Exploring variations in health-care expenditures—What is the role of practice styles?

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Abstract

Variations in medical resource usage, both across and within geographical regions, have been widely documented. In this paper, we explore physician practice styles as a possible determinant of these variations. In particular, we exploit patient mobility between physicians to identify practice styles among general practitioners (GPs) in Austria. We use a large administrative data set containing detailed information on a battery of different health-care services and implement a model with additive patient and GP fixed effects that allows flexibly for systematic differences in patients’ health states. We find that, although GPs explain only a small part of the overall variation in medical expenses, heterogeneities in spending patterns among GPs are substantial. Conditional on patient characteristics, we document a difference of € 751.47 per patient per year in total medical expenses (which amounts to roughly 45% of the sample mean) between high- and low-spending GPs.

KEYWORDS

health-care expenditures, physician behavior, practice styles, statistical decomposition

JEL CLASSIFICATION

I11; I12; C23

1 INTRODUCTION

In health-care markets, patients have only limited information about treatment options and have to trust their physicians to provide appropriate medical care. However, physicians differ in their beliefs about the efficacy and appropriateness of medical interventions; hence, the same patient may be treated differently depending on the physician she visits. Such heterogeneities in the provision of care—often termed practice styles—are one possible explanation for the widely observed variations in medical resource usage across and within regions (see, e.g., Skinner, 2011; Chandra, Cutler, & Song, 2012). Practice styles also raise questions on the equity and efficiency of health-care systems, since their presence may imply that patients are over- or undertreated.

A key issue in identifying practice styles is to separate supply- and demand-side variation in resource usage. Certain physicians may simply use more resources than others because their patients are sicker on average. Existing studies largely use observable patient characteristics to control for differences in patient populations. For example, Epstein and Nicholson (2009) analyze the variation in cesarean section rates both within and between health-care markets. They show that the variation across U.S. obstetricians within a market is about twice as large as the variation between markets. Phelps, Mooney, Mushlin, and Perkins (1994) and Phelps (2000) analyze annual health-care spending among individuals within...
a U.S. health insurance plan and document a substantial amount of variation at the physician level. Similarly, Grytten and Sørensen (2003) and Kristensen, Olsen, Schroll, Thomsen, and Halling (2014) find large variations among primary care providers in Denmark and Norway. A potential concern in these studies is that they do not account for systematic matching between patients and physicians, which could potentially bias their results.

In this paper, we exploit patient mobility between physicians to identify practice styles among general practitioners (GPs) in Austria. We use a large administrative data set containing detailed information on a battery of different health-care services, most importantly doctors’ fees, sick leaves, hospitalizations, and drug expenditures. We implement a model with additive patient and GP fixed effects that allows for systematic differences in patients’ health states. Finkelstein, Gentzkow, and Williams (2016) used a similar framework with patient and location fixed effects to identify geographic variation in Medicare utilization through patient migration between geographic areas. Because our data allow us to match patients to GPs, we are able to identify the variation in medical service usage at a more granular level. We interpret the estimated GP fixed effects from this model as a measure of practice styles and provide variance decomposition analyses in order to discuss their relative importance in explaining the overall variation in health-care service provision. We provide descriptive evidence suggesting that mobility between patients and GPs is conditionally exogenous, which is a necessary assumption for identification.

Consistent with earlier research, we find that most of the variance in health-care utilization is indeed explained by patient needs and preferences. However, we find that, after controlling for patient heterogeneities, practice styles exhibit a substantial amount of variation as well. Ranking physicians according to their practice style measures, we show that total health-care expenditures in the top decile are 24.3% above the average expenditure level, and the difference between the top and bottom decile is € 751.47 in expenses per patient per year, which amounts to roughly 45% of the sample mean. We also find larger effects for services that are more directly influenced by the treating GP such as billed physician fees and screening expenditures. Finally, we analyze how physician demographics and local medical sector conditions are related to our practice style measures.

2 | BACKGROUND AND DATA

2.1 | Theoretical considerations

Factors both on the demand and supply side can influence treatment choices and have been put forward as explanations for the variation in the use of health-care services. In most markets, demand is highly dependent on income and prices. In the health-care sector, however, their influence is often limited due to insurance coverage and price regulations. Health status and patient preferences also affect demand, but differences in the use of medical resources across and within regions are often considered too large to be explained by these factors alone (Chandra et al., 2012).

On the supply side, variation in financial incentives, abilities, and beliefs of health-care providers can influence health-care utilization. Compared with other markets, the supply side is likely to play a more important role in health care, as patients often have little information about treatment options. However, there is also uncertainty on the provider side about the efficacy and appropriateness of treatments. Physicians are confronted with a myriad of combinations of symptoms, diseases, and patient characteristics on the one hand and constantly changing treatment technologies on the other. Understanding the relationship between potential treatments and their consequences for all patients seems impossible for the individual physician; hence, some disagreement about the optimal health production function between physicians is likely (Phelps, 2000). In this context, the concept of practice styles suggests that doctors form opinions about the appropriate treatment of patients, which could originate from differences in education, training, experience, personality, or other factors.

2.2 | Institutional background

Austria has a comprehensive social security system that includes mandatory public health insurance. A total of 22 social security institutions cover roughly 99.9% of the population (Hofmarcher, 2013). Affiliation to one of these institutions is determined by occupation and place of residence and, therefore, cannot be chosen freely by patients. The insured person have access to a wide range of services including visits to GPs and specialists in the outpatient care sector, inpatient

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1 Abowd, Kramarz, and Margolis (1999) pioneered the application of similar models with employer and employee fixed effects in the labor economics literature. These models have been used excessively to study employer-speciﬁc wage premiums in several countries (e.g., Abowd et al., 1999; Abowd, Kramarz, & Roux, 2006; Card, Heining, & Kline, 2013; Card, Cardoso, & Kline, 2016)
care, and prescription medicines. Most health-care-related costs are covered by the public health insurance with no or only minor co-payments. Patients may also visit noncontracted physicians who are not affiliated with a social security institution and can receive care in private hospitals. Payments for these services are usually only partially refunded.

GPs are typically self-employed physicians providing care in individual practices. There is no mandatory gatekeeping function in Austria, meaning, patients have no obligation to consult a specific physician before receiving (specialized) inpatient or outpatient care. Traditionally, however, GPs or family doctors play an important role within the health-care system. They usually serve as the first point of contact for general health concerns, provide primary care, and can refer patients’ to medical specialists and hospitals for further treatment. Insured persons can choose their own family doctor, but sticking to a specific physician is encouraged, both informally and formally. Individual physicians are expected to build trusting relationships with their patients and are obliged by law to document their medical histories, including diagnoses, treatments, and all prescribed drugs, which should help them to advise and treat patients appropriately.

Furthermore, for each quarter of the year, the health insurance only covers expenses at a single GP. Therefore, changing a GP without a valid reason, such as a change of residence, means patients will incur costs because they may not be reimbursed by insurance. GPs are obliged to treat insured persons if they have a contract with a social security institution and may only refuse patients in exceptional cases. The perceived quality and the availability of GPs rank highly in international comparisons. For example, 93% of Austrians think that the quality of GPs is good, and 94% state that GPs are easy to access. The overall averages of these two measures for the European Union are 84% and 88%, respectively (European Commission, 2007).

2.3 | Data

For our empirical analysis, we use data from the Upper Austrian Health Insurance Fund, which provide detailed information on health-care utilization in both the inpatient and outpatient sector for the years 2005–2012. With more than one million insured, the insurance fund covers roughly three-quarters of the Upper Austrian population, one of the nine federal states in Austria. The pool of insured comprises mostly private-sector employees, but also includes co-insured dependents, retirees, and unemployed individuals. Apart from information on health-care utilization such as doctors’ fees, prescribed drugs, sickness absences, and hospital stays, the data also contain patients’ demographic characteristics.

In addition, we augment the data with socioeconomic information on doctors, taken from the Upper Austrian Medical Chamber, and with inpatient records, including the cost of hospital treatments, based on the Austrian diagnosis-related group (DRG) system (Hagenbichler, 2010).

Thus, our data include most health-care expenditures covered by public health insurance. However, in some cases, patients may also visit hospitals’ outpatient departments, free of charge, in which case the corresponding costs of care are not captured by any of our data sources. Public acute care hospitals in Austria are legally obliged to have outpatient departments offering emergency treatment as well as testing and treatment methods not covered by GPs and specialists outside the hospital (Hofmarcher, 2013, p. 183). Hence, these departments are primarily designed for medical emergencies, but some patients may use them as a substitute for visits to independently practicing outpatient GPs or specialists. Although we do not observe patient visits, we do have information on drug prescriptions issued in outpatient departments, and the related expenditures are included in our measure of total drug expenditures.

We construct a matched patient–GP panel by aggregating the individual health-care utilization for each patient on an annual basis and then assign each patient to a specific GP. The GP we assign ought to be the patient’s family doctor. Unlike in Scandinavian countries and in many health insurance plans in the United States, where each person is typically registered at a specific primary health-care provider, patients in Austria can switch between GPs under certain conditions (see Section 2.2). Thus, we implement a simple algorithm that determines a patient’s family doctor. First, we compute the total doctor’s fees billed for every patient–GP–year triple in the data. Second, we pick the GP who billed the highest fees for every patient in each year. In a case where no fees were recorded for a patient in a given year, we assume that the family doctor is still the GP who billed the highest total of fees in the previous year. Using information on insurance status, we only include observations of persons who are insured throughout the calendar year. In total, the data contain 8,743,451 observations for 1,294,460 patients matched to 857 GPs, yielding an average of roughly 1,510 patients per GP.

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1 DRG tariff data are available for most hospitals in Upper Austria. However, for some smaller hospitals and visits to hospitals in other federal states, we only observe the length of the hospital stay. We impute missing data using a fee per hospital day, which is fixed for every calendar year. This fee is set by the federal government to compensate hospitals for patients outside the DRG-system (OÖ Landesregierung, 1997).

2 In 2012, we have data on visits to hospital departments but not on costs. For 2012, we observe a total 1.3 million visits, whereas GPs and specialists recorded a total of 13.6 million visits.
In Table S1 in the Supporting Information, we summarize the characteristics of GPs used in our empirical analysis. Physicians are, on average, 52 years old, 13% are female, and 33% maintain an on-site pharmacy. Most GPs studied in Vienna, followed by Innsbruck and Graz, with only a small fraction having studied abroad. In addition to socioeconomic characteristics, we provide several measures of local health-care provision: 31% of GPs practice in cities with hospitals, and the average physician density (calculated as the number of physicians per 1,000 insured individuals at the district level) is 0.77 for GPs and 0.94 for specialists.

### 2.4 Measurements of health-care utilization

We analyze the following measures of health-care utilization:

1. total medical expenditures,
2. doctors’ fees,
3. days of sick leave,
4. days of hospitalization,
5. drug expenses, and
6. general health screening expenditures,

all of which are aggregated on an annual basis. Here, total medical expenditures are composed of the sum of doctors’ fees in the outpatient sector, the total cost of prescribed drugs, and the total cost of inpatient treatments in a given calendar year. Although the GP may not be directly responsible for all services ascribed to this category, we include this measure because the GP may influence a patient's health-care utilization indirectly, for example, by providing information, suggesting medical treatments, or shaping the lifestyle of his patients. Doctors’ fees are determined based on a fee-for-service-type system, where contracted GPs receive a flat payment for a consultation, and may earn additional marginal revenues for specific treatments (such as injections, bandage application, or performing an electrocardiogram). In addition, we use the aggregate number of days of absence due to sickness, days of hospitalization, drug expenses, and preventive screening expenditures as outcomes. The latter is an interesting outcome, because both anecdotal evidence and earlier research (Hackl, Halla, Hummer, & Pruckner, 2015) suggest that much of the variation in screening participation is induced by supply heterogeneities. Thus, it provides an interesting benchmark for the other outcomes.

For doctors’ fees, sick leave, hospital stays, and drug expenses, we further differentiate between total, billed, and induced services. Billed services are those that are billed directly by the family doctor, whereas induced services are all those that can be traced back to the family doctor, for example, through referrals, including services billed by the GP herself. Finally, total services are all services in the respective category the patient utilized, regardless of the prescribing physician. Note that, by definition, all billed services are included in the induced services, and all induced services are included in the total services. Consider the following example. Suppose a person visits his GP to discuss a health issue, who then refers the patient to a radiologist to perform an X-ray to clarify possible causes. Shortly after, his condition worsens dramatically, and he goes to the hospital where he is cured and released after 3 days. The GP bills € 50 to the insurance fund, the radiologist € 70, and the hospital treatment costs € 1,500. Then, according to our definition, the GP has € 50 billed, € 120 induced, and € 1,620 total expenses for this patient.

Table 1 shows the descriptive statistics of the outcome variables. In general, health-care utilization varies considerably among individuals. On average, total medical expenditures sum to roughly € 1,688 per patient per year (with a relatively high standard deviation of 5,339), whereas average GP-induced doctors’ fees are about € 125, of which € 87 are billed directly by the GP. Across patients, GPs bill on average € 159,251 to the insurance fund per year. In terms of sick leave, a GP certifies, on average, 3.48 days per patient — here, billed and induced days of sick leave coincide because GPs rarely refer patients to other doctors to issue a sick leave certificate. In total, a GP certifies around 4,444 days of sick leave per year. Furthermore, GPs induce an average of 0.37 days of hospitalization and € 163 of drug expenses per patient per year. Screening expenditures make up for approximately € 8,711 of a GP’s remunerations.

In Table 2, we report the average per patient per year GP-induced medical services across deciles of the respective outcome’s distribution (note that the calculations in this table are based exclusively on nonzero observations). Here, we

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4Because of missing data, information on characteristics is only available for 684 of the 857 GPs. For our main analysis, we can use the universe of doctors, because we do not require these additional information.
5To calculate the densities, we count the number of insured persons and the number of physicians who have at least one patient for each quarter, and use the average values for the full period. We exclude dentists from the calculation, because dental care can be seen as a separate sector, with little connection to other forms of health care.
### TABLE 1  Descriptive statistics

| Variable                                      | Patient per year | GP per year |
|-----------------------------------------------|------------------|-------------|
| Total medical expenses in EUR                 | 1,687.97         | 2,154,864.93 |
| Doctors’ fees in EUR (billed)                 | 86.87            | 110,892.60  |
| Doctors’ fees in EUR (induced)                | 124.75           | 159,250.77  |
| Doctors’ fees in EUR (total)                  | 304.55           | 388,787.44  |
| Days of sick leave (billed)                   | 3.48             | 4,444.43    |
| Days of sick leave (induced)                  | 3.48             | 4,442.04    |
| Days of sick leave (total)                    | 7.18             | 9,163.30    |
| Hospital days (induced)                       | 0.37             | 466.58      |
| Hospital days (total)                         | 2.22             | 2,831.14    |
| Drug expenses in EUR (induced)                | 162.79           | 207,822.87  |
| Drug expenses in EUR (total)                  | 279.46           | 356,762.27  |
| Preventive health screening cost in EUR       | 6.82             | 8,711.70    |

**Additional patient-level controls**

| Age of the patient                           | 38.63            | 22.51       |
| Exogenous hospital days in \( t - 1 \)       | 2.03             | 8.40        |
| Patient was pregnant in \( t \)              | 0.02             | 0.12        |

**Number of observations**

| Patients/GPs × years | 8,743,451 | 6,849 |
|----------------------|-----------|------|
| Patients/GPs         | 1,294,460 | 857  |

*Note.* This table provides summary statistics of outcome and control variables used to estimate the Abowd, Kramarz, and Margolis regressions, with means and corresponding standard deviations being provided both per patient per year and per GP per year. Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations. Abbreviation: GP, general practitioner. “Billed” are services that are directly billed by the GP to the sickness fund.

“Induced” are services that can be traced back to the GP, e.g. through referrals.

“Total” are all services utilized by the patient independent of the billing or prescribing doctor.

### TABLE 2  Average induced medical services per patient per year

| Decile | Average induced medical services per GP per patient per year |
|--------|-------------------------------------------------------------|
|        | Doctor’s fees    | Sick leave | Hosp. days | Drug expenses |
| 1      | 17.23            | 1.64       | 1.63       | 5.81          |
| 2      | 25.45            | 3.48       | 3.00       | 10.02         |
| 3      | 40.66            | 5.00       | 4.00       | 15.99         |
| 4      | 57.23            | 6.00       | 5.00       | 24.78         |
| 5      | 77.34            | 7.00       | 6.00       | 40.55         |
| 6      | 101.68           | 8.45       | 7.00       | 70.29         |
| 7      | 136.67           | 10.93      | 8.86       | 130.95        |
| 8      | 187.97           | 14.72      | 11.89      | 250.99        |
| 9      | 272.18           | 22.04      | 16.75      | 498.69        |
| 10     | 593.39           | 71.04      | 36.49      | 1,700.19      |

*Note.* For each medical service, we stratify the sample into 10 equally sized bins. In each decile, we then calculate the mean of the respective medical service across patient–year observations within the bin. Observations with zeros on each variable are dropped before calculating means and deciles. The total number of observations in the data is 8,743,451 for 1,294,460 patients of 857 GPs. Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations. Abbreviation: GP, general practitioner.

See substantial variability in medical service utilization. In the lowest decile, doctors’ fees are, on average, about €17, whereas they are €593 in the highest decile. The lowest 10% of certified sick leave is an average of 1.64 days, whereas it is 71 days in the top 10%. Also, for hospital stays and drug expenses, we see a large range in the induced services and a gradual monotonic increase the farther we go upward along its distribution.
3 | METHODS

3.1 | Determining practice styles and assessing their relative importance

To identify practice styles, we use a decomposition procedure proposed by Abowd, Kramarz and Margolis, (1999, hereafter, AKM) widely used in the labor economics literature.6 Suppose health-care utilization $y_{it}$ of patient $i = 1, \ldots, N$ at time $t = 1, \ldots, T_i$ can be described by the following two-way additive fixed effects model:

$$y_{it} = \psi_{d(it)} + \theta_i + x_{it}'\beta_i + r_{it},$$  

where $d = 1, \ldots, D$ denote GPs, with $d(it)$ being the family GP of patient $i$ at time $t$, $\psi_{d(it)}$ and $\theta_i$ are fixed effects on the GP- and patient-level, respectively, $x_{it}$ is a vector of time-varying observables (a cubic in patient age, hospital days in $t - 1$, a binary variable indicating pregnancy in $t$, and a flexible time trend), and $r_{it}$ is a stochastic error term, which is i.i.d. with $E(r_{it} | \psi_{d(it)}, \theta_i, x_{it}, t) = 0$.

The fixed effects $\psi_{d(it)}$ are our measure of practice style. They can be interpreted as GP-specific deviations from the sample mean of $y_{it}$ that are orthogonal to patient characteristics. Patient health is measured through the time-invariant fixed effects $\theta_i$ and the vector $x_{it}$, which captures observable time-varying health determinants, including a dummy variable equal to unity if $i$ was pregnant in year $t$ (and zero otherwise), the number of days spent in hospitals in year $t - 1$, where referrals were not from a GP, a cubic in age, and flexible time dummies. Finally, the residual $r_{it}$ captures random health shocks. In order to estimate the model in Equation (1), we use the approach of Mihaly, McCaffrey, Lockwood, and Sass (2010) that within-transforms on the GP-level and imposes a sum-to-zero constraint on their fixed effects $\psi_{d(it)}$, which are then centered around zero.

Once we have an estimate for our practice style measure, we are interested to which extent it contributes to the overall variation in health-care expenditures. We proceed by decomposing the variance of each of our outcomes, following Card et al. (2013). Since each $y_{it}$ is a linear combination of $\psi_{d(it)}, \theta_i, x_{it}\beta_i$, and $r_{it}$, we can write

$$\text{Var} (y_{it}) = \text{Var} (\psi_{d(it)}) + \text{Var} (\theta_i) + \text{Var} (x_{it}\beta_i) + \text{Var} (r_{it}) + 2 \cdot \text{Cov} (\psi_{d(it)}, \theta_i) + 2 \cdot \text{Cov} (\psi_{d(it)}, x_{it}\beta_i) + 2 \cdot \text{Cov} (\theta_i, x_{it}\beta_i),$$

where each component is estimated using its sample analog.7 We are specifically interested in the percentage contribution of the GP fixed effect to the overall variance. For such percentage calculations, we omit the covariance terms in Equation (2), which are often estimated to be negative. If we included them, the relative contributions of the estimated GP fixed effects would be slightly higher (these calculations are shown in the Supporting Information).

3.2 | Patient mobility and identification

The key prerequisite for identification in our model is patient mobility. We can only separate the effects of patient and GP heterogeneity on health-care utilization if a sufficient number of patients move to new GPs within our observation period. In Table S2, we summarize the mobility in the data. A total of 713,708 patients stay with their GP over the entire period, whereas 399,043 patients move exactly once (hence, a total of 85.96% of all observations either never move or move once), 138,715 move twice, and so on.8

In addition, we require mobility between patients and doctors be exogenous, conditional on our observables $x_{it}$, the patient fixed effect $\theta_i$, and the GP fixed effect $\psi_{d(it)}$. A fundamental problem associated with our analysis is that patients are not allocated randomly to GPs. If a patient’s preference for a certain treatment is not accommodated by her family doctor, she may “shop” at different physicians until her demand is met. In our framework, this type of endogenous sorting does not pose an identification problem, as long as the motives for transitioning to a new GP can be conditioned on patient

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6 A variant of the AKM estimator was recently introduced to the health economics literature by Finkelstein et al. (2016).

7 For instance, the estimate for $\text{Var} (y_{it})$ is given by

$$\text{Var}(y_{it}) = \frac{1}{(NT_i - 1)} \sum_{t=1}^{T_i} \sum_{i=1}^{N} (y_{it} - \bar{y}).$$

8 We restrict our analysis to the largest connected set of movers, namely, those patients who are connected either directly or indirectly by patients' transitions between GPs. The largest connected set comprises over 99% of all observations.
observables, the patient fixed effect, or the GP fixed effect. Thus, even if the patient selects a new GP based on her inherent propensity to provide medical services (captured by $\psi_d(i)$) identification is guaranteed.

However, there may still be unobserved time-varying heterogeneities among patients that drive mobility. Thus, we provide descriptive evidence in favor of the exogenous mobility assumption using a number of analyses that have been suggested in the literature (Card et al., 2013; Card et al., 2016; Card, Devicienti, & Maida, 2014; Finkelstein et al., 2016). For example, strong indicators for exogenous mobility are flat health-care utilization profiles, before and after patients move to new GPs. In Figure 1, we plot average-adjusted GP-induced doctors' fees over time relative to the time of the GP transition. We see that utilization profiles are relatively flat until 2 years before the move, dip somewhat immediately before the move, but then recover and remain slightly above pre-move levels. The reason why utilization drops before the move is likely an artifact of our family doctor definition. In years when patients do not have medical expenses, we assume that the family doctor remains the same as the year before. Thus, if patients do not see their GP regularly, we would expect a dip in expenditures before the transition, since we attribute the zero expenses to the origin GP. This is confirmed by the upper left panel of Figure S1a, where we draw a similar graph but exclude patients with zero expenses in a given period. Doing so, the dip disappears. Overall, the changes in utilization are small in magnitude, both pre- and post-move. As pointed out by Finkelstein et al. (2016), bias may also result when certain health shocks coincide with the GP move and are correlated with pre- and post-move utilization. For example, this can occur if a patient moves to a high-prescribing GP immediately after experiencing a negative health shock. In this case, we would not see any change in the pre-move trends, but would expect the post-move trends to show a spike, which then gradually fades. Figure 1 suggests that this is not a problem in our data. Notice that $t_0$ is the first year with the new GP. Instead of spiking, adjusted GP fees return roughly to pre-move levels in this period. In $t_1$, the second year with the new GP, adjusted GP fees are €7 or 6.9% higher compared with $t_{-2}$, the year before the dip, and remain stable at approximately this level. The profiles of our other health-care utilization measures exhibit very similar trends (see Figure S1a).

In Figure 2, we further distinguish between upward and downward movers on the basis of GPs' estimated practice style measures. We see that those moving from a high-use to a lower-use physician (solid line) have a flat utilization profile before their move, but then experience lower utilization levels after their move. For upward movers (dashed line), we see an opposite picture. In case of endogenous mobility, we would expect utilization to adjust before the move, thereby causing, at most, a small discontinuous jump at the time of the move. For example, if a patient's health status deteriorates steadily and is correlated with utilization at the pre- and post-move GP, we expect a systematic downward trend in the

**FIGURE 1** GP-induced doctors' fees of patients moving to a new GP. GP, general practitioner.
utilization profile. However, the rather large discontinuities following GP transitions as evident in Figure 2 suggest that utilization does not systematically adjust before moves.

In Figure 3, we plot the mean absolute changes in GP-induced doctors’ fees for upward and downward movers simultaneously. If the additivity assumption of our model holds (which is a necessary condition for exogenous mobility; see, e.g., Card et al. 2013), then these changes should be symmetric. Suppose medical care utilization is properly described by Equation (1), and let the average unconditional utilization of patient $i$ at GP $d$ be given by $\bar{y}_{id} = \theta_i + \psi_{id} + z_{id}$, where $z_{id}$ is a stochastic error term. Consider two GPs, $A$ and $B$, with $\psi_A > \psi_B$. Then, the increase in utilization after moving from GP $B$ to GP $A$ is $\psi_A - \psi_B$, and the increase in utilization from moving from $A$ to $B$ is $\psi_B - \psi_A$. That is, changes from moving upwards and downwards are symmetric if patient and GP fixed effects are orthogonal.

Figure 3 clearly suggests that the additivity assumption implied by our model is met. Each scatter represents a pair of deciles of the estimated GP fixed effect distribution that movers are transitioning between, where the average change for upward movers within the pair is plotted on the horizontal axis, and the average change for downward movers is plotted on the vertical axis. Scatter 5–1, for example, represents the change in expenses for upward movers from GPs in Decile 1 to 5 on the horizontal axis and the change in expenses for downward movers from Decile 5 to 1 on the vertical axis. If the solid line fitted through the scatter points coincides with the 45-degree diagonal (represented by the dashed line), the symmetry assumption holds. In this case, the increase in medical expenses through moving upwards the GP fixed effect distribution is approximately equal to the decrease in expenses caused by moving downwards. Formally, we find no statistically significant difference between the fitted line and the 45-degree diagonal at the 1% significance level ($F_{1,43} = 4.97, p = .031$).

In Table 3, we test whether there are systematic differences in residual doctors’ fees of upward and downward movers prior to a move. In each panel, we compare the mean residual fees of movers moving up or down the GP fixed effect distribution to the residual fees of movers who stay within their fixed effect quartile (e.g., 1 to 1, 2 to 2, and so on). In the absence of exogenous mobility, we expect upward movers to already have higher doctors’ fees than those who move within the same GP fixed effect quartile and vice versa (see also Ahammer, Horvath, and Winter-Ebmer ; 2017). However, this is not what we see. The red numbers indicate that deviations occur in the direction we expect under endogenous mobility (i.e., upwards movers had higher mean residual expenses, and vice versa), whereas green figures indicate that deviations

FIGURE 2  GP-induced doctors' fees around GP transitions, split by upward and downward movers. GP, general practitioner.
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FIGURE 3 Symmetry of changes in medical expenses by moving to a new GP. GP, general practitioner

TABLE 3 Residual medical expenses for movers

| Quartile | # movers | M     | SD   | Difference | # movers | M     | SD   | Difference |
|----------|----------|-------|------|------------|----------|-------|------|------------|
| 1 to 1   | 105,426  | 1.0000| 99.22| 0.000      | 121,173  | -8.2354| 98.97| 0.000      |
| 1 to 2   | 58,578   | 0.2944| 99.57| -0.706     | 68,557   | -8.5145| 99.21| -0.279     |
| 1 to 3   | 45,894   | -0.8149| 98.76| -1.815     | 54,065   | -7.3919| 99.02| 0.844      |
| 1 to 4   | 47,530   | -2.1020| 104.41| -3.102     | 53,991   | -9.0069| 105.16| -0.771     |
| 2 to 1   | 65,358   | 0.2366| 99.81| 0.721      | 75,266   | -10.5056| 105.19| 1.074      |
| 2 to 2   | 51,290   | -0.4841| 92.70| 0.000      | 59,946   | -11.5793| 91.37| 0.000      |
| 2 to 3   | 46,691   | 0.3712| 100.18| 0.855      | 54,408   | -11.7861| 101.34| -0.207     |
| 2 to 4   | 47,356   | -2.9759| 112.71| -2.492     | 54,732   | -9.8008| 118.05| 1.778      |
| 3 to 1   | 53,406   | 1.8191| 108.64| 2.983      | 61,440   | -13.5532| 109.59| -0.777     |
| 3 to 2   | 50,118   | -0.3707| 100.30| 0.794      | 57,641   | -12.1765| 101.87| 0.600      |
| 3 to 3   | 41,593   | -1.1642| 99.15| 0.000      | 49,398   | -12.7765| 105.70| 0.000      |
| 3 to 4   | 51,438   | -1.2383| 108.28| -0.074     | 64,569   | -10.4914| 117.05| 2.285      |
| 4 to 1   | 38,526   | 1.6616| 126.81| 1.277      | 45,246   | -15.9198| 207.53| -1.754     |
| 4 to 2   | 38,431   | -0.3972| 111.57| -0.782     | 44,432   | -15.8753| 112.59| -1.709     |
| 4 to 3   | 51,438   | -0.3010| 107.78| -0.686     | 62,167   | -15.0839| 113.25| -0.918     |
| 4 to 4   | 70,041   | 0.3850| 122.84| 0.000      | 81,474   | -14.1660| 123.53| 0.000      |

Note: This table reports mean residual medical expenses obtained from an Abowd, Kramarz and Margoli decomposition with induced doctors’ fees as the outcome. General practitioners are classified into quartiles based on their estimated fixed effect. Differences are calculated with respect to movers who stay in the same GP fixed effect quartile (1 to 1, 2 to 2, 3 to 3, 4 to 4). If the difference shows the sign we expect under endogenous mobility (i.e., upward movers had higher residual expenses than stayers), it is marked in red, otherwise in green. The total number of observations in the data is 8,743,451 for 1,294,460 patients of 857 general practitioners. Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

We conclude that patient–GP mobility is very likely exogenous in our sample.
3.3 Explaining GP fixed effects

The estimated GP fixed effects are interpreted as a measure of physicians' practice styles. That is, they reflect the average tendency of a physician to favor more (or less) intensive medical interventions for patients than other physicians do, after allowing for patient differences. To explore the determinants of these practice styles, we use the predicted GP fixed effects \( \hat{\psi}_d \) from Model (1) as the dependent variable in the following linear model:

\[
\hat{\psi}_d = \alpha + z_d \phi' + w_d \delta' + \zeta_d.
\]

where \( z_d \) are observable GP characteristics, such as age, sex, having an on-site pharmacy, and the university where the GP studied. The vector \( w_d \) captures the attributes of the local health-care sector, including the density of physicians and a dummy variable indicating whether the doctor's office is in a city that has a hospital. We estimate Model (4) separately for each individual utilization measure in order to reveal potential heterogeneity in practice styles with respect to the type of health care.

4 RESULTS

4.1 Variance decomposition

We estimate Model (1) for each outcome separately and then decompose the observed variance using Equation (2). Table 4 summarizes the results, showing the standard deviations of the estimated patient (\( \theta_i \)) and GP (\( \psi_d \)) fixed effects, time-varying covariate index (\( x_{it} \phi \)), residuals (\( r_{it} \)), and the correlations between the components. The lower panel of Table 4 shows how much of the overall heterogeneity in health-care utilization can be attributed to each of the individual components of the model.9

The results indicate that most of the observed heterogeneity in health-care utilization can be attributed to patient-level differences measured by their individual fixed effects and time-varying explanatory variables. For instance, the patient fixed effect and the patient-level explanatory variables together account for over 73% of the variance in induced doctor's fees. Differences in patients' health states that require different levels of medical treatment and patients' preferences for care may contribute to this large heterogeneity. We also observe a considerable amount of residual variation, which we interpret as temporary health shocks that are not captured by observable characteristics and patient fixed effects.

The GP fixed effect, our measure of practice style, varies substantially less in comparison with the other components. Depending on the outcome, it explains between 0.05% and 4.29% of the total variance. The share is higher for services that are more closely related to the GP. For instance, in the case of doctors' fees, GPs account for 0.51% of the observed variation in amounts billed, 0.39% of the induced fees, and only 0.23% of total fees. Among the components of total health-care costs, GPs explain the least amount of variation in total drug expenses and total hospitalizations. A plausible explanation is that, compared with doctors' fees, hospital stays and drug consumption are relatively more dominated by health-care needs, and there is less discretion in decision-making. With 4.29%, the largest amount of explained variation is observed in expenses for general health screening. This is what we expect, because physicians' opinions and beliefs with respect to the value of such screening programs vary substantially. Thus, some physicians actively promote screening to their patients, whereas others do not.10

Relative to the other model components, the variation explained by practice styles seems negligible. This is a consequence of the large demand-side differences in health-care needs, which vary considerably both within (i.e., over the life cycle) and across patients. The elderly and those with serious or chronic illnesses require more and higher-cost medical attention than those who are younger and healthier. Thus, even within a single practice—where, by definition, practice style cannot explain any variation—health-care expenditures vary widely.

In a next step, we therefore want to know to which extent health-care utilization varies across GPs with different practice styles if we account for differences in patients' health demand. Essentially, this allows us to compare GPs with similar patient populations. Persisting differences in utilization may then point to inefficient over- or undertreatment of patients. In Table 5, we show the average estimated GP fixed effects by deciles of the respective outcome's distribution.11 This is

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9 Percentage calculations that also consider the covariance terms in Equation (2) can be found in Table S3.
10 See also Hackl et al. (2015), who use the variation in GPs' screening recommendations in Upper Austria as an instrument for screening participation, and find a substantial first stage effect.
11 Figure S2g shows the distribution of the predicted GP fixed effects graphically.
### TABLE 4  Results from the Abowd, Kramarz and Margoli model decomposition analysis

|                      | Total doctors' fees | Days of sick leave | Hospital days | Drug expenses | Screening expenses |
|----------------------|---------------------|--------------------|---------------|---------------|-------------------|
|                      | billed (1)          | total (2)          | induced (3)   | total (4)     | induced (5)       |
| Mean of outcome      | 1687.97             | 86.87              | 304.55        | 124.75        | 3.48              |
|                      |                     |                    |               |               |                   |
|                      |                     |                    |               |               |                   |
| Standard deviations and cross-correlations |                     |                    |               |               |                   |
| Outcome ($y$)        | 5,339.31            | 119.15             | 389.02        | 204.64        | 1.55              |
| Patient fixed effect ($\theta$) | 3,827.96          | 100.03             | 345.70        | 162.53        | 7.88              |
| GP fixed effect ($\psi$) | 188.42             | 11.93              | 27.33         | 16.42         | 1.01              |
| Explanatory variables ($x\beta'$) | 3,652.35          | 116.37             | 365.86        | 160.37        | 2.39              |
| Residual ($r$)       | 4,130.26            | 65.83              | 264.48        | 126.24        | 13.23             |
| Corr($\theta, \psi$) | -0.03               | 0.03               | -0.02         | 0.02          | -0.03             |
| Corr($\psi, x\beta'$) | -0.01              | 0.00               | -0.02         | 0.03          | -0.01             |
| Corr($\theta, x\beta'$) | -0.59             | -0.59              | -0.68         | -0.51         | -0.19             |

**Variance in percentage of total variance (neglecting covariance terms)**

|                      | Patient fixed effect ($\theta$) | GP fixed effect ($\psi$) | Explanatory variables ($x\beta'$) | Residual ($r$) |
|----------------------|---------------------------------|--------------------------|-----------------------------------|----------------|
|                      | 32.50                           | 0.08                     | 29.59                             | 37.84          |
|                      | 35.71                           | 0.51                     | 48.32                             | 15.46          |
|                      | 36.88                           | 0.23                     | 41.31                             | 21.58          |
|                      | 38.65                           | 0.39                     | 37.63                             | 23.32          |
|                      | 25.44                           | 0.42                     | 2.35                              | 71.79          |
|                      | 26.75                           | 0.17                     | 4.08                              | 68.99          |
|                      | 25.44                           | 0.42                     | 2.34                              | 71.80          |
|                      | 29.54                           | 0.12                     | 12.78                             | 57.56          |
|                      | 27.79                           | 0.15                     | 2.93                              | 69.13          |
|                      | 48.00                           | 0.05                     | 16.53                             | 35.42          |
|                      | 48.76                           | 0.11                     | 18.06                             | 33.07          |
|                      | 27.08                           | 4.29                     | 6.90                              | 61.73          |

**Note.** This table presents results of the decomposition analysis based on the (Abowd et al., 1999) model in Equation (2). We present estimated standard deviations and relative variance contributions of each model component—that is, $\hat{y}$, $\hat{\theta}$, $\hat{\psi}$, $\hat{x\beta'}$, $\hat{r}$, as well as $\text{Corr}(\theta, \psi)$, $\text{Corr}(\psi, x\beta')$, and $\text{Corr}(\theta, x\beta')$—for all 12 outcomes. The total number of observations in the data is 8,743,451 for 1,294,460 patients of 857 GPs. Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations. In order to calculate percentage contributions of our Abowd, Kramarz and Margoli model components, we purposely neglect the three covariance terms $2 \cdot \text{Cov}(\theta, \psi)$, $2 \cdot \text{Cov}(\psi, x\beta')$, and $2 \cdot \text{Cov}(\theta, x\beta')$ in Equation (2). The reason is that the variance of $y$ would then be comprised both positive and negative numbers, so individual percentages are difficult to interpret because the positive components $\hat{\theta}$, $\hat{\psi}$, $\hat{x\beta'}$, and $\hat{r}$ do not sum up to 1. Put differently, we omit the last three terms in Equation (2) and assume that the variance of $y$ is comprised only $\theta$, $\psi$, $x\beta'$, and the residual $r$. An alternative percentage calculation using also the covariance terms can be found in Table S3.
intriguing, as these effects can be interpreted as deviations from GPs who have an average level of health-care utilization, after allowing for differences in both observable and unobservable patient characteristics. The results suggest tremendous disparities in resource use. Considering total expenses, GPs in the bottom decile have, on average, €341.87 lower expenses, which is 20.3% less than the sample mean of €1,687.97. Similarly, the expenses of GPs in the top decile are, on average, €409.6, or 24.3% above the sample mean. The total range between the bottom and the top decile is €751.47, which amounts to almost 45% of the sample mean. Furthermore, the deciles show a monotonic increase in resource use, moving from low-use to high-use deciles, and that deviations from the sample mean tend to be distributed symmetrically.

Similar patterns can be observed for the analyzed components of health-care utilization. Analogous to the share of the explained variation, the observed deviation from average behavior tends to be larger for services that are more directly influenced by the treating GP. For example, fees billed by a GP in the top decile are 33.1% higher than the average fees (a deviation of €28.75 compared with mean expenses of €86.87), whereas the deviation for total doctor fees is only 20%. Similarly, the top decile for induced hospital days is 62.2% above the sample mean but only 30.2% for total hospital days.

The largest range in relative terms occurs in screening expenses. The average deviation in the top decile is €10.13, meaning that expenditures in that decile are 148.5% greater than the mean expenditures of €6.82. In the top and bottom deciles, health-care utilization may be driven by a small number of outliers at the ends of the distribution. However, the large heterogeneity remains when the top and bottom deciles are ignored. In the decile with the second highest spending, expenses deviate between 8.2% (total doctors’ fees) and 48.1% (screening expenses) from the sample means.

A natural sensitivity analysis is to check whether our decomposition results change if we exclude certain movers from the sample whose motives for transitioning to new GPs may potentially be considered endogenous. For example, patients who move to a GP whose practice is far away from their place of residence may be less likely to choose the GP randomly, as opposed to patients who choose a GP nearby. We therefore gather information on patients’ and GPs’ zip codes and calculate the distance between their centroids. In Table S4 (column 2), we then perform an AKM decomposition on total medical expenditures (similar to the one in Table 4, column 1), where only patient–GP pairs are considered whose geographical distance is 15 km (approx. 9 mi) or less. We find very similar results to the baseline in column (1). Importantly, the variance explained by the GP fixed effects in this subsample is only 0.04 percentage points higher than in the full sample, which is economically negligible.

In a related test, we exclude patients from the sample who transition to a new GP but remain in the same zip code as before the move (whom we term “doc shoppers”). Excluding those patients in column (3), the decomposition results are again similar to the baseline. In particular, our practice style measure differs only by 0.01 percentage points between samples, which is also economically negligible. Furthermore, we exclude observations (column 4) and patients (column 5) where we observe referrals between GPs, because systematic referrals between GPs could be an indication of endogenous patient mobility.12 Finally, in column (6), we include imputed data on hospital outpatient department visits to test if the missing information on these visits biases the results.13 Table S4 shows that these additional checks yield very similar results compared with our baseline specification. Consistent with the descriptive evidence discussed in Section 3.2, these robustness checks support our identification assumption, suggesting that patient mobility is largely exogenous in our sample.

### 4.2 Explaining GP heterogeneity

Table 6 shows the estimation results for Equation (4), where we explore correlates of the predicted GP fixed effects. As a measure of practice style, a larger fixed effect indicates a preference for higher medical resource use (after allowing for patient differences). Considering physicians’ characteristics, we find that total expenses decrease slightly with age, as a result of decreases in doctor fees and in the number of hospital days. The expenditures for general health checks also decrease with age, while there is a positive effect on the number of induced and billed days of sick leave. Experience in medical care and recent changes in medical training could explain an effect of physicians’ age on medical resource

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12When analyzing the raw data, we found that such referrals between GPs are rare and mostly related to visits to nursing homes and services provided as substitute for the family doctor.

13We impute visits using information on drugs prescribed by hospital physicians. Due to data limitations, we miss multiple visits within one month and all visits without drug prescription.
### Table 5
Average deviations in outcomes across deciles of the practice style measure distribution

| Decile | Total Doctors' fees billed | Total Doctors' fees induced | Days of sick leave billed | Days of sick leave induced | Hospital days total | Hospital days induced | Drug expenses total | Drug expenses induced | Screening expenses |
|--------|-----------------------------|-----------------------------|---------------------------|---------------------------|-------------------|---------------------|-------------------|---------------------|--------------------|
| Mean   | 1687.97                    | 86.87                       | 304.55                    | 124.75                    | 3.48              | 7.18                | 3.48              | 2.22                | 0.37               |
| 1      | -341.87                    | -23.20                      | -40.37                    | -48.31                    | -1.96             | -1.85               | -2.04             | -0.58               | -0.23              |
| 2      | -188.21                    | -12.50                      | -24.34                    | -18.22                    | -1.06             | -1.01               | -1.06             | -0.30               | -0.13              |
| 3      | -126.02                    | -8.57                       | -16.44                    | -11.75                    | -0.74             | -0.68               | -0.74             | -0.20               | -0.08              |
| 4      | -70.65                     | -5.24                       | -10.08                    | -7.72                     | -0.54             | -0.41               | -0.54             | -0.11               | -0.05              |
| 5      | -19.64                     | -2.66                       | -5.21                     | -3.79                     | -0.33             | -0.18               | -0.33             | -0.04               | -0.02              |
| 6      | 30.74                      | 0.25                        | 0.24                      | 0.35                      | -0.12             | 0.03                | -0.11             | 0.05                | 0.01               |
| 7      | 74.75                      | 3.24                        | 5.50                      | 4.31                      | 0.11              | 0.35                | 0.11              | 0.12                | 0.04               |
| 8      | 126.92                     | 7.06                        | 12.89                     | 8.51                      | 0.43              | 0.67                | 0.43              | 0.21                | 0.07               |
| 9      | 197.02                     | 12.35                       | 24.85                     | 14.15                     | 0.76              | 1.13                | 0.76              | 0.34                | 0.12               |
| 10     | 409.60                     | 28.75                       | 60.99                     | 31.49                     | 1.86              | 2.21                | 1.86              | 0.67                | 0.23               |

**Note:** This table presents average deviations from the sample mean for every outcome variable across deciles of the estimated GP fixed effect distribution. For every outcome, we first build deciles of the estimated GP fixed effect distribution. Within each decile, we then calculate the mean of the outcome within this decile and compare it to its overall sample mean. In each decile, there are between 85 and 86 GPs, the number of patients within each decile is available upon request. **Source:** Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.
### TABLE 6: Explaining practice styles

|                      | Total          | Doctor fees | Drug expenses | Hospital days | Days of sick leave | Screening expenses |
|----------------------|----------------|-------------|---------------|---------------|-------------------|-------------------|
|                      | expenses       | Total       | Induced | Billed | Total       | Induced | Billed | Total       | Induced | Billed | Total       | Induced | Billed | Total       | Induced | Billed | Total       | Induced | Billed | Total       | Induced | Billed |
| **Physician characteristics** |                |             |         |        |             |         |        |             |         |        |             |         |        |             |         |        |             |         |        |
| Age                  | -2.925*        | -0.525**    | -0.98  | -0.463*** | -309       | -0.031   | -0.004*| -0.000    | -0.011 | -0.029***| -0.028***| -0.103***|
| (-2.38)              |               | (-2.97)     | (-0.87) | (-5.89) | (-1.44)    | (-0.18)  | (-2.09) | (0.41)    | (1.68)  | (5.26)  | (5.06)    | (3.64)  |        |             |         |        |             |         |        |             |         |        |
| Female               | 80.535***      | 6.667*      | 2.857  | 0.338  | 0.706      | -0.467   | 0.143***| -0.002    | 0.298*  | 0.178   | 0.160     | -0.340  |        |             |         |        |             |         |        |             |         |        |
| (3.65)               |              | (2.10)      | (1.40) | (0.24)  | (0.18)     | (-0.15)  | (3.68)  | (-0.16)  | (2.48)  | (1.78)  | (1.63)    | (-0.67) |        |             |         |        |             |         |        |             |         |        |
| Onsite pharmacy      | 18.917         | -5.111*     | -1.786 | -0.799  | 2.149      | 9.643*** | 0.644* | 0.048***  | 0.075   | -0.037  | -0.031    | -1.989***|        |             |         |        |             |         |        |             |         |        |
| (1.10)               |              | (-2.07)     | (-1.11) | (-0.73) | (0.72)     | (3.86)   | (2.13)  | (4.73)    | (0.80)  | (0.47)  | (0.41)    | (-5.04) |        |             |         |        |             |         |        |             |         |        |
| **Medical degree from University** |            |             |         |        |             |         |        |             |         |        |             |         |        |             |         |        |             |         |        |             |         |        |
| Innsbruck            | 2.109         | -1.284      | 1.750  | -1.048  | 2.472      | 3.843    | -0.000 | 0.027**   | -0.110  | -0.095  | -0.087    | -0.334  |        |             |         |        |             |         |        |             |         |        |
| (0.14)               |              | (-0.58)     | (1.22) | (-1.06) | (0.92)     | (1.71)   | (-0.02) | (3.00)    | (-1.30) | (-1.35) | (-1.26)   | (-0.94) |        |             |         |        |             |         |        |             |         |        |
| Graz                 | -8.676        | -4.332      | -6.666 | -0.796  | -3.906     | -0.451   | 0.004  | 0.012     | -0.168  | -0.005  | -0.010    | 0.027   |        |             |         |        |             |         |        |             |         |        |
| (-0.37)              |              | (-1.28)     | (-0.31) | (-0.53) | (-0.95)    | (-0.13)  | (-0.10) | (0.85)    | (-1.31) | (-0.05) | (0.09)    | (0.50)  |        |             |         |        |             |         |        |             |         |        |
| Abroad               | 69.346        | 4.476       | 5.751  | 8.925*  | -10.994    | -7.068   | 0.185  | 0.057     | -0.073  | 0.022   | 0.020     | 2.309   |        |             |         |        |             |         |        |             |         |        |
| (1.03)               |              | (0.46)      | (0.92) | (2.07)  | (-0.94)    | (-0.72)  | (1.56)  | (1.46)    | (-0.20) | (0.07)  | (0.07)    | (1.49)  |        |             |         |        |             |         |        |             |         |        |
| **Local health care sector** |            |             |         |        |             |         |        |             |         |        |             |         |        |             |         |        |             |         |        |             |         |        |
| GP density           | 247.797**     | 4.855       | 10.051 | 10.083* | 20.104     | 31.442** | 0.490* | 0.143**   | -1.092* | -1.811***| -1.740***| -3.563* |
| (3.27)               |              | (0.45)      | (1.43) | (2.08)  | (1.52)     | (2.86)   | (3.68)  | (3.22)    | (-1.64) | (-5.28) | (-5.18)   | (-2.05) |        |             |         |        |             |         |        |             |         |        |
| Specialist density   | -118.325***   | -4.363      | 0.815  | 0.547   | -1.136     | -3.575   | -1.80***| -0.90***  | 0.433***| 0.670***| 0.661***  | 2.246***|
| (-5.69)              |              | (-1.46)     | (0.42) | (-0.41) | (-0.31)    | (-1.18)  | (-4.94) | (-4.14)  | (3.82)  | (7.13)  | (7.17)    | (4.70)  |        |             |         |        |             |         |        |             |         |        |
| City with hospital   | 86.636**      | 14.796***   | -2.136 | -0.965  | 0.569      | -5.501   | 0.092* | -0.011    | -0.002  | 0.353***| 0.355***  | -0.633  |        |             |         |        |             |         |        |             |         |        |
| (3.24)               |              | (3.84)      | (-0.86) | (-0.56) | (0.12)     | (-1.42)  | (1.97)  | (-0.71)  | (0.01)  | (-2.91) | (-3.00)   | (-1.03) |        |             |         |        |             |         |        |             |         |        |
| Constant             | 40.248        | 25.821*     | -3.490 | 18.643***| 0.471      | -22.419  | -0.23  | -1.03*    | -1.94   | -0.739  | -0.697    | 6.922***|
| (0.47)               |              | (2.09)      | (-0.44) | (3.39)  | (0.03)     | (-1.80)  | (-0.15) | (-2.05)  | (-0.41) | (-1.90) | (-1.83)   | (3.50)  |        |             |         |        |             |         |        |             |         |        |
| Mean of outcome      | 1687.97       | 304.55      | 124.75 | 86.87   | 279.46     | 162.79   | 2.22   | 0.37      | 7.18    | 3.48    | 3.48      | 6.82    |        |             |         |        |             |         |        |             |         |        |
| R²                   | 0.092         | 0.087       | 0.013  | 0.063   | 0.012      | 0.072    | 0.096  | 0.151     | 0.059   | 0.134   | 0.130     | 0.133   |        |             |         |        |             |         |        |             |         |        |

Note. Number of Observations is 684. Figure S1b compares the distribution of estimated GP fixed effects for all GPs with those included in these regressions. * Physicians who studied in Vienna are the base group. Robust t statistics in parentheses, * p < .05, ** p < .01, *** p < .001. Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.
use.\textsuperscript{14} In addition, the physician–patient relationship may depend on age, for example, affecting a patient's trust in his physician's decisions, and subsequently, the propensity to seek care at different institutions.

On average, female GPs have higher total expenses than those of their male GPs counterparts, an effect driven largely by differences in the number of hospital days. Interestingly, there is no significant effect of gender on the number of hospital days induced by referrals, suggesting that the difference in total hospital days is caused by other factors. Furthermore, we find that the presence of an on-site pharmacy increases expenditures on drugs prescribed by the GP, but there is no significant effect on total drug expenditures. This implies that prescriptions by other doctors offset the expenses induced by GPs who dispense drugs. Patients of physicians who have an on-site pharmacy tend to have lower total outpatient expenditures, but a higher number of hospital days. This could indicate a substitution of care by outpatient specialists with hospital care. In other words, these physicians more often refer their patients directly to hospitals.

We may expect that a physician's medical training has long-term consequences on his or her beliefs about the efficacy of medical interventions and treatment patterns, in general. However, we do not find that the universities where GPs earned their medical degrees have a large effect on their patients' health-care utilization. The point estimates of place of study on total expenses are statistically insignificant, and we only find small effects on individual health-care services. A limitation is that, following graduation from medical universities, GPs still require 3 years of postgraduate training in hospitals, where they rotate through the medical specialties to gain additional knowledge and practical experience. Compared with in-class education, this phase may be more important in shaping individual practice styles.

Additional variables measure the characteristics of the local health-care sector, namely the density of practicing GPs and specialists at the district level, and a dummy variable indicating whether a physician is practicing in a city with a hospital. The direction of the associated effects is unclear a priori. On the one hand, a higher number of health-care providers may incur supplier-induced demand or, if it exists, decrease the undersupply of services, for example, because of reduced waiting times for care. On the other hand, increased competition for a given level of demand could entail a lower amount of services that can or need to be provided by individual physicians. With regard to total expenditures, the results show an increase with the density of practicing GPs. The effect comes from increase billed doctor fees, induced drug expenditures, and the number of hospital days. The existence of a hospital is positively associated with total expenditures, largely attributable to the increase in the number of hospital days. In contrast, the density of specialists has a negative impact on total expenditures by reducing hospital stays. These results are consistent with the expectation that treatment by medical specialists is, to some extent, substitutable with hospital care. Days of sick leave are negatively associated with GP density and hospital availability. Here, a plausible explanation is that with increased supply, patients visit other GPs or hospitals more often when sick. Interestingly, the opposite effect is observed for specialist density. The same pattern—increases with specialist density and decreases with GP density—is revealed for screening expenses. With regard to the characteristics of the local health-care sector, an important limitation is that the district borders are of political relevance, but the district may not correspond well to the area relevant to the patient seeking health care.

\section{Conclusion}

We examine the variation in practice styles using administrative panel data from Austria. In contrast to the existing literature, we exploit patient mobility between doctors to identify practice styles. Our models incorporate additive patient and doctor fixed effects that allow flexibly for unobserved heterogeneity among patients. We provide descriptive evidence suggesting that patient mobility is conditionally exogenous. Estimated GP fixed effects are interpreted as measures of physicians’ practice styles, that is, the tendency of a physician to favor more (or less) medical treatment, after allowing for patient differences.

Although most of the variation in annual health-care utilization can be attributed to patient characteristics, we find that between 0.05\% and 4.29\% of the total variance can be attributed to GPs. Patients differ enormously in their health states and health-care needs, thus we are not surprised by this relatively small fraction which is explained by GPs. However, ranking GPs according to their estimated practice style measures, we find a substantial variation in medical resource usage patterns, even after allowing for patient differences. For high-usage physicians, the average level of health-care utilization is, depending on the health-care service under consideration, 20\% to 148.5\% higher than that of an average

\textsuperscript{14}There is mixed evidence on the relationship between physician age and patients' health-care utilization. Consistent with our results, Shih and Tai-Seale (2012) find that less experienced physicians are more prone to order tests, procedures or prescriptions suggested by patients that otherwise would not have been offered. In contrast, Cutler, Skinner, Stern, and Wennberg (2019) find that age is positively associated with the probability to recommend intensive care beyond what would be indicated by current clinical guidelines.
physician. For GPs in the top decile of the distribution, total medical expenses are €409.6 per patient per year higher than
the sample mean. Given that on average 77,873 patients are treated every year by GPs in the top decile, this amounts to
treatment cost of €31,897,024 which cannot be explained by patient needs and preferences. This suggests that practice
styles are an important determinant of health-care utilization. However, our analysis remains agnostic about the actual
appropriate level of health care, that is, whether and to what extent physicians with above (below) average expenditures
over treat (undertreat) patients.

The results can be compared with those in the existing literature using different methods and data from different health-
care systems. Phelps et al. (1994) analyze the annual medical spending of individuals in a U.S. health insurance plan, but
use observable characteristics and severity-of-illness measures to allow for patient differences among physicians. They
find that total expenses in the top decile are, on average, 24.7% ($185) larger than those of the sample mean ($750),
which is very close to the estimated deviation of 24.3% in the top decile of total expenses in our analysis. In a similar
study, Phelps (2000) finds an even higher deviation of 59.4% for the top-spending decile. Kristensen et al. (2014) examine
annual fee-for-service expenditures in Danish primary care. They find that between 3.8% and 9.4% of the variation can
be attributed to the individual GP clinic, which is a considerably higher fraction than that shown in our decomposition
results. Differences in the data and method used and in the health-care systems may explain the larger estimates. For
example, in contrast to Austria, GPs in Denmark act as strict gatekeepers to the rest of the health-care system, which
likely increases their influence on patients' health-care utilization. With regard to sick leave, using a multilevel random
intercept model, Aakvik, Holmás, and Islam (2010) find that most of the variation (more than 98%) in Norwegian patients'
length of sick leave is attributed to patient factors rather than influenced by variation in GP or municipality-level charac-
teristics. Although our approach differs and we capture both the extensive and the intensive margin of sick leave, we also
find that GPs explain only a small fraction of the total variance.

Identification in our analysis relies upon the exogenous mobility assumption, because there is no random matching
between patients and GPs. Although our tests find little evidence for endogenous mobility, a very small bias can not
be completely ruled out. Relatedly, patients who never move GPs add only little information to our estimated practice
style measure Andrews, Schank, and Upward (2004); hence, it is unclear to what extent our results are generalizable
to patients who remain with the same GP for an extended period of time. A further limitation is that the underlying
data only capture health-care costs covered by the health insurance. Patients’ out-of-pocket expenditures for visits to
noncontracted physicians and over-the-counter drugs may also be affected by GPs’ practice styles, which may complement
or be a substitute for care covered by the public health insurance.

In addition, the analysis does not explain how practice styles evolve. Our finding that university education is not related
to the observed heterogeneity is consistent with Epstein and Nicholson (2009), showing that physician training has only
small effects on the variation of c-section rates. Related literature suggests that physicians respond to financial incen-
tives, which could introduce variation in treatment patterns (Johnson, 2014; Jacobson, Chang, Earle, & Newhouse, 2017).
However, GPs in our data set operate under the same contract with the public health insurance and work within a small
geographical area, so that financial incentives should be similar. A plausible explanation is that individual (personality)
characteristics are important determinants of practice styles. Finally, our results cannot determine the optimal level of
care, that is, whether above-average utilization levels are actually too high. Further research is required using data on
patients’ well-being in order to answer such questions.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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