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The closer the better: does better access to outpatient care prevent hospitalization?

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Abstract

In 2010-2012 new outpatient service locations were established in poor Hungarian micro-regions. We exploit this quasi-experiment to estimate the extent of substitution between outpatient and inpatient care. Fixed-effects Poisson models on individual-level panel data for years 2008-2015 show that the number of outpatient visits increased by 19% and the number of inpatient stays decreased by 1.6% as a result, driven by a marked reduction of potentially avoidable hospitalization (PAH) (5%). In our dynamic specification, PAH effects occur in the year after the treatment, whereas non-PAH only decreases with a multi-year lag. The instrumental variable estimates suggest that a one euro increase in outpatient care expenditures produces a 0.6 euro decrease in inpatient care expenditures. Our results (1) strengthen the claim that bringing outpatient care closer to a previously underserved population yields considerable health benefits, and (2) suggest that there is a strong substitution element between outpatient and inpatient care.

JEL: C23, C26, I10

Keywords:

Administrative panel data, Inpatient care, Outpatient care, Potentially avoidable hospitalization, Quasi-experiment, Substitution effect

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Csökkenti-e a járóbeteg-ellátáshoz való jobb hozzáférés a kórházi tartózkodást?

Elek Péter – Molnár Tamás – Váradi Balázs

Összefoglaló

2010 és 2012 között új járóbeteg szakrendelőket létesítettek húsz elmaradott magyarországi kistérségben. Ezt a kvázi kísérletet használjuk ki a járó- és fekvőbeteg-ellátás közötti helyettesítés mértékének becslésére. A 2008–2015 közötti egyéni szintű paneladatokon becsült fix hatású Poisson-modelljeink azt mutatják, hogy a járóbeteg-szakellátási megjelenések száma 19%-kal nőtt, a kórházi tartózkodások száma pedig 1,6%-kal csökkent a fejlesztések hatására, és a potenciálisan elkerülhető hospitalizáció (potentially avoidable hospitalization, PAH) ennél nagyobb mértékben, 5%-kal csökkent. Dinamikus modellspecifikációnk szerint a PAH-hatások rögtön a fejlesztés utáni évben jelentkeztek, a nem potenciálisan elkerülhető kórházi tartózkodás viszont csak több éves késleltetés után kezdett csökkenni. Instrumentális változós becsléseink alapján a járóbeteg-szakellátási költségek egy forinttal való növekedése 0,6 forinttal csökkenti a fekvőbeteg-kiadásokat. Eredményeink arra utalnak, hogy (1) a járóbeteg-ellátás közelebb hozása a korábban nem ellátott lakossághoz érdemi egészségnyereséggel jár, (2) és jelentős helyettesítés figyelhető meg a járó- és fekvőbeteg-ellátás között.

JEL: C23, C26, I10

Tárgyszavak:

Adminisztratív paneladatok, fekvőbeteg-ellátás, járóbeteg-ellátás, potenciálisan elkerülhető kórházi tartózkodás, kvázi kísérlet, helyettesítési hatás

The closer the better: does better access to outpatient care prevent hospitalization?

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Abstract

In 2010-2012 new outpatient service locations were established in poor Hungarian micro-regions. We exploit this quasi-experiment to estimate the extent of substitution between outpatient and inpatient care. Fixed-effects Poisson models on individual-level panel data for years 2008-2015 show that the number of outpatient visits increased by 19% and the number of inpatient stays decreased by 1.6% as a result, driven by a marked reduction of potentially avoidable hospitalization (PAH) (5%). In our dynamic specification, PAH effects occur in the year after the treatment, whereas non-PAH only decreases with a multi-year lag. The instrumental variable estimates suggest that a one euro increase in outpatient care expenditures produces a 0.6 euro decrease in inpatient care expenditures. Our results (1) strengthen the claim that bringing outpatient care closer to a previously underserved population yields considerable health benefits, and (2) suggest that there is a strong substitution element between outpatient and inpatient care.

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1 Introduction

How to best allocate limited public resources across outpatient and inpatient healthcare services to achieve maximum improvement in health outcomes is one of the perennial questions of health policy all over the world.

To inch closer to answering that question, we have to understand, disentangle and accurately measure the relationships between those two levels of care. Does the provision of more outpatient care, while itself improving health outcomes, also generate more hospitalization episodes and/or make them longer, or, to the contrary, does it help to avoid costlier inpatient care later on? What are the respective and aggregate changes in health care expenditures? In this paper we use panel data from a quasi-experimental setting provided by an expansion of specialist outpatient care in Hungary between 2010 and 2012, greatly improving access, to contribute to answering those questions. Besides observational or cross-sectional studies, the earlier quasi-experimental literature mainly uses data from the United States, hence little is known about the substitution / complementation effects in countries whose health care sector is characterized by different institutional and regulatory frameworks and financing arrangements.

At the highest level of abstraction, nationwide health policy planning is about maximizing improvements in the health outcomes of the population constrained by limited public and private resources. This is done through financing many functional channels of the health care system, but, in OECD countries, most expenditure goes to curative and rehabilitative care, and, within that, two of the most important functions are outpatient care, upon which 1.2-7.5% of Gross Domestic Product (GDP) is expended; and inpatient care, with 1.5-3.4% of

GDP (2015 data from OECD [2017]). Given these enormous expenses, the importance of any reliable evidence that can contribute to even a marginal improvement of health outcomes by better allocation of resources across these two subsectors cannot be overstated. Such evidence can help policy makers decide whether additional public resources are put to better use by being channelled toward expanding outpatient or inpatient care. In what follows, we first present the possible mechanisms of substitution and complementation and the empirical literature so far, then the Hungarian context, followed by the data, the methods, our results and, finally, our conclusions.

2 Mechanisms of substitution and complementation

What are the possible theoretical mechanisms of interaction between inpatient and outpatient care? Fortney et al. [2005], building on the work of Starfield [1994] and others identify the following mechanisms of substitution (i.e. more outpatient care decreases hospitalization) and complementation (more outpatient care preduces more inpatient care).

Mechanisms of Substitution:

- Early detection of an illness in outpatient care can make treatment possible at that level and obviate the need for hospitalization. This substitution mechanism, they claim, could have both short-term (e.g. prevention of hospitalization for asthma by prevention and early treatment of exacerbations) and long-term effects (e.g. prevention of stroke by the treatment of hypertension).
- The management of chronic health conditions in outpatient care (e.g. routine testing or patient education) can also prevent or at least delay the need for inpatient care -

control of blood sugar to avert kidney failure in patients with diabetes mellitus is a classic example of this.

- Depending on the rules and incentives built into healthcare system of the country in question, doctors in outpatient care could have a formal gate-keeping role as well: in many cases their referral can be required for hospitalization.

Mechanisms of Complementation:

- Treatment in outpatient care might call for supplemental or ancillary care provided in hospitals (e.g. diagnostic laboratory tests).
- The detection in outpatient care of illnesses (e.g. cancer, serious mental illness) that are best treated by a specialist, in hospital. This mechanism could especially affect patients who have not used primary care services for a long period of time and who have a greater number of undetected illnesses.
- The identification (through close monitoring) of acute episodes of chronic illnesses that require specialty or inpatient treatment. This mechanism is particularly relevant for disorders with symptoms that may fluctuate in severity over time (e.g. angina or major depressive disorder).

The empirical literature is rather mixed in terms of whether the substitution or the complementation effect dominates. Miller [2012] analysing a Massachusetts reform (a health insurance reform was introduced that differentially affected the costs of outpatient and inpatient care) and Rubenstein et al. [1996] analysing the effects of a reorganization to increase access to primary care for veterans in Virginia both found a drop in hospitalization in response to more access to primary care. Bindman et al. [1995], Gill and Mainous III [1998], Falik et al. [2001] and Rittenhouse and Shortell [2009] in their cross-sectional studies found

substitution effects as well.

On the other hand, Kaestner and Sasso [2015] found that in the United States an increased outpatient spending was associated with more hospital admissions; the Rand and the Oregon health insurance experiments also showed that improving the availability of medical services through a more generous health insurance coverage was associated with an increase in the use of emergency room services and hospitalization (Newhouse [1993], Finkelstein et al. [2012]).

A third group of studies found neither substitution nor complementation effects. Looking into the same Massachusetts reform as Miller [2012], Kolstad and Kowalski [2012] found that gaining insurance was associated with a decrease in hospital admissions through emergency department, an increase in hospital admissions through other channels, and no change in total hospitalizations. The instrumental variables analysis by Fortney et al. [2005] indicated that an increase in primary care encounters was associated with a decrease in specialty medical encounters but was not associated with an increase in physical health admissions, or outpatient costs.

One promising method to try to sharpen the results in the empirical literature, exemplified by Dusheiko et al. [2011], has been to narrow down the focus upon hospitalizations for conditions considered especially sensitive to timely and effective management in primary care. E.g. Kolstad and Kowalski [2012], whose inconclusive results put them in the no effect camp above, actually find a substitution effect when zooming in on the effects upon preventable hospitalization.

3 Institutional context

In addition to being, in sum, rather inconclusive, many of these studies are also observational or cross-sectional, making the establishment of causal relationships hard. In the case of papers based on a quasi-experimental or experimental setup, the source of variation that makes identification possible consists in changes in the financing (insurance) mechanism alone and almost all of them examine the United States. Our source of variation is different and our evidence comes from a very different, but by no means internationally unique institutional setting, shared by most post-communist EU member states (e.g. Poland and the Czech Republic) and the countries emerging from the Soviet Union like Russia and Ukraine (Marrée and Groenewegen [1997]). In such countries our research question has never been addressed before.

As summarised by Elek et al. [2015], Hungary is a post-communist EU member state of slightly less than 10 million inhabitants with a single payer health insurance and de facto universal coverage. In 2015, Hungary spent 7.2% of its GDP on healthcare, 1.8% of the GDP on outpatient (including government- and household-financed primary and specialist outpatient) and 1.9% of the GDP on inpatient care (OECD [2017]). The basic benefit package is free of out-of-pocket payments for the patients at the point of care (including outpatient care), although informal gratuity payments are widespread. Primary care by general practitioners is financed by capitation; most outpatient services are financed by the budget based on fee-for-service points, under a system that scores procedures on the basis of their complexity and resource requirements, whereas inpatient services, almost exclusively provided in state-run and -financed hospitals, are reimbursed through a combined payment

system based on diagnosis-related groups (acute care) and per diem rates (chronic care).

The relatively high share of outpatient care in provision and financing is due to the heritage of the Semashko-type healthcare system, common in countries once under Soviet dominance. Central to that model was a multi-tiered system of care with a strict referral system and strongly differentiated network of service providers, with outpatient specialist care, provided in dedicated polyclinics and thus separated from primary care, one of the distinct tiers of healthcare provision (see Gaál et al. [2011], Kornai and Eggleston [2001]). Concentrating on the relationship between this type of care and inpatient care can, arguably, provide more precise information on substitution / complementation than what can be obtained in healthcare systems where data on primary and specialized ambulatory care are lumped together.

The health status of the Hungarian population is among the poorest in the EU with a life expectancy at birth of 75.7 years, tailing the EU average by 4.9 years, with even worse parameters in rural micro-regions in which the intervention we use for identification took place.

The intervention we base our quasi-experimental specification on is the same as used in Elek et al. [2015]. Between 2010 and 2012 around 430 thousand people gained better access to specialist outpatient care in Hungary when the government created outpatient units in 20 rural micro-regions, which previously lacked capacity. (The investments were funded by the Social Infrastructure Operative Programme [SIOP] 2.1.2. of the European Union.) Locations for the new units were selected based on the applications of municipalities, making a case for need and demand. Funding accounted for 500-1000 million HUF (2-4 million euros) per unit, generally covering 90-95% of the costs of the establishment of the new units to the

municipalities if they complied with a set of administrative requirements (e.g. providing a minimum of services for a minimum of hours/month, keeping the unit in operation for at least five years). Competition for scarce funds was not an issue: sufficient funds were allocated to be able to subsidize all likely applicants eligible under those rules. The newly created units (all still in operation as of 2016) provide comprehensive service for the population of the micro-regions with at least 14 separate specialties at each location. As a result, basic specialist outpatient care in the following four specialties: internal medicine, surgery, obstetrics-gynecology and pediatrics may now be reached by around 310 thousand more people by car in 20 minutes than before.

At the same time, other parts of Hungary experienced relatively few changes in the management of outpatient care between 2008 and 2015. Hence an appropriate control group of micro-regions could be identified, in which the health care indicators may be compared to those in the micro-regions where new outpatient service locations were established (the treated micro-regions). The impact of the improvement in accessibility can then be estimated as the difference between the changes in the treated and control groups.

It is this treatment that we use in the paper to identify the sign, the magnitude and the lag of the effect of more outpatient treatment upon hospitalization at the individual level.

4 Data and descriptive statistics

We use anonymized individual-level administrative data on inpatient stays and specialist outpatient visits, exclusively provided to us for this research project by the Hungarian National Healthcare Services Centre (ÁEEK). Data cover years 2008-2015 for the population

of 20 treated and 20 control micro-regions with approximately 1,060,000 people in Hungary (around 10% of the population of the country). The control micro-regions were chosen with propensity score matching to approximate the pre-treatment demographic, socio-economic and health characteristics of the treated micro-regions. Elek et al. [2015] provide details on the matching procedure as well as on the treated-control balance in terms of the observed pre-treatment characteristics.[1]

The annual panel dataset used in our analysis contains for each person-year the number of inpatient stays (and of its certain subgroups, see below), the number of specialist outpatient visits (and of its certain subgroups), the estimated inpatient and outpatient care expenditures as well as demographic information such as gender, year of birth and settlement of residence.[2] Year of death is also recorded for those who died during the period. We omit newborns from the sample, hence restrict the analysis to those at least two years of age.

Annually, around 13% of the population of the control micro-regions was hospitalized. We also define potentially avoidable hospitalization (PAH), i.e. hospitalization due to ambulatory care sensitive conditions (ACSCs), based on the ICD-10 category of the primary diagnosis of the inpatient episode. Our main definition for PAH follows Purdy et al. [2008] as described

[1]Elek et al. [2015] use 21 control micro-regions but in this analysis we exclude the micro-region of Szikszó because acute inpatient care was abolished in its hospital during the examined period hence it cannot be used as a control micro-region when effects on inpatient care are analyzed.

[2]The dataset covers only those people who appeared at least once in outpatient or inpatient care between 2008 and 2015. This is a negligible restriction for two reasons. First, other administrative data (the linked labour-health panel dataset processed by the Institute of Economics, Centre for Economic and Regional Studies of the Hungarian Academy of Sciences, see e.g. Bíró and Elek [2018] for its health variables) suggest that less than 2.5% of the (18-74 year old) inhabitants of the examined micro-regions did not appear at all in either outpatient or inpatient care during another eight year long period (2003-2011). Second, we use fixed-effects Poisson and logit models in our main analysis, and the always zero observations drop out in the estimation of these models.

in detail by Eggli et al. [2014].[3] According to this definition around 2.4% of the population was hospitalized due to an ACSC in a given year. We classify this category into the following subgroups (see Appendix 1 for details):

- cardiology-related conditions (angina, congestive heart failure, hypertension) (0.8%),
- pulmonology-related conditions (asthma, COPD) (0.6%),
- diabetes complications (0.3%),
- conditions due to non-adeqaute specialist outpatient care (e.g. ear, nose, throat infection) (0.3%) and
- conditions due to non-adequate primary care (e.g. influenza) (0.6%).

Figure 1 shows that hospitalization probability and case number as well as the probability of PAH decreased more in the population of the treated group than of the control group after 2010-2012, when the new outpatient units started to operate in the treated micro-regions. (Most new units were established in 2011.) We will also examine certain other subgroups of hospitalization such as acute and chronic episodes.

We note that the original data refer to only those inpatient events that started and also terminated within 2008-2015, therefore some inpatient stays are missing for 2015. All figures in the paper show adjusted data for 2015 by assuming that inpatient events with year of discharge different from year of admission constituted the same share of all inpatient events in 2015 as in 2013-2014. This adjustment increases inpatient case numbers by only 1.2%, and does not affect substantially our later results. For details see Appendix 2.

[3]As a robustness check, we also defined PAH following the European Collaboration for Healtcare Optimization (ECHO) project (see Thygesen et al. [2015]), which examines hospitalization due to angina, congestive heart failure and strictly defined diabetes complications for people at least 40 years old, asthma and COPD for people at least 18 years old and dehydration complications for people at least 65 years old. Our results do not change substantially when this alternative definition is used.

Meanwhile, according to Figure 1, the number of outpatient visits grew much more rapidly in the treated than in the control micro-regions after 2010-2012. We will specifically examine outpatient visits associated with certain ACSCs such as those in cardiology, pulmonology or diabetes, defined by the ICD-10 code of the outpatient event. We hypothesize that a growing ratio of patients treated in outpatient care with such conditions may have caused the decreased prevalence of PAH.

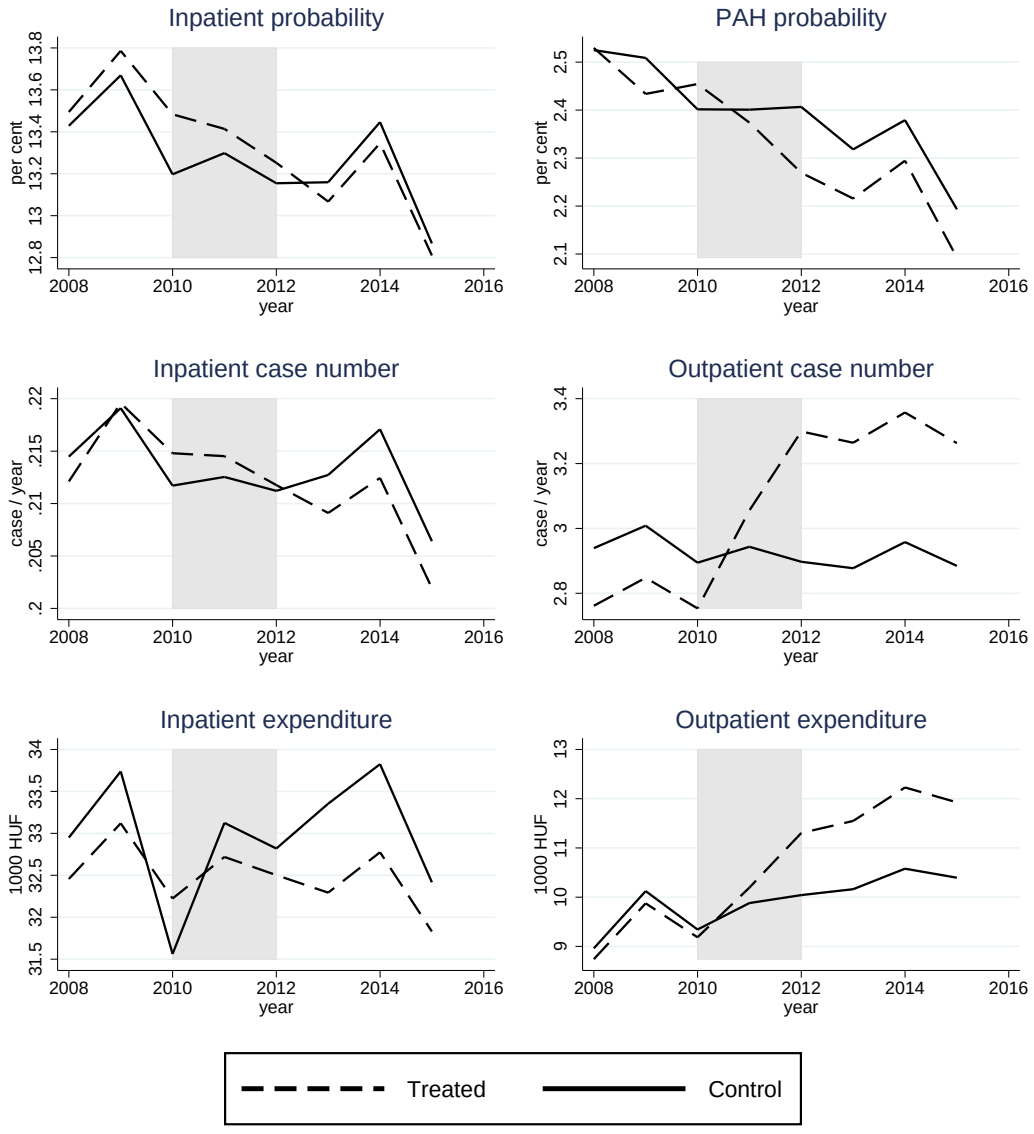
Finally, the lower two graphs in Figure 1 show that while outpatient expenditures increased, the estimated inpatient expenditures decreased in the treated compared to the control micro-regions.[4]

Obviously, outpatient and inpatient care use are strongly correlated on the individual level. In the control micro-regions, patients hospitalized in a given year visited (non-laboratory) outpatient care 2.9 times more often in the previous year than non-hospitalized patients, and the difference persists when age and gender are controlled for. However, these cross-sectional correlations are non-causal. Estimation of a causal relationship between outpatient and inpatient care requires a quasi-experiment such as the establishment of the new outpatient locations in our case.

Figure 1 shows that the treated and control micro-regions are not completely balanced with respect to pre-treatment outcomes: outpatient care use was slightly lower in the treated than in the control group before 2011, possibly as a result of existing outpatient capacities in some control micro-regions. (According to Elek et al. [2015], weekly specialist outpatient

[4]Individual-level expenditures are approximated based on the financing rules of the Hungarian health care system but they cannot be calculated precisely from the data at hand because some financial variables of minor importance are missing. Hence our results on expenditures only give rough estimates on the financial interactions between outpatient and inpatient care.

Figure 1: Per capita use of inpatient and (non-laboratory) outpatient care in the treated and control micro-regions



hours per 1000 inhabitants were 3.8 on average in Hungary, 1.2 in the control group and a negligible 0.6 in the treated group in 2008.) Therefore we apply a difference-in-difference–type analysis to measure the treatment effect (and check the pre-treatment parallel trends in the treated and control group with a placebo test). We use three explanatory variables to control for possible exogenous changes in health care supply in the examined period: the number of wider regional (county-) level number of hospital beds; the ratio of unfilled GP practices in the settlement of the individual; and the availability of special one-day ambulatory services (aimed at providing certain treatments in internal care, neurology and physiotherapy) that started to operate in some treated and control micro-regions in the examined period. For details see Appendix 3.

Beyond an impact assessment of the establishment of the new outpatient units, we use this quasi-experiment to estimate the structural effect of bringing outpatient care one minute closer to the residence of the individual on hospitalization. Therefore we define the travel time (in minutes) needed to reach the nearest outpatient unit by car from the settlement of each individual. This distance measure decreased in the treated micro-regions from 24 min in 2008 to 10 min in 2012, while it was essentially unchanged (21 min on average) in the control micro-regions.

5 Methods

5.1 Effects of the new outpatient locations

For person i in year t, let y_{it} denote the number of hospital admissions (or the number of its various subcategories), d_{it} the dummy variable for belonging to the treated group after the treatment, T_{it} the calendar year dummies and z_{it} the control variables (a cubic function of individual age and the health care supply variables described above). In our baseline models we estimate the effect of the treatment on the expected number of admissions, $E(y_{it})$, with fixed-effects (FE) Poisson models, and on the probability of hospitalization, $\Pr(y_{it} > 0)$, with FE logit models:

$$E(y_{it}) = \exp(\beta_d d_{it} + \beta_T T_{it} + \beta_z z_{it} + c_i^p) \quad (1)$$

$$\Pr(y_{it} > 0) = \text{logit}\left(\gamma_d d_{it} + \gamma_T T_{it} + \gamma_z z_{it} + c_i^l\right), \quad (2)$$

where β-s and γ-s are the parameters, c_i^p and c_i^l denote the individual-level heterogeneity and logit is the logistic function. We treat c_i-s, the fixed effects, as completely unrestricted. They control for, among others, any pre-treatment differences in the health status of the individuals, and also for any time-constant differences in individuals such as their gender. For the estimation of FE Poisson and FE logit models see e.g. Wooldridge [2010].

The FE models estimate the treatment effect using within-person variation, i.e. by calculating how the probability and frequency of hospitalization of a given person changed as a result of the treatment compared to the evolution in the control group. These models usually give more credible inference than e.g. pooled methods on panel data because it is difficult

to control for all individual-level pre-treatment differences in the latter models. However, if there is a slight change in the probability of death in the treated compared to the control group (large and statistically significant effects are unlikely to occur in the 3-4 years after the establishments), FE and pooled models may yield different estimates because dying patients are selected out of the sample at a slightly different rate in the two groups. Therefore, as a robustness check, we also estimate pooled logit models on the hospitalization probability and its subcategories:

$$\Pr\left(y_{it} > 0\right) = \text{logit}\left(\gamma_d d_{it} + \gamma_T T_{it} + \gamma_z z_{it} + \gamma_w w_{it}\right), \tag{3}$$

where w_{it} now contains additional controls such as the gender [interacted with the age] and the micro-region of the individual.

We estimate further models with different dependent or explanatory variables:

- a pooled logit model (3) on the probability of death;
- a version of (2) where the travel time to the nearest outpatient service location, m_{it} is the treatment variable, instead of d_{it};
- FE Poisson and FE logit models (1)-(2) on the number of outpatient cases and on the probability of receiving outpatient care, respectively, for person i in year t, and on its ACSC-related subcategories;
- FE linear models on inpatient and outpatient expenditures of person i in year t.

Besides, we estimate dynamic treatment effects with versions of the above models. Let $l_{it}^{(k)} = d_{i,t-k} - d_{i,t-k-1}$ indicate the period exactly k years after the establishment of the new

outpatient location in the micro-region of person i. Then, in the FE Poisson equation

$$E\left(y_{it}\right)=\exp\left(\beta_0 l_{it}^{(0)}+\beta_1 l_{it}^{(1)}+\beta_2 l_{it}^{(2)}+\beta_{3+} d_{i,t-3}+\beta_T T_{it}+\beta_z z_{it}+c_i^p\right), \tag{4}$$

β_k $(k=0,1,2)$ measure the treatment effect exactly after k years, and β_{3+} shows the effect after three or more years. (More lags cannot be included because only about four years have passed after the initiation of the new outpatient locations.) We use hospitalization, PAH, non-PAH case numbers and probabilities as well as outpatient case numbers as dependent variables in the dynamic models.

A crucial assumption behind these models is the parallel line assumption, i.e. that after netting out the effect of the control variables, the outcome variables in the treated micro-regions would have changed in the absence of the treatment in the same way as they actually did in the control micro-regions. Therefore we estimate a version of (4) for years 2008-2010, before the treatment:

$$E\left(y_{it}\right)=\exp\left(\beta_{g,2008}\cdot g_i\cdot I_{\{t=2008\}}+\beta_{g,2009}\cdot g_i\cdot I_{\{t=2009\}}+\beta_T T_{it}+\beta_z z_{it}+c_i^p\right), \tag{5}$$

where g_i denotes the group of the (later) treated micro-regions, $I_{\{t=k\}}$ the calendar year dummies, and we test whether $\beta_{g,2008}=\beta_{g,2009}=0$, i.e. the group differences – after controlling for the explanatory variables – are the same in 2008, 2009 and 2010, where the latter difference is captured by the individual fixed effects.

5.2 Substitution between outpatient and inpatient care

The most important advantage of the establishment of the new outpatient units is that we can exploit this quasi-experiment to estimate the causal impact of more frequent outpatient care use on inpatient care use. Formally, we estimate fixed-effects linear instrumental variable (FE IV) models of the form

$$E\left(y_{it}\right) = \delta_x x_{it} + \delta_T T_{it} + \delta_z z_{it} + c_i^n, \tag{6}$$

where, in the baseline IV specification, y_{it} is the number of hospital admissions and x_{it} is the number of outpatient care visits for person i in year t, and x_{it} is instrumented with d_{it}, the treatment dummy. Here we use a linear model because fixed effects and instrumental variables are computationally not straightforward to incorporate simultaneously in a Poisson model.

We also estimate the substitution / complementation effect in terms of outpatient and inpatient expenditures, i.e. by using inpatient expenditures as the dependent variable and outpatient expenditures as the endogenous explanatory variable, instrumented by the treatment variable, in a FE IV model.

Furthermore, the long panel dataset at our disposal enables us to measure the dynamics by using contemporary and lagged outpatient care use variables as endogenous explanatory variables, instrumented by the contemporary and lagged treatment dummies. Formally, we estimate FE IV models of the form

$$E\left(y_{it}\right) = \delta_0 x_{it} + \delta_1 x_{i,t-1} + \delta_T T_{it} + \delta_z z_{it} + c_i^n, \tag{7}$$

where x_{it} and $x_{i,t-1}$ are (jointly) instrumented by d_{it} and $d_{i,t-1}$. Here we only include one lag since the pre-treatment period contains only two or three years for most micro-regions.

6 Results

Table 1 presents the estimated treatment effects on the use of inpatient and outpatient care. (Descriptive statistics of the variables used in the models are shown in Tables 8–10 of Appendix 4.) The columns on the left display the annual baseline probabilities of receiving a certain type of care in the control group, along with the effects of the treatment on these probabilities. Odds ratios (i.e. $\exp(\gamma_d)$) are shown, which roughly correspond in the case of inpatient care to multiplicative changes in probabilities because hospitalization is relatively rare in the population. The columns on the right give the baseline case numbers (per 100 inhabitants) and the multiplicative effects of the treatment on them (i.e. $\exp(\beta_d)$ in the FE-Poisson models). The lower panel of the Table contains the baseline expenditure values in the control group and how the treatment affects them.

The first panel of Table 1 shows that both the overall odds of hospitalization and the overall number of hospital admissions decreased by about 1.5% as a result of the establishment of new outpatient units. Non-ACSC related hospitalization remained essentially unchanged on average in the four years after the treatment, but ACSC-related inpatient stay decreased substantially (odds by 7% and case number by 5%). This was driven by a reduction in cardiology, diabetes-related and specialist care specific PAH, which have ORs around 0.91-0.93. Meanwhile, pulmonology-related PAH did not decrease at all.

The slightly negative effect on hospitalization and the more substantial effect on PAH

persist in various other specifications. According to Table 2, pooled logit models give similar estimates (OR=0.993 for overall hospitalization and OR=0.94 for PAH), and they also show that death was not affected statistically significantly by the new outpatient locations in the medium term. Table 3 displays the effects if the treatment is measured by the reduction in travel time to the nearest outpatient care provider by car, instead of the treatment dummy. A one-minute reduction in travel time decreases PAH much more strongly than non-PAH (OR=0.9965 vs. 0.9989, i.e. the change in odds is threefold for PAH), and cardiology and diabetes-related PAH are particularly influenced.

Table 5 of Appendix 4 contains further robustness checks. They show that although the probability of chronic hospitalization (including rehabilitation and nursing services) decreased more than average (OR=0.95), the probability of "core" hospitalization (i.e. acute admissions with at least one night in the hospital) also seemed to decrease (OR=0.989), with marked reduction among acute PAH (OR=0.95). According to the table, the results are not governed by the creation of the special one-day ambulatory services in some treated and control micro-regions because similar treatment effects are estimated when the sample is restricted to those micro-regions where the newly founded one-day services had lower than median availability (as measured by per capita case numbers) after 2011.

Turning back to the main results, according to the second panel of Table 1, the improved accessibility of ambulatory care increased outpatient case numbers by 19% in the non-laboratory and 15% in the laboratory segment. Cardiology and diabetes-related outpatient case numbers grew faster, while pulmonology-related case numbers increased slower than average. Remarkably, the number of laboratory tests with ACSC-related cardiology and diabetes diagnoses roughly doubled, and the ratio of patients having annually at least

one laboratory test with such diagnoses approximately tripled. Since the standard protocol for the treatment of diabetes mellitus includes regular blood tests such as HbA1c screening to check long-term blood glucose levels, this suggests that a growing number of diabetes patients became treated according to the protocol, implying a health gain for the population.

The third panel of Table 1 displays the changes in health care expenditures. Per capita inpatient expenditures decreased by about 800 HUF (2.8 euros) or by 2.5% of the average expenditure, at about the rate of the reduction of inpatient case numbers. This suggests a roughly constant case mix (i.e. expenditure by inpatient episode). Meanwhile, per capita outpatient expenditures increased by about 1300 HUF (4.4 euros) or by 13% of the average expenditure, in good accordance with the estimated effect on outpatient case numbers.[5]

[5]Comparison of outpatient and inpatient spending is further complicated by the fact that drugs prescribed in ambulatory care are partially financed by out-of-pocket co-payment by the patient, whereas in inpatient care, the full cost of medication is borne by the hospital and thus factored into the amount of the reimbursement. We have no data to measure the size of this difference but it might introduce a slight upward bias in our estimate of inpatient savings.

Table 1: Effects of the establishment of new outpatient locations

	Probabilities (FE logit)			Case numbers (FE Poisson)		
	Baseline (per cent)	Odds ratio	S.E.	Baseline (per 100)	Multiplicative effect	S.E.
Inpatient care						
Overall	13.3	0.985**	(0.0058)	21.3	0.984**	(0.0064)
Not PAH	11.9	0.998	(0.0061)	18.4	0.991	(0.0070)
PAH	2.4	0.932***	(0.012)	2.9	0.950***	(0.013)
-Cardiology	0.80	0.906***	(0.019)	0.93	0.909***	(0.020)
-Pulmonology	0.58	1.005	(0.027)	0.74	1.035	(0.030)
-Diabetes	0.27	0.934**	(0.032)	0.31	0.945	(0.033)
-Specialist care specific	0.31	0.932**	(0.030)	0.32	0.935*	(0.033)
-Primary care specific	0.59	0.981	(0.024)	0.61	0.975	(0.027)
Outpatient care						
Overall non laboratory	54.6	1.232***	(0.0052)	293	1.185***	(0.0036)
- Cardiology	5.8	1.290***	(0.011)	11	1.209***	(0.011)
- Pulmonology	4.2	1.203***	(0.013)	8.7	1.043***	(0.012)
- Diabetes	2.3	1.325***	(0.025)	5.3	1.204***	(0.015)
Overall laboratory	31.4	1.107***	(0.0050)	105	1.148***	(0.0059)
- Cardiology	1.7	2.586***	(0.037)	2.9	1.786***	(0.035)
- Pulmonology	0.33	1.349***	(0.050)	0.70	1.126**	(0.060)
- Diabetes	0.76	3.118***	(0.079)	1.4	2.038***	(0.050)
	Expenditures (FE linear)					
	Baseline (1000 HUF)	Effect	S.E.			
Inpatient	32.6	-0.82***	(0.26)			
Outpatient	9.9	1.28***	(0.040)			

Cluster-robust standard errors are displayed for all models apart from FE logit.
Controls: fixed effects, cubic age, calendar year dummies, health care supply variables
Number of observations: 7,412,000. Number of periods: 8. Number of people: 1,037,000
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2: Pooled logit models on the probability of death and of inpatient events

	Baseline (per cent)	Odds ratio	S.E.
Death	1.2	1.012	(0.017)
Overall hospitalization		0.994	(0.0052)
PAH		0.939***	(0.011)
-Cardiology		0.944***	(0.019)
-Pulmonology		0.924***	(0.022)
-Diabetes		0.958	(0.031)
-Specialist care specific		0.971	(0.031)
-Primary care specific		0.924***	(0.021)

Cluster-robust standard errors are displayed.
Controls: cubic age interacted with gender, calendar year dummies, micro-region of residence, health care supply variables
See Table 1 for baseline probabilities of inpatient stay.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 2 shows the estimated β_k parameters from the dynamic equation (4). (The numerical values of the parameters, along with robustness checks from FE and pooled logit models, are displayed in Table 7 of Appendix 4.) While outpatient case numbers responded quickly to the opening of the new locations, inpatient case numbers reacted with a lag (and decreased by 2-3% after three years). According to the right panel of the figure, the lagged reaction was caused by non-PAH case numbers that became statistically significantly reduced by the end of the period, while PAH case numbers decreased right after the opening of the new locations.

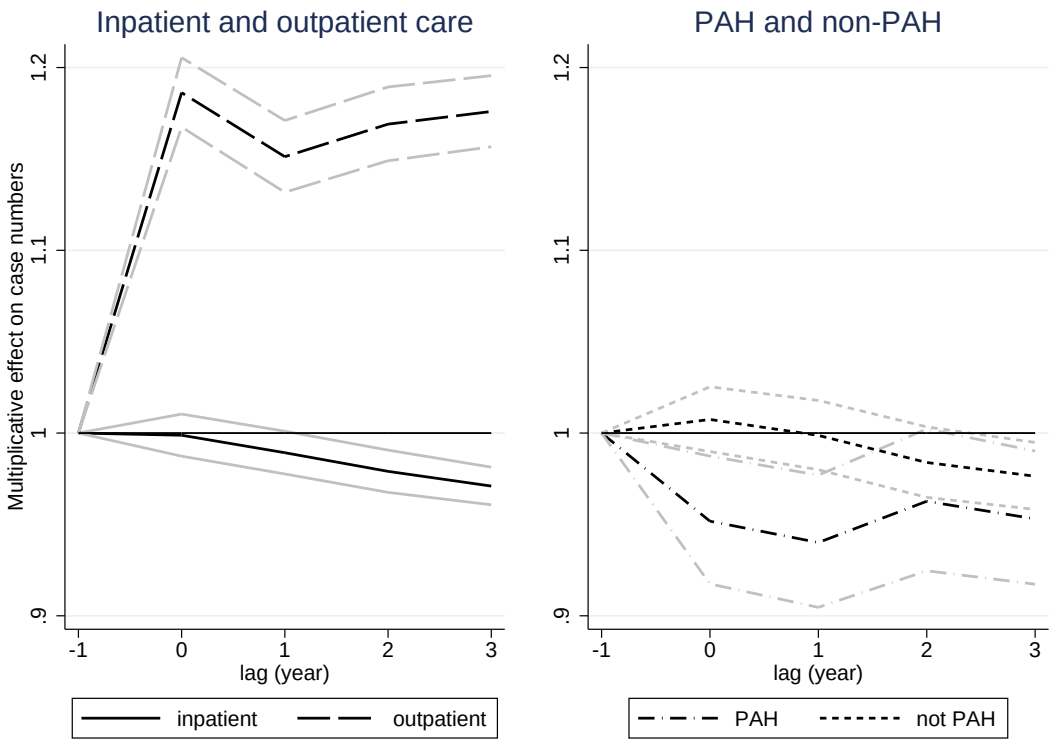
The test of the pre-treatment parallel line assumption, detailed in Table 6 of Appendix 4, shows that inpatient case numbers and its two subcategories changed in a roughly parallel way in the treated and the control micro-regions before the treatment (p-values are larger than 0.1). If anything, hospitalization in the treated micro-regions grew a bit – but statistically not significantly – faster compared to the control micro-regions, so the rate of

Table 3: Effects of bringing outpatient care closer by one minute with car

	Odds ratio of a one minute reduction	S.E.
Hospitalization	0.9984***	(0.00030)
Not PAH	0.9989***	(0.00031)
PAH	0.9965***	(0.00066)
-Cardiology	0.995***	(0.0011)
-Pulmonology	1.000	(0.0014)
-Diabetes	0.996**	(0.0018)
-Specialist care specific	0.997*	(0.0017)
-Primary care specific	0.998	(0.0013)

Controls: fixed effects, cubic age, calendar year dummies, health care supply variables. Model: FE logit
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 2: Dynamic effects of the establishment of new outpatient locations on case numbers (with 95% confidence intervals). For exact numbers see Table 7 of Appendix 4.



decrease after the treatment might by slightly underestimated. Meanwhile, the parallel line assumption is rejected for outpatient case numbers but the estimated difference in slopes (around 1%) is negligible compared to the change after the treatment (19%).

Finally, Table 4 shows the estimated structural effects of increased outpatient care use on inpatient care use (as measured by case numbers and expenditures), when the outpatient indicators are instrumented with the treatment dummy. The static estimates suggest that one more (non-laboratory) outpatient case of the patient decreases the number of hospital admissions by about 0.01 and a one HUF increase in outpatient expenditures implies a 0.6 HUF reduction in inpatient expenditures. According to the dynamic models that contain the outpatient indicators and their lags (instrumented by the treatment dummy and its lag), the reduction in the use of inpatient care seems to occur with a lag. This is consistent with the hypothesis that improved outpatient care decreases the need for inpatient care through the better availability of prevention and treatment of chronic diseases.

Table 4: Structural effects of increased outpatient care indicators on inpatient care indicators

	Parameter	S.E.	Lagged parameter	S.E.
Dependent var.: Inpatient case number				
Endogenous explanatory var:				
- Outpatient case number	-0.010***	(0.0034)		
- Outpatient case number and its lag	-0.0058	(0.0035)	-0.013***	(0.0033)
Dependent var.: Inpatient expenditure				
Endogenous explanatory var:				
- Outpatient expenditure	-0.642***	(0.215)		
- Outpatient expenditure and its lag	-0.292	(0.356)	-0.511*	(0.284)

Cluster-robust standard errors are displayed.
Instrumental variables: treatment dummy and its lag. Controls: fixed effects, cubic age, calendar year dummies, health care supply variables. Model: FE IV.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

7 Conclusions

Our quasi-experimental estimates indicate that bringing outpatient care closer to a previously underserved population may yield considerable effects and not just short term ones.

As already shown in Elek et al. [2015], indicators of outpatient care use (expenditures and number of visits) increased right after the new outpatient centers were established.

But what is the effect of more access to specialist outpatient services upon inpatient care? Controlling for health care supply variables, fixed effects, and patient age, we find marked substitution effects between outpatient care and hospitalization. As theory predicts, there is smaller effect upon inpatient care when leaving out potentially avoidable hospitalization due to ambulatory care sensitive conditions, but it is larger when concentrating upon potentially avoidable hospitalization. It is especially strong in the two specialisations of diabetes and cardiology. In the case of these two fields, we find corresponding sizeable increases in outpatient laboratory case numbers, strengthening the case that out of the different theoretical mechanisms, management of chronic health conditions in outpatient care is of great importance.

The dynamics of the effects is also noteworthy: as can be expected the substitution effects are stronger if we allow for a lag of several years for the additional outpatient care to take effect. The substitution effect upon potentially avoidable hospitalization (PAH) is exerted more rapidly than upon hospitalization for other diagnostic groups, indicating that in those specializations direct substitution mechanisms are present. We interpret the fact that, with a lag of several years, the substitution effect upon non-PAH also becomes significant as a sign that, in addition to prevention due to early detection, other, slower mechanisms of

substitution, notably, better management of chronic conditions are also present.

Finally, the effects concerning expenditures are also significant and sizable. Even though the official Hungarian reimbursment fees may not exactly reflect variable social costs of the treatment (and fix costs are not addressed at all) we consider it remarkable that, according to our estimates, the extra (variable) cost of additional outpatient care (HUF 1300) is partially cancelled out by savings in financing the hospitalization of the patients in question (HUF 800).

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Appendix 1: Potentially avoidable hospitalization (PAH)

Category	ICD-10 code
Cardiology	
- Angina	I20, I240, I248, I249, I250, R072, R073, R074, Z034, Z035
- Congestive heart failure	I11, I130, I255, I50, J81
- Hypertension	I10, I1191
Pulmonology	
- Asthma	J450, J451, J458, J459, J46
- COPD	J20, J40, J41, J42, J43, J44, J47
Diabetes	E10, E11, E12, E13, E14
Specialist care specific	
- Ear, nose, throat infections	H66.0, H66.1, H66.2, H66.3, H66.4, H66.9, H67, J02, J03, J040, J06, J312
- Convulsions, epilepsy	G253, G40, G41, O150, O151, O152, O159, R560, R568
- Dental conditions	A690, K02, K03, K04, K05, K06, K08, K098, K099, K12, K13
- Pelvic inflammatory disease	N70, N73, N74
- Perforated/bleeding ulcer	K20, K210, K219, K221, K226, K250, K251, K252, K254, K255, K256, K260, K261, K262, K264, K265, K266, K270, K271, K272, K274, K275, K276, K280, K281, K282, K284, K285, K286, K920, K921, K922
- Pyelonephritis	N10, N11, N12, N136, N159, N300, N308, N309, N390
Primary care specific	
- Cellulitis	I891, L01, L02, L03, L04, L080, L088, L089, L88, L980
- Gangrene	R02
- Dehydratation, gastroenteritis	A020, A04, A059, A072, A080, A081, A083, A084, A085, A09, K52
- Influenza, pneumonia	A481, A70, J10, J11, J12, J13, J14, J153, J154, J157, J159, J160, J168, J181, J182, J188, J189
- Iron or other nutr. def. anaemia	D500, D508, D509, D510, D511, D512, D513, D518, D520, D521, D528, D529, D531, D571, D580, D581, D590, D591, D592, D599, D601, D608, D609, D610, D640, D641, D642, D643, D644, D648
- Nutritional deficiency	E40, E41, E42, E43, E550, E643
- Other vaccine prev. diseases	A35, A36, A37, A80, B05, B06, B161, B169, B180, B181, B26, G000, M014

Only primary diagnoses were considered because secondary diagnoses were not available.
Age was restricted to at least two years.
Categorization is based on Purdy et al. [2008].

Appendix 2: Missing inpatient stays in 2015

The original sample refers to only those inpatient events that started and also terminated within 2008-2015, therefore some inpatient stays are missing for 2015. All figures in the paper show adjusted data for 2015 by assuming that inpatient events with year of discharge different from year of admission constituted the same share of all inpatient events in 2015 as in 2013-2014. This adjustment increases inpatient case numbers by only 1.2% but inpatient expenditures by 4.5% for 2015 because longer and hence more expensive inpatient stays are more likely to carry over to the next year than shorter ones.

The estimation results are essentially unaffected by this sample restriction. If a small share of inpatient events are missing randomly in 2015 in the treated and the control group, the selection effect is completely captured by the calendar year dummy in the FE Poisson model because of its multiplicative structure, and the situation is similar in the FE logit model because the modelled probabilities are small.

In principle, the FE linear model of the expenditures may be more sensitive to the sample restriction. However, if we impute the additional 4.5% of expenditures for 2015 using the patterns of the previous years, it only changes the elasticity in Table 4 by about 0.01.

Appendix 3: Health care supply variables

We control for local health care supply with the following variables in our regressions.

First, possible changes in inpatient capacities in the micro-region or the wider region may have influenced hospitalization rates differently in the treated and control group. Apart from the micro-region of Szikszó (which was excluded from the control group exactly because acute inpatient care was abolished there, implying a sudden reduction in the rate of hospitalization for its inhabitants) the other examined micro-regions did not have substantial inpatient capacities (hospital beds) throughout the whole observed period, so there is no need to control for inpatient supply on the micro-regional level. At the same time, we control for the logarithm of the wider regional (county-) level number of hospital beds in our regressions.

Second, we control for the availability of GP care by using the ratio of unfilled GP practices in the settlement of the individual.

Third, at the time of the establishment of the new outpatient units, special one-day ambulatory services started to operate in some treated and control micro-regions, which were aimed at providing certain treatments in internal care, neurology and physiotherapy at the ambulatory level instead of the hospital level. These new services may have had some subtle substitution effect between outpatient and inpatient care. We control for their local availability by using the annual micro-regional per capita level of the number of one-day ambulatory cases in our regressions. Since such services were established only in around half of the treated micro-regions (and also in some control micro-regions), this local availability proxy can be included in our models. We also perform robustness checks (see Table 5 in Appendix 4) to show that our results are not governed by these one-day ambulatory services.

Appendix 4: More details of the estimated models

Table 5: Robustness checks of the treatment effect on inpatient probabilities

	Odds ratio	S.E.
Acute and chronic care		
Acute care (excluding one-day care)	0.989*	(0.0061)
Acute PAH	0.954***	(0.013)
-Cardiology	0.949**	(0.023)
-Pulmonology	0.992	(0.030)
-Diabetes	0.923**	(0.035)
-Specialist care specific	1.010	(0.036)
-Primary care specific	0.969	(0.026)
Chronic care	0.949***	(0.015)
Sample restricted to micro-regions with low availability of special one-day services		
Overall hospitalization	0.989	(0.0069)
PAH	0.950***	(0.015)

Controls: see Table 1. Model: FE logit

In the lower panel the sample was restricted to those micro-regions that had lower than median per capita case number of special one-day ambulatory services after 2011. It contains the population of 10 treated and all but one control micro-regions.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Testing the parallel line assumption on case numbers for years 2008-2010

	Multiplicative interaction terms of treated vs. control group with years				p-value of both terms = 1
	2008 vs. 2010		2009 vs. 2010		
	Effect	S.E.	Effect	S.E.	
Overall non-lab outpatient care	0.984***	(0.0044)	0.994	(0.0042)	0.001
Overall inpatient care	0.984*	(0.0091)	0.995	(0.0085)	0.174
PAH	0.972	(0.020)	0.968*	(0.018)	0.188
Not PAH	0.984	(0.0099)	0.999	(0.0093)	0.170

Cluster-robust standard errors are displayed.
Controls: see Table 1. Model: FE Poisson.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Dynamic effects of the establishment of new outpatient locations

	0 year		1 year		2 years		3+ years	
	Effect	S.E.	Effect	S.E.	Effect	S.E.	Effect	S.E.
FE Poisson for outpatient case numbers								
Overall non-lab	1.186***	(0.0098)	1.151***	(0.010)	1.169***	(0.010)	1.176***	(0.010)
FE Poisson for inpatient case numbers								
Overall	0.999	(0.0059)	0.989*	(0.0060)	0.979***	(0.0059)	0.971***	(0.0053)
PAH	0.952***	(0.018)	0.940***	(0.018)	0.963*	(0.020)	0.953**	(0.019)
Not PAH	1.007	(0.0090)	0.999	(0.0097)	0.984	(0.0098)	0.976**	(0.0093)
FE logit for inpatient probabilities								
Overall	1.005	(0.0090)	0.993	(0.0091)	0.975***	(0.0089)	0.973***	(0.0079)
PAH	0.928***	(0.019)	0.926***	(0.019)	0.936***	(0.019)	0.929***	(0.017)
Pooled logit for inpatient probabilities								
Overall	1.016**	(0.0075)	0.995	(0.0077)	0.980***	(0.0076)	0.984**	(0.0069)
PAH	0.943***	(0.016)	0.931***	(0.016)	0.940***	(0.017)	0.927***	(0.015)

Controls: see Tables 1–2

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Descriptive statistics of inpatient dependent variables

	Control micro-regions						Treated micro-regions					
	2008-09		2010-12		2013-15		2008-09		2010-12		2013-15	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Inpatient probabilities (per cent)												
Overall	13.55	34.22	13.22	33.87	13.13	33.77	13.64	34.32	13.38	34.05	13.04	33.68
Not PAH	12.07	32.58	11.82	32.28	11.81	32.27	12.15	32.67	12.00	32.49	11.76	32.21
PAH	2.52	15.66	2.40	15.31	2.29	14.96	2.48	15.56	2.37	15.20	2.19	14.65
-Cardiology	0.83	9.08	0.79	8.88	0.80	8.89	0.77	8.77	0.74	8.59	0.71	8.38
-Pulmonology	0.61	7.80	0.60	7.71	0.54	7.30	0.62	7.84	0.57	7.50	0.53	7.25
-Diabetes	0.35	5.90	0.27	5.21	0.22	4.65	0.37	6.03	0.30	5.43	0.23	4.74
-Specialist care spec.	0.32	5.64	0.31	5.55	0.31	5.58	0.29	5.35	0.29	5.41	0.29	5.42
-Primary care spec.	0.58	7.63	0.60	7.75	0.59	7.68	0.60	7.75	0.64	7.95	0.59	7.67
Inpatient case numbers (per 100 inhabitants)												
Overall	21.68	78.31	21.18	75.98	21.13	77.32	21.58	75.79	21.37	75.84	20.71	74.65
Not PAH	18.61	72.62	18.23	70.17	18.35	72.02	18.60	70.33	18.52	70.41	18.08	69.65
PAH	3.07	22.31	2.95	22.10	2.78	21.20	2.98	21.47	2.85	21.15	2.62	20.32
-Cardiology	0.96	11.67	0.92	11.49	0.92	11.55	0.89	11.09	0.86	11.00	0.81	10.79
-Pulmonology	0.79	12.17	0.77	12.05	0.69	11.22	0.76	11.22	0.70	10.8	0.64	10.36
-Diabetes	0.40	7.50	0.31	6.56	0.24	5.68	0.41	7.35	0.33	6.66	0.25	5.77
-Specialist care spec.	0.32	6.23	0.32	6.44	0.32	6.30	0.30	6.11	0.31	6.26	0.30	6.05
Primary care spec.	0.60	8.39	0.63	8.79	0.61	8.53	0.63	8.91	0.66	9.05	0.62	9.03
Inpatient expenditures (1000 HUF / inhabitant)												
Overall	33.14	157.58	32.35	159.07	32.60	158.06	32.65	154.41	32.40	153.5	31.84	155.89
N. of obs.	944,550		1,427,989		1,426,575		893,343		1,356,140		1,363,032	

Table 9: Descriptive statistics of outpatient dependent variables

	Control micro-regions						Treated micro-regions					
	2008-09		2010-12		2013-15		2008-09		2010-12		2013-15	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Outpatient probabilities (per cent)												
Overall non-lab	56.32	49.60	54.83	49.77	53.20	49.90	54.88	49.76	55.50	49.7	55.66	49.68
-Cardiology	6.09	23.92	5.75	23.28	5.64	23.07	6.40	24.47	6.45	24.57	6.87	25.29
-Pulmonology	4.09	19.79	4.35	20.40	4.18	20.02	4.10	19.83	4.49	20.7	4.91	21.61
-Diabetes	2.08	14.28	2.23	14.78	2.44	15.43	2.03	14.11	2.36	15.18	2.68	16.15
Overall lab	30.29	45.95	31.55	46.47	32.05	46.67	30.12	45.88	31.98	46.64	33.57	47.22
-Cardiology	1.74	13.07	1.62	12.63	1.66	12.77	1.49	12.13	2.47	15.53	3.08	17.29
-Pulmonology	0.33	5.73	0.33	5.76	0.32	5.67	0.32	5.66	0.34	5.83	0.32	5.65
-Diabetes	0.82	9.01	0.75	8.64	0.74	8.57	0.54	7.32	0.94	9.64	1.15	10.64
Outpatient case numbers (per 100 inhabitants)												
Overall non-lab	297.38	594.18	291.16	580.61	290.65	589.24	280.47	549.11	303.66	591.37	329.49	645.38
-Cardiology	11.98	62.00	11.16	62.06	11.13	66.01	12.76	65.12	13.38	72.94	14.49	73.89
-Pulmonology	8.17	59.19	8.95	68.03	8.67	68.13	7.92	54.26	8.57	58.47	9.06	61.45
-Diabetes	5.11	46.47	5.19	45.74	5.51	45.96	5.07	45.92	5.69	47.98	6.65	52.93
Overall lab	99.61	329.79	106.96	351.26	107.06	344.69	99.51	346.38	114.18	382.26	124.83	384.04
-Cardiology	2.93	32.17	3.00	38.19	2.96	34.56	2.77	33.17	4.24	41.95	5.26	42.62
-Pulmonology	0.78	32.41	0.74	22.78	0.73	25.88	0.54	12.5	0.62	15.69	0.56	15.10
-Diabetes	1.50	21.87	1.33	19.44	1.31	19.21	1.07	20.04	1.67	22.92	2.17	26.07
Outpatient expenditures (1000 HUF / inhabitant)												
Overall	9.54	25.51	9.76	27.75	10.38	28.19	9.31	25.94	10.23	27.8	11.90	29.87
N. of obs.	944,550		1,427,989		1,426,575		893,343		1,356,140		1,363,032	

Table 10: Descriptive statistics of explanatory variables

	Control micro-regions						Treated micro-regions					
	2008-09		2010-12		2013-15		2008-09		2010-12		2013-15	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Treatment	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.45	0.43	1.00	0.00
Age	40.38	22.07	40.32	22.42	40.29	22.64	39.99	21.96	39.96	22.34	39.93	22.59
Squared age / 100	21.17	19.38	21.29	19.62	21.36	19.74	20.82	19.17	20.96	19.44	21.05	19.60
Cubic age / 1000	126.82	156.15	128.24	158.82	129.10	160.21	123.92	153.90	125.60	156.86	126.65	158.57
Year (2008)	0.50	0.50	0.00	0.00	0.00	0.00	0.50	0.50	0.00	0.00	0.00	0.00
Year (2009)	0.50	0.50	0.00	0.00	0.00	0.00	0.50	0.50	0.00	0.00	0.00	0.00
Year (2010)	0.00	0.00	0.33	0.47	0.00	0.00	0.00	0.00	0.33	0.47	0.00	0.00
Year (2011)	0.00	0.00	0.33	0.47	0.00	0.00	0.00	0.00	0.33	0.47	0.00	0.00
Year (2012)	0.00	0.00	0.33	0.47	0.00	0.00	0.00	0.00	0.33	0.47	0.00	0.00
Year (2013)	0.00	0.00	0.00	0.00	0.33	0.47	0.00	0.00	0.00	0.00	0.33	0.47
Year (2014)	0.00	0.00	0.00	0.00	0.33	0.47	0.00	0.00	0.00	0.00	0.33	0.47
Year (2015)	0.00	0.00	0.00	0.00	0.33	0.47	0.00	0.00	0.00	0.00	0.33	0.47
Special one-day services	0.00	0.00	0.04	1.49	0.59	1.29	0.00	0.00	1.33	2.84	3.35	3.58
Log hospital beds in county	7.98	0.38	7.98	0.37	7.94	0.34	8.03	0.35	8.02	0.35	7.98	0.33
Unfilled GP practices (%)	6.16	22.02	6.78	22.44	8.6	24.31	2.47	11.98	4.45	17.79	6.32	21.1
N. of obs.	944,550		1,427,989		1,426,575		893,343		1,356,140		1,363,032	

Special one-day services: average case number in the micro-region per 100 inhabitants
Unfilled GP practices: per cent in the settlement