Geographic and Socioeconomic Variation in Healthcare: Evidence from Migration

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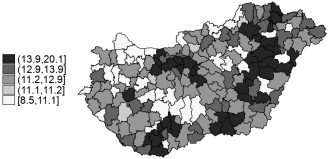
K T I Közgazdaságtudományi Intézet

Motivation

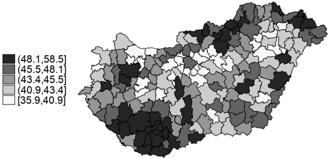
- **Socioeconomic differences** in health and healthcare use even in developed countries
  - Low-income groups have **worse health** (e.g. in life expectancy)
  - **Effective access** may differ across groups
    - 27% of patients with low level of education reported unmet needs for healthcare (Eurostat, 2019)
- **Large geographic variation** in healthcare use across all types of systems
  - Per capita utilization difference in the highest vs. lowest spending area is e.g. 84% in the US and 53% in Hungary

District-level healthcare spending in Hungary

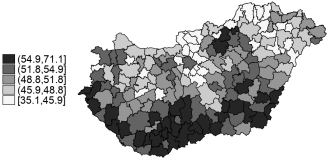
Outpatient spending



Inpatient spending



Drug spending



Sources of regional variation

- Main sources of variation
  - **Patient share** (demand side)
    - health status
    - preferences
  - **Place share** (supply side)
    - capacities (number of physicians, equipment)
    - physicians' belief, practice style
    - local climate and local economic conditions
- **Decomposition: using moves across districts**
- Policy implications
  - High place share suggests inefficiencies in the supply of health care
  - Heterogeneity: understanding the sources can help to target policies

Related literature

- Sources of **regional variation** in healthcare utilization using mover identification
  - *Finkelstein et al. (2016), Moura et al. (2019), Salm and Wübker (2020), Godoy and Huitfeldt (2020), Zeltzer et al. (2021), Johansson and Svensson (2022), Badinski et al. (2023)*
- Sources of **socioeconomic differences** in healthcare utilization
  - Demand-side: *Acton (1975), Lleras-Muney and Glied (2008), Allin and Hurley (2009), Cutler and Lleras-Muney (2010)*
  - **Supply-side**: *Brekke et al. (2018), Chen and Lakdawalla (2019), Martin et al. (2020); Turner et al. (2022)*

Public healthcare system in Hungary

- Single-payer system with universal coverage, which is free at the point of use (apart from pharmaceuticals).
- Primary care:
  - Provided by law at place of residence or nearby
- Specialist outpatient care:
  - Available in almost all district centres
- Inpatient care:
  - Available in half of district centres, but county seats provide higher level of services
- Prescribed pharmaceuticals

Administrative dataset

A random 50% sample of the 2003 population of Hungary for years 2009–2017 (approx. 5 million people)

Matched administrative dataset on healthcare and labour market variables

- **Demography**: Gender, age, occurence and time of death, district of residence
  - 197 districts in Hungary (with approx. 50,000 population on average)
- **Healthcare**:
  - **Outpatient care** (by specialties): number of visits & spending
  - **Inpatient care** (by specialties): number of days & spending
  - **Prescribed pharmaceuticals** (ATC categories): number of prescriptions and spending
- **Labour market**: labour force status, earnings, pensions

Movers

- Definition: county of residence changed exactly once in 2010-2016
- Age at time of move: 30-79
- Excluding Budapest-agglomeration moves

Model

$$E\left(y_{it}\right) = \exp\left(\alpha_i + \gamma_{j(i,t)} + \tau_t + x_{it}\lambda\right)$$

- y_{it}: health care utilization of individual i in period t
- α_i: individual i effect
- $\gamma_{j(i,t)}$: district j effect
- τ_t: time effect.

- We choose an exponential specification because of the nature of the variables (count or spending data with many zeros).

Estimation: difference-in-differences

- Identification depends on the presence of movers.
- t_i^0 : time of move for individual i, $o(i)$ the origin, $d(i)$ the destination district
- Then the equation can be written into a difference-in-differences-type framework:

$$E\left(y_{it}\right) = \exp\left(\alpha_i' + \tau_t + \mathbb{I}_{\{t \geq t_i^0\}} \times \theta \times \Delta_i + x_{it}\beta\right)$$

- where $\Delta_i = \log \overline{y}_{d(i)} - \log \overline{y}_{o(i)}$ is the log difference of average utilization of the destination and origin district
- θ, the place share, is the parameter of interest.

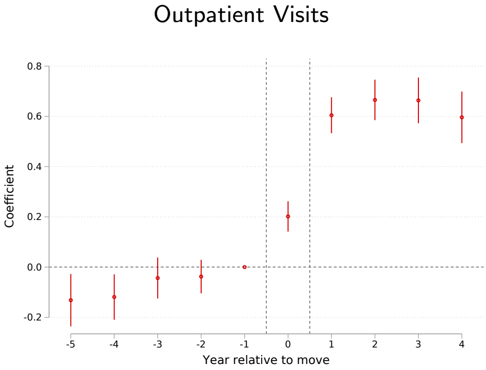
Estimation: event study

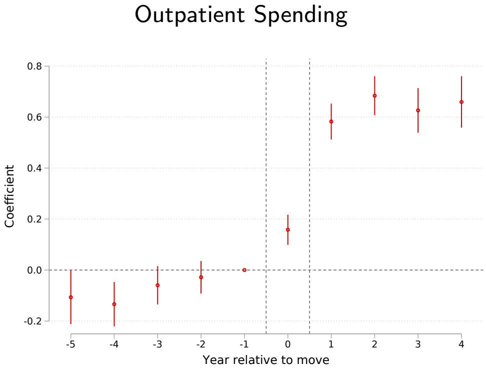
- Besides the above DiD-type analysis, we also estimate event study versions:

$$E\left(y_{it}\right) = \exp\left(\alpha_i' + \tau_t + \sum_{k=-5}^{k=4} \theta_k \times \mathbb{I}_{\{k=t-t_i^0\}} \times \Delta_i + x_{it}\beta\right).$$

- The models are estimated with fixed-effects Poisson regression.

Event-study results: outpatient care





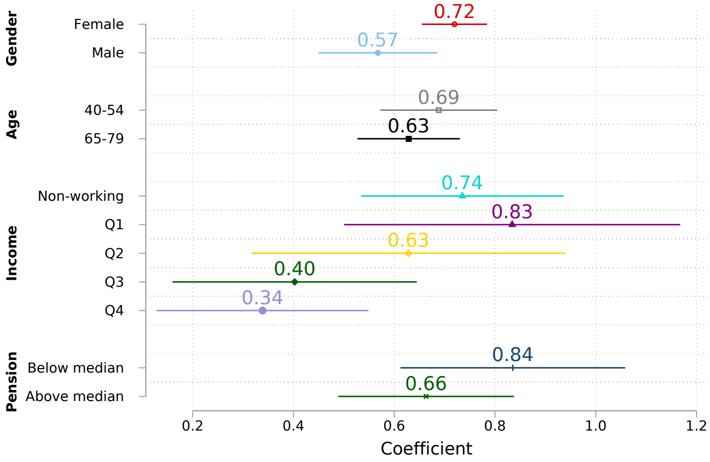
Place shares (θ) from DiD estimation

	(1) Outpatient care	(2) Inpatient care	(3) Pharmaceuticals
Frequency	0.659***	0.0136	0.183***
	(0.0316)	(0.148)	(0.0397)
Spending	0.659***	0.252	0.305*
	(0.0298)	(0.191)	(0.170)
Observations	266,290	128,271	257,731

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note: Difference-in-differences estimates of place effects. Controls include calendar year fixed effects and gender – age group interactions. For each utilization type, the first row shows a measure of frequency and the second row shows spending. Frequency measures are outpatient visits, inpatient days, and number of prescriptions.

Heterogeneity of outpatient place share



95% CIs of θ, estimated on subgroups

Possible mechanisms

- Place share is higher among low-ses people
  - which is not driven by differences in health (no difference by health status).
- Supply-side constraints may include:
  - **Capacity constraints** may affect some patients disproportionately
  - Quality of physician-patient communication
  - Unconscious bias and discrimination

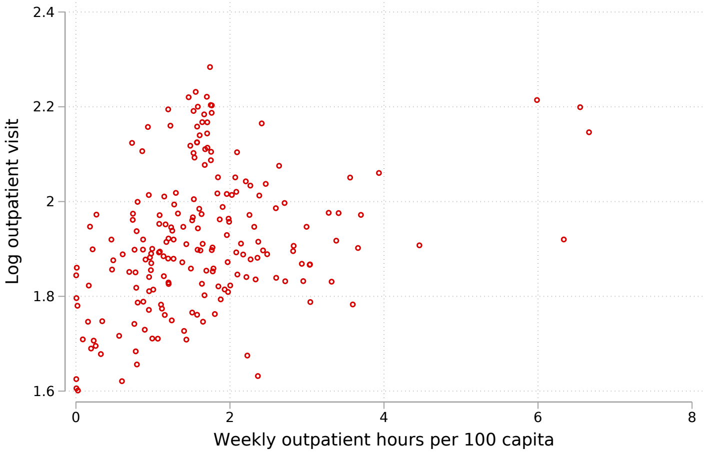
Determinants of healthcare use

- We study how **district-level observables** affect healthcare use.
  - Part of the endogeneity can be removed by observing movers.
- We estimate fixed-effects Poisson regressions

$$E\left(y_{it}\right) = \exp\left(\alpha_i + z_{j(i,t)}\eta + x_{it}\lambda\right)$$

- where $z_{j(i,t)}$ is a vector of observable district characteristics
  - healthcare capacities (outpatient hours, hospital beds)
  - geography (distance from county seat)
  - socioeconomic conditions (average taxable income)

Outpatient capacities and visits



Capacities matter (estimates using movers)

	Outpatient visits	Outpatient spending	Inpatient days	Inpatient spending
Outpatient hours,	0.079***	0.102***	-0.059**	-0.005
per 100 capita	(0.006)	(0.007)	(0.029)	(0.020)
Hospital beds,	-0.047***	-0.097***	0.129*	0.072
per 100 capita	(0.016)	(0.018)	(0.073)	(0.052)
County seat	-0.172***	-0.226***	0.121	-0.048
	(0.025)	(0.028)	(0.115)	(0.080)
Distance from	-0.018***	-0.019***	0.017	-0.016
county seat, 10 km	(0.004)	(0.005)	(0.018)	(0.013)
Log income	-0.005	-0.027	0.169	-0.143
per capita	(0.040)	(0.048)	(0.167)	(0.141)

Robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

- Movers react strongly to changes in outpatient capacities
  - even stronger effects for **women** and **low-ses** patients
- Substitution between inpatient and outpatient care

Conclusion

- **Place effects** account for **66%** of the variation in outpatient spending, **31%** in drug spending, while do **not** play a role in inpatient spending.
- There is **heterogeneity** in outpatient place shares:
    - 65-78% for low-income groups, and
    - 23-55% for high-income groups.
- Positive association between district-level outpatient spending and **capacities**
    - stronger for female and low-income groups.
- Effective access is not universal, and there are inefficiencies on the supply side.

Thank you for your attention!