Effects of Travel Time on Healthcare Utilization:

Evidence from Norway*

Rosanna N. I. Johed[†] and Kjetil Telle[‡]

September 27, 2019

Very preliminary and incomplete, please do not cite or circulate. Any comments are most welcome.

Abstract

It is well documented that patients with a long travel time to health care tend to utilize the services less than patients close-by. To the extent that this variation is unwarranted, it involves over- or under-utilization and thus excessive costs and possibly deteriorated health. Using individual-level data of the entire Norwegian population for a decade, we calculate the exact travel time from each inhabitant's home to the office of its assigned general practitioner (GP). First, we confirm that patients with a long travel time visit the GP less than patients living close-by. Second, we estimate the causal effect of travel time on utilization, relying solely on plausibly exogenous variation in the travel time from annual improvements in roads from 2010 to 2017. For the general population, we estimate precise zero-effects of travel time on utilization. For some sub-groups, like people receiving disability pensions or living far away from the services, our estimates suggest modest effects of longer travel time on reductions in utilization. Overall, though, our preliminary results suggest that further centralization of GP services would have limited impacts on utilization.

Keywords: Health care services, general practitioner, travel time, utilization.

JEL classification: I10, E32, J6.

*Preliminary and incomplete draft. Please excuse typos, errors and stream-of-consciousness feel of this draft. We are grateful for helpful comments and suggestions from Manudeep Bhuller as well as a number of seminar participants. Financial support from the Norwegian Research Council (Helsevel 256678) is acknowledged.

[†]University of Oslo and Statistics Norway: E-mail: rosanna.johed@ssb.no

[‡]Statistics Norway, Research Dept., e-mail kjetil.telle@ssb.no, phone + 47 9806 0779, address Statistics Norway, Box 8131 Dep, NO-0033 Oslo; and Norwegian Institute of Public Health.

1 Introduction

Centralization of specialized health care services has shown to improve the outcome of patients over a range of treatments in OECD countries, though effects are sometimes negligible or possibly detrimental for acute conditions ([Fiva et al., 2014, Grytten et al., 2014]). One likely important reason for the benefits of centralization of specialist services, is the ability of the health personnel to obtain more experience in the condition of the patient (REFS; Doyle et al. 2018). However, the possibilities and advantages for specific experience is less clear in primary care, and the evidence on effects of centralizing primary care remains scarce (REFS). One concern with centralizing primary care, is that patients seek the general practitioner too little and too late. A number of previous studies have documented that patients living further away from the health care services have lower rates of healthcare utilization [Kelly et al., 2016]. Undertreatment, as well as over-treatment, induces costs both to the patient and society.

Using individual-level data on the entire Norwegian population over a decade, we estimate the effect of travel time to the resident's assigned general practitioner (GP) on health care utilization. Well-identified estimates of effects of travel time on health care utilization is important for deciding how centralized the services should be, balancing monetary costs of decentralization and health-related costs from patients utilizing services too little. A number of studies suggest a distance decay association ([Kelly et al., 2016]), i.e. that patients with long travel time utilize the services less than those with shorter travels, but there are few studies trying to elicit the causal effect of travel time on utilization.[1] With access to exact geographic location of the residential home and the location of the GP's office for every Norwegian resident and GP, we can utilize temporal variation in travel time from road improvements to transparently estimate causal effects. Our identification strategy eliminates bias from health-related residential relocation, as well as health-related change of GP.

We reproduce the commonly found distance decay association. Residents living farther away from their GP see their GP less often. During a year, about 66 percent of the residents with a travel time up to 10 minutes visit their GP at least once, while 59 percent of the residents with more than 20 minutes to travel do so. If the underlying health of these residents were the same, such a difference in utilization would suggest excessive over- or under-utilization. Our results, however, suggest that the association is driven by health-related selection in distance to GP: When we only rely on plausibly exogenous variation in travel time from improvements in roads, we estimate a precise zero-effect of travel time on utilization for our main sample. As expected, we also find that shorter travel time to the GP reduces electronic consultations with the GP, and that shorter travel time to the GP also reduces slightly specialist consultations.

[Sub-sample analyses and specification tests will be undertaken]

The costs of decentralized services come in the form of more consultations and possibly also of lower

[1] For some specific services, there are some studies that reliably estimate causal effects of distance on utilication. For example, REF find that the likelihood of participating in mamography screening for women in Maine?, US, increases when the mamography-bus stops close-by, especially in the winter. Other studies?

treatment quality (REF?). A possible benefit of short travel time is that patients seek the services sufficiently frequent to avoid delayed diagnosing, with associated excess treatment costs and deteriorated health. Our findings suggest that the concern for decay in utilization from increases in travel time is unwarranted in the Norwegian context, and thus that services can be further centralized without affecting overall utilization.

2 Conceptual Framework and Previous Literature

2.1 Conceptual Framework

Theories of demand for health care services were pioneered by Grossmann (1972), building on theories of human capital by e.g. Becker (1964). The expansion of health insurance and public insurance legislation in the US, and universal and publicly funded health care services in welfare states like Norway, implies that out-of-pocket payments for the patient in need of health care has a small or negligible effect on determining utilization. Acton (1975) proposes a model with small out-of-pocket costs and underlines the role of opportunity costs of time in restricting demand, and especially travel time, travel costs and time costs of undertaking medical treatment.

In the stylized model of Acton (1975), the consumer maximizes utility over two goods (health care services and a composite good) subject to a time constraint that can be dividied between work, time- and non-time-consuming utilization of health care services and of the composite good. The model provides several predictions. The one most relevant for our analysis, is that as out-of-pocket prices decline, demand becomes relatively more responsive to the costs of time — and that shorter travel time increases demand. He also finds that demand increases in wealth (lump-sum), while the effect of labor-income is ambiguous (income effect vs. substitution effect). Thus, the impact of unemployment or disability is not clear, as the drop in the alternative value of time raises demand (for disability, the deteriorated health condition may also raise demand), but the drop in income reduces demand. In the model of Grossman (1972) (abstracting from the costs of time) demand for health care services increases in age and declines in education.

In line with the incentives in such models, we may also expect travel time to affect demand differently across patients with varying characteristics. Obviously, the utilization of non-marginal patients - like those with critical needs (or no need) of services - are unlikely to be affected by empirically relevant changes in travel time. For elective treatment, general health checks or presumably self-contained diseases, travel time may substantially affect whether the GP is visited or not. In the model of Acton (1975) additional assumptions are needed (cross-derivatives) to provide predictions across groups, like the effect of travel time on demand across a high- and low-earner.

The prediction that demand declines in travel time is in line with most observational studies, and often labeled the *distance decay association* in the medical literature [Haynes, 2003].

2.2 Previous empirical literature and our contribution

Empirical findings largely support that patients living far away from health care services utilize the services less than those living close-by. Indeed, it seems that such a negative association also exists between travel time and health [Kelly et al., 2016]. This *distance decay* association in health and utilization is found in many industrialized countries under different health care systems, for various measures of distance, utilization and health, and in developing countries [Ludwick et al., 2009, Brewer et al., 2012, Celaya et al., 2006, Friedman et al., 2013, Buor, 2003]. There are also studies specifically looking at primary care that find distance decay associations [Strauss et al., 2006, Monnet et al., 2008] , though some also find unclear or opposite associations [Lankila et al., 2016]. In Norway, [Raknes et al., 2013] look at variation in travel distance at the municipal level, and find support for a distance decay association across ten municipalities in Southern Norway.

Utilization of health care is known to vary considerably across patient characteristics [Haynes, 2003]. Women visit the GP more often than men up to their fifties, whereafter the relationship turns. Ethnic background, income and education also matters for the utilization pattern, as well as health condition [Buor, 2003, Haynes, 2003, Brewer et al., 2012, Grytten et al., 2011]. People on disability pension, sick leave or unemployment benefits belong to groups where health care needs are likely to be higher than in the overall population, and they also see the GP more frequently [Grytten et al., 2005].

How the distance decay varies across patient characteristics is not well-documented. Previous studies have looked at many subgroups of patients, but none has described it systematically across groups. With access to the overall population of Norway, we will estimate the effect of travel time for different patient groups.

Moreover, we are not aware of any previous study attempting to estimate the causal effect of travel time on utilization in an overall population. Earlier studies have looked at correlations between travel time and utilization, sometimes controlling for observable individual characteristics. Measures of travel time are occasionally based on the exact address of the nearest health service, sometimes on the exact address of the patient, but mostly on more aggregate measures like zip codes or weighted average centroids of e.g. municipality [Kelly et al., 2016, Lake et al., 2011, Engelman et al., 2002, Judge et al., 2011, Goldberg et al., 2014, Rodkey et al., 1997, Markin et al., 2011].

We use exact residential- and GP location, and calculate the travel time by car on the given roads and speed-regulations for various measures of utilization, and estimate both the distance decay association and the causal effect of travel time on utilization. Our effect estimates are based on arguably exogenous variation in travel time stemming from the construction of new roads over time.

3 Empirical Methods

3.1 The correlation

In line with the majority of previous observational studies on the distance decay association, we too expect a negative correlation between travel time and utilization. The correlation between utilization (U) in a given year t and travel time (T) at the beginning of the same year, is obtained by the following model:

$$U_{i,t} = \alpha + \beta^{OLS} T_{i,t} + \lambda x_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where U is a variable capturing utilization in year t for individual i. The term α is a constant and T is the travel time from individual i's home to individual i's GP at the beginning of year t. x is a vector of individual characteristics to control for observable differences measured at the beginning of year t. Interactions between covariates such as age and gender are also included, since we expect the visits to ones GP to depend on the combination of age and gender; and $\varepsilon_{i,t}$ is an error term of unobserved factors. The coefficient of interest, β^{OLS}, captures the (conditional) correlation between travel time and utilization in the year.

3.2 Unobserved individual characteristics

Even after controlling for observables, β^{OLS} cannot be given a causal interpretation since T is likely endogenous. One reason for the endogeneity is that choice of residential location, choice of GP, need factors (others than controlled for) and time preferences are expected to be correlated with travel time and affect utilization. To circumvent the most obvious endogeneity issues, we utilize the panel structure of our data and look at how travel time affects the utilization over time. Consider the following fixed effects model,

$$U_{i,t} = \beta^{FE} T_{i,t} + c x_{i,t} + \alpha_t + \gamma_i + \varepsilon_{i,t}, \tag{2}$$

where i indicates the individual, t refers to the year and U is a variable capturing utilization. The term α_t is a vector of calendar year fixed effects included to control for increased utilization over time, extraordinary epidemic influenza in some years or unemployment shocks; γ_i is a vector of individual fixed effects included to control for time-invariant individual characteristics including (self-selected) initial travel time, level of need etc.; T is the travel time (in minutes) from individual i's home to individual i's GP in year t; x is a vector of (possibly time varying) individual characteristics included to control for compositional differences (and changes); and the error term $\varepsilon_{i,t}$ is assumed to have a conditional expectation of zero.

The coefficient of interest, β^{FE}, captures the effect of a reduction in travel time on the increase in utilization, under the assumption that for the same individual, temporal variation in $T_{i,t}$ does not correlate with temporal variation in $\varepsilon_{i,t}$.

3.3 Variation within individual- and GP locations

The estimate of β^{FE} will, however, be biased if e.g. patients move closer to the GP or switch to a GP located near-by as a result of a surge in needs of the services. For example, an elderly person starting to need more help might move to a nursing home which is closer to the GP. Such selection on unobservables sorting people to residential- and GP locations contributes to an upward bias in estimates of the effect of travel time on GP utilization.

To disallow such endogenous variation, we add the interaction of individual- and residential location , ς_{ij}. This means that we do not only have one fixed effect per individual, but one fixed effect for every residential location of every individual. This specification does not use the possibly endogenous variation in travel time from the individual relocating closer (or farther) to the GP:

$$U_{it} = b^{i*adr} T_{it} + cx_{it} + a_t + \varsigma_{ij} + e_{it}, \tag{3}$$

where the coefficient of interest, $b^{i_{adr}}$, captures the effect of a reduction in travel time on the increase in utilization, $U_{i,t}$.

Travel time variation now cannot stem from the patient moving closer to the GP. The only remaining variation in travel time is either road improvements, that the GP relocates or that the individuals switches to a GP located closer to the individual's home. A change in GP location can be (plausibly) exogenous to the individuals needs (from the GP retiring and the patient being transferred to a new GP or the GP changing location), while if the individual changes to a GP closer to his or her home, it may very well be a result of surging needs. The latter would suggest positive selection on unobservables, implying an upward bias in our estimate of the effect of travel distance on utilization.

We can, however, handle the latter problem by not using variation from changes in GP locations, i.e. by letting the fixed effects be GP-location and individual specific, ρ_{ik}, where k is the location of the GP office and i refers to the individual. The specification allows individuals to switch GP but the variation from the switch is not used to identify the effects of travel time. Variation in travel time now stems from individuals moving (without changing GP) or from road improvements. Again, the coefficient of interest b^{i*GP} captures the effect of a reduction in travel time on the increase in utilization, given that there is no correlation between T_{it} and e_{it} within a unit of individual and GP location. Standard errors are clustered at individual level to allow for dependent observations within an individual over time (Cameron and Miller 2014). The model is formulated as follows:

$$U_{it} = b^{i*GP} T_{it} + cx_{it} + a_t + \rho_{ik} + e_{it}, \tag{4}$$

Clearly, this model suffers from endogenous residential relocation, and we thus combine this model with the one (Eq. 3) above, to handle both possibly endogenous residential- and GP relocation.

Our preferred model simultaneously deals with the previous two issues and interact an individual´s residential address, j, with the assigned GP´s location, k, captured in the term θ_{jk}. The variation in travel time hence stems solely from road improvements at the unique combination of individual- and GP locations. The model can be formulated as follows:

$$U_{it} = b^{i_{adr}*GP}T_{it} + cx_{it} + a_t + \theta_{jk} + e_{it}, \tag{5}$$

Now, the coefficient of interest, $b^{i_{adr}*GP}$, is capturing the effect of travel time on utilization for people experiencing road improvements.

Standard errors are clustered at home address and GP location level to allow for dependent observations within an individuals home address and GP location over time (Cameron and Miller 2014).

4 Context and data

4.1 General practitioners in Norway

Norway has a universal and uniform health care system that aims to offer equal access to high quality health care. All inhabitants are covered by the public insurance scheme, and both private health insurance and private providers without reimbursement from the public insurance scheme, remain rare. Except some dental services, all important health services are covered by the public universal scheme. Most providers are public, but there are also numerous for-profit and not-for-profit private providers operating under the scheme[2]. The more specialized and advanced the service is, the more rare are private providers, while in primary care - especially among general practitioners - private providers are in majority. By international standards, Norway has a high coverage of general practitioners (GP) per capita, and the number of GPs has increased steadily from approximately 3,600 in 2001, to 4,100 in 2010, and to approximately 4,760 in 2017.

Since June 2001 every Norwegian resident is assigned to one and only one GP. The main intention of the GP reform was to improve availability and quality of the primary physicians services, and give the patient right to choose GP. The GP is responsible for providing primary physician services to the residents assigned to his or her list, and GPs typically have 1,000 to 1,500 patients on the list. There has been a decline in average number of residents on a GP's list from 1,200 in 2005 toward 1,000 today. The municipality of residence is responsible to make sure the inhabitants can be assigned a GP, and to ensure an appropriate number of GPs within the municipality. Some municipalities collaborate with a neighboring municipality regarding the GP services.

Patients are allowed to choose and change GP up to twice a year, given that there are GPs with vacancies on their list. About 1/3 of municipalities has in 2017 less than two GPs with vacancies, remarkably reducing

[2]Private providers not operating under the scheme is extremely rare, though there are a few firms, mostly providing (advanced) general practitioner services, in the 3-4 biggest cities.

the real possibility of changing GP. About 3-400,000 patients (there are about 5 million residents in Norway) change GP every year. A patient is intended to consult the GP to whom she is assigned and the GP prioritizes patients on the list. Residents can have a GP in whatever place in Norway they want, and one keeps the GP if moving unless one takes actions to change. In 2017, only about 0.3 percent of Norwegian residents were not connected to a GP, a share that is almost constant over the years. Patients pay a a low out-of-pocket price for each consultation, limited to a maximum co-payment of approximately 2,000 NOK (2017) per year.

4.2 Data sources

Our analysis utilizes data from several sources. The general practitioner registry provides information on all GPs in Norway since 2001, and the link between the GP and the residents on the list of each GP (with unique id for both resident and GP). The reimbursement register of the insurance scheme (KUHR) contains information on date and detailed reimbursement codes, including a tariff explaining type of consultation (from 2006-)[3].

Data from several administrative registers are maintained by Statistics Norway (SSB). These registers contain demographic information (gender, month and year of birth, country of origin, municipality of residence, coordinates of home, etc.), socioeconomic data (education, annual earnings, sick leave benefits, disability pension, unemployment benefits, etc.) and firm-level information (coordinates of the location of the GP-office, etc.). We combine information on individual level across registries and over time using a unique personal identifier provided all residents at birth or upon immigration, and on firm-level using unique firm identifiers.

4.3 Sample

The linked data contain annual information of all Norwegian residents connected to a GP from 2010 to2017. The assigned GP and the travel time to that GP by January each year, is used together with GP-visits from the whole calendar year. We allow people to enter and exit the sample (e.g. move abroad and immigrate, get born, etc.). Persons who pass away are excluded from the sample the following year.

Individuals are observed on average 6.9 out of 8 years yielding approximately 38,686,955 person-year observations.

4.4 Variable definitions

Our main explanatory variable is travel time to the assigned GP, calculated as the shortest travel time in minutes by car. For each calendar year 2010-2017, we calculate the distance between the resident's home address and the location of the office of the resident's GP in January. The road maps for the years available

[3]Kuhr of varying quality for earlier years REF

to us are for 2010, 2013, 2014, 2015, 2016 and 2017, and the calculations account for both distance by available roads and speed limits. Thus, changes in the travel time between two addresses come from road improvements (i.e. tunnels, bridges, new roads, crossings etc.) and changes in speed limits.[4] In most of our analyses, we will winosorize the travel time at the 95th percentile in the year (we do not want the observations in the long right tale to heavily affect the result, but results winsorizing at 99th percentile or not winsorizing at all yield similar qualitative results). Travel time in minutes is our main explanatory variable, but we will also provide some information using distance in kilometers by road (the road that takes the shortest time to drive by car) .

Our main outcome variable is GP utilization, measured as yearly face-to-face visits to a GP. For all outcome variables we construct three margins The extensive margin is a dummy that is one if the individual consulted (face-to-face) the GP at least once in the calendar year. The intensive unconditional margin is measured as a count variable capturing the number of days (0-365) the individual visited its GP (we do not count more than one visit per day, as this would be hard to identify in a meaning full way in the data). The intensive conditional margin captures the number of consultations given that the person consulted the GP at least one day (1-365). We do also undertake analyses on electronic consultations to the GP (defined as a consultation electronically, by phone or letter) and specialist consultations (outpatient clinic, internal medicine, specialist in gynecology, eye, ear, nose and throat- specialists) based on the same three margins. [We plant to also undertake analyses on utilization of the emergency ward.]

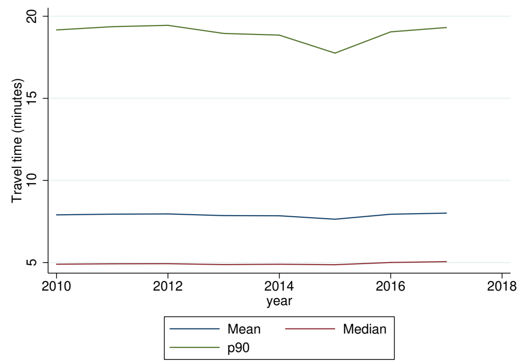
Control variables cover gender, age, highest achieved education, earnings, (sick leave, unemployment and disability pension), municipality. Age is divided into seven groups: 0-3; 4-18; 19-30; 31-50; 51-69; 70-89; 90+ . We separate between six groups of education levels calculated over individuals above age 30, where one group is for missing and unknown educations. Earnings are measured as total gross pension-qualified earnings calculated for people aged 16-67 and we divide earnings into five equally sized groups of percentiles and one group for missing. Municipality capture the municipality of residence at the entry into the calendar year. Sick leave, unemployment and disability pension, are dummies set to one if the individual has received benefits stemming from these activities within the previous year.

4.5 Summary statistics

Summary statistics for base year 2010 is presented in Appendix A. People have approximately 8 minutes in average to the GP, with a standard deviation of 8.4 minutes and a median just below 5 minutes. The travel time is constant over the years, see Figure 1 The share who visit the GP at least once in a year is 0.64, and number of yearly GP visits about 2.37 in our main analytic sample.There is an increase in both the share

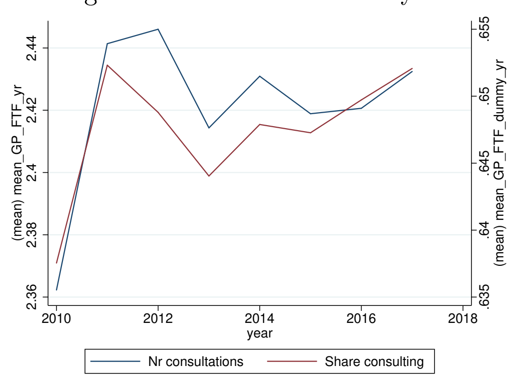
[4]To reduce calculation time and for confidentiality reasons, we have calcuated travel time from the centroid of 100*100 meter square of the home and office address. For some office addresses, and also some home addresses, in the early years of our data, we were not able to unequivocally identify the coordinates, in which case we used the coordinates of the median residental home within the zip code of the address.

Figure 1: Travel time over years



Travel time by year in mean, median and p90. N=38,686,955

Figure 2: Consultations over years



Number GP consultations face to face (left y-axis) and the share consulting the GP (right y-axis) over years. N=38,686,955

who consult the GP and the number of yearly visits over the sample period, see Figure 2

Average age is 39 years, and it is an even share of men and women. On average, the education of the residents is just below lower tertiary level and the income about 293,000 NOK (≈€35,000) in 2010, while 3.8 percent received any unemployment benefits in the year, 6.4 percent any disability benefits and 15.6 percent any sick leave benefits.

5 Empirical Findings

5.1 Graphical Evidence

From Figures 4 and 3 we see that there is quite some variation across Norwegian municipalities in the percentage of the population that visited GP in 2017 and the travel time from home to the GP. The maps suggest that residents in municipalities with long travel time tend to visit the GP less frequently.

From Figure 5 it is evident that a higher proportion of individuals with short, in contrast to long, travel time visiteted the GP. From Figure 6 we also see that inhabitants wiht shorter travel time also visited the GP more days.

For individuals who experience a change in travel time from 2010 to 2017, a reduction in travel time is associated with increased utilization, see Figure 7. Changes in travel time over the years are positive for some inhabitants and negative for other, and therefore the average and median travel time variation is fairly stable around zero, see Figure **??**

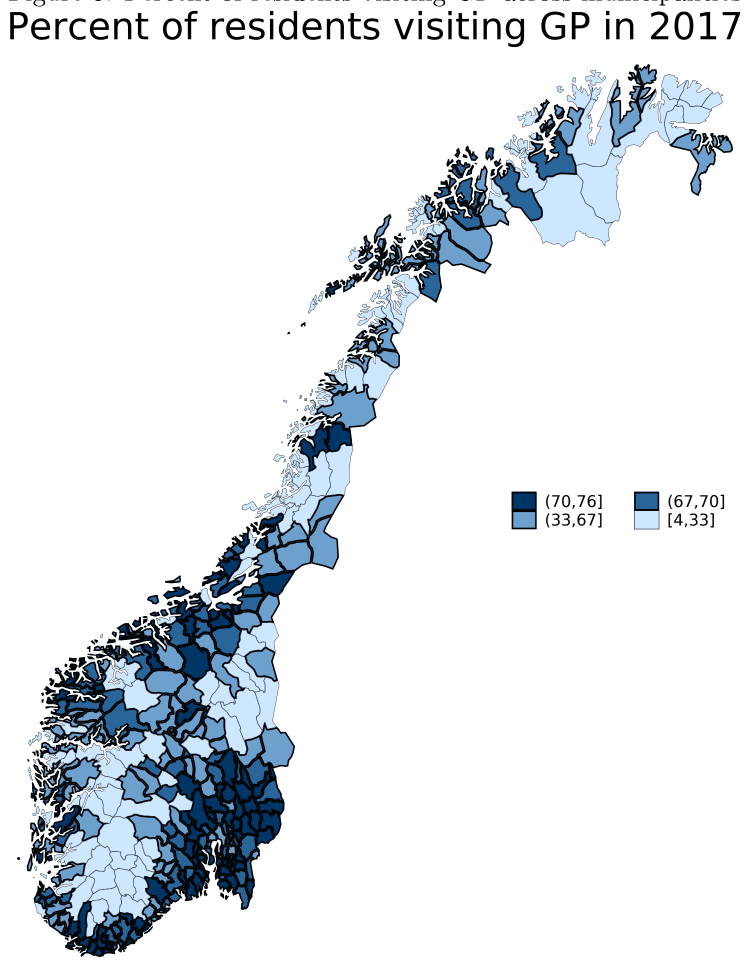
5.2 Regression results

5.2.1 Association and unobserved individual characteristics

Table 1 contain associations between travel time (in minutes) and utilization [now we use linear regression models (OLS) throughout, but we will check for robustness to e.g. logistic models]. As expected, all columns show a statistically significant inverse association, both for the extensive, intensive and intensive conditional margin. In the first column, we report the correlation with controls for age and sex, while in column 2 we have included their interaction as well as education level, total income and municipality. We see that including more controls only reduces the estimates slightly, and the effect on the extensive margin is about -0.002. Since about 65 percent of the population visits the GP in a year, this represent a relative change of about 0.3 percent per minute higher probability of visiting the GP FTF for a one minute reduction in travel time. The corresponding estimate for number of visits is about -0.01, suggesting that a 10 minute reduction in travel time increases the GP visits by 0.1 per year. With 5 million residents visiting the GP on average 2.4 times a year in our data, an average decrease of 0.1 visits translates into about one million twohundred thousand visits per year.

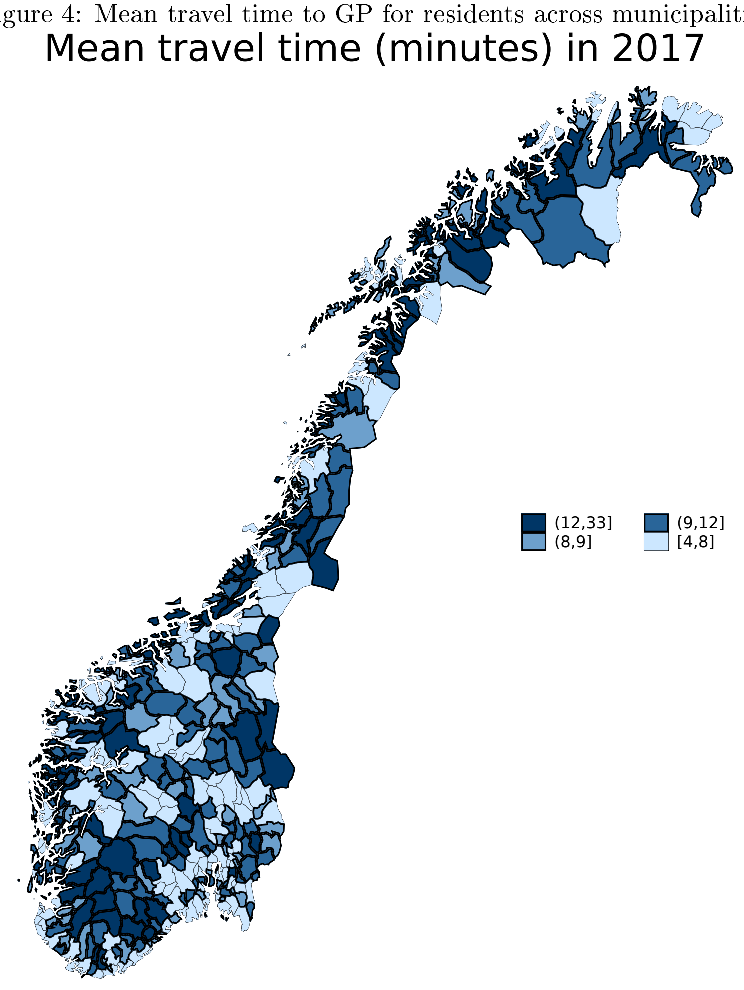
In column 3 we have added individual-, and calendar year fixed effects, and now there is a noteworthy drop in the estimate on the extensive margin, suggesting that accounting for time-invariant individual characteristics is important.

Figure 3: Percent of residents visiting GP across municipalities



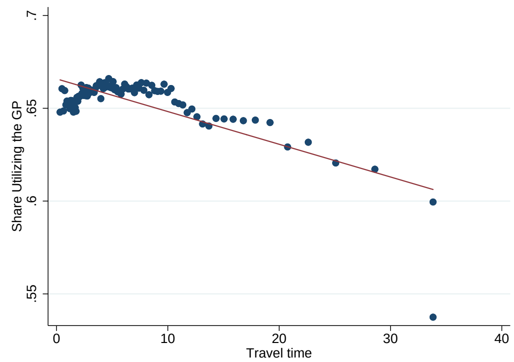
Percent of the residents of each Norwegian municipality that visited a GP at least once in 2017.

Figure 4: Mean travel time to GP for residents across municipalities



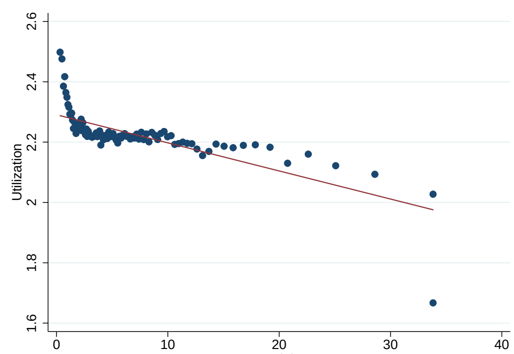
Average travel time (in minutes) from home to the office of the GP for the residents of each Norwegian municipality in 2017.

Figure 5: Share of the population visiting the GP declines by travel time



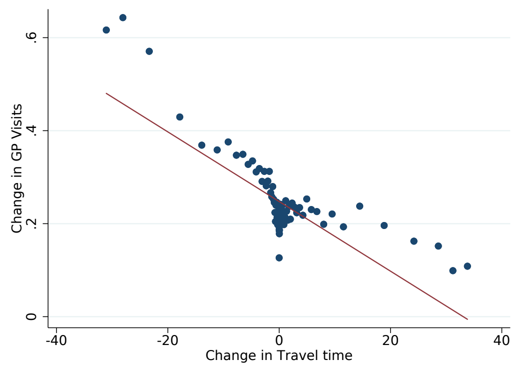
Share of the population visiting the GP in a calendar year by travel time in percentiles. Data for all years (2010-2017, N= 38,686,955). Travel time winsorized at the 95th percentile.

Figure 6: Visits to the GP declines by travel time



Number of visits to the GP per capita in a calendar year by travel time in percentiles. Data for all years (2010-2017, N= 38,686,955). Both travel time and GP-visits winsorized at the 95th percentile.

Figure 7: Visits to GP increases 2010-2017 when travel time drops 2010-2017



Change in number of GP visits 2010 to 2017 by change in travel time 2010 to 2017 (in minutes) Both travel time and GP-visits winsorized at the 95th percentile. N=4,202,805

5.2.2 Variation within individual- and GP locations

Table 2 report the estimated results restricting the (plausible) endogenous variation from health-related residential relocation or change in GP.

Column 4 presents the estimate when we restrict variation in travel time to not stem from residential moves, using only units of fixed individual and residential address.

The result on the extensive margin is now about 25 percent of the individual fixed effect estimate in column 3 above.

Column 5 instead evaluates the within individual- and GP-location, restricting variation in travel time to not stem from changes in GP location.

Column 6 presents the result of our preferred model, restricting variations in travel time to stem solely from road improvements, and neither from residential moves nor changes in GP. The estimate suggests that travel time has no effect on the extensive margin nor on the intensive unconditional margin, where the estimate both drops significantly to about 10 respectively 5 percent of the estimate in column 3, and is statistically insignificant, see also figure 8 (intensive conditional margin is to be updated). These estimates are similar if we include controls for labor income and education level, or if we do not winsorise.

5.2.3 Associations for E-consultations

Table 3 report the associasions between travel time in minutes and electronic consultaitons. Associations in column 1 adjusts for age and gender, column 2 adds interaction between them and controls for total income, education and municipality and column 3 adds fixed effects for individual and calendar year. All columns show a statistically significant association, positive on the extensive- and intensive unconditional margin and,

Table 1: Associations

	(1)	(2)	(3)
	OLS	OLS	FE
Dependent variable	Pr[Utilizing GP]	Pr[Utilizing GP]	Pr[Utilizing GP]
Travel time	-.0024888	-.0021677	-.0014029
	(9.40e-06)	(9.41e-06)	(.0000164)
	-264.86/***	-230.34/***	-85.58/***
Dependent variable	Nr. GP Visits	Nr. GP Visits	Nr. GP Visits
Travel time	-.0135111	-.0119037	-.0094007
	(.0000617)	(.0000619)	(.0001023)
	-218.89/***	-192.35/***	-91.89/***
Dependent variable	Conditional nr. GP Visits	Conditional nr. GP Visits	Conditional nr. GP Visits
	-.0081418	-.0078377	-.0098182
	(.0000887)	(.000089)	(.0001556)
	-91.82/***	-88.03/***	-63.10/***
Additional covariates:		x	x
Fixed effect *individual and calendar year*			x

Note: The table presents associations between travel time (in minutes) and utilization of GP in 2010-2017, using separate models for the extensive, intensive margin and intensive conditional margin (currently both estimated using linear regression, OLS). N= 38,809,339 (main analytic sample, cf. Section 4). For intensive conditional margin: N= 25, 173, 336. Estimates are adjusted for age group and gender. Additional covariates include educational level, municipality, total income and interaction between gender and age group.. Standard errors allow for dependent observations within individual over time. Mean of travel time, number of visits and share visiting the GP in year is 7.96 min, 2.20 visits and 64.9 percent, respectively. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively.

Table 2: Estimated effect of travel time on utilization

	(4) FE i*adress	(5) FE i*GPaddress	(6) FE i-adr*gp-adr
Dependent variable	Pr[Utilizing GP]	Pr[Utilizing GP]	Pr[Utilizing GP]
Travel time	-.0003795	-.0011261	-.0001432
	(.0000266)	(.0000223)	(.0001254)
t	-14.27/***	-50.55/***	-1.14
Dependent variable	Nr. GP Visits	Nr. GP Visits	Nr. GP Visits
Travel time	-.0046006	-.0071923	-.0004503
	(.0001644)	(.0001329)	(.000904)
t	-27.98/***	-54.11/***	-.50
Dependent variable	Conditional GP Visits	Conditional GP Visits	Conditional GP Visits
Travel time			
t			
Additional covariates:	x	x	
Share with variation	38 %	42 %	31%

Note: The table presents estimates of the effect of travel time (in minutes) on utilization of GP in 2010-2017, using separate models for the extensive, intensive margin and intensive margin conditional on GP utilizaiton (currently estimated using linear regression, OLS). Column 4 provides results from models with one fixed effect per individual and home address (cf Eq. 3); column 5 with one fixed effect per individual and GP address (cf Eq. 4); and column 6 with one fixed effect per individual and home address and GP address (cf Eq. 5). N= 38,809,339 (main analytic sample, cf. Section 4). For intensive conditional margin: N= 25, 173, 336. All model adjust for age group, gender, and calendar year fixed effects. Additional covariates include educational level, municipality, total income and interaction between gender and age group. In column 4 and 5, standard errors allow for dependent observations within individual over time. In column 6, standard errors allow for dependent observations within home address and GP location over time. Mean travel time, number of visits and share visiting the GP is 7.96 min, 2.20 visits and 64.9 percent, respectively. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. In column (4) the share refers (last line) to the individuals observed within a certain address who experience variation within this cell (observed at least twice) contrary to our expectations, negative association the extensive margin. The correlation on the extensive margin is negative and suggests a marginal effect of -.0006. Since about 30 percent of the population consults the GP electronically in a year, this represent a relative change of about 0.2 percent higher probability of utilizing electronic consultations per minute less travel time. The estimate changes slightly when including more controls and fixed effect at individual and calendar year, se column .2 and 3.

The corresponding estimate for number of visits is about .0000894, suggesting that a 10 minute increase in travel time increases the electronic consultations by 0.000894 per year. The corresponding estimate on the intensive conditional margin is .0045778 and suggests that a 10 minute reduction in travel time increase the number of yearly electronic consultations by 0.05 given that one utilize electronic consultaitons. About 1.4 million residents electronically consult the GP on average 2.2 times a year in our data, hence an average increase of 0.05 visits translates into about onehundred and fiftythousand electronic consultations per year.

5.2.4 Effect estimates for E-consultations

Table 4 contain the estimated results for different sources of varation in travel time. Again column 4 presents the estimate when we restrict variation in travel time to not stem from residential moves, using only units of fixed individual and residential address. Column 5 evaluates the within individual- and the GP-location, restricting variation in travel time to not stem from changes in GP location. Column 6 presents the result of our preferred model, restricting variations in travel time to stem solely from road improvements, and neither from residential moves nor changes in GP. The estimates in column 6 are tatistically significant and as expected positive on all margins. For the extensive margin the estimate suggests a marginal effect of .0017385 suggesting a relative change of about 0.5 percent higher probability of electronically consulting the GP per one more minut of travel time.

5.2.5 Associations for specialist consultations

Table 5 report the associations between travel time to the GP and consultations to a specialist. All the estimates suggests an inverse statistically significant association. Column 1 reports the association adjusting for age and gender and suggests the marginal extensive association to be -.0006976 implicating a relative change of about 0.1 percent higher probability of visiting a specialist for a one minute reduction in travel time to the GP. The association is about 1/3 of the corresponding association for GP consultaitons

5.2.6 Effect estimates for specialist consultations

Table 6 report the estimated results of travel time on specialist consultations. Column 4 presents the estimate when we restrict variation in travel time to not stem from residential moves, using only units of fixed individual and residential address. Column 5 evaluates the within individual- and the GP-location, restricting variation in travel time to not stem from changes in GP location. The estimated results all

Table 3: Associations electronic consultations

	(1) OLS	(2) OLS	(3) FE
Dependent variable	Pr[Utilizing E-cons]	Pr[Utilizing E-cons]	Pr[Utilizing E-cons]
Travel time	-.0006041	-.0003709	-.0004121
	(8.92e-06)	(8.95e-06)	(.0000159)
t	-67.72/***	-41.45/***	-25.96/***
Dependent variable	Nr. E-consultations	Nr. E-consultations	Nr. E-consultations
Travel time	.0000894	.0006567	-.0005255
	(.0000348)	(.000349)	(.0000597)
t	2.57/**	18.79/***	-8.80/***
Dependent variable	Conditional nr. E-cons	Conditional nr. E-cons	Conditional nr. E-cons
	.0045778	.0045848	.0011208
	(.0000866)	(.0000868)	(.0001771)
t	52.89/***	52.83/***	6.33/***
Additional covariates:		x	x
Fixed effect *individual and calendar year*			x

Note: The table presents associations between travel time (in minutes) and utilization of electronic GP consultations in 2010-2017, using separate models for the extensive, intensive margin and intensive conditional margin (currently estimated using linear regression, OLS). N= 38,809,339 (main analytic sample, cf. Section 4). For intensive conditional margin: N= 13, 260, 385. Estimates are adjusted for age group and gender. Additional covariates include educational level, municipality, total income and interaction between gender and age group. In column 3 tandard errors allow for dependent observations within individual over time. Mean of travel time, number of electronic consultations and share electronically consulting the GP in year is xx min, 0.8 e-consultations and 34.2 percent, respectively. Mean nr. of electronic consultations conditional on consulting the GP electronically is 2.34. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively.

Table 4: Estimated effect of travel time on electronic utilization

	(4) FE i*adress	(5) FE i*GPaddress	(6) FE i-adr*gp-adr
Dependent variable	Pr[Utilizing E-cons]	Pr[Utilizing E-cons]	Pr[Utilizing E-cons]
Travel time	.0001704	-.0003353	.0017385
	(.0000263)	(.0000215)	(.000135)
t	6.49/***	-15.61/***	12.88/***
Dependent variable	Nr. E-consultations	Nr. E-consultations	Nr. E-consultations
Travel time	.0011935	-.0006924	.0072003
	(.0000969)	.0000765	.0004787
t	12.32/***	-9.05/***	15.04/***
Dependent variable	Conditional nr. E-cons	Conditional nr. E-cons	Conditional nr. E-cons
	.0031329	.0006752	.0121419
	(.0002975)	(.0002494)	(.0013447)
	10.53/***	2.71/***	9.03/***
Additional covariates:	x	x	
Share with variation			

Note: The table presents estimates of the effect of travel time (in minutes) on electronic utilization of GP in 2010-2017, using separate models for the extensive, intensive margin and intensive margin conditional on utilizaiton (currently estimated using linear regression, OLS). Column 4 provides results from models with one fixed effect per individual and home address (cf Eq. 3); column 5 with one fixed effect per individual and GP address (cf Eq. 4); and column 6 with one fixed effect per individual and home address and GP address (cf Eq. 5). N= 38,809,339 (main analytic sample, cf. Section 4), for intensive conditional margin: N= 13, 260, 385. All model adjust for age group, gender, and calendar year fixed effects. Additional covariates include educational level, municipality, total income and interaction between gender and age group. In column 4 and 5, standard errors allow for dependent observations within individual over time. In column 6, standard errors allow for dependent observations within home address and GP location over time. Mean travel time, number of visits and share utilizing electronic consultations is 8 min, 0.8 e-consultations and 34.2 percent, respectively. Mean travel time and nr. of electronic consultations conditional on consulting the GP electronically is xx min and 2.34 times. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. In column (4) the share refers (last line) to the individuals observed within a certain address who experience variation within this cell (observed at least twice) suggest a statistically significant inverse effect on all margins when restricting variation in travel time to steem from either GP- relocation or residential moves. Column 6 presents the result of our preferred model, restricting variations in travel time to stem solely from road improvements, and neither from residential moves nor changes in GP. The estimate changes sign to positive on all margins. For the extensive margin the estimate is significant and a marginal effect of .0003646 suggest a relative change of about 0.06 percent lower probability of consulting a specialist per one minut less travel time to the assigned GP. .

5.2.7 Soubgroups

Tables 8 - 13 report the association and estimated effect of travel time on GP visits on the extensive margin for different subgroups. For all subgroups, the estimates for the effect are from our preferred model where we restrict variation in travel time to stem from road improvements and controling for (at most) age and gender. The estimates for the association is (generally) controlling for several control variables (see also the specific table).

Disabled

Table 8 refers to persons on disability benefit. Column 1 reports the association adjusting for age, gender and year, and interaction age and gender. Column 2 controls also for total income, education and municipality. The last two columns reports the estimates of our preferred model restricting variations in travel time to stem solely from road improvements. Column 3 adjusts for age, gender and interaction between them and year. Column 4 adds controls for total income, education and municipality. As expected, all columns show a statistically significant inverse association and estimated effect. The association is approximately the same as on population level (-.0023529 vs. main sample: -.0024888 see table 1). For people on disability benefit there is a statistically significant marginal effect of about the same size as the association, -.0022959, suggesting a relative change of about 0.3 percent higher probability of consulting the GP per one minut less travel time.

Long travel time

Similarly, table 9 report the association and estimated effect of travel time on GP utilization for persons living at least 15 minutes (in travel time by car) away from the GP. All the results show an inverse statistically significant relationship. The relative size of the association is above twice as big for people living farther away versus for the whole population. The inverse effect on the extensive margin for people living far away is -.0049948. About 60 percent of the subpopulation who live farther away visit the GP in a year, this represent a relative change of about 0.8 percent per minute.

Table 5: Associations specialist consultations

	(1) OLS	(2) OLS	(3) FE
Dependent variable	Pr[Utilizing Specialist]	Pr[Utilizing Specialist]	Pr[Utilizing Specialist]
Travel time	-.0002754	-.0005703	-.0006976
	(9.18e-06)	(9.19e-06)	(.0000162)
t	-30.01/***	-62.04/***	-43.10/***
Dependent variable	Nr. Specialist consultations	Nr. Specialist consultations	Nr. Specialist consultations
Travel time	-.0042708	-.006584	-.0070119
	(.0001099)	(.0001105)	(.0002039)
t	-38.86/***	-59.60/***	-34.38/***
Dependent variable	Conditional nr. Spec. cons	Conditional nr. Spec. cons	Conditional nr. Spec. cons
	-.0051917	-.0067224	-.0072192
	(.0001707)	(.0001716)	(.0003475)
t	-30.42/***	-39.17/***	-20.78/***
Additional covariates:		x	x
Fixed effect *individual and calendar year*			x

Note: The table presents associations between travel time (in minutes) and utilization of specialist consultations in 2010-2017, using separate models for the extensive, intensive margin and intensive conditional margin (currently estimated using linear regression, OLS). N= 38,809,339 (main analytic sample, cf. Section 4). For intensive conditional margin: N= . Estimates are adjusted for age group and gender. Additional covariates include educational level, municipality, total income and interaction between gender and age group. In column 3 standard errors allow for dependent observations within individual over time. Mean of travel time, number of specialist consultations and share consulting a specialist in year is xx min, 3.13 consultations and 60.7 percent, respectively. Mean nr. of specialist consultations conditional on consulting a specialsit is 5.15. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively.

Table 6: Estimated effect of travel time on specialist utilization

	(4)	(5)	(6)
Estimation method	FE i*address	FE i*GP address	FE i-addr*gp-addr
Dependent variable	Pr[Utilizing Specialist]	Pr[Utilizing Specialist]	Pr[Utilizing Specialist]
Travel time	-.0002842	-.0006863	.0003646
	(.0000259)	(.0000227)	(.0001318)
t	-10.96/***	-30.21/***	2.77/***
Dependent variable	Nr. Specialist consultations	Nr. Specialist consultations	Nr. Specialist consultations
Travel time	-.0021775	-.0060713	.0027009
	(.000311)	(.0002681)	(.0013695)
t	-7.00/***	-22.64/***	1.59
Dependent variable	Conditional nr. Spec. cons	Conditional nr. Spec. cons	Conditional nr. Spec. cons
	-.0015521	-.0055344	.0012341
	(.0005221)	(.0004988)	(.0025996)
	-2.97/***	-11.10/***	.47
Additional covariates:	x	x	
Share with variation			

Note: The table presents estimates of the effect of travel time (in minutes) on electronic utilization of GP in 2010-2017, using separate models for the extensive, intensive margin and intensive margin conditional on utilizaiton (currently estimated using linear regression, OLS). Column 4 provides results from a model with one fixed effect per individual and home address (cf Eq. 3); column 5 with one fixed effect per individual and GP address (cf Eq. 4); and column 6 with one fixed effect per individual home address and GP address (cf Eq. 5). N= 38,809,339 (main analytic sample, cf. Section 4). For intensive conditional margin: N= 23, 569, 087. All models adjust for age group, gender, and calendar year. Additional covariates include educational level, municipality, total income and interaction between gender and age group. In column 4 and 5, standard errors allow for dependent observations within individual over time. In column 6, standard errors allow for dependent observations within an individuals home address and GP location over time. Mean travel time, number of visits and share visiting the GP is 8 min, 0.8 e-consultations and 34.2 percent, respectively. Mean nr. of electronic consultations conditional on consulting the GP electronically is 2.34. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. In column (4) the share refers (last line) to the individuals observed within a certain address who experience variation within this cell (observed at least twice)

Income

Table 10 report the association and estimated effect for different income quantiles. There is a statistically significant inverse association between travel time and whether one visit the GP for all income quantiles, of about the same size, varying from 0.0024-0.003. The effect estimates are (inverse and) insignificant for the five income quantiles and for the group with no income it suggests a positive significant (at 5 percent) effect 0.0242366 (longer travel time higher probability of utilizing the GP).

Gender

Table 11 report the association and estimated effect for men and women. The estimates suggests a statistically significant inverse association similar for both genders varying between 0.002-0.003 and likewise for the effect estimates.

Age

Table 12report the association and estimated effect for different age groups. The estimates suggests a statistically significant inverse association varying from 0.002 for age groups in the span 19-69 years to 0.004 for persons over 80 years. Similarly the effect estimates are statistically significant and suggests an inverse effect of about 0.002-0.003, being slightly higher for the very oldest and youngest.

Education

Table 13 report the association and estimated effect for different educational levels. In line with our main result, we find a statistically significant inverse association for all levels of educaiton. The effect estimates are inverse for all levels of education, and statistically significant for secondary and higher tertiary education.

6 Conclusions

[To be included]

References

[Acton, 1975] Acton, J. P. (1975). Nonmonetary factors in the demand for medical services: Some empirical evidence. *Journal of Political Economy*, 83(3):595–614.

[Brewer et al., 2012] Brewer, N., Pearce, N., Day, P., and Borman, B. (2012). Travel time and distance to health care only partially account for the ethnic inequalities in cervical cancer stage at diagnosis and mortality in new zealand. *Australian and New Zealand Journal of Public Health*, 36(4):335–342.

[Buor, 2003] Buor, D. (2003). Analysing the primacy of distance in the utilization of health services in the ahafo-ano south district, ghana. *The International journal of health planning and management*, 18(4):293–311.

[Celaya et al., 2006] Celaya, M. O., Rees, J. R., Gibson, J. J., Riddle, B. L., and Greenberg, E. R. (2006). Travel distance and season of diagnosis affect treatment choices for women with early-stage breast cancer in a predominantly rural population (united states). *Cancer Causes & Control*, 17(6):851–856.

[Engelman et al., 2002] Engelman, K. K., Hawley, D. B., Gazaway, R., Mosier, M. C., Ahluwalia, J. S., and Ellerbeck, E. F. (2002). Impact of geographic barriers on the utilization of mammograms by older rural women. *Journal of the American Geriatrics Society*, 50(1):62–68.

[Fiva et al., 2014] Fiva, J. H., Hægeland, T., Rønning, M., and Syse, A. (2014). Access to treatment and educational inequalities in cancer survival. *Journal of health economics*, 36:98–111.

[Friedman et al., 2013] Friedman, J. M., Hagander, L., Hughes, C. D., Nash, K. A., Linden, A. F., Blossom, J., and Meara, J. G. (2013). Distance to hospital and utilization of surgical services in haiti: do children, delivering mothers, and patients with emergent surgical conditions experience greater geographical barriers to surgical care? *The International journal of health planning and management*, 28(3):248–256.

[Goldberg et al., 2014] Goldberg, D. S., French, B., Forde, K. A., Groeneveld, P. W., Bittermann, T., Backus, L., Halpern, S. D., and Kaplan, D. E. (2014). Association of distance from a transplant center with access to waitlist placement, receipt of liver transplantation, and survival among us veterans. *Jama*, 311(12):1234–1243.

[Grossman, 1972] Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, 80(2):223–255.

[Grytten et al., 2014] Grytten, J., Monkerud, L., Skau, I., and Sørensen, R. (2014). Regionalization and local hospital closure in norwegian maternity care. the effect on neonatal and infant mortality. *Health Services Research*, 49(4):1184–1204.

[Grytten et al., 2011] Grytten, J., Skau, I., and Sørensen, R. (2011). Do expert patients get better treatment than others? agency discrimination and statistical discrimination in obstetrics. *Journal of health economics*, 30(1):163–180.

[Grytten et al., 2005] Grytten, J., Sørensen, R. J., and Skau, I. (2005). Fastlegeordningen: marked, legedekning og tilgjengelighet.

[Haynes, 2003] Haynes, R. (2003). Geographical access to health care. *Access to health care*, pages 13–35.

[Judge et al., 2011] Judge, A., Caskey, F. J., Welton, N. J., Ansell, D., Tomson, C. R., Roderick, P. J., and Ben-Shlomo, Y. (2011). Inequalities in rates of renal replacement therapy in england: does it matter who you are or where you live? *Nephrology Dialysis Transplantation*, 27(4):1598–1607.

[Kelly et al., 2016] Kelly, C., Hulme, C., Farragher, T., and Clarke, G. (2016). Are differences in travel time or distance to healthcare for adults in global north countries associated with an impact on health outcomes? a systematic review. *BMJ Open*, 6(11).

[Lake et al., 2011] Lake, I., Jones, N., Bradshaw, L., and Abubakar, I. (2011). Effects of distance to treatment centre and case load upon tuberculosis treatment completion. *European Respiratory Journal*, 38(5):1223–1225.

[Lankila et al., 2016] Lankila, T., Näyhä, S., Rautio, A., Rusanen, J., Taanila, A., and Koiranen, M. (2016). Is geographical distance a barrier in the use of public primary health services among rural and urban young adults? experience from northern finland. *Public health*, 131:82–91.

[Ludwick et al., 2009] Ludwick, A., Fu, R., Warden, C., and Lowe, R. A. (2009). Distances to emergency department and to primary care providers office affect emergency department use in children. *Academic Emergency Medicine*, 16(5):411–417.

[Markin et al., 2011] Markin, C., Roessel, L., Lai, G., Turner, M., and Barst, R. (2011). 18 does geographic distance from a pulmonary hypertension center delay diagnosis and treatment? a reveal registry analysis. *The Journal of Heart and Lung Transplantation*, 30(4):S14.

[Monnet et al., 2008] Monnet, E., Ramée, C., Minello, A., Jooste, V., Carel, D., and Di Martino, V. (2008). Socioeconomic context, distance to primary care and detection of hepatitis c: a french population-based study. *Social science & medicine*, 66(5):1046–1056.

[Raknes et al., 2013] Raknes, G., Hansen, E. H., and Hunskaar, S. (2013). Distance and utilisation of out-of-hours services in a norwegian urban/rural district: an ecological study. *BMC health services research*, 13(1):222.

[Rodkey et al., 1997] Rodkey, S. M., Hobbs, R. E., Goormastic, M., and Young, J. B. (1997). Does distance between home and transplantation center adversely affect patient outcomes after heart transplantation? *The Journal of heart and lung transplantation: the official publication of the International Society for Heart Transplantation*, 16(5):496–503.

[Strauss et al., 2006] Strauss, K., MacLean, C., Troy, A., and Littenberg, B. (2006). Driving distance as a barrier to glycemic control in diabetes. *Journal of general internal medicine*, 21(4):378.

Appendix

A

Table 7: Summary statistics

Base year 2010	Mean	p50	SD	N
Explanatory variable:				
Travel time (minutes)[*]	7.94	4.90	8.38	4,644,280
Background variables:				
Men	49.9 %	0	0.50	4,644,280
Age	39.64	39	23.13	4,644,280
Education (level)[a]	1.9	2	0.86	2,759,881
Earnings (NOK)[b]	292,800	272,088	573,320	2,992,990
Share on disability benefits[c]	6.38 %		24.42 %	4,644,280
Share on sick leave benefits[d]	15.55 %			4,644,280
Share on unemploym. benefits[e]	3.80 %			4,644,280
Outcome variables:				
GP FTF:				
Extensive GP utilization (share) [f],[*]	63.94 %	1	48.0 %	4,644,280
Intensive Nr. of GP visits[f],[*]	2.3715	1	3.512.59	4,644,280
Intensive conditional nr. of GP visits[f],[*]	3.71	2	3.78	2,969,587
ELECTRONIC CONSULTATIONS:				
Extensive e-consultaitons (share) [g]	30.37 %	0	45.98 %	4,644,280
Intensive nr. of e-consultations[g]	0.671	0	1.60	4,644,280
Intensive conditional nr. of e-consultaitons[g]	2.21	1	2.25	1,410,302
SPECIALIST CONSULTAITONS:				
Extensive specialist consultaitons (share)	60.99 %	1	48.79 %	4,644,280
Intensive nr. of specialist consultations	3.03	1	5.73	4,644,280
Intensive conditional nr. of specialist consutlaitons	4.97	3	6.65	2,832,374

Note: Summary statistics for base year 2010, winsorized at p95 in travel time and nr of GP visits*. Background variables are measured the year prior to utilization. The sample includes Norwegian residents assigned to a GP in 2010 in total 4,644,280 different individuals See Section 4.2- 4.4 for details.

[a] Calculated over individuals above the age of 30, with known non-missing data on education, summarized excluding unknown educational levels. Educational levels refers to: 0 "No education", 1 "Primary education", 2 "Secondary education", 3 "Lower tertiary Education", 4 "Higher Tertiary education".

[b] Calculated in NOK over individuals aged 16-67.

[c] Calculated over individuals who recieve positive amount of disability benefit

[d] Calculated over individuals who recieve positive amount of sick leave benefits

[e] Calculated over individuals who recieve positive amount of unemployment benefits

[f] Calculated over visits to the GP in 2010 that requires a "face-to-face" meeting

[g] Calculated over electronic consultations to a GP in 2010

[h] Calculated over specialist consultations in 2010

[*] Non-winsorized sample: travel time: mean;18.498, median; 4.900, SD: 90.498. Utilization (dummy visited GP): mean; 63.94 %, SD; 48.1 %. Utilization (nr. of GP visits): Mean; 2.371, SD; 3.508

B

Table 8: Association and estimated effect for people on Disability benefit

	Dependent variable: Pr[Utilizing GP]			
	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	FE	FE
Travel time (min)	-.0023529	-.00183	-.0022959	-.001868
	(.0000352)	(.000035)	(.0000513)	(.0000508)
t	-66.91/***	-52.35/***	-44.78/***	-36.79/***
Additional covariates:		x		x
calendar year dummies/FE calendar yr	x	x	x	x
interaction gender agegroup	x	x		

Estimation results for the effect of travel distance on the extensive margin FTF GP consultations, for subgroup on disability pension. Year 2010-2017. N=2,148,251. Standard errors allow for dependent observations within individuals residential address and GP-location) Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. All estimates are adjusted for age, gender and year. Additional covariates refer to interaction agegroup and gender, education, municipality and total income. Column 3 and 4 has one fixed effect per individual addres and GP address and standard errors allow for dependent observations within home address and GP location over time. The share who utilize the GP is 78.96 percent, mean travel time is XX min.

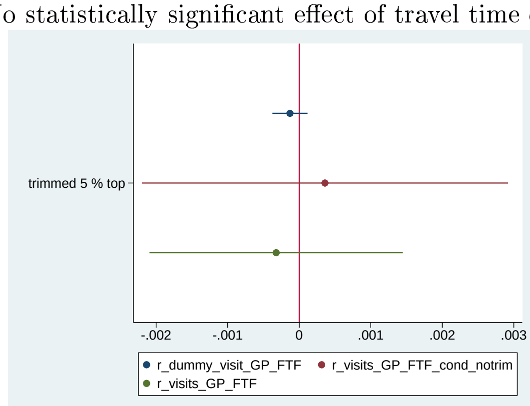
C

Table 9: Associations and estimated effect for people with long travel time

	Dependent variable: Pr[Utilizing GP]			
	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	FE	FE
Travel time (min)	-.0057308	-.0051143	-.0055476	-.0049948
	(.00003)	(.0000301)	(.000041)	(.000041)
t	-191.01/***	-169.97/***	-135.36/***	-121.72/***
Additional covariates:		x		x
Calendar year dummies/FE calendar yr	x	x	x	x
Interaction gender agegroup	x			
Observations	5,390,646	5,390,646	5,390,646	5,390,646

Estimation results for the association and effect of travel distance on GP FTF consultations, for subgroup living at least 15 minutes away from the GP. Year 2010-2017. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. All estimates adjusted for age and gender. Additional covariates refer to interaction agegroup and gender, education, municipality and total income. Column 3 and 4 has one fixed effect per individual address and GP address and standard errors allow for dependent observations within residential address and GP-location over time.Share consulting the GP FTF is 59.61 percent, mean travel time to the GP is xx min.

Figure 8: No statistically significant effect of travel time on GP FTF



Coeficient plot of the effect road improvemetns on GP FTF consultations for the extensive margin (dummy-blue), intensive margin conditioning on utilization(red) and intensive unconditional margin (green) Data for all years (2010-2017), N= 38, 809, 339. Conditional margon N= 25,173,336.CI at 5 percent

D

Table 10: Association and effect estimates for income levels

	Dependent variable: Pr[Utilizing GP]					
Estimation method:	OLS	OLS	OLS	OLS	OLS	OLS
	No income	Q1	Q2	Q3	Q4	Q5
Travel time (min)	-.0024035 (.0000248)	-.002964 (.000026)	-.0023857 (.0000205)	-.0026305 (.0000213)	-.0024615 (.0000222)	-.0026005 (.0000237)
t	-96.73/***	-113.78/***	-116.65/***	-123.70/***	-110.68/***	-109.54/***
Estimation method:	FE	FE	FE	FE	FE	FE
	No income	Q1	Q2	Q3	Q4	Q5
Travel time (min)	(.0120822)	-.0001605 (.0003669)	-.0004385 (.0003335)	-.0000689 (.0002766)	-.0004951 (.0003149)	-.0004677 (.0003107)
t	2.01/**	0.662	-1.31	-0.25	-1.57	-1.51
Observations	5,517,909	6,658,342	6,658,276	6,658,275	6.658.259	6.658.268
Mean	0.6281	0.4993	0.6469	0,7453	0.7121	0.6285

Estimation results for the effect of travel distance on FTF GP consultations, for 5 quantiles of income levels and one group for zero or missing income. All estimates are adjusted for year, age, gender and interaction between age and gender. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. All estimates are adjusted for year, age, gender and interaction agegroup and gender. Fixed effect estimates has one fixed effect per individual address and GP address and standard errors allow for dependent observations within home address and GP location over time.

Table 11: Association and estimated effect for men and women

	Dependent variable: Pr[Utilizing GP]			
	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	FE	FE
Men:				
Travel time (min)	-.0027921	-.0025158	-.0028563	-.0026393
	(.0000133)	(.0000133)	(.0000183)	(.0000183)
t	-210.32/***	-189.26/***	-155.67/***	-143.97/***
Observations	19,444,277	19,444,277	19,444,277	19,444,277
Mean dummy GP FTF	0.5895	0.5895	0.5895	0.5895
Estimation method	OLS	OLS	FE	FE
Women:				
Travel time (min)	-.0021596	-.001749	-.0020144	-.0016896
	(.0000133)	(.000626)	(.0000185)	(.0000184)
t	-162.75/***	-131.81/***	-109.17/***	-91.82/***
Observations	19,365,0625,390,646	5,390,646	5,390,646	5,390,646
Mean dummy GP FTF	0.5895	0.5895	0.5895	0.5895
Additional covariates:		x		x

Estimation results for the association and effect of travel distance on the extensive margin FTF GP consultations for men and women. Year 2010-2017. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. All estimates adjusted for age and calendar year. Additional covariates refer to education, municipality and total income. Column 3 and 4 has one fixed effect per individual address and GP address and standard errors allow for dependent observations within home address and GP location over time.

Table 12: Associations and estimated effects for age groups

	Dependent variable: Pr[Utilizing GP]						
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Age group interval	0-3	4-18	19-30	31-50	51-69	70-89	80+
Travel time (min)	-.0032618	-.0027046	-.0023432	-.0024704	-.0020783	-.0032484	-.0041013
	(.0000536)	(.0000261)	(.0000192)	(.0000179)	(.0000199)	(.0000299)	(.0001168)
t	-60.82/***	-103.76/***	-121.90/***	-137.98/***	-104.54/***	-108.59/***	-35.12/***
Estimation method	FE	FE	FE	FE	FE	FE	FE
Age group interval	0-3	4-18	19-30	31-50	51-69	70-89	80+
Travel time (min)	-.0031959	-.0025729	-.0023892	-.0025551	-.0021655	-.0025481	-.0034835
	(.0000605)	(.0000334)	(.0000227)	(.0000143)	(.0000304)	(.0000483)	(.0001851)
t	-52.80/***	-76.95/***	-105.21/***	-105.03/***	-71.28/***	-52.75/***	-21.10/***
Observations	1,386,890	7,215,197	6,085,998	10,809,721	8,759,075	4,146,177	406,281
Mean dummy GP FTF	0.6947	0.5212	0.6008	0.6425	0.7222	0.7948	0.5569

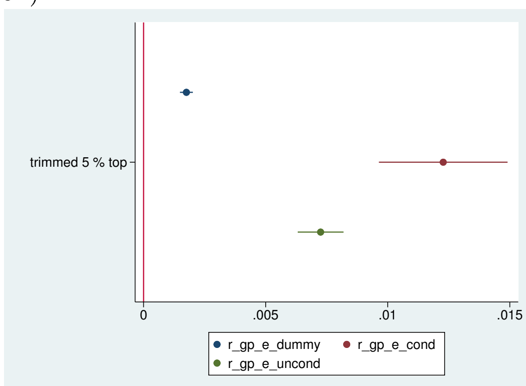
Estimation results for the association and effect of travel distance on the extensive margin FTF GP consultations, for seven age group intervals. Year 2010-2017. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. All estimates adjusted for gender and year. FE estimates has one fixed effect per home address and GP address and standard errors allow for dependent observations within home address and GP-location over time.

Table 13: Associations and estimated effects for levels of education

	Dependent variable: Pr[Utilizing GP]					
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS
Education	No	Primary	Secondary	Lower tertiary	Higher Tertiary	Unknown/
Travel time (min)	-.004818 (.0002451)	-.001712 (.0000209)	-.0020533 (.0000194)	-.0023323 (.0000286)	-.002962 (.0000537)	-.002677 (.0000462)
t	-19.64/***	–81.82/***	-105.95/***	–81.56	-55.15/***	-57.95/***
Additional covariates	x	x	x	x	x	x
Estimation method	FE	FE	FE	FE	FE	FE
Education	No	Primary	Secondary	Lower tertiary	Higher Tertiary	Unknown
Travel time (min)	-.0028882 (.0026785)	-.0001764 (.0002283)	-.0004833 (.0002205)	-.0002066 (.000384)	-.0016577 (.0009256)	-.0001233 (.0006535)
t	-1.08	-0.77	-2.19/**	-0.54	-1.79/*	0.19
Observations	75,821	7,640,045	9,472,515	4,404,297	1,230,949	1,585,415
Mean dummy GP FTF	0.7281	0.7069	0.7129	0.6942	0.6018	0.5976

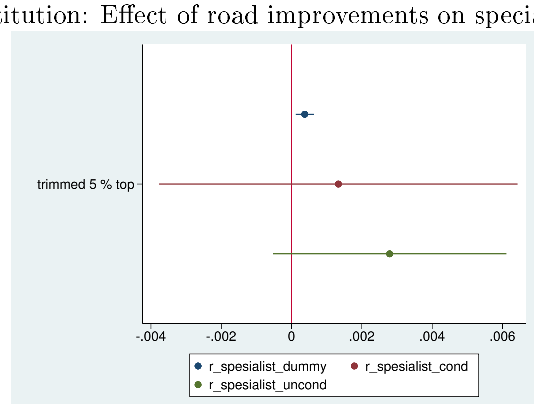
Estimation results for the association and effect of travel distance on the extensive margin FTF GP consultations, for levels of education, calculated for age >= 30 (for people with non-missing information). Year 2010-2017. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by ***, ** and *, respectively. All estimates adjusted for year, gender, age group, and interaction between gender and age group. Additional covariates refer to municipality and total income FE estimates has one fixed effect per home address and GP address and standard errors allow for dependent observations within home address and GP-location over time.

Figure 9: Robustness: (shorter) Travel time has a positive statistially significant effect on electronic consultations (less electronic utilization)



road improvemetns on electronic consultations for the extensive (dummy-green), intensive margin conditioning on utilization(blue) and intensive unconditional margin (red) Data for all years (2010-2017), N= .CI at 5 percent

Figure 10: Substitution: Effect of road improvements on specialist consultations



road improvemetns on electronic consultations for the extensive (dummy-red), intensive margin conditioning on utilization(green) and intensive unconditional margin (blue) Data for all years (2010-2017), N= . Travel time winsorized at the 95th percentile.CI at 5 percent