

1 **Antibiotics to outpatients in Norway – assessing effect of**  
2 **latitude and municipality population size using quantile**  
3 **regression in a cross sectional study**

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## 20 **Abstract**

### 21 **Background**

22 High antibiotic consumption rates are associated to high prevalence of antimicrobial  
23 resistance. Geographical differences in dispensing rates of antibiotics are frequently  
24 analysed using statistical methods addressing the central tendency of the data. Yet,  
25 examining extreme quantiles may be of equal or greater interest if the problem relates  
26 to the extremes of consumption rates, as is the case for antimicrobial resistance.

27 The objective of this study was to investigate how geographic location (latitude) and  
28 municipality population size affect antibiotic consumption in Norway.

### 29 **Methods**

30 We analysed all outpatient antibiotic prescriptions ( $n > 14\,000\,000$ ) in Norway  
31 between 2004 and 2010 using quantile regression. Data were stratified by year and we  
32 aggregated individual data to municipality, county or latitudinal range. We specified  
33 the quantile regression models using Directed Acyclic Graphs and selected the model  
34 based on Akaike Information Criteria.

### 35 **Results**

36 Yearly outpatient antibiotic consumption in Norway varied up to tenfold at  
37 municipality level. We found geographical variation to depend on the number of  
38 inhabitants in a municipality and on latitude. These variables interacted, so that  
39 consumption declined with increasing latitude when municipality population sizes  
40 were small, but the effect of latitude diminished as the number of inhabitants  
41 increased. Aggregation to different levels of spatial resolution did not significantly  
42 affect our results.

43 **Conclusion**

44 In Norway, outpatient antibiotic dispensing rates decreases with latitude at a rate  
45 contingent on municipality population size. Quantile regression analysis provides a  
46 flexible and powerful tool to address problems related to high, or low, dispensing  
47 rates.

48 **Keywords**

49 Antibiotic consumption, municipality size, latitude, quantile regression.

50 **Background**

51 Geographic variation in outpatient antibiotic dispensing rates, a proxy for  
52 consumption rates, has important public health implications as high consumption rates  
53 increase the risk of antimicrobial resistance. It is imperative to identify where  
54 consumption is too high to guide targeted preventive measures. Typically, geographic  
55 differences are assessed using analytical methods addressing the central tendency of  
56 the dispensing rates.[1-9] Considering the public health implications of high vs low  
57 antibiotic use, examining the characteristics of the extreme quantiles may be of  
58 greater interest. Though an examination of determinants of high and low use we can  
59 not only investigate a potential over consumption. We can also draw conclusions on  
60 what determines patients (or prescribers) with a low rate of prescriptions. If we only  
61 focus on central tendencies we risk losing information on how our predictor variables  
62 behaves at the most interesting parts of our data.

63 Studies on regional antibiotic consumption often rely on different levels of  
64 aggregation of individual data. Firstly, several antibiotics may be aggregated to

65 antibiotic groups to reduce the complexity of the dataset. Secondly, individuals may  
66 be aggregated to different geographical entities like municipality or county.[4, 10, 11]  
67 Aggregation may influence measures of consumption due to the Modifiable Areal  
68 Unit Problem (MAUP)[12], with unpredictable effects on regression parameters[13],  
69 and may increase variance heterogeneity, with geographical units (e.g. municipalities)  
70 with small population sizes displaying greater variance in consumption than units  
71 with high population size.

72 In Norway there are 428 municipalities, 19 counties and 4 health regions (5 health  
73 regions prior to 2007). The number of dispensed Defined Daily Doses/1000  
74 inhabitants/day (DID) for outpatients at the county level in 2010 varied between 13.5  
75 and 18.9.[14] The lowest DID at county level were in the North.

76 The objectives of this study were to investigate the effect of municipality latitude and  
77 municipality population size on antibiotic consumption, focusing on high and low  
78 consuming municipalities in Norway.

## 79 **Methods**

80 Data on dispensed antibiotics for the period 2004-10 and population estimates were  
81 provided by the Norwegian Prescription Database (NorPD) and Statistics Norway.[14,  
82 15] A detailed description of NorPD is given by Furu.[16] The database contains  
83 information on all dispensed drugs to outpatients ) in addition to demographic data.  
84 Patients are registered with an encrypted ID, month and year of birth (the same  
85 variables are recorded for death), gender and both municipality and county where they  
86 live. Likewise, the prescribers are registered with month and year of birth, gender and  
87 the same variables on residence. Prescriber profession and speciality is also recorded.

88 The prescribed drug is registered with ATC code, the DDD and the reimbursement  
89 code. Further, the prescription has a date, number of packages, a Nordic article  
90 number and a free text for area of application. Finally the pharmacy is registered with  
91 a name, licence and in which municipality and county it is located. From this database  
92 we extracted 14 132 020 individual prescriptions from ATC group J01, and prior to  
93 aggregation we excluded prescriptions for methenamine (J01XX05), and entries with  
94 erroneous ATC-codes and implausible values (e.g. age of prescribers or patients,  
95 unreasonably large amounts for single prescriptions, and erroneous ATC codes).  
96 Cases with missing or wrong data on municipality codes or cases dispensed on  
97 Svalbard were also removed.

98 We defined the outcome by aggregating the number of DDD for all antibiotics and  
99 calculated the age adjusted DID for each municipality and county.

## 100 **Exposure variables**

101 Latitude was assigned to municipalities in three different ways; a latitude ranking  
102 (South-North) according to the latitude of a municipality's county (1 through 19), a  
103 rank based on latitude of the municipalities (1 through 428), and finally we divided  
104 the 428 ranks into 19 intervals with even number of municipalities and assigned a  
105 latitude rank to each cluster of municipalities. All ranks for latitude were based on  
106 administrative centre coordinates.[17, 18] The number of inhabitants in municipalities  
107 were log transformed.

## 108 **Statistics**

109 Prior to choosing statistical method and model, we inspected the data for  
110 heteroscedasticity and nonlinearity in the relationship between antibiotic  
111 consumption, population size and latitude. This revealed a data structure violating the

112 assumption of constant variance of antibiotic consumption over municipality sizes,  
113 favouring the choice of quantile regression (QR). QR is suited for, but not limited to,  
114 data with heterogeneous variance.[19-21] An illustration of the data structure and the  
115 variation for 2010 is given in Supporting Information (SI) Fig. 1.

116 In order to control for confounding effects we used the Directed Acyclic Graphs  
117 (DAG) methodology suggested by Shrier and Platt[22] to identify covariates to  
118 include in the statistical model choosing the minimal adjustment set reported from this  
119 analysis. For our DAG model we explored the relationship between the following  
120 variables: Latitude, geographical entity,

121 Given the covariates from the DAG analysis, we investigated two models and used  
122 Akaike Information Criteria (AIC) for model selection.[23] The full model, where all  
123 variables are allowed to interact, was compared to a reduced model where municipality  
124 population size and latitude were included as main effects only. We included year as a  
125 categorical variable to estimate independent regression surfaces for each year. This  
126 variable interacts with all other variables in both models.

127 We set levels of antibiotic consumption for table and figures to the 80<sup>th</sup>, 50<sup>th</sup> and 20<sup>th</sup>  
128 percentile, and compared three versions of the chosen model; 1) municipalities ranked  
129 after the county latitude (1-19); 2) municipalities clustered in 19 areas constructed  
130 solely by latitude along a South-North axis; 3) municipalities ranked after  
131 municipality latitude (1-428). We estimated the p-values for the parameter estimates  
132 with a Markov chain marginal bootstrap with 500 replicates. [21, 24]

133 To create a suitable database for analysis, we used the statistical software SPSS  
134 (version 21.0.0).[25] We used the statistical software R (version 3.02) for all  
135 analytical purposes with the packages quantreg (version 5.05), rgl (version 0.03.935),

136 and diagram (version 1.6.2). [24, 26-28] The DAG was created and analysed in  
137 DAGitty (version 2.0).[29] We used ImageJ (version 1.47) to construct a video for the  
138 SI.[30]

## 139 **Results**

140 Consumption of outpatient antibiotics declined with increasing latitude (South-North  
141 axis) (Fig. 1 and SI Video 1). Consumption also depended on the number of  
142 inhabitants in a municipality and variation was largest where population size was low.  
143 Over the study period we found 6-10-fold difference in consumption of antibiotics  
144 (measured in DIDs) among Norwegian municipalities. The main effect of  
145 municipality population size on antibiotic consumption was largest for the lower  
146 percentiles, decreasing for higher percentiles of consumption (Fig. 2).

147 The decline in antibiotic consumption with increasing latitude was contingent on  
148 municipality population size, and the effect of latitude was reduced as municipality  
149 population size increased. The curved regression surfaces for 2010 illustrate this  
150 interaction between latitude and municipality size detected at both the 20<sup>th</sup> and 80<sup>th</sup>  
151 percentile (SI video 1 displays surfaces for all years). The interaction effect was  
152 present from the 20<sup>th</sup> through the 80<sup>th</sup> percentile (Fig. 2, Table 1). However, below the  
153 20<sup>th</sup> and above the 80<sup>th</sup> percentile the interaction effect was less pronounced and  
154 estimates were not statistically different from zero (Fig. 2).

155 The full model fitted the data best and had the lowest AIC ( $\Delta$  AIC = 132, 116 and 24  
156 for the 20<sup>th</sup>, 50<sup>th</sup> and 80<sup>th</sup> percentile respectively). The lowest antibiotic consumption,  
157 at both the 20<sup>th</sup> and 80<sup>th</sup> percentile, was found in Northern Norway, in municipalities  
158 with small population sizes (Table 1, Fig. 2, SI Video 1).

159

160 We found no evidence for MAUP effects when we aggregated the data at three  
161 different levels of spatial resolution (Table 1).

## 162 **Discussion**

163 We detected a 10-fold difference antibiotic consumption, measured in DID, among  
164 Norwegian municipalities. Consumption was highest at lower latitudes and in larger  
165 municipalities. The rate of reduction in consumption with increasing latitude was  
166 contingent on municipality population size. Lower DID in the northern counties  
167 correlates with an increasing number of municipalities with small population sizes in  
168 this part of the country. Our data are unsuitable for explaining any causal relation  
169 relationships behind these findings. Although we find an effect of latitude on the  
170 consumption of antibiotics this is most likely an proxy for other, unmeasured  
171 variables. If we allow ourselves to speculate; prescriber density, temperature,  
172 variations in infectious diseases and possibly different antibiotic resistance patterns  
173 along the latitude gradient can have an effect. Therefore, latitude is a devious variable  
174 for predicting drug consumption.

175 Highlighting differences in antibiotic consumption is important in the public health  
176 perspective. Low levels of consumption may reflect underuse resulting in negative  
177 health outcomes, and unnecessary high use is associated with high prevalence of  
178 antimicrobial resistance.

179 By addressing percentiles of antibiotic consumption, QR allows to model the higher,  
180 or lower, consumption rates, and is thereby a valuable inferential tool in  
181 pharmacoepidemiological studies,[20] providing essential information for antibiotic



182 stewardship and conservancy. Further, in the context of geographical studies,  
183 aggregation often leads to strong variance heterogeneity, which can be effectively  
184 handled by the nonparametric QR.

185 We found no evidence for MAUP effects. The observed differences in parameter  
186 estimates between models 1 through 3 are expected, as the covariate latitude differs  
187 between the models. However, the tendency for parameter estimates does not change.

### 188 **Strengths and weaknesses**

189 The NorPD captures all prescriptions to outpatients in Norway, but contains limited  
190 information on underlying diseases. Possible differences in indications for treatment  
191 between regional units are not addressed in the present study.

192 For some years, the regression surfaces for the 20<sup>th</sup> percentile and the 80<sup>th</sup> percentile  
193 cross close to the highest values of population size. This reflects some bias in the  
194 regression estimates due to few observations for municipalities with the highest  
195 number of inhabitants.

196 By aggregating individual prescriptions to geographical levels information is  
197 inevitably lost. At the same time, individual data pose analytical challenges with  
198 respect to dependency of data connected to patients, prescribers and time.

199 A recent paper advised on selection criteria for geographical units.[31] Our study  
200 meets some of those criteria (biological relevance, how easily results are  
201 communicated, and missing values within geographical areas). MAUP is likely an  
202 issue when data were aggregated to county level. We have tried to assess whether  
203 different levels of aggregation affected our results and we conclude that we can  
204 exclude MAUP effects between the models we have investigated. However, we have

205 not addressed a full aggregation of all variables, and we do not explore all  
206 possibilities of MAUP effects.

207 Comparing European studies on differences in geographical antibiotic consumption  
208 poses two challenges; firstly, variation between countries is substantial. [11, 32, 33]  
209 Secondly, the geographical effects on consumption within countries varies, and it is  
210 difficult to obtain predictors for this variation.[4]

211 The North-South differences found in Italy [34] and the east-west gradient in  
212 Germany [4] are comparable to the latitude gradient in Norway. The German, Italian  
213 and present Norwegian studies use different analytical approaches. The Italian study  
214 relies on the periodic prevalence of antibiotic consumption, whereas the German and  
215 our study rely on aggregated individual consumption.

216 A recent study revealed a large variation in periodic prevalence between districts and  
217 found an effect of area deprivation on odds of being prescribed antibiotics. In this  
218 study individual data were utilized in a multilevel statistical analysis.[9] Both the  
219 German and our study aggregate to the lowest political and administrative level. Our  
220 results show that this aggregation level is appropriate for summarizing and  
221 interpreting the data for regional consumption in Norway.

## 222 **Conclusions**

223 Antibiotic consumption, measured as DID, varies 10-fold between Norwegian  
224 municipalities. The decline in antibiotic consumption along latitude is associated with  
225 municipality size. Although geographical differences may exist, we do not consider  
226 latitude to be a good predictor of antibiotic use in Norway.

227 Municipality population size has a clear effect on consumption, and its interaction  
228 with latitude must be taken into account.

229

## 230 **List of abbreviations**

231 AIC Akaike Information Criteria

232 ATC Anatomical Therapeutic Chemical classification system

233 DAG Directed Acyclic Graph

234 DDD Defined Daily Dose

235 DID DDD/1000 inhabitants/day

236 MAUP Modifiable Areal Unit Problem

237 NorPD Norwegian Prescription Database

238 OLS Ordinary Least Squares regression

239 QR Quantile Regression

240 REC The Regional Committee for Medical and Health Research Ethics

241 SI Supporting Information

## 242 **Ethics and Consent statement**

243 The Norwegian Directorate permitted access to NorPD data for Health and Social

244 Affairs (project 06/4951), and The Regional Committee for Medical and Health

245 Research Ethics (REC) (project 144/2006), in addition to the Data Protection Official

246 for research at the University Hospital of North Norway (project 001/07), approved  
247 the study.

## 248 **Competing interests**

249 None.

## 250 **Authors contributions**

251 PH had the main responsibility for specifying research questions, data preparation,  
252 data analysis, figures, and interpretation of results. PH also had the main  
253 responsibility for writing the first draft of the manuscript.

254 RP supervised the statistical analysis and computer programming work.

255 GSS initiated the project.

256 ASF acquired the data.

257 LS supervised and complemented literature searches, and had main responsibility for  
258 completing the manuscript.

259 All authors contributed to discussions on study design, choice of DAG model,  
260 analytical approach, the interpretation of results and approved the final version of the  
261 manuscript.

## 262 **Availability of data**

263 All data are available from the NorPD.

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267 Arctic University of Norway.  
268 UiT – The Arctic University of Norway had no role in planning of the project,  
269 analysis of data, interpretation of results or writing of the manuscript.

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364 **Table 1** Parameter estimates for the main effects and the interaction term in a linear  
 365 QR for three quantiles in three different models

		<b>Parameter estimates<sup>1</sup></b>		
<b>Percentile</b>	<b>Variable</b>	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>
20 <sup>th</sup>	South-North axis	<b>-0.77</b>	<b>-0.03</b>	<b>-0.70</b>
percentile	Log (Inhabitants)	<b>1.41</b>	<b>1.65</b>	<b>1.52</b>
	South-North axis * Log (Inhabitants)	<b>0.17</b>	<b>0.01</b>	<b>0.15</b>

50 <sup>th</sup>	South-North axis	<b>-1.01</b>	<b>-0.05</b>	<b>-1.00</b>
percentile	Log (Inhabitants)	0.31	0.69	0.50
	South-North axis * Log (Inhabitants)	<b>0.25</b>	<b>0.01</b>	<b>0.24</b>
80 <sup>th</sup>	South-North axis	<b>-0.85</b>	<b>-0.04</b>	<b>-1.01</b>
percentile	Log (Inhabitants)	-0.30	-0.18	-0.42
	South-North axis * Log (Inhabitants)	<b>0.21</b>	<b>0.01</b>	<b>0.25</b>

366 <sup>1</sup> Bold figures are estimates which are significantly different from zero at the  $\alpha=0.05$   
367 level. Parameter estimates for intercept and interactions with year investigated are  
368 omitted. Model 1: Municipalities ranked along latitude based on county. Model 2:  
369 Municipalities ranked along latitude. Model 3: Municipalities ranked along latitude in  
370 19 intervals. Data from the NorPD.

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