THE AMBIGUOUS EFFECT OF GP COMPETITION: THE CASE OF HOSPITAL ADMISSIONS

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SUMMARY
In the theoretical literature on general practitioner (GP) behaviour, one prediction is that intensified competition induces GPs to provide more services resulting in fewer hospital admissions. This potential substitution effect has drawn political attention in countries looking for measures to reduce the growth in demand for hospital care. However, intensified competition may induce GPs to secure hospital admissions a signal to attract new patients and to keep the already enlisted ones satisfied, resulting in higher admission rates at hospitals. Using both static and dynamic panel data models, we aim to enhance the understanding of whether such relations are causal. Results based on ordinary least square (OLS) models indicate that aggregate inpatient admissions are negatively associated with intensified competition both in the full sample and for the sub-sample patients aged 45 to 69, while outpatient admissions are positively associated. Fixed-effect estimations do not confirm these results though. However, estimations of dynamic models show significant negative (positive) effects of GP competition on aggregate inpatient (outpatient) admissions in the full sample and negative effects on aggregate inpatient admissions and emergency admissions for the sub-sample. Thus, intensified GP competition may reduce inpatient hospital admissions by inducing GPs to provide more services, whereas, the alternative hypothesis seems valid for outpatient admissions. © 2016 The Authors.

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KEY WORDS: general practitioner (GP); competition; hospital care; admission to hospital; dynamic panel data model

1. INTRODUCTION

Is competition between primary care physicians or general practitioners (GPs) significantly influencing the demand for hospital services? Health authorities from different jurisdictions—for instance, the UK and Norway—advocate that intensified competition will lead to lower demand for hospital care. Thus, competition is instrumental in terms of reducing the growth in health care costs by inducing substitution of costly hospital care by less costly primary care. However, a sober view of the potential benefits of intensified competition between GPs should account for the possibility that the demand for hospital care will not significantly change at all or may even increase.

An important role for the GPs is to act as advocates for their enlisted patients, thereby helping to secure their patients’ access to high-quality services. The flip side of the coin is that a GP is expected to act as a gatekeeper, too, whose contribution is to reduce the demand for hospital care by providing care at the primary care level. Rightly, in a patient list system in which GPs are remunerated with a combination of fee-for-service and

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capitation, a situation of spare list capacity can induce GPs to provide more and longer consultations. Herein also lies the potential for a higher quality of services provided by the primary care sector. Higher spare list capacity resulting from intensified competition can result in fewer referrals from GPs to hospitals and thereby lower admission rates at hospitals, at least for services that are substitutes for hospital care.

On the other hand, in principle, the greater the competition, the more likely it is that the gatekeeper role is weakened, resulting in higher demand for inpatient and outpatient care for which GP services are potential substitutes.1 This effect is driven by a potential misconception by patients: hospital care is the better option and GPs that are able to secure access to hospital care have a competitive advantage. Thus, intensified competition may lead to a higher number of referrals leading to higher admission rates and higher aggregate health care costs than necessary in terms of providing adequate care.

In a recent paper, Godager et al. (2015) provide a theoretical model of GP behaviour describing these two opposing effects. In their model, GPs behave as if their preferences are a weighted average of profits and patients’ (expected) benefits. Physicians are paid according to a fee-for-service and capitation contract with a national insurance system. When GPs compete vigorously for patients, they may adjust their practice styles to put more weight on patient benefits. Alternatively, a more competitive GP market may endow patients with better outside options. This implies a better bargaining outcome for them. In conclusion, the model establishes an argument for taking into consideration two opposing effects: (i) in a more competitive market leading to a higher weighting of patient benefits, the GP refers the patient to hospital more often, and (ii) in a more competitive market with a given total demand for GP services, the GP refers the patient to the hospital less often.

In terms of studies on how competition influences physicians’ behaviour,2 there seems to be a divergence between the responses of physicians working in the US health care system and those working in a national health care system such as the British and Norwegian systems. Focussing here on the effect of competition on hospital admissions, we do not present studies on GP competition that have examined different outcomes than ours.3

Gaynor and Town (2011) review the extensive empirical literature on competition in the health care markets in the US. Bradley and Ricketts (2010) find that the higher the density of primary care physicians in a geographical area, the fewer inpatient and emergency room visits. Fortney et al. (2005) find that a higher number of primary care facilities in a district is associated with a decrease in specialty medical encounters. The overall impression is that the association between competition and hospital care is negative.

In the European context,4 the conclusion is quite the opposite. Studies show that the association between competition and admissions is insignificant, or if there is a significant association, it is positive. Gravelle et al. (2003) provide analyses of data from the British NHS. They find a positive association between density of physician and admissions to hospitals. Morris et al. (2003) report no significant association between competition and admissions in the NHS system, a result that lends no support to the ‘stronger GP competition, less hospital care demand’ hypothesis either. Carlsen and Norheim (2003) find that doctors generally perceive themselves as less concerned with the gatekeeper role under a new patient list system introduced in Norway. GPs felt

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1In a Norwegian context, patients in need of surgical procedures and post-surgical medical attendance are in general likely to be referred to hospital regardless of degree of competition. Likewise for medical treatment demanding specialized medical equipment and skills.
2Numerous studies show that physicians change their behavior when financial incentives change. McGuire (2000, 2011) provides an overview of such studies.
3An example from quite a different regulatory regime compared to the Norwegian one, Gravelle et al. (2016) study the effects of changes in competition on the prices GPs in Australia charge for consultations. Patients pay the difference between the price set by the GP and a fixed reimbursement from the national tax-funded Medicare insurance scheme. Gravelle et al. (2016) find within areas that GPs with distant competitors charge higher prices and a smaller proportion of their patients make no out-of-pocket payment.
4Not all European countries have a gatekeeper function in the sense that a patient needs a referral to access secondary care, as is the case in Denmark, Italy, Netherlands, Norway, Portugal, Slovak Republic, Spain and the United Kingdom. In some countries, a referral is not necessary at all, for example, Austria, Czech Republic, Greece, Iceland, Luxembourg and Sweden. In Belgium, France, Germany, Ireland and Switzerland, patients are financially encouraged to obtain a referral from primary care physicians but are not obliged to do so (Paris et al., 2010).

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it more important to provide better services and to keep patients satisfied, that is, GPs’ consciousness of the gatekeeper role has diminished. Iversen and Ma (2011), using radiology referral data from Norway, find that GPs facing a shortage of patients refer more often than GPs who do not. Tjerbo (2010), using Norwegian data, reports that competition among GPs does not affect inpatient services. Tjerbo reports reduced use of ambulatory care, though. Godager et al. (2015) find that intensified competition between Norwegian GPs has either insignificant or positive associations on GPs’ referrals of patients to hospital care. Based on Italian data, Atella and Deb (2008), although not a study of GP competition per se concludes that primary care physicians and specialists are substitute sources of medical care.

We use rate of open list practices in a municipality as a measure of competition between GPs. We study variations in admission rates at public hospitals rather than referrals. The reason is twofold: (i) we do not have referral data available, but we do have information on inpatient and outpatient admissions, the hospital at which patients are treated and the municipality in which patients live, and (ii) the policy of increasing competition is meant to reduce (the growth of) hospital usage by substitution of hospital care with increased GP effort. In the Norwegian context, a referral to hospital from a GP or private specialist under contract with the health authorities is in most cases subsequently followed by either an inpatient or outpatient admission.

Based on the theoretical arguments developed by Godager et al. (2015), we find it plausible that the higher number of GP practices with spare list capacity, the stronger is competition between GPs in a given geographical area. If stronger competition leads to significantly higher admission rates, then the weaker gatekeeper effect dominates the substitution effect. If intensified competition manifests itself in significantly lower admission rates, the substitution effect dominates. In a specific geographical area, the two opposing effects may cancel each other out such that stronger competition does not lead to significant changes in the number of total number of admissions to hospitals.

However, the weaker gatekeeper effect and the substitution effect may dominate the other depending on the patient type in question. We add sub-studies as alternative ways of testing the theoretical arguments: studies of changes in the inpatient–outpatient–emergency ‘mix’; disease specific studies and cohort specific studies.

There are several ways in which our study contributes to the existing literature. In particular, to obtain information on health care use, previous research employs cross-sectional survey data, but it is well recognized that surveys based on self-reported data are subject to measurement error that arises when respondents are asked to recall past health care use (Clarke et al., 2008). Instead, our data come from register data, where recall bias is likely to be less of a concern. Moreover, one would expect that the location decision of a GP and the desired number of patients may depend on the demand for health services in an area. Hence, the competition measure—the share of GPs with open list—could be endogenous. The existing empirical literature neither addresses this issue nor gives an indication of whether the effect of GP competition and hospital admissions is causal or not. Using both static and dynamic panel data models, this paper further aims to shed light on the issue of causality.

We find significant negative effects of intensified GP competition on aggregate inpatient hospital admissions and significant positive effects on outpatient admissions. Particularly, results based on both the dynamic models—the difference generalized method-of-moments (DIF-GMM) and the system generalized method-of-moments (SYS-GMM)—estimators show a negative effect on aggregate inpatient admissions for all patients and the sub-sample of patients aged between 45 and 69 years. A significant positive effect observed for outpatient admissions (full sample) and a negative effect on emergency admissions for the sub-sample of patients aged between 45 and 69 years.

Section 2 gives a short description of some important institutional features of the primary and specialist health care sectors in Norway. Section 3 describes the data and defines the variables used in the empirical part.

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5Data on the number of GPs with open list, that is, fewer patients than what a GP want to have, as registered in the national patient–GP list system, and data on number of practices that do not have spare capacity are used to calculate the competition measure.

6Unfortunately, the health authorities in Norway do not collect data on how many referrals that are turned down by hospitals. We believe referrals of this kind constitute a fairly small share of the total number of referrals that are received by hospitals.
Section 4 discusses the econometric issues, while the empirical results are presented in Section 5. Discussion and concluding remarks are gathered in Section 6.

2. INSTITUTIONAL SETTING

Like most Western countries, Norway has faced an increased demand for health care as a result of new medical technologies, changing demographics and strong population growth. As the willingness to expand health care resources through increased taxes and co-payments has been limited, the health care sectors have been increasingly required to take into account a strict budget constraint (Gerdtham, 2012). In Norway, as elsewhere, this economic problem has been met by reforms that in essence represent some form of intensified competition, either directly or indirectly.

In Norway, the responsibility of providing primary care services belongs to local authorities (i.e. municipalities), of which there are approximately 430 ranging in size from a few hundred inhabitants to several hundred thousand inhabitants. Many municipalities are classified as rural ones with relatively long distances to the nearest hospital. Ageing of the population is an issue in many municipalities, both rural and urban ones, both in terms of providing capacity and quality of primary care services. The major primary care services are home care services for older people, although the sharpest increase in demand in the last 10 years has come from younger groups of the population, short-term and long-term care in institutions, and physician/GP services.

The institutional and regulatory framework of a health care system influences the incentives facing health care providers. Following the introduction of a patient list system in 2001, most physicians receive a capitation payment for each patient on the list, in addition to fee-for-service remuneration. A minority of GP practices are on fixed salary contracts with the local authorities, with a share of 4.5% in 2014.7

A physician can have up to 2500 patients on his/her list. The minimum list size is 500 patients. On average, in 2014 GPs had a list of 1132 patients. The number has decreased from 1175 in 2001. Number of GPs has increased from 3661 to 4512 in the same period.8

Information on list sizes is transparent through a web based service allowing patients to keep track of their physician’s list size and spare list capacity, as well as that of all other GPs under contract in the list patient system. This information makes changes of physician fairly easy for patients. Patients can change physician twice a year at most. The annual switching rate because of ‘patient dissatisfaction’ (excluding GP-initiated switches and patient initiated switches because of address changes) has been about 3% in the period 2012–2014.9

A GP may want to reduce the number of patients on the list but cannot do so without applying to the local authorities. The same goes for an increase of number of patients, i.e., an increase in the ‘ceiling’. Furthermore, local authorities decide the number of GP licenses that are available. In sum: there is neither free exit nor free entry but still opportunities for competition. In principle, changes in degree of competition as we have defined it can happen for a number of reasons. GPs retire and the new GPs want to have more patients on their lists; GPs can be granted the permission to increase the number of patients on their list (increase the ‘ceiling’) and local authorities can decide to contract with more GPs to increase the coverage and/or to promote more choice for patients.10

Inpatient hospital care is by and large provided by state-owned hospitals with a small but growing provision from private actors under contract with the regional health authorities. On the other hand, private clinics or specialists receive approximately 30% of outpatient referrals in a given year. There are approximately 60 public

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7https://helsedirektoratet.no/statistikk-og-analyse/fastlegestatistikk
8https://www.ssb.no/en/helse/statistikker/helsetjko/aar
9Switching based on patients own initiative was 1.7% in 2014, while switching because of reduced list size was 1.3% in 2014. See https://helsedirektoratet.no/Documents/Statistikk%20og%20Analyse/Fastlegestatistikk/Fastlegestatistikk%202014%20hovedtall.pdf.
10Unfortunately, data on most of the “exit/entry” possibilities are not available. The share of patient switching due to reduced GP practices or GP practice closures is available though. The share, measured the last quarter of a year, is fairly small (1.6%) and stable in the period 2012–2015.
hospitals located across the country. Hospitals are remunerated on the basis of a DRG-based prospective system for inpatient care. Outpatient care is remunerated on the basis of outpatient tariffs with some procedures earning DRG-based remuneration.

3. DATA AND VARIABLES

3.1. Data

Two registers are used in this study. Data on hospital admissions are extracted from the Norwegian Patient Register (NPR) for the period 2001–2009. Municipal or local area variables—including a measure of the intensity of GP competition and other GP attributes, and socio-demographic variables characterizing municipalities—come from Statistics Norway’s KOSTRA (an abbreviation for ‘municipality-state-reporting’) database.

In the NPR data, each admission to hospital is registered as one observation. For example, if an individual uses hospital care more than once in the course of a calendar year, each occasion is considered to be a separate admission. On the other hand, if someone does not use any sort of hospital care during a calendar year, the individual is not registered in our dataset. Around 870,000 admissions per year are recorded in our NPR dataset. In total, our analyses are based on approximately 7,800,000 admissions or observations for the period 2001–2009.

As we do not observe the non-users in the dataset, we construct a hospital care use variable that is group based. Each group is uniquely characterized by a set of categorical variables: age-group (19 groups), gender (male/female: two groups), year (nine periods: nine groups) and patients’ home municipality (where they live) (430 municipalities: 430 groups). Ideally, our dataset should consist of 147,060 groups (i.e., $19 \times 2 \times 9 \times 430$). However, it could be the case that not all municipalities cover all age groups, and/or all age groups may not use all types of hospital care and/or not all age groups are represented as hospital care users in all years. Some of the aforesaid possibilities occurred in our data, so consequently we have ended up with 132,900 patient groups in the full sample analyses.

The subsample of patients consisting of patients aged between 45 and 69 years (age groups 10–14) should ideally consists of 37,244 groups ($5 \times 2 \times 9 \times 424$), but because of ‘missing values’, our analyses are based on 35,452 patient groups.

3.2. Dependent variables

3.2.1. Four dependent variables for each patients group. We construct four dependent variables for each patient group described in section 3.1: per capita number of aggregate inpatient admissions ($all_{\text{inpat}}$); two alternative paths for inpatient admissions, planned ($pl_{\text{inpat}}$) and emergency ($em_{\text{inpat}}$), and outpatient ($out_{\text{pat}}$) hospital admissions.

The measure of hospital admissions for each patient group is calculated in the following way: total number of hospital admissions within each patient group (nominator), is divided by the total number of inhabitants in that group (denominator). This measure can be defined as per capita hospital admissions by a specific patient group. For illustration, a group is defined as patients who are aged between 50 and 54, female, have used inpatient services during the year 2009 and live in the municipality of Oslo. We find 1,370 aggregate inpatient admissions for this specific group consisting of 16,507 inhabitants. Using this information, we calculate per capita aggregate inpatient admissions for the group as follows: $\frac{1370}{16507} = 0.083$.
Tables I and II give the definitions and descriptive statistics of the dependent variables used in the analyses. For the full sample (all patients), aggregate inpatient admission (all_inpat) varies throughout the period 2001–2009 with a ‘low’ in 2005 and a ‘peak’ in 2007, as seen in Table II. The major factor behind the fluctuation is changes in emergency admissions (em_inpat). Both planned admissions (pl_inpat) and outpatient admissions (out_pat) are fairly stable throughout the period.

Figure 1 depicts average aggregate inpatient admissions, planned inpatient admissions, emergency admissions and outpatient admissions by age group. As the figure shows, there are variations across the age groups. Aggregate inpatient admissions decreases for the very young, increases from age group 3, decreases from age group 7 and increases from age group 9 onward. Emergency admissions are the driving force behind this pattern. Planned admissions show an upward trend from age group 3 onward except for the sharp decrease from age group 18 to 19. Outpatient admissions fall from age group 1 to a low and relatively stable level. From age group 15, there is an upward trend.

3.2.2. Admission rates and patient heterogeneity. To motivate the sub-studies, comments on hospital admission rates and patient heterogeneity are warranted.

First, a change in aggregate number of admissions at hospitals is a relevant criterion when studying the effect of increased competition in a geographical area. In theory, GPs remunerated on the basis of pure capitation, may behave sub-optimal from a social perspective: (i) the gatekeeper role is weak because the incentive to refer patients to hospital is strong, that is, under-provision of own services and (ii) the incentive to keep patients satisfied may lead to selection, that is, patients with low expected effort level for given level of remuneration are receive more services and follow-up compared to patients demanding high effort relative to the remuneration level.

| Variables        | Definition                                                  | All patient                     | Patients age between 45 and 69 |
|------------------|-------------------------------------------------------------|---------------------------------|---------------------------------|
|                  |                                                             | Mean/proportion (Standard deviation) | Mean/proportion (Standard deviation) |
| all_inpat        | Per-capita aggregated inpatient admissions               | 0.2554 (0.2532)                | 0.2012 (0.0814)                |
| pl_inpat         | Per-capita planned admissions                             | 0.0760 (0.2216)                | 0.0871 (0.0427)                |
| em_inpat         | Per-capita emergency admissions                           | 0.1849 (0.2128)                | 0.1154 (0.0523)                |
| out_pat          | Per-capita outpatient admissions                          | 0.0128 (0.0437)                | 0.0063 (0.0086)                |
| phys_comp        | Proportion of general practitioner (GP) with open list   | 0.5103 (0.2488)                | 0.5367 (0.2408)                |
| perc_capa_gp     | Number of GP per 1000 inhabitants                         | 0.8266 (0.1747)                | 0.8302 (0.1623)                |
| phys_fixed       | Percentage of fixed-salaried GPs                          | 7.4939 (19.256)                | 7.8941 (19.040)                |
| phys_age         | Average age of the GPs                                    | 47.795 (3.7893)                | 47.853 (3.7785)                |
| Second_diagnosis | Average number of secondary diagnosis                     | 1.7204 (0.7813)                | 1.7571 (0.7789)                |
| Male             | Whether patient is male = 1 or female = 0                 | 0.4661 (0.4989)                | 0.4845 (0.4998)                |
| low_edu_local    | Proportion of the inhabitants with low education in a municipality | 31.236 (6.7359)                | 30.763 (7.0136)                |
| low_inc_local    | Proportion of the inhabitants with low income in a municipality | 15.109 (3.0383)                | 15.167 (2.8241)                |
| unem_local       | Unemployment rate in the municipalities                   | 2.4685 (1.0585)                | 2.5305 (1.1326)                |
| dis_local        | Disability rate in the municipalities                     | 8.4144 (2.1705)                | 8.2668 (2.2128)                |
| size_local       | Municipality population size (in 1000)                    | 118.08 (184.84)                | 161.07 (223.67)                |
| age_local        | Proportion of the inhabitants with age 67 years and over in a municipality | 13.209 (2.5879)                | 13.094 (2.5561)                |
| mean_dist        | Mean distance to the hospital (in km)                     | 61.628 (75.621)                | 58.832 (74.417)                |
| central_hos      | Central hospital                                          | 0.4199 (0.3960)                | 0.3693 (0.3864)                |
| Regional_hos     | Regional hospital                                         | 0.2553 (0.2852)                | 0.2690 (0.2724)                |
| Local_hos        | Local hospital                                            | 0.2266 (0.2579)                | 0.2448 (0.2537)                |
| County_hos       | County hospital                                           | 0.0982 (0.2137)                | 0.1169 (0.2151)                |
| Number of patient|                                                            | 7 802 133                     | 2 047 372                      |
| Number of patient-group/observation | | 132 900 | 35 452 |
Table II. Descriptive statistics for the dependent variables and GP characteristics over time: 2001–2009

| Variable | 2001   | 2002   | 2003   | 2004   | 2005   | 2006   | 2007   | 2008   | 2009   |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
|          | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) | Mean (SD) |
| all_inpat | 0.218 (0.211) | 0.296 (0.255) | 0.281 (0.262) | 0.218 (0.202) | 0.214 (0.183) | 0.240 (0.333) | 0.325 (0.286) | 0.325 (0.286) | 0.224 (0.238) |
| pl_inpat  | 0.071 (0.073) | 0.075 (0.067) | 0.088 (0.098) | 0.073 (0.083) | 0.071 (0.057) | 0.096 (0.609) | 0.073 (0.061) | 0.073 (0.061) | 0.061 (0.118) |
| em_inpat  | 0.151 (0.174) | 0.224 (0.225) | 0.198 (0.237) | 0.149 (0.166) | 0.144 (0.156) | 0.168 (0.232) | 0.254 (0.253) | 0.254 (0.253) | 0.167 (0.198) |
| out_pat   | 0.014 (0.041) | 0.012 (0.034) | 0.012 (0.035) | 0.011 (0.032) | 0.012 (0.046) | 0.013 (0.030) | 0.012 (0.023) | 0.014 (0.035) | 0.015 (0.085) |
| phys_comp | 0.600 (0.221) | 0.569 (0.245) | 0.601 (0.220) | 0.541 (0.253) | 0.509 (0.246) | 0.484 (0.243) | 0.457 (0.242) | 0.448 (0.242) | 0.408 (0.246) |
| percapita_gp | 0.823 (0.172) | 0.824 (0.168) | 0.814 (0.175) | 0.825 (0.169) | 0.820 (0.170) | 0.827 (0.169) | 0.829 (0.176) | 0.834 (0.183) | 0.841 (0.186) |
| phys_fixed | 9.480 (22.21) | 9.042 (21.57) | 9.300 (21.85) | 7.938 (19.76) | 7.509 (19.40) | 7.061 (18.79) | 6.489 (17.49) | 5.836 (16.10) | 5.333 (15.23) |
| phys_age  | 46.44 (3.409) | 46.95 (3.491) | 46.44 (3.404) | 47.73 (3.639) | 48.05 (3.620) | 48.31 (3.715) | 48.48 (3.836) | 48.63 (4.008) | 48.77 (3.965) |
A pure capitation system is rare. Rather it is customary to combine capitation with some sort of activity based financing, fee-for-service as in the Norwegian list patient system, modifying the incentives under a pure capitation system. Still, the policy of increasing number of GPs with the aim of reducing the growth rate in aggregate hospital admissions, rest on a negative relationship between hospital admissions and competition, that is, the substitution effect leads to a significant reduction in hospital admissions. Rightly, abstracting from conditions that GPs normally do not handle, increased competition gives GPs all else equal stronger incentive to deliver good quality care and follow-up of patients compared to a situation with weaker competition. The challenge from a policy perspective is that good quality care and follow-up may not only consist of GPs own effort but also GPs relying on the use of hospital services.

Second, changes in degree of competition may alter the inpatient–outpatient–emergency ‘mix’ of admissions. Inpatient admissions may increase for specific diagnoses for which waiting times are relatively long and substitutes for hospital care are not available at GP level. While the gatekeeper role may not be weakened in terms of planned inpatient admissions in general, because of procedures needed to facilitate such an admission, it is more likely that it is weakened in relation to outpatient admissions. Outpatient referrals can potentially be a cost-effective way for GPs to execute good follow-up of patients, in particular follow-up of patients demanding high (excepted) level of effort from the GP relative to the remuneration level. On the other hand, the substitution effects may contribute to reduce referrals to outpatient care, in particular for patients demanding low levels of effort from the GP relative to the remuneration level for a particular service/effort. Thus, the aggregate effect of changes in competition on outpatient admissions from a specific GP may depend on the composition of patients on the list.

Figure 1. Average use of hospital care by age-group
Third, if the substitution effect is dominant in a geographical area, we expect to find that the rate of emergency admissions is reduced. The reason is that we believe a patient admitted to hospital as an emergency patient (with or without referral from the GP) may signal the opposite of good quality care and follow-up. A GP can avoid emergency admissions by increased effort, which subsequently can facilitate a planned admission, inpatient or outpatient, if necessary. GP signals competence and avoids discomfort and stress for the patient, and lowers the risk of complications. However, the weaker gatekeeper effect may come into play if GPs, as a response to stronger competition, increase the number of outpatient referrals in an effort to avoid emergency admission. In sum, the rate of emergency admissions may well become significantly lower and the rate of outpatient admissions significantly higher as a result of stronger competition.

Fourth, in general it is reasonable to believe that middle-aged people are the most frequent users of GP services. In Norway, elderly people use GP services relatively less often than other age groups because many of them receive institutional care or home care services that are substitutes for direct GP services. In other words, it may be the case that GP attributes, including intensity of GP competition in a municipality, do not affect hospital admissions of older citizens. To avoid unnecessary noise in the estimations, we use a subsample of patients consisting of patients aged between 45 and 69 years to make the competition analysis sharper.

Fifth, based on the subsample of patients aged between 45 and 69 years, we also disaggregate aggregate hospital admissions into five different disease groups: asthma, coronary heart disease (CHD), chronic obstructive pulmonary disease (COPD), hypertension and diabetics. These diseases are among the most frequent causes of hospitalization for people in the subsample. Patients with an ambulatory care sensitive condition (ASCS), as these conditions are frequently termed, are interesting in the sense that emergency admissions for such chronic conditions are interpreted as a sign of sub-optimal coordination of care between primary care and specialist care. Emergency admissions for ACSC are avoidable if proper care and follow-up is provided by primary care services (see for instance Blunt, 2013), that is, ASCS are conditions for which GP effort can be a substitute for hospital services.

We believe patients with chronic conditions in general are not affected to the same degree by changes in competition as other groups of patients. Patients with chronic conditions are likely to be followed-up by their respective clinics at hospitals and they are likely to receive follow-up by other primary care services than GPs (e.g. home visits by trained nurses; receive instructions in self-care etc). Thus, neither inpatient nor outpatient admissions are likely to be significantly affected. However, emergency admissions may be significantly affected depending on the role GPs have in the care for list patients with an established chronic condition.

3.3. Independent variables

3.3.1. GP-level predictors. Our main explanatory variable is the intensity of the competition among GPs in a municipality. For a given population of patients, we construct the ratio ‘GPs with open lists/All GP practices’ for each group. Godager et al. (2015) also use this variable as an indicator of competition. The variable is denoted phys_comp. We use three other GP-level attributes too: (i) the number of GP’s per 1000 inhabitants in the municipality (percapita_GP); (ii) the percentage of fixed-salaried GPs measured as: ‘GPs on fixed salary/All GPs×100’ (phys_fixed); and (ii) average age of the GPs working in a municipality (phys_age).

Interestingly, as Table II shows, our measure of competition (phys_comp) shows a downward trend from 2001 to 2009 indicating that competition has increased in the period. A likely cause of the fairly stable development in GPs per capita (percapita_gp) is that number of GPs has increased in the same period, as mentioned in section 2. Finally, notice that the share of GPs on fixed salary (phys_fixed) is reduced while the average age of GPs (phys_age) is more or less unchanged between 2001 and 2009.

3.3.2. Patient-group level covariates. Control variables at patient-group level include: average number of secondary diagnoses to control for patient-level health status (second_diagnosis), and patient’s gender (gender).
unem

are used as the base category. 

reduce omitted variable biases that can be related to three different circumstances. 

Low

Male

phys

Second_diagnosis

Low_Edu_Local

Low_Inc_Local

unem_local

dis_local

size_local

age_local

mean_dist

central_hos

Regional_hos

Local_hos

Number of observations

(groups)

R-squared

Note: Cluster (municipality) standard errors are in the parentheses. 

*", ***, and *** represent significance level at the 10%, 5% and 1% level respectively. 

All regressions include time dummies and OLS regressions include age-group dummies as well.

3.3.3. Local/municipality level covariates. Socio-demographic characteristics of the municipalities include and are defined as: (i) proportion of people with only primary school (low_edu_local); (ii) proportion of people with low income (low_inc_local); (iii) unemployment rate (unem_local); (iv) disability rate (dis_local); (v) proportion of people aged >67 (age_local) and (vi) population size (size_local). The variable mean_dist is the average distance from a local authority centre to the nearest hospital.

3.3.4. Hospital-level attributes. As a control of observable hospital-level characteristics, we categorize hospitals with regard to whether they are (i) centrally located hospitals with relatively large catchment areas (central_hos); (ii) regional hospitals (regional_hos); (iii) local and specialized hospitals (local_hos) or (iv) county hospitals (county_hos). The hospital level attributes are then created by patient-groups. To be concrete, the variables are created as the proportion of patients within a group using a specific type of hospital in a specific year. Both demand and supply side factors can influence the distribution of patients between types of hospitals, for example, diagnoses (demand factor) and waiting times (supply factor). The variables are in a sense proxies for the equilibrium distribution of patients a given year. In the estimations, county hospitals are used as the base category.

4. ECONOMETRIC ISSUES

We first estimate a simple static ordinary least square (OLS) model where we control for a number of patient-group specific attributes, and municipal and hospital characteristics. This estimation approach is likely to produce omitted variable biases that can be related to three different circumstances.

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14 For example, patient group #10, all male patients living in Oslo municipality in the year 2008, 12%, 37%, 29% and 22% of the patient used central, regional, local and county hospital, respectively.
First, patient groups and municipalities are likely to have unmeasured attributes that may affect the intensity of hospital use. These unobserved factors are most likely correlated with the explanatory variables if not controlled for in the regressions. We estimate static fixed-effects models to address the potential bias.

Second, another source of omitted variable bias is related to the assumption that uses of hospital care are static, that is, described merely by contemporaneous characteristics and conditions. While current circumstances obviously affect admissions, current use of health care may also depend on previous uses. To avoid this sort of omitted variable bias, a dynamic panel data model is needed.

Third, the direction of causality between hospital admissions and competition between GPs is not a settled issue. The location decision of a GP may depend on the demand for health services in a municipality or in an area. To be specific, municipalities whose inhabitants are (relatively) frequent users of health care services or show relatively high demand for such services, are more attractive municipalities, all else equal, compared to municipalities with lower (expected) demand. This implies that the variables phys_comp and per-capita_gp are probably endogenous. Similarly, a GP’s decision to be remunerated on a fixed-salary basis (phys_fixed) or based on fee-for-service may also depend on local demand conditions. One possible mechanism, all else being equal, is that in low-demand municipalities, GPs may be motivated to work on a fixed salary, while in high-demand municipalities, they may be motivated to work on the basis of fee-for-service. GPs’ average age may also be an endogenous attribute, as more experienced or aged GPs may be attracted to areas where demand for care is higher. In sum, not controlling for endogeneity will result in biased estimates of the effect of these variables on hospital care uses.

The aforesaid estimation problems can be overcome through a natural experiment, but for most economics applications, experiments are too expensive or even infeasible. Alternatively, to break the correlation between endogenous regressors and the error term, one estimation strategy is to use instrumental variables (IV). In IV estimates, the endogenous right-side variables are replaced by their predicted values that depend on ‘instruments’ that do not appear directly in the relation of interest. The paucity of valid instruments, however, requires considerable ingenuity from the analyst. Instead, we assume that the only available instruments are ‘internal’—that is, they are created from the lags of the instrumental variables (Rodman, 2009).
Table IV. All disease and all types of admissions: results based on dynamic models for all patients

| Variables                          | Aggregated inpatient admissions (all_input) | Planned (pl_input) |
|------------------------------------|---------------------------------------------|-------------------|
|                                    | DIF-GMM         | SYS-GMM            | DIF-GMM         | SYS-GMM            |
| $h_{it-1}$                         | 0.0550*** (0.0314) | 0.5301*** (0.2621) | 0.0732*** (0.0296) | 0.0621*** (0.0230) |
| $h_{it-2}$                         | 0.3386 (0.297)   | —                  | —               | —                  |
| phys_comp                          | -0.1524** (0.0810) | -0.0561** (0.0225) | 0.0195 (0.0538)  | 0.0322 (0.0258)    |
| perc_capita_gp                     | 0.1513*** (0.0732) | 0.0023 (0.0465)    | 0.0564 (0.0515)  | 0.0087*** (0.0347) |
| phys_fixed                         | 0.0005 (0.0010)  | -0.0005 (0.0006)   | 0.0002 (0.0006)  | -0.0005*** (0.0002) |
| phys_age                           | 0.0046 (0.0037)  | 0.0114 (0.0013)    | -0.0024 (0.0023) | -0.0004 (0.0007)   |
| Second_diagnosis                   | -0.0008 (0.0009) | 0.0046** (0.0026)  | 0.0003 (0.0006)  | 0.0088*** (0.0007) |
| Low_Edu_Local                      | 0.0006 (0.0004)  | 0.0008 (0.0005)    | 0.0002 (0.0002)  | 0.0008*** (0.0002) |
| Low_Inc_Local                      | 0.0019 (0.0014)  | 0.0009 (0.0011)    | 0.0006 (0.0009)  | -0.0003 (0.0007)   |
| unem_local                         | 0.0002 (0.0020)  | -0.0010 (0.0013)   | 0.0011 (0.0012)  | 0.0010 (0.0008)    |
| dis_local                          | -0.0111*** (0.0035) | -0.0004 (0.0008)  | -0.0051*** (0.0025) | -0.0010*** (0.0004) |
| size_locall                        | -0.0013 (0.0010) | -0.0001 (0.0000)   | 0.0002 (0.0006)  | 0.0000 (0.0000)    |
| age_local                          | -0.0032 (0.0039) | 0.0020 (0.0013)    | 0.0026 (0.0026)  | -0.0006 (0.0011)   |
| mean_dist                          | 0.0000 (0.0000)  | 0.0000 (0.0000)    | 0.0000 (0.0000)  | 0.0000 (0.0000)    |
| central_hos                        | -0.0058 (0.0079) | -0.0096** (0.0050) | -0.0032 (0.0053) | 0.0027 (0.0033)    |
| Regional_hos                       | -0.0052 (0.0089) | -0.0079 (0.0051)   | 0.0011 (0.0059)  | -0.0153*** (0.0030) |
| Local_hos                          | -0.0040 (0.0084) | 0.0098 (0.0078)    | -0.0029 (0.0059) | 0.0185*** (0.0038) |
| AR (2) test (p-value)              | 0.52 (0.60)      | -0.54 (0.59)       | -0.21 (0.84)     | -0.55 (0.58)       |
| Sargan test (p-value)              | 11.26 (0.42)     | 10.13 (0.75)       | 12.11 (0.36)     | 16.87 (0.26)       |
| Number of observations             | 94 192 (15 269)  | 94 192 (15 269)    | 94 192 (15 269)  | 112 095 (15 722)   |
| Number of instruments              | 34               | 38                 | 34               | 38                 |
| R-squared$^a$                      | 0.014            | 0.460              | 0.020            | 0.028              |

Note: Corrected standard errors are in the parentheses.

$^a*$, $^**$ and $^***$ represent significance level at the 10%, 5% and 1% level, respectively.

All regressions include time dummies.

$^a$In xtabond2 the R-squared is not readily available; we compute it as the squared correlation coefficient between actual and fitted values.

To capture causal effects and state dependence, we therefore employ panel GMM-regressions of the first differences. The estimator by Arellano and Bond (1991), often denoted DIF-GMM, and the estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998), denoted SYS-GMM, are both frequently used to estimate dynamic panel data models with unobserved heterogeneity. In the present setting, they are believed to be ideal choices for eliminating the impact of time-invariant attributes, while at the same time accounting for possible endogeneity of GP characteristics. We specify the following dynamic per capita patient-group hospital admission function:

$$
\begin{align*}
    h_{it} &= \beta_0 + \delta h_{it-1} + \lambda G_{mt} + \beta x_{it} + \gamma S_{int} + \mu_i + v_i + e_{int}
\end{align*}
$$

for $i=1,...,n$, $m=1,...,M$ and $t=1,...,T$, where $i$ is the patient-group specific indicator, $m$ is the municipal indicator, $t$ is the time indicator, $x_{it}$ is the per capita hospital care use by patient group $i$ living in municipality $m$ in time period $t$, and $h_{it-1}$ is the hospital care use by patient-group $i$ living in municipality $m$ at time period $t-1$.

$G_{mt}$ is a vector of GP attributes in municipality $m$ at time period $t$, where all variables are considered to be endogenous. The vector $x_{it}$ contains other explanatory and control variables in municipality $m$ at time $t$, which include municipal socio-demographic indicators, that is, level of education, income, unemployment, disability, population size, age composition and distance to hospital. $S_{int}$ is a vector representing type of hospital care use by patient-group $i$ living in municipality $m$ at time period $t$. $v_i$ is an unobserved patient-group-specific time-invariant effect, $\mu_i$ is a period-specific intercept term common to all patient groups captured by year

$^a$In some models we also use hospital care use at time period $t-2$ ($h_{it-2}$) as a regressor.

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In DIF-GMM, sequential exogeneity and zero serial and cross-section correlation of \( e \) implies that the following moment conditions hold:

\[
E(h_{im,t-s} \Delta e_{int}) = \theta(i) \cdot i, \cdot t \cdot n \cdot s = 2, \ldots, \infty.
\]

which can be written more compactly as \( E(Z_{im} \Delta e_{im}) = 0 \) for \( im = 1,2, \ldots, N \), where \( Z_{im} \) is the \((T-2) \times m\) instrument matrix of the form:

\[
Z_{im} = \begin{bmatrix}
0 & 0 & \cdots & 0 & \cdots & 0 \\
0 & h_{im1} & h_{im2} & \cdots & 0 & \cdots \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
0 & 0 & \cdots & h_{im1} & \cdots & h_{im,T-2}
\end{bmatrix}
\]

and \( \Delta e_{im} \) is the \((T-2)\) vector \((\Delta e_{im3}, \Delta e_{im4}, \ldots, \Delta e_{imT})\). In equation 3 rows corresponds to the first-differenced equations for the periods \( t=3,4,\ldots, T \) for patient group \( i \) live in municipality \( m \). These are the moment restrictions exploited by the DIF-GMM estimator, implying that the use of lagged levels dated \( t-2 \) and earlier as instruments for the equations in the first-differences (Arellano and Bond, 1991). For example, \( h_{im1} \) is the only instrument that can be used for equation 2 for period \( t=3 \), and \( h_{im1} \) and \( h_{im2} \) both can be used for period \( t=4 \), and vector \((h_{im1}, h_{im2}, \ldots, h_{im,T-2})\) can be used instruments for period \( t=T \).

We assume, GP level explanatory variables-\( G_{im} \) is correlated with \( v_{i} \) and endogenous in the sense that \( E(x_{im}, e_{im}) \neq 0 \) for \( i = 1, \ldots, N \) and \( s \leq t \). They are also treated similarly as with the dependent variable \( h_{im} \). For GP level explanatory variables, the lagged levels \( G_{m,t-2}, G_{m,t-3} \) and longer lags are valid instruments for periods \( t=3,4,\ldots \).
Nevertheless, allowing lagged equation are instrumented with their own second equation, additional instruments can be obtained. Therefore, the variables in levels in the second levels equation to obtain a system of two equations: one differenced and one in levels. By adding the differences of the instrument variables are uncorrelated with the

The SYS-GMM estimator augments DIF-GMM estimation by making the additional assumption that the first differences of the instrument variables are uncorrelated with the fixed effects. The SYS-GMM estimator uses the levels equation to obtain a system of two equations: one differenced and one in levels. By adding the second equation, additional instruments can be obtained. Therefore, the variables in levels in the second equation are instrumented with their own first differences. This usually increases efficiency (Roodman, 2009). Nevertheless, allowing lagged first-differences to be used as instruments in the levels equations, an additional assumption needs to be fulfilled, and can be written formally as: \( E(\Delta h_{m,t-s} | \epsilon_{i,m,t}) = 0 \) \( \forall i, t \) and \( s = 1, \ldots, \infty \). That is, the first-differences of the dependent variable must not be correlated with the errors.16

Table V. All disease and all types of admissions: results based on static models (OLS and fixed-effects) for patients age between 45 and 69 years

| Variables            | Aggregated inpatient admissions (all_inpat) | Planned (pl_inpat) |
|----------------------|--------------------------------------------|-------------------|
|                      | OLS            | FE       | OLS            | FE       |
| phys_comp            | −0.0158*** (0.0033) | −0.0024 (0.0031) | 0.0029 (0.0024) | −0.0006 (0.0021) |
| percapita_gp         | 0.0031 (0.0056)  | 0.0066 (0.0060) | 0.0154*** (0.0035) | −0.0020 (0.0041) |
| phys_fixed           | 0.0000 (0.0000) | 0.0000 (0.0001) | 0.0000 (0.0000) | 0.0000 (0.0001) |
| phys_age             | −0.0005*** (0.0002) | −0.0004 (0.0003) | −0.0003** (0.0001) | −0.0003 (0.0002) |
| Male                 | 0.0202*** (0.0016) | −0.0003 (0.0011) |                   |           |
| Second_diagnosis     | −0.0007 (0.0008)  | 0.0011 (0.0007) | −0.0007 (0.0005) | −0.0005 (0.0005) |
| Low_Edu_Local        | 0.0002 (0.0002)  | 0.0001 (0.0002) | 0.0006*** (0.0002) | −0.0002 (0.0002) |
| Low_Inc_Local        | −0.0008 (0.0006) | −0.0003 (0.0006) | −0.0005 (0.0005) | 0.0002 (0.0007) |
| unem_local           | 0.0011 (0.0011)  | −0.0029*** (0.0012) | −0.0002 (0.0008) | −0.0030*** (0.0013) |
| dis_local            | 0.0036*** (0.0006) | 0.0032 (0.0018) | 0.0006 (0.0005) | 0.0007 (0.0015) |
| size_locall          | 0.0000*** (0.0000) | 0.0003 (0.0002) | 0.0000 (0.0000) | 0.0000 (0.0002) |
| age_local            | −0.0006 (0.0004) | 0.0014 (0.0027) | 0.0009*** (0.0003) | 0.0020 (0.0014) |
| mean_dist            | 0.0000*** (0.0000) | 0.0000 (0.0000) | 0.0000*** (0.0000) | 0.0000 (0.0000) |
| central_hos          | −0.0006 (0.0044) | 0.0059 (0.0661) | 0.0016 (0.0036) | −0.0018 (0.0048) |
| Regional_hos         | −0.0332*** (0.0049) | 0.0105 (0.0646) | −0.0192*** (0.0041) | 0.0007 (0.0050) |
| Local_hos            | 0.0098*** (0.0053) | 0.0059 (0.0600) | 0.0042 (0.0046) | 0.0043 (0.0047) |
| Number of observations | 35 452 | 35 452 (4225) | 35 452 | 35 452 (4225) |
| (groups)             | 0.342          | 0.004     | 0.111          | 0.009     |
| R-squared            |               |           |               |           |

Note: Cluster (municipality) standard errors are in the parentheses.

* and ** represent significance level at the 10%, 5% and 1% level, respectively.

All regressions include time dummies and OLS regressions include age-group dummies as well.

...T (as also illustrated in equation 3 for the lagged dependent variable as a regressor). The rest of the explanatory variables (i.e. included in \( x, S \) and \( \mu \) vector) are treated as strictly exogenous; hence, each variable in \( x, S \) and \( \mu \) vector can enter the instrument matrix in the conventional instrumental variables fashion, that is, in first differences, with one column per instrument.16

The lagged levels are often found to be rather poor instruments (in terms of bias and imprecision) for first differenced variables that are used in the DIF-GMM specifications (Blundell and Bond, 1998). Alternatively, the SYS-GMM estimator augments DIF-GMM estimation by making the additional assumption that the first differences of the instrument variables are uncorrelated with the fixed effects. The SYS-GMM estimator uses the levels equation to obtain a system of two equations: one differenced and one in levels. By adding the second equation, additional instruments can be obtained. Therefore, the variables in levels in the second equation are instrumented with their own first differences. This usually increases efficiency (Roodman, 2009). Nevertheless, allowing lagged first-differences to be used as instruments in the levels equations, an additional assumption needs to be fulfilled, and can be written formally as: \( E(\Delta h_{m,t-s} | \epsilon_{i,m,t}) = 0 \) \( \forall i, t \) and \( s = 1, \ldots, \infty \). That is, the first-differences of the dependent variable must not be correlated with the errors.18

16For example, if we do allow all available lags are to be used as instruments then there would be 28 instruments for lag dependent variable \( h_{mats} \), 28 for each GP level endogenous (strictly) variable (i.e. specifies lags 2 and longer as to consider instruments), and 18 instruments for 18 strictly exogenous variables. For such a specification of our DIF-GMM model, the total number of instruments would be 158 \((28 + 28 \times 4 + 18)\).

17For the same specification exemplified in footnote 14 for DIF-GMM, here we would get eight extra instruments (since we have data on 9 years) for lag dependent variable \( h_{mats} \) and seven extra instruments for per GP level endogenous variable. The total number of instruments for SYS-GMM would be 194 \( (28 + 8) + (28 + 7) \times 4 + 18 \).

18There is, however, one important caveat that needs to be mentioned. Since SYS-GMM uses more instruments than DIF-GMM it may not be appropriate to employ SYS-GMM with a dataset having a small number of groups. The reason is that when the number of instruments is greater than the number of groups, the Sargan/Hansen test may be weak (for Roodman, 2009).
The validity of these additional instruments can be tested by using standard Sargan/Hansen tests of over-identifying restrictions, and by using a ‘difference-in-Sargan/Hansen’ test as to compare between the DIF-GMM and SYS-GMM specifications (Arellano and Bond, 1991; Roodman, 2009). The calculation of this SYS-GMM estimator is discussed in more detail in Blundell and Bond (1998).

In our analyses, we also employ the SYS-GMM estimation approach. However, we acknowledge that the number of instruments in a SYS-GMM can potentially grow very large, causes problems of overfitting in finite samples and weakens the Sargan/Hansen test of instrument validity up to the point. To minimize this problem, we take two steps to limit the instrument count as suggested by Roodman (2009). First, we only use instruments at $t – 3l – 5$, and thus leave out all instruments beyond $t – 3l – 5$. Second, we ‘collapse’ the instrument set, which means creating one instrument for each variable and lag distance, rather than one for each period, variable, and lag distance. We report the Windmeijer (2005) robust corrected standard errors, as recommended. Test for serial correlation and standard Sargan/Hansen test of over-identifying restrictions are performed for all specifications. Finally, we report the goodness of fit for all models (both static and dynamic), and also the number of instruments used in the dynamic models.

### 5. RESULTS

Table III reports the results of two alternative static models: OLS and fixed effects. The OLS estimates show that aggregate *inpatient* admissions (−0.021) and *emergency* admissions (−0.015) are negatively associated

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| Variables        | OLS (em_inpat) | FE (em_inpat) | OLS (out_pat) | FE (out_pat) |
|------------------|----------------|---------------|---------------|--------------|
| phys_comp        | −0.0048***     (0.0019) | 0.0005 (0.0019) | 0.0114***     (0.0012) | 0.0000 (0.0009) |
| percapita_gdp    | 0.0130***      (0.0048) | 0.0006***     (0.0031) | 0.0168***     (0.0021) | 0.0026 (0.0017) |
| phys_fixed       | 0.0000         (0.0000) | 0.0000 (0.0000) | 0.0001***     (0.0000) | 0.0000 (0.0000) |
| phys_age         | −0.0002***     (0.0001) | 0.0001 (0.0001) | 0.0000 (0.0001) | 0.0002***     (0.0001) |
| Male             | 0.0262***      (0.0010) | —              | 0.0002 (0.0003) | —              |
| Second_diagnosis | −0.0008***     (0.0005) | 0.0001 (0.0004) | −0.0002 (0.0002) | −0.0002 (0.0001) |
| Low_Edu_Local    | 0.0001 (0.0001) | 0.0002 (0.0001) | 0.0003***     (0.0001) | 0.0000 (0.0000) |
| Low_Inc_Local    | −0.0003 (0.0000) | −0.0002 (0.0004) | −0.0003 (0.0002) | −0.0004***     (0.0002) |
| unem_local       | 0.0022***      (0.0006) | −0.0014***    (0.0007) | −0.0007***     (0.0003) | −0.0005 (0.0003) |
| dis_local        | 0.0020***      (0.0003) | 0.0034***     (0.0011) | −0.0008***     (0.0002) | −0.0003 (0.0007) |
| size_local       | 0.0000***      (0.0000) | 0.0004***     (0.0002) | 0.0000***      (0.0000) | 0.0001***     (0.0001) |
| age_local        | 0.0005***      (0.0003) | 0.0032 (0.0025) | 0.0009***      (0.0002) | 0.0016***     (0.0009) |
| mean_dist        | 0.0000 (0.0000) | 0.0000 (0.0000) | 0.0000 (0.0000) | 0.0000 (0.0000) |
| central_hos      | −0.0065***     (0.0027) | 0.0001 (0.0039) | −0.0017 (0.0015) | −0.0014 (0.0016) |
| Regional_hos     | −0.0169***     (0.0034) | −0.0009 (0.0041) | −0.0009 (0.0020) | −0.0014 (0.0021) |
| Local_hos        | 0.0035 (0.0033) | 0.0005 (0.0041) | 0.0003 (0.0020) | −0.0008 (0.0017) |
| Number of observations (groups) | 35 452 | 35 452 (4225) | 35 452 | 35 452 (4225) |
| R-squared        | 0.311          | 0.011         | 0.278         | 0.067         |

---

19In some model specification we use further deeper lags (i.e. $t – 6l – 7$) for the endogenous regressors provided that our models satisfy Sargan/Hansen test of overidentifying restrictions.

20We use `xtabond2` command for the estimation of DIF-GMM and SYS-GMM models, authored by Roodman.In all specifications, we use ‘collapse’ sub option as to create the columns of this Z matrix (equation 3) into a single column, which embodies the same expectation, but conveys less information as it will only produce a single moment condition. In this context, the collapsed GMM instrument set will be the same implied by standard IV, with a zero replacing the missing value in the first usable observation. Further, we use ‘orthogonal’ deviations sub option instead of ‘first differences’. For details on the estimation procedure and options, see Roodman (2009).

21Note that, `xtabond2` command does not report the R-squared (i.e. not readily available); we compute it as the squared correlation coefficient between actual and fitted values.
with GP competition. On the other hand, planned admissions (0.010) and outpatient (0.015) admissions are positively associated with GP competition. However, the fixed-effects estimations do not show any significant association of these relations.

The OLS estimates further show that per-capita GP (\(percapita_{gp}\)) and fixed-salaried GP (\(phys\_fixed\)) is positively associated with planned admissions and outpatient admissions. Whereas, the fixed-effects estimations show that this GP attribute (\(percapita_{gp}\)) is positively associated with emergency admissions and outpatient admissions. Physician average age (\(phys\_age\)) is negatively associated with all types of hospital admissions.

Table IV describes the estimation results based on the dynamic models for the full sample. Notice that for two alternative GMM estimation approaches (DIF-GMM and SYS-GMM) ‘lag of admissions’ (\(h_{int-1}\) and/or \(h_{int-2}\)) significantly affects current admissions. This result justifies the use of a dynamic model specification. Table IV also shows that in both the DIF-GMM (−0.152) and SYS-GMM (−0.056) specifications, GP competition (\(phys\_comp\)) negatively and significantly influences aggregated inpatient admissions.

A few words on the interpretation of coefficients: Using the SYS-GMM result as an example, on average, a 0.1 point increase in the share of GPs with open list (\(phys\_comp\)), per capita aggregated inpatient admissions (\(all\_inpat\)) decreases by 0.056/10 = 0.0056. The impact of changes in \(phys\_comp\) on \(all\_inpat\) can also be measured by using elasticity: a 1% increase in the share of GPs with open list decreases per capita aggregated inpatient admissions with 0.11% on average across groups, evaluated at the sample (unconditional) means of \(phys\_comp\) and \(all\_inpat\). Using the sample means reported in Table I, the elasticity is given by the expression 
\[ e = -0.0561 \times \frac{1.103}{2554} = -0.11. \]
On the other hand, the SYS-GMM analysis also shows that GP competition positively and significantly effects outpatient admissions (0.111). A 0.1-point increase in the share of GPs with open list (phys_comp), per capita outpatient admissions (out_pat) increases by 0.1101/10 = 0.0111. Again, using the sample means reported in Table I, the elasticity is given by the expression \( e = \frac{5103}{0128} = 4.42 \), that is, an 1% increase in phys_comp gives a 4.42% increase in outpatient admissions.

The proportion of GPs with an open list has fallen quite considerably though, from 0.600 to 0.408 (Table II), that is, competition is weaker. Overall, from 2001 to 2009, the competition measure is reduced by 32%. Based on the yearly mean values reported in Table II, calculating the percentage change from one year to the other, we find that the yearly reduction is 4.6% on average. However, the equivalent average changes in the (unconditional) mean values of out_pat and all_inpat—both signs and sizes varies across years—are 1.4% and –1.3%, respectively, contradicting our (conditional) estimates.

Per capita GP (percapita_gp) positively and significantly effects aggregate admissions in DIF-GMM model; however, this significant effect disappears in the SYS-GMM model. SYS-GMM estimations also show that planned admissions (0.069) are positively and emergency admissions (–0.064) are negatively influenced by per capita GP. Moreover, the SYS-GMM estimation approach also reveals that phys_fixed negatively effects planned admissions and that outpatient admissions are negatively affected by GPs’ averages age (phys_age).

Notice that the Sargan/Hansen tests of over-identifying restrictions are found satisfactory for all alternative dynamic models specifications (see the lower rows of Table V) and the ‘difference-in-Sargan/Hansen’ test also favours our SYS-GMM models. Because SYS-GMM specifications increases efficiency (Roodman, 2009), therefore we put emphasis on the SYS-GMM estimation results. Having said that, we may conclude that GP-competition, per-capita GP and GP’s age negatively affect aggregate admissions, emergency admissions and outpatient use, respectively, while GP-competition and per-capita GP positively influence outpatient and planned inpatient admissions, respectively.

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22All yearly changes are negative except for the change from 2002 to 2003, which is positive.

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As mentioned before, middle-aged people are probably more frequent users of GP services compared with other groups of people, at least in the Norwegian context. Indeed, to avoid unnecessary noise in the estimations, we re-estimate all the models (static and dynamic) for patients aged between 45 and 69 years (age groups 10–14). For this subsample, as seen in Table V, we find similar OLS results for the full sample: aggregate inpatient admissions (−0.016) and emergency admissions (−0.005) are negatively associated with GP competition; however, outpatient admissions (0.011) are positively associated with GP competition. For this subsample, positive and significant association also appears between per-capita GP and planned, emergency and outpatient hospital use. Moreover, the fixed-effects estimations support positive and significant association only for emergency admission. Analogous with the full sample estimations, OLS estimations also show phys_age is negatively associated with all types of hospital admissions.

Table VI illustrates the estimation results based on the dynamic models for the subsample. Similar to the full sample, for both the DIF-GMM and SYS-GMM approaches, ‘lag of admissions’ (Lag_{t−1}) significantly affects current admissions for the subsample. Moreover, the results for the test for serial correlation and the Sargan/Hansen test of overidentifying restrictions are found to be satisfactory for both the DIF-GMM and SYS-GMM estimations (see the lower rows of Table VI). Therefore we only focus on the results for the SYS-GMM estimations. As seen in Table VI, like for the full sample, phys_Comp negatively affect aggregate inpatient admissions (−0.093) and emergency admissions (−0.061). Positive signs for per-capita GP on planned inpatient (0.076) and outpatient admissions (0.076), as for the full sample as well. The variable phys_age negatively influence aggregate inpatient admissions (−0.005), whereas, such effect is found positive for Phys.fixed (0.001).

To deepen our understanding further, for this subsample, the aforesaid modelling exercises have also been applied to specific chronic diagnoses, as mentioned above.

The results based on our dynamic models (SYS-GMM), in particular, indicate a significant negative effect of competition is only observed in the case of hypertension (−0.036). Positive and significant effects of per-capita GP are detected for inpatient admissions related to asthma and hypertension. Physician age is found to positively influence asthma admissions, while Physician age negatively affects diabetic admissions (see Table A in Appendix).

6. DISCUSSION AND CONCLUDING REMARKS

In the theoretical literature on GP behaviour, one prediction is that intensified competition induces GPs to provide more services of potentially higher quality. In consequence, higher spare list capacity may result in fewer admissions by replacing hospital care with increased GP effort. This potential effect has drawn political attention in countries looking for measures to reduce the growth in demand for hospital care. However, it is also conceivable that intensified competition leads to a ‘liberal’ referral policy from GPs compared with a situation with less intense competition. Admissions are used as a signal to attract new patients and to keep the already enlisted ones. The end result may be higher levels of demand for hospital care. This paper aims to broaden the understanding of whether or not changes in the intensity of GP competition affect hospital admissions.

First, focusing on hospital admissions is a fruitful approach in terms of analysing whether competition induces substitution of costly hospital care by comparatively less costly primary care or not.

Second, we use dynamic panel data estimations—approaches not utilized in the previously mentioned studies—along with traditional static techniques. We believe that dynamic panel data estimations are suitable for capturing omitted or unobserved/unmeasured attributes that may hinder the estimation of causal relations.

Third, the theoretical model referred to in the introduction does not give guidance, at least not explicitly, on the potential diverse effects of competition in different segments of the market. Our empirical analyses shed light on this issue analysing the effects of changes in competition on different types of admissions.

In several countries, capitation payments and patient lists have been implemented in order to restrain soaring health care costs (Kalda et al., 2003). Governments argue that a patient list system improves the doctor–patient relationship and promotes continuity of care. Capitation fees, which are payments per registered patient, provide incentives for GPs to offer high-service quality, by retaining and attracting additional patients. Patients,
on the other hand, may switch to another GP if the service quality does not meet minimum expectations. Thus, patient movements in primary care may operate as an incentive for quality improvements and efficiency. Katz’s (Katz, 2013) theoretical contribution is of relevance here. Katz is critical to the argument put forward by third-party payers, both governmental and private, that competition will result in ‘more bang for their buck’. The intuition behind the argument is that a competitive care provider has stronger incentives to raise its quality to attract patients—and thereby potentially to steal market shares—than a monopoly provider would have. A corollary of this intuition is the belief that greater competition leads to stronger share-stealing effects and, thus, higher equilibrium quality. Katz argues that this intuition and its corollary are incomplete and, consequently, incorrect: increased competition can lead to lower, as well as higher, equilibrium quality.

A policy of promoting primary care to reduce demand for hospital care is a strategy with limited empirical support so far. In a European context, as discussed above, studies show that intensified competition is either insignificant or positively associated with GPs’ referrals of patients to hospital care. Our results are not directly comparable to the specific Norwegian studies (e.g. Iversen and Ma, 2009, Tjerbo, 2010 and Godager et al., 2015) because they focus either on admission to specific services or resource spending rather than admissions. Here, by distinguishing between planned inpatient, emergency and outpatient admissions, our results illustrate the potential importance of the ambiguous effect of competition. The satisfactory results from the tests for serial correlation and the Sargan/Hansen test of over-identifying restrictions for both the GMM estimators indicate a negative causal effect of GP competition on aggregate admissions for the full sample and for the subsample patients aged 45 to 69.

The significant negative effect of competition on aggregate inpatient admissions seems by and large driven by the negative effect on emergency admissions, which, importantly, constitutes the major type of admissions to hospital. However, outpatient admissions increase as a response to stronger competition. One explanation of why we find positive effect on outpatient referrals and a negative effect on inpatient referrals is that GPs in competitive areas are referring inappropriately. Because patients like being referred to specialist care, GPs are referring more patients to specialists in outpatient clinics expecting that these patients are less likely to be admitted as inpatients. This is more likely to happen for acute care/surgical patients, rather than patients with chronic disease who may just be being monitored more by specialists more often than before and therefore not likely to be admitted.

The significant negative effects on aggregate admissions and emergency admissions are confirmed in the studies of patients aged between 45 and 69 years of age. The effects on inpatient and outpatient admissions are insignificant (positive signs in the SYS-GMM estimations though). In the disease specific analyses, we find significant negative effect only in the case of hypertension.

In Norway, the substitution effect, which has drawn political attention in countries looking for measures to reduce the growth in demand for hospital care, is by and large related to emergency admissions. An interpretation of this finding is, as mentioned in section 3.2, that an emergency admission may signal the opposite of good quality care and follow-up. A GP can avoid emergency admissions by increased effort, and as such avoid doubt about the follow up of patients: Competition sharpens the need to avoid negative reputation effects.

The ‘weaker gatekeeper’-effect seems to dominate the substitution effect in relation to planned inpatients care and outpatient care only. We interpret these results as a confirmation of the need to be somewhat humble still in terms of what increased competition can achieve. However, the results from our study represent to some extent a ‘rehabilitation’ of the hypothesis that competition between primary care physicians or GPs can significantly reduce demand for inpatient hospital services.

Our analysis is not without limitations, though. The main weakness is that we use municipality-level data of GP characteristics and that we are not able to link an individual GP and his/her patients in the data. Furthermore, for outpatient admissions, our data include public hospitals only, not admissions based on referrals from private specialists. Moreover, the panel GMM-regressions approach used in our analyses deals with time-invariant unobserved factors but not omitted time-variant factors. However, the health care system in Norway in the period studied here has been ‘stable’ in the sense that no major institutional changes were introduced.

To conclude, although we find significant negative effect of GP competition on aggregate hospital admissions, nevertheless, more research is still needed. We think that a promising way forward is to study disease-
specific groups of patients and their demand for hospital care, as we have partly done here. To achieve this, we need to be able to ‘match’ data on individual patients with their GPs and to combine these with data describing intensity of GP competition in the relevant geographical areas or markets.

Patients with so-called ambulatory-care-sensitive conditions (ACSC)—for example, COPD, asthma and diabetes—and their demands for planned and emergency admissions may be interesting in this context along with specific non-chronic conditions. ACSC patients are normally in need of follow-up care from primary care services. Emergency admissions for ACSCs are indicators of poor co-operation between primary care and hospital care even if the emergency admissions are dealt with in a satisfactory way at the hospital. GPs’ behavioural responses towards chronic patients can influence demand for hospital care for this group of patients in a way that differs from that for other groups of patients.

**APPENDIX**

### TABLE A. DISEASE SPECIFIC ANALYSES OF AGGREGATED INPATIENT ADMISSIONS FOR PATIENTS’ AGE BETWEEN 45 AND 69 YEARS: RESULTS BASED ON DYNAMIC MODELS

| Variables          | sh_ad_asthma  | sh_ad_chd    | sh_ad_copd   | sh_ad_dia    | sh_ad_hpten |
|--------------------|---------------|--------------|--------------|--------------|-------------|
| h_t0               | 0.2120** (0.0946) | 0.0005 (0.0007) | 0.1160 (0.0755) | 0.0014*** (0.0056) | -0.0008 (0.0007) |
| h_t1               | 0.1160 (0.0755) | 0.0005 (0.0007) | 0.0008 (0.0007) | 0.0008 (0.0007) | 0.0008 (0.0007) |
| phys_comp          | -0.2436 (0.2475) | 0.0032 (0.0036) | 0.0005 (0.0041) | 0.0032 (0.0036) | 0.0032 (0.0036) |
| perc capita gp     | 0.2247 (0.1635) | 0.0003 (0.0004) | 0.0003 (0.0004) | 0.0003 (0.0004) | 0.0003 (0.0004) |
| phys fixed         | 0.2447 (0.1635) | 0.0003 (0.0004) | 0.0003 (0.0004) | 0.0003 (0.0004) | 0.0003 (0.0004) |
| phys age           | 0.0204 (0.0172) | 0.0004 (0.0007) | 0.0004 (0.0007) | 0.0004 (0.0007) | 0.0004 (0.0007) |
| Age                | 0.0011 (0.0011) | 0.0002 (0.0005) | 0.0002 (0.0005) | 0.0005 (0.0007) | 0.0005 (0.0007) |
| Male               | 0.0017 (0.0017) | 0.0020 (0.0035) | 0.0020 (0.0035) | 0.0005 (0.0007) | 0.0005 (0.0007) |
| Second diagnosis   | 0.0004 (0.0011) | 0.0025 (0.0083) | 0.0002 (0.0035) | 0.0002 (0.0035) | 0.0002 (0.0035) |
| Low Edu Local      | 0.0020*** (0.0008) | 0.0017 (0.0017) | 0.0035 (0.0096) | 0.0002 (0.0035) | 0.0002 (0.0035) |
| Low Inc Local      | -0.0010 (0.0014) | -0.0031 (0.0068) | 0.0020 (0.0035) | 0.0020 (0.0035) | 0.0008 (0.0008) |
| Unem local         | -0.0039* (0.0020) | -0.0012 (0.0028) | 0.0036 (0.0047) | 0.0036 (0.0047) | 0.0036 (0.0047) |
| Dis local          | -0.0002** (0.0001) | -0.0002 (0.0004) | 0.0003 (0.0003) | 0.0003 (0.0003) | 0.0003 (0.0003) |
| Size local         | 0.0083 (0.0150) | 0.0032 (0.0053) | 0.0001 (0.0002) | 0.0001 (0.0002) | 0.0001 (0.0002) |
| Age local          | 0.0054 (0.0068) | 0.0000 (0.0000) | 0.0000 (0.0000) | 0.0000 (0.0000) | 0.0000 (0.0000) |
| Mean dist          | 0.0004 (0.0013) | 0.0001 (0.0000) | 0.0001 (0.0000) | 0.0001 (0.0000) | 0.0001 (0.0000) |
| Central_hos        | 0.0000 (0.0000) | 0.0000 (0.0000) | 0.0000 (0.0000) | 0.0000 (0.0000) | 0.0000 (0.0000) |
| Regional_hos       | -0.0142 (0.0312) | -0.0142 (0.0312) | -0.0142 (0.0312) | -0.0142 (0.0312) | -0.0142 (0.0312) |
| Local_hos          | -0.0347** (0.0166) | -0.0347** (0.0166) | -0.0347** (0.0166) | -0.0347** (0.0166) | -0.0347** (0.0166) |
| AR (2) test (p-value) | 0.005 (0.001) | 0.0001 (0.0005) | 0.0005 (0.0033) | 0.0005 (0.0033) | 0.0005 (0.0033) |
| Sargan test (p-value) | 6.95 (0.22) | 4.29 (0.64) | 1.98 (0.92) | 6.86 (0.33) | 2.27 (0.32) |
| Number of observations (groups) | 24 358 (3887) | 30 143 (4158) | 28 574 (4095) | 22 991 (3860) | 20 375 (3705) |
| Number of instruments | 29 | 30 | 30 | 30 | 26 |
| R-squared          | 0.005 | 0.0001 | 0.005 | 0.033 | 0.005 |

Note: Cluster (municipality) standard errors for static models and corrected standard errors for the dynamic models are in the parentheses.

* * * and ** * * represent significance level at the 10%, 5% and 1% level, respectively.

All regressions include time dummies and OLS regressions include age-group dummies as well.

In xtobond2 the R-squared is not readily available; we compute it as the squared correlation coefficient between actual and fitted values.
Note: Cluster (municipality) standard errors for static models and corrected standard errors for the dynamic models are in the parentheses.

"**" and

"***" represent significance level at the 10%, 5% and 1% level, respectively.

All regressions include time dummies and OLS regressions include age-group dummies as well. 

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