Chapter 17
Multi-dimensional Panels in Health Economics with an Application on Antibiotic Consumption

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17.1 Literature

17.1.1 Multi-D panels in health economics

Variation in healthcare use and health outcomes across geographical regions, healthcare providers, and physicians is extensively documented in the literature, and it is a major concern of health policy. To disentangle the sources of these variations, (multidimensional) panel data are often used. In the absence of experiments, quasi-experimental variation is created by migration of patients and doctors across geographic regions, or by patients' switching between providers or doctors. The availability of administrative datasets has facilitated such studies over the past ca. two decades.

Following Abowd, Kramarz and Margolis (1999), Finkelstein, Gentzkow and Williams (2016) introduced the mover identification strategy in health economics in order to disentangle individual heterogeneity from the role of place-specific characteristics in health care utilization. Since their seminal work, a number of studies applied the same identification strategy on datasets from several countries: Moura, Salm, Douven and Remmerswaal (2019); Godøy and Huitfeldt (2020); Salm and Wübker (2020); Zeltzer, Einav, Chasid and Balicer (2021); Johansson and Svensson (2022), see Table 17.1 for an overview. Also, Table 17.2 provides a summary of papers using physician fixed effects in their modelling strategy.

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Table 17.1: Overview of literature using mover identification

Study	Indices (i-j-t)	Fixed effects
Finkelstein et al. (2016)	Patient - hospital referral region - year	$\alpha_i + \gamma_j + \theta_t$
Molitor (2018)	Physician - hospital referral region - year	event study with γ_j^{orig}
Moura et al. (2019)	Patient - province - year	$\alpha_i + \gamma_j + \zeta_t$
Godøy and Huitfeldt (2020)	Patient - region - year	$\alpha_i + \gamma_{j(it)}$
Salm and Wübker (2020)	Patient - region - year	$\alpha_i + \gamma_j + \kappa$
Zeltzer et al. (2021)	Patient - region - year	only event study
Johansson and Svensson (2022)	Patient - region - year	$\alpha_i + \rho_j + \theta_t$
Badinski et al. (2023)	Patient - region - year - physician	$\alpha_i + \gamma_{j(it)} + \theta_t + \delta_d$

Table 17.2: Overview of literature using patient, physician, and time FE

Study	Indices (i-j-t)	Fixed effects
Patients switching doctor		
Bennett et al. (2015)	Patient - physician - diagnosis - time	$\delta_t + (\gamma_{it} + \lambda_{jt} + \psi_{dt})$
Skipper and Vejlin (2015)	Patient - physician - purchase number	$\theta_i + \psi_j + Q_{tc}$
Koulayev et al. (2017)	Patient - physician - year	$\delta_i + \gamma_j + \sigma_{ij}$
Brekke et al. (2019)	Patient - physician - year	$\psi_i + \delta_j + \omega_t$
Ahammer and Schober (2020)	Patient - GP - year	$\theta_i + \psi_{j(it)}$
Currie and MacLeod (2020)	Patient - physician - year	$\alpha_i + \gamma_t$
Fadlon and Van Parys (2020)	Patient - physician - year	$\alpha_i + \delta_j$
Others		
Natali et al. (2023)	Substance-department-year	$\eta_i + \alpha_j + \delta_t + \gamma_{ij} + \lambda_{it}$
Finkelstein et al. (2021)	Origin-destination	

More recently, Badinski et al. (2023) introduced three dimensions simultaneously: patients, places and physicians. Their model is identified by cross-region migration of patients and physicians, and by variation in within-region matching.

Random effect panel models have also been applied in various settings in the health economics literature. For instance, in an analysis of prescription behaviors, Crea, Galizzi, Linnosmaa and Miraldo (2019) look at physician–patients over time, and treat the pair-specific effects as unobserved random variables. Chen, McAlpine, Lawson, Finelli and Saarela (2023) use random effects when analyzing how the observed variation in cancer surgical care received at patient level can be decomposed into hospital performance, surgeon performance within hospital, patient case-mix, and unexplained (residual) variation.

17.1.2 Empirical analyses of antibiotics use

A smaller literature investigates the role of physicians or healthcare institutions in antibiotics use:

- Bíró and Elek (2019) analyze the effect of primary care availability on antibiotic consumption and on the quality of antibiotic prescribing behavior. They use settlement-month panel data, and estimate fixed effects regression with settlement and time effects.
- Bennett et al. (2015) analyze of the effect of competition on antibiotic use in Taiwan. They apply panel regression models with doctor and patient fixed effects and time effects. Relatedly, Zykova (2020) analyzes the link between competition among general practitioners and regional antibiotic consumption in Norway, without a panel application.
- Allen et al. (2022) investigate the effect of working under pressure on antibiotics prescribing among English GPs. They estimate fixed effects panel regression model with GP and time fixed effects.
- In two related papers, Currie, Lin and Zhang (2011) and Currie, Lin and Meng (2014) use the results from audit studies conducted in China to investigate (1) the impact of patients' knowledge of appropriate antibiotics use on antibiotics prescription; (2) the impact of physicians' financial incentives on antibiotics prescriptions. These studies do not involve the use of panel data.
- Huang, Ribers and Ullrich (2022) show that machine learning can ease the prediction problem of diagnosing bacterial infection, thus can decrease the need for antibioc prescriptions.

17.2 Data

Data on the use of antibiotics, covering the entire population of Hungary, come from the National Healthcare Services Centre (NHSC) through an agreement between the

NHSC and the Institute of Economics, Centre for Economic and Regional Studies of the Hungarian Academy of Sciences. It is an individual-level panel data set, covering years 2010 to 2016. It contains information on pharmaceuticals in the Anatomical Therapeutic Chemical (ATC) group J01 (antibiotics with systemic use) that were purchased through pharmacies, hence only relate to the ambulatory setting and exclude hospital care. Only prescription drugs are recorded (over-the-counter sales are excluded) but this is not a limitation because of the prescription-only status of antibiotics in Hungary. The NHSC data provides information on the type (name, identifier code and detailed ATC code) of the antibiotic medication, the date of the purchase, the amount purchased and the associated expenditure (the sum of social security and out-of-pocket payments). Using the (anonymized) individual identifier and data of the purchase, we construct an individual-level monthly panel of antibiotic use (days of therapy and antibiotics spending), plugging in zero for each individual-month when no antibiotics purchase is observed.

The NHSC data set also includes records on the hospital stays and outpatient specialist visits of each individual who purchased antibiotics at least once over 2010-2016. In these records, we observe the zip code of the patient's address, the patient's year of birth, and gender. We use these records to impute the zip code of the patients for each month.

Each record of antibiotics purchase includes a unique identifier of the prescribing physician. Using this information, we impute the identifier of the (potentially) prescribing physician for each individual-month by taking the yearly mode of the physicians who prescribed antibiotics for the given individual in the given year.

We use the T-STAR municipal statistical system of the Central Statistical Office of Hungary to obtain information on the availability of pharmacies. This data set is a settlement-level annual panel, including information on the number of pharmacies per settlement, which we merge to the NHSC data after converting the zip codes to settlement codes in the NHSC data.

17.3 Methods

Our first exercise is the decomposition of the variance of antibiotics prescriptions to individual, place, and time effects, following Finkelstein et al. (2016) and Badinski et al. (2023). We will consider the application of both fixed effects and random effects specifications.

We estimate the following model of antibiotic consumption of patient i living in area (municipality) j in year t:

$$y_{ijt} = \alpha_i + \gamma_j + \theta_t + \varepsilon_{ijt}, \tag{17.1}$$

where α_i, γ_j, and θ_t are individual, place, and time fixed effects, respectively. ε_{ijt} is the idiosyncratic error term. We will consider extending the model with physician effects, as well.

Second, we focus on the place-based drivers of antibiotic consumption. We use the event study framework of Finkelstein et al. (2016) to measure the impact of location on antibiotic consumption, and to illustrate the validity of our identifying assumptions. Our identification originates from individuals moving across settlements. We estimate

$$y_{ijj't} = \alpha_i + \sum_{k=-2}^{k=2} \theta_k \times \mathbb{I}_{\{k=t-t_i^0\}} \times (\bar{y}_{j'} - \bar{y}_j) + \tau_t + \varepsilon_{ijj't} \tag{17.2}$$

where t_i^0 is the year of move of individual i, and thus, k is the relative year of move. The main variable of interest is $(\bar{y}_{j'} - \bar{y}_j)$, which is the difference of the average healthcare utilization in the destination (j') and the origin (j) municipalities. The corresponding coefficient estimate, θ_k can be interpreted as the place share, i.e., the share of geographic variation that is explained by place-specific characteristics.

Finally, we estimate the impact of the availability of pharmacies on the consumption of antibiotics. Our focus in this exercise is on how the inclusion of individual, time, and place effects modify the estimated effects. The idea is that in a simple OLS regression, the coefficient of the availability pharmacies (defined e.g., by a binary indicator if there is at least one pharmacy in the settlement or note) may capture unobserved individual characteristics and settlement characteristics. For identification, we use that the number of pharmacies varies over time, and that individuals move across settlements.

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