Do Municipal Attributes Predict GP Recruitment Problems?

Association between Attributes of Norwegian Municipalities and Problems in Recruiting General Practitioners

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Date of Submission: May 2023
Thesis submitted as part of the Master of Philosophy Degree in Health Economics, Policy and Management

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Abstract

Norwegian municipalities increasingly have difficulties to find and employ general practitioners. With the introduction of “Fastlegeordningen” in 2001, the primary model for GP coverage became is entrepreneurial with mixed financing of capitation and activity based renumerations. Norwegian municipalities are very heterogenous in various dimensions. The majority is somewhat rural and differ in geographic, socioeconomic, and demographic attributes. This project set out to investigate whether and how these attributes predict the existence and severity of a GP recruitment problem. To this end, self-reported data via a Norwegian newspaper and registry data via registries has been used to depict recruitment issues. Data from Norway’s statistical institute was used for municipal attributes. The data is complicated with strongly skewed distributions and noise. A variety of methods were therefore employed to create dependent variables and to regress them on municipal attributes. The focus was to capture both the *existence* and *severity* of municipal recruitment problems. Regression methods include (ordered) logistical and linear regression. Detailed descriptive statistics of the dataset were produced and reported. The project finds that from 2015, there is a clear increasing trend in both the number of municipalities with recruitment problems, but also the population affected by it. The trend has picked up pace in the years since the last public report in 2020. Recruitment problems are no longer confined to rural areas, but are spreading to more populous cities. Models had overall low explanatory power (R^2<0.2). Positively associated with recruitment problems were population, driving distance to major population centres, and share of inhabitants over 65. Negatively associated were average list length, share of female inhabitants and share of inhabitants with more than four years of university. Other notable results were that the list length of doctorless lists is lower than the overall list length of municipalities with a recruitment problem (endogenous list length), and that the share of inhabitants with elementary school as their highest education is a positive predictor of recruitment problems. The project concludes that further research on the factors influencing endogenous and average list length may be useful to better understand the relation between municipal attributes and the recruitment of GPs.

Acknowledgments

I would like to thank my supervisor, Jonas Met Kinge for his insight and focus on what is relevant to the scientific community. Proofreading contributions by Thomas Campbell-James and Klaus Lenz were helpful and direly needed. Special thanks to my housemates Caleb and Mari, as well as Vilde Lindefjeld for their support and special contributions. Inspiration was taken from ChatGPT when it comes to coding STATA and “what does a good conclusion section contain”. Also, a big shoutout to Dr. Nicholas “Nick Cox” J. Cox, whose name I have probably read more times during this thesis than that of my five most cited references. He has 31200 posts as of today- and he is online right now- on the Statalist.org forums. Last but not least, my thanks go to the University of Oslo for employing me as a research assistant for the semester.

List of Abbreviations

Abbreviation	Meaning
GP	General Practitioner
Mcp	Municipality
FLO	Fastlegeordningen

1. Introduction

1.1. Introduction

The organisation of General Practitioners (GP) in Norway (No.: Fastlege) was reformed and codified in 2001 in the so called "Fastlegeordningen"- General Practitioner List Registry. Its goal is to provide all necessary general health services in good quality at the correct time and that all persons residing in Norway have a GP assigned to them (Helse-og-omsorgsdepartementet, 2001/2012). The law established GPs as self-employed entrepreneurs in contract with the municipality as the standard business model for primary health care provision. It defines the responsibilities and privileges of doctors, municipalities, and patients. Most importantly, it implemented a codified relationship between a doctor and patient in the form of lists – every patient should be on one doctor's list. GP renumeration is directly related to the number of patients on their list (list length). Since 2001, several reforms and additions have been made to the law and its implementation. The policy is deemed successful in achieving its goals (Vista-Analyse, 2019).

In contrast, the General Practitioner List Registry has come under pressure over the last decade, as GPs were given larger shares of the tasks in the healthcare system (Vista-Analyse, 2019). Simultaneously the overall production of the healthcare system increased due to an aging population and the expansion of available treatment options (Saunes et al., 2020). The GP vocation is described as increasingly unattractive and many GPs have expressed their desire to quit due to the high workload (Vista-Analyse, 2019).

Today, there is a recruitment crisis for GPs in Norway. Municipalities struggle to fill their responsibilities to provide primary healthcare to their residents (Helse-og-omsorgsdepartementet, 2020). Thus, they struggle to contract in enough doctors that work enough hours to provide the necessary health care coverage. The problem occurred in rural municipalities at first, but has since spread to some medium and large municipalities (Helse-og-omsorgsdepartementet, 2020). As a symptom of this, stand-ins (No.: Vikar) for GPs are so hard to attract, that a northern municipality offered ca. 10 times the usual renumeration (Nyhus et al., 2022).

The newspaper VG compiled a map displaying a qualitative description of recruitment problem severity over two periods (Nave, 2021). This inspired this project's central research question:

Which municipality attributes predict their recruitment problem?

To address this question, this project will analyse different aspects of the recruitment problem and their variance across municipalities and relate it to their attributes.

1.2. The Norwegian Primary Healthcare Structure – Fastlegeordningen

Norwegian GP payment has a target of 30% capitation and 70% Fee-for-service (FFS). Each resident may choose a doctor and become part of the list, unless it is full. The patient list determines the capitation payment directly – each patient on the list yields a monthly lump-sum amount to the practitioner. Capitation payment has shown less growth than overall physicians' wages (Abelse et al., 2021) and time-used per patient has increased (Rebnord & Eikeland, 2018). Hence, the incentive to supply list spaces rather than providing services has decreased. As of 1 May 2023, capitation payments are adjusted for listed patient and municipality attributes (HELFO, 2023).

GP contracts are individual and differ across municipalities. These can be divided into three categories: Full entrepreneur, 8-2 deal and salaried. A full entrepreneur GP is solely responsible for all necessary investments and risks as well as all rewards associated with his practice. This involves a high amount of capital investment and financial risk for new doctors when entering the market. To offset this daunting entry, the 8-2 model shifts some risks and investments to the municipality. In effect, the physician rents a practice space from the municipality while paying an annual fee. In both scenarios the doctor receives the activity and capitation payments. A salaried GP is a regular employee and works for a salary paid by the municipality, with the wage being subject to negotiations. The activity renumeration paid by FLO and co-payments are received by the municipality.

(Abelse et al., 2021) recommends an increase in capitation payments for GPs to increase labour supply. It mentions differences in between municipalities in their ability to contract enough GP labour. This project is a starting point for understanding how these differences affect recruitment difficulties and may contribute to a future payment scheme which discriminates municipalities in their GP capitation payments.

1.3. Recruiting GPs in general and in Norway in particular

1.3.1. International

This chapter will review the literature existing on the problem of recruiting and retaining GPs worldwide, particularly in Norway. The literature focuses on the effectiveness of certain policies and measures to improve GP recruitment. Based on which mechanisms effective policies are employing, information on what motivates students and GPs to choose their vocation/location can be deduced. This information will then be used to generate hypotheses for data analysis. Factors relevant to choosing medical specialisations vary across countries and cultural contexts (Puertas et al., 2013).

There are fundamentally two sides to the problem of GP recruitment: The number of medical graduates that choose to become GPs and where these GPs choose to work. The most typical example of the latter is the difficulty for rural communities to attract physicians. Manning general healthcare positions in rural areas is a problem in many countries, including high (Weinhold & Gurtner, 2014) and middle and low income countries (Lehmann et al., 2008). Large parts of the literature therefore deal with recruitment problems in rural areas. Testing association of recruitment problems and "rurality" of municipalities in Norway will be conducted. Most open positions for GPs in Norway are in areas with problems recruiting GPs. A graduate considering the GP profession can try to find work in popular areas or can take one of the "free" lists in less sought-after areas. The decision of where to work is therefore connected to the decision of whether to become a GP at all.

Renumeration and other financial benefits are a common incentive to improve recruitment and retention of GPs. Bonding-policies, which provide financial incentives in return for bonding to local services in hard-to-staff areas are a prime example of such. The majority of such policies are reported to be effective – evidence quality is however mixed, and some of it suggests that doctors may leave rural areas once their bonding time expires (Verma et al., 2016). Qualitative approaches find that financial factors and other extrinsic factors were of lesser relevance to recruitment and retention compared to, for example, recognition (Marchand & Peckham, 2017).

Origin of the medical student and placement during undergraduate studies are of relevance. Both recruitment from and undergraduate studies in rural areas are associated with higher retention of GP in that area (Verma et al., 2016). The Physician Shortage Area Program in the USA has seen large successes with selectively admitting applicants who grew up and plan to practice in rural areas (Rabinowitz et al., 2022). This implies that individual connections to a geographic location may be relevant for the GP's choice. An older systematic review supports these results (Brooks et al., 2002). The data largely stems from outside of Europe and its relevance to the Norwegian context is questionable.

Individual characteristics are also shown to be of importance for students choosing whether to become a GP. Job stress, job attributes and geographical location of the practice and work-life balance are an issue (Marchand & Peckham, 2017). Undesirable on-call arrangements and lack of opportunity for vacation or continued medical education are also reasons given for not choosing a GP position in a rural area (Viscomi et al., 2013). One study also shows that parent's socioeconomic status negatively predicts the choice of becoming a GP (Senf et al., 2003).

1.3.2. Specific to Norway

The main reasons named by GPs who have left their specialisation are administrative burden and small professional community (Birkeli et al., 2020).Which educational institution physicians attended is correlated with the choice of a GP career among Norwegian physicians (Wesnes et al., 2012). Graduates from the largest population centre, Oslo, have one of the lowest chances to choose a GP career. Only graduates from Germany were showing lower probabilities. Some of the results were not significant.

Rural area GPs work particularly long hours (Rebnord et al., 2020). While the weekly workload was already high at an average of 50 hours per week in 2014, it has since increased to 55.6 hours in 2018 (Rebnord & Eikeland, 2018). There is also evidence for increased work stress for Norwegian GPs in the period of 2010 to 2019 (Rosta et al., 2020).

Previous analysis of related registry data has found that doctors quitting their contract is associated with less populous municipalities and shorter individual list length (Abelsen et al., 2015). This result is based on data from the period between 2001 and 2014. Decreasing trends with higher absolute doctorless lists and population before 2010 can be attributed to problems related to the introduction and establishment of the new framework policy in 2001 (Abelsen et al., 2015). For the period up to 2014 Abelsen et. al. also finds that the less populous the municipality is, the longer is the period for which a doctorless list remains doctorless.

1.4. Recent Public Reports

In April 2023, a report ordered by the Norwegian Government on the status of its primary health care was released (Telle et al., 2023). It was created by a committee selected from national health institute, academia, municipal administrators and general practice specialists. Their mission was to propose changes to Primary Health Care, particularly general practice and parts of emergency services where GPs are concerned, with the goal of making the services more sustainable. The report suggests a multitude of reform changes, but due to its publication being late into this project, only the one regarding the remunerative system for GPs will be treated in this thesis.

The aforementioned committee contracted the National Health Institute (FHI) to process available data, with the goal of creating a knowledge base for the committee‘s own report (Delalic et al., 2023). This supplementary rapport employs data from the same registry as this one, while adding some from other sources to make up for missing datapoints which were not reported in at the time. The latest datapoint used was from the end of 2020. They find that population on doctorless lists was highest in 2001 and beginning of 2021, and conclude that the number of patients on doctorless lists is increasing, but the share of total population is stable. This project's findings are in contradiction to their interpretation- there is a trend of increasing population on doctorless lists in the country, both in absolute and in relative terms.

Said report also finds that patient's continuity of care and access to health is not necessarily affected by being on doctorless lists. This was however subject to geographic differences- with more rural municipalities experiencing less continuity and access to healthcare on doctorless lists. This may explain some of the findings of this project with regards to rurality.

2. Methods

2.1. Summary

First step was to obtain the data. The VG dataset was received in raw form, while the FLO dataset was received via application from Helsedata.no. The application was formed with the intent to gain enough data, and several characteristics were requested but not used. This was also the reason to request quarterly data.

Before and during the creation of dependant variables, the question of what defines a recruitment problem came up. The results of internal discussion are in the chapter on dependent variables (2.1).

From the two datasets, a total of five dependent variables were generated. Three of them were used in the main reporting, two were reported in the appendix, and all models based on three other variables did not make the cut due to overlapping results. Due to the skewed distributions of population and dependent variables, categorical transformations of dependant variables were formed. Both categorical and continuous variables were used for regression analysis to ensure robustness of results in spite of challenging data.

Data from six different SSB databases was included. Most datasets depicted persons as unit and were normalized to per capita per the total population reported in the respective SSB dataset. Exceptions to this are data on income and area. Different variables from the same dataset were regressed individually to see which were the best predictors. For example, SSBs data on education reports the number of people by their highest level of education. Regressions with different levels of education were tested to check which one is the best proxy for education by their significance. Other datasets and predictors were tested but discarded due to messy data, missing years or rows, and small municipalities being excluded due to privacy. To calculate the driving distance between municipal administration centres and the closest medical educational university, data from an online map service (Virtualearth.net) was used via API and driving distance was calculated using a VBA macro in Microsoft Excel.

The regression models applied were (ordered) logistical and linear regression. For the categorical variables, (ordered) logistical regression was used. For continuous variables, linear regression was used.

After testing and discussing several combinations of explanatory variables, dependent variables, and methods, it was decided to report three dependant variables in a main table and in fanned tables. Due to a contradictive result in the effect of population, geographical variables were regressed one by one and in combination with average list length to check against multicollinearity and identify overlapping variation. A similar procedure, albeit less fine, grained was done for demographic and socioeconomic variables. VIF scores were calculated here applicable and variables above a score of three dropped. To compare with Goddard et. Al. and to check for time-lagged effects, the change in the main dependent variables was calculated for the years comparable to the VG dataset (2017,2021). The change was then regressed on the explanatory variables of 2017. In total, eight regression tables are reported in the results section, and four more for validation and comparison to other papers in the appendix.

Regressions for absolute values of the dependent variables were also performed but quickly discarded as the skewed population and dependent variable distribution makes the results unreliable and confusing. An ordinal model based on the absolute number of doctorless lists is reported in the appendix.

While creating descriptive statistics, patterns of interest in the data became apparent. The findings from these are reported in 0.

Note that all regressions include dummy variables for individual years which are not reported. All regressions were done in Stata 17. Some calculations, tables and figures were completed in Microsoft Excel 365.

Another concern is that of endogenous list length, which only occurred during the project when assessing descriptive statistics. To account for that, a variable was formed by multiplying the overall average list length in the municipality that year with the corresponding number of doctorless lists. This variable was used for one of the regressions in the appendix. The issue is further discussed in the results-section.

2.1. Variable Explanation

Variable/ Suffix	**Explanation**
* _pc	Variable is normalized per 1000 inhabitants
ln_*	Variable is transformed with the natural logarithm
area	Surface area
population	Total population according to FLO dataset
Dist_medical_uni	Driving distance to closest medical education university (Oslo Trondheim Bergen Tromsø)
pplover65_pc	Number of persons 65 years or older per 1000 inhabitants
females_pc	Number of females per 1000 inhabitants
4yearsUni_pc	Number of inhabitants with four or more years of university education per 1000 inhabitants
unemployed_pc	Number of unemployed inhabitants per 1000 eligible inhabitants
immigrants_pc	Number of first- and second-generation immigrants per 1000 inhabitants
mortality65_pc	Number of deaths of persons under 65 years in the year per 1000 inhabitants
avg_list_length	Ratio of population from FLO dataset and number of doctorless lists
Doctorless lists dummy	A dummy that is equal to one if doctorless lists is larger than zero, and takes the value zero otherwise
VG 3 colours	An ordinal variable translating the colours on the VG map into numbers. One is green, two is yellow, and three is red.
Doctorless pop	Number of patients on a list without doctor.
Doctorless pop pc	Number of patients on a list without doctor per 1000 inhabitants
Lists	Number of lists (fastlegeavtaler)
Doctorless lists	Number of lists which are currently not staffed with a GP
Doctorless lists pc	Number of doctorless lists per 1000 inhabitants
Avg inc	Average income in the municipality and year
Med inc	Median income in the municipality and year

Table 1: Explanation of variable terminology and content

2.1. Municipal Amalgamation (Kommunesammenslåing)

In the period from 2001 to 2020, several changes occurred in the organisational structure of Norwegian municipalities. Of particular concern for this project is the municipal amalgamation in 2018-2020, which rearranged 119 municipalities into 47, leaving the country at 356 municipalities (Regjeringen.no, 2020). Changing the structure of the units of observation, the municipalities, will create variation in the data that is not related to the variation of interest and may bias results. It also creates challenges when processing, cleaning and matching data.

The datasets marked with «all municipalities» in Table 4 underwent further processing to match them with the FLO dataset. In this process, the municipalities were merged sequentially via their pre-2019 numbers and names with a table containing both former and recent municipal names and numbers. Two municipalities that were split rather than consolidated were excluded. Consolidated municipalities had their numbers from before 2019 aggregated by two procedures. For count-type variables, rows before the year of merging would consist of the sum of the old municipalities' values. For descriptive statistics, a simple mean was used. This introduces a bias for unevenly sized units being merged, as the data from municipalities with lower population will be given too much weight in the new mean. The majority of mergers took place in 2019 and 2020. Years after 2020 are unaffected. Table 2 shows that the difference in mean average income between affected and unaffected municipalities is comparable before and after the merging.

	(1) avg inc 2017	(2) avg inc 2018	(3) avg inc 2019	(4) avg inc 2020	(5) avg inc 2021
Affected	-7807	-7913	-10059	-5799	-7754
_cons	420432	435142	455243	463277	505273
N	352	354	353	353	353

Table 2: Linear regression of average income on whether a municipality was affected by municipal amalgamation. "Affected" is a dummy variable =1 if the row belongs to a municipality affected by the merger. Avg inc therefore depicts the mean across the average income in municipalities for unaffected municipalities, and the deviation for affected ones in the affected row.

2.1. Models (dependent variables)

The three specifications reported in the results section use three distinct dependent variables: a binary variable (a *dummy variable)* to indicate *whether* a recruitment problem exists, an ordinal variable taking the values 1,2,3 to represent the severity of the problem from the VG data, and a continuous variable based on population of doctorless lists per capita. This section will describe the makeup and purpose of each dependent variable.

The doctorless list dummy ($empty\_list\_adj$) is created for the purpose of measuring *whether* there is a recruitment issue. It is based on the data of vacant GP contracts (fastlegeavtaler). Its advantage is that it captures the existence of the problem well. Disadvantages are that the severity of the problem or its impact on population is not taken into account at all. The variable ignores whether 1% or 100% of the municipality's population is missing a doctor – only that it is missing a doctor.

If the average over all quarters of a year is larger or equal to 1, the variable takes the value 1, otherwise 0. For municipalities with few lists and assuming small fluctuations, this boils down to including only municipalities with at least one doctorless list throughout the entire year. Municipalities that experience larger within-year fluctuations will not be affected by the adjustment.

The VG data represents the self-reported severity of the recruitment issue in said municipalities on a scale from green (1) to red (3). As such, it reports on both the existence and severity of the recruitment problem, with severity referring to how difficult it is to hire doctors. This model serves both for result generation, but also to validate the results of other specifications, as its data and approach are relatively straightforward and not subject to the issue of per-capita bias or skewed distributions of the data.

The third specification is a linear regression of the population on doctorless lists per 1000 inhabitants. Its purpose is to provide a measure that reflects the effect on the population relative to its size. Note that this measure reports high numbers for municipalities with small populations due to one doctor sometimes serving entire municipalities. The share of such affected municipalities is significant – 25% of all municipalities have three lists or fewer (Table 7). It is calculated by dividing the total population of municipality and year by the total number of lists in the municipality and year.

3. Data

3.1. General Practitioner Register (Fastlegeordningen, FLO)

On request, Helsedata.no provided quarterly data on GP coverage and related variables. The dataset includes the number of lists, number of lists without doctor, population registered to lists with and without doctor and other variables for each municipality and quarter from Q2 2001 to Q4/2022. The municipalities in the data are divided according to the borders in 2020. Most datapoints represent a snapshot of the last day of the quarter. The dataset contains 30828 rows of data across 355 municipalities. The municipality 3051 Rollag is not included in the dataset. This dataset excludes citizens which are not on a GP list. The number is however small and can be neglected (Delalic et al., 2023).

For lists without doctor, there are 23244 datapoints clarified as missing in the original data. It is presumed that zeros were coded as missing data. These were replaced with zeros under the condition that a population on a list without a doctor was also zero. This leaves the variable with less than 20 missing values in total, same as the other relevant variables.

The FLO data was received in quarterly segments rather than point measurements at the end of the year. Hence it had to be aggregated to fit the yearly data of the other data sources. To this end, variables were averaged across quarters.

3.2. VG

The Norwegian Newspaper VG has published a series of articles about the recruitment crisis of GPs. Journalists interviewed all municipalities twice, in 2017 and 2021, as to the extent of their recruitment problem. The results are published as articles, including also maps over all municipalities coloured in three[1] different colours (Nave, 2021). Green, yellow and red mark increasing levels of severity. A work-in-progress datasheet coding the colours in the maps of both years to numbers was received from Jonas Met Kinge. The datasheet had 27 individual strings determining seven different colours. This was condensed down to three colours. Some

[1] There are actually five colours on the map, grey and orange. Those indicate municipalities that do not exist in 2018 anymore due to municipal amalgamation, and the meaning of orange is unknown. Orange is assumed to be red, but the impact is negligible.

refinement based on the VG article was made. To match the data to the municipality borders of 2020, values for consolidated municipalities were averaged and then rounded. There is also an article published which included 7 colours, however it was not clearly evident which year the data belongs to and how it relates to the other maps (Sæther & Nærø, 2017). It therefore was neglected.

3.3. SSB

The explanatory variables were sourced from Statistics Norway's (SSB) database. Table 4 depicts said datasets, and Table 3 shows the municipalities which were excluded from the datasets due to various reasons. Some datasets contained data on Svalbard, "Kontinentalsokkel" and other items ("delte og uoppgitte kommuner"), which were excluded from the dataset. Two municipalities were excluded as outliers due to their extreme size. Oslo (0301) for its population and Guovdageaidnu – Kautokeino (5430) for its area.

Name of municipality	Number	Reason
Snillfjord	1613, 5012	Split up rather than consolidated
Tysfjord	1850	Split up rather than consolidated
Rollag	3051	Missing in FLO set
Oslo	0301	Population outlier
Guovdageaidnu – Kautokeino	5430	Area Outlier

Table 3: Excluded municipalities from SSB datasets

Source	Content	Municipal organisation
11618	Employment	2020
09817	Immigration	All municipalities
07459	Demographics	2020
12983	Mortality	2020
05854	Income	All municipalities
09280	Area of land and fresh water	2020
09429	Education	All municipalities

Table 4: Table of datasets taken from SSB. 2020 implies that the data table was processed by SSB for the municipal structure in 2020, while "all municipalities" denotes that the data was exported for each municipality and year as is and processed by the author.

3.4. Other

To account for the change in municipality organisation across the period of 2001-2020, a list of municipality names and numbers provided by Kartverket.no was used (*Kommune- og regionsendringer 2020*, 2020).

4. Results

4.1. Descriptive Statistics

4.1.1. Summary Statistics

Figure 1 shows histograms of population in municipalities. The distribution of population among the relevant Norwegian municipalities is strongly skewed. The majority of municipalities are small, with a median population of 4.709 inhabitants. Table 7 shows summary statistics of variables relevant to the analysis. Table 6 and Table 6 are frequency tables depicting the ordinal variables. The population distribution is skewed and has a fat right tail. The 75th percentile of the included municipalities is at a population of 12 962, the 90th at 28,492, yet there are another 30 municipalities encompassing a large share of the population.

Population is correlated with average list length in the municipality, as can be seen in Figure 2. These figures are also the basis for the decision to leave out the most populous municipality, Oslo. They also give cause for running validity checks with leaving out several more of the most populous cities. There is also indication for a non-linear relationship.

Socioeconomic and demographic variables seem to have relatively close medians and means, implying that their distribution is not as skewed. All dependent variables are heavily skewed in the original data, as there are many years with few municipalities that have a recruitment issue.

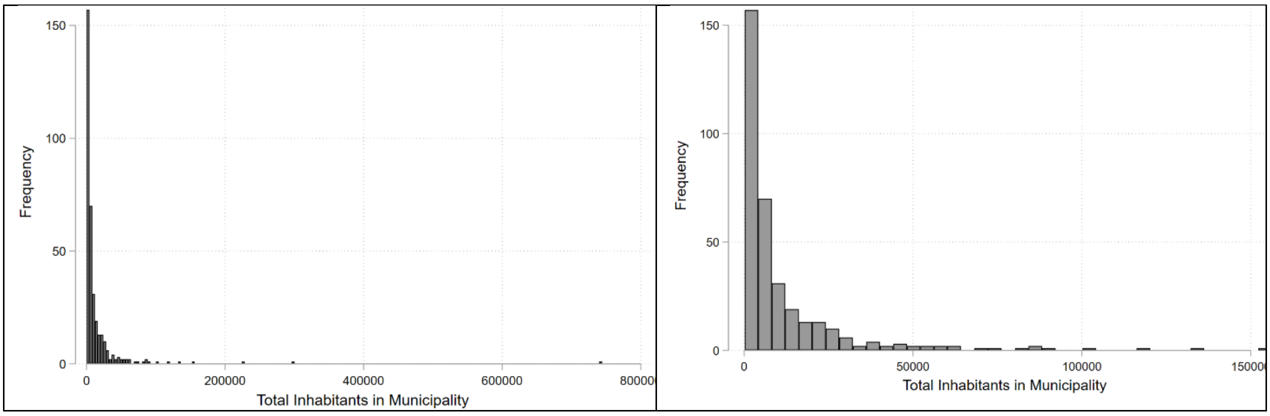

Figure 1: Histograms (bin width 4000) of the population of Norwegian municipalities. Left includes all municipalities, including Oslo. Right diagram is excluding the three most populous municipalities for better visibility of the bulk of observations.

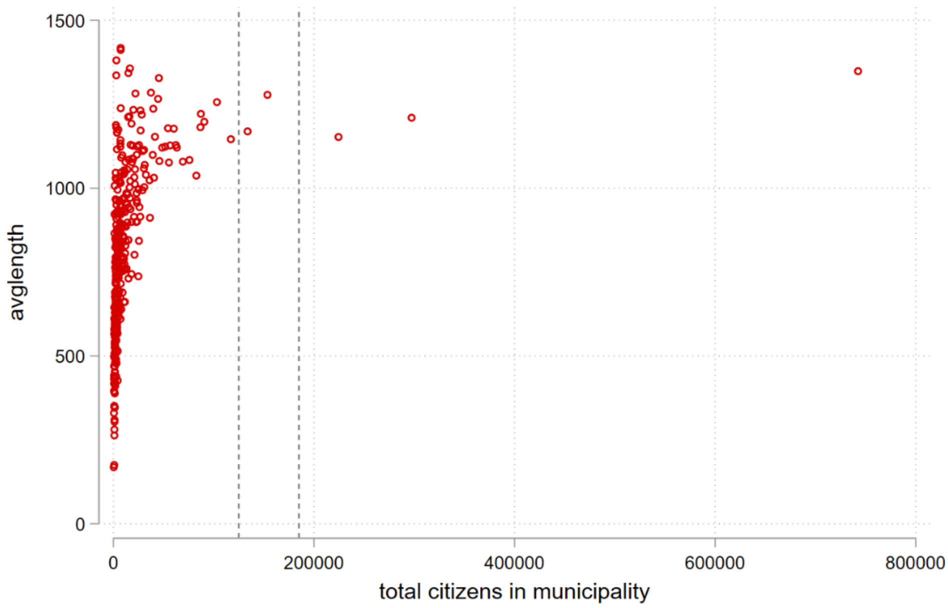

Figure 2: Scatterplot of average list length and total municipal population in year 2021. The dotted lines mark the middle between the third and fifth most populous municipality and the next-smaller one respectively.

	VG 3 Colours			
year	0	1	2	Total
2017	213	134	7	354
2021	197	115	41	353
Total	410	249	48	707

Table 5:Frequency of three-colours VG data

Doctorless List Dummy		
Year	1	Total
2010	48	48
2011	39	39
2012	38	38
2013	42	42
2014	40	40
2015	37	37
2016	30	30
2017	34	34
2018	43	43
2019	57	57
2020	69	69
2021	92	92
Total	569	569

Table 6:Frequency table for the doctorless lists dummy indicator.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max	(6) p25	(7) p50	(8) p75	(9) p90
area	4,228	834.6	803.1	6.280	5,210	272.4	609.8	1,123	1,861
population	4,225	12,787	25,811	126.8	297,175	2,071	4,709	12,962	28,492
Dist_medical_uni	4,228	220.6	158.5	2	866	107	189	292	432
pplover65_pc	4,178	54.14	14.22	20.26	101.4	44.50	53.30	64.43	72.27
females_pc	4,178	491.8	10.45	435.4	529.6	486.8	492.8	498.4	503.5
4yearsUni_pc	4,212	45.51	25.40	4.724	225.5	30.17	39.70	52.43	72.69
unemployed_pc	4,178	325.7	41.23	202.5	453.4	297.0	325.5	353.9	380.3
immigrants_pc	4,225	107.9	51.42	0	354.7	72.94	101.8	134.3	175.3
mortality65_pc	4,178	1.286	0.766	0	10	0.868	1.188	1.569	2.116
avg_list_length	4,225	896.3	273.3	126.8	1,805	699.8	904.3	1,104	1,245
Doctorless lists dummy	4,228	0.132	0.339	0	1	0	0	0	1
VG 3 colours	4,228	0.0814	0.312	0	2	0	0	0	0
Doctorless pop	4,225	113.7	414.0	0	7,962	0	0	0	361.5
Doctorless pop pc	4,225	23.47	93.21	0	1,000	0	0	0	40.08
Lists	4,225	11.86	20.48	1	245.5	3	5	12.25	26
Doctorless lists	4,225	0.250	0.731	0	7.250	0	0	0	1
Doctorless lists pc	4,225	0.0672	0.265	0	3.919	0	0	0	0.148
Avg inc	4,212	402,083	61,781	270,200	881,100	356,175	398,300	440,700	481,400
Med inc	4,212	356,011	46,312	233,900	535,100	321,000	354,900	388,800	416,800

Table 7: Summary statistics of dependent, explanatory, and other variables. FLTR: Observations, mean, standard deviation, minimum, maximum, 25th percentile, median, 75th percentile, 90th percentile

4.1.2. Endogenous List Length

In each year between 0.4 and 8.7% of municipalities have positive values for doctorless lists yet zero population on a doctorless list. Furthermore, the average list length for doctorless lists is smaller on average than the average list length for all lists within a municipality. Table 8 shows the differences in mean list length between doctorless lists and all lists for municipalities with a recruitment problem. Municipalities without recruitment problem were excluded as their average list length is higher on average and would distract from the relevant direct comparison. The table indicates a clear difference between overall and doctorless list length. A paired t-test showed that the two means are significantly different from one another. The table also shows that there are municipalities where the average doctorless list is longer than the overall average list length.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max	(13) p10	(15) p50
(1) All lists length (cond)	754	804.6	263.4	168.1	1,525	427.4	800.2
(2) Doctorless list length (cond)	754	476.9	332.6	0	1,375	0	500.9
(3) Within mcp difference (2)-(3)	754	327.7	336.8	-559.3	1,364	-26.50	261.8

Table 8:Summary statistics for the average list lengths of different sets of lists in municipalities with a recruitment problem. Data ranges from 2010 to 2022. (1): Average length of all lists, conditional on the municipality having doctorless lists (2) Average length of doctorless lists in such municipalities (3) The difference between the two within municipality and year

4.1.3. Development of Recruitment Problem over Time

Figure 3 depicts the development of persons on a list without doctor over time, and highlights the relation to the population distribution among municipalities. The current framework for GP contracts was established in 2001, and the total population without doctor is decreasing until its minimum in 2015- three years after the latest large reform of healthcare services (Samhandlingsreform). From there it rises with increasing slope. The *share of population on doctorless lists* connected-dots-line shows the relative increase to total population. The *share of municipalities with doctorless lists* line states that the number of municipalities with at least one doctorless list has also steadily risen since 2015. In 2022, 100 municipalities had at least one whole list which was without doctor for the entire year.

An increasing number of municipalities faces recruitment issues, and the population on doctorless list is increasing

The years from 2015 to 2022 show an increasing trend in contrast to previous years, and 2020 already marked an all-time-high in terms of both relative and absolute population on a doctorless list. Also, in 2020 there were fewer municipalities affected, but more population was on a doctorless list, indicating a spread of being doctorless to longer lists. Note that this graph is a conservative estimate; it excludes doctorless lists due fluctuations in small municipalities, and does not account for endogenous list length. A similar graph including calculating the doctorless population if every doctor had an average list length can be found in the appendix (Figure 5).

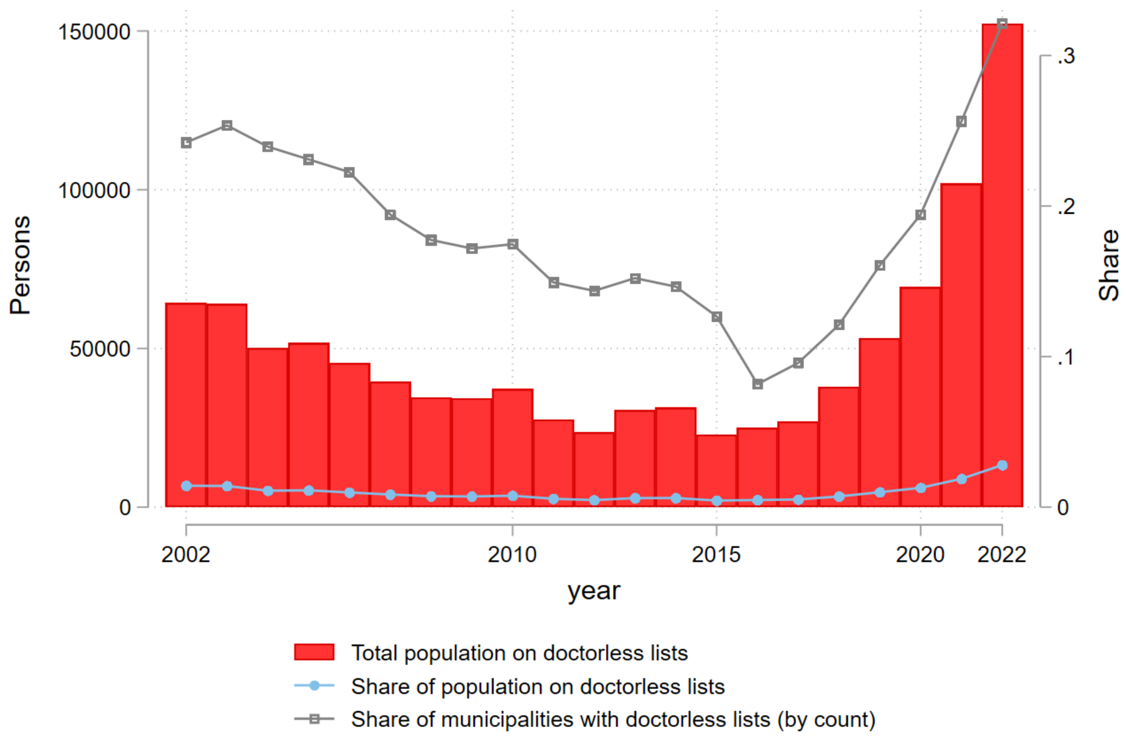

Figure 3: Share of affected municipalities compared with share of affected population and total affected population across time.

Figure 4 shows the mean population of municipalities with at least one doctorless list, and the same for all municipalities to represent national population growth. The conditional mean of municipalities with at least one doctorless list is clearly increasing over time. Furthermore, it increases considerably faster than national population. This indicates that the recruitment problem is present in increasingly large municipalities.

The three largest cities are excluded in one series due to them presenting as outliers in terms of population. Oslo having an open list or not greatly influences mean population among municipalities with a doctorless list, yet it is not that relevant to the point of the graph. A full series has been included for completeness. A drop in 2020 can be observed, which can be attributed to the COVID-19 Pandemic.

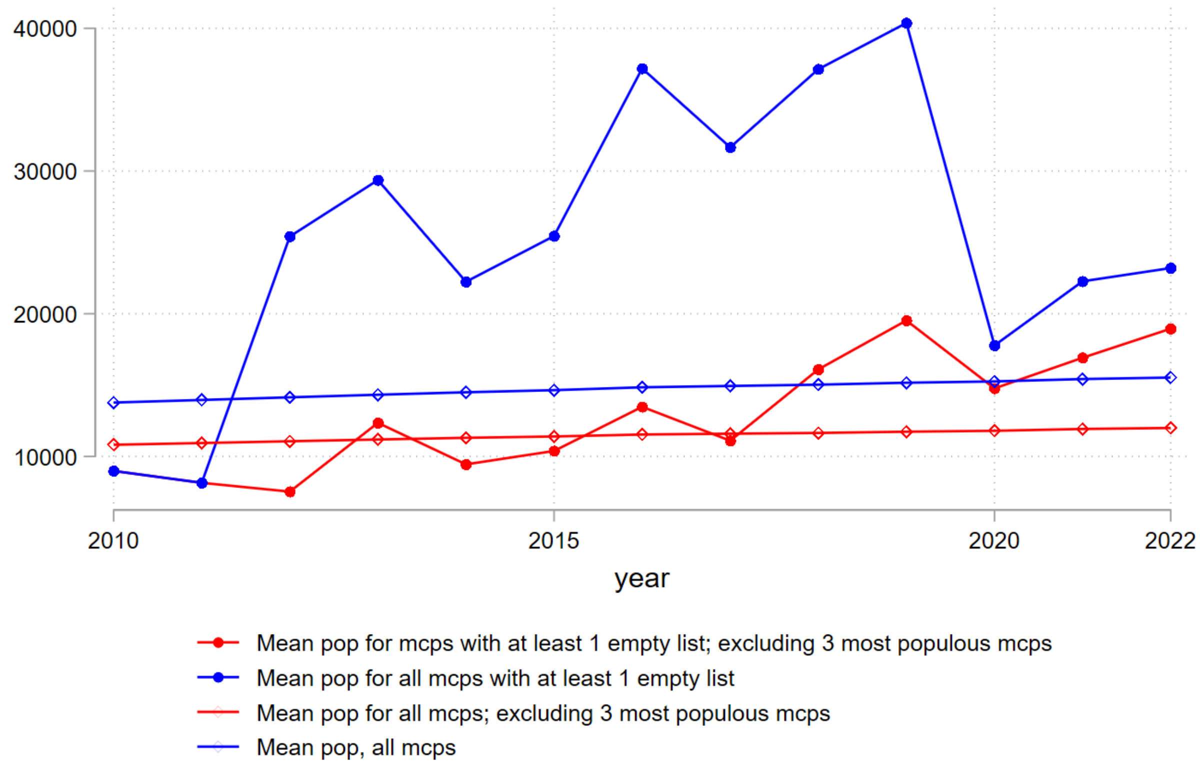

Figure 4: Average population of municipalities with doctorless lists compared to overall population growth; depicted for both all municipalities and excluding the three most populous ones.

4.2. Regression Results

4.2.1. Summary

Table 9 shows the results of the three main specifications using geographical and socioeconomic explanatory variables as well as average list length. Table 10 to Table 12 show specifications on individual geographical variables for the same dependent variables. Table 13 through Table 15 show the same but for socioeconomic and demographic variables. The following text presents the main results.

Higher population is positively associated with recruitment issues

The most prominent result is that ceteris paribus, higher population predicts a higher probability for a municipality to have a recruitment problem. This holds for most specifications, with the exception being the per-capita specification of doctorless population. Table 12 depicts the regression for different sets of explanatory geographical variables. The effect of population seen in the other regression tables is likely overshadowed by the effect of the per-capita measure of the recruitment problem. A very small municipality will be measured for a very large recruitment problem –- *per 1000 inhabitants*. This can explain the negative coefficient of population. Upon inclusion of average list length, the coefficient turns positive.

The result is initially unintuitive, as higher population is associated with more urban areas which again are typically better staffed with doctors. However, this denotes that given two municipalities with hypothetically equal attributes except higher population, the one with higher population is more likely to have a recruitment issue. Furthermore, note that most municipalities are of small population (Table 7) and this effect is to be interpreted in that context.

The extra analysis based on population in categories (Appendix, Table 17) supports the above results. Municipalities with 5000 or more population are more likely to have a doctorless list or have worse self-reported problems with recruitment. The negative relationship between population and population on doctorless lists is also present, but similarly it turns positive upon inclusion of average list length. The same analyses for the period of 2002-2014 rather than 2010-2021 however finds more ambivalent results and negative coefficients (Appendix, Table 20).

Driving distance to medical teaching university is positively associated with recruitment issues

Driving distance to the closest medical teaching university is a consistent predictor of recruitment problems. Its coefficients are significant and positive in most specifications. While there is indication in the literature that decentralization of medical education locations and recruitment issues are associated, this cannot be clearly determined from this result. The variable is liable to capture some of the variation that is due to rurality. It is unclear whether this can be attributed to the distance from the location of teaching as the literature suggests. However, the variable is significant and relevant in models with many other variables that are related to rurality, such as area, population and average list length. This indicates that there is inherent value to the particular variation of the distance to a medical teaching university. Since these universities also coincide with the four major local population centres, it is hard to distinguish whether it is about the distance to education, or if the driving distance to the closest major population centre is just a particularly good proxy for rurality.

Area is individually associated with recruitment issues, but its variation is better explained by other geographical variables and average list length

Area has no significant effect in the VG model. For the remaining specifications, positive coefficients are found, which are also significant in models with few covariates. Particularly the inclusion of average list length reduces the coefficient size for both models.

Population age and share of females do predict recruitment problems, but the sign is unclear.

The relative number of older patients in the municipality is measured as number of inhabitants over 65 years per 1000 inhabitants. It has differing impacts across specifications. For specifications with all variables there is some positive association between older demographics and a recruitment issue and none for share of females (Table 9). The coefficient is significant for dummy and VG model, and positive but non-significant in the doctorless population model. Specifications including different sets of explanatory variables show conflicting effects of older demographics. When only including demographical variables (share of females and share of people over 65), a negative coefficient can be observed for the dummy and VG models. In the absence of geographical variables, older population is negatively associated with recruitment issues.

The effect of an increased number of females on the dependent variables is negative or insignificant in the doctorless population models, and has coefficients of different signs for the doctorless list models. The inclusion of average list length changes the sign to positive while keeping the coefficient significant.

There is overlap in the variation of socioeconomic variables. Education is the most significant variable in models with many covariates

Premature mortality has no significant predictive value for a recruitment issue in any model or specification. The share of unemployed inhabitants has a positive or insignificant relation with the recruitment issues. The coefficient loses significance upon the inclusion of geographical variables in both the dummy and the doctorless population model, but remains significant in specifications with demographic variables and average list length. The share of first- and second-generation immigrants has positive or insignificant coefficients. Its effect wanes upon inclusion of average list length and other variables. Median income has a significant relationship with recruitment issues, but it reduces upon inclusion of average list length. It was excluded from specifications with many variables due to multicollinearity.

The results of the 2010-2021 period are weakly congruent with the predictors of the change in recruitment problem between 2017 and 2021, as well as alternative specifications

Table 16 shows the main models applied to explain the change in the recruitment problem between 2017 and 2021, using the explanatory variable values from 2017. The positive association with recruitment problems found for municipal population and demography can also be found in the difference estimation. The exception is that the model using doctorless population is clearly not finding an effect of population on the change in recruitment problem. In the context of change over time and the positive relationship of population on the recruitment issue, this is consistent with the increasing conditional mean population in municipalities with doctorless lists, reported in Figure 4. Other findings from the main analysis could not be reproduced here. This is likely due to the reduced number of datapoints and statistical power.

Population density is not a good predictor for a recruitment problem

Table 23 shows the three dependent variables in fanned regressions on population density, driving distance to medical university and average list length. Population density quickly becomes insignificant when paired with the two other variables. Splitting it up into area and population individually yields more significant results to explain the data.

Higher average list length is negatively associated with recruitment problems in FLO dataset, but not in VG set

All specifications on the FLO dataset yield negative and largely significant coefficients for the effect of average list length on recruitment problems. The effect in the VG dataset is not as clear. When geographical variables are included, the coefficient is negative. In specifications without geographical variables however, and in particular when paired only with median income (Table 14), a positive coefficient can be observed.

4.2.2. Validation Checks

Several validation checks were executed. All of them confirmed or at least did not significantly contradict the reported results. The results hold for repeating the analysis while excluding the three, five, and ten most populous municipalities in the country. The results on VG hold for using the alternative seven colour model that was received in the preliminary dataset. The regression on the doctorless lists dummy also yields the same results for a linear probability model rather than logistical regression. Coefficients and signs were consistent for using ordered logistical regression on a three-tiered ordinal variable, based on both absolute and per-capita doctorless lists.

4.3. Result Tables

4.3.1. Main Regression tables

	(1) Logit: Doctorless Lists Dummy	(2) Ologit: VG-3	(3) Linear: Doctorless population per1000 inhabitants
ln_area	0.0614	0.239^{**}	-1.227
	(0.0492)	(0.0834)	(1.409)
ln_population	1.377^{***}	0.471^{***}	7.284^{***}
	(0.0884)	(0.124)	(2.142)
dist_medical_uni	0.00143^{***}	0.00131^{*}	0.110^{***}
	(0.000320)	(0.000556)	(0.0102)
pplover65_pc	0.00424	0.00969	0.440^{**}
	(0.00472)	(0.00799)	(0.135)
females_pc	-0.00418	-0.000465	-0.172
	(0.00549)	(0.00953)	(0.164)
mortality65_pc	-0.0202^{***}	-0.00337	-0.125
	(0.00315)	(0.00407)	(0.0789)
unemployed_pc	-0.000349	0.00269	0.0445
	(0.00136)	(0.00226)	(0.0382)
immigrants_pc	0.00321^{**}	0.000823	0.0177
	(0.00118)	(0.00155)	(0.0352)
4yearsUni_pc	-0.0918	0.0520	-1.314
	(0.0686)	(0.120)	(1.920)
avg_list_length	-0.00581^{***}	-0.00120^{*}	-0.0489^{***}
	(0.000378)	(0.000532)	(0.00812)
_cons	-6.481^{*}		49.02
	(2.664)		(77.51)
N	4159	694	4159
R^2			0.081

*Table 9:Main results table. (1) Logit on doctorless lists indicator dummy. (2) Ordered logistical regression on 3-color VG data. (3) Linear regression on doctorless population per capita. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to them presenting as outliers being Outliers in population and area respectively. Standard Errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001*

4.3.2. Fanned Regressions Geographical variables

Doctorless lists dummy	(1)	(2)	(3)	(4)	(5)
ln_area	0.276***			0.214***	0.0886*
	(0.0436)			(0.0443)	(0.0444)
ln_population		0.122***		0.260***	1.123***
		(0.0338)		(0.0377)	(0.0680)
dist_medical_uni			0.00215***	0.00260***	0.00137***
			(0.000244)	(0.000271)	(0.000289)
avg_list_length					-0.00582***
					(0.000363)
_cons	-3.321***	-2.615***	-2.079***	-5.781***	-6.902***
	(0.315)	(0.325)	(0.155)	(0.475)	(0.477)
N	4228	4225	4228	4225	4225

*Table 10: Logit-Regression on doctorless-list-indicator dummy variable. Different specifications for geographical variables including specification without average list length. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to them presenting as outliers being Outliers in population and area respectively. Standard errors in parentheses; *- p < 0.05, ** p < 0.01, *** p < 0.001*

VG - 3	(1)	(2)	(3)	(4)	(5)
ln_area	-0.0688			-0.0430	-0.0810
	(0.110)			(0.124)	(0.125)
ln_population		0.501***		0.482***	0.634***
		(0.104)		(0.110)	(0.159)
dist_medical_uni			-0.00192*	-0.000395	-0.000758
			(0.000906)	(0.000952)	(0.000991)
avg_list_length					-0.00119
					(0.000873)
/					
cut1	0.701	5.522***	0.729***	5.003***	4.947***
	(0.693)	(0.935)	(0.217)	(1.303)	(1.276)
N	703	701	703	701	701

*Table 11: Ordered Logit regressions on VG 3-color data. Different specifications for geographical variables including specification without average list length. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to them presenting as outliers being Outliers in population and area respectively. Standard errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001*

Doctorless pop pc	(1)	(2)	(3)	(4)	(5)
ln_area	4.365***			1.693	0.237
	(1.284)			(1.264)	(1.276)
ln_population		-9.764***		-4.368***	3.243*
		(1.114)		(1.165)	(1.621)
dist_medical_uni			0.138***	0.124***	0.108***
			(0.00876)	(0.00946)	(0.00974)
avg_list_length					-0.0535***
					(0.00796)
_cons	2.012	112.7***	-1.242	28.60*	27.36*
	(9.422)	(10.71)	(5.180)	(13.74)	(13.67)
N	4225	4225	4225	4225	4225
R^2	0.012	0.027	0.064	0.068	0.078

*Table 12:Linear regression on doctorless population per capita. Different specifications for geographical variables including specification without average list length. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to them presenting as outliers being Outliers in population and area respectively. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

Doctorless list dummy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln_area								0.0614
								(0.0492)
ln_population								1.377***
								(0.0884)
dist_medical_uni								0.00143***
								(0.000320)
pplover65_pc	-0.00269	-0.0224***					-0.0226***	0.00424
	(0.00312)	(0.00365)					(0.00401)	(0.00472)
females_pc	-0.00932*	0.0137**					0.0170***	-0.00418
	(0.00418)	(0.00466)					(0.00485)	(0.00549)
mortality65_pc			-0.00772	-0.0766			-0.0819	-0.0918
			(0.0599)	(0.0566)			(0.0582)	(0.0686)
unemployed_pc			0.00166	0.00272*			0.00384**	-0.000349
			(0.00116)	(0.00116)			(0.00120)	(0.00136)
immigrants_pc			0.00364***	0.00280**			0.00225*	0.00321**
			(0.000995)	(0.000995)			(0.00107)	(0.00118)
4yearsUni_pc			-0.00597**	0.00389			0.000174	-0.0202***
			(0.00214)	(0.00229)			(0.00245)	(0.00315)
med_inc_knok					-0.00329	0.00538**		
					(0.00172)	(0.00193)		
avg_list_length		-0.00227***		-0.00175***		-0.00182***	-0.00241***	-0.00581***
		(0.000208)		(0.000191)		(0.000183)	(0.000224)	(0.000378)
_cons	3.155	-5.073*	-2.183***	-1.090**	-0.619	-1.495**	-7.830***	-6.481*
	(2.093)	(2.211)	(0.401)	(0.415)	(0.521)	(0.532)	(2.367)	(2.664)
N	4178	4175	4159	4159	4212	4209	4159	4159

*Table 13: Logit-Regression on doctorless-list-indicator dummy variable. Different specifications for socioeconomic and demographic variables including specification without average list length. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to them presenting as outliers being Outliers in population and area respectively. Standard errors in parentheses; *- p < 0.05, ** p < 0.01, *** p < 0.001*

Ologit VG-3	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln_area								-0.115
								(0.145)
ln_population								0.781***
								(0.213)
dist_medical_uni								-0.000439
								(0.00105)
pplover65_pc	-0.0191*	-0.0112					-0.00270	0.0164
	(0.00950)	(0.0109)					(0.0121)	(0.0138)
females_pc	0.0270	0.0155					0.00954	-0.0113
	(0.0138)	(0.0159)					(0.0163)	(0.0180)
mortality65_pc			-0.189	-0.222			-0.222	-0.240
			(0.210)	(0.225)			(0.228)	(0.248)
unemployed_pc			0.000632	0.000311			0.000313	-0.00280
			(0.00345)	(0.00350)			(0.00355)	(0.00394)
immigrants_pc			-0.000542	-0.000303			-0.000186	-0.000351
			(0.00209)	(0.00210)			(0.00220)	(0.00237)
4yearsUni_pc			0.0156**	0.0114*			0.0106	-0.000646
			(0.00501)	(0.00552)			(0.00581)	(0.00673)
med_inc_knok					0.0129**	0.00791		
					(0.00499)	(0.00559)		
avg_list_length		0.000962		0.000966		0.00113*	0.000757	-0.000964
		(0.000674)		(0.000579)		(0.000572)	(0.000695)	(0.000904)
N	698	696	694	694	701	699	694	694

*Table 14: Ordered Logit regressions on VG 3-color data. Different specifications for socioeconomic and demographic variables including specification without average list length. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to them presenting as outliers being Outliers in population and area respectively. Standard errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001*

Doctorless pop pc	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln_area								-1.227
								(1.409)
ln_population								7.284***
								(2.142)
dist_medical_uni								0.110***
								(0.0102)
pplover65_pc	0.668***	0.173					0.107	0.440**
	(0.100)	(0.113)					(0.125)	(0.135)
females_pc	-0.872***	-0.267					-0.204	-0.172
	(0.139)	(0.152)					(0.157)	(0.164)
mortality65_pc			2.308	-0.394			-0.460	-1.314
			(1.951)	(1.939)			(1.940)	(1.920)
unemployed_pc			0.0965**	0.131***			0.130***	0.0445
			(0.0374)	(0.0370)			(0.0373)	(0.0382)
immigrants_pc			0.0622	0.0422			0.0397	0.0177
			(0.0332)	(0.0328)			(0.0345)	(0.0352)
4yearsUni_pc			-0.433***	-0.107			-0.0770	-0.125
			(0.0640)	(0.0696)			(0.0729)	(0.0789)
med_inc_knok					-0.532***	-0.250***		
					(0.0553)	(0.0611)		
avg_list_length		-0.0595***		-0.0649***		-0.0601***	-0.0604***	-0.0489***
		(0.00647)		(0.00586)		(0.00581)	(0.00669)	(0.00812)
_cons	423.7***	208.3**	6.026	51.85***	185.1***	159.8***	142.5	49.02
	(69.32)	(72.53)	(12.92)	(13.39)	(16.90)	(16.87)	(75.84)	(77.51)
N	4175	4175	4159	4159	4209	4209	4159	4159
R^2	0.030	0.049	0.025	0.053	0.030	0.054	0.053	0.081

Table 15: Linear regression on doctorless population per capita. Different specifications for socioeconomic variables including specification without average list length. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to them presenting as outliers being Outliers in population and area respectively. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.3.3. Difference across time with main specs

	(1) Deterioration Empty Lists Dummy	(2) Deterioration VG Dummy	(3) Change in doctorless pop per capita
main			
ln_area	-0.0327	-0.115	-0.771
	(0.155)	(0.145)	(6.911)
ln_population	0.853***	0.781***	4.892
	(0.230)	(0.213)	(10.60)
dist_medical_uni	-0.00000565	-0.000439	0.0657
	(0.00106)	(0.00105)	(0.0504)
pplover65_pc	0.0421**	0.0164	1.339*
	(0.0146)	(0.0138)	(0.677)
females_pc	-0.0282	-0.0113	-0.110
	(0.0181)	(0.0180)	(0.845)
4yearsUni_pc	-0.00333	-0.000646	-0.0105
	(0.00725)	(0.00673)	(0.368)
unemployed_pc	0.00201	-0.00280	-0.0186
	(0.00409)	(0.00394)	(0.194)
immigrants_pc	0.00158	-0.000351	0.0727
	(0.00256)	(0.00237)	(0.122)
mortality65_pc	-0.0981	-0.240	-1.092
	(0.232)	(0.248)	(10.15)
avg_list_length	-0.000696	-0.000964	-0.0214
	(0.000955)	(0.000904)	(0.0433)
_cons	3.001	-0.305	-18.25
	(8.447)	(8.318)	(397.1)
N	344	345	342
R^2			0.030

*Table 16: Regression on the change of the dependent variables between 2017 and 2021, regressed on 2017 values of explanatory variables. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to them presenting as outliers being Outliers in population and area respectively. Standard errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001*

5. Discussion

5.1. Summary

This project finds a robust positive relationship between population and the existence of a recruitment problem. This result is in contradiction to previous studies (Abelsen et al., 2020; Delalic et al., 2023). Several robustness checks do support the result. Descriptive analysis shows an increasing trend in both affected municipalities, overall doctorless population and in the mean population among affected municipalities. Rurality measured as driving distance to major population centres is a good predictor and is positively associated with recruitment problems. The effects of demographic and socioeconomic factors are not as clear, but largely as expected. This project also finds evidence for endogenous list lengths, to the point that many doctorless lists are empty.

5.2. Strengths and Weaknesses

On one hand, compiling and analysing the dataset was challenging due to its complexity and noise. Processing data from municipal amalgamation into valid, usable data was difficult and a learning experience. The techniques used for amalgamation are favour simplicity over accuracy due to time constraints. The effect of it is however limited, as demonstrated on income values. Getting an overview over the patterns and relations in the data took time, and it is not certain that the understanding gained is correct. There may be mistakes and weaknesses that are not known or remain unreported. There were also improvements and weaknesses that remained due to scope constraints. On the other hand, many different specifications and models were calculated, and the results have proven robust to these tests.

5.2.1. Strengths

This thesis used a variety of dependent variable transformations and methods to describe and analyse the relation between recruitment issues and municipal attributes. While all models and specifications have flaws, the generation of several dissimilar approaches generated robust results in spite of the challenges.

The use of three different perspectives on the recruitment problem gives a well- rounded and robust picture of the results. The three perspectives are Existence, Self-reported, and Severity of the recruitment problem. Particularly the inclusion of self-reported data as a very dissimilar data source and type compared to the FLO dataset gives the results extra robustness. It is not subject to many of the weaknesses of data generation and processing in the above section.

The results of simple descriptive statistics provide data on a relevant trend in access to healthcare and recruitment issues, and how it is distributed across municipalities. Although the analysis is simple, it is robust against most of the problems that regression analysis bears and yet provides interesting results.

5.2.2. Weaknesses

The biggest issue is the skewed nature of the distribution of the recruitment problem across municipalities, as well as population and area. These problems are alleviated by using logarithmic transformation, binning into binary and ternary ordinal variables, and using self-reported ordinal data as comparator. In particular the dummy specification on whether a municipality has a doctorless list is reliable, as it ignores all considerations of severity of the problem. The linear regression on doctorless population per capita on the other hand is likely to be most affected by it.

Normalizing variables to per-capita values came with its own problem. Both doctorless lists and population on doctorless lists were problematic when transformed as per 1000 inhabitants. The doctorless list value would be very small and highly correlated to average list length. The population on doctorless list value would experience very high volatility for small municipalities- a municipality with 700 inhabitants and one doctorless list has 1000 doctorless list patients- is that really “worse” than a municipality with 3000 out of 4000 inhabitants on a doctorless list? To account for this problem, a multitude of dependant variables and transformations was used.

Multicollinearity was addressed by removing income from models with other socioeconomic variables. VIF analysis showed high values for income only, with all other values being below three. Other weaknesses which are hard to address are omitted variable bias and limited independent variance in only 355 municipalities. Some data is missing for unknown reasons, both from FLO and SSB datasets.

This project set out as an exploratory work, trying to find as much information as possible. While other scientific papers start with a hypothesis, then define a model and test it, this project tested many models and reported the ones that carried relevant information. This was important as no such analysis had been attempted before for Norwegian municipalities, but it also introduces bias due to the increased share of undocumented and maybe even unconscious decisions taken by the author.

Some features were left out due to the author not being aware of it. The issue of scaling variables for the regression was not considered. This would have improved regression quality but also the interpretation of coefficients. For example, normalizing the coefficient into ordinal variables based on one standard deviation deltas would have been useful. The author also failed to include the centrality index (SSB, 2020) due to not knowing about it until it was too late. Its inclusion would have improved comparisons to other, especially recent, studies, and provided an alternative predictor for rurality.

Another weakness may be the proxy quality of GP list registry data to represent recruitment problems. A recent government report finds that patients on lists without doctor only experience a relatively small reduction in both contacts and continuity with a GP (Delalic et al., 2023). This indicates that access to primary healthcare is more complex than the binary question of whether a list is staffed or not. The results of this project are somewhat robust against this problem by using self-reported data in parallel. Said data is however noisier and does not support all the results found from the FLO dataset.

5.2.3. Low predictive power

Overall, the predictive power of the model was low. Reported regression coefficients do not exceed 0.1, and have not exceeded 0.2 during any analysis made in this project. The first possibility is that the occurrence of recruitment problems is simply just *random.* For illustration, it is conceivable that Norwegian municipalities outside the two most urbanized counties are equally unattractive, and the reason why some have recruitment issues is simply due to idiosyncratic retirement age of the last generation of GPs. However, the results show that there are statistically significant relations between attributes and recruitment issues. This indicates that there is more to the occurrence of recruitment issues than just chance.

Another possibility is the specification of the functional forms. During this project, binning, logarithmic transformations and per-capita normalization were used for explanatory variables. Binning into binary and ternary variables, and per-capita normalization were used for the dependent variables. Values Population on doctorless lists per capita in the data shrink with increasing population. This suggests that a non-linear functional form may have been suitable. Models with binned dependent variables offer some robustness to these issues. However, in hindsight it may have been desirable to also break more explanatory variables into bins to test for such issues.

Another explanation for low explanatory power is the temporal dimension. Attributes in year T may predict a recruitment effect in year $T + t$ rather than in year T. Causes for this may be the structural effects of policy only take effect after a while. None of the main models are able to pick up such effects. The model depicting differences across time however could, but did not garner significant results. Its weaknesses are that it only includes one year of data and one period of change, namely the years 2017 to 2021.

Finally, this project may have simply failed to include the right variables. It is conceivable that there exist other variables out there which perfectly predict the recruitment problems. First and foremost, inclusion of the centrality index (SSB, 2020) would have contributed to better comparability with the recent government reports, through a standardized measurement of rurality. Other variables were included in the dataset but not reported in final regressions due to various reasons. These included data on the usage of surface area, share of population with access to recreational terrain and the number of cinemas. Some of these variables yielded significant coefficients in certain models and specifications. Reasons for leaving them out included missing observations, missing years, suspicion of corrupted data with too little time to clean it up and problematic aggregation caused by municipal amalgamation. With ample time and resources, including these areas may yield better predictions. Another area of interest is to investigate the distance of municipalities to the decentralized medical education locations and how it interacts with the driving distance to the major ones located in population centres.

5.3. Comparison to previous studies

5.3.1. Abelsen et. al. Duration of general practitioner contracts

Abelsen et Al. (2015) find that less populous municipalities' lists are doctorless for longer periods, and have more numerous doctorless lists. That can be interpreted as a negative relationship between population and recruitment problems in municipalities. In contrast, this project finds a positive relationship between the *existence* of a recruitment problem and municipal population. It also finds a relationship between population and number of doctorless list patients, whose sign is conditional on the inclusion of list length. These results hold for both specification of the population variable, namely as three-tiered set of binary variables, or as continuous variable.

Abelsen et. al. report a table indicating the share of patients on doctorless lists among all list patients within each population bracket –thus, doctorless population per capita within the bracket. They find that this share is inversely correlated to the size of the population bracket (Abelsen et al., 2015). This indicates a negative correlation between population and patients on doctorless list. This is supported by the results in this project. Without controlling for average list length, a negative relation is found. Upon its inclusion however the coefficient turns positive. A possible explanation for this is that in doctorless population per-capita specifications, small municipalities may report very high doctorless population (see 4.1.14.2.1., 2nd paragraph for an example).

One may speculate that controlling for list length somewhat brings the analysis more towards the absolute number of doctorless patients. Compare a municipality with 500 out of 1000 inhabitants without a doctor has a list length of 500, and a municipality with 1000 out of 5000 and a list length of 1000. Reporting this per capita will yield 50% and 20% respectively, even though the larger municipality has effectively the same number of doctors missing and in absolute terms more doctorless population. Yet it would report with a lower value in the doctorless population per capita variable. The primary difference is list length, and controlling for it should alleviate per-capita exaggeration.

This project robustly finds that the number of municipalities with at least one doctorless list within the population brackets does not support Abelsen et. al.'s findings. Models 1 and 4 in Table 17 show that municipalities in the smallest population bracket are less likely to have at least one doctorless list. Table 19 shows that the absolute frequency of municipalities with at least one doctorless list is about the same for all population brackets. However, smaller municipalities are so much more numerous, explaining the regression results.

Another difference are the analysed periods. Abelsen et. al. analysed the period of 2001 until 2014, while this project focuses on 2010-2021. Using the methodology of this analysis on the earlier period yields more unclear and negative relations between population and recruitment issues as it does for the later period. The simplest explanation is then that the facts have changed between periods. This implies that something has shifted in the way GPs allocate themselves to municipalities that has changed the effect, such that more populous municipalities are now more likely to struggle with recruitment than before. The reasons for this could be many, ranging from cultural changes in what young medical students desire in life, the bureaucratic changes to the GP profession in Norway, or that students from rural areas have better access to medical studies today.

An alternative explanation may be that the quality of doctorless lists as a proxy for recruitment problems has improved since 2010. It is conceivable that delayed adaptation and establishment of the GP list framework was a major contributor for the logging of doctorless lists in the early period. This would not necessarily imply a recruitment or healthcare access problem. A correlation with population can be explained through the slower adaptation to bureaucratic changes in rural areas. Once this effect faded due to eventual adaptation, other effects may become dominant and could now be found in the data.

5.3.2. Goddard et al. Findings

Goddard et al. (2010) report that population density has a positive association with GP supply in Scotland and England in 2006. This is in contrast to the findings in this project. Population density is inherently negatively associated with a recruitment problem in the FLO data. However, its variation is better explained by measures of rurality. Larger population, however, does predict a recruitment problem both in FLO and in VG data. This indicates a positive relationship between population density and recruitment issues, which translates to a negative relation to local GP supply. Note that the units of observation used in the paper – primary care trusts – have less dispersed population density and are considerably larger than the average Norwegian municipality.

Regarding the share of unemployed persons, the findings are contradictive. This paper finds a positive or insignificant effect on recruitment problems, while Goddard et al. found a positive effect on local GP supply. The weak significance in both findings indicates that uncaptured variation may be an underlying reason for the effect. One possible explanation is the general correlation of prosperity in the unit of observation, which is likely to be of different nature with units of observation differing strongly in population. It is also conceivable that the relation between unemployment and GP recruitment issues is different in the two regions.

Regarding health, Goddard et al. find a positive effect of bad health on GP supply when singling out the variable. This project finds no significant relation. This may be due to the weaker representation of not-good health that is mortality in persons under 65 years. It was however not possible to use better data such as BMI, obesity or self-reported habits, as this data was often omitted from small municipalities due to privacy. Small municipalities are important to this project as they are a-priori expected to have recruitment problems. Omitting them would have introduced bias for one of the major questions in this thesis. Obtaining approval for aggregate versions of the data was not within scope of the project.

5.3.3. Findings from the Status of Norway's Primary Healthcare report

A recent report on the status of Norway's primary health care system (Allemennlegetjenesten) recommends the increase of the renumeration per list patient for GPs. This is reasoned with current lack of list capacity. Additionally, increased income from listed patients will strengthen potential and incentive to use other methods like more personal and digitalisation to increase supply of list capacity (Telle et al., 2023). The current project finds that shorter average list length is a predictor for recruitment issues. This can be conceived as doctors in rural areas struggling to serve many patients due to travel time. Enabling GPs in areas with low list length may make the areas both better supplied with list capacity and increase their attractiveness for recruitment.

5.3.4. Findings from the Continuity in Primary Healthcare report

Delilac et al. in their recent report find that recruitment issues are worse in non-central areas and that the situation is largely constant with data stretching to the end of 2020 (Delalic et al., 2023). Their findings on the influence of rurality are consistent with the findings in this project. Driving distance to the closest major population centre is a good predictor for recruitment problems across all models. Regarding the lack of a trend in overall population share, the statement may have been arguably correct at the time. However, in the two added years of data, the share of population on doctorless lists has increased substantially. The results in Figure 3 show a clearly increasing trend since 2015, in particular since 2020. Delilac et al. report an overall share of doctorless population of 2% for 2020. This dataset reports 1.28% for 2020 and 1.88% and 2.78% for 2021 and 2022 respectively. This discrepancy is worrisome and investigation of its cause would be interesting. However, the sign of the difference between this project's results and Delilac et al.'s report only reinforces the relevance of an increasing trend in doctorless population. It is also worth noting that the result of increasing conditional mean population among municipalities with a recruitment problem indicates that the containment of the problem to rural areas is declining.

Note that the report had some methodological differences in dealing with lists in unnamed municipalities, which however should not have an effect on the numbers of this magnitude.

5.3.5. Policy Change: Adjusted Capitation Payment Based on List Characteristics

GPs in Norway will, from 1st May 2023 onwards, receive their list-based renumeration in rates adjusted for population characteristics. Among other characteristics, the renumeration will increase for female and older list patients, as well for lists for municipalities with a share of more than 28% of persons with elementary school (barneskole) as their highest education (HELFO, 2023). This project finds that municipalities with a higher share of female inhabitants have less of a recruitment problem, while those with an older demography are more likely to face a recruitment problem. While this project uses persons with 4 or more years of higher education per capita for the results chapter, Table 24 in the appendix reports specifications including persons with elementary school as their highest education. The coefficients are significant and positive, indicating that municipalities with many persons with little education are more likely to have a recruitment problem.

The policy change is in line with both common theory as well as this project's findings regarding age and education-based adjustments. In the case of the female share of inhabitants, however, the policy is in opposition to the results of this project. A possible explanation is that there are two effects of opposing signs in the data. One effect could be the increased healthcare demand presented by women, increasing the demand for doctors and creating work for GPs that is only partially rewarded through list financing compared to a list patient who creates little activity. The other mechanism could be that the share of females is a proxy for a well-functioning municipality and as such is a better place to have a GP practice. Competing effects would also explain the differing levels of significance, as the models represent different variations of similar but not identical problems. In one specification, one effect may dominate, whereas they may be even in another model, yielding a non-significant coefficient. Note that there also is a significant difference between an increased renumeration based on the individual list patient and the municipality in which the practice is located.

5.4. Endogenous list length

This project finds evidence that list length is endogenous depending on the list being staffed or not. It is unlikely to be caused by an error in the data. One indicator for it not being due to a data error is the absence of municipalities with doctorless populations and fully staffed lists. If such cases were to exist, the error would appear both ways, a data error would be more likely. Given the intuitive explanation available for the phenomenon, data error is not the most likely explanation for the phenomenon.

Some municipalities have negative differences. This implies that doctorless lists are longer than the average list in that municipality. One could speculate this may occur only in small municipalities. An alternative theory is that it occurs in municipalities where lists are imperfect substitutes for one another. An example could be an area with multiple local population centres, which are geographically divided. It is an interesting topic of research to investigate the potential of endogenous list length as a mitigation mechanism. Telle et. Al. find in their report that patients on doctorless lists only have a small reduction in their healthcare utilization. As such, endogenous list length may present a patient coping mechanism for missing GPs. In that case, the reasons why some municipalities see endogenous list length and others do not may be of interest as a direction of research.

Endogenous list length may lead also lead to misrepresentation of the recruitment problem in two ways. When considering doctorless population as indicator, endogenous list length "hides" the cost of this patient adaptation. Switching to available staffed lists may reduce the access to healthcare due to for example longer waiting and travel times. An account of the cost of switching GP is given by Iversen & Lurås (2011). As such, endogenous list length leads to an underreport of the effect of the recruitment problem. This is to be considered when reviewing the model using population on doctorless list per capita, found in the main regression results.

On the other hand, using the doctorless lists as single indicator for the recruitment problem not only ignores the effect it has on the population, it also ignores the positive effect of endogenous list length. The loss of access to healthcare is shown to be limited for patients on doctorless lists (Delalic et al., 2023). Municipalities whose patients have the option to substitute their lists may be less vulnerable to losing access to healthcare and GP services.

One way to further investigate endogenous list length could make use of an individual list's history- data that is available to FLO. It is conceivable that a longer a list stands doctorless, the more patients will leave the list. Future analysis into this topic could employ a time series analysis of individual lists to test this hypothesis.

5.1. Other

This project finds that rural areas are more likely to have a recruitment issue, which is in line with expectations. An interesting finding here is that driving distance from major population centres is a better predictor than population density.

Higher share of educated people is commonly associated with socioeconomically better functioning municipalities, and also associated with less rurality. Finding that higher shares of well-educated inhabitants is associated with a lower probability of a recruitment issue is consistent with this expectation. Notably, we do find the opposite in one of the fanned regressions in the VG data (Table 14). The variation in the VG data is liable to be quite different due to its self-reported nature. Municipalities that do not show an urgent recruitment problem in the FLO data may still struggle to attract and contract qualified candidates, or at least maintain the impression that they are struggling.

Several of the fanned regressions show that coefficients change their sign upon the inclusion of other variable groups. This can be explained by two-fold effects. For example, age may be correlated with population and rurality. Inclusion of geographical variables will then explain that part of demographical variation better, producing a coefficient with a different sign for the remaining effect. It can be interpreted as a change in demography while geographic variables are kept unchanged. This phenomenon appears frequently in the fanned regressions, and the interpretation of these many differences is sometimes difficult and time consuming. Due to time constraints, this project settles on providing the tables of fanned regressions to the reader as basis for future research.

One big question mark is the inclusion of average list length in the regressions. It has influence on the effect of other variables and has itself significant and large coefficients. It is related to the dependent variables and correlated, but not extensively. The highest correlation coefficient found with the dependent variables in the FLO dataset is 0.35 with doctorless lists per capita. It is strongly correlated with population, however. There are two basic interpretations to this. Either, average list length is a result of natural municipality attributes. For illustration, in very spread-out municipalities a doctor serves fewer patients due to longer travel times, reducing the number of patients on their list. This interpretation would imply inherent usefulness as a predictor and warrant its inclusion. The other interpretation is that average list length is associated with the quality of a municipality that this study attempts to proxy for and will therefore overshadow other socioeconomic variables. This question came up late during the project, and is quite fascinating. There is little literature on the subject and further investigation of it unfortunately exceeds the scope of this project.

6. Conclusions

This project aimed to investigate which municipality attributes predict the municipality to have a problem recruiting general practitioners. Employing two very different datasets and different methods and variable transformations, some predictors were identified. The dataset was also used to create relevant descriptive statistics about the situation of access to primary healthcare in Norwegian municipalities.

Descriptive statistics have shown an increasing trend in doctorless patients in Norway from 2015, and that the average size of affected municipalities is increasing. This trend is particularly strong in the years 2020-2022 and there is no indication of an end. This is in contradiction to the latest report on this issue which found stagnation in 2020. While there are policies to address some of the problems coming into effect as this is written (HELFO, 2023), the trend is worrisome.

As to what should be done about it, this project also offers some insight. The best predictors of a municipal recruitment problem are population, rurality, demography, education and average list length, with average list length being a difficult entry to the list. Population as a predictor offers little in terms of actionability. The results on demography, or at least age, and education confirm the direction of the aforementioned policy change. The strong association between lower average list length and recruitment problems indicates that the proposed policies set to increase average list length in troubled areas is indeed suitable to improve the access to healthcare in rural municipalities.

This project also offers openings for interesting directions of further research. The data on Norwegian municipalities and their recruitment issues is complex and this project highlighted aspects that led to more questions rather than providing answers. Topics for future research include the strong relation between average list length and recruitment issues, other predictive variables which were left on the cutting floor due to various constraints, the investigation of the effect of decentralized medical teaching locations and more advanced intertemporal analysis of the recruitment issue.

In conclusion, this study did establish that using municipal attributes to explain recruitment issues has some potential. However, there remain challenges and the field is largely unexplored. The author hopes that this thesis will serve to develop a better understanding of the variation that, so far, only enjoys a partial explanation.

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8. Appendix / Alternative specifications

8.1. Explanatory variable population in categories

	(1) Doctorless lists dummy	(2) VG-3	(3) Doctorless population pc	(4) Doctorless lists dummy	(5) VG-3	(6) Doctorless population pc
main						
pop_20000	0.416***	0.683***	-27.34***	2.404***	1.421***	5.275
	(0.119)	(0.206)	(4.049)	(0.184)	(0.279)	(4.903)
pop_5000	0.345***	0.182	-14.85***	1.675***	0.657**	7.010
	(0.0976)	(0.171)	(3.193)	(0.136)	(0.209)	(3.680)
pop_0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
avglength				-0.00419***	-0.00174***	-0.0768***
				(0.000263)	(0.000423)	(0.00671)
_cons	-1.752***		38.23***	1.241***		99.44***
	(0.149)		(5.099)	(0.231)		(7.339)
N	4228	703	4225	4225	701	4225
R^2			0.021			0.051

*Table 17:Time period: 2010-2021 (VG only 2017 and 2021): Fanned regression for grouped population variable on Recruitment problem dummy (logistical regression), VG 3 colour data (ordered logistical regression,) and doctorless population per capita (linear regression). Explanatory variables represent dummy variables of population size: Larger than 20.000, between 5.000 and 19,999, and less than 4.999; Standard errors in parentheses p < 0.05, ** p < 0.01, *** p < 0.001*

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
pop_0	4,236	0.516	0.500	0	1
pop_5000	4,236	0.320	0.466	0	1
pop_20000	4,236	0.164	0.370	0	1

Table 18: Summary statistics of the population dummy variables.

	Pop <5.000	5.000<= Pop <20.000	20.000 < Pop	Total
Fully Staffed	155	88	41	284
At least 1 doctorless list	27	22	20	69
Total	182	110	61	363

Table 19: Frequency table for municipalities affected with at least one doctorless list vs fully staffed ones, by population bracket. Year is 2020

	(1) Doctorless lists dummy	(2) Doctorless population pc	(3) Doctorless lists dummy	(4) Doctorless population pc
main				
pop_20000	-0.126	-53.57***	1.998***	-7.727
	(0.113)	(5.302)	(0.165)	(6.254)
pop_5000	-0.172*	-40.72***	1.297***	-9.234*
	(0.0848)	(3.976)	(0.119)	(4.572)
pop_0	0	0	0	0
	(.)	(.)	(.)	(.)
avglength			-0.00417***	-0.0995***
			(0.000211)	(0.00753)
_cons	-1.073***	77.13***	2.039***	158.7***
	(0.129)	(6.696)	(0.203)	(9.012)
N	4589	4587	4587	4587
R^2		0.044		0.079

*Table 20: Time period: 2002-2014; Fanned regression for grouped population variable on Recruitment problem dummy (logistical regression), and doctorless population per capita (linear regression). VG data is not analysed as data is only available for 2017 and 2021. Explanatory variables represent dummy variables of population size: Larger than 20.000, between 5.000 and 19,999, and less than 4.999 (omitted due to baseline); Standard errors in parentheses p < 0.05, ** p < 0.01, *** p < 0.001*

8.2. Frequency tables for ordinal transformations

Value	1	2	3	Total
Year	No.	No.	No.	No.
2010	293	44	18	355
2011	302	29	24	355
2012	304	28	23	355
2013	301	24	30	355
2014	303	22	30	355
2015	310	25	20	355
2016	325	19	11	355
2017	320	20	14	354
2018	311	25	18	354
2019	296	34	23	353
2020	284	38	31	353
2021	260	47	46	353
Total	3609	355	288	4252

Table 21: Frequency table of the ordinal variable to represent absolute empty lists

8.3. Alternative Specifications

	(1) Doctorless lists categorical 3	(2) Calculated doctorless pop	(1) Doctorless lists categorical 3	(2) Calculated doctorless pop
ln_area	0.0669	3.115	0.154**	17.19
	(0.0479)	(8.857)	(0.0485)	(8.768)
ln_population	1.475***	238.2***	0.570***	144.1***
	(0.0879)	(13.51)	(0.0651)	(11.65)
dist_medical_uni	0.00129***	0.200**	0.00267***	0.407***
	(0.000311)	(0.0648)	(0.000295)	(0.0623)
pplover65_pc	0.00377	0.448	0.0113*	0.897
	(0.00451)	(0.841)	(0.00449)	(0.841)
females_pc	-0.00624	-2.150*	-0.0135*	-3.044**
	(0.00528)	(1.039)	(0.00545)	(1.027)
4yearsUni_pc	-0.0181***	-2.139***	-0.0167***	-2.553***
	(0.00284)	(0.490)	(0.00303)	(0.496)
unemployed_pc	-0.000214	-0.312	-0.00160	-0.351
	(0.00134)	(0.242)	(0.00128)	(0.240)
immigrants_pc	0.00276*	0.0567	0.00299**	-0.0364
	(0.00111)	(0.220)	(0.00111)	(0.221)
mortality65_pc	-0.0933	-10.59	-0.0277	-6.160
	(0.0674)	(12.18)	(0.0679)	(12.08)
avg_list_length	-0.00627***	-0.659***		
	(0.000377)	(0.0515)		
_cons		-61.41		425.0
		(491.9)		(486.6)
N	4183	4183	4159	4159
R^2		0.113		

*Table 22: Alternative dependent variables regressed on full set with and without average list length. Model 1: Ordinal transformation of absolute doctorless lists. Fully staffed =1, <1.25 lists open =2, >1.25 lists open =3. Model 2 is doctorless population accounted for endogenous list length, thus doctorless lists x average list length. Standard errors in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001*

8.4. Figure 5Graph that includes hypothetical doctorless population

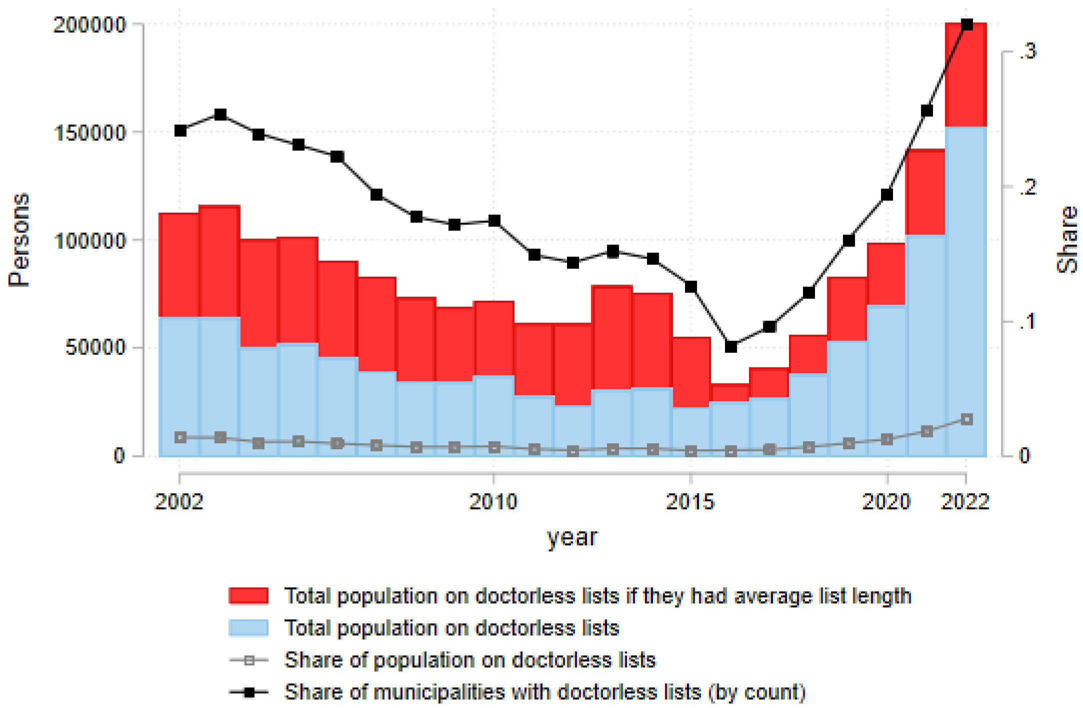

Figure 5: Bar Diagram depicting the development of different statistics on doctorless population. Red Bars are calculated by multiplying the average list length within the municipality with the number of doctorless lists in the municipality.Regression table that shows the relevance of population density

8.5. Regression using population density

	(1) Dummy	(2) VG	(3) Doctorless population	(4) Dummy	(5) VG	(6) Doctorless population	(7) Dummy	(8) VG	(9) Doctorless population
main									
population density	-0.000850	-0.00112	-0.0784***	0.000178	-0.000591	-0.0258	0.00134*	-0.000673	0.0190
	(0.000516)	(0.000789)	(0.0142)	(0.000508)	(0.000802)	(0.0143)	(0.000529)	(0.000880)	(0.0154)
dist_medical_uni				0.00225***	0.00132**	0.134***	0.00166***	0.00137**	0.107***
				(0.000258)	(0.000474)	(0.00907)	(0.000280)	(0.000509)	(0.00970)
avg_list_length							-0.00112***	0.0000818	-0.0468***
							(0.000201)	(0.000359)	(0.00606)
_cons	-1.852***		26.94***	-2.440***		-5.014	-1.378***		41.07***
	(0.0496)		(1.561)	(0.0881)		(2.641)	(0.205)		(6.517)
N	4225	701	4225	4225	701	4225	4225	701	4225
R^2			0.007			0.056			0.069

Table 23: Main models regressed on population density, driving distance to medical university and average list length. Excludes Oslo (0301) and Guovdageaidnu – Kautokeino (5430) due to being Outliers
*Standard errors in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001*

8.6. Regression table on the effect of elementary school education

	Dummy	VG	Doctorless population	Dummy	VG	Doctorless population	Dummy	VG	Doctorless population
main									
barneskole_pc	0.00297***	0.000277	0.261***	0.00374***	0.000393	0.127***	0.00397***	-0.00185	0.135***
	(0.000729)	(0.00138)	(0.0240)	(0.000912)	(0.00162)	(0.0268)	(0.00106)	(0.00198)	(0.0307)
ln_area				0.134**	0.248**	0.511	0.0981	0.235**	-0.771
				(0.0473)	(0.0758)	(1.282)	(0.0512)	(0.0828)	(1.401)
ln_population				1.080***	0.410***	5.372**	1.164***	0.444***	8.356***
				(0.0701)	(0.0959)	(1.656)	(0.0801)	(0.111)	(1.972)
dist_medical_uni				0.00124***	0.00126*	0.0923***	0.00155***	0.00140*	0.100***
				(0.000310)	(0.000546)	(0.0102)	(0.000332)	(0.000570)	(0.0105)
pplover65_pc							0.0163***	0.0133	0.494***
							(0.00481)	(0.00786)	(0.134)
females_pc							-0.0109	-0.00294	-0.107
							(0.00558)	(0.00965)	(0.164)
unemployed_pc							-0.000917	0.00338	-0.0500
							(0.00142)	(0.00245)	(0.0386)
immigrants_pc							0.000653	0.00104	0.0184
							(0.00109)	(0.00150)	(0.0318)
mortality_pc							-0.127	0.0723	-2.097
							(0.0690)	(0.121)	(1.900)
avg_list_length				-0.00497***	-0.00143**	-0.0570***	-0.00463***	-0.00129*	-0.0511***
				(0.000358)	(0.000503)	(0.00775)	(0.000366)	(0.000526)	(0.00799)
_cons	-2.799***		-56.22***	-9.325***		-33.64*	-5.414		-18.41
	(0.233)		(7.460)	(0.675)		(17.13)	(2.785)		(78.73)
N	4212	701	4209	4209	699	4209	4159	694	4159
R^2			0.027			0.075			0.077

*Table 24: Fanned regression analysis of the three main specifications on different sets of variables, in particular to show the effect of persons with little education per capita. Standard errors in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001*