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

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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. 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 healthcare 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, while GPs explain a relatively 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.

JEL Classification: I11, I12, C23.
Keywords: Healthcare expenditures, practice styles, physician behavior, statistical decomposition.

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I. Introduction

In healthcare 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., Chandra et al., 2012; Skinner, 2012). Practice styles that cannot be explained by patient needs or preferences also raise questions on the equity and efficiency of healthcare systems, since it 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 healthcare markets. They show that the variation across U.S. obstetricians within a market is about twice as large as the variation between markets. 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, Grytten and Sørensen (2003), and Kristensen et al. (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 healthcare 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.[1] Recently, Finkelstein et al. (2016) used a similar framework with patient and location fixed effects to identify geographic variation in Medicare utilization through patient migration between geographic areas. Since our data allows 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 healthcare service provision. We provide several tests to show that mobility between patients and GPs is conditionally exogenous, which is a necessary assumption for identification.

[1] Abowd et al. (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, 2006; Card et al., 2016, 2013)

Consistent with earlier research we find that most of the variance in healthcare 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 healthcare 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.

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 GPs and specialists in the outpatient care sector, inpatient care, and prescription medicines. Most healthcare related costs are covered by the public health insurance with no or only minor copayments. 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 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 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).

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 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 cost 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. 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.[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.

We construct a matched patient–GP panel by aggregating the individual healthcare 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 healthcare provider, patients in Austria can switch between GPs under certain conditions (see section II.1). 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

[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).

[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.

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 onsite 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

We analyze the following measures of healthcare 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 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 be-

[4] Because 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.

[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.

tween *'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. 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 healthcare 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:

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

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

where $d = 1, \ldots, D$ denote GPs, with $d(it)$ being the family GP of patient i at time t, $\psi_{d(it)}$ and θ_i are fixed effects on the GP- and patient-level, respectively, $\mathbf{x}_{it}$ is a vector of time-varying observables, and r_{it} is a stochastic error term, which is *i.i.d.* with $\mathrm{E}(r_{it} \mid \psi_{d(it)}, \theta_i, \mathbf{x}_{it}, t) = 0$.

The fixed effects $\psi_{d(i,t)}$ 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 θ_i and the vector $\mathbf{x}_{it}$, 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 (1), we use the approach of Mihaly et al. (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 healthcare 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 $\psi_{d(it)}$, θ_i, $\mathbf{x}_{it}\boldsymbol{\beta}'$, and r_{it}, we can write

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

where each component is estimated using its sample analog.[7]

III.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 healthcare utilization if a sufficient number of patients move to new GPs within our observation period. In Table A.4 we summarize the 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.[8]

In addition we require mobility between patients and doctors be exogenous, conditional on our observables $\mathbf{x}_{it}$, the patient fixed effect θ_i, and the GP fixed effect $\psi_{d(it)}$. A fundamental problem

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

$$\widehat{\mathrm{Var}(y_{it})} = \frac{1}{(NT_i - 1)} \sum_{i=1}^{N} \sum_{t=1}^{T_i} (y_{it} - \bar{y}), \tag{3}$$

where $\bar{y}$ is the sample mean of 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.

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 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 $\psi_{d(it)}$) identification is guaranteed.

However, there may still be unobserved time-varying heterogeneities among patients that drive mobility. Thus, we provide several tests for the exogenous mobility assumption that have been suggested in the literature (Card et al., 2016, 2014, 2013; Finkelstein et al., 2016). For example, strong indicators for exogenous mobility are flat healthcare utilization profiles, before and after patients move to new GPs. In Figure A.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 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 is likely an artifact of our family doctor definition. In years where 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.[9] Note that the changes in utilization are very 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 A.1 suggests that this is not a problem in our data.

In Figure A.2 we further distinguish between upward and downward movers based on 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 utilization profile. However, the rather large discontinuities immediately before GP transitions as evident in Figure A.2 suggest that utilization does not systematically adjust before moves.

In Figure A.3, we plot the mean absolute changes in GP induced doctors' fees for upward

[9] If we plot a time series of doctors' fees where we exclude patients with zero expenses in every given period, the dip vanishes and pre-move utilization profiles are flat. This graph is available upon request.

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 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. Scatter 5–1, for example, represents the change in expenses for upward 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. 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 differences between the fitted line and the 45-degree 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. 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 et al., 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), while green figures indicate that deviations occur in the opposing direction (upwards movers had lower expenses, and vice versa). In total, 14 differences occur in the opposing direction, while only 10 occur in the direction we expect under endogenous mobility. 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:

$$\hat{\psi}_d = \alpha + \mathbf{z}_d \boldsymbol{\phi}' + \mathbf{w}_d \boldsymbol{\delta}' + \zeta_d, \tag{4}$$

where $\mathbf{z}_d$ are observable GP characteristics, such as age, sex, having an onsite 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 (4) separately for each individual utilization measure in order to reveal potential heterogeneity in practice styles with respect to the type of healthcare.

IV. Results

IV.1. Variance decomposition

We estimate model (1) for each outcome separately and then decompose the observed variance using equation (2). 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 indicate that most of the observed heterogeneity in healthcare utilization can be attributed to patient-level differences measured by their individual fixed effects and 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, varies relatively less in comparison with the other 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 each of the individual components of the model. 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. It 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 relatively more 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 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, while others do not.[10]

Although the overall variation due to physician practice styles appears to be relatively small, when ordering GPs according to their estimated practice style measures we find tremendous disparities in resource use comparing GPs at the top and at the bottom of the distribution. In Table A.7 we show the average estimated GP fixed effects by deciles of the respective outcome's distribution.[11] These effects can be interpreted as deviations from GPs who have an average level of healthcare utilization, after allowing 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. The total variation 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 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, meaning that expenditures in that decile are 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.

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

IV.2. Explaining GP heterogeneity

Table A.8 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 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, 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 onsite 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 onsite 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

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 several tests on the identifying assumption 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.

While most of the variation in annual healthcare 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 healthcare 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 healthcare utilization is, depending on the healthcare service under consideration, 20% to 148.5% higher than that of an average 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.[12] This

[12]Note that for this back-of-the-envelope calculation we assume that the average number of patients treated per year is orthogonal to the deviation in total medical expenses between GPs in the top decile of the practice style measure distribution and the sample mean.

suggests that practice styles are an important determinant of healthcare 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 overtreat (undertreat) patients.

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 or 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 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 incentives, which could introduce variation in treatment patterns (Jacobson et al., 2017; Johnson, 2014). 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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A. Tables & Figures

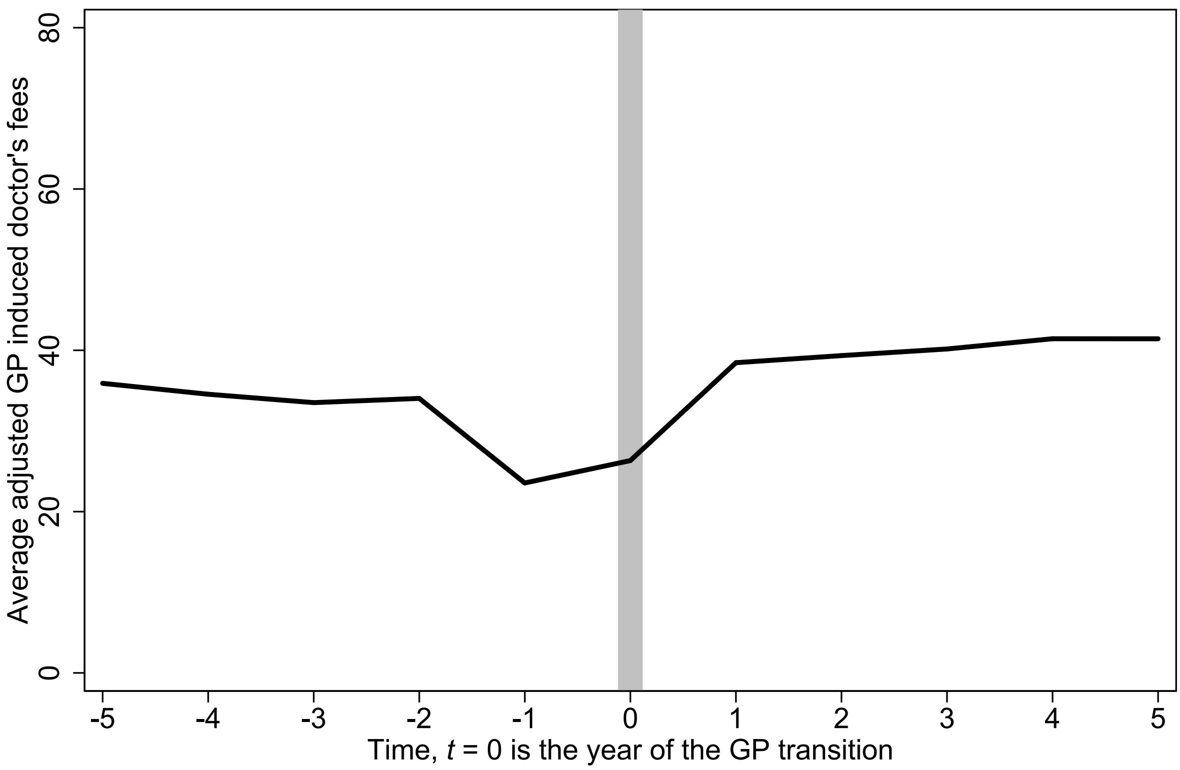
Table A.1 — GP characteristics.

	Mean
Age	52.10
Female	0.13
Onsite 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.

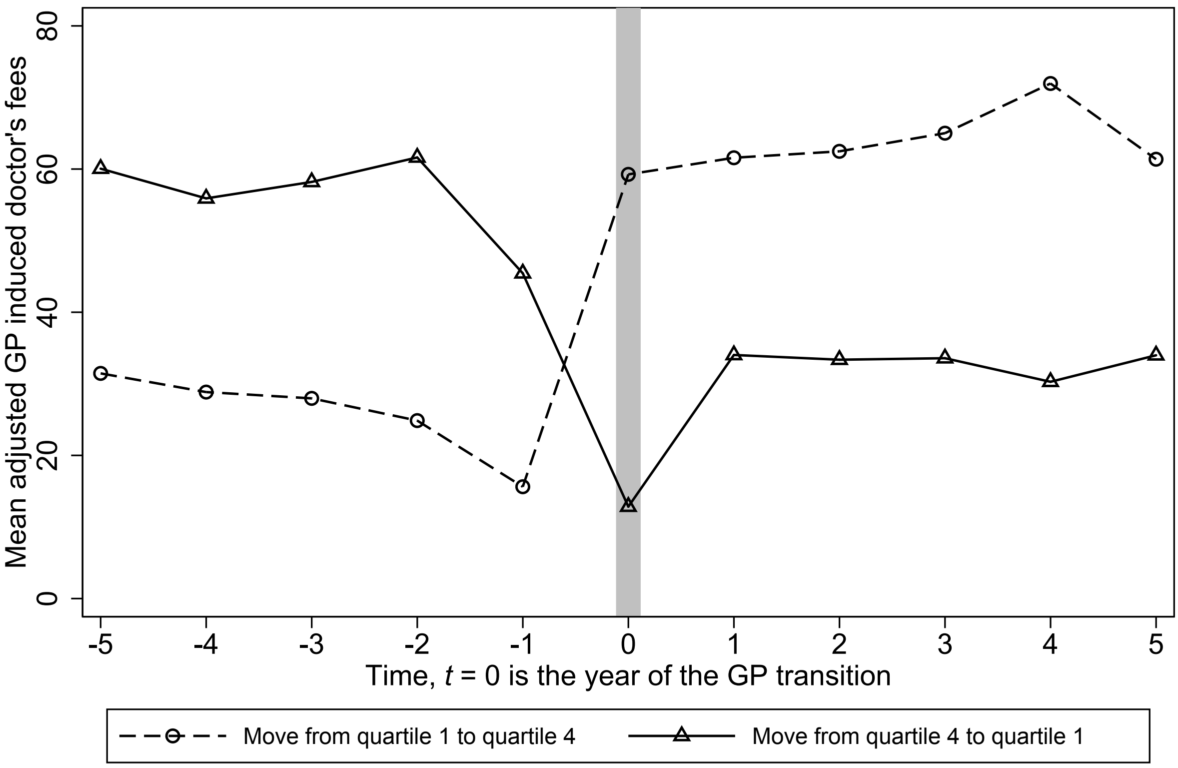
FIGURE A.1 — GP induced doctors' fees of patients moving to a new GP.



Note: These graph depict average linear time-trend, age, and gender adjusted GP induced doctors' fees 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.

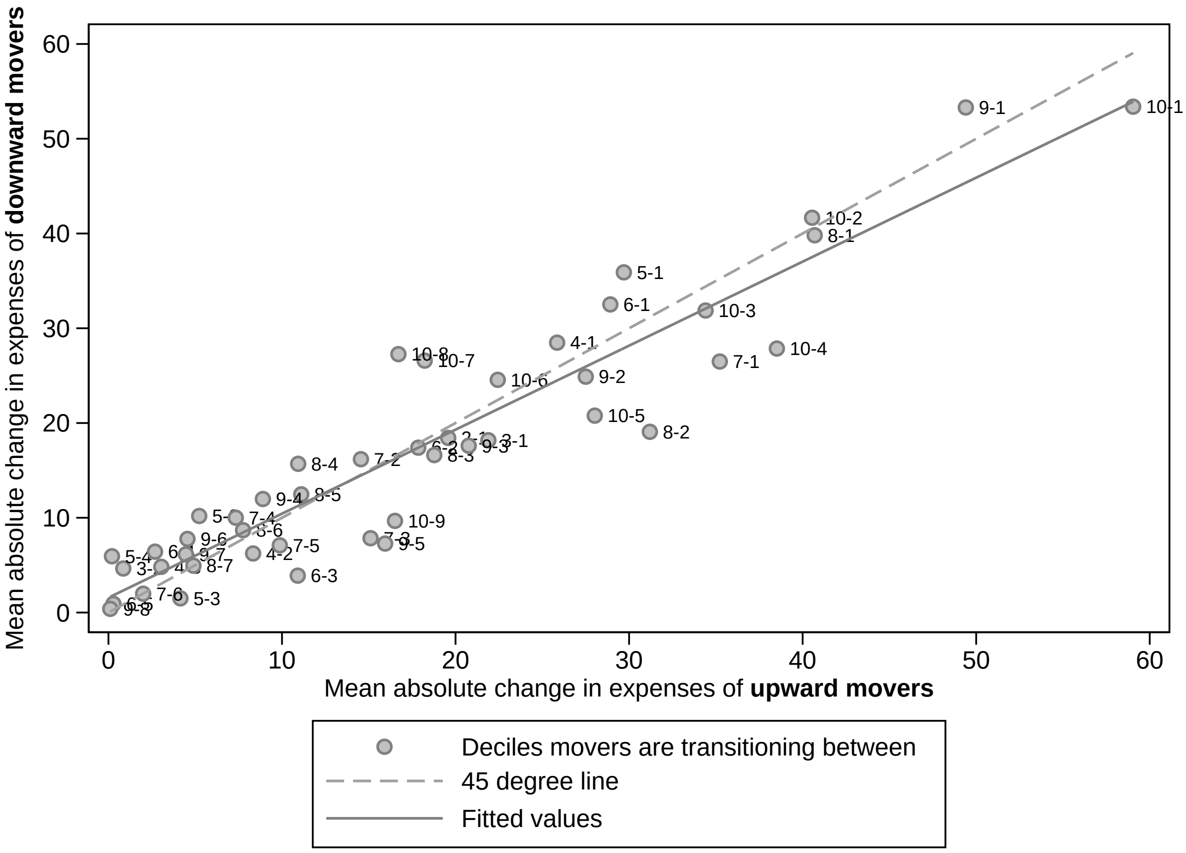
Figure A.2 — GP induced doctors' fees around GP transitions, split by upward and downward movers.



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 upward 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: Deciles are based on the respective outcome's distribution. Observations with zeros on each 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 sign we expect under *endogenous* mobility (i.e., upward movers had higher residual expenses than stayers), it is marked in red, otherwise in green.

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

Table A.6 — Results from the 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
Corr(θ, ψ)	−0.03	0.03	−0.02	0.02	−0.03	−0.02	−0.03	−0.05	−0.02	−0.01	−0.01	0.06
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
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)	2.85×10^{7}	1.42×10^{4}	1.51×10^{5}	4.19×10^{4}	240.92	639.23	240.80	81.77	8.28	1.80×10^{6}	5.30×10^{5}	467.67
Patient fixed effect (θ)	1.47×10^{7}	1.00×10^{4}	1.20×10^{5}	2.64×10^{4}	62.06	169.78	62.01	26.09	2.30	1.05×10^{6}	3.04×10^{5}	128.82
GP fixed effect (ψ)	3.55×10^{4}	1.42×10^{2}	7.47×10^{2}	2.70×10^{2}	1.02	1.11	1.03	0.11	0.01	1.07×10^{3}	7.15×10^{2}	20.40
Explanatory variables ($\mathbf{x}\boldsymbol{\beta}'$)	1.33×10^{7}	1.35×10^{4}	1.34×10^{5}	2.57×10^{4}	5.73	25.90	5.69	11.29	0.24	3.63×10^{5}	1.13×10^{5}	32.84
Residual (r)	1.71×10^{7}	4.33×10^{3}	6.99×10^{4}	1.59×10^{4}	175.11	437.89	175.00	50.84	5.73	7.78×10^{5}	2.06×10^{5}	293.64
$2 \cdot \mathrm{Cov}(\theta, \psi)$	-4.49×10^{4}	7.78×10^{1}	-3.75×10^{2}	1.12×10^{2}	−0.55	−0.50	−0.55	−0.18	−0.01	-9.16×10^{2}	-3.15×10^{2}	6.56
$2 \cdot \mathrm{Cov}(\psi, \mathbf{x}\boldsymbol{\beta}')$	-1.49×10^{4}	-6.83×10^{1}	-2.23×10^{1}	-1.20×10^{2}	0.12	0.28	0.12	−0.01	0.00	-3.12×10^{2}	-2.58×10^{2}	0.37
$2 \cdot \mathrm{Cov}(\theta, \mathbf{x}\boldsymbol{\beta}')$	-1.65×10^{7}	-1.38×10^{4}	-1.72×10^{5}	-2.65×10^{4}	−2.57	4.77	−2.50	−6.38	0.00	-3.93×10^{5}	-9.38×10^{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 (2). 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 (2). 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 (2) 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.

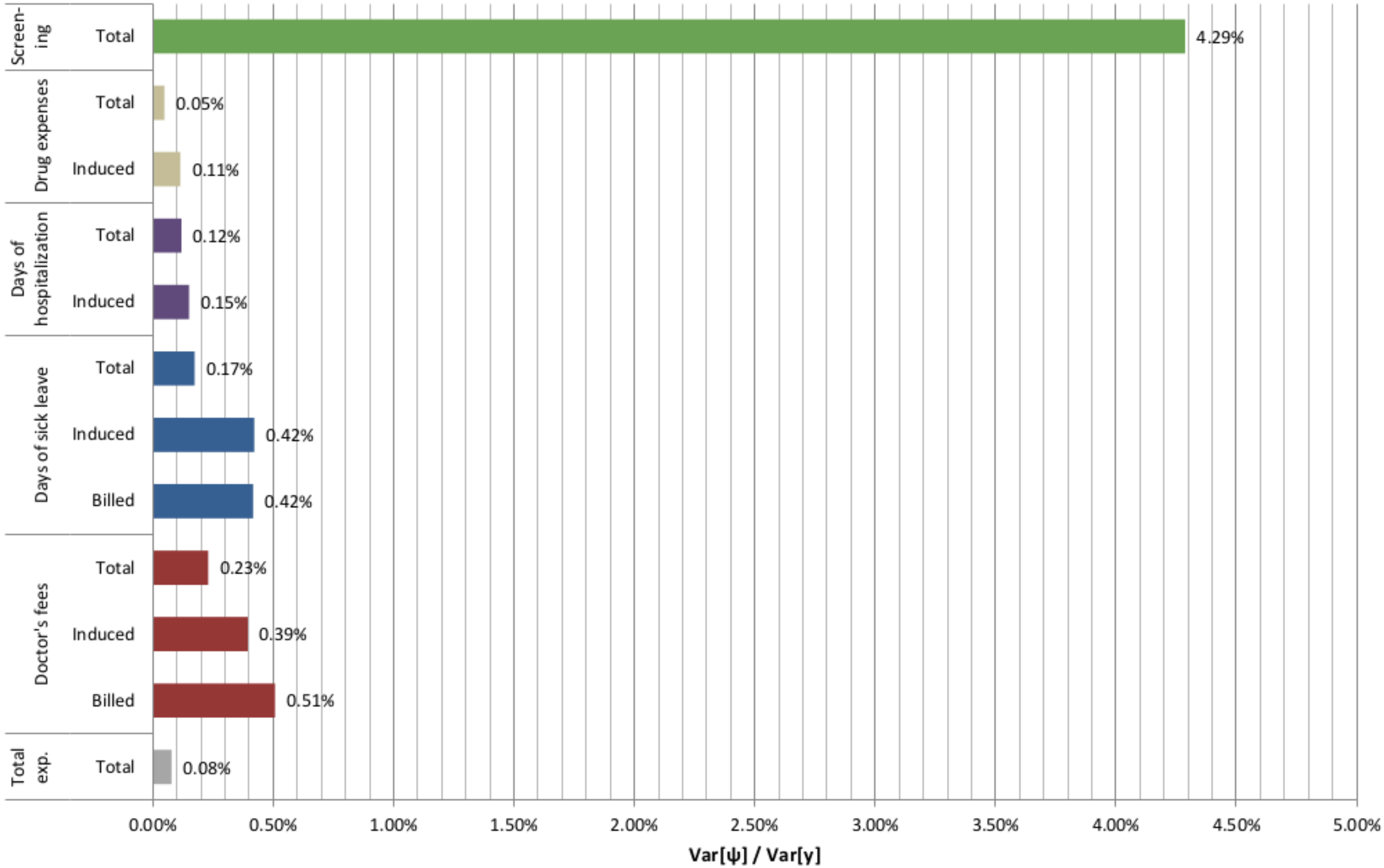
TABLE A.7 — Average deviations in outcomes across deciles of the practice style measure distribution.

	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 — Percent of overall variation explained by practice styles 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 (2) 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 practice styles.

	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)
Onsite 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,

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

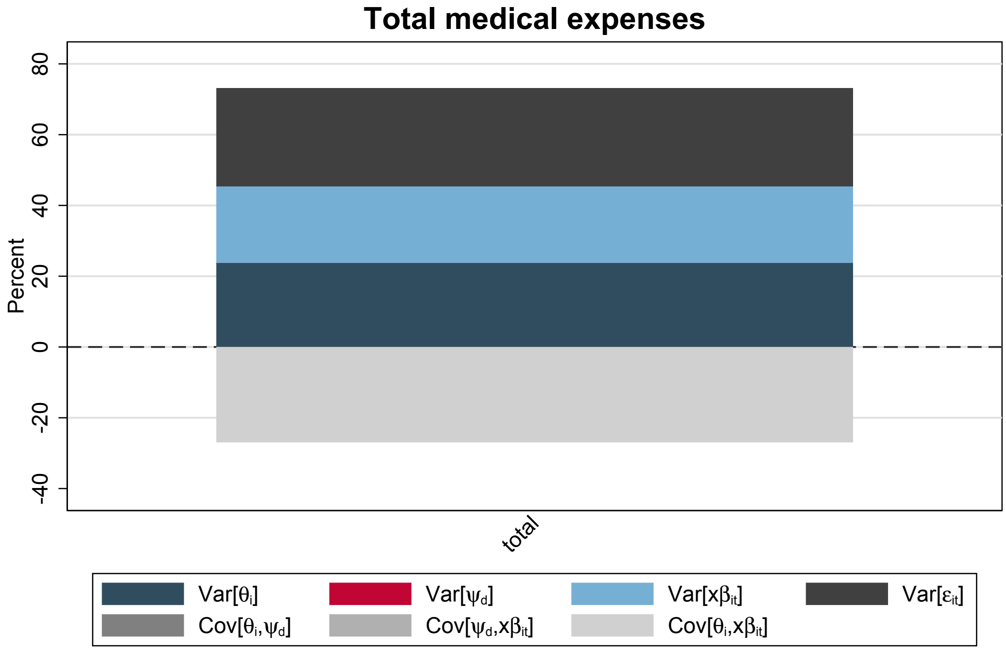
where i denotes the patient, d denotes the GP and t is time. Due to the model being linear in the time-dependent observables $\mathbf{x}_{it}$, the patient fixed effect θ_i, the general practitioner (GP) fixed effect ψ_d, and the residual r_{it}, the variance of the outcome y_{it} can be decomposed as

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

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 that the three covariance terms in equation (A.2) equal zero in order to avoid percentage calculations with negative numbers.

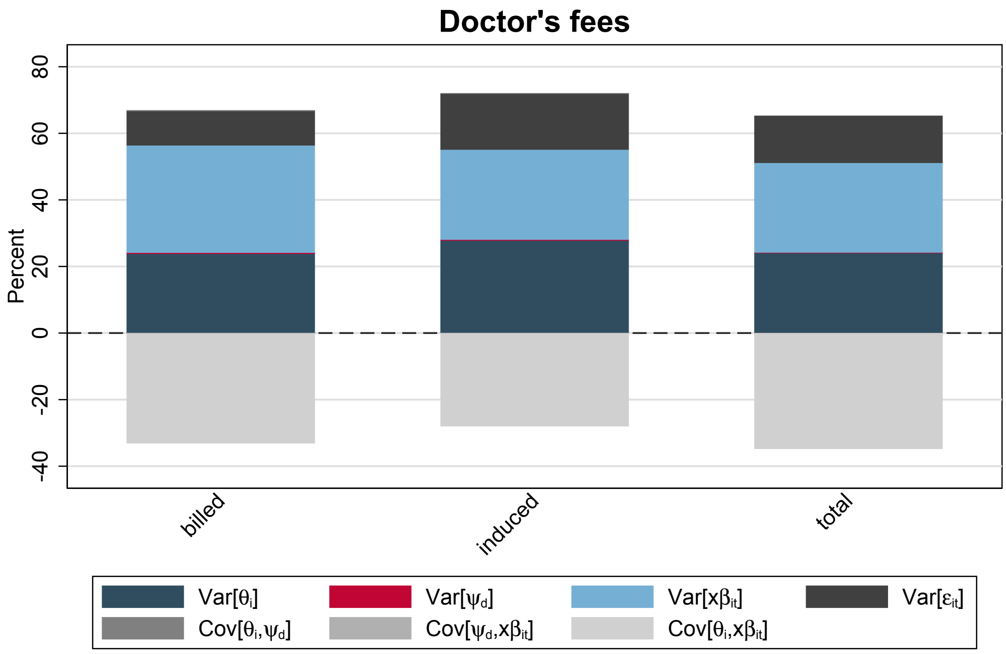
In Figures A.5 through A.10 we *do* report variance decompositions in which we include these negative percentages. For every outcome—i.e., total medical expenditures in Figure A.5, doctors' fees in A.6, days of sick leave in A.7, hospitalizations in A.8, drug expenditures in A.9, and screening expenditures 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.



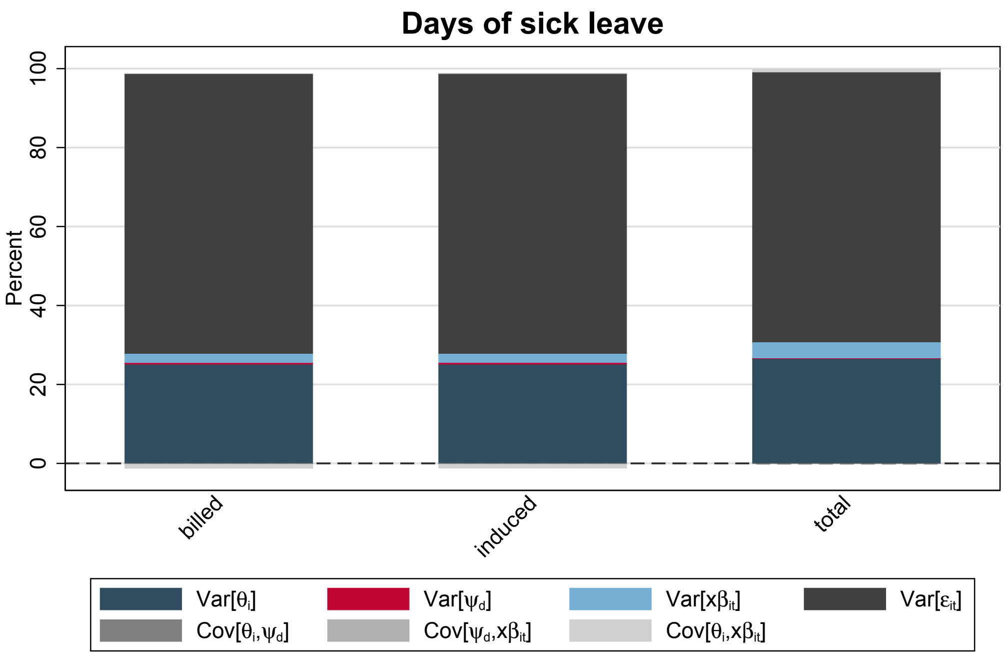
Note: This graph depicts the variance decomposition of total expenditures specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include 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.



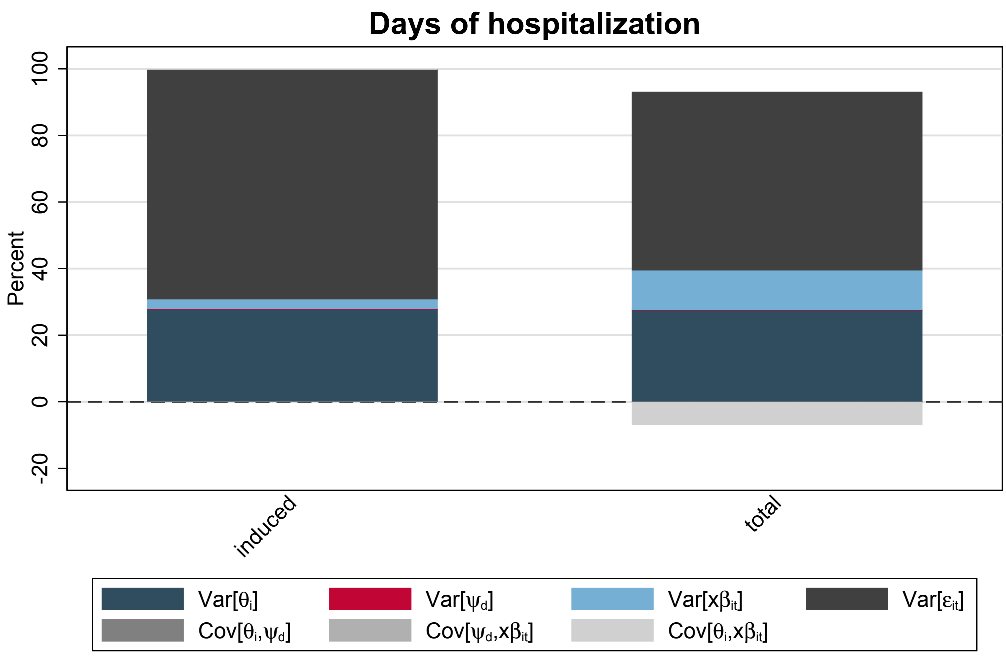
Note: This graph depicts the variance decomposition of doctors' fees specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the 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.



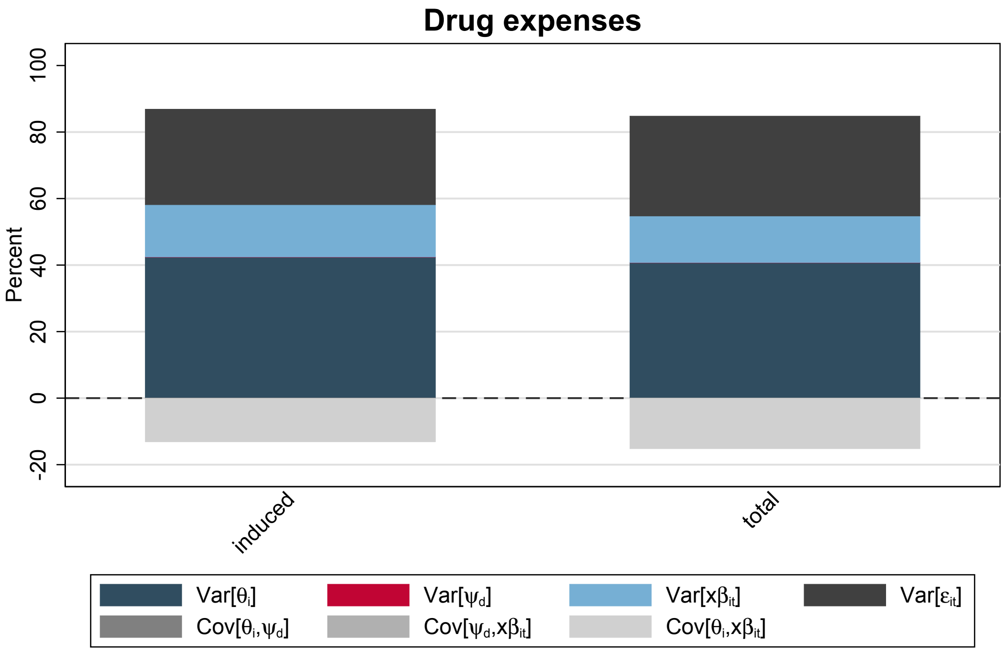
Note: This graph depicts the variance decomposition of days of sick leave specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include 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.



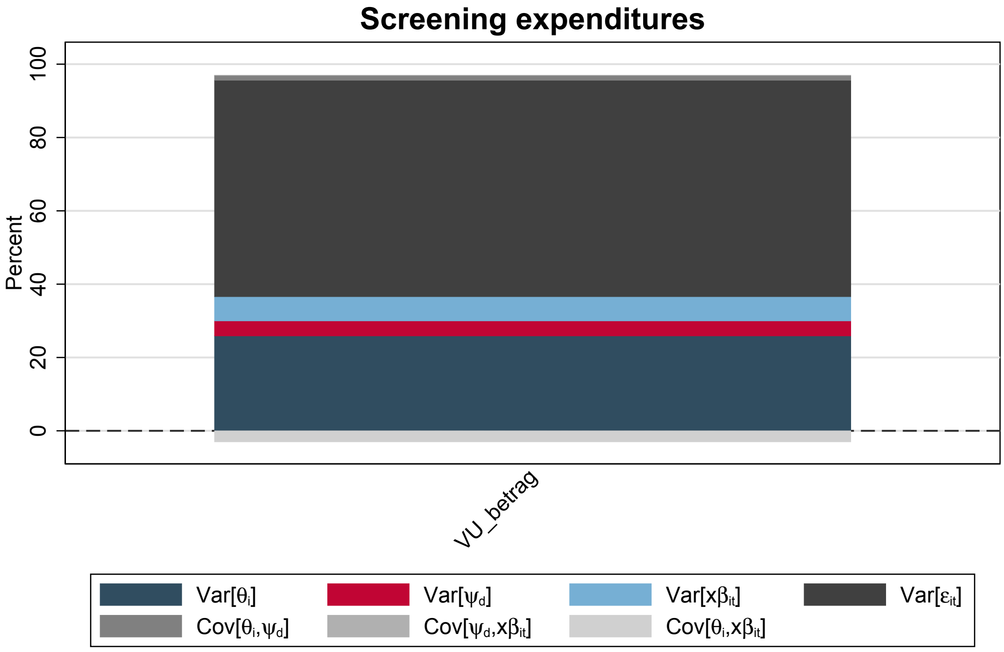
Note: This graph depicts the variance decomposition of days of hospitalization specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the covariance terms $2 \cdot \widehat{\mathrm{Cov}}(\theta, \psi)$, $2 \cdot \widehat{\mathrm{Cov}}(\psi, \mathbf{x}\boldsymbol{\beta}')$, 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.9 — Variance decomposition of drug expenditures.



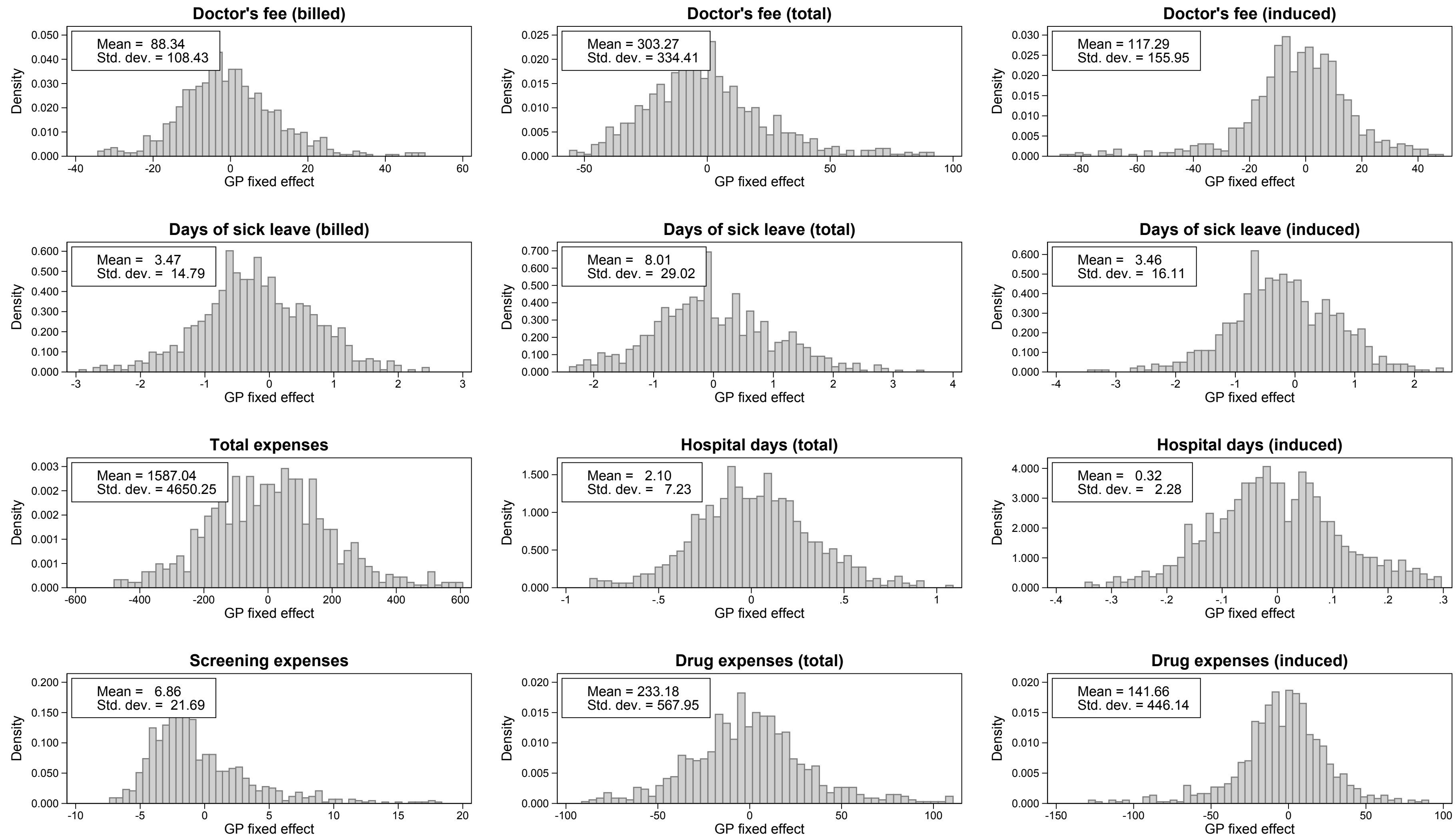
Note: This graph depicts the variance decomposition of drug expenditures specified in equation (A.2) based on the Abowd, Kramarz and Margolis (1999) model. Each bar indicates a component's estimated percentage contribution to the outcome $\hat{y}$, where percentages only sum to 100 if we also include the covariance terms $2\cdot\widehat{\text{Cov}}(\theta,\psi)$, $2\cdot\widehat{\text{Cov}}(\psi,\mathbf{x}\boldsymbol{\beta}')$, 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.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 $2 \cdot \widehat{\text{Cov}}(\theta, \psi)$, $2 \cdot \widehat{\text{Cov}}(\psi, \mathbf{x}\boldsymbol{\beta}')$, 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.11 — Densities of estimated practice style measures 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 (2). 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.