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Exploring Variations in Healthcare Expenditures – What is the Role of Practice Styles?

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Abstract

Variations in the use of medical resources, both across and within geographical regions, have been widely documented. Whenever these variations cannot be explained by differences in patient needs or preferences, they may result in some individuals being over-treated, while others are under-treated, thus raising questions on the equity and efficiency of healthcare systems. One explanation for these variations is differences in medical practice styles; that is, physicians may develop their own treatment patterns based on their beliefs about the efficacy of medical interventions. We use a large administrative data set from Upper Austria to study the practice styles among primary care physicians. We decompose the use of healthcare services into patient characteristics, patient and physician fixed effects, and stochastic health shocks. Physician fixed effects are interpreted as a measure of practice styles, which are then related to observable physician characteristics and to attributes of the local healthcare sector.

JEL Classification: I11, I12, C23.
Keywords: Health care expenditures, variation, practice styles, physician behavior.

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I. Introduction

Regional variations in medical resource usage are widely documented. For example, in Italy, Portugal and Germany, the cesarean section rate is 50% higher than it is in Finland (OECD, 2014), and U.S. per capita spending on Medicare in New York City, NY, and Miami, FL, is more than twice as high as that than in low-spending regions, such as Salem, OR (Gottlieb et al., 2010). These variations may result from either demand- or supply-side heterogeneities, for example, patients' health or physicians' preferences for certain treatments. Ideally, doctors are perfect agents who provide treatments in a way the patient would if he or she had perfect information. Therefore, whenever variations in healthcare usage cannot be explained by differences in patient needs and preferences, it may well be that some patients are over-treated while others are under-treated, which raises questions concerning the equity and efficiency of health systems.

One explanation for the observed supply-side variations is medical practice styles. Doctors may differ in their beliefs about the efficacy of medical interventions and, thus, develop different treatment patterns over time. In this study, we use a large administrative data set from Austria to examine the practice styles among general practitioners (GPs). When health issues arise, these physicians are typically the patient's first contact with the health system and an access point to further treatment by specialists and hospitals. Therefore, physicians can potentially have a significant effect on patients' overall medical resource use. Consequently, we first aggregate *all* observed medical care costs for every patient, and then analyze her GP's impact on these costs. Next, we disaggregate the overall resource use into different treatments, such as drug prescriptions and hospitalizations. Here, we also distinguish between treatments provided directly by the GP and those that were referred by her. For all these outcome variables, we perform statistical decomposition analyses, enabling us to isolate the effect of practice styles.

Previous attempts to quantify the effects of practice styles mainly use so-called patient vignettes, where physicians are faced with hypothetical scenarios, and then are questioned on how they would treat patients with specific made-up health conditions. For example, Sirovich et al. (2008) and Cutler et al. (2013) study primary care physicians and cardiologists in the United States, and find large differences in how the physicians would treat the same fictional patient. They further show that physicians' beliefs about appropriate practice styles are correlated with regional spending levels.

A second strand of literature, which is more closely related to our study, relies upon real-world data on treatments and expenditures to study practice variation. These studies often use patient characteristics and severity-of-illness measures, based on patient diagnoses, to control for systematic differences across patients. Phelps et al. (1994) and Phelps (2000) analyze annual healthcare spending among individuals within a U.S. health insurance plan, and document a substantial amount of variation at the physician level. Similarly, Kristensen et al. (2014) and Grytten and Sørensen (2003) show large variations among primary care providers in Denmark and Norway. Although studies show a high correlation between severity of illness measures and observed resource utilization (Brilleman et al., 2014; Huntley et al., 2012), it is unclear how well they can approximate patients' objective health status. Similarly to the choice of appropriate treatment, diagnostic styles may vary at the physician level and be correlated with treatment styles. Furthermore, health conditions are not recorded if individuals do not seek treatment or consult a physician, and patients' treatment preferences may also be important. In summary, the observed practice variation may be partly explained by unobserved differences among patients.

In this study, we exploit the longitudinal nature of our data and estimate models with additive patient and doctor fixed effects, thereby allowing for time-varying observables and (unobserved) constant heterogeneity. Abowd et al. (1999) pioneered the application of similar models with employer and employee fixed effects in the labor economics literature. These models which have been used excessively to study employer-specific wage premiums in several countries (e.g., Abowd et al., 1999, 2006; Card et al., 2016, 2013). In the context of healthcare utilization, Finkelstein et al. (2016) recently used a similar framework, but they incorporate location (instead of physician) fixed effects in order to study the determinants of geographic variation in the United States.[1] In contrast, our data allow us to use GP-level fixed effects (which Finkelstein et al. may capture with their location fixed effects as well), which we can use to examine the variation in healthcare utilization due to physician practice styles. We do so by decomposing the observed variation into observable factors and into patient and GP fixed effects, which we use as a proxy for doctors' practice styles. Then, we explore whether the GP characteristics and attributes that characterize local healthcare provision are related to the estimated GP fixed effects.

II. Background and data

II.1. Institutional background

Austria has a comprehensive social security system which 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 institution is determined by occupation and place of residence and, therefore, cannot be chosen freely by patients. The insured have access to a wide range of services including visits to general practitioners (GPs) and specialists in the outpatient care sector, inpatient 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 non-contracted 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

[1] A related multilevel variance decomposition approach incorporating random intercepts at the patient, GP, and municipality levels has also been used by Aakvik et al. (2010) with Norwegian data. However, their outcomes, are restricted to sickness absences.

no mandatory gate-keeping 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 healthcare 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. Remaining with 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. The perceived quality and the availability of GPs rank highly in international comparisons. For example, 93 % of Austrians think 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).

The dispensing of prescription drugs is highly regulated, and done primarily done by privately owned pharmacies. Under certain restrictions, physicians in rural areas are allowed to dispense pharmaceuticals themselves, whereby they earn a mark-up on every drug they prescribe (see, e.g., Ahammer and Zilic, 2017). This service is intended to improve access to prescription drugs in areas without community pharmacies.

II.2. Data

For our empirical analysis, we use data from the *Upper Austrian Health Insurance Fund*, which provide detailed information on healthcare utilization in both the inpatient and outpatient sector for the years 2005–2012. With more than one million insured, the *Upper Austrian Health 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 healthcare 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 costc of hospital treatments, based on the Austrian *diagnosis-related group* (DRG) system (Hagenbichler, 2010).[2]

Thus, our data include most healthcare expenditures covered by public health insurance. How-

[2]DRG cost 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).

ever, 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.[3] Although these departments are primarily designed for medical emergencies, they may also serve as substitutes for visits to GPs and specialists in the outpatient sector. Unlike the case of visits, information on drug prescriptions issued in outpatient departments are available, and the related expenditures are included in our measure of total drug expenditures.

For our empirical analysis, we construct a matched patient–GP panel by aggregating the individual healthcare utilization for each patient on an annual basis, and then assigning 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 healthcare provider, patients in Austria can freely switch between GPs without formal restrictions, with the exception of that discussed earlier, namely that GPs may only be changed once per quarter). 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. 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.

In Table A.1, we summarize the characteristics of GPs used in our empirical analysis.[4] Physicians are, on average, 52 years old, 13 % are female, and 33% maintain an in-house pharmacy. Most GPs studied in Vienna, followed by Innsbruck and Graz, with only a small fraction studied abroad. In addition to socioeconomic characteristics, we provide several measures of local healthcare 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.[5]

II.3. Measurements of healthcare utilization

In the course of our empirical analysis, we decompose the following measures of healthcare utilization by patient-level heterogeneity, GP-level heterogeneity, and stochastic health shocks:

(1) total medical expenditures,
(2) doctors' fees,
(3) days of sick leave,

[3] 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.

[4] Because of missing data, information on characteristics is only available for 684 of the 857 GPs.

[5] To 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 healthcare.

(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 healthcare 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 ECG). 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 et al., 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 *billed* $\subseteq$ *induced* $\subseteq$ *total* services. Consider the following example. Suppose a patient is referred from GP A to GP B, who bills € 50 to the insurance fund. Then, according to our definition, GP A has zero billed expenses, € 50 induced expenses, and € 50 total expenses. On the other hand, GP B has € 50 billed expenses, € 50 induced expenses, and € 50 total expenses.

Table A.2 shows the descriptive statistics of the outcome variables. In general, healthcare 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 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 A.3, we report the average per patient per year GP-induced medical services across deciles of the respective outcome's distribution (note that these calculations are based exclusively on non-zero observations). Here we 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.

III. Methods

III.1. Variance decomposition

For our empirical analysis we use decomposition procedure proposed by Abowd, Kramarz and Margolis (1999, hereafter, AKM) widely used in the labor economics literature.[6] Consider the following two-way additive fixed effects model:

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta}' + \theta_i + \psi_{d(it)} + r_{it}, \tag{1}$$

where $i = 1, \ldots, N$ denote patients, $d = 1, \ldots, D$ denote GPs, with $d(it)$ being the dominant GP (i.e., the family doctor) of patient i at time $t = 1, \ldots, T_i$,[7] and y_{it} is the respective healthcare utilization measure under consideration (see section II.3 for a detailed overview of all outcomes used). Time-invariant effects are split into a patient-specific effect θ_i and a GP fixed effect $\psi_{d(i,t)}$. The vector $\mathbf{x}_{it}$ captures observable health characteristics, 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 referral were not from a GP, a cubic in age, and time dummies. The residual r_{it} is *i.i.d.*, with $\mathrm{E}(r_{it}|\mathbf{x}_{it}, \theta_i, \psi_{d(it)}, t) = 0$ and $\mathrm{Var}(r_{it}) < \infty$. Without loss of generality, we further assume that r_{it} consists additively of a random match component η_{idt}, a unit root component m_{it}, and an idiosyncratic error ν_{it}. That is,

$$r_{it} = \eta_{idt} + m_{it} + \nu_{it}, \tag{2}$$

where η_{idt}, m_{it}, and ν_{it} have a zero conditional mean and finite variance. In order to estimate equation (1), we use the approach of Mihaly et al. (2010) that within-transforms the data and imposes a sum-to-zero constraint on the GP-level fixed effects $\psi_{d(it)}$. The estimated fixed effects are then centered on zero, and can be interpreted as deviations from the sample mean of y_{it}.

Identification of the model in (1) requires mobility between patients and doctors. We can only separate the effects of patient and GP heterogeneity on healthcare utilization if a sufficient number of patients move to new GPs within our observation period. In Table A.4, we summarize the

[6] The AKM estimator was recently introduced to the health economics literature by Finkelstein et al. (2016).

[7] We define the dominant GP as the practitioner who billed the highest amount of medical expenses for individual i in year t.

mobility in the data. A total of 713,708 patients stay with their GP over the entire period, while 399,043 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. We restrict our analysis to the largest connected set of movers, namely, those patients who are connected either directly or indirectly by transitions between GPs (the largest connected set comprises over 99% of all observations). In addition, we require the mobility between patients and doctors to be exogenous, conditional on our observables $\mathbf{x}_{it}$, the patient fixed effect θ_i, and the GP fixed effect $\psi_{d(it)}$. In particular, we have to rule out mobility based on η_{idt}. That is, patients' motives for transitioning to a new GP have to be orthogonal to the random match component. In section III.2, we discuss this issue in detail. In general, our tests all point strongly to mobility being conditionally exogenous in our sample of patients and doctors.

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 $\mathbf{x}_{it}\boldsymbol{\beta}'$, θ_i, $\psi_{d(it)}$, and ε_{it}, we can write

$$\begin{aligned}\mathrm{Var}(y_{it}) =& \mathrm{Var}(\mathbf{x}_{it}\boldsymbol{\beta}') + \mathrm{Var}(\theta_i) + \mathrm{Var}(\psi_{d(it)}) + \mathrm{Var}(\varepsilon_{it}) \\ &+ 2\,\mathrm{Cov}(\mathbf{x}_{it}\boldsymbol{\beta}', \theta_i) + 2\,\mathrm{Cov}(\mathbf{x}_{it}\boldsymbol{\beta}', \psi_{d(it)}) + 2\,\mathrm{Cov}(\theta_i, \psi_{d(it)}),\end{aligned} \tag{3}$$

where each component is estimated using its sample analog. For instance, the estimate for $\mathrm{Var}(y_{it})$ is given by

$$\widehat{\mathrm{Var}(y_{it})} = \frac{1}{(N^* T_i - 1)} \sum_{i=1}^{N} \sum_{t=1}^{T_i} (y_{it} - \bar{y}), \tag{4}$$

where

$$\bar{y} = \frac{1}{N^* T_i} \sum_{i=1}^{N} \sum_{t=1}^{T_i} y_{it}. \tag{5}$$

Similarly, the estimate for $\mathrm{Cov}(\theta_i, \psi_d)$ is

$$\widehat{\mathrm{Cov}(\theta_i, \psi_d)} = \frac{1}{N^* T_i} \sum_{i=1}^{N} \sum_{t=1}^{T_i} (\hat{\theta}_i - \bar{\hat{\theta}})\hat{\psi}_d \tag{6}$$

where $\bar{\hat{\theta}}$ is the mean of the estimated patient fixed effects.

III.2. Identification

Identification of the AKM model specified in the previous section III requires that mobility between patients and doctors be conditionally exogenous. 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 simply '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 time-varying patient-level observables $\mathbf{x}_{it}$, the patient fixed effect θ_i, or the GP fixed effect $\psi_{d(it)}$. Thus, even if the patient selects a new GP based on his inherent propensity to provide medical services (captured by the fixed effect $\psi_{d(it)}$) identification is guaranteed.

However, there may still be unobserved heterogeneities among patients that drive mobility. Thus, we follow the existing literature (Card et al., 2013, Card et al., 2016, Card et al., 2014 and Finkelstein et al., 2016) and provide tests for the exogenous mobility assumption. For example, strong indicators for exogenous mobility are flat healthcare utilization profiles, before and after moves. 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 utilization profile. 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.

Consider Figures A.1 and A.2, in which we plot the average GP-induced doctors' fees over time relative to the time of the GP transition. We see that utilization profiles are remarkably flat until two years before the move, dip immediately before the move, but then recover and remain at pre-move levels. The reason why utilization drops before the move may be an artifact of our family doctor definition, because in years where patients do not have medical expenses, we assume that the family doctor remains the same as the year before, but changes whenever there are expenditures greater than zero. The changes in utilization are very small in magnitude, both pre- and post-move. In Figure A.2, we distinguish further between upward and downward movers, based on GPs' estimated resource-use levels. 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 Figure A.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 from 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 A.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 (see the graph's notes for a more detailed description). If the solid line fitted through the scatter points coincides with the 45-degree diagonal, the symmetry assumption holds. Formally, we find no statistically significant differences between the fitted line and the diagonal at the 1% significance level ($F_{1,43} = 4.97$, $p = 0.031$).

In Table A.5, we test whether there are systematic differences in residual doctors' fees of upward and downward movers prior to a move.[8] 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 (Ahammer et al., forthcoming). However, this is not what we see. The green numbers indicate that deviations occur in the right direction, while red figures indicate that deviations occur in the wrong direction. In total, 14 differences occur in the wrong direction, while only 10 occur in the right direction. This is clearly not an indicator of a systematic pattern. We conclude that patient–GP mobility is very likely exogenous in our sample.

III.3. Explaining GP fixed effects

The estimated GP fixed effects are interpreted as a measure of physicians' practice styles. That is, the 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:

$$\hat{\psi}_d = \alpha + \mathbf{z}_d \boldsymbol{\phi}' + \mathbf{w}_d \boldsymbol{\delta}' + \zeta_d, \tag{7}$$

where $\mathbf{z}_d$ are observable GP characteristics, such as age, sex, having an in-house pharmacy, and the university where the GP studied. The vector $\mathbf{w}_d$ captures the attributes of the local healthcare 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 (7) separately for each individual utilization measure in order to reveal potential heterogeneity in practice styles with respect to the type of healthcare.

[8] This test on the exogenous mobility assumption was introduced by Ahammer et al. (forthcoming).

IV. Results

IV.1. Variance decomposition

We estimate model (1) for each outcome separately and then decompose the observed variance using equation (3). Table A.6 summarizes the results, showing the standard deviations of the estimated patient (θ_i) and GP (ψ_d) fixed effects, time-varying covariate index ($\mathbf{x}_{it}\boldsymbol{\beta}$), residuals ($r_{it}$) and the correlations between the components. The corresponding variances and cross-variances are shown in the second panel.

The results suggest that large parts of the observed heterogeneity in healthcare utilization are driven by patient-level differences, and can be linked to the individual fixed-effects and the time-varying explanatory variables. For instance, the standard deviation of the patient fixed effects is 3,828 for total medical expenses while it is only 163 for the induced doctors' 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, is less variable in comparison with these components. The standard deviation is 188 for total medical expenses, and 16 for induced doctors' fees.

The lower panel of Table A.6 shows how much of the overall heterogeneity in healthcare utilization can be attributed to the individual terms in the decomposition. It shows that between 0.05 % and 4.29 % of the total variance is explained by the GP fixed-effects. Figure A.4 provides a graphical comparison of all outcome variables, and reveals that the share of explained variation 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 healthcare costs, GPs explain the least amount of variation in total drug expenses and total hospitalizations. A plausible explanation is that, compared to doctors' fees, hospital stays and drug consumption are dominated by healthcare 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 large heterogeneity could be explained by the fact that physicians' opinions and beliefs with respect to the value of such screening programs vary. Thus, some physicians actively promote screening to their patients, while others do not.[9]

In light of the large overall variance in healthcare utilization, GPs' influence on resource use appears to be negligible. However, an interesting question is how physicians' behavior varies after allowing for patient differences. To this end, we further analyze the distribution of the predicted

[9]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.

GP fixed effects. Table A.7 shows the average fixed effects by deciles of the respective outcome's distribution.[10] These effects can be interpreted as deviations from GPs who have an average level of healthcare utilization, accounting for differences in both observable and unobservable patient characteristics. 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. Furthermore, the deciles show a gradual 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 healthcare 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 to 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, which is 148.5 % greater than the mean expenditures of € 6.82. In the top and bottom deciles, healthcare 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. In summary, the distribution of the estimated GP fixed effects suggests that physicians do have an economically significant influence on their patients' healthcare utilization.

IV.2. Explaining GP heterogeneity

Table A.8 shows the estimation results for equation (7), 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 use. 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,

[10]Figure A.11 in the Web Appendix shows the distribution of the predicted GP fixed effects graphically.

an effect driven largely by differences in the number of hospital days. Interestingly, there is a statistically significant effect for total days, but not for the number hospital days induced by referrals, suggesting that the difference is not caused directly by the treating physician. Furthermore, we find that the presence of an in-house 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 in-house 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' healthcare utilization. The point estimates of place of study on total expenses are statistically insignificant. Studying in Innsbruck tends to have a positive effect on the number of induced hospital days, and studying abroad increases billed doctor fees, but these effects are compensated for by reductions in other health resources. A limitation is that, following graduation from medical universities, GPs still require three years of postgraduate training in hospitals, where they rotate through the medical specialties to gain additional knowledge and practical experience. Compared to in-class education, this phase may be more important in shaping individual practice styles.

Additional variables measure the characteristics of the local healthcare 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 healthcare 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 healthcare 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 healthcare.

V. Conclusion

In this study, we examine the variation in practice styles using administrative panel data from Austria. Using two-way additive fixed effects models, we decompose the observed variation in healthcare utilization into time varying characteristics and into patient and GP fixed effects. We interpret the estimated GP fixed effects as a measure of physicians' practice styles, that is, the tendency of a physician to favor more (or less) medical treatment, after allowing for patient differences.

We find that between 0.05 % and 4.29 % of the total variance in annual healthcare utilization can be attributed to the GPs. This small fraction can be explained by the fact that patients differ enormously in their health states and healthcare needs, and that this variation seems to be responsible for large parts of the observed heterogeneity. When we analyze spending patterns, after allowing for patient differences, the results show economically significant variation in medical resource use. In the top deciles, the average level of healthcare utilization is 20 % to 148.5 % higher than that of an average physician, suggesting that practice styles are an important determinant of healthcare utilization.

The results can be compared to those in the existing literature using different methods and data from different healthcare 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 healthcare systems may explain the larger estimates. For example, in contrast to Austria, GPs in Denmark act as strict gate-keepers to the rest of the healthcare system, which likely increases their influence on patients' healthcare utilization. With regard to sick leave, using a multilevel random intercept model, Aakvik et al. (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 practice or differences in municipality-level characteristics. 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. A further limitation is that the underlying data only capture healthcare costs covered by the health insurance. Patients' out-of-pocket expenditures for visits to non-contracted 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 suggests that either postgraduate training or individual (personality) characteristics that are not affected by medical training are important. 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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A. Tables & Figures

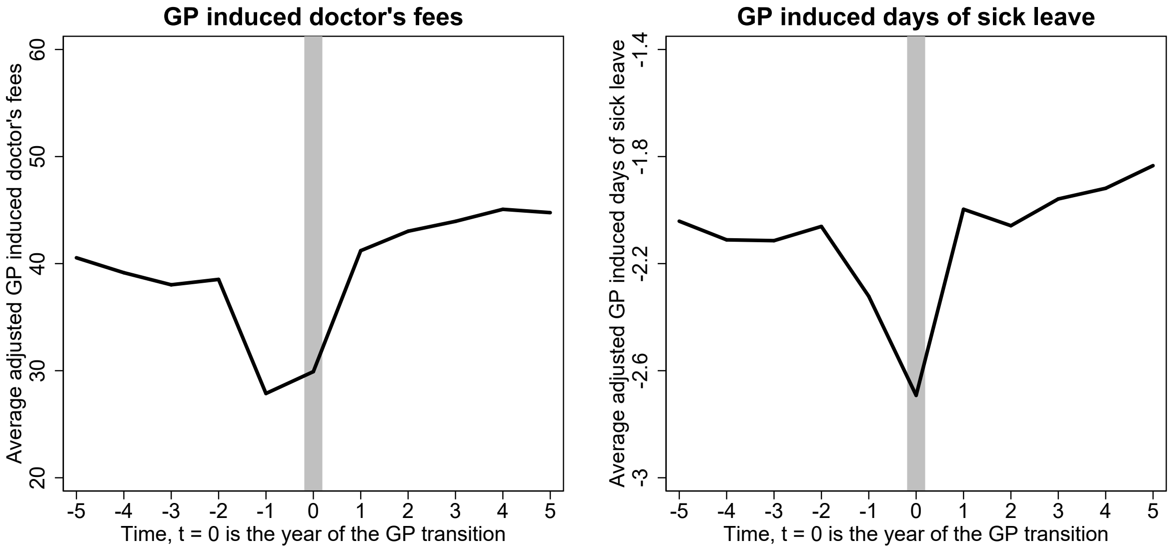
Table A.1 — GP characteristics.

	Mean
Age	52.10
Female	0.13
In-house pharmacy	0.33
City with hospital	0.32
GP density	0.77
Specialist density	0.94
Studied in Vienna	0.49
Studied in Innsbruck	0.39
Studied in Graz	0.12
Studied abroad	0.01

Note: This table summarizes the characteristics of GPs used to analyze determinants of estimated GP fixed effects, $D = 684$.

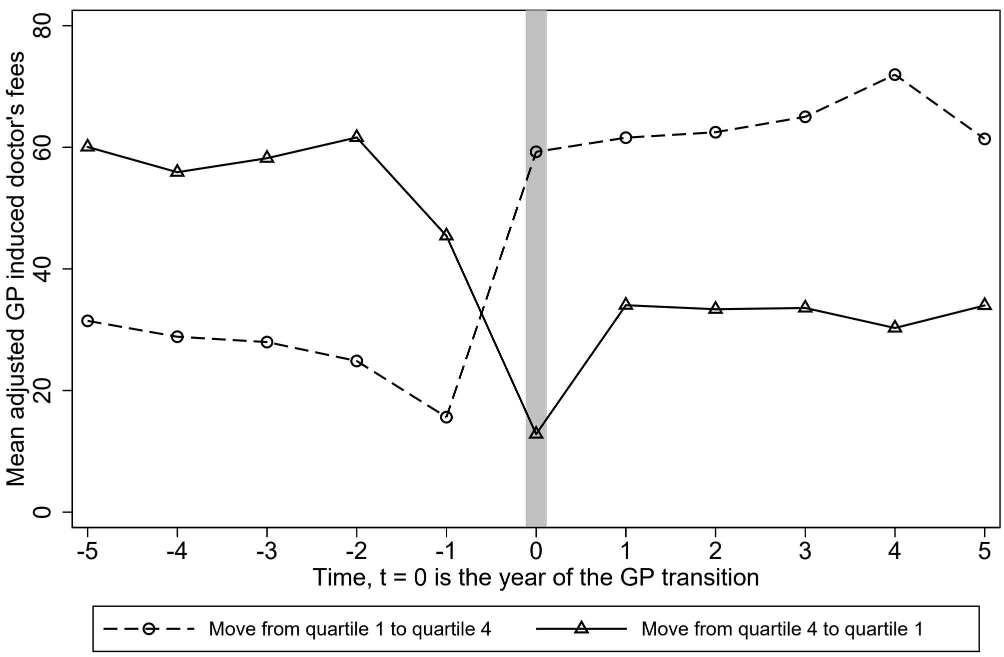
Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

Figure A.1 — Event study of medical service utilization of individuals moving to a new GP.



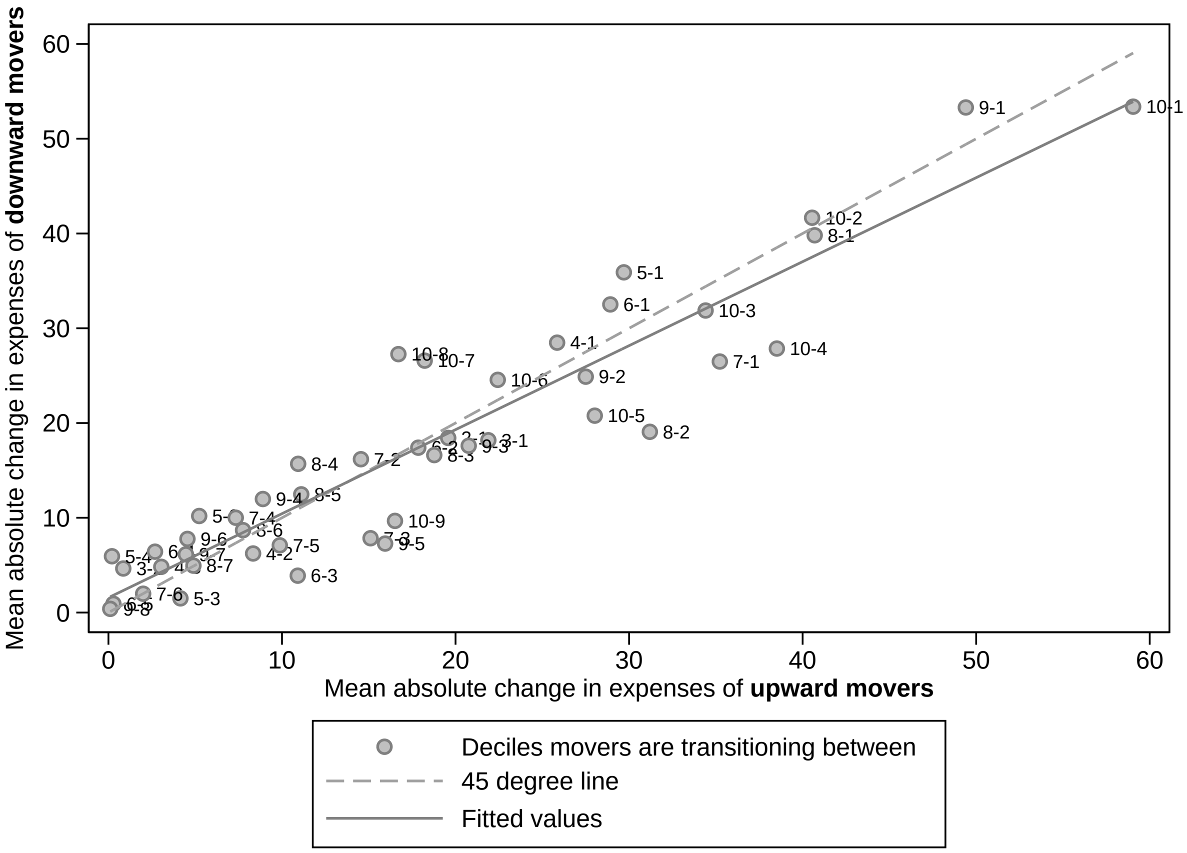
Note: These graph depict average linear time-trend adjusted GP-induced doctors’ fees (left graph) and days of sick leave (right graph) for patients who move to a new GP. On the horizontal axis is time in years relative to the move.
Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

Figure A.2 — Event study of GP-induced doctors’ fees split by upward and downward movers.



Note: These graph depict average adjusted GP induced doctors’ fees for patients who move from a GP whose AKM fixed effect in terms of induced doctors’ fees is estimated to be in the first quartile of the GP fixed effect distribution to a GP whose fixed effect is estimated to be in the fourth quartile of the GP fixed effect distribution (– –o– – , *‘upward mover’*) of the to a new GP; and for a patient who moves from a quartile four GP to a quartile one GP (——△—— , *‘downward mover’*). On the horizontal axis is time in years relative to the move.
Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

FIGURE A.3 — Symmetry of changes in medical expenses by moving to a new GP.



Note: This graph depicts the mean absolute change in medical expenses for upward and downward movers. We categorize GPs in deciles based on their estimated GP fixed effect in terms of induced doctors' fees, each scatter indicates a decile pair movers are transitioning between (e.g., 5-1 depicts the change in expenses for upaward movers from GPs in decile 1 to decile 5 on the horizontal axis, and the change in expenses for downward movers from decile 5 to decile 1 on the vertical axis).

Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

Table A.2 — Descriptive statistics.

	per patient per year		per GP per year	
	Mean	Std. dev.	Mean	Std. dev.
Total medical expenses in EUR	1,687.97	5,339.31	2,154,864.93	1,498,977.17
Doctors' fees in EUR (billed)[a]	86.87	119.15	110,892.60	74,668.87
Doctors' fees in EUR (induced)[b]	124.75	204.64	159,250.77	109,860.59
Doctors' fees in EUR (total)[c]	304.55	389.02	388,787.44	264,392.06
Days of sick leave (billed)[a]	3.48	15.52	4,444.43	3,736.74
Days of sick leave (induced)[b]	3.48	15.52	4,442.04	3,738.81
Days of sick leave (total)[c]	7.18	25.28	9,163.30	6,842.23
Hospital days (induced)[b]	0.37	2.88	466.58	386.77
Hospital days (total)[c]	2.22	9.04	2,831.14	1,989.06
Drug expenses in EUR (induced)[b]	162.79	727.95	207,822.87	152,906.01
Drug expenses in EUR (total)[c]	279.46	1,342.79	356,762.27	257,669.22
Preventive health screening cost in EUR	6.82	21.63	8,711.70	10,806.40
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		

Note: This table provides summary statistics of outcome and control variables used to estimate the AKM 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.

[a] 'Billed' are services that are directly billed by the GP to the sickness fund.
[b] 'Induced' are services that can be traced back to the GP, e.g. through referrals.
[c] 'Total' are all services utilized by the patient independent of the billing or prescribing doctor.

Table A.3 — Average induced medical services per GP per patient per year.

	Average induced medical services per GP per patient per year			
Decile	Doctor's fees	Sick leaves	Hosp. stays	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: Observations with zeros on the respective variable are dropped before calculating means and deciles.

Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

Table A.4 — Number of moves per patient during the observation period.

# of moves	Cases	Percent	Cum. pct.
0	713,708	55.14	55.14
1	399,043	30.83	85.96
2	138,715	10.72	96.68
3	34,983	2.70	99.38
4	6,772	0.52	99.90
5	1,102	0.09	99.99
6	132	0.01	100.00
7	5	0.00	100.00
Total	1,294,460	100.00	

Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

Table A.5 — Residual medical expenses for movers.

	Residual medical expenses							
	2 years prior to move				1 year prior to move			
Quartile	# movers	Mean	Std. dev.	Difference	# movers	Mean	Std. dev.	Difference
1 to 1	105426	1.0000	99.22	0.000	121173	-8.2354	98.97	0.000
1 to 2	58578	0.2944	99.57	-0.706	68557	-8.5145	99.21	-0.279
1 to 3	45894	-0.8149	98.76	-1.815	54065	-7.3919	99.02	0.844
1 to 4	47530	-2.1020	104.41	-3.102	53991	-9.0069	105.16	-0.771
2 to 1	65358	0.2366	99.81	0.721	75266	-10.5056	105.19	1.074
2 to 2	51290	-0.4841	92.70	0.000	59946	-11.5793	91.37	0.000
2 to 3	46691	0.3712	100.18	0.855	54408	-11.7861	101.34	-0.207
2 to 4	47356	-2.9759	112.71	-2.492	54732	-9.8008	118.05	1.778
3 to 1	53406	1.8191	108.64	2.983	61440	-13.5532	109.59	-0.777
3 to 2	50118	-0.3707	100.30	0.794	57641	-12.1765	101.87	0.600
3 to 3	41593	-1.1642	99.15	0.000	49398	-12.7765	105.70	0.000
3 to 4	55410	-1.2383	108.28	-0.074	64569	-10.4914	117.05	2.285
4 to 1	38526	1.6616	126.81	1.277	45246	-15.9198	207.53	-1.754
4 to 2	38431	-0.3972	111.57	-0.782	44432	-15.8753	112.59	-1.709
4 to 3	51438	-0.3010	107.78	-0.686	62167	-15.0839	113.25	-0.918
4 to 4	70041	0.3850	122.84	0.000	81474	-14.1660	123.53	0.000

Note: This table reports mean residual medical expenses obtained from an AKM decomposition with induced doctors' fees as the outcome. GPs 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 expected sign (i.e., upaward movers have higher residual expenses than stayers), it is marked in green, otherwise in red.

Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

TABLE A.6 — Results from AKM model decomposition analysis.

	Total expenses	Doctors' fees			Days of sick leave			Hospital days		Drug expenses		Screening expenses
		billed	*total*	*induced*	*billed*	*total*	*induced*	*total*	*induced*	*total*	*induced*	
Mean of outcome	1687.97	86.87	304.55	124.75	3.48	7.18	3.48	2.22	0.37	279.46	162.79	6.82
Standard deviations and cross-correlations												
Outcome (y)	5339.31	119.15	389.02	204.64	15.52	25.28	15.52	9.04	2.88	1342.79	727.95	21.63
Patient fixed effect (θ)	3827.96	100.03	345.70	162.53	7.88	13.03	7.87	5.11	1.52	1026.90	551.71	11.35
GP fixed effect (ψ)	188.42	11.93	27.33	16.42	1.01	1.05	1.01	0.32	0.11	32.67	26.75	4.52
Explanatory variables ($\mathbf{x}\boldsymbol{\beta}'$)	3652.35	116.37	365.86	160.37	2.39	5.09	2.39	3.36	0.49	602.66	335.72	5.73
Residual (r)	4130.26	65.83	264.48	126.24	13.23	20.93	13.23	7.13	2.39	882.11	454.35	17.14
$\mathrm{Corr}(\theta, \psi)$	−0.03	0.03	−0.02	0.02	−0.03	−0.02	−0.03	−0.05	−0.02	−0.01	−0.01	0.06
$\mathrm{Corr}(\psi, \mathbf{x}\boldsymbol{\beta}')$	−0.01	−0.02	0.00	−0.02	0.03	0.03	0.03	−0.01	−0.01	−0.01	−0.01	0.01
$\mathrm{Corr}(\theta, \mathbf{x}\boldsymbol{\beta}')$	−0.59	−0.59	−0.68	−0.51	−0.07	0.04	−0.07	−0.19	0.00	−0.32	−0.25	−0.12
Variances and cross-covariances												
Outcome (y)	$2.85{\times}10^7$	$1.42{\times}10^4$	$1.51{\times}10^5$	$4.19{\times}10^4$	240.92	639.23	240.80	81.77	8.28	$1.80{\times}10^6$	$5.30{\times}10^5$	467.67
Patient fixed effect (θ)	$1.47{\times}10^7$	$1.00{\times}10^4$	$1.20{\times}10^5$	$2.64{\times}10^4$	62.06	169.78	62.01	26.09	2.30	$1.05{\times}10^6$	$3.04{\times}10^5$	128.82
GP fixed effect (ψ)	$3.55{\times}10^4$	$1.42{\times}10^2$	$7.47{\times}10^2$	$2.70{\times}10^2$	1.02	1.11	1.03	0.11	0.01	$1.07{\times}10^3$	$7.15{\times}10^2$	20.40
Explanatory variables ($\mathbf{x}\boldsymbol{\beta}'$)	$1.33{\times}10^7$	$1.35{\times}10^4$	$1.34{\times}10^5$	$2.57{\times}10^4$	5.73	25.90	5.69	11.29	0.24	$3.63{\times}10^5$	$1.13{\times}10^5$	32.84
Residual (r)	$1.71{\times}10^7$	$4.33{\times}10^3$	$6.99{\times}10^4$	$1.59{\times}10^4$	175.11	437.89	175.00	50.84	5.73	$7.78{\times}10^5$	$2.06{\times}10^5$	293.64
$2 \cdot \mathrm{Cov}(\theta, \psi)$	$-4.49{\times}10^4$	$7.78{\times}10^1$	$-3.75{\times}10^2$	$1.12{\times}10^2$	−0.55	−0.50	−0.55	−0.18	−0.01	$-9.16{\times}10^2$	$-3.15{\times}10^2$	6.56
$2 \cdot \mathrm{Cov}(\psi, \mathbf{x}\boldsymbol{\beta}')$	$-1.49{\times}10^4$	$-6.83{\times}10^1$	$-2.23{\times}10^1$	$-1.20{\times}10^2$	0.12	0.28	0.12	−0.01	0.00	$-3.12{\times}10^2$	$-2.58{\times}10^2$	0.37
$2 \cdot \mathrm{Cov}(\theta, \mathbf{x}\boldsymbol{\beta}')$	$-1.65{\times}10^7$	$-1.38{\times}10^4$	$-1.72{\times}10^5$	$-2.65{\times}10^4$	−2.57	4.77	−2.50	−6.38	0.00	$-3.93{\times}10^5$	$-9.38{\times}10^4$	−14.96
Variance in % of total variance (neglecting covariance terms)[a]												
Patient fixed-effect (θ)	32.50%	35.71%	36.88%	38.65%	25.44%	26.75%	25.44%	29.54%	27.79%	48.00%	48.76%	27.08%
GP fixed-effect (ψ)	0.08%	0.51%	0.23%	0.39%	0.42%	0.17%	0.42%	0.12%	0.15%	0.05%	0.11%	4.29%
Explanatory variables ($\mathbf{x}\boldsymbol{\beta}'$)	29.59%	48.32%	41.31%	37.63%	2.35%	4.08%	2.34%	12.78%	2.93%	16.53%	18.06%	6.90%
Residual (r)	37.84%	15.46%	21.58%	23.32%	71.79%	68.99%	71.80%	57.56%	69.13%	35.42%	33.07%	61.73%

Note: This table presents results of the decomposition analysis based on the Abowd, Kramarz and Margolis (1999) model in equation (3). We present both estimated standard deviations and estimated variances of each model component—i.e., $\hat{y}$, $\hat{\theta}$, $\hat{\psi}$, $\mathbf{x}\hat{\boldsymbol{\beta}}'$, $\hat{r}$, as well as $\widehat{\mathrm{Corr}}(\theta, \psi)$, $\widehat{\mathrm{Corr}}(\psi, \mathbf{x}\boldsymbol{\beta}')$, and $\widehat{\mathrm{Corr}}(\theta, \mathbf{x}\boldsymbol{\beta}')$—for all twelve outcomes. Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

[a] In order to calculate percentage contributions of our AKM model components, we purposely neglect the three covariance terms $2 \cdot \mathrm{Cov}(\theta, \psi)$, $2 \cdot \mathrm{Cov}(\psi, \mathbf{x}\boldsymbol{\beta}')$, and $2 \cdot \mathrm{Cov}(\theta, \mathbf{x}\boldsymbol{\beta}')$ in equation (3). The reason is that the variance of y would then be comprised of both positive and negative numbers, so individual percentages are difficult to interpret because the positive components $\hat{\theta}$, $\hat{\psi}$, $\mathbf{x}\hat{\boldsymbol{\beta}}'$, and $\hat{r}$ do not sum up to 1. Put differently, we omit the last three terms in equation (3) and assume that the variance of y is comprised only of θ, ψ, $\mathbf{x}\boldsymbol{\beta}'$, and the residual r. Alternative percentage calculations are available upon request.

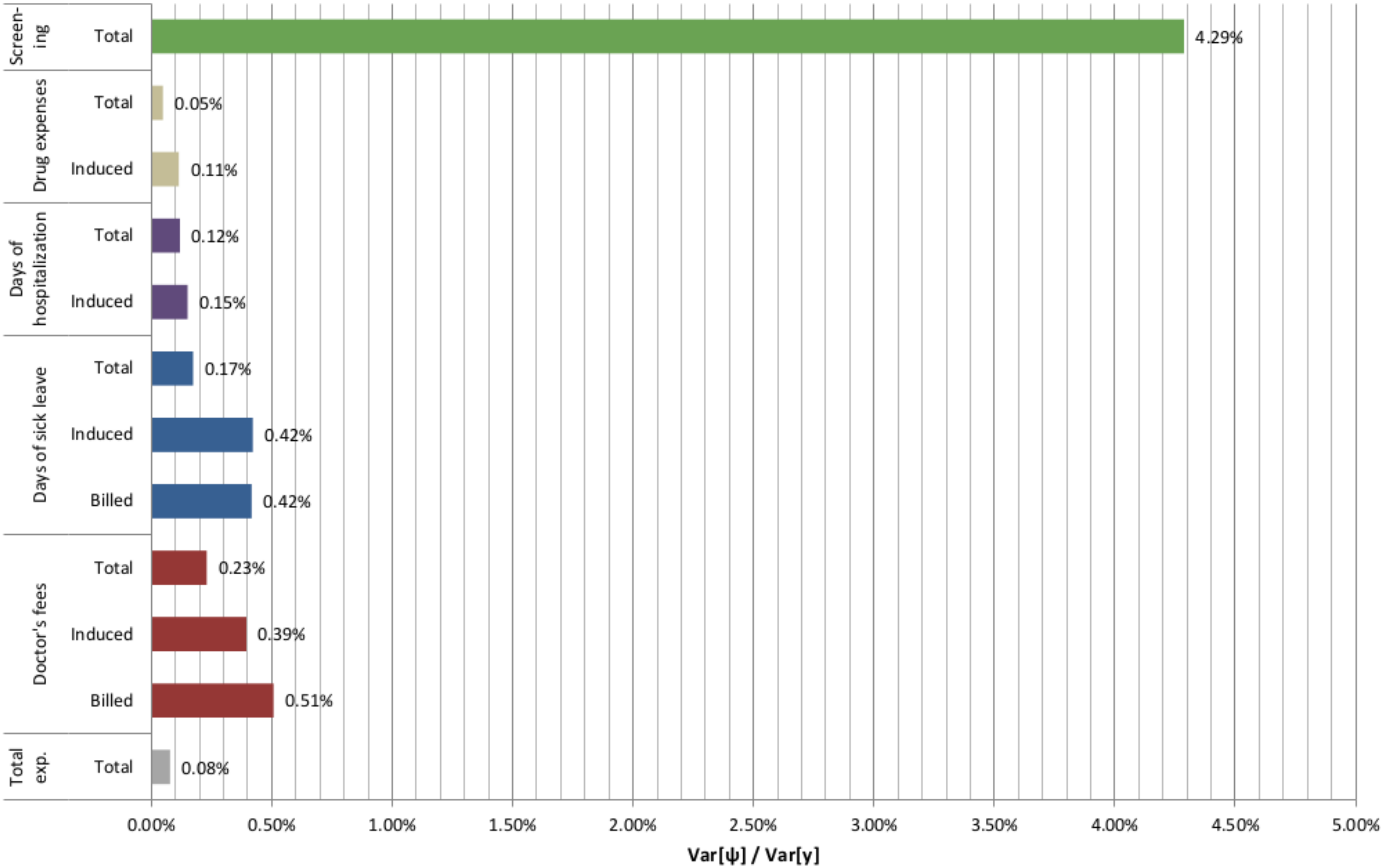
Table A.7 — Average deviations in outcomes across deciles of the AKM GP fixed effect distribution.

	Total expenses	**Doctors' fees**			**Days of sick leave**			**Hospital days**		**Drug expenses**		**Screening expenses**
		billed	*total*	*induced*	*billed*	*total*	*induced*	*total*	*induced*	*total*	*induced*	
Mean of outcome	1687.97	86.87	304.55	124.75	3.48	7.18	3.48	2.22	0.37	279.46	162.79	6.82
Decile												
1	−341.87	−23.20	−40.37	−48.31	−1.96	−1.85	−2.04	−0.58	−0.23	−65.11	−74.37	−5.67
2	−188.21	−12.50	−24.34	−18.22	−1.06	−1.01	−1.06	−0.30	−0.13	−32.57	−28.70	−3.88
3	−126.02	−8.57	−16.44	−11.75	−0.74	−0.68	−0.74	−0.20	−0.08	−19.66	−18.34	−3.02
4	−70.65	−5.24	−10.08	−7.72	−0.54	−0.41	−0.54	−0.11	−0.05	−11.63	−11.51	−2.37
5	−19.64	−2.66	−5.21	−3.79	−0.33	−0.18	−0.33	−0.04	−0.02	−3.99	−5.85	−1.72
6	30.74	0.25	0.24	0.35	−0.12	0.03	−0.11	0.05	0.01	2.95	0.89	−1.09
7	74.75	3.24	5.50	4.31	0.11	0.35	0.11	0.12	0.04	9.51	6.34	−0.13
8	126.92	7.06	12.89	8.51	0.43	0.67	0.43	0.21	0.07	17.89	13.13	1.30
9	197.02	12.35	24.85	14.15	0.76	1.13	0.76	0.34	0.12	30.11	22.98	3.28
10	409.60	28.75	60.99	31.49	1.86	2.21	1.86	0.67	0.23	73.31	53.23	10.13

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.

FIGURE A.4 — Illustration of GP fixed effects for different outcomes.



Note: In this graph, we compare estimated GP fixed effects $\hat{\psi}_d$ across outcomes. The reported percentages are based on the figures in Table A.6 where the covariance terms in equation (3) are assumed to be zero in order to avoid percentage calculations with negative numbers.

Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

Table A.8 — Explaining GP fixed effects.

	Total expenses	Doctor fees			Drug expenses		Hospital days		Days of sick leave			Screening expenses
		total	*induced*	*billed*	*total*	*induced*	*total*	*induced*	*total*	*induced*	*billed*	
Physician characteristics												
Age	−2.925*	−0.525**	−0.098	−0.463***	−0.309	−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)
In-house pharmacy	18.917	−5.111*	−1.758	−0.799	2.149	9.643***	0.064*	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[a]												
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	−0.666	−0.796	−3.906	−0.451	−0.004	0.012	−0.168	−0.005	0.010	0.271
	(−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)	(−2.64)	(−5.28)	(−5.18)	(−2.05)
Specialist density	−118.325***	−4.363	0.815	−0.547	−1.136	−3.575	−0.180***	−0.050***	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	−0.023	−0.103*	−0.194	−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

Note: Number of Observations is 684. [a] Physicians who studied in Vienna are the base group. Robust t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.

Web Appendix

This *Web Appendix* (not for publication) provides additional material discussed in the unpublished manuscript 'Exploring Variations in Health Care Expenditures – What is the Role of Practice Styles?' by Alexander Ahammer and Thomas Schober.

Variance decomposition graphically

Recall the hierarchical fixed effects model proposed by Abowd, Kramarz and Margolis (1999) which we use to analyze medical service provision,

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta}' + \theta_i + \psi_d + r_{it}, \tag{A.1}$$

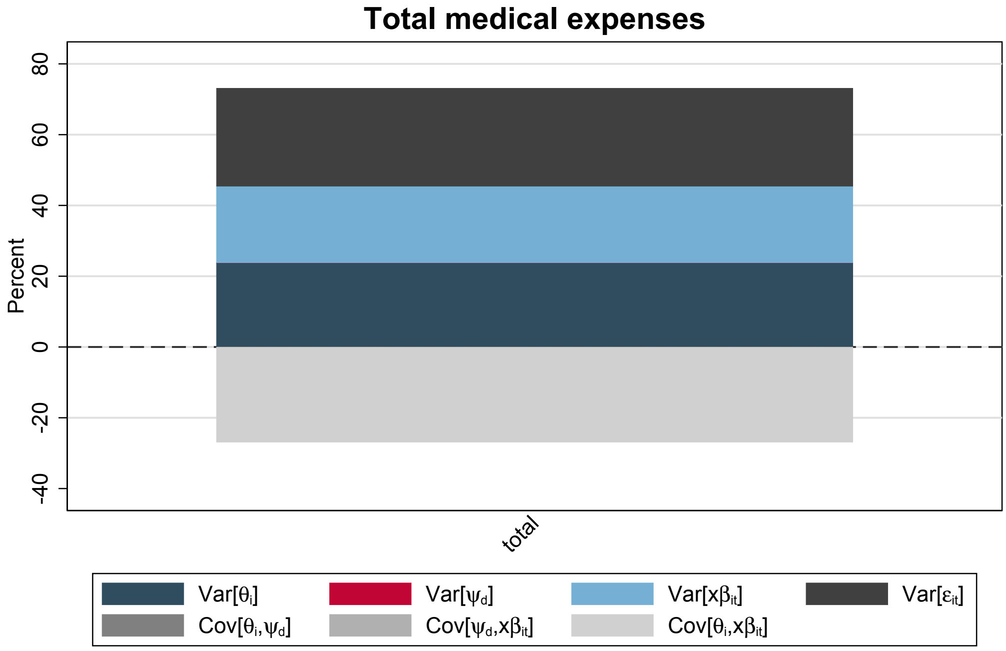
where i denotes the patient, d denotes the GP and t is time. Due to the model being linear in the time-dependent observables $\mathbf{x}_{it}$, the patient fixed effect θ_i, the general practitioner (GP) fixed effect ψ_d, and the residual r_{it}, the variance of the outcome y_{it} can be decomposed as

$$\begin{aligned} \mathrm{Var}(y_{it}) =& \mathrm{Var}(\mathbf{x}_{it}\boldsymbol{\beta}') + \mathrm{Var}(\theta_i) + \mathrm{Var}(\psi_{d(it)}) + \mathrm{Var}(\varepsilon_{it}) \\ &+ 2\,\mathrm{Cov}(\mathbf{x}_{it}\boldsymbol{\beta}', \theta_i) + 2\,\mathrm{Cov}(\mathbf{x}_{it}\boldsymbol{\beta}', \psi_{d(it)}) + 2\,\mathrm{Cov}(\theta_i, \psi_{d(it)}), \end{aligned} \tag{A.2}$$

where each component is estimated through its sample analogue. In order to determine percentage contributions of θ, ψ, $\mathbf{x}\boldsymbol{\beta}'$, and r, we assumed the three covariance terms in equation (A.2) to equal zero in order to avoid percentage calculations with negative numbers.

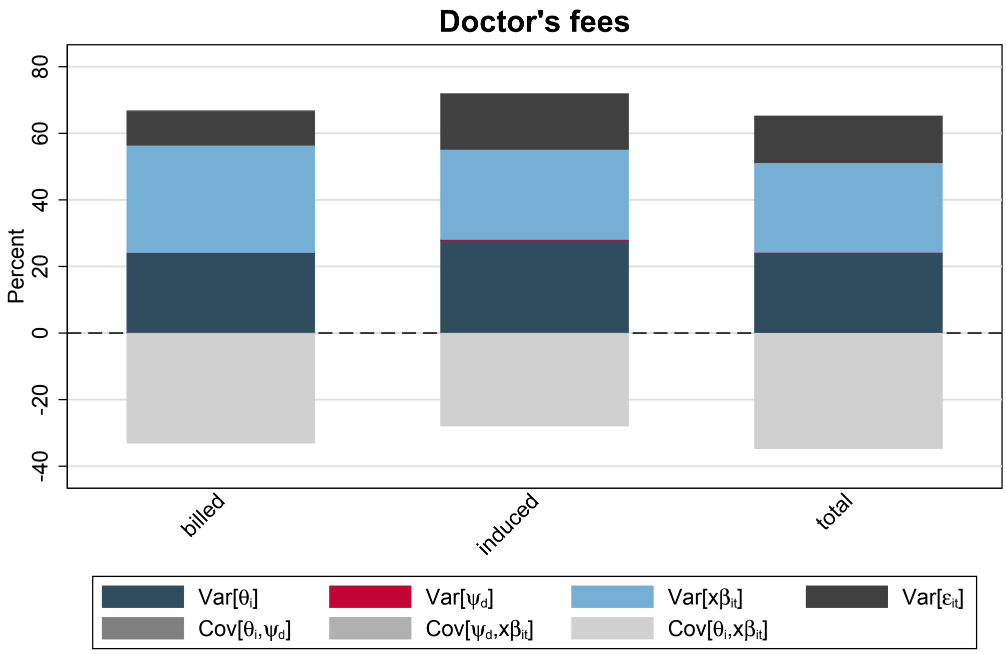
In Figures A.5 until A.10 we *do* report variance decompositions in which we include these negative percentages. For every outcome—i.e., total medical expenditures in Figure A.5, doctors' fees in A.6, days of sick leave in A.7, hospitalizations in A.8, drug expenditures in A.9, and screening expenditures in Figure A.10—we provide stacked bar charts which indicate percentage contributions of all terms specified in equation A.2. In general, the blue bars can be interpreted as the part of total variance explained by patient-side heterogeneities (e.g., in health endowments captured by $\hat{\theta}_i$ and time-varying needs and preferences captured by $\mathbf{x}\hat{\boldsymbol{\beta}}$), the red part are GP-side heterogeneities, the black bars are stochastic health shocks, and the gray bars represent the portion of total variance explained by the covariances between the individual components. A detailed discussion the the variance decomposition is provided in section IV in the main paper.

Figure A.5 — Variance decomposition of total medical expenditures.



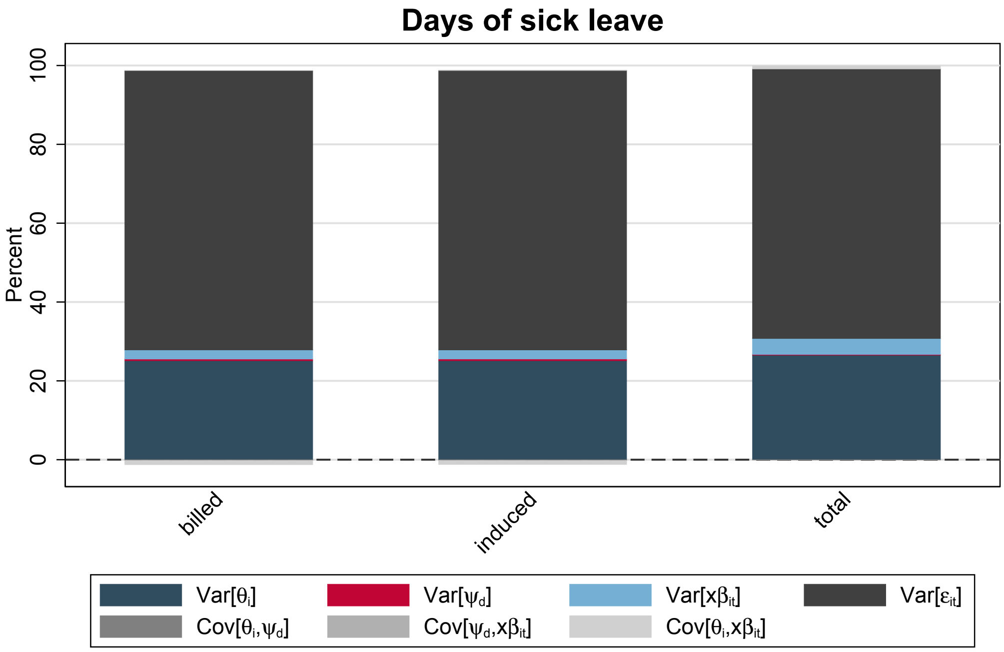
Note: This graph depicts the variance decomposition of total expenditures specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the covariance terms $2 \cdot \widehat{\text{Cov}}(\theta, \psi)$, $2 \cdot \widehat{\text{Cov}}(\psi, \mathbf{x}\boldsymbol{\beta}')$, and $2 \cdot \widehat{\text{Cov}}(\theta, \mathbf{x}\boldsymbol{\beta}')$ even if they are smaller than zero, which explains why some percentages may be negative.

Figure A.6 — Variance decomposition of doctors' fees.



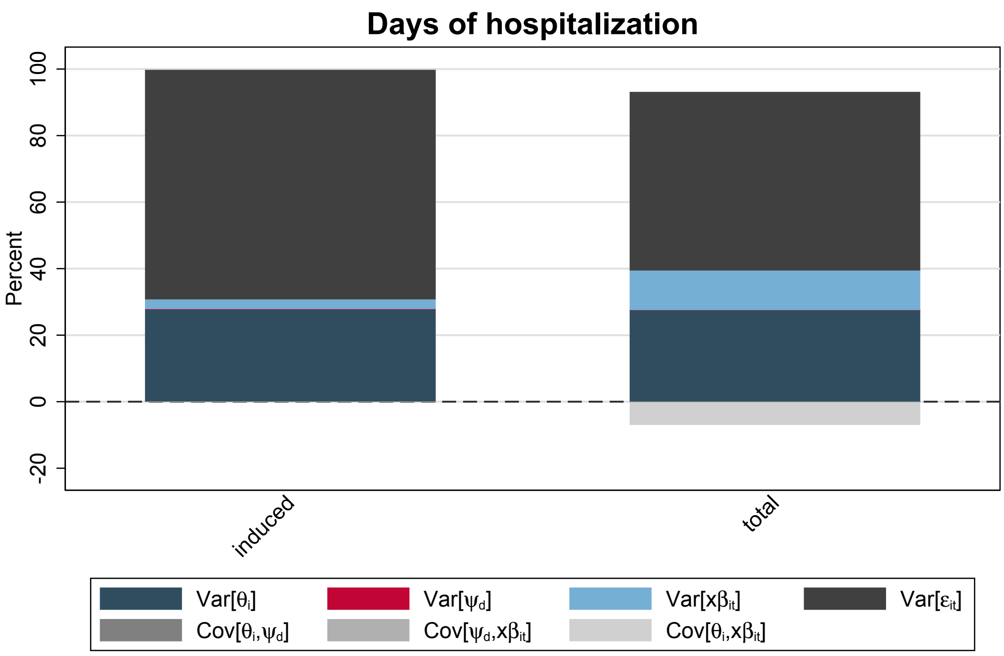
Note: This graph depicts the variance decomposition of doctors' fees specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the covariance terms $2 \cdot \widehat{\text{Cov}}(\theta, \psi)$, $2 \cdot \widehat{\text{Cov}}(\psi, \mathbf{x}\boldsymbol{\beta}')$, and $2 \cdot \widehat{\text{Cov}}(\theta, \mathbf{x}\boldsymbol{\beta}')$ even if they are smaller than zero, which explains why some percentages may be negative.

FIGURE A.7 — Variance decomposition of doctors' fees.



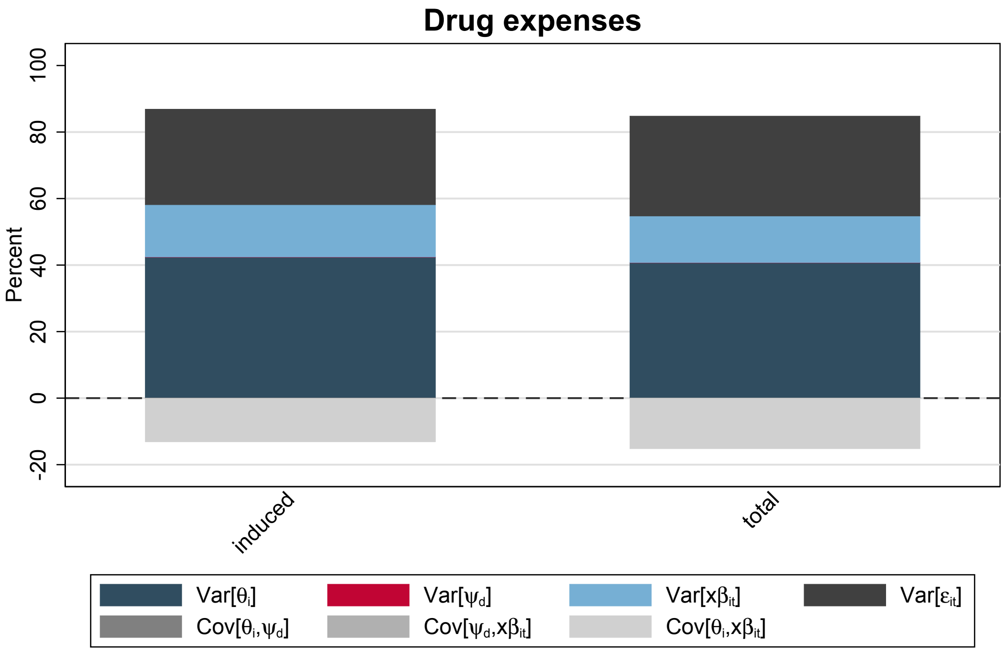
Note: This graph depicts the variance decomposition of days of sick leave specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the covariance terms $2\cdot\widehat{\text{Cov}}(\theta,\psi)$, $2\cdot\widehat{\text{Cov}}(\psi,\mathbf{x}\boldsymbol{\beta}')$, and $2\cdot\widehat{\text{Cov}}(\theta,\mathbf{x}\boldsymbol{\beta}')$ even if they are smaller than zero, which explains why some percentages may be negative.

Figure A.8 — Variance decomposition of days of hospitalization.



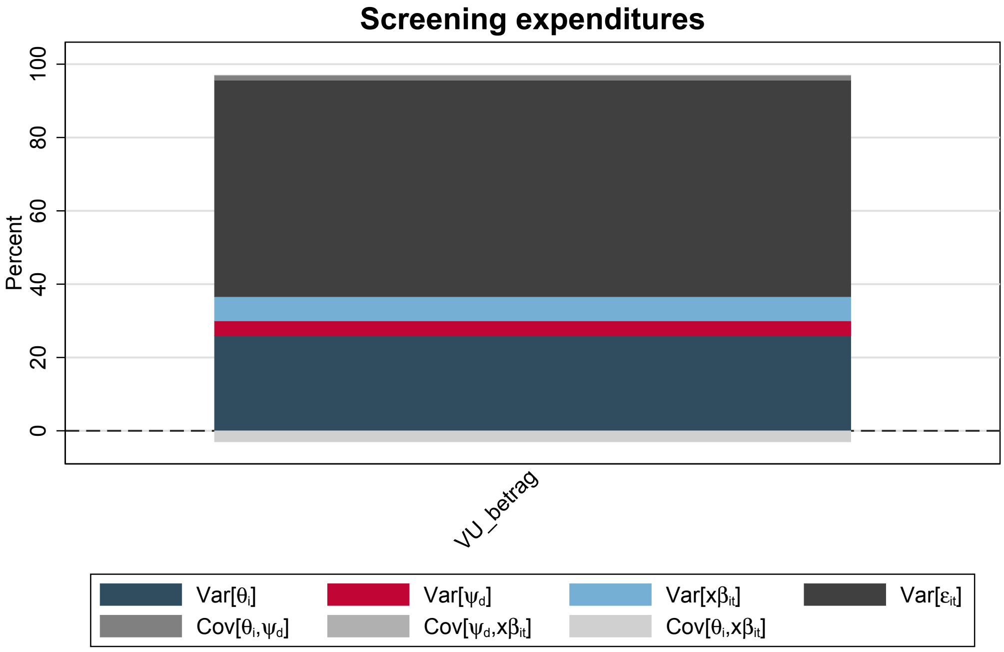
Note: This graph depicts the variance decomposition of days of hospitalization specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the covariance terms $2 \cdot \widehat{\text{Cov}}(\theta, \psi)$, $2 \cdot \widehat{\text{Cov}}(\psi, \mathbf{x}\boldsymbol{\beta}')$, and $2 \cdot \widehat{\text{Cov}}(\theta, \mathbf{x}\boldsymbol{\beta}')$ even if they are smaller than zero, which explains why some percentages may be negative.

FIGURE A.9 — Variance decomposition of drug expenditures.



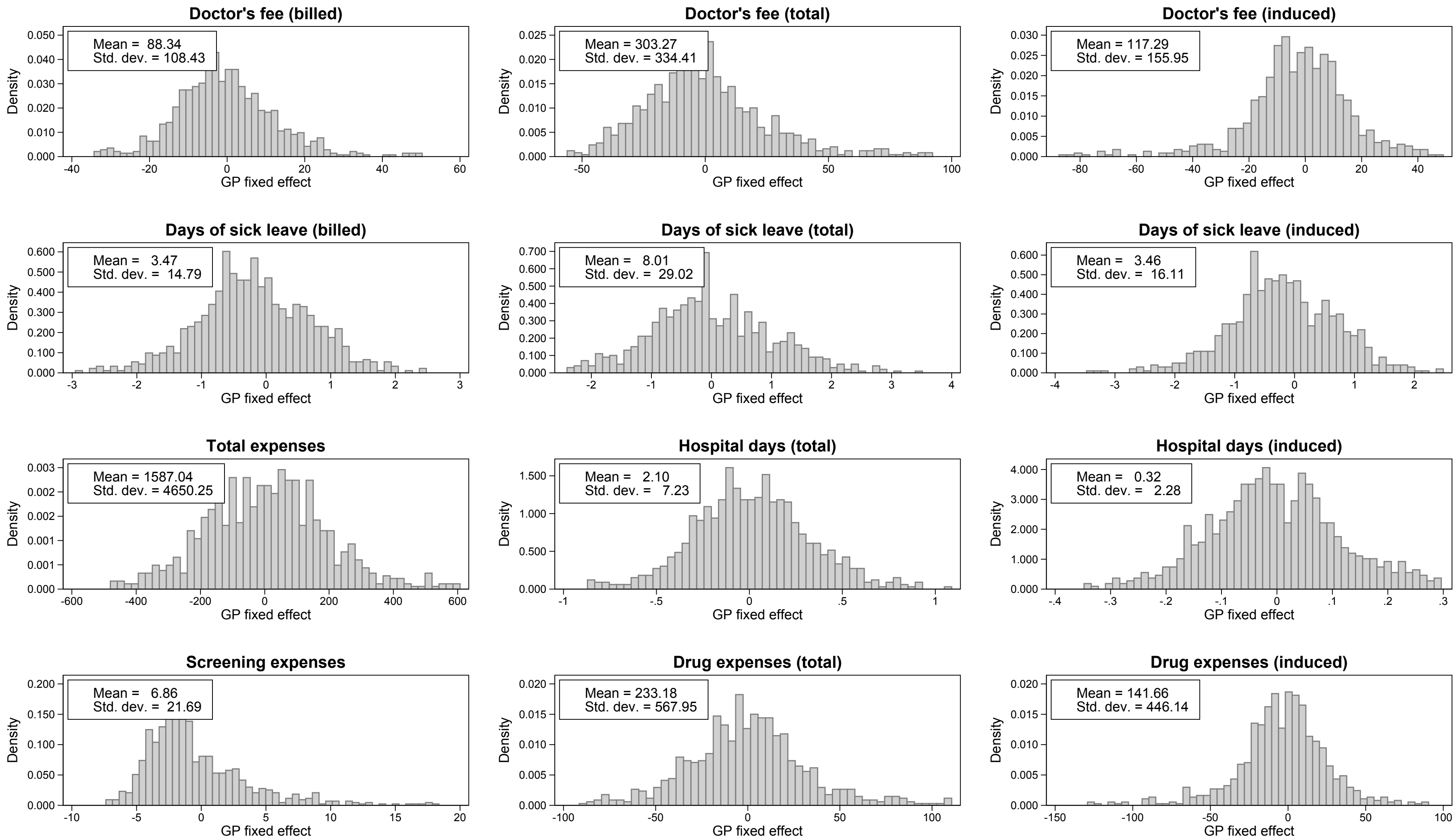
Note: This graph depicts the variance decomposition of drug expenditures specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the covariance terms $2\cdot\widehat{\mathrm{Cov}}(\theta,\psi)$, $2\cdot\widehat{\mathrm{Cov}}(\psi,\mathbf{x}\boldsymbol{\beta}')$, and $2\cdot\widehat{\mathrm{Cov}}(\theta,\mathbf{x}\boldsymbol{\beta}')$ even if they are smaller than zero, which explains why some percentages may be negative.

FIGURE A.10 — Variance decomposition of screening expenditures.



Note: This graph depicts the variance decomposition of screening expenditures specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the covariance terms $2 \cdot \widehat{\mathrm{Cov}}(\theta, \psi)$, $2 \cdot \widehat{\mathrm{Cov}}(\psi, \mathbf{x}\boldsymbol{\beta}')$, and $2 \cdot \widehat{\mathrm{Cov}}(\theta, \mathbf{x}\boldsymbol{\beta}')$ even if they are smaller than zero, which explains why some percentages may be negative.

Figure A.11 — Densities of estimated AKM GP fixed effects for different outcomes.



Data is trimmed based on percentile bounds (lower bound: 1st percentile, upper bound: 100th percentile).

Note: This graph depicts the distribution of estimated GP fixed effects $\hat{\psi}_d$ for various outcomes (the sample consists of D = 857 GPs). Estimation of fixed effects is based on the AKM model in equation (3). For illustrational purposes we trimmed the 1st and 100th percentile of the GP fixed effect distribution, which caused 16 GPs to drop from the sample.

Source: Based on Upper Austrian Sickness Fund 2005–2012 matched patient–GP panel, own calculations.