation in the European Economic Area, language requirements and professional registration with the Norwegian Directorate of health can also prove to be barriers to participation in the market (Simoens and Hurst, 2006) (Simoens et al., 2005). The European Commission's SEPEN (Support for Health Workforce Planning and Forecasting Expert Network), which aims to develop strategies to address workforce challenges, relates that the health care workforce of a country can be shaped by the following internal forces: aging, recruitment and retention, geographic distribution, and skills mismatches (European Commission).

Health systems are strongly dependent on the presence of a sufficiently trained and educated workforce that is equipped to respond to the current challenges faced by the country (Weltgesundheitsorganisation et al., 2021). Some of these challenges include increased life expectancy and therefore increased health care demand. Among OECD countries, Norway remains to have the highest life expectancies in Europe, reaching 82.7 years in 2017, as a result of effective public health policies and a reduction in the prevalence of risk factors (OECD et al., 2021). However, health workers' projections indicate a shortage could emerge by 2035 (OECD et al., 2021) due to growing health and long-term care needs due to population aging and workforce retirement. Doctors and nurses are among the most significant profession groups that are essential to the functioning of a health care system. Since the time and financial costs of training these professionals are high, it is necessary to obtain projections to allow for the development of health workers' policies e.g. increasing medical education or outsourcing the training abroad (Scheffler and Arnold, 2019). There are only four universities in the country that provide medical education, as the government caps training slots annually. Norway relies heavily on a foreign-trained health workforce. In 2020, 41% of doctors and 6% of nurses practicing in Norway received their training abroad in countries like Poland, Hungary, and Slovakia (OECD et al., 2021).

This health care worker shortage was especially exacerbated by the COVID pandemic, in which thousands of individuals were hospitalized and needed high-level care. According to Statistics Norway, there was a shortage of 7,000 nurses nationwide in 2020. With the COVID pandemic, a survey carried out by the Nurses' Organization Sykepleien demonstrated that 72% of respondents have considered quitting or changing their jobs in the past 12 months, with the most common reasons including poor staffing, physical and psychological strain, and unhappiness with pay. Eventually, Norway demonstrated a significant increase of over 10% in staff shortages since 2021, with the reasons being increased staff illness and the inability to recruit new staff (Aguzzoli et al., 2021).

Clearly, a projection of the health care professionals in the next 20 years may help decision-makers plan accordingly on how to meet and adapt to these health care workforce challenges, in order to maintain the quality and safety of the Norwegian health care system. This study attempts to predict and analyze the health workers in Norway for having a better perspective of a sustainable health workforce as the main part of a sustainable health care system. In essence, this paper highlights a dynamic situation in which a broad-based policy focuses on achieving and maintaining a sustainable workforce. For instance, the possible health workforce shortage in the near future in Norway could be mitigated by strengthening the education and training of new doctors and nurses and reducing dropout rates both from nursing studies and the nursing profession.

In addition to the number of health workers, there has been a debate in recent years as to whether Norway spends more or less on health care compared to other high-income OECD countries (Morgan et al., 2017). The OECD reports regarding health spending are published according to either per capita or gross domestic product (GDP). This may lead to a comparative discussion since Norway is one of the highest spenders on health when the report comes to "health expenditure per capita", while in terms of "health expenditure as a share of GDP" it is much closer to the OECD average (Morgan et al., 2017).

Chapter 1: Background

The shortage of health workers is still a continuous discussion among OECD countries. Such shortages might be exacerbated by the upcoming retirement of the “baby-boom” generation of doctors and nurses (Co-operation and Development, 2016). According to one study, a shortage of nearly 400,000 doctors across 32 OECD countries and a shortage of nearly 2.5 million nurses across 23 OECD countries in 2030 is projected (Scheffler and Arnold, 2019). Many OECD countries have anticipated this wave of shortage by developing different strategies at the national level. Some led to many new doctors and nurses entering the labor market by increasing student intakes in medical and nursing education, while others have increased retention rates of doctors and nurses in the profession by increasing pension reforms and other factors.

At the international level, states have joint to various conveniences and alliances to work together to address a global crisis in human resources for health. For instance, since the inception of Global Health Workforce Alliance in 2006, the health workforce brought to the fore in international health policy arenas. Thereafter many countries were encouraged to sign commitments to cope with health workforce bottlenecks. The 2010 Second Global Forum on Human Resources for Health, provided an opportunity to identify persisting gaps and reach a consensus on solutions (Afzal et al., 2011). In 2014, World Health Assembly (WHA) adopted a new strategy that included analysis and estimates to quantify and project the global shortage of health workers (Scheffler et al., 2018b). This strategy which is known as the Global Strategy on Human Resources for Health drew upon two complementary reports about the global health workforce labor market in 2013 and 2030. The former (health workforce requirements for universal health coverage and the Sustainable Development Goals) quantifies the health workforce requirements through an innovative empirical approach (Organization, 2016), while in the latter (Global Health Workforce Labor Market Projections for 2030) the difference between the needs-based and demand-based analysis of the global shortages of health workers were highlighted and a much higher global demand-based shortage of health workers was projected (Liu et al., 2017). In 2015, United Nations adopted the 2030 Agenda for Sustainable Development providing 17 Sustainable Development Goals (SDGs) as a universal call to action to end poverty, reduce inequality, improve health and education, and spur economic growth – all while tackling climate change and working to preserve our oceans and forests. For the attainment of many of the 17 SDGs, especially health (SDG3), decent work and economic growth (SDG8), gender equality (SDG5), and migration (SDG10), an adequate, motivated, and well-distributed health workforce is a crucial requirement. (Organization, 2017). Since the development of SDGs, sustainability has been coming to place with greater ambitions for universal access to health (Scheffler et al., 2018a).

In all individual policies or joint platforms, projection plays a hidden and crucial role. In this context, the use of models is an essential feature of making projections. These models make the decision-makers able to rationalize policy options based on a financially feasible picture of the future. A variety of projection models have been developed and applied yet. There are so many variables that play a part in determining the future health workforce in these models. Typically, these include demographic growth and change; health policy and related legislation; technological change; burden of disease; service and provider utilization; relevant service quality standards; organizational efficiency; skills mix; individual provider performance; public demand and expectations; and availability and means of financing (Organization, 2010).

There are four common approaches used to build projection models. The first one is the workforce-to-population ratio method. This approach is least demanding in terms of data, on the basis of proposed thresholds for workforce density (e.g. doctors per 10000 population). Aside from population growth, this simple approach does not address other key variables. The second approach is the health needs method. This is a more in-depth approach that entails collecting and analyzing a range of demographic, socio-cultural, and epidemiological data. According to changes in patterns of disease, injuries, and disabilities and the numbers and kinds of services required to respond to these outcomes, this approach explores likely changes in population needs for health services.

The third approach is the service demands method. This approach requires consideration of multiple variables, as well as collecting and using the data relevant to these variables. This approach draws on observed health services utilization rates for different population groups. Then, in order to determine the scope and nature of expected demands for services, these rates will be applied to the future population profile. Eventually, these will be converted into required health personnel by means of established productivity standards or norms. The last approach is the service targets method. This is an alternative approach that specifies targets for the production of various types of health services and the institutions providing them based on a set of assumptions. Then, this approach determines how they must evolve in number, size, and staffing in accordance with productivity norms. Each of these approaches has its advantages and limitations. At some point, health system planners and managers must determine which of them are most amenable to policy intervention (Organization, 2010).

There is a number of health workforce projection models using different approaches. Those widely used in low- and middle-income countries are the WHO's workforce supply and requirements projection model, the WHO Western Pacific Regional Office (Organization, 2001), Regional Training Centre (WPRO/RTC) health workforce planning model (Dewdney, 2000), and The United Nations Development Program’s integrated health model. The WHO's workforce supply and requirements projection model is one of the most powerful and useful projection models (Hall, 1998) and is used to support health workforce planning in various contexts (Lexomboon and Punyashingh, 2000). This model offers various options including the workforce-to-population ratio and needs-based approaches to projecting health workforce mentioned earlier. The WPRO/RTC model is considered most useful where the population size and the staff categories needing to be projected are small. This model has been used in a number of countries in Africa, Asia, and the Caribbean (Dewdney and Kerse, 2000). The UN Development Program's integrated health model is developed in the context of supporting countries to estimate the resource requirements for achieving the health-related Millennium Development Goals (Merrick, 2007). This model can be used in health systems planning by means of projection and costing of all required public health resources, including human resources, to deliver an integrated package of services. There are also more models like the Western Pacific Workforce Projection Tool (WWPT) to complement the WHO instruments listed above (Organization, 2010). The WWPT tool incorporates a limited number of variables, including population growth, as well as health worker training costs, salaries, and attrition rates. In all models, demographic change is a dominant variable in any consideration of future projections.

In Norway, the projection model known as HELSEMOD has been in use at Statistics Norway (SSB) since the mid-1990s. This model is a calculation tool used to project the supply and demand for different types of health and social care personnel (Roksvaag and Texmon, 2012). The HELSEMOD projects the supply and demand for 20 different groups of health care personnel, uses a utilization-based approach on the demand side and a stock-flow approach on the supply side. On the demand side, the baseline scenario considers utilization patterns of health services, population structure, and the impact of economic development on utilization rates. It assumes that economic growth will lead to higher expectations and the ability to expand health and social services. The supply-side considers average working hours, labor force participation, exit for various reasons, students' admissions to relevant educational programs, and completion rates of studies (Ono et al., 2013).

In 2000, greater work was started to obtain a better and more complete overview of the labor market for health and social workers in Norway, which also provided a better data basis for the projections. The purpose of this work was to make the best possible use of existing registers. As a result, the current statistics on employment for health and social workers have been register-based from 2004 onwards (Roksvaag and Texmon, 2012). Recently, updated and improved demand-based and supply-based projections have been prepared by SSB according to different educational groups directed toward health and care. The main improvements of the model are made on the demand side, compared to the former projections published in 2012, where demand is highly dependent on the aging of the Norwegian population for important groups of health personnel working in hospitals and local government health and care services.

In this study, we have developed a model separately from SSB to project a few groups of health workers as well as health spending. The main difference between this model and HELSEMOD is that the demographic change is the only driver in our model, while HELSEMOD considers more components. We wish to explore to which extent trends in the number of health care workers and spending can be explained purely by population growth factors in the past, and what the result will be if the trends continue. The selected method that has been used in our model is regression analysis which is a technique for the modeling and analysis of numerical data consisting of values of a dependent variable (response variable) and of one or more independent variables (explanatory variables).

Chapter 2: Data

The data of this study is collected from two different sources; OECD.stat and SSB.no. OECD or Organization for Economic Co-operation and Development is an intergovernmental economic organization with 38 member countries including Norway. OECD.stat includes data and metadata for OECD countries and selected non-member economies. The data in terms of health workers (e.g. total health and social workers, number of doctors, nurses, and caring personnel) in Norway is obtained from the 2021 OECD dataset. This edition presents the latest data over time and up to 2020. The rest of the data related to health spending and Norway's population from 2002 to 2020 as well as the projected population from 2021 to 2040 is collected from SSB.no (Statistics Norway). This national statistical institution is the main producer of official statistics for Norway. The latest SSB dataset is updated in 2022, however, we consider its data just until 2020 and afterward as a projection. The reason for that is to synchronize OECD data with SSB data.

There are various definitions for health workers. According to WHO, health workers are defined (Organization, 2006) as "all people engaged in actions whose primary intent is to enhance health". Even though the term "health worker" covers a broad range of health care personnel, this study is restricted to only a few categories including doctors, nurses, and caring personnel. Doctors' indicator is defined as the number of "practicing" doctors providing direct care to patients and not including "professionally active" doctors who are working in the health sector as managers, educators, researchers, etc. (OECD, 2020) Likewise, nurses' indicator is defined as the total number of "practicing" nurses, providing direct care to patients, but excluding "professionally active" nurses who are working in the health sector as managers, educators, researchers, and etc. (Co-operation and Development., 2018) Caring personnel, including both health care assistants in institutions and home-based personal care workers, refers to those health workers who provide direct personal care and assistance with activities of daily living to patients, residents, and persons who are in need of such care due to effects of physical or mental condition. Caring personnel are under direct supervision of medical, nursing, or other health professionals and work in a variety of health care settings such as hospitals and clinics as well as private homes and other independent residential settings (OECD, 2021).

In addition to the projection of health care personnel, this study will also explore the health expenditures during the next two decades. Health care is financed through a government-compulsory arrangement mixed with voluntary health insurance and private funds such as households' out-of-pocket payments, NGOs, and private corporations. In this study, the health expenditures indicator is presented as total health spending in million Norwegian Krone (million NOK). This indicator measures the final consumption of health care goods and services including collective services (prevention and public health services) as well as health administration and personal health care (curative care, rehabilitative care, long-term care, ancillary services, and medical goods), but excluding spending on investments (OECD., 2018). The health spending data produced by SSB has not been inflated over time. Thus, as illustrated in *Table 1*, the health spending statistics in this study are inflated by the rate of increase in prices over the period of 2002 to 2020.

Year	**Health Spending (million NOK)**	**Consumer Price Index**	**Discounted Health Spending (million NOK)**
2002	140 502	78.7	200 309
2003	149 312	80.7	207 594
2004	157 283	81	217 866
2005	165 823	82.3	226 067
2006	175 371	84.2	233 689
2007	189 209	84.8	250 345
2008	207 544	88	264 619
2009	220 368	89.9	275 031
2010	230 785	92.1	281 152
2011	245 441	93.3	295 161
2012	260 182	93.9	310 888
2013	274 246	95.9	320 859
2014	293 507	97.9	336 379

2015	315 207	100	353 662
2016	328 134	103.6	355 373
2017	339 948	105.5	361 537
2018	356 241	108.4	368 729
2019	375 453	110.8	380 197
2020	386 690	112.2	386 690

Table 1. Modified health spending with consideration of Consumer Price Index

Among all data used in our model, health spending is the only one that is modified before inputting to our dataset and the rest of them are used without any change. Regarding the names of variables, each component is abbreviated in the dataset before using in the model. *Table 2* shows the abbreviation of variables.

Name	Content	Source
m017	male population 17 years old and younger	SSB
m1849	male population between 18 and 49 years old	SSB
m5979	male population between 59 and 79 years old	SSB
m80	male population 80 years old and older	SSB
f017	female population 17 years old and younger	SSB
f1849	female population between 18 and 49 years old	SSB
f5979	female population between 59 and 79 years old	SSB
f80	female population 80 years old and older	SSB
p017	total population 17 years old and younger	SSB
p1849	total population between 18 and 49 years old	SSB
p5979	total population between 59 and 79 years old	SSB
p80	total population 80 years old and older	SSB
nodoctors	total number of doctors	OECD
nonurses	Total number of nurses	OECD
nocp	total number of caring personnel	OECD
thsw	total health and social worker	OECD
hs	Health spending	SSB

Table 2. Abbreviation of variables

Chapter 3: Methods

3.1. Linear regression

This study has applied the linear regression method firstly, to build a model by quantifying the relationship between input (the demographic data) and outcomes (health workers and spending), and later using the model to project the outcomes.

Normally, linear regression is divided into two types: simple linear regression and multiple linear regression. Simple linear regression is a statistical method to study relationships between two continuous variables denoted x and y. Variable x is regarded as the predictor, explanatory, or independent variable and variable y is regarded as the response, outcome, or dependent variable. Here, we will use only the "predictor" and "response" terms to refer to the variables encountered in this study.

Simple linear regression, as it gets its adjective "simple," is a regression model to study the relationship between only one predictor and one response variable. The word "linear" refers to the fact that the model is linear in the relationship between the predictor and response variables. For a simple linear regression model

$$y = \beta_0 + \beta_1 x + \varepsilon$$

β_0 is the y-axis intercept meaning how much is the predicted value of y when x is 0, and β_1 is the regression coefficient meaning how much we expect y to change as x increases. A $\beta_1 > 0$ indicates a positive relationship between predictor and response demonstrating an increase in x results in increasing y, whereas a $\beta_1 < 0$ indicates a negative relationship between predictor and response demonstrating an increase in x results in decreasing y. Also, ε is the residual (error) term, or how much variation is between an actual value of y and a predicted value of y ($\hat{y}$). The assumptions underlie the simple linear regression model are that the errors are independent normal random variables with mean zero and constant variance σ^2 ($N(0, \sigma^2)$). The squares of these residuals are minimized to find the best fitting line. This line is used to study the nature of the relation between x and y

variables as well as the projection of response variables. The equation for the best fitting line is

$$\hat{y} = b_0 + b_1 x$$

where $\hat{y}$ is the predicted or fitted value of y, b_1 is the slope of the fitting line, and b_0 is the y-axis intercept.

In a multiple linear regression model, we use the adjective "multiple" to indicate that our model has at least two predictors. For a multiple linear regression model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon$$

we have k predictor variables, which means we have $k+1$ regression parameter including β_0. Everything mentioned about the simple linear regression model can be extended, with at most minor modification, to the multiple linear regression model. Hence, β_0 is the y-axis intercept or in other words predicted value of y for all $x_i = 0$ $(i = 1\ldots, k)$. β_i $(i = 1\ldots, k)$ is the i^{th} regression coefficient meaning how much we expect y to change if only x_i increases while other predictors are constant. A positive β_i indicates a positive relationship between x_i and y, whereas a negative β_i indicates a negative relationship between x_i and y. Also, the error term ε in the multiple linear regression model follows the same assumptions as the simple linear regression model that the ε have a normal distribution $N(0, \sigma^2)$. Moreover, the best fitting line in a multiple linear regression model is

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_k x_k$$

where $\hat{y}$ is the predicted or fitted value of y, b_0 is the y-axis intercept, and b_i $(i = 1\ldots, k)$ is the slope of the fitting line associated with x_i. We are able to find this line by inputting the collected data to Stata and using regression commands. The basic linear regression command is *regress.* However, before using *regress*, we need to define the data as a time series since they are ordered in time and their position relative to the other observations must be maintained.

3.2. Time series data and linear regression – additional challenges

A time series is a sequence of observations of the same variable(s) made over time. Usually, the observations are made at evenly spaced times like monthly or yearly. For instance, in this study, Norway's population which is presented as an ordered sequence from 2002 to 2040 is a time series. *tsset* is a simple way to tell Stata which variable in our dataset represents time. This command sorts and indexes the data appropriately for use *regress*. *tsset* is followed by the variable name, here *year*, that identifies the time variable.

In time series data one often has an additional challenge of correlated residuals. This autocorrelation or serial correlation happens when the random errors in the model are correlated over time. In other words, this phenomenon is detected when each random error at one specific time is linearly related to the error at the previous time instead of being independent of one another. Autocorrelation Function (ACF) is a way to measure the linear relationship between a random error at time t and the random error that is k time periods apart. The simplest ACF is the correlation between values that are one time period apart and measures when $k=1$ in the above. This time gap that is considered as the value of k is called lag.

ACF can be sometimes remedied by introducing lagged values of predictors as regressors. To see if this is a problem in a standard regression model, the Durbin-Watson test should be sufficient. Durbin–Watson test is a way to detect the presence of correlated residuals at lag 1 and applies when the predictors are strictly exogenous. For the linear regression model

$$y_t = \beta X_t + \varepsilon_t$$

we may consider situations in which the error at one specific time (ε_t) is linearly related to the error at the previous time. That is, the errors themselves follow a linear regression model that can be written as

$$\varepsilon_t = \rho\, \varepsilon_{t-1} + u_t.$$

Here, u_t term is a new error term which requires to be normal $N(0,\sigma^2)$ as well as independent and identically distributed (i.i.d.). Also, $|\rho|<1$ is called the autocorrelation parameter. Durbin-Watson test examines the autocorrelation parameter ρ. For Durbin-Watson test

$$H_0 : \rho = 0$$
$$H_1 : \rho \neq 0$$

the null hypothesis implies the error term in one period is not correlated with the error term in the previous period, while the alternative hypothesis implies the error term in one period is correlated with the error term in the previous period, either positively or negatively. For negative correlations of ρ ($H_0 : \rho<0$) or for positive correlations of ρ ($H_0 : \rho>0$), the Durbin-Watson test also accommodates the one-sided alternatives. Also, the test statistic for the Durbin-Watson test on a data set of size n is given by:

$$d = \frac{\sum_{t=2}^{n} (e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t{}^2}$$

Where $e_t = y_t - y_{t-1}$ are the residuals from the ordinary least squares fit. Under the null d is equal to 2, the test statistic for the Durbin-Watson test can take on values between 0 and 4. Values of d less than 2 suggest positive autocorrelation ($\rho>0$), whereas values of d greater than 2 suggest negative autocorrelation ($\rho<0$). Calculating the exact distribution of the d statistic is difficult, but there are tables for certain significance values that provide empirical lower bounds (d_L) and upper bounds (d_U) to make a decision. Extended tables for the d statistic based on the sample size and the number of predictors have been published by Savin and Whitezz. In testing for positive autocorrelation, the null hypothesis rejects when d statistic is less than d_L, whereas it fails to reject the null hypothesis when d statistic is greater than d_U. If the d statistics is between the lower and upper bound ($d_L \leq d \leq d_U$), then the test is inconclusive. The Durbin–Watson test command in Stata is *estat dwatson*. This command computes the Durbin–Watson d statistic to test for first-order serial correlation in the disturbance.

When the lags of predictors are used, in order to decide the number of lags and check if the autocorrelation indeed disappears, we can use Durbin's alternative test with an assumption that predictors are not strictly exogenous. Durbin extended an alternative test to the more general serial correlation process

$$\varepsilon_t = \rho_1\, \varepsilon_{t-1} + \ldots + \rho_p\, \varepsilon_{t-p} + u_t$$

where u_t is independent and identically distributed (i.i.d.) with variance σ^2 but is not assumed or required to be normal for the test. For Durbin's alternative test

$$H_0 : \rho_1 = 0,\ \ldots,\ \rho_p = 0$$
$$H_1 : \text{At least one } \rho_i \neq 0 \text{ (for } i = 1,\ \ldots,\ p\text{)}$$

the null hypothesis implies there is no serial correlation up to order p, where the alternative is that at least there is one autocorrelation. The test statistic for the Durbin's alternative test is F. If the F statistic is less than critical F value with 5% significant level, we will not reject the null hypothesis; meaning there is no lags in time series and the model is stationary.

Durbin's alternative run in Stata under the command *estat durbinalt*. If there are not so many observations, we will use the *small* option. Thus, the command will be *estat durbinalt, small.*

3.3. Multicollinearity

Sometimes building a model is not only summarized to running *tsset* and *regress* commands and a model may face some problems. The most challenging one is called multicollinearity. Multicollinearity is defined as a moderate or high correlation of two or more predictors in a regression model with one another. Generally, small to moderate multicollinearity may not be problematic but severe multicollinearity can bias the estimated coefficients, and thus limit the interpretations of them and the research conclusions we can draw from the analysis. Obvious examples of predictors that result in multicollinearity are a person's GPA between different subjects, measurement of different symptoms commonly present in a diagnosis, and etc.

Despite the problems caused by multicollinearity; it does not prevent good, precise predictions of the response if the goal is simply to predict *y* from a set of *x* variables (Alin, 2010). However, our purpose in this study is not only to predict *y* but also, we want to use the individual regression coefficients to explain how *y* is affected by each *x* variable. Then, the statistical consequences of multicollinearity will cause problems because these effects cannot be separated. In presence of multicollinearity, the signs of coefficients may switch from positive to negative or vice versa. Also, the estimates are very sensitive to minor changes in the model since the standard errors of the estimated coefficients increase. Note that the standard errors are used in the calculation of the confidence intervals for the slope parameters. As a result, multicollinearity affects the statistical power of the analysis and makes it more difficult to specify the correct model. As more predictors are added to the model, these problems can be exacerbated. Our raw data include 10 possible predictors categorized by age groups and gender. The high number of possible predictors in relation to the fairly short time series for fitting the model increase the potential presence of multicollinearity in our model.

One simple way to explore multicollinearity in a regression model is estimating a correlation matrix. This matrix is a table containing the correlation coefficients between every pair of variables. The higher the correlation coefficient between two *x* variables, the more multicollinearity we have between those variables.

There are several ways to reduce multicollinearity in a regression model. One way is to remove one or more of the violating predictors. However, it would not make sense to exclude variables in this analysis, since it would imply disregarding possibly large population groups from the model. An alternative is to linearly combine predictors, such as adding them together. This change yields less multicollinearity in the regression model. We demonstrate this by reducing the other effect of multicollinearity as a direct consequence of the previous effects. The P-Value associated with the t-test for each predictor obtains from the table of the estimated coefficients. The P-Value provides a probability for a hypothesis test where $H_0 : \beta_k = 0$; meaning that the k^{th} predictor has no correlation with the response variable. Multicollinearity may yield different conclusions in hypothesis tests for $\beta_k = 0$ depending on which predictor variables are in the model. If the P-Value is less than 0.05 significance level, it provides sufficient evidence to reject the null hypothesis. This means there is a significant relationship between predictor and response variable. By contrast, if the P-Value is more than 0.05 significance level, there is not sufficient evidence to reject the null hypothesis and the relationship between predictor and response variable is not significant.

3.4. Assessing model fit

After fitting the regression model, we need to determine how well the model fits the data. We use the statistical measure R^2 to evaluate the goodness of fit of the regression model. The R^2 measures the proportion of variation in the response variable explained by all predictors. In other words, R^2 shows how well the data fit the regression model. R^2 can take any value between 0 to 1. For instance, an R^2 of 90% reveals that 90% of the variability observed in the response variable is explained by the regression model. Generally, a higher R^2 indicates more variability is explained by the model. This statistical measurement makes us able to explain whether we get a very good fit up to 2020 just by using population growth as an explanatory factor.

After optimizing the model, we run the model under three projection scenarios; the low alternative, the main alternative, and the high alternative. All three alternatives project the population of Norway in the period 2021-2040, but with the different level assumption for the main demographic components; fertility, life expectancy, and immigration. The main alternative indicates that the medium level assumption has been used for all three components, whereas the low and high alternatives are the low and high assumptions respectively have been used for the demographic components. The low and high alternatives produce a probability interval around the deterministic medium assumptions to provide users with a formal assessment of the uncertainty. An overall overview of demographic changes under all three alternatives is presented in the following.

3.5. Sensitivity analyses according to population growth alternatives

The demographic change under the main alternative scenario is illustrated in *Figure 1*. According to this figure, the growth of the total population of Norway is ascending during the whole period; with significant growth in the period 2002-20, 18%, and weaker growth in the projection period 2021-40, 8%. The decrease in growth is a result of decreasing in the growth of all subset groups during the projection period, except the population higher than 80 years old. The population growth of this group is only 14% during the period 2002-20, whereas it is doubled during the projection period. Population growth, particularly in the form of rapidly aging populations, will affect patterns of morbidity, and consequently health care workers and spending. Hence, the growth in the elderly population has a significant impact on the future of health resources as more people get older, the need for health care services increases.

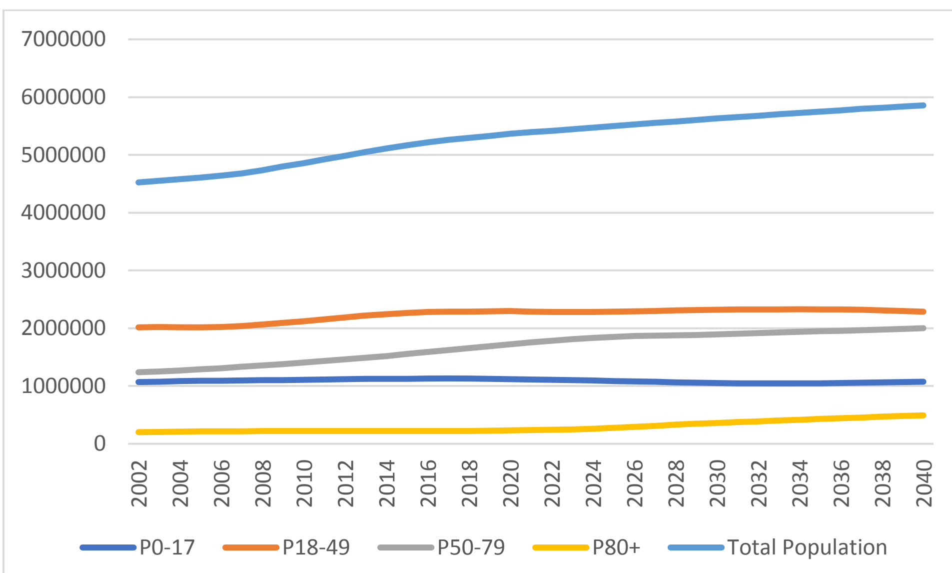

Figure 2.The main alternative demographic

The population of the second-oldest age group, 50 to 79 years old, is growing rapidly from the beginning of the period up to 2026 and will be linear afterward until the end of the period. It seems this age group, compared to people older than 80 years old, has less effect on health resources. However, the increasing population of this group may increase or decrease the number of health workers depending on whether the preventive care or curative care policy focuses on this age group.

Among all subset groups, the population of 18 to 49 years old has the least effect on health resources. This age group consists of the healthiest people who need less preventive and curative care compared to other groups. However, the population of this age group is fairly higher than other groups and a significant change in its population may lead to an impact on the growth of health resources. During the period 2002-20 the growth, 14%, is much more than the growth during the projection period, 0; demonstrating the effect of this age group on health resources during the first two decades is much more than the second two decades.

Ultimately, the growth of the youngest age group, under 17 years old, is wave-shaped and slightly more complicated to interpret. The growth during 2002-18 and 2034-40 is ascending, whereas the growth during the rest of the period is descending. The total negative growth outweighs the total positive growth and leads to a total growth of − 3% during the whole period. This negative growth results in decreasing in those health resources that are correlated with this age group.

Figure 2 illustrates the demographic growth under the low alternative scenario during the period of 2002- 40. Obviously, the total population growth under the low alternative scenario is less than the total population growth under the main alternative scenario. The shape of each individual age group under the low alternative scenario is somewhat similar to the main alternative. The differences between these alternatives are in the amount of growth.

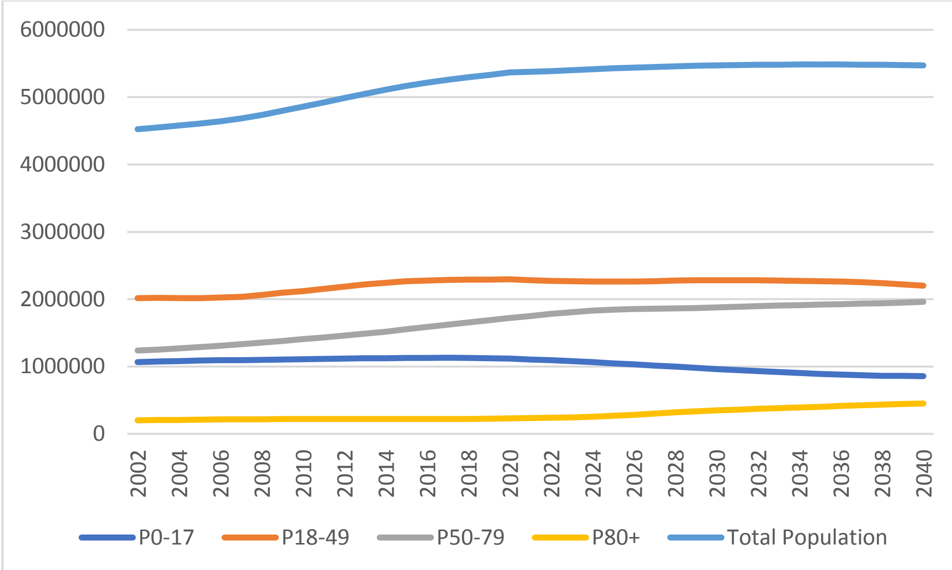

Figure 3.Low alternative demographic

In the low alternative, the growth of children and young people under 17 years old is quite descending during the whole projection period, − 22%, while this growth in the main alternative is less descending up to 2034 but ascending afterward. This variation between alternatives may lead to different results in the projection of health workers and spending; particularly for those ones that are stronger correlated with the population under the age of 17.

The growth of the age group 18 to 49 years old is wave-shaped for both alternatives, with a difference in total growth during the entire projection period, 0, in the main alternative and − 3 % in the low alternative. This negative growth may result in a reverse effect between this age group and health care resources where an increase in one leads to decreasing another.

Under the low alternative scenario, the growth of the age group 50 to 79 years old during the projection period is so close to the main alternative, 12 % and 14 % respectively. Likewise, the growth of the age group higher than 80 years old in low and main alternative are close to each other. Due to this small variation between alternatives, the projection of those health care resources.

The demographic growth under the high alternative scenario during the period of 2002-40 is illustrated in *Figure 3*. As you see in this figure, the total population growth is increasing, even though the growth for each individual group is not always ascending.

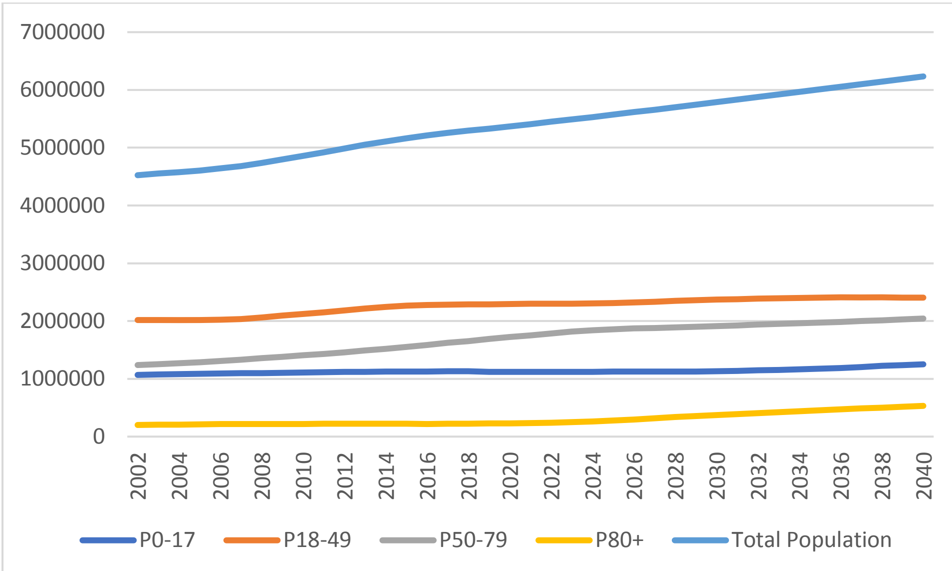

Figure 4.The high alternative demographic

In contrast to the two other alternatives, the growth of the youngest age group, under 17 years old, is significantly descending during the whole projection period, 12 %. The significant variation between alternatives results in an uncertain assessment of health care resources; particularly those ones that are strongly correlated with this age group. This means that if the demographic changes towards the low alternative, the health care resources will decrease. By contrast, if the demographic changes towards the high alternative, the health care resources will decrease. The same happens to the population 18 to 49 years old where the growth is 4 % during the entire projection period, while for low and main alternatives the growth is − 3 % and 0 respectively.

Under the high alternative scenario, the growth of the age group 50 to 79 years old during the entire projection period, 16 %, has a small variation from the main alternative and low alternative, 14 %, and 12 %, respectively. This small variation leads to a more precise projection of this age group, which in turn, leads to a better prediction of health resources. The same happens to the age group higher than 80 years old. Like other alternatives, the population of older than 80 years old under the high alternative scenario is growing drastically with the least variation from the two other alternatives.

Chapter 4: Model building

In order to show how we model the raw data to a multiple linear regression; we proceed with our research question. There are five outcomes in our study (total health and social workers, doctors, nurses, caring personnel, and health spending) that we would like to project. However, we choose only one of them, *nodoctors*, as an example of this methodology and we a build regression model according to the main alternative. A similar model building strategy is applied to other groups and under alternatives. As explained in the method section, the linear regression command is *regress*, however, we need to define the data as a time series using *tsset*.

Table 3 illustrates the estimated coefficients table results from regression of *nodoctors* on all predictors.

nodoctors	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
m017	0.09055	0.0714	1.27	0.234	- 0.0685	0.2496
m1849	0.08743	0.0221	3.94	0.003	0.0379	0.1368
m5079	- 0.3932	0.1637	-2.40	0.037	- 0.7581	- 0.0284
m80	0.0323	0.1834	0.18	0.864	- 0.3763	0.4409
f017	0.1309	0.0926	1.41	0.188	- 0.0755	0.3374
f1849	- 0.1053	0.03012	-3.50	0.006	- 0.1725	- 0.0382
f5079	0.4898	0.1839	2.66	0.024	0.0799	0.8997
f80	0.2753	0.1833	1.50	0.164	- 0.1330	0.6838
cons	-204523.6	70117.61	-2.92	0.015	-360755.4	-48291.82

Table 3. The estimated coefficients table of nodoctors regression on all predictors

The R^2 in regard to this model is high 0.9994; meaning 99.94% of variation in number of doctors explained by all of predictors. Now, in order to check the presence of multicollinearity in our model, we need to drew a correlation matrix. *Table 4* illustrates the correlation matrix of gender/age variables.

	m017	m1849	m5079	m80	f017	f1849	f5079	f80
m017	1							
m1849	-0.19	1						
m5079	-0.47	0.92	1					
m80	-0.74	0.65	0.85	1				
f017	0.99	-0.24	-0.52	-0.76	1			
f017	-0.21	0.99	0.92	0.65	-0.26	1		
f017	-0.49	0.91	0.99	0.86	-0.54	0.91	1	
f017	-0.75	0.55	0.76	0.98	-0.77	0.54	0.78	1

Table 4. Correlation matrix of gender/age variables

As it appears in the above correlation matrix, the correlation among some of the variables is fairly high. The strongest relationships are between different genders of the same age groups which demonstrates the presence of multicollinearity made by gender category. Among the predictors with strong relationships, we choose two predictors of the same age group but in different gender, *m5079* and *f5079*. We proceed by reviewing the output of a series of regression analyses (the regression of the response *nodoctors* on the predictor *m5079* and *f5079* individually, and once both *m5079*and *f5079* altogether). Compiling the results is summarized in *Table 5*.

Model	b_3	*Std. err.* (b_3)	b_7	*Std. err.* (b_7)
Only *m5079*	0.0472	0. 0011	---	---
Only *f5079*	---	---	0.0557	0.0017
Both *m5079*and *m5079*	0.1287	0. 0225	– 0.0965	0.0267

Table 5. Summary table of regression of nodoctors on m5079 and f5079 individually and altogether

As shown in *Table 5*, we obtain wildly different estimates of the slope parameter for *f5079*! If *f5079* is the only predictor included in our model, we claim that for every additional female increase between ages of 50 to 79 years old, the number of doctors *increases* by 0.0557 person. On the other hand, if *m5079* and *f5079* are both included in our model, we claim that for every additional female increase between ages of 50 to 79 years old, holding *m5079* constant, the number of doctors surprisingly *decreases* by

0.0965. Thus, when predictor variables are highly correlated, the estimated regression coefficient of any one variable depends on the other predictors in the model.

Moreover, the standard error for the estimated slope b_3 obtained from the model including both *m5079* and *f5079* is about 21 times larger than the standard error for the estimated slope b_3 obtained from the model including only *m5079*! Likewise, the standard error for the estimated slope b_7 obtained from the model including both *m5079* and *f5079* is about 16 times larger than the standard error for the estimated slope b_7 obtained from the model including only *f5079*! Increasing standard errors of the estimated slopes leads to wider confidence intervals, which in turn, leads to less precise estimates of the slope parameters.

In order to reduce multicollinearity, we combine the observations in the same age groups but with a different gender. For instance, variable *m5079* which is the population of males in the age group of 50 to 79 years, combines with variable *f5079* which is the population of females in the age group of 50 to 79 years, and so on. Furthermore, the total number of predictors reduces from 8 to 4 predictors. Thus, the new variables define as:

$$p017 = m017 + f017$$
$$p1849 = m1849 + f1849$$
$$p5079 = m5079 + f5079$$
$$p80 = m80 + f80$$

where *p017* is the population in the age group of 0 to 17 years, *p1849* is the population in the age group of 18 to 49 years, *p5079* is the population in the age group of 50 to 79 years, and *p80* is the population in the age group of higher than 80 years.

This change yields less multicollinearity in our regression model. In *Table 3*, the P-value associated with the t-test for testing, for example, $H_0\colon \beta_{m80} = 0$ is 0.864. Here, the P-value is much more than 0.05 significance level which does not let us reject the null hypothesis. In other words, the number of doctors is not significantly related to the male population in the age group higher than 80 years old. The same results obtain for *m017, f017*, and *f80* where none of these variables are significant at the 0.05 level. What is going on here is that *m017*, *m80*, *f017*, *and f80* do not explain much of the remaining variability in the number of doctors.

Now we explore multicollinearity in the modified regression model where we have combined the variables in order to remove the effect of gender. The regression of the *nodoctors* on new predictors *p017, p1849*, *p5079, p80* illustrates in *Table 6*.

nodoctors	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
p017	0.0270	0.0110	2.45	0.028	0.0034	0.0507
p1849	- 0.0035	0.0034	-1.05	0.311	- 0.0109	0.0037
p5079	0.0227	0.0021	10.52	0.000	0.0181	0.0273
p80	0.0628	0.0223	2.81	0.014	0.0149	0.1108
cons	-48245.77	5189.338	-9.30	0.000	-59375.79	-37115.74

Table 6.The estimated coefficients table of nodoctors regression on new predictors

As shown in *Table 6*, the P-value of all predictors, except *p1849*, is less than 0.05 significance level; meaning there is a significant relationship between predictors and the response variable. The P-value of *p1849* is 0.311 which is more than 0.05 significance level. We can say there is not sufficient evidence to reject the null hypothesis and the number of doctors is not significantly related to the male population between 18 to 49 years old. This multicollinearity may result from the correlation of *p1849* with other variable(s). The correlation matrix of age variables is show in *Table7*.

	p017	p1849	p5079	p80
p017	1			
p1849	-0.23	1		
p5079	-0.51	0.91	1	
p80	-0.76	0.60	0.82	1

Table 7. Correlation matrix of age variables

We can see in the above table *p1849* has a strong correlation with its next variable *p5079*. This justifies the multicollinearity in the new regression model partially.

Even though multicollinearity still exists in the non-gender regression model, however, it is fairy less than the model containing both age groups and gender. The new model is specified correctly and we do not combine more predictors with each other. Thereafter, we continue with this model.

To show whether there is any need for lags, the Durbin–Watson statistic is used.

Durbin–Watson d-statistic (5,19) = 1.546632

The Durbin–Watson *d* statistic, 1.54, is close to the center of its distribution ($d = 2.0$). Given 19 observations and 4 predictors (excluding the constant term) in the model, for a test of the null hypothesis of no autocorrelation versus the alternative of positive autocorrelation (values of *d* less than 2 suggest positive autocorrelation), the lower bound of the *d* statistic is 0.859 and the upper bound is 1.848 at the 5% significance level. We would reject the null if $d <0.859$, and we would fail to reject if $d >1.848$. A value falling within the range (0.859 1.848) leads to no conclusion about whether or not to reject the null hypothesis. Hence, we cannot make a clear conclusion about the null hypothesis.

Alternatively, we use Durbin's alternative test with an assumption that predictors are not strictly exogenous. Thus, Durbin's alternative for the number of doctors is:

Lags (p)	**F**	**df**	**Prob > F**
1	0.094	(1, 13)	0.7635

H_0: no serial correlation

The critical *F* value with 5% significant level with 1 numerator ($df_1=1$) and 13 denominator ($df_2=13$) degrees of freedom is 4.6672, which is too larger than the Durbin's alternative *F* statistic. Therefore, there is no evidence to reject the null of no first-order serial correlation. This means that there is not any serial correlation in the model which in turn, there is no need for lags and the model can be assumed to be stationary.

Eventually, we need to check how well the model fits the data using R^2. The R^2 associated with the regression model obtained from *regress* command is 0.998; demonstrating 99.83% of the variability observed in the response variable during the period 2002-20 is explained by the regression model. This high R^2 shows the data fit the regression model well.

Chapter 5: Results

5.1. Total health and social workers

Before a review is given for the individual personnel groups, we present an overview of the total health and social workers in the period 2002 to 2040. The R^2 of total health and social workers is 0.9977. The high R^2 indicates the data fit the regression model well. This is also shown graphically in *Figure 4* where the real observations up to 2020 (black points) are so close to the regression line.

The growth of total health and social workers will apply to all alternatives, mostly main and high alternatives. The growth during the entire projection period under the main and high alternative scenarios is 24 % and 44 % respectively, while the growth under the low alternative scenarios is only 2 %. The variation between alternatives mainly results from the extent of growth in the youngest and oldest age groups.

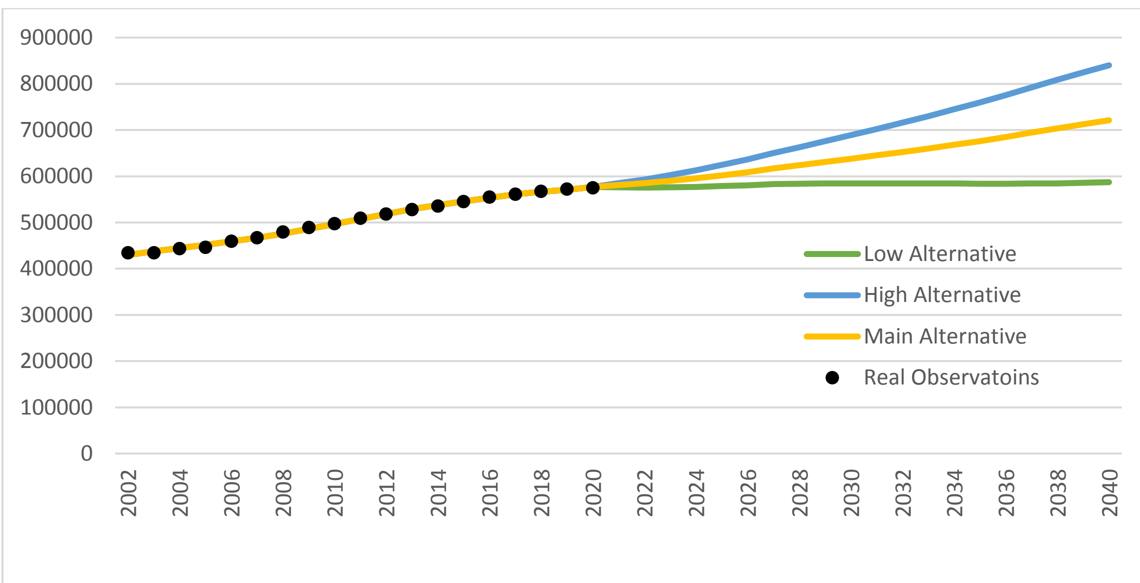

Figure 5. Projection of total Health and Social workers based on main, low, and high alternatives

According to the main alternative, the total health and social workers is growing unevenly during the entire projection period, by 24 %. The growth at the beginning of the projection period is weaker than before, while it is going to be stronger towards the end of the period when it is assumed that the number of people over 80 years old will increase sharply. Hence, there is not much concern regarding the total number of health and social workers in the next few years and the health care system will be able to continue with the same number of workers as before. But in long term, the need for health workers will increase. If the demographic development follows the high alternative scenario, the need for health workers will emerge even sooner, at the beginning of the period. On the other hand, if the demographic development follows the low alternative, the need for health and social workers will be somewhat constant during the entire projection period. Even though the total number of health workers is increasing according to the main alternative, the growth of individual groups is not necessarily all increasing at the same tempo.

5.2. Doctors

The R^2 of doctors is 0.9983; meaning 99.83% of the variability observed in the number of doctors is explained by the regression model. This closeness is also illustrated in *Figure 5*. As you see in the graph, the real observations and the fitted values are so close to each other.

Regarding the projection of doctors, it is expected that the number of doctors grows increasingly faster each year since the beginning of the projection period. The growth will be one of the highest among all staff groups, 73 %, by 2040. This acceleration is primarily due to the fact that doctors are employed in activity areas where the older part of the population makes up the largest proportion of users. This is especially true from 2020 when growth in need of doctors increases sharply as a result of expected faster growth in the elderly population. Even the number of doctors under the low alternative scenario is assumed to grow, by 42 %, during the projection period; meaning there will be undoubtedly a significant need for doctors in the next two decades. If the demographic components follow the high alternative, this growth will be even higher than expectations, 99 %.

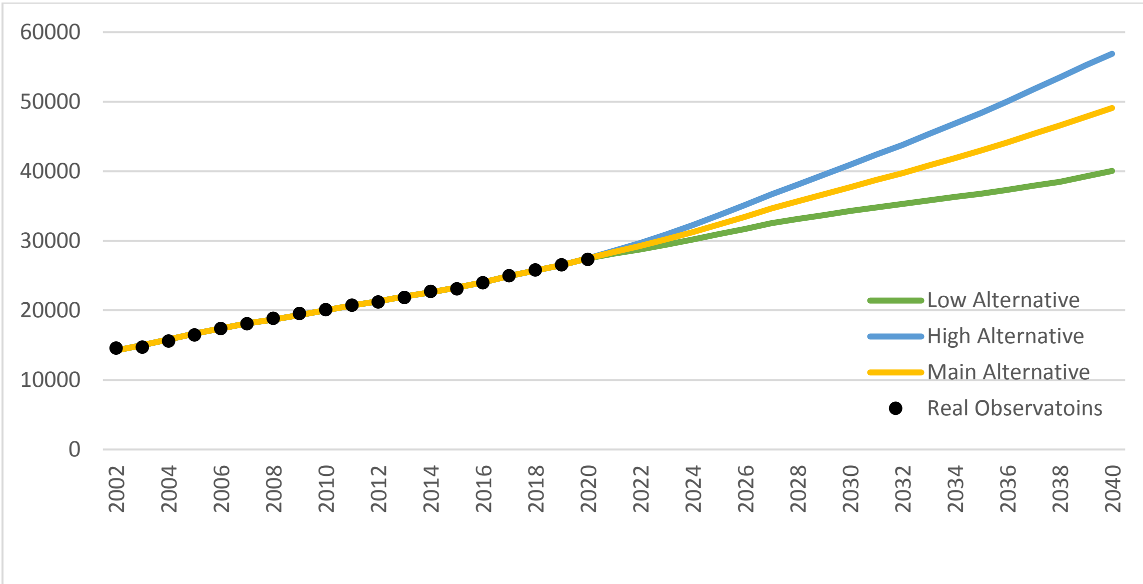

Figure 6 Projection of doctors based on main, low, and high alternatives

5.3. Nurses

Similar to doctors, the model of nurses fits the data well. The R^2 of nurses is 0.9988. Thus, all the observations up to 2020 fall on the regression line.

The number of nurses according to all three alternatives is illustrated in *Figure 6*. According to the main alternative, the growth in the number of nurses is assumed to be weak at the beginning of the projection period but it will be stronger towards the end of the period. This is primarily due to the fact that the nurses are mainly employed in preventive health work aimed at children and young people. As you have seen in *Figure1*, the population of the age group under 17 is decreasing during the first decade of the projection period, while it will be increasing afterward. This results in more significant growth in the number of nurses in the second decade of projection, 15 %, compared to the first decade, 4 %. Moreover, there is a great variation between alternatives mainly resulting from the variation of the young population (age group 0-17 years old) between alternatives. As you see in *Figure 2*, the growth of the population in the age group 0-17 is negative; meaning the low alternative population of young people is decreasing during the projection period. By contrast, as shown in *Figure 3*, the growth of this population under the high alternative scenario is positive.

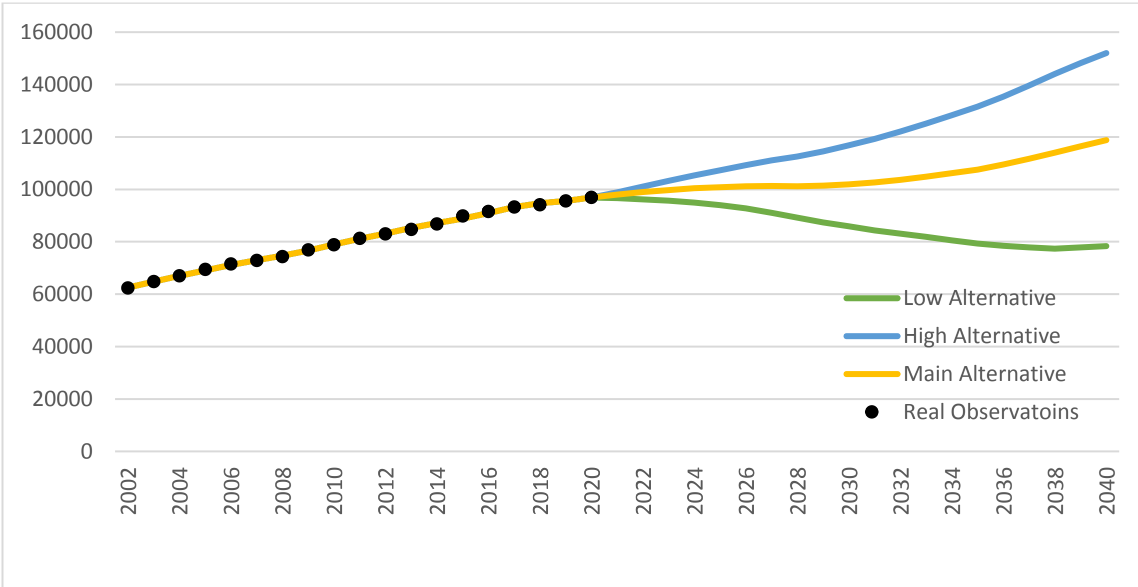

Figure 7. Projection of nurses based on main, low, and high alternatives

5.4. Caring personnel

Similar to other groups, the high R^2 in regard to caring personnel, 0.9957, demonstrates the regression model explains observations very well (see *Figure 6*).

Moreover, the number of caring personnel based on all three alternative scenarios illustrates in *Figure 6*. The graph of caring personnel is similar to the graph of nurses where growth is weaker at the beginning of the projection period, according to the main alternative, compare to the end of the period. Also, the growth of caring personnel under low and high alternatives is similar to the ones in the number of nurses. Hence, the same results obtained from the number of nurses can be used for the number of caring personnel. Similar to nurses, caring personnel are employed to provide health services to children and young people under the age of 17.

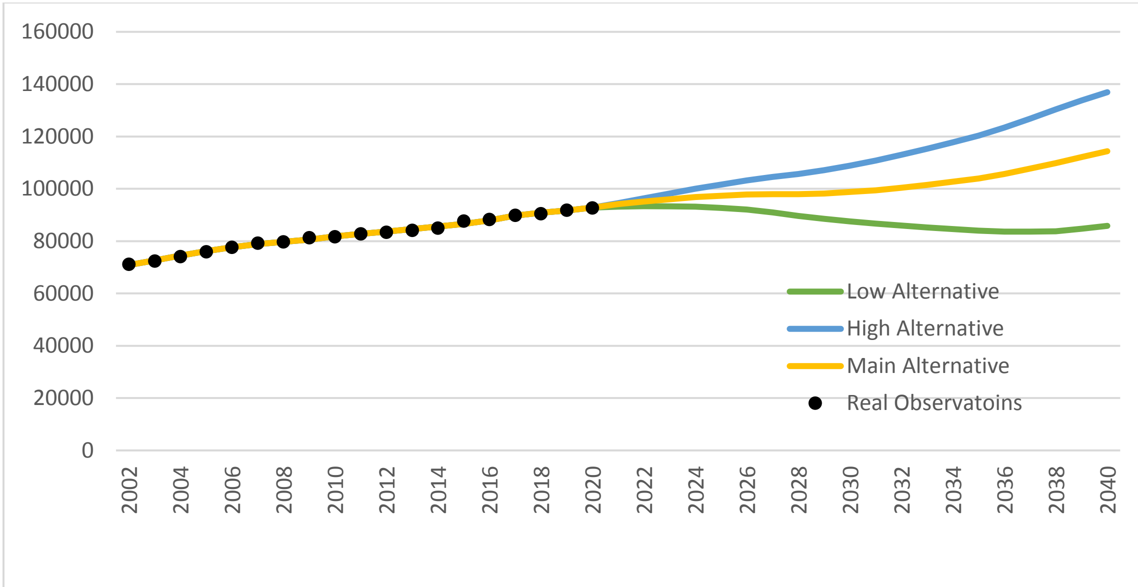

Figure 8. Projection of Caring Personnel based on main, low, and high alternatives

5.5. Health spending

As illustrated in *Figure 8*, the demographic effects on health expenditures are modelled. Firstly, the R^2 is high enough, 0.9973; meaning the observed values and fitted values fit very well.

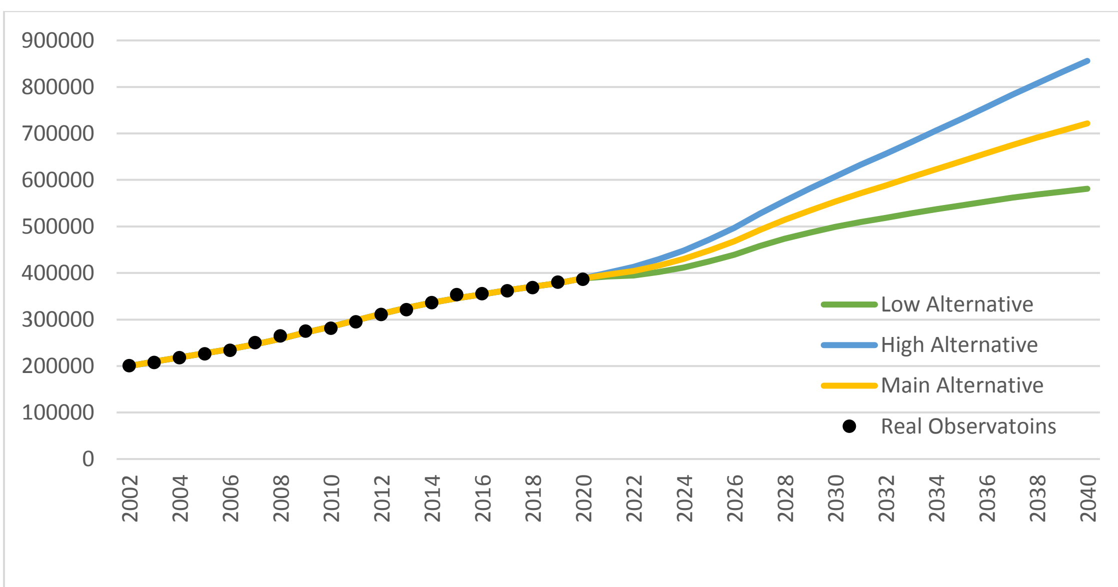

Figure 9. Projection of health spending based on main, low, and high alternatives

Furthermore, the growth in total health spending is assumed to be very high during the projection period. This growth is primarily a result of expected growth in the elderly population, older than 80, who are the most health demanding proportion of the population. In fact, health spending has the strongest relationship with old people compared to other age groups. By the final years of the projection period, an increase number of elderly population results in an increasing in expenditures.

The growth of health spending during the projection period is fairly higher than the growth during the period of 2002-20. The annual average growth of health spending during the period of 2002-20 is 9940 mNOK per year, while this amount during the projection period is 16242 m NOK per year demonstrating the health expenditures will increase during the next two decades.

There is a fairly high variation between alternatives resulting from the variation in population; particularly age group over 80 years. This variation makes the assessments of health spending difficult and put the estimations under uncertainty. However, health spending continues its growth at the same pace. Under the low alternative the annual average growth during the projection period is assumed to be 9440 mNOK per year which is close to the annual average growth in the period 2002-20.

Chapter 6: Discussion

Our model is built under certain assumptions. Firstly, the threshold P-Value for all hypothesis tests is 5% significant level. Also, it is assumed that the numerators and denominators are homogenous; meaning, for example, all doctors are equally productive and will remain so and all populations have similar needs, which will remain constant. Moreover, the only driver in our model is population, while there are more key drivers that affect a health care demand such as rising incomes, productivity constraints, and technological progress (Lorenzoni et al., 2019). This impact probably will be exacerbated by the uncertainty of population projection in the period 2021-40. As a remedy, in addition to the main alternative scenario where the medium assumptions are considered for demographic growth, a second set of projections is produced to reflect alternative scenarios in which the lowest and highest alternatives are assumed. The assumptions that underlie these scenarios are consistent with the least and most demographic growth. Eventually, we have disregarded the impact of COVID-19 on health resources. The number of health personnel and health spending are observed in the period 2002-20, while the pandemic has emerged in Norway at the beginning of 2020 and continues until the present. Therefore, we have assumed there is not much information about the volatility of the recent pandemic; especially with consideration of the fact that the degree of uncertainty surrounding health care grows larger with each additional projection year (Truffer et al., 2010). Even though these assumptions narrow our study, however, all of them are not necessarily limitations to our analyses since using population as a sole factor gives a very good fit to the data up to 2020. Also, a reduction in demand has never been observed in the past, even if data were extended back to the 1950s.

According to the results, the growth of doctors and health spending is more significant than the growth of nurses and caring personnel. Under the main scenario, the model predicts a growth of 72% in the population of doctors and 81% in health spending during the entire projection period. Even under low alternatives, the growth is still increasing. This significant growth is mainly because of the high correlation between these outcomes and the demographic change of elderly people, particularly older than 80 years old. The population of this age group is going to be increasing during the entire projection period. This may lead to significant growth in demand for doctors starting from the beginning to the end of the projection period. In order to cope with a possible shortage of doctors in the near future, there should be an emphasis on short-term plans for supplying doctors to the health market. While some solutions like task-shifting (the process of delegation whereby tasks are moved from the highly specialized workforce to less specialized health workers) can be considered a short-term remedy, more fundamental and long-term plans are also needed (Lehmann et al., 2009). One way to meet this increasing demand is to rely on potential labor outside of the country and recruit foreign doctors (Bludau, 2021). The trend of health spending somewhat is similar to doctors with weaker growth at the beginning of the period. Similar to doctors, health spending is correlated with the age group older than 80 years old. This age group is the most health demanding among other groups and curative care is possibly another reason for increasing their health and care expenditures. However, we are able to amplify somewhat the modest impact that aging by itself will have on health spending by driving up per capita health spending for all age groups (Reinhardt, 2003). Also, by increasing the cost-effectiveness of health care expenditure, while maintaining accessibility for vulnerable groups, we can provide more opportunities to invest in health care (Testori Coggi and Hackbart, 2013).

The growth of nurses and caring personnel, both 21%, is less than other outcomes. This is due to the fact that the growth of these outcomes has a correlation with the growth of young people, particularly younger than 17 years old. It is assumed the population of this age group is not constant through the entire projection period, while it is decreasing at the beginning of the period, it is going to increase towards the end of the period. Following this demographic change, it is assumed the future need for nurses and caring personnel in the second decade of projection is more than in the first decade. This is actually good news for policymakers who need more time to doing some fundamental changes. With long-term investments in the supply of nurses and caring personnel in the first decade of projection, like increasing educational capacity, we can cope with significant growth in the second decade. These policies may result in a slight surplus of nurses and caring personnel at the beginning of the projection period but help to improve the resilience of the system to cope with the shortage of these groups in the second decade of projection. All of these policies come to place when the demographic components follow the main alternative. If the level of assumptions changes to the high or low alternative, the strategies regarding the number of nurses and caring personnel completely change. In the former, the growth is relatively high during the whole projection period, similarly to the number of doctors and health spending. Thus, the same policies and decisions were made regarding the number of doctors possibly working for the nurses under this alternative. In the latter, the growth is descending almost throughout the projection period; meaning we will not even face a shortage of nurses but also, we need to cope with the challenge of the surplus of this group. Increasing growth in demand for health workers is also reflected in the total number of health and social workers with a growth of 24% by the end of 2040.

The results of this study are fairly reliable as the validity of the model is proved. We can discuss that it is better to check the ability of the model to fit the historical data prior to projection. This reality check helps to evaluate the precision of our model and is done with help of R^2. The R^2 in regard to each health worker and spending is high (all R^2s are higher than 99.5%) demonstrating all outcomes have followed a very close trend to population-by-age factors during the entire period 2002-20. This small variation between the fitted values produced by our model and the historical data shows the model was able to justify the number of health workers and spending in the past, and the projection will be trustworthy if the trends continue. This is a characteristic of our model which separates it from the SSB projection model, HELSEMOD.

Our model is also comparable with HELSEMOD in other aspects. We have considered some compromises and simplifications in our model. The level of detail and complexity of our model reflects both the availability of data and underlying assumptions about technical capacity. The HELSEMOD, compare to our model which is a simple population-by-age driven projection model, is a more complex model. The

HELSEMOD takes into account more resources and activities that collectively define the major characteristics of the health system and its labor market. However, even the HELSEMOD, to a considerable extent, cannot account for all of the many complexities of a real health system. For instance, it is impossible to know how better life expectancy will improve health and demand for care, or whether family support, productivity, etc. will change. It is hereby hard to say if the HELSEMOD will perform better than a simple population-by-age driven model. Even though it seems to be hard to support this assumption, however, no real change has been seen in data so far and the demand of our model has been very closely related to the population-by-age increase in historical data; demonstrating the model performance was good enough.

The results of our model are also comparable with results obtained from the HELSEMOD reports. According to the 2013 OECD report, the HELSEMOD projection model explores various scenarios on both the supply and demand side during the projection period 2010-35. On the demand side and under the "demographic changes only" scenario, HELSEMOD projected 36% growth in the population of doctors and 49.2% growth in the population of nurses by the end of 2035 (Ono et al., 2013). The growth of doctors and nurses projected by our model is 72% and 21% respectively, by the end of 2040. Both models show an increase in the number of doctors and nurses with a difference between projected values. This increase in the number of health workers has been also reflected in terms of man-year in a more updated report. According to the 2019 Statistics Norway report, the demand for man-years from the entire health sector will increase from just over 309,000 in 2018 to just over 415,000 in 2035. There will thus be around 35% growth in the staffing requirement from 2018 to 2035. But this is assuming a constant amount of family care up 2035. Incorporating a model for improving health, 1% higher service standard and 0.5% higher health sector productivity per year gives a rough estimate of the projected total man-years in 2035 in case of no effect of these three factors. It is then around 450 000, or an increase of 48%. The man-years in this model are particularly concentrated on the oldest age group (Hjemås et al., 2019) so that it is assumed population aging is a major driver of the annual growth in health demand .

States may not always face shortage of health care personnel across the country but only in specific places. Hence, an uneven geographical distribution of health care personnel, and shortages in rural areas remain another challenge. The sparse population distribution in Norway, with its close to 5 million people occupying 385,000 square kilometers, could be a contributor to this internal shortage – with vast portions of its rural areas in the North suffering the most shortages. One example is the county of Finnmark which is the northernmost area of Norway and covers an area that is larger than Switzerland, however, has only a population of about 75,000 people. The remoteness, harsh climate, and low population are major factors that decrease location desirability and difficulty to retain workers locally. This is most heavily noticeable among doctors – while rural areas have always historically faced difficulties in recruitment, nowadays, even larger towns and cities in Norway are struggling. The number of municipalities facing the recruitment of doctors has increased by more than six times in the past few years (Brekke et al., 2021). Similarly, the workforce dropout rate for nurses, especially those working in long-term care, is significant (OECD et al., 2021). This section will then examine various policies enacted in various OECD countries that aim to target this supply among health care professionals.

Unequal distribution and supply of doctors exist in most countries, even in advanced high-income countries (Ono et al., 2010). Many countries have outlined policies that aim to reduce this supply shortage and or maldistribution, and these policies can be outlined into three broad strategies: the first, targeting future doctors, namely, increasing number of doctors entering the workforce in the specified country (both countrywide or locally, in the case of rural shortages), second, targeting current doctors, which aims to reduce turnover and reduction of workforce by providing incentives, and third, by increasing participation of non-doctors health care providers in service delivery, among other innovations such as telemedicine (Ono et al., 2010).

The first strategy is to increase the medical education intake nationally. In many European countries, governmental policies restrict the number of places provided by medical schools throughout the country, or also the number of specialist training places (OECD, 2014). Norway is among the countries that only control the former, but not the latter. Among its four medical schools, the annual intake has increased from 367 students per year in the 1970s, up to 636 in 2019. However, the Grimstad Committee has determined that this is insufficient, and recommended adding another 440 study places within the next couple of decades (Olsen et al., 2021). Within this strategy, there could still be however a marked imbalance between the rural and urban supply of doctors. Although there are currently innovative programs in existence in Northern Norway that provide medical education in the Arctic rural counties of Troms og Finnmark and Nordland, Norway is still having a struggle in recruiting and retaining doctors to rural areas with many unfilled positions reported (Teräs et al., 2020).

Two strategies employed in Australia and Canada may assist in helping alleviate this imbalance. In Australia, there were two placement schemes that accept students into medical school that requires students to sign a contract with conditions that require them to work in primary care in rural areas – the Bonded Medical Places (BMP) Scheme, and the Medical Rural Bonded Scholarship (MRBS) Scheme (Mason, 2013). In the BMP Scheme, students do not receive financial support, but have an allotted slot in medical school that they would otherwise not receive, however, they must work in a district of doctors shortage for a period equal to the length of training received. In the more generous MRBS scheme, students receive financial support and sign a contract with the Australian government to work in a rural area for up to six years after specialist training. The latter program has had over 1,200 participants since its inception. This has since transitioned into a more streamlined program that now only requires three years of rural service after completion of the degree (OECD, 2014). In Canada, satellite campuses and multiple training sites are used to provide medical student education in the far north where the population density is sparse. The Northern Ontario School of Medicine (NOSM) recruits students who are local and/or have remote, aboriginal, or French-speaking backgrounds, and provides a Rural Recruitment and Retention

Initiative that is a loan repayment program for its students. The program has indicated that up to 70% of its graduates' train in family medicine in rural regions, demonstrating its success (Strasser and Lanphear, 2008).

The second strategy is to target doctors who are in current practice, to maximize their practice in underserved areas. This may include financial incentives, but also increased regulation that may affect their practice location choice. Financial incentives could be wage-related, or non-wage related which can be one-off payments (Barber et al., 2019). In Germany, many states offer incentives for first-time doctors who are starting their practice, which can range from 15,000 up to 60,000 euros. This can be used to set up their clinic, buy clinic equipment, or hire staff. In some of these states, it comes with a contract of return to service obligation of up to five to ten years. In Canada, the Northern Ontario Rural Recruitment and Retention Initiative provides a grant of 80,000 up to 120,000 Canadian dollars for rural area practices that are opening for the first time. The second financial incentive is wage-related, which are recurring payments throughout the doctor's career. These incentives can vary widely based on the country and are highly dependent on the structure and variation of the health care system. One example is a basic income guarantee for some qualified doctors who are starting out their practice – which is provided in France, which gives up to 55,000 euros per year. In Denmark, a similar program exists in which the government guarantees to provide a specific sum per patient if a doctor does not reach the quota of 1,600 enlisted patients in a particular time frame.

One last strategy is the introduction or expansion of non-doctor health care provider roles, such as nurse practitioners, pharmacists or doctor assistants that can provide primary care to patients (Delamaire and Lafortune, 2010). In Norway, this introduction is still currently in its first phases – leading universities have started offering master's level programs in nursing, however, adaptation into the Norwegian health care system is still in progress.

Nurses comprise among the largest percentages of the health care workforce by population and are therefore an essential component of the functioning of a country's health care system. However, just as with doctors, many OECD countries still have labor shortages in this profession due to a variety of factors. Many diverse strategies exist to increase the nursing workforce. As with doctors, some countries regulate the number of nurses entering nursing schools, such as England, Spain, or Sweden, while others do not, and leave it up to each nursing school, as it is with the US or Norway. In the former, governmental policies to increase the number of spots in schools can help alleviate the shortage, while in the latter, this is left up to free-market forces in which wages determine the demand and number of applicants to programs.

In some countries, nursing can be perceived as a low prestige profession secondary to medicine, and hence advertising campaigns to promote application increases have been used. For example, in Belgium, leaflets were provided to high school students across the country to promote enrollment in nursing schools. In the US, a widely publicized campaign in coordination with the company Johnson and Johnson, called The Campaign for Nursing's Future, targeted the young population through posters, videos, and advertisements in order to increase nursing school enrollment. In Australia, a program similar to the BMP Scheme for nurses was set up. A rural and remote Nurse Scholarship Scheme was created to encourage the intake of nurses in rural programs.

Despite the attempts to increase supply by targeting school recruitment, this may not be enough, and so many OECD countries resort to immigration of foreign well-trained nurses with equivalent qualifications. This is especially apparent among Scandinavian countries, where nurses from other European countries such as Spain, Lithuania, and Poland are steadily increasing. European Union directives that allow reciprocal recognition of professional qualifications from one country to another have made this possible. However, a significant barrier to this becoming a more accepted solution is the cultural and linguistic differences that cannot be easily bridged (Teräs et al., 2020).

All of the policies and strategies offered in this study were according to the projected growing health demand. However, we have to bear in mind that the projection model has developed with regard to data availability and limitations. There are still some uncertainties that may impact the precision of the projections. There is a possibility that the elderly becoming more active and healthier; hence, the care and consumption of a growing older population may not be so costly to finance and they provide significant economic and societal benefits (Cylus et al., 2019). Also, the development and use of labor-saving technology can reduce the health sector’s traditional reliance on labor. Some technology (i.e. revolutionizing drug development, equipping high-tech devices, using nanotechnology, telehealth, and etc.) is an effective response to the economic pressure from the labor market (Freitas, 1999).

Chapter 7: Conclusion

The health care labor shortages projected up to 2040 may not occur if the number of health workers could be increased. In addition, there is also a major challenge in regard to achieving a more effective distribution and deployment of health workers. These challenges associated with increasing health costs may lead the health care system toward a tragedy. With an understanding of the future labor market for health workers, more strategic policies can be developed to improve both the supply and distribution of health workers to achieve both public health goals and address economic forces. As a response to meet growing health demand in the near future, the policies such as increasing the medical education intake or reforming regulations could potentially lead to an increase in health care workers and cost-effective approaches. Also, other plans like bringing technology to health care or changing the population lifestyle, particularly elderly people, have an adverse effect on health demand and can be helpful to reduce the growing health demand.

Workforce projection plays an important role in setting strategic policies; however, they cannot be undertaken in isolation. They are normally part of some larger strategic process as they are highly dependent on other developments in the health system of the country. Consequently, a broader social and economic context such as availability of resources (human, financial, and technical) and leadership and commitment by senior officials should exist.

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