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MODELING INTERREGIONAL PATIENT MOBILITY: THEORY AND EVIDENCE FROM SPATIALLY EXPLICIT DATA*

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This article provides theory and evidence on the spatial determinants of regional patient flows. We develop a theoretical model that explains a patient's choice to consult a general practitioner by a measure of spatial accessibility. We empirically test this gravity-type model using regional patient flows and detailed data on the spatial distribution of residents and physicians in Austria. Our measure of spatial accessibility is a crucial determinant of patient flows that substantially increases the explanatory power of regular gravity models. Counterfactual simulations show heterogeneous effects of exiting physicians on health-care accessibility and patient mobility.

1. INTRODUCTION

Equitable access to health care is crucial to ensure the fundamental human right to health for all (WHO, 2008). However, the possibility to use medical services differs substantially across patients and regions. Recently, the often cited policy goal of equitable accessibility to critical health-care infrastructure (UNDP, 2015) has been challenged by observed or expected shortages in the number of primary care physicians, especially in rural areas (WHO, 2018). These shortages are commonly attributed to a wave of retirement of the so-called "baby-boom" generation (OECD, 2016).[1] At the same time, there is a reluctance of younger physicians to settle in rural areas (Ono et al., 2013) despite the increasing demand of the aging population. Scarce physician supply directly affects patient well-being through lower service capacity as well as increased travel times and costs. The aim of this article, therefore, is to evaluate the role of regional differences in accessibility of primary health-care providers for patient mobility.

In a broader context, economic interactions across space are influenced by the distribution of demand and supply factors. In order to evaluate how goods, services, and people sort across

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[1] In 2018, almost one third (31.5%) of all physicians in Austria were over 55 years old. This share was even higher in Germany (44.9%) and Italy (55.8%) (Eurostat, 2020).

geographic space, an influential body of literature builds on gravity models that highlight the important role of trade and travel costs (often termed "bilateral resistance").[2] Although gravity models have been successful to explain trade and migration flows across countries and regions, recent contributions show that gravity and congestion forces determine commuting patterns even at a subregional level (Ahlfeldt et al., 2015; Monte et al., 2018). As regional heterogeneity in the distribution of supply and demand is a key driver behind those flows, it is important to exploit detailed information at the finest possible scale. This is especially true for the health-care market, where patients have strong preferences for proximity, and physicians' capacity constraints are often binding, such that they might serve a limited number of patients only or provide lower quality if demand is high. Both mechanisms increase patient mobility by diverting patients away from their closest provider. Hence, this article introduces a measure of "spatial accessibility" that incorporates the geographic distribution of demand and supply factors as well as congestion forces within regions to predict interregional patient flows.

We estimate a theory-guided gravity equation of patient flows that accounts for regional heterogeneity in accessibility of general practitioners (GPs). In our theoretical framework, we model a patient's choice to consult a physician in a particular region. Notably, our measure of accessibility does not only depend on distances between regions, but rather takes into account the intraregional distribution of both potential patients and physicians, as well as congestion at the physician level. The model implies a gravity-type equation that predicts the probability of a patient to see a physician in a particular region. This probability increases with a higher accessibility measure and is also influenced by the accessibility of all other regions. Patients' decisions do not depend on prices because, in our empirical application to a public health-care system, service fees are fixed and covered, for example, by social insurance contributions. We further demonstrate that under restrictive assumptions, namely, abstracting from intraregional heterogeneity and congestion forces, our model nests a standard gravity equation with only bilateral distance. This approach guides our empirical analysis, where we investigate the importance of our measure of spatial accessibility relative to bilateral indicators of travel costs, like interregional distance or travel time.

In the empirical analysis, we test the theoretical model's implications by analyzing patient mobility across Austrian regions. In order to generate a measure of spatial accessibility, we apply a variant of the two-step floating catchment area (2SFCA) method, developed in the field of applied geography (see Radke and Mu, 2000). Our measure is based on very detailed information regarding the spatial distribution of the residential population (demand) and the exact locations of all GPs (supply) in Austria, instead of on endogenous factors such as actual utilization of health services or GP quality. To the best of our knowledge, we are the first to estimate a theory-based gravity equation with a measure of spatial accessibility, especially in the context of health care.[3] Our results show that spatial accessibility is an important determinant of patient mobility and considerably improves the explanatory power of the gravity model. Notably, accounting for spatial accessibility renders the main variable of interest in the gravity literature—namely, interregional distance—insignificant.

Our approach allows predicting changes in patient mobility following supply-side shocks, which would not be possible in a standard gravity framework that only relies on bilateral re-

[2] The gravity equation has become the standard approach in modeling trade flows, see Tinbergen (1962) for an early application; Anderson (1979), Eaton and Kortum (2002), and Anderson and van Wincoop (2003) for other influential contributions in this field; and Yotov et al. (2016) for an introduction and an overview. Furthermore, gravity models have been used to investigate flows of foreign direct investments (Anderson, 2011; Lay and Nolte, 2017) or equity investments (Portes and Rey, 1998, 2005), and to analyze commuting patterns (Persyn and Torfs, 2016) or student mobility (Beine et al., 2018), among other areas. In the field of health economics, Levaggi and Zanola (2004) and Fabbri and Robone (2010) have applied gravity models to investigate interregional patient flows.

[3] Measures of spatial accessibility relying on the 2SFCA method are typically used to accurately quantify the accessibility of locally produced and consumed services in a descriptive way. Empirical contributions in this context aim to detect under-served areas (Luo and Wang, 2003; Luo and Qi, 2009; Radke and Mu, 2000) or to relate differences in accessibility across neighborhoods to the socio-economic status of their residents (Dai and Wang, 2011; Pennerstorfer and Pennerstorfer, 2021).

sistance. Market exits or relocations of outpatient GPs affect the accessibility measures and thus welfare, which consequently influences patients' choices which doctors to consult. In a first set of simulations, we document heterogeneous changes in spatial accessibility within regions, depending on the exact locations of physicians leaving the market. Guided by our theory, this heterogeneity translates into regional variation in patient flows: If physicians leaving the market are clustered in space, bordering regions are strongly affected, whereas patient mobility is only moderately influenced if the same number of GPs leaving the market is scattered throughout the region. In a second set of simulations, we evaluate the effect of the retirement of public GPs on accessibility if these exiting physicians are only replaced in certain regions (rural versus urban). These counterfactual analyses are of high policy relevance for countries with a public health-care system, as demographic change and rural exodus of physicians tend to deteriorate equitable access to health-care services.

We contribute to recent developments of (quantitative) spatial economics (Ahlfeldt et al., 2015, 2020; Dingel and Tintelnot, 2020; Heblich et al., 2020; Monte et al., 2018) by integrating the concept of spatial accessibility in a gravity framework. Ahlfeldt et al. (2015) rely on computed travel times based on the transportation network and self-reported travel times to estimate a gravity equation of commuting flows across Berlin districts. Using distances between counties' centroids, Monte et al. (2018) analyze a gravity framework of commuters applied to U. S. data. Both studies use the regression results for their subsequent counterfactual analysis. As welfare and policy implications depend on these estimates, it is crucial to take into account information on the measure of bilateral resistance in as much detail as possible.[4]

Although the health-care sector is a highly policy-relevant industry, empirical contributions on spatial aspects are still relatively scarce. The empirical literature on patient mobility—which has been referred to as "revealed accessibility" (Joseph and Bantock, 1982)—has focused mainly on hospital services (Avdic, 2016; Balia et al., 2018; Bruni et al., 2008; Congdon, 2000, 2001; Fabbri and Robone, 2010; Levaggi and Zanola, 2004; Smith et al., 2018). The few studies investigating outpatient services are either conducted in the United States (see, e.g., Dai, 2010; LaVela et al., 2004; Schmitt et al., 2003), or are descriptive in the sense that potential accessibility is not used to predict utilization patterns (such as Bauer and Groneberg, 2016; Joseph and Bantock, 1982). Those contributions using an econometric framework to model patient mobility usually calculate Euclidean or travel distances between regions as indicators of spatial accessibility (e.g., Balia et al., 2018; Fabbri and Robone, 2010; LaVela et al., 2004; Schmitt et al., 2003). We contribute to this literature by highlighting the important role of spatial accessibility in a theory-guided estimation of patient flows, where we exploit supply and demand information at a finer spatial scale than interregional flow data.

Our approach of augmenting a gravity model with a measure of spatial accessibility is not limited to the health-care market, but is also relevant for other applications where exact locations of demand (e.g., consumers of goods and services, importers, workplaces, students) and supply (e.g., producers, service providers, exporters, workers, universities) are important. Although country-level data might be sufficient for analyzing trade in goods (at least for reasonably small countries), even information at a subnational level (like U. S. states or EU NUTS 1 regions) might not be accurate enough for investigating trade in services, commuting patterns, or patient mobility. In these cases, our approach can contribute to standard econometric models based on bilateral distance by improving the explanatory power of these models.

The remainder of the article is organized as follows: Section 2 introduces the concept of spatial accessibility in a theoretical model of patient flows. Section 3 describes the empirical strategy, including the calculation of the measure of spatial accessibility and the econometric model specifications. Moreover, it details the data sources and the variables used in the empirical analysis. Finally, the regression and simulation results are presented and discussed in Section 4, whereas Section 5 concludes.

[4] Recent contributions in the trade literature highlight the importance of intranational trade costs (Agnosteva et al., 2019; Coşar and Demir, 2016; Donaldson, 2018).

2. THEORY

2.1. *Institutional Background.* Our analysis focuses on GPs in the public outpatient sector, who are responsible for primary health care in Austria.[5] In order to theoretically model regional patient flows, some information about the underlying institutional setting is helpful at this point. Patients are free to choose their health-care provider without restrictions regarding the utilization of services outside their own district or state. Patients can decide to see a different GP quarterly without any cuts in cost coverage. The choice of provider within Austria for these so-called "first contacts" (i.e., the first contact within a given quarter of the year) with a GP is not restricted by financial considerations for the patient (Bachner et al., 2018). As argued by Pohlmeier and Ulrich (1995), it is therefore plausible to assume that the patient freely chooses whether and where to seek care (provider and location) for the initial contact with a GP, whereas supply-side inducement is more likely for follow-up and specialist visits. On the supply side, the number of public (i.e., contracted) physicians in a region is strictly regulated. Based on the number of insured individuals (i.e., potential patients), each social health insurance fund negotiates a placement plan (*Stellenplan*) with the regional chambers of physicians (*Landesärztekammern*) for each political district. The negotiated distribution of these contracted outpatient physicians is required by law to take into account differences in regional infrastructure, such that each insured person has a choice between at least two outpatient physicians who can be reached within a reasonable travel time (Renner, 2019; Stepan and Sommersguter-Reichmann, 2005). However, although the number of public physicians is strictly regulated at the district level, physicians are free to locate anywhere within that district. Austrian outpatient physicians are paid based on a mix of contact capitation and fee-for-service according to fixed tariffs that do not differentiate between physician locations (i.e., between urban and rural regions). One important (financial) incentive for physicians to locate in remote areas is that they are allowed to run an on-site pharmacy if there is no pharmacy in their municipality or within a 6-km radius of their practice. This enables them to directly dispense the prescribed medication to their patients and earn a mark-up.[6] Despite this additional source of income, there is an increasing shortage of public physicians willing to locate in rural areas.

Apart from public physicians, there are also private physicians practicing in the outpatient sector. These private providers do not have a contract with a social health insurance fund, hence, patients have to make out-of-pocket payments for the provided services.

2.2. *Theoretical Measure of Spatial Accessibility.* We operationalize the concept of spatial accessibility by the so-called 2SFCA method (see, e.g., Radke and Mu, 2000). To guide our empirical approach and gain intuition of the underlying mechanisms, we first construct the theoretical counterpart of the 2SFCA method in this section. Subsequently, we integrate this measure of spatial accessibility in a spatial model along the lines of Monte et al. (2018). Our model implies a gravity equation for patient flows and brings forth novel testable predictions to be confronted with data in the empirical part in Section 3.

Guided by the institutional background, we employ a theoretical measure of spatial accessibility, which incorporates proximity between potential patients[7] and physicians as well as congestion forces. We consider one country (Austria), which is divided into a finite number of regions S. One region s is endowed with a fixed measure of physicians, $L_s > 0$, and a fixed number of patients, $K_s > 0$. Each patient k chooses to see a physician l in a destination region d, who provides the highest utility, which depends on several determinants. In this section, we

[5] Note that pediatricians are considered specialists in Austria and are therefore not included in our analysis.

[6] In 2019, around 21% of all public outpatient physicians had an on-site pharmacy.

[7] For brevity, and because almost every resident will eventually become a patient when seeking care at a primary care provider, we will use "potential patient" and "patient" interchangeably in Section 2. In describing our empirical analysis, we make a clear distinction between patients' observed contacts (endogenous) and their places of residence (exogenous).

focus on one central aspect of utility, which is spatial accessibility.[8] Intuitively, our approach can be characterized as follows. We start from the perspective of an individual patient and consider the determinants that affect the service provision of a specific GP. We then aggregate the individual measures at the regional level, as we are ultimately interested in modeling patient flows across regions. In line with the idea of the 2SFCA method, our measure of spatial accessibility is constructed in *two* steps.

In a first step, we model a physician's service provision level, which we denote by R_l. It depends on two components: (i) the number of patients within a GP's catchment area and (ii) the respective distances to each of the patients within this area. In line with our empirical counterpart, we assume the following functional form:

$$R_l = \frac{1}{\sum_k f(dist_{lk})}, \tag{1}$$

where $f(dist_{lk})$ is a function that decreases in the distance between patient k and physician l. The catchment area includes all patients within a specified distance.[9] For patients outside this area, the distance function is defined as $f(dist_{lk}) = 0$, such that their weight is zero in Equation (1). A physician's service provision level thus depends negatively on the number of patients within a GP's catchment area. Intuitively, a higher number of patients reduces the time allocated to one patient (e.g., due to a lower frequency of follow-up visits) and hence the quality of the medical service. Given the number of other patients, this "congestion" force plays a larger role when distances to these patients within the catchment area are short (because a larger fraction of the other patients will consider the respective GP).

Note that in Equation (1) we do not account for differences in need of potential patients within the catchment area when calculating the service provision level and give every resident the same weight (conditional on the distance between physicians and potential patients). Furthermore, we do not consider a physician's service quality (when calculating the service provision level) and hence assume that GPs offer homogeneous quality. Differences in need and service quality can easily be incorporated in the empirical model by giving potential patients or physicians different weights when calculating the service provision level R_l.[10]

In the *second* step, we take the perspective of a patient k living in region o, and determine the accessibility of physicians in region d, denoted by A_{kod}. Using the service provision level of physician l, as shown in Equation (1), weighted by the respective distance between a patient and a GP, and summing over all physicians in region d, we obtain:

$$A_{kod} = \sum_{l \in L_d} R_l f(dist_{kl}) = \sum_{l \in L_d} \frac{f(dist_{kl})}{\sum_k f(dist_{lk})}. \tag{2}$$

Again, $f(dist_{kl})$ is a decreasing function of distance between patient k and physician l, which implies that a given level of service provision by physician l increases the spatial accessibility to a larger extent when distances are short. Summing over all distance-weighted service provision levels of physicians determines the accessibility of region d. Note that this accessibility measure is based on relatively exogenous characteristics (the location of both physicians and residents) instead of endogenous variables like actual utilization of health services or GP quality (e.g., opening hours).[11] Our approach is thus in the spirit of Kessler and McClellan

[8] The detailed utility function will be described in the subsequent section.

[9] In the empirical analysis, we specify an inverse power function for $f(dist_{lk})$, and set the distance of the catchment area at 100 km. See Subsection 3.2 for details.

[10] We account for different needs according to the sex–age group of the patients in one of the sensitivity analyses (see Subsection 4.3 for details).

[11] A relatively high accessibility level implies a high physicians density (relative to the local population) and hence, more intense competition. This could lead to increases in quality (e.g., opening hours) and thus in actual utilization of health services.

(2000) to explain actual patient mobility (patients' endogenous choices) by exogenous factors (in our case: spatial accessibility). The empirical implementation of Equation (2) will be discussed in Section 3 in detail. Before we introduce our measure of accessibility in a spatial economics model, we summarize its main components and intuition as follows.

INTERPRETATION. *From the perspective of patient k, the accessibility of physicians in region d* (A_{kod})

(i) increases in the number of accessible physicians within region d (i.e., those physicians where $f(dist_{kl}) > 0$*);*
(ii) increases in the service provision level (R_l) *of all physicians in region d, which itself depends on the number and proximity of all other patients within the catchment area; and*
(iii) decreases with the distance between patient k and all physicians in region d.

Note that our accessibility measure in Equation (2) captures regional differences. In Appendix A.1.2, we show a variant of our model that focuses on physician-specific accessibility.

In the following section, we embed the concept of physicians' accessibility from Equation (2) into a spatial model that implies a gravity equation for patient flows across regions. Although the residence of patients is fixed, they are geographically mobile to choose the region that offers the maximum utility for seeing a doctor.[12]

2.3. *Patients' Preferences.* In modeling the preference structure of patients, we focus on determinants that influence the accessibility of physicians in a region and abstract from further components of utility.[13] The preferences of a patient k, who lives in region o and consults a physician in region d, captures a composite amenity measure:

$$U_{kod} = a_{kod} A_{kod}, \tag{3}$$

which consists of two parts. As a first component, patients in o have idiosyncratic tastes for seeing a doctor in d denoted by a_{kod}. These shocks imply that patients have different preferences regarding physicians across locations. In modeling this heterogeneity in preferences, we follow Monte et al. (2018) and Heblich et al. (2020) by assuming that the amenity shocks a_{kod} are drawn from a Fréchet distribution[14]:

$$G_{od}(a) = e^{-M_{od} a^{-\epsilon}}, \tag{4}$$

where the scale parameter M_{od} determines the average amenities of living in region o and seeing a physician in region d. Amenities include all factors that affect the ease of traveling but are not captured by distance (e.g., availability of public transportation or quality of the road network).[15] The shape parameter $\epsilon > 1$ reflects the dispersion of amenities. Hence, it controls the sensitivity of location decisions with respect to economic variables and—importantly in our case—with respect to spatial accessibility, which enters preferences as a second component.[16] For given idiosyncratic tastes for region d, patients prefer seeing a doctor there when accessibility of the region is high. Put differently, heterogeneous amenity shocks ensure that

[12] As we focus on cross-sectional data in the empirical analysis, we abstract from residential location choice over time.

[13] In an earlier working paper version (Irlacher et al., 2021), we follow the recent spatial economics literature and assume a Cobb–Douglas–type utility function over consumption and housing (see Redding and Rossi-Hansberg, 2017, and Redding, 2022).

[14] The use of extreme value distributions has been shown to be useful to derive gravity equations of international trade (Eaton and Kortum, 2002) and of commuting flows (Monte et al., 2018).

[15] The role of amenities is discussed in more detail in Subsection 3.2.

[16] The smaller the shape parameter ϵ, the greater the heterogeneity in idiosyncratic amenities, and the less sensitive are location decisions with respect to other variables.

patients make different choices about their doctor's region when faced with the same accessibility measure. In line with the institutional background described above, these decisions are not affected by direct costs of consulting GPs.[17]

REMARK 1. Note that bilateral (iceberg) traveling costs between regions o and d do not enter explicitly in the utility function, but are subsumed in our spatial accessibility measure. In Subsection 2.5, we show under which restrictive assumptions this approach nests a standard gravity equation featuring bilateral distance between o and d as a proxy for bilateral traveling costs.

In a next step, we use the probabilistic nature of our model to derive a gravity equation of regional patient flows.

2.4. *Gravity Equation of Patient Flows.* Each patient chooses a physician in the region that offers the maximum utility:

$$U_k = \max\{U_{kod}; d \in S\}. \tag{5}$$

The probability that a patient in region o derives the maximum utility from seeing a doctor in region d is:

$$\lambda_{kod} = Pr[U_{kod} \geq \max\{U_{kos}; s \neq d\}]. \tag{6}$$

Note that this decision depends on the accessibility of physicians in this region and how distant the patient is to those doctors relative to other patients. As utility in Equation (3) is a monotonic function of idiosyncratic amenities a_{kod} that follow a Fréchet distribution, its maximum is also Fréchet distributed: $G_{kod}(U) = e^{-\Psi_{kod}U^{-\epsilon}}$, where $\Psi_{kod} = M_{od}A^{\epsilon}_{kod}$. We use this property together with the fact that the probability in Equation (6) can be written as $\lambda_{kod} = \int_0^{\infty} \Pi_{s\neq d} Pr(U_{kos} \leq U)dG_{kod}(U)$, which leads to a gravity-type equation for patient flows[18]:

$$\lambda_{kod} = \frac{M_{od}A^{\epsilon}_{kod}}{\sum_s M_{os}A^{\epsilon}_{kos}} = \frac{M_{od}\left(\sum_{l\in L_d} \frac{f(dist_{kl})}{\sum_k f(dist_{lk})}\right)^{\epsilon}}{\sum_s M_{os}\left(\sum_{l\in L_s} \frac{f(dist_{kl})}{\sum_k f(dist_{lk})}\right)^{\epsilon}}. \tag{7}$$

A patient from region o is more likely to consult a physician in region d if the average amenities M_{od} are larger. Although this bilateral component is specific to the region pair, the accessibility measure A_{kod} differs across patients from the same origin region o and captures heterogeneity in spatial accessibility of doctors. The Fréchet shape parameter influences the relative importance of spatial accessibility. A larger ϵ implies that idiosyncratic amenities are less dispersed and accessibility becomes more important in determining patient flows. According to Equation (7), each patient from region o faces different distances to physicians located in destination d. Note that a standard gravity framework with only bilateral costs does not take into account this heterogeneity. The term $\sum_s M_{os}A^{\epsilon}_{kos}$ captures "multilateral resistance," which is patient-specific and includes average amenities as well as physicians' accessibility of all possible destinations. This term captures general equilibrium adjustments in addition to the direct effects of accessibility. In particular, changes in accessibility between two regions will also affect patient flows between all other regions. Although we control for multilateral resistance through fixed effects in the empirical analysis, these general equilibrium adjustments will be considered as endogenous variables in our counterfactual analysis in Subsection 4.4.

[17] In Appendix A.1.2, we briefly discuss the role of physician-specific prices.

[18] The derivation of the gravity equation for patient flows is shown in Appendix A.1.1.

To focus on the patient's choice of physicians, we have abstracted from commuting and hence workplace decisions in the theoretical model. In the empirical part, we discuss the role of commuting at the end of Subsection 3.2 and control for commuting flows in the regression analysis of patient mobility.

2.5. *Relation to a Standard Gravity Equation.* In order to highlight the role of spatial accessibility in determining patient flows across regions, we show under which restrictive assumptions our framework collapses to a standard gravity equation. In a first step, we shut down spatial heterogeneity within regions by assuming that all physicians and patients are located in one point, respectively.[19]

RESTRICTIVE ASSUMPTION 1. *There is no intraregional heterogeneity in distances between patients, that is, all patients (physicians) of one region are located in one point.*

This assumption implies that the measure of accessibility only captures information on interregional distances. Hence, intraregional differences of distances between patients and physicians are not taken into account. In this case, the service provision level in Equation (1) is identical for all physicians in destination d and reduces to $R_d = 1/[\sum_z K_z f(dist_{dz})]$. Note that Equation (1) takes into account all patients and their individual distances, including intra- and interregional heterogeneity. In contrast, the simplified version abstracts from intraregional distances. Hence, from the perspective of region d, this simplified measure only sums over all potential origin regions z, as all patients within an origin z, K_z, face the same distance. From the perspective of a patient in origin o, the accessibility measure under Restrictive Assumption 1 can be written as follows: $A^{r1}_{od} = L_d R_d f(dist_{od})$. Inserting the service provision level leads to

$$A^{r1}_{od} = \frac{L_d f(dist_{od})}{\sum_z K_z f(dist_{dz})}. \tag{8}$$

Compared to Equation (2), the accessibility measure is identical for all patients from one region. As a second step, we additionally assume that all patients within the catchment area of a physician affect the service provision level to the same degree, irrespective of their actual distance.

RESTRICTIVE ASSUMPTION 2. *Congestion only depends on the number of physicians relative to patients, that is, all patients within a catchment area enter into the service provision measure with the same weight.*

With this second assumption, the accessibility measure in Equation (8) simplifies to

$$A^{r2}_{od} = \frac{L_d f(dist_{od})}{\sum_z K_z}. \tag{9}$$

Note that the latter measure only considers origins z for which $f(dist_{dz}) > 0$ in Equation (8). This implies that all patients within the catchment area enter with a weight of one, irrespective of their distance. Inserting Equation (9) into the gravity equation (7), we obtain

$$\lambda_{od} = \frac{M_{od}\kappa_{od}^{-\epsilon}\left(\frac{L_d}{\sum_z K_z}\right)^{\epsilon}}{\sum_s M_{os}\kappa_{os}^{-\epsilon}\left(\frac{L_s}{\sum_s K_s}\right)^{\epsilon}}, \tag{10}$$

[19] Note that this does not have to be the same point. Here, it is only important to assume that all patients of one region have identical distances to physicians of a particular region.

where $\kappa_{od} = 1/[f(dist_{od})]$ represents bilateral (iceberg) traveling costs, which would reduce patients' utility as in a commuting framework à la Monte et al. (2018). Equation (10) resembles a standard empirical specification of the gravity equation with both destination as well as origin fixed effects and a measure of bilateral distance as a proxy for traveling costs. This analysis has shown that our augmented framework nests the standard gravity model as a special case. Moreover, we conclude that bilateral distance should not play a role in determining regional patient flows once we drop Restrictive Assumptions 1 and 2 and make use of our spatial accessibility measure. To summarize, our theoretical analysis highlights two main implications, which are stated in the following propositions.

PROPOSITION 1. *Controlling for multilateral resistance and average amenities, patient flows between regions o and d are determined by a measure of spatial accessibility, which captures intraregional distances and congestion forces. A higher accessibility measure A_{kod} increases the probability that a patient k located in o consults a physician in d.*

PROPOSITION 2. *Accounting for spatial accessibility implies that bilateral distance no longer predicts interregional patient flows. The augmented gravity equation nests a standard framework if intraregional heterogeneity (i) in distances between patients and physicians and (ii) in the measure of congestion is not taken into account.*

Based on these propositions, the goal of the following empirical analysis is to determine the relevance of our refined accessibility measure compared to a standard gravity approach. In particular, the regression analysis enables us to quantify the relative importance of the two main ingredients in our spatial accessibility measure, namely intraregional heterogeneity (Restrictive Assumption 1) and congestion forces (Restrictive Assumption 2).

3. EMPIRICAL STRATEGY

In this section, we first outline how to empirically test the propositions of the theoretical model. Subsequently, we describe the available data on patient mobility and discuss how we utilize information on different levels of spatial aggregation to generate variables explaining interregional patient flows.

3.1. *Analyzing Patient Flows.* In order to test the theoretical model, we start with the gravity-type equation for patient flows (7), summarizing the probability that patient k living in region o consults a physician in region d, that is, $\lambda_{kod} = M_{od}A^{\epsilon}_{kod}/\sum_s M_{os}A^{\epsilon}_{kos}$. Taking the logarithm of this equation gives

$$(11) \qquad \log(\lambda_{kod}) = \epsilon \log(A_{kod}) + \log(M_{od}) - \log\left(\sum_s M_{os}A^{\epsilon}_{kos}\right).$$

The term $\sum_s M_{os}A^{\epsilon}_{kos}$ captures multilateral resistance and can be accounted for by patient-level fixed effects. As we observe the patients' destination choices only at the regional level, we take regional aggregates of both patients' decisions and accessibility levels in Equation (11). We thus aggregate the probabilities of consulting a physician in region d, λ_{kod}, over all patients in region o and analyze the number of patients $y_{od} = \sum_k \lambda_{kod}$ (patient flow), as outlined in the following regression equation:

$$(12) \qquad \log(y_{od}) = \gamma_0 + \gamma_1 \log(A_{od}) + \gamma_2 \log(M_{od}) + \tau_o + \mu_d + \varepsilon_{od}.$$

We aggregate individual accessibility measures to derive the respective variable at the district pair level (i.e., $A_{od} = \sum_k A_{kod}$). The variable M_{od} indicates the average amenities of living in region o and consulting a GP in region d (see Subsection 3.2 for details). τ_o and μ_d denote directional regional fixed effects, accounting for all kinds of push and pull factors as well as multilateral resistance. Although we do not account for intraregional differences in physicians' service quality, the regional fixed effects control for quality differences across districts. γ_0, γ_1, and γ_2 are the parameters to be estimated and ε_{od} indicates the error term.

Following the empirical literature applying gravity models (see, in particular, Santos Silva and Tenreyro, 2006; Yotov et al., 2016), we estimate Equation (12) using a Poisson pseudo-maximum-likelihood (PPML) estimator, which allows us to include the endogenous variable (patient flows y_{od}) in levels instead of in logarithms.[20] This approach acknowledges that patient flows are count data and circumvents the problem that the logarithm of zero is undefined. The endogenous variable on patient mobility includes intraregional patient flows (i.e., patients who utilize health care in their district of residence). Inference is based on a robust sandwich covariance matrix estimator to account for potential heteroskedasticity in the error term. This approach yields unbiased results even in the presence of overdispersion (Wooldridge, 1999).[21]

3.2. *Data and Variables.* The dependent variable y_{od} is based on a data set comprising all patient flows between the 115 political districts in the Austrian public outpatient sector in 2016, amounting to 13,225 observations (including intradistrict patient flows).[22] An analysis at a lower level of regional aggregation is impeded, because information on health-care utilization is highly sensitive and thus restricted at a spatially (more) disaggregated level.

These data were provided by the Main Association of the Austrian Insurance Funds. We follow Pohlmeier and Ulrich (1995) and treat each patient's first consultation of a GP in each quarter as a "first contact," and all other consultations as "follow-up visits."[23] We count the number of first contacts with a public GP in each quarter as a measure of patient mobility from the origin district o (patient's district) to the destination district d (physician's district). We restrict the measure of health-care utilization to first contacts instead of including follow-up visits, because in case of the former the decision whether and where to go lies entirely within the discretion of the patient, whereas the latter might be influenced by the GP recommending a follow-up visit (i.e., self-referral). In total, 21,268,245 first contacts with public GPs were recorded during the entire year of 2016, which corresponds to 0.62 contacts per capita per quarter. Of these around 21 million contacts, almost 3 million (about 14%) occurred outside the patients' districts of residence.

In order to explain patient mobility, we utilize data from various sources that are available at different levels of spatial aggregation. In order to calculate the measure of spatial accessibility based on the 2SFCA method, we exploit spatially highly granular data on the residential

[20] The Poisson model specifies that each patient flow y_{od} is drawn from a Poisson distribution, and that the expected patient flow is given by $E(y_{od}) = \exp(\gamma_0 + \gamma_1 \log(A_{od}) + \gamma_2 \log(M_{od}) + \tau_o + \mu_d)$. See Greene (2003) for details. Note that this Poisson model provides the same interpretation of the parameters as in the log-log-specification outlined in Equation (12).

[21] We prefer a Poisson over a hurdle or a zero-inflated Poisson model, because zero and positive patient flows are the result of the same qualitative process (see, e.g., the discussion in Greene, 2003). Both outcomes are determined by individual choices without institutional barriers. In fact, although more than half of the patient flows comprise 20 or less individuals, only 4.7% of all flows are exactly zero.

[22] Our analysis is restricted to contacts with public GPs. Contacts with private GPs are not routinely collected by the social insurance funds as these constitute private transactions between the patient and the physician. Further, the city of Vienna is divided into 23 districts. The districts Eisenstadt, Rust, and Eisenstadt-Umgebung had to be aggregated due to data limitations.

[23] We are aware that misclassifications are possible if an episode of care goes beyond the end of a quarter. We are able to identify first contacts in our data set because the social health insurance funds' reimbursement rates to public physicians are higher if it is a patient's first visit within a year's quarter. The reason for the higher fee-for-service is to compensate the higher effort, as first contacts are usually more (time-)consuming for physicians than follow-up visits. See also the discussion in Pohlmeier and Ulrich (1995), who face a similar issue in distinguishing between first contacts and follow-up visits. We address this issue again in the sensitivity analysis (see Subsection 4.3).

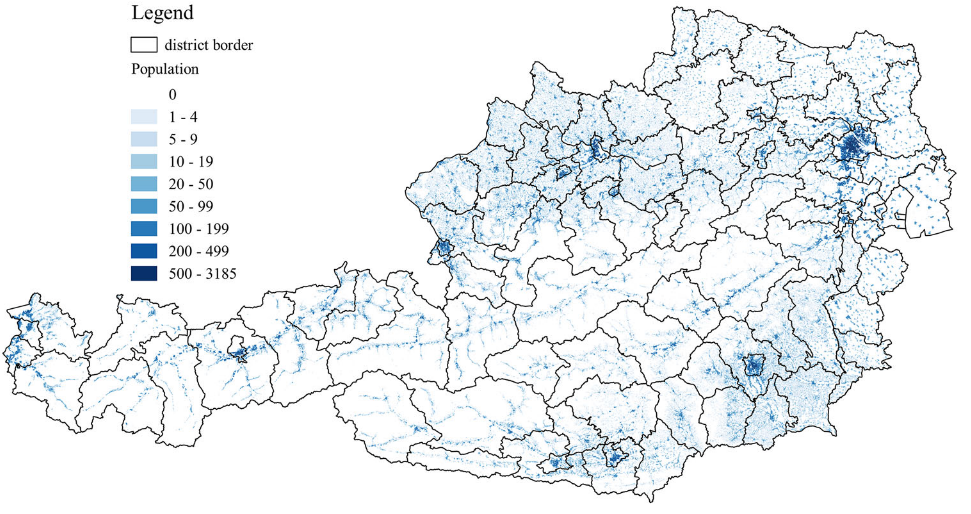


FIGURE 1

MAP OF RESIDENTIAL POPULATION AT 250×250 METER GRID-CELL LEVEL

population and the physicians' locations.[24] Data on the residential population were collected by the Austrian Statistical Office (Statistics Austria) in 2015 and are provided at the grid-cell level. The grid cells are independent of administrative boundaries and the size of one cell is 250 m $\times$ 250 m. Each person is assigned to exactly one cell based on their postal address. This provides very detailed information about the spatial distribution of the population, as one square kilometer (square mile) is represented by 16 (41) cells. The spatial distribution of the population is illustrated in Figure 1.

Information on all outpatient physicians was obtained in June 2017 through a web-scraping routine that collects data from the Web sites of all state-level chambers of physicians (*Landesärztekammern*).[25] These data include the physicians' exact locations (addresses and geocodes), their specializations, and whether they hold contracts with health insurance funds. We restrict the sample to all GPs and differentiate between public and private ones. A public GP is defined as a physician who holds a contract with at least one of the Austrian health insurance funds. All other outpatient GPs are classified as private. The spatial distribution of public GPs is illustrated in Figure 2.

The spatial accessibility of all physicians located in region d for patient k is stated in Equation (2). The distance between patient k and physician l, $dist_{kl} = dist_{lk}$, is calculated as the Euclidean distance between the centroids of the grid cells hosting patient k and physician l, respectively.[26] The distance to a GP located in the same grid cell is set to 125 m to approximate the travel distance within one grid cell. Note that this approach is also applied to calculate the accessibility measure for physicians located within the patients' districts of residence (i.e., when $o = d$).

We use a simple inverse power function $f(dist_{lk}) = dist_{lk}^{-\beta}$ to calculate the measure of spatial accessibility, which is one of the most popular distance decay functions (Kwan, 1998). We therefore follow recent applications of the two-stage floating catchment area method (see, e.g., Dai, 2010; Dai and Wang, 2011; Delamater, 2013), arguing that a continuous distance de-

[24] See Bergs and Budde (2022) for an overview of the recent increase in the availability of small-scale spatial data.

[25] The data were collected by the dwh GmbH (http://www.dwh.at/) within the K-Projekt DEXHELPP (http://www.dexhelpp.at/). Detailed description of the web-scraping process can be found in Wastian et al. (2018) and Rippinger et al. (2019).

[26] We do so because information on the spatial distribution within grid cells is not available (for patients), and for computational reasons (for GPs).

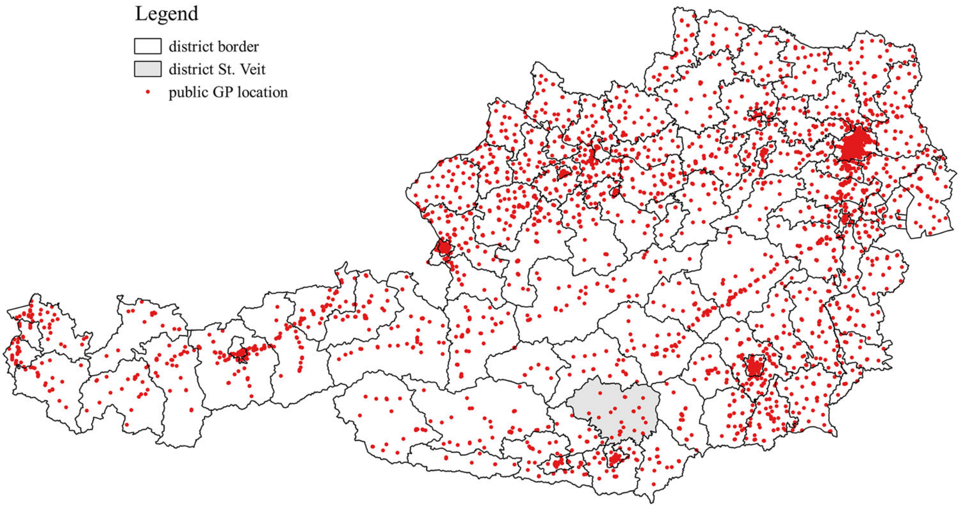


FIGURE 2

MAP OF PUBLIC GP LOCATIONS

cay function can capture changes in spatial accessibility better than binary (applied in Luo and Wang, 2003; Radke and Mu, 2000) or discrete ones (adopted by Luo and Qi, 2009) used in earlier versions of this method. The catchment area is set to 100 km, and thus $f(dist_{lk}) = 0$ if the distance between patient and physician exceeds this threshold value.[27] Individual accessibility measures are aggregated at the district pair level, that is, $A_{od} = \sum_k A_{kod}$. The parameter β of the inverse power function will be determined endogenously by the data (see Subsection 4.1). If two districts are far away, the spatial accessibility $A_{od} = 0$ and the logarithm is undefined. We follow Battese (1997) and replace the undefined values by $\log(A_{od}) = 0$, and include a dummy variable in the regressions, indicating whether missing values are imputed.

It is important to emphasize that the distance decay function $f(dist_{lk}) = dist_{lk}^{-\beta}$ is convex and decreases with distance. The accessibility measures of all residents of one region to physicians in another district are thus higher on average compared to the accessibility calculated at the average distance, a characteristic known as Jensen's inequality (Jensen, 1906). Calculating the accessibility measure based on the average distance between two regions therefore underestimates the average accessibility. The difference—and thus the error when relying on district–pair–level indicators—is large if distance is important (i.e., the distance decay parameter β is large), if the distribution of the residential population and the GP locations are spatially dispersed, and if the distance between two regions is small. If the distance between two regions is large, the intraregional distribution of patients and physicians is less relevant.

In addition to the particular measure of spatial accessibility outlined above, we also use simplified versions of this index. In a first step, we abstract from intraregional heterogeneity (see Restrictive Assumption 1 in Subsection 2.4). Based on the distribution of the population and the physicians, we calculate the population-weighted centroid and the physician-weighted centroid for each region, and use the Euclidean distance between these two locations as a measure of $dist_{od}$. Using this distance enables us to calculate a simplified accessibility measure, denoted by A_{od}^{r1}, following Equation (8). If we further assume that the level of congestion only depends on the number of physicians relative to patients within the catchment area (Restrictive Assumption 2), the logarithm of the accessibility measure simplifies to a

[27] Restricting the catchment area to 100 km is to some extent arbitrary. However, estimating the relationship between patient flows and distance nonparametrically suggests that patient flows are not significantly different from zero at this distance (see Figure A.1 in Appendix A.2.1).

region–pair–specific function of distance, in addition to variables captured by origin and destination fixed effects (see Equations 9 and 10). When applying both restrictive assumptions, we use the Euclidean distance between the regions' population-weighted centroids as a measure of $dist_{od}$.[28] In order to obtain a measure for the average distance within each district, we randomly draw 10,000 pairs of locations (grid cells) of each district and take the average Euclidean distance between these location pairs.

We do not directly observe the variable M_{od} in Equation (12) indicating the average level of amenities of living in region o and seeing a physician in region d. We therefore initially follow Ahlfeldt et al. (2015) and assume that this variable is composed of an origin-specific part $\tilde{M}_o$ and a destination-specific part $\hat{M}_d$ in a multiplicative way, such that $\log(M_{od}) = \log(\tilde{M}_o \hat{M}_d) = \log(\tilde{M}_o) + \log(\hat{M}_d)$ is controlled for by the regional fixed effects.

However, the average amenities M_{od} could also include a bilateral component that influences the ease of traveling not captured by distance (or travel time). For example, conditional on travel distance and time, patients may find it more comfortable to travel by train than by bus, might prefer a direct train connection over connections necessitating to change trains, or value public transport modes providing (free) Wi-Fi.[29] We thus follow Monte et al. (2018) in an alternative model specification and use commuter flows as indicators of bilateral amenities M_{od}, because these (unobserved) bilateral amenities are expected to influence both commuter and patient flows.[30]

Furthermore, working in a particular region might increase the workers' preferences of choosing a physician there as well, because marginal travel costs are likely to be small when seeing a GP close to the workplace. Commuting patterns are available at the district–pair level and are collected by Statistics Austria in 2015. These data include employees working in their districts of residence ("within-district commuters"). As commuting flows are zero for some district pairs, we again replace $\log(M_{od}) = 0$ in these cases and include a dummy variable, indicating that the respective values have been imputed.

Summary statistics for all relevant variables of our analysis are presented in Table 1.

4. EMPIRICAL RESULTS

In this section, we start by discussing how we select the necessary parameters to calculate the spatial accessibility measures. We then present the results of the econometric analysis and several sensitivity checks. Based on these regression results, we investigate counterfactual scenarios to illustrate how changes in the supply (and thus accessibility) of GP services affect spatial accessibility and patient mobility.

4.1. *Selection of Distance Function.* In order to specify the distance decay function $f(dist_{lk}) = dist_{lk}^{-\beta}$ for calculating the accessibility measure A_{od}, we have to determine the appropriate parameter β. Ideally, we could draw on patient-level data and model the individual patients' choices of their physicians, similar to Kessler and McClellan (2000) and Gowrisankaran et al. (2018) in modeling patients' hospital choices, and derive the parameter β from these estimates. Lacking these data, we estimate Equation (12) with the spatial accessibility measures A_{od}^{r1} and A_{od}, respectively, as well as regional fixed effects τ_o and μ_d as regressors. We vary the exponential parameters β for the distance decay function $f(dist_{lk})$

[28] In the sensitivity analysis, we use car travel times instead of Euclidean distances. In order to calculate driving times, a local open source routing machine, based on a street network from *Die Geofabrik*, was used. See https://www.geofabrik.de/ and http://project-osrm.org/ for details.

[29] Schmid et al. (2019) provide empirical evidence that time travel costs differ substantially between different transport modes, and Bounie et al. (2019) estimate the travelers' valuations of mobile phone and internet networks when using public transport.

[30] We use aggregated commuter flows instead of commuter shares as a proxy for average amenities M_{od}. Note that the corresponding parameter estimated $\hat{\gamma}_2$ is identical in both variants, due to taking the logarithm of M_{od} in addition to including regional fixed effects.

TABLE 1
SUMMARY STATISTICS

Variable	Mean	Std. Dev.	Min	Max	N
Patient flows (y_{od})	1,608.19	16,978.59	0.00	541,193.00	13,225
Residential population	74,602.51	42,600.17	11,332.00	273,107.00	115
Number of public GPs	35.50	18.06	5.00	114.00	115
Number of private GPs	40.73	39.90	6.00	281.00	115
Spatial accessibility based on 2SFCA method					
Public GPs (A_{od})					
with $f(dist_{lk}) = dist_{lk}^{-5}$	0.31	3.69	0.00	113.97	13,225
with $f(dist_{lk}) = dist_{lk}^{-2.8}$	0.31	3.62	0.00	113.49	13,225
with $f(dist_{lk}) = dist_{lk}^{-0.3}$	0.31	0.91	0.00	34.77	13,225
Public GPs, Restrictive Assumption 1 (A_{od}^{r1})					
with $f(dist_{od}) = dist_{od}^{-5}$	0.31	2.84	0.00	114.00	13,225
with $f(dist_{od}) = dist_{od}^{-2.1}$	0.31	2.04	0.00	112.43	13,225
with $f(dist_{od}) = dist_{od}^{-0.3}$	0.31	0.94	0.00	27.54	13,225
Public GPs normalized (A_{od}^{nrm})					
with $f(dist_{lk}) = dist_{lk}^{-5}$	648.72	7,544.97	0.00	267,704.90	13,225
with $f(dist_{lk}) = dist_{lk}^{-2.8}$	648.72	7,092.97	0.00	258,833.40	13,225
with $f(dist_{lk}) = dist_{lk}^{-0.3}$	648.72	1,903.17	0.00	66,553.40	13,225
Private GPs (A_{od}^{pri})					
with $f(dist_{lk}) = dist_{lk}^{-5}$	0.35	5.27	0.00	280.92	13,225
with $f(dist_{lk}) = dist_{lk}^{-2.8}$	0.35	5.09	0.00	279.64	13,225
with $f(dist_{lk}) = dist_{lk}^{-0.3}$	0.35	1.43	0.00	85.68	13,225
Distance					
Euclidean distance (in km) between					
population-weighted centroids ($dist_{od}$)	172.32	116.20	0.50	551.08	13,225
geographical centroids ($dist_{od}^{geo}$)	172.21	115.62	0.50	548.66	13,225
Driving time by car (in min, tt_{od})	179.23	105.06	0.50	525.51	13,225
Number of commuters (M_{od})	304.42	2,286.39	0.00	94,802.00	13,225

NOTE: In order to obtain a measure for the average distance within each district we randomly draw 10,000 pairs of locations (grid cells) within each district and take the average Euclidean distance between these location pairs. In order to estimate the average travel time within a district, we first perform a linear regression of travel time on the Euclidean distance for all district pairs where $o \neq d$, and then use the results to predict travel times within districts ($o = d$). Variable on commuters includes within-district commuters.

and choose the value providing the best goodness-of-fit. Table A.1 in Appendix A.2.1 reports different indicators regarding the fit of the model, namely, the Akaike information criterion (AIC), the Bayesian information criterion (BIC),[31] and the value of the log-likelihood function, but suppresses the parameter estimates for brevity. With this approach, we follow the guidelines outlined in Cameron and Trivedi (2005, pp. 278 ff.) for discriminating between nonnested models within the likelihood framework.[32] All these indicators suggest calculating the spatial accessibility measures A_{od}^{r1} and A_{od} with a distance decay function of $f(dist_{lk}) = dist_{lk}^{-2.1}$ and $f(dist_{lk}) = dist_{lk}^{-2.8}$, respectively.[33]

[31] $AIC = -2 \cdot LL + h \cdot npar$, where LL indicates the value of the log-likelihood function, $npar$ represents the number of parameters in the model, and $h = 2$. For calculating the BIC, h is set to the logarithm of the number of observations.

[32] Empirical studies using information criteria to select models or variables are manifold, including applications to select the distributional form of the error term in duration models (Diaby et al., 2014), the optimal number of classes in latent class models (Choi and Mokhtarian, 2020), or the optimal number of time-lags in time-series models (Loy et al., 2021).

[33] Alternatively, we could choose different values for the distance decay parameter β (and hence different values for A_{od}) in each model specification to optimize the values for AIC, BIC, and the log-likelihood function. However, this would make it difficult to compare parameter estimates between different models. We therefore stick with a single value for β for each of the accessibility measures A_{od} and A_{od}^{r1}, but show that the regression results are robust to smaller and larger values of the distance decay parameter β. See Table A.2 and Table A.3 in Appendix A.2.2 for details.

TABLE 2
MAIN ANALYSIS—REGRESSION RESULTS

	Model 0	Model 1	Model 2	Model 3
Population-weighted distance, $\log(dist_{od})$	-2.798^{***}			
	(0.353)			
Accessibility of GPs after RA1, $\log(A^{r1}_{od})$		1.307^{***}		
		(0.198)		
Accessibility of GPs, $\log(A_{od})$			0.616^{***}	0.425^{***}
			(0.003)	(0.009)
Number of commuters, $\log(M_{od})$				0.489^{***}
				(0.019)
Constant	18.178^{***}	9.278^{***}	9.849^{***}	6.434^{***}
	(1.281)	(0.696)	(0.024)	(0.145)
Origin fixed effects	Yes	Yes	Yes	Yes
Destination fixed effects	Yes	Yes	Yes	Yes
Number of obs.	13,225	13,225	13,225	13,225
Log-likelihood	−25,995,758	−24,757,597	−780,106	−549,204
BIC	51,993,698	49,517,387	1,562,404	1,100,620
AIC	51,991,975	49,515,656	1,560,674	1,098,874

NOTE: All models estimate inter-regional patient flows by using a Poisson pseudo-maximum-likelihood (PPML) estimator and include origin- (patient-) and destination- (physician-) regional fixed effects. A^{r1}_{od} indicates the spatial accessibility measure under Restrictive Assumption 1 (RA1), that is, when all patients (all physicians) of one region are located in one spot. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

In general, a higher parameter β is associated with a steeper distance decay, implying that proximity becomes more important and that GPs further away contribute less to the spatial accessibility measure.[34] Figure A.2 in Appendix A.2.1 shows the spatial distribution of the accessibility measure at the individual level, $A_{ko} = \sum_d A_{kod}$, for $\beta = 2.8$ and $\beta = 0.3$, illustrating that accessibility is more evenly distributed across space for lower parameter values. If β takes a very high value, the spatial distribution of accessibility levels becomes congruent with the distribution of GP locations in Figure 2. The summary statistics of the dyad-specific accessibility measure A_{od} for different values of β, reported in Table 1, underpin this observation, as the variation of the accessibility measure increases with β.

4.2. *Regression Results.* In our base model (Model 0), which closely follows the standard gravity framework and, hence, applies the Restrictive Assumptions 1 and 2 (see Equations 9 and 10), we only include the distances between population-weighted centroids in addition to origin and destination fixed effects. In the next specification (Model 1), we use the "simple" spatial accessibility measure, A^{r1}_{od}, for public GPs based on Restrictive Assumption 1, that is, when we ignore intraregional heterogeneity (see Equation 8). In Model 2, we relax both restrictions, but assume that the average amenities M_{od} are composed of an origin- and a destination-specific part and are therefore captured by regional fixed effects. Finally, in the main model specification (Model 3), we add inter- and intraregional commuter flows as a proxy for average bilateral amenities M_{od}. Table 2 summarizes the regression results for the four models outlined above, with the spatial accessibility measures based on the distance decay functions selected in Subsection 4.1. All model specifications include directional (origin and destination) regional fixed effects.

Model 0 resembles the standard gravity equation and includes the population-weighted centroid-to-centroid Euclidean distance as the only dyad-specific variable. The estimated parameter is significantly negative, suggesting that a 1% increase in distance is associated

[34] With $\beta = 2.8$, doubling the distance between a patient and a GP location decreases the physician's contribution to the accessibility measure by about 86%.

TABLE 3
SENSITIVITY ANALYSIS—ADDITIONAL CONTROL VARIABLES

	Model 3a	Model 3b	Model 3c
Accessibility of GPs, log (A_{od})	0.425***	0.425***	0.456***
	(0.009)	(0.009)	(0.026)
Number of commuters, log (M_{od})	0.483***	0.489***	0.497***
	(0.018)	(0.020)	(0.020)
Population-weighted distance, log ($dist_{od}$)	−0.023		
	(0.021)		
Accessibility of private GPs, log (A_{od}^{priv})			−0.034
			(0.026)
Constant	6.536***	6.434***	6.407***
	(0.153)	(0.145)	(0.147)
Origin fixed effects	Yes	Yes	Yes
Destination fixed effects	Yes	Yes	Yes
Dummy for same federal state	No	Yes	No
Number of obs.	13,225	13,225	13,225
Log-likelihood	−548,740	−549,197	−546,277
BIC	1,100,614	1,094,783	1,099,700
AIC	1,098,862	1,093,023	1,097,948

NOTE: All models estimate interregional patient flows by using a Poisson pseudo-maximum-likelihood (PPML) estimator and include origin- (patient-) and destination- (physician-) regional fixed effects. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

with 2.80% lower patient flows. Substituting the population-weighted distance with the simple accessibility measure (Model 1) slightly improves the goodness-of-fit (according to BIC, AIC, and the log-likelihood value) and shows that a 1% increase in accessibility is associated with a 1.31% increase in patient mobility. Using an accessibility measure based on the 2SFCA method (Model 2) greatly improves the model's explanatory power according to our goodness-of-fit measures.[35] The elasticity of patient flows with respect to accessibility of public GPs takes a point estimate of 0.62, which is significantly positive at the 0.1% level. In Model 3, when including commuters as a proxy for average amenities between two districts, the coefficient on accessibility of public GPs decreases to 0.43, but is still significantly different from zero. A 1% increase in the number of commuters is associated with 0.49% higher patient flows between districts. The goodness-of-fit measures show that the full model, which is based on the theoretical framework outlined in Section 2, has the highest explanatory power compared to all other presented specifications. We thus find strong empirical evidence in support of Proposition 1, namely, that spatial accessibility is an important determinant of patient mobility.

4.3. *Sensitivity Analysis.* The parameter estimates on the relationship between spatial accessibility and patient mobility are remarkably robust to a number of sensitivity analyses, covering potential limitations of the main empirical specification.

Additional control variables: We first include additional explanatory variables, as reported in Table 3. We test Proposition 2 by adding the population-weighted distance to our preferred specification (i.e., Model 3, reported in Table 2), to see whether this affects the coefficient γ_1 of the main explanatory variable, A_{od}. Including both the accessibility measure and distance in one regression (see Model 3a in Table 3) shows that the parameter estimate on distance, $dist_{od}$, is negligibly small and not significantly different from zero, whereas the estimated co-

[35] As the AIC and BIC are difficult to interpret, we also calculate McFadden's adjusted R^2, which increases from 0.70 in Model 0 to 0.99 in Model 3. However, as for nonlinear models the interpretation of such pseudo-R^2s is disputed (see Cameron and Trivedi, 2005, for a discussion), these figures must be interpreted cautiously.

efficient of A_{od} is virtually unaffected. Compared to Model 0, the point estimate of $dist_{od}$ declines (in absolute values) from −2.80 to −0.02 and thus by more than 99%. As suggested by our theoretical model and the resulting Proposition 2, the mere distance between districts does neither significantly nor substantially contribute to explaining patient mobility, once we include our measure of spatial accessibility (based on rich information on the locations of patients and physicians).

To account for other potential covariates, we add a dummy variable that equals one if the patient's district and the physician's district are in the same state, and zero otherwise (Model 3b). Even though the borders of the nine federal states in Austria do not restrict patients in their choice of physicians, they might impose other barriers (e.g., public transport providers differ between states). Furthermore, the Austrian outpatient sector is not limited to public GPs, but also includes those who do not have a contract with one of the public health insurance funds, so-called private GPs (*"Wahlärzte"*). Patients might prefer a private GP over a public one either to reduce waiting time, receive increased consultation length, or because private physicians also practice at the local hospital and refer to their outpatient office following an inpatient treatment. To account for a potential substitution effect between public and private physicians, we add the same accessibility measure based on the 2SFCA method for private physicians (Model 3c). The parameter estimates on the accessibility of public GPs, A_{od}, and on commuters, M_{od}, are hardly affected by including additional explanatory variables and only change by a small and statistically insignificant amount. As expected, the accessibility of private GPs, A_{od}^{priv}, is negatively associated with patient flows in the public sector, although the coefficient is not significantly different from zero.

Accounting for differences in demand: In the main analysis, we only consider the patients' places of residence (relative to a GP's location) when calculating the service provision level R_l in Equation (1) as an (inverse) indicator of congestion. However, the need for health-care services varies substantially between different sociodemographic groups of patients. Utilization rates for sex–age cohorts (as indicators for different demand levels), reported in Table A.4 in Appendix A.2.3, show that the average number of consultations ranges from 2.3 (for girls below 10 years) up to 30.5 (for females aged 90 or older), suggesting that different age cohorts contribute to the congestion of GPs to very different degrees.[36]

To account for differences in demand, we weight all patients based on the average number of consultations of the respective sex–age cohort (in addition to the patients' distance to the respective GP) when calculating the service provision level R_l. We use data available at the grid-cell level that contain information on the age distribution (for both males and females) of the residential population in 10-year intervals.[37] The weights are based on utilization rates at the national level and are thus independent of local accessibility. The corresponding accessibility measure A_{od}^{weight} is much smaller (and averages only 0.04 compared to 0.31), because patients consult public physicians about eight times per year on average. However, the correlation coefficient between the unweighted and the weighted accessibility measure, A_{od} and A_{od}^{weight}, is as high as 0.9986. Although the distribution of potential patients across space is very uneven, making the accessibility measure A_{od} superior to the mere distance between the regions' centroids, the demographic composition of the population is rather homogeneous. Thus, accounting for the sex–age composition of the population does not substantially im-

[36] These weights are based on the number of consultations in 2017, because data on health-care utilization disaggregated by sex–age cohorts for 2016 are unavailable to us.

[37] We utilize a slightly different data source to calculate the service provision level R_l based on sex–age cohort-specific weights. While the main analysis is based on the population census from January 1, 2015, this sensitivity analysis uses data from the labor market statistics from October 31, 2014. Both data sets are register-based data and are collected by Statistics Austria, but the labor market statistics reports the age distribution of the population in a more disaggregated way, which is important for this sensitivity analysis. If the number of inhabitants in one grid cell is three or less, demographic information is not reported due to privacy concerns. This information is thus unavailable for about 1% of the population. For these individuals, the weights are based on the average number of GP consultations of the entire population.

TABLE 4

SENSITIVITY ANALYSIS—PATIENTS WEIGHTED BY UTILIZATION RATES

	Model 2a	Model 3d	Model 3e	Model 3f
Accessibility of GPs, log (A_{od}^{weight})	0.617***	0.422***	0.422***	0.434***
	(0.003)	(0.009)	(0.008)	(0.024)
Number of commuters, log (M_{od})		0.496***	0.491***	0.503***
		(0.019)	(0.018)	(0.020)
Population-weighted distance, log ($dist_{od}$)			−0.023	
			(0.021)	
Accessibility of private GPs, log (A_{od}^{priv})				−0.014
				(0.025)
Constant	11.160***	7.278***	7.381***	7.239***
	(0.024)	(0.160)	(0.166)	(0.161)
Origin fixed effects	Yes	Yes	Yes	Yes
Destination fixed effects	Yes	Yes	Yes	Yes
Number of obs.	13,225	13,225	13,225	13,225
Log-likelihood	−810,447	−548,837	−548,361	−548,405
BIC	1,623,087	1,099,886	1,098,943	1,099,041
AIC	1,621,357	1,098,141	1,097,190	1,097,281

NOTE: All models estimate interregional patient flows by using a Poisson pseudo-maximum-likelihood (PPML) estimator and include origin- (patient-) and destination- (physician-) regional fixed effects. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. The accessibility measure A_{od}^{weight} is based on a service provision level with patients weighted by the average number of GP consultations of the patients' sex–age cohort in 2017. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

prove the model, despite the large differences in utilization between young and old residents. Consequently, using the weighted accessibility measure A_{od}^{weight}, as reported in Table 4, gives virtually identical results compared to using the unweighted index A_{od}.[38]

Identifying first contacts: So far, we have investigated patient mobility based on initial contacts, which we identify as a patient's first consultation of a public physician within a given quarter of the year. However, episodes of care do not end at the end of a quarter, and follow-up visits within one care episode might be (misleadingly) considered as a first contact by this approach. As we do not observe individual care episodes to identify first contacts more precisely, we have to rely on first visits within a quarter as a proxy for (unobserved) initial contacts. In order to show that our results are not driven by this (potentially imprecise) identification of first contacts, we investigate patient mobility based on all 63,080,600 consultations of public GPs in Austria in 2016 (compared to 21 million first visits within a quarter). The results, provided in Table 5, show that the main findings are robust to this modification. The point estimates on spatial accessibility A_{od} are slightly larger, but not significantly different from the corresponding parameter estimates based on only first contacts (within the quarter), reported in Tables 2 and 3. Further, the main conclusion that our proposed model is superior to the standard gravity model in predicting patient flows remains valid.

Travel time to proxy travel costs: In the empirical literature on commuting behavior, it is well-established that travel costs are better proxied by travel time than by (Euclidean or travel) distance (see, e.g., Glaeser and Kahn, 2004).[39] Ideally, we could draw on travel times instead of Euclidean distances between grid cells to construct our accessibility measure A_{od}. This approach is impeded by the large number of grid cells (roughly 1.3 million in Austria),

[38] Note that the respective parameter estimates of this sensitivity analysis are directly comparable to the coefficients reported in Tables 2 and 3, despite the smaller values of A_{od}^{weight}, because the accessibility measures are included in logarithmic form in all models.

[39] Van Ommeren and Dargay (2006) estimate that the ratio between pecuniary and time travel costs is as low as 0.14. This result suggests that travel time is a very good proxy of overall travel costs. When investigating the city structure of Berlin, Ahlfeldt et al. (2015) also use travel times between city blocks as indicators of commuting costs.

TABLE 5
SENSITIVITY ANALYSIS—PATIENT MOBILITY BASED ON ALL GP CONSULTATIONS

	Model 0a	Model 1a	Model 2b	Model 3g	Model 3h
Pop.-weighted distance, $\log(dist_{od})$	−2.877 ***				−0.027
	(0.389)				(0.020)
Accessibility of GPs after RA1, $\log(A^{r1}_{od})$		1.342 ***			
		(0.215)			
Accessibility of GPs, $\log(A_{od})$			0.635 ***	0.441 ***	0.441 ***
			(0.003)	(0.009)	(0.009)
Number of commuters, $\log(M_{od})$				0.497 ***	0.490 ***
				(0.020)	(0.019)
Constant	19.430 ***	10.283 ***	10.849 ***	7.373 ***	7.497 ***
	(1.379)	(0.708)	(0.024)	(0.152)	(0.163)
Origin fixed effects	Yes	Yes	Yes	Yes	Yes
Destination fixed effects	Yes	Yes	Yes	Yes	Yes
Number of obs.	13,225	13,225	13,225	13,225	13,225
Log-likelihood	−79,573,737	−75,508,968	−2,018,316	−1,422,017	−1,420,327
BIC	159,149,656	151,020,128	4,038,824	2,846,245	2,842,875
AIC	159,147,934	151,018,398	4,037,094	2,844,500	2,841,122

NOTE: All models estimate inter-regional patient flows (all consultations rather the first contacts) by using a Poisson pseudo-maximum-likelihood (PPML) estimator and include origin- (patient-) and destination- (physician-) regional fixed effects. A^{r1}_{od} indicates the spatial accessibility measure under Restrictive Assumption 1 (RA1), that is, when all patients (all physicians) of one region are located in one spot. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

and the extremely time-consuming calculation of travel times between all of them. Furthermore, the empirical literature based on data from the United Kingdom suggests that Euclidean distance, driving time, and driving distance to emergency departments are highly correlated, and that straight-line distance as a proxy for perceived accessibility and reported driving time to hospitals is as good as GIS-based unimpeded travel time (Fone et al., 2006; Haynes et al., 2006). Although in our sample, the correlation between the population-weighted Euclidean distance and the driving time by car between the regions is as high as 0.96, we investigate the sensitivity of our results when using travel time tt_{od} instead of the Euclidean distance $dist_{od}$.

The corresponding results are reported in Table 6. Including travel time as the only explanatory variable in addition to regional fixed effects (Model 0b) shows that the association of travel time with patient mobility is significantly negative, with a point estimate of −3.32. Using travel time instead of Euclidean distance between population-weighted centroids (see Model 0 in Table 2) increases the model's fit, suggesting that in our case travel time is indeed a better proxy for travel costs than distance. When we include the driving time instead of distance in addition to spatial accessibility A_{od} and the number of commuters M_{od}, as summarized in Model 3i in Table 6, the estimated coefficient of travel time remains significantly negative. Although distance—consistent with the predictions of our theoretical model, summarized in Proposition 2—does not contribute to explaining patient mobility once we include our measure of spatial accessibility A_{od}, considering driving time between district centroids adds some explanatory power. However, the parameter estimate on spatial accessibility, A_{od}, is again significantly positive, the point estimate decreases slightly from 0.43 (when we include distance instead of travel time, see Model 3a in Table 3) to 0.33, whereas the point estimate on travel time declines substantially (in absolute terms) from −3.32 to −0.44.

Alternatives to account for multilateral resistance: The starting point of our empirical analysis was the gravity-type equation (7) for the probability of a patient consulting a physician in a particular district, $\lambda_{kod} = M_{od}A^{\epsilon}_{kod}/\sum_s M_{os}A^{\epsilon}_{kos}$. Although the denominator can be captured by individual fixed effects after a logarithmic transforma-

TABLE 6
SENSITIVITY ANALYSIS—TRAVEL TIME TO PROXY TRAVEL COSTS

	Model 0b	Model 3i
Travel time by car in minutes, log (tt_{od})	−3.319***	−0.436***
	(0.040)	(0.023)
Accessibility of GPs, log (A_{od})		0.331***
		(0.009)
Number of commuters, log (M_{od})		0.509***
		(0.016)
Constant	19.932***	7.645***
	(0.257)	(0.125)
Origin fixed effects	Yes	Yes
Destination fixed effects	Yes	Yes
Number of obs.	13,225	13,225
Log-likelihood	−4,525,502	−456,483
BIC	9,053,186	915,187
AIC	9,051,464	913,434

NOTE: All models estimate interregional patient flows by using a Poisson pseudo-maximum-likelihood (PPML) estimator and include origin- (patient-) and destination- (physician-) regional fixed effects. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

tion, the multilateral resistance term is not precisely (but only approximately) accounted for by regional fixed effects when we aggregate individual probabilities at a regional level. In general, $\log[E(y_{od})] = \log(\sum_k \lambda_{kod}) = \log[\sum_k (M_{od}A^{\epsilon}_{kod}/\sum_s M_{os}A_{kos})] \neq \log(M_{od}) + \log(A_{od}) - \log(\sum_s M_{os}A^{\epsilon}_{os})$, with $A_{od} = \sum_k A^{\epsilon}_{kod}$, because the denominator is patient-specific and depends on the exact location of patient k within region o. We address this issue in two ways: First, we account for multilateral resistance at an individual level and normalize the individual spatial accessibility $A^{nrm}_{kod} = A_{kod}/\sum_d A_{kod}$, such that $\sum_d A^{nrm}_{kod} = 1$ for all patients, resulting in bilateral accessibility levels $A^{nrm}_{od} = \sum_k A^{nrm}_{kod}$ (see Model 3j reported in Table 7). Second, we calculate the multilateral resistance $mlr_o = \sum_s \sum_k M_{os}A_{kos}$, and include this term as an additional explanatory variable.

As the multilateral resistance term is origin specific, we exclude regional fixed effects at this level, but include the population size of the patient's region instead. We neglect destination fixed effects in one specification (Model 3k), but take these dummy variables into account in an alternative variant (Model 3l), as reported in Table 7. The parameter estimate of the normalized measure of spatial accessibility A^{nrm}_{od} is significantly positive, and the point estimate of 0.46 is similar to the one of the nonnormalized accessibility measure A_{od} in Model 3, reported in Table 2. If we include a variable for the multilateral resistance term instead of regional fixed effects, the explanatory power of the model declines somewhat, but the parameter estimates of our measure of spatial accessibility A_{od} remains virtually unaffected, irrespective of excluding (Model 3k) or including destination fixed effects (Model 3l). The parameter estimates of the multilateral resistance term are significantly negative in both model specifications, indicating that patient flows to one region decrease with the spatial accessibility and average amenities of other regions.

Alternative distance decay for private GPs: Finally, we use alternative distance decay functions to calculate the accessibility measure for private GPs, A^{priv}_{od}, and apply different βs for the inverse power function $f(dist_{lk}) = dist^{-\beta}_{lk}$. We do so because we did not endogenously determine the optimal β for the calculation of A^{priv}_{od}, as we did for A_{od} in Subsection 4.1. As reported in Models 3m to 3p in Table 8, the estimated coefficients for the spatial accessibility to public GPs, A_{od}, remain significantly positive and vary only slightly.

TABLE 7
SENSITIVITY ANALYSIS—ALTERNATIVES TO ACCOUNT FOR MULTILATERAL RESISTANCE

	Model 3j	Model 3k	Model 3l
Accessibility of GPs, $\log(A_{od})$		0.464***	0.446***
		(0.024)	(0.009)
Accessibility of GPs (normalized), $\log(A_{od}^{nrm})$	0.460***		
	(0.009)		
Number of commuters, $\log(M_{od})$	0.768***	0.373***	0.424***
	(0.014)	(0.050)	(0.018)
Multilateral resistance term, $\log(mlr_o)$		−0.163***	−0.087**
		(0.019)	(0.027)
Population (in logs)		0.528***	0.365***
		(0.045)	(0.055)
Constant	0.503***	1.502**	3.120***
	(0.073)	(0.483)	(0.491)
Origin fixed effects	Yes	No	No
Destination fixed effects	Yes	No	Yes
Number of obs.	13,225	13,225	13,225
Log-likelihood	−586,600	−1,024,787	−642,870
BIC	1,175,410	2,049,640	1,286,888
AIC	1,173,665	2,049,587	1,285,982

NOTE: All models estimate inter-regional patient flows by using a Poisson pseudo-maximum-likelihood (PPML) estimator. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

TABLE 8
SENSITIVITY ANALYSIS—ALTERNATIVE DISTANCE DECAY FOR PRIVATE GPS

	Model 3m $\beta = 0.5$	Model 3n $\beta = 1.0$	Model 3o $\beta = 1.5$	Model 3p $\beta = 2.0$
Accessibility of GPs, $\log(A_{od})$	0.447***	0.461***	0.475***	0.471***
	(0.009)	(0.013)	(0.019)	(0.025)
Accessibility of private GPs, $\log(A_{od}^{priv})$	−0.213***	−0.155***	−0.127***	−0.079*
	(0.020)	(0.031)	(0.038)	(0.038)
Number of commuters, $\log(M_{od})$	0.494***	0.496***	0.500***	0.500***
	(0.020)	(0.020)	(0.019)	(0.019)
Constant	6.536***	6.618***	6.624***	6.513***
	(0.148)	(0.160)	(0.172)	(0.162)
Origin fixed effects	Yes	Yes	Yes	Yes
Destination fixed effects	Yes	Yes	Yes	Yes
Number of obs.	13,225	13,225	13,225	13,225
Log-likelihood	−536,988	−542,289	−543,914	−545,442
BIC	1,076,206	1,086,808	1,090,058	1,093,114
AIC	1,074,446	1,085,048	1,088,298	1,091,354

NOTE: All models estimate interregional patient flows by using a Poisson pseudo-maximum-likelihood (PPML) estimator and include origin- (patient-) and destination- (physician-) regional fixed effects. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Using a less pronounced distance decay function (i.e., a smaller β) to calculate A_{od}^{priv} results in significantly negative parameter estimates for this variable, indicating that private and public GPs can be considered as substitutes. Furthermore, the point estimates for A_{od}^{priv} are larger (in absolute terms) for smaller values of β. This, together with the improved goodness-of-fit statistics, suggests that the ideal β for calculating private GPs' accessibility is smaller than that for calculating public GPs' accessibility, indicating that proximity is relatively less important when choosing a private health-care provider. This seems plausible, as consulting a private physician—contrary to a public one—usually requires out-of-pocket payments, likely leading to a differentiation of physicians in quality (especially in terms of time spent with the patient) and pricing.

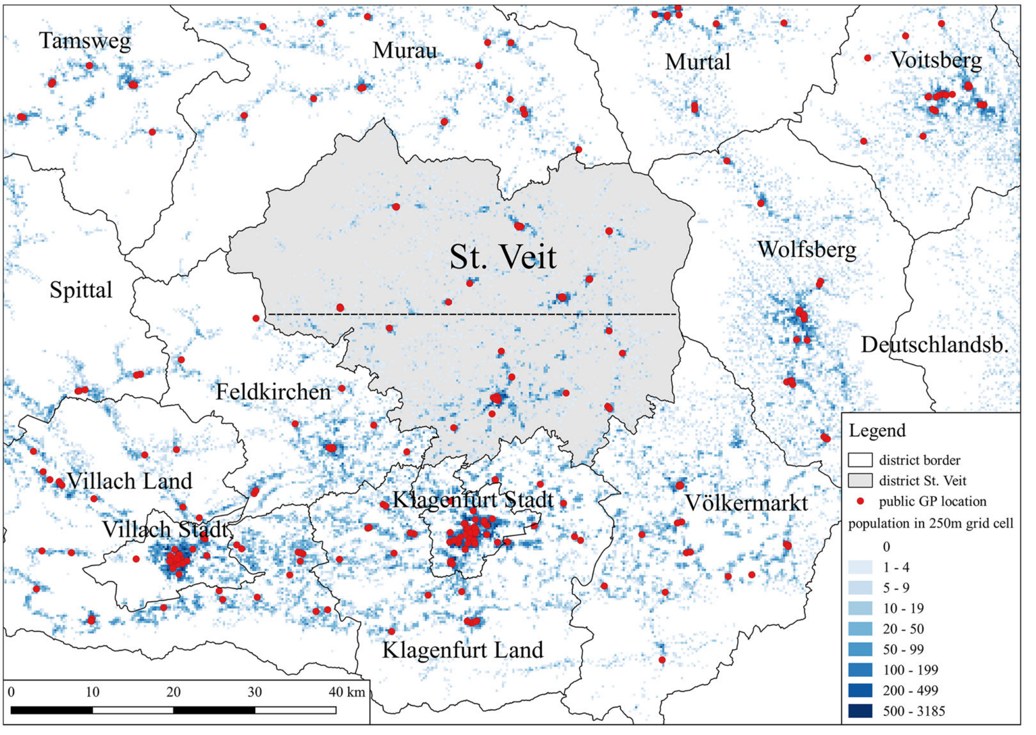
4.4. *Simulation of Counterfactual Scenarios.* Based on the regression results, we can predict the effects of supply-side shocks, such as the exit, entry, or relocation of public GPs on spatial accessibility and thus on welfare. Changes in spatial accessibility affect patients' choices about which physician to consult, and thus inter-regional patient mobility. To illustrate this, we conduct two sets of simulation experiments: First, we focus on one district and evaluate the impact of several physicians relocating or leaving the market, and second, we evaluate the effect of the exit of GPs who are already past the statutory retirement age. The first simulation exercise serves as an illustration of the predictive properties of our model, whereas the second highlights how our model can support evidence-based policymaking.

4.4.1. *Simulation for illustration of model properties.* In the first simulation exercise, we focus on the district St. Veit, indicated by gray shading in Figure 2, because this is a typical rural region with difficulties of attracting outpatient GPs: The district has about 55,000 inhabitants and lacks an urban agglomeration, its population has declined over the last decades, and the share of the elderly is high. Furthermore, the spatial distribution of the population within the region and the transport connections to neighboring districts are quite heterogeneous, at least partly due to topographical reasons. The district hosts 32 GPs and less than 10% of the population consults a physician outside their region of residence. St. Veit has strong economic ties with neighboring regions in the south-west: 18% of the employed residents of St. Veit commute to the federal state's capital Klagenfurt, and about 2.6% to Klagenfurt Land as well as Feldkirchen. The shares of commuters to the other districts bordering St. Veit are much lower (between 0.2% and 1.1%), whereas 65% work in their own district.

In four counterfactual scenarios, we investigate the effects of supply-side shocks in this district on spatial accessibility and thus on patient mobility. Specifically, we simulate changes in patient flows (i) if the 16 GPs of the northern part of this region leave the market (scenario 1), (ii) if the 16 GPs of the southern part leave the market (scenario 2), (iii) if 16 randomly selected GPs leave the market (scenario 3), or (iv) if the number of GPs remains unaffected, but 16 randomly selected GP locations are dissolved, whereas the remaining 16 locations host two GPs (scenario 4). The district of St. Veit, its neighboring regions, the GP locations, and the spatial distribution of the population are illustrated in Figure 3.

The change in the number or locations of physicians influences the accessibility measure A_{kod} to physicians in St. Veit and thus the patients' accessibility levels $A_{ko} = \sum_d A_{kod}$. The impact on accessibility at the patient level is displayed in Figure 4 for these four scenarios. The effect on spatial accessibility is higher the closer patients are located to physicians leaving the market and diminishes with distance, but is not confined by regional borders.[40] Note that the way these supply-side shocks affect accessibility across space is directed by the distance decay function $f(dist_{lk}) = dist_{lk}^{-\beta}$, determined endogenously by the data. Following Equation (3), a change in spatial accessibility leads to a proportional change of a patient's utility, and can thus be interpreted as the welfare effect due to variations in the service provision level of primary health care. Intuitively, there are two reasons for a decline in welfare if physicians leave the market: First, patients have to travel further on average to consult a GP. Second, the remaining physicians in the vicinity are more congested and service quality declines. Although the number of first contacts with a GP is not affected due to the construction of the model (since it is assumed that each patient chooses the physician with the highest utility), it should be

[40] Whereas Figure 4 reports the relative change in accessibility, Table A.5 in Appendix A.2.4 summarizes the average change in accessibility at the regional level, indicating large differences in the average effects for the different scenarios under scrutiny (for residents of both St. Veit and its neighboring regions).



NOTES: Map section displays the distribution of the population and all public GP locations in and close to the district of St. Veit. The dashed line separates the 16 northern from the 16 southern GPs of St. Veit. In four simulation experiments, we evaluate the effects on patient mobility if the 16 northern GPs leave the market (scenario 1), if the 16 southern GPs leave the market (scenario 2), if 16 randomly selected GPs leave the market (scenario 3), or if the number of GPs remains unaffected, but 16 randomly selected GP locations are dissolved, whereas the remaining 16 locations host two GPs (scenario 4).

FIGURE 3

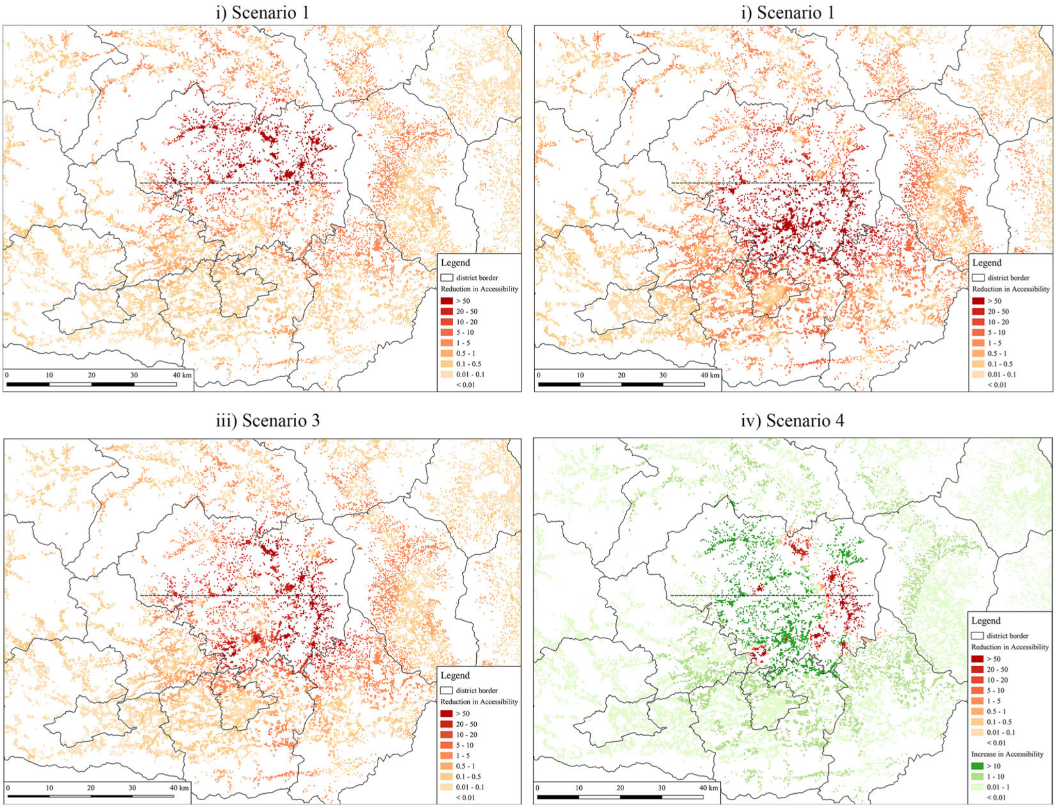
BASELINE FOR SIMULATION EXPERIMENTS

noted that "more heavily congested" physicians may well lead to a smaller number of consultations due to fewer follow-up visits.

The changes in accessibility affect the patients' choices of their GPs and therefore patient mobility. This is of high policy relevance, because replacing physicians who are retiring may be particularly difficult in some parts of a region (in our application: in the thinly populated northern area of the district). As a baseline scenario, we calculate the expected probability of each individual to consult a GP in a particular district, based on the gravity-type equation for patient flows (7) and on the parameter estimates of Model 3, reported in Table 2:

$$\hat{\lambda}_{kod} = \frac{M_{od}^{\hat{\gamma}_2} A_{kd}^{\hat{\gamma}_1}}{\sum_s M_{os}^{\hat{\gamma}_2} A_{ks}^{\hat{\gamma}_1}}. \tag{13}$$

Aggregating the probabilities of individual patients at the district–pair level results in estimated patient flows, serving as a benchmark for comparison with our counterfactual scenarios. The change in the number or locations of physicians affects the accessibility measure A_{kod} to physicians in St. Veit and thus patient flows from other districts to St. Veit. It also influences outward-bound patient mobility via the multilateral resistance term, because physicians in St. Veit will be more "congested" and consulting physicians in other districts becomes relatively more attractive. Although we focus on the effects of these four counterfactual scenarios on patient flows from and to St. Veit to keep the discussion concise, we are aware that patient



NOTES: Figures illustrate changes in spatial accessibility at the individual level, $A_{ko} = \sum_d A_{kod}$, relative to the baseline scenario (in %), if the 16 northern GPs leave the market (scenario 1), if the 16 southern GPs leave the market (scenario 2), if 16 randomly selected GPs leave the market (scenario 3), and if the number of GPs remains unaffected, but 16 randomly selected GP locations are dissolved, whereas the remaining 16 locations host two GPs (scenario 4).

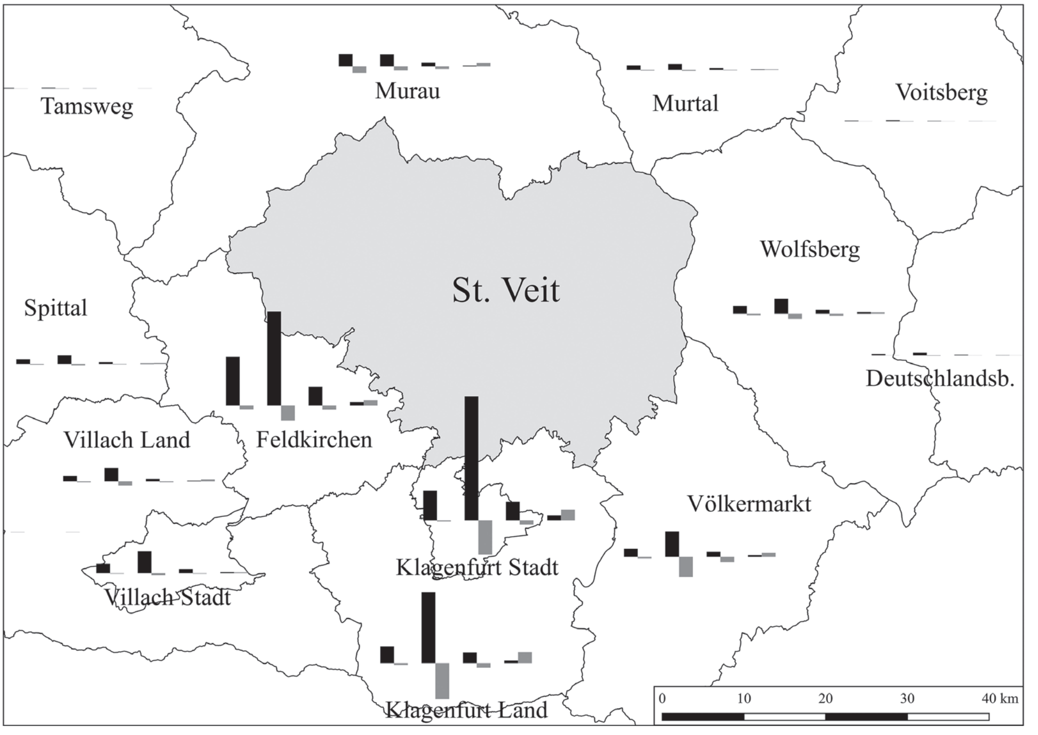
FIGURE 4

RESULTS OF SIMULATION EXPERIMENTS—EXPECTED CHANGE IN AGGREGATE ACCESSIBILITY

mobility between region–pairs other than St. Veit are also influenced due to changes in the multilateral resistance term. These general equilibrium adjustments are reported in patient flow matrices (see Tables A.6 to A.9 in Appendix A.2.4).

The expected effects of these four scenarios on patient flows from and to St. Veit are illustrated in Figure 5 and shown in the table below the map. If 16 physicians in the north of the district leave the market, nearly 6,000 additional residents of St. Veit see a GP in a region outside their district of residence (scenario 1). The share of inhabitants of St. Veit consulting GPs outside their district of residence thus increases by nearly 11 percentage points (pp). Patient inflows are expected to decline, but by a much smaller amount in absolute terms (by about 800 patients). If the 16 physicians in the south leave the market (scenario 2), the effects are generally much larger: 15,000 (27 pp) additional residents of St. Veit switch to GPs located in other districts, mostly to the districts in the south-west. Patient inflows decline substantially by 4,600, mostly attributable to the south-western neighbors. Most of the patients from other regions, who do not choose a physician in St. Veit anymore due to large-scale market exits, pick a GP in their district of residence in both counterfacutal scenarios (between 60% and 88%; see Tables A.6 and A.7 in Appendix A.2.4 for details).

Some aspects of these results are worth highlighting: First, the effects of scenario 2 are much larger compared to scenario 1. Second, the implications of market exits of GPs in the south on patient mobility are heavily concentrated to the south-western regions, which are



	Change in patient flows St. Veit $\Longrightarrow$ other districts				Change in patient flows other districts $\Longrightarrow$ St. Veit			
Scenario	1	2	3	4	1	2	3	4
Klagenfurt Stadt	1,078	4,499	676	182	−44	−1,240	−150	387
Feldkirchen	1,767	3,411	677	123	−142	−551	−146	192
Klagenfurt Land	610	2,578	389	103	−65	−1,293	−167	402
Villach Stadt	349	797	154	40	−18	−69	−16	32
Wolfsberg	280	548	145	58	−59	−188	−77	49
Murau	453	442	132	30	−242	−141	−93	120
Villach Land	195	480	90	23	−41	−155	−36	71
Vökermarkt	296	918	183	65	−62	−734	−195	143
Spittal	172	315	66	15	−31	−54	−18	30
Murtal	162	215	60	19	−28	−36	−17	20
Deutschlandsberg	48	92	22	8	−5	−17	−5	6
Voitsberg	23	38	10	3	−5	−12	−5	5
Tamsweg	16	25	6	1	−6	−8	−3	5
other districts	410	623	166	55	−58	−109	−41	47
$\sum$	5,860	14,982	2,774	727	−806	−4,609	−969	1,510
Δ share (in pp)$^{a)}$	10.6	27.1	5.0	1.3	−1.5	−8.3	−1.8	2.7

NOTES: Map section displays the simulation results of market exits of GPs in the district of St. Veit (shaded gray) on patient mobility. Black bars indicate the change in the number of patients from St. Veit to the respective district, whereas gray bars indicate the change in the number of patients from the respective district to St. Veit. Expected effects on patient mobility between other district pairs are not displayed. The first pair of bars indicates the expected effect on patient mobility if the 16 northern GPs leave the market (scenario 1), the second pair illustrates the impact if the 16 southern GPs leave the market (scenario 2), the third pair depicts the consequences if 16 randomly selected GPs leave the market (scenario 3), and the fourth pair displays the influence if the number of GPs remains unaffected, but 16 randomly selected GP locations are dissolved, whereas the remaining 16 locations host two GPs (scenario 4). The corresponding figures are provided in the table below the figure. Figures in $^{a)}$ denote the expected change in patient mobility over the total population in St. Veit in percentage points (pp).

FIGURE 5

RESULTS OF SIMULATION EXPERIMENTS—EXPECTED CHANGE IN PATIENT MOBILITY also more strongly affected than the neighboring districts in the north-east if the physicians in the north leave the market (scenario 1). The substantial differences between these two scenarios are mainly due to intraregional heterogeneity: If the southern GPs leave the market, the inhabitants affected most strongly (i.e., patients living close to these physicians) are mainly located in the very south of the St. Veit district. For these patients, physicians in the densely populated regions in the south-west are good substitutes, and many of them are expected to choose a doctor there. Additionally, the strong economic ties between these two regions (indicated by a large number of commuters) make them even more attractive. In scenario 1 (when the northern GPs leave the market), many of the most strongly affected patients are located close to the geographical centroid of the region. In this case, physicians in the southern part of their district of residence or even in the bordering regions in the south-west (due to strong economic ties) are often better alternatives than GPs in the thinly populated region bordering St. Veit in the north.

If the physicians leaving the market are randomly selected (scenario 3), the effects on patient mobility are much smaller: Patient flows from St. Veit to other districts increase by only 2,800 (5 pp), and inflows from other districts decline by less than 1,000 patients. Although the utility of patients declines due to a lower quality of the medical service (because the GPs are more "congested," see Figure 4), proximity seems to outweigh this reduction in service quality for most patients. If the number of GP locations declines while the number of physicians remains unaffected (scenario 4), patient outflows increase marginally by about 700 people. As the GPs are less congested, patient inflows increase slightly.

The counterfactual scenarios in this section illustrate that the pure number (or the share) of physicians leaving the market is a poor proxy to evaluate the effects on (aggregated) patient mobility, and to determine which other regions are also influenced by this supply-side shock. In the scenarios investigated, the number of patients choosing a doctor in a district where half of the physicians exit the market may decline by a total of 19,600 (scenario 2) or by merely 3,700 (scenario 3), depending on the exact locations of these physicians, the spatial distribution of the population, and the attractiveness of GPs in neighboring regions as viable alternatives.

Note that we would not be able to investigate these counterfactual scenarios in a standard gravity model when relying on cross-sectional data only, because regional fixed effects would absorb the impact of the (region-specific) number of GPs. Excluding regional fixed effects or utilizing panel data would enable us to estimate the relationship between patient mobility and the number of physicians, and thus to predict the effects of GPs leaving the market on patient flows. However, even in this case information on intraregional heterogeneity is not accounted for, and differentiating between scenarios 1, 2, and 3 (where only the exact locations of the exiting GPs within a region differ) would not be possible. The counterfactual scenarios presented here highlight that this intraregional heterogeneity is of key importance to explain patient mobility.

4.4.2. *Simulation of the retirement and replacement of public GPs.* In the second set of simulations, we focus on scenarios with high policy relevance and evaluate the market exit (without replacement) of public GPs who are 65 years or older, that is, who have already reached the statutory retirement age. In 2017, this was the case for 307 physicians, or about 7.5% of all public outpatient GPs in Austria.[41] Because the policy goal of equal accessibility to critical health-care infrastructure is especially challenged in rural areas, we distinguish between urban and rural regions and focus on patients with poor accessibility to public GPs. In particular, we simulate what share of patients will end up with low accessibility if all public GPs over

[41] Demographic information on outpatient GPs is available at the municipal level and not at the individual level for data protection reasons. The age distribution of physicians in a municipality is therefore randomly assigned to these physicians. Nevertheless, the data are relatively accurate because the municipalities are mostly small regional units with an average of 4,000 inhabitants and 40 km^2.

TABLE 9

RESULTS OF SIMULATION EXPERIMENTS—EXPECTED CHANGE IN POPULATION WITH LOW ACCESSIBILITY

	Population (Total)	Public GPs ≥ 65 (Total)	(Share)	(Share)	Population with Low Accessibility Δ Share Based on Scenarios			
					1	2	3	4
Urban	2,224,732	113	12.90	1.95	+0.24	+0.00	+0.17	+0.09
Intermediate	2,636,821	81	6.25	1.69	+0.36	+0.11	+0.02	−0.05
Rural	3,717,736	113	5.92	20.71	+2.77	+2.60	+0.02	−0.90
Total	8,579,289	307	7.52	10.00	+1.37	+1.16	+0.06	−0.38

NOTE: All shares are in percentages, and all changes in shares are in percentage points. We define that patients have poor accessibility to public physicians if they fall below the first decile of the spatial accessibility measure A_{ko} for the current number and spatial distribution of public physicians. In all four scenarios, all public GPs aged 65 or older leave the market. In scenario 1, none of these GPs are replaced by new physicians. In scenario 2 (scenario 3), only exiting GPs in rural (urban) regions are not replaced. In scenario 4, exiting GPs in urban regions are not replaced, exiting GPs in intermediate regions are replaced by one physician, and exiting GPs in rural regions are replaced by two physicians (at the location of the exiting GPs).

65 years retire and (i) are not replaced by new practitioners in any region (scenario 1), (ii) are not replaced in rural regions (scenario 2), (iii) are not replaced in urban regions (scenario 3), and (iv) are replaced by two physicians, but only in rural regions (scenario 4). The first two scenarios represent a laissez faire approach of the government, where either no new physicians can be hired for the unfilled positions or the few physicians entering the market prefer to practice in urban areas, leaving the rural positions unfilled. The last two scenarios, on the other hand, reflect what would happen if the government took a more active role in recruiting GPs for unfilled positions in the countryside, or even incentivizing group practices after the retirement of a rural GP.[42]

For our simulations, we categorize regions as urban if the population density of the municipality is above 2,000 residents per km^2, and as rural if the population density is below 190.[43] All other regions are classified as "intermediate" (i.e., neither urban nor rural). Further, we consider patients as having relatively low accessibility to public GPs if they fall within the first (i.e., the lowest) decile of our spatial accessibility measure A_{ko} based on the initial number and spatial distribution of public physicians. Of the 307 GPs aged 65 years or older, 113 are in urban areas and 113 are in rural regions, as indicated in Table 9. Although the shares of residents from urban or intermediate regions with low accessibility are less than 2%, more than 20% of all residents of rural areas face relatively poor spatial accessibility. This sharp difference is not necessarily due to a different ratio of physicians to patients in rural and urban regions, but rather due to the importance of spatial proximity to the physician, which is more difficult to ensure in regions with low population density.

In the first scenario of these simulation experiments, all GPs aged 65 and older retire (i.e., exit the market) and are not replaced by a new physician. As a result, the share of patients with low levels of spatial accessibility increases by 1.37 pp from 10% to 11.37% (see Table 9). The increase is largest in rural regions (+2.77 pp), whereas we expect a smaller increase in urban (+0.24 pp) and intermediate areas (+0.36 pp). When only physicians in rural (scenario 2) or urban regions (scenario 3) retire without a successor, the corresponding region type is the most affected. However, the exit without replacement of rural GPs increases the share of patients with low spatial accessibility by 2.60 pp in those areas, whereas the impact of the exit of physicians in urban regions on the respective population is much smaller (+0.17 pp). The to-

[42] National policies to increase service provision in rural areas include subsidizing parts of the initial investments and costs associated with taking over a practice (as implemented by some provinces in Austria), allowing physicians to employ other physicians to improve work–life balance of rural physicians (as implemented in Austria in 2019) or differentiating tariffs between urban and rural physicians.

[43] We set the threshold density to 190 to ensure that the number of public GPs aged 65 or older is the same for rural and urban regions. This is important for simulating scenario 4, as described below.

tal increase in low accessibility is also higher in scenario 2 (+1.16 pp) compared to scenario 3 (+0.06 pp). In the final simulation experiment (scenario 4 in Table 9), all 113 public GPs in urban regions who are at least 65 years old retire and are not replaced, whereas in rural areas all retired GPs are replaced and an additional 113 GPs enter the market, holding the total number of GPs (aggregated across all regions) constant. For simplicity, we assume that they enter in the same location as the retiring physicians in rural areas. As a result, the share of patients in urban areas with poor spatial accessibility is expected to increase by 0.09 pp, whereas this share decreases by 0.90 pp for patients in rural areas. It should be noted that the total share of patients with poor accessibility (−0.38 pp) could be further reduced if the locations of the new rural GPs are chosen more carefully.

Our simulations predict that a "do-nothing" policy approach adversely affects rural areas, where the share of the population with poor accessibility to public GPs would grow even larger. Conversely, if policies successfully encourage GPs to fill open positions in rural instead of urban areas, the overall share of patients with low accessibility would decline. This highlights the applicability of our model to evaluate and compare the impact of specific government interventions on welfare and equality related to the access to health-care services.

5. CONCLUSION AND OUTLOOK

We estimate a theory-guided gravity equation of patient flows and highlight the important role of spatial accessibility. Compared to gravity frameworks with only bilateral resistance such as distance or travel time, our measure of spatial accessibility takes into account intraregional heterogeneity of supply and demand as well as congestion forces at the physician level. We introduce this concept into a spatial economics model and estimate a gravity equation of patient flows across regions. The analysis is based on spatially detailed data of the residential population at the grid-cell level and the exact locations of all GPs in Austria. Spatial accessibility has a significantly positive effect on patient mobility and predicts patient flows more accurately than usually applied measures of bilateral resistance. Moreover, we show that the coefficient of bilateral distance becomes insignificant when controlling for spatial accessibility. Our results are illustrated by simulating the effects of GPs leaving the market or changing their locations. This counterfactual analysis would not be possible relying on a standard gravity model without these accessibility measures. We show that the number of patients choosing a physician in a different region does not only depend on the size of the shock (i.e., the number of physicians leaving the market), but also on the exact locations where these shocks occur. Our counterfactuals document heterogeneous changes in spatial accessibility within regions, which induces patients to switch to other districts. As this "congests" physicians and thus reduces service quality, the negative effects on service provision following market exits in one region spill over to other, predominantly neighboring, regions. We further highlight the policy relevance of our research by simulating the effects of retirement and (non)replacement of GPs over 65 years on the health-care accessibility in rural versus urban regions. Simulations such as these can be used, for example, to inform national and regional governments about the welfare consequences of supply-side interventions in the physician market.

Our approach of augmenting a gravity model with measures of spatial accessibility is not limited to the health-care market. As long as indicators of demand and supply are available at a finer spatial scale than bilateral flow data, similar measures of spatial accessibility that go beyond bilateral distance can be calculated and used to analyze determinants of various flow variables. This is especially relevant in research fields where data privacy concerns are high or data are simply not recorded at a disaggregated level. A possible application of our approach could be to use spatially explicit information on plant locations and the distribution of workers to simulate the short-term effects of mass layoffs (e.g., following plant closures) on commuting patterns. Due to lower demand for labor, the remaining nearby plants become more "congested," and it becomes more difficult for laid-off workers to find jobs in the remaining plants of that region, which affects interregional worker mobility. Thus, our approach is best applicable to analyze short-term changes in economic interactions, especially if entry barriers for suppliers (e.g., of jobs or services) exist either because market entry is publicly regulated or very time- and resource intensive, and if changing residence is associated with high costs and therefore impedes immediate moving. Although we are interested in short-run changes of mobility, it is left for future research to account for long-run consequences such as endogenous location decisions of supply and demand.

APPENDIX A

A.1 *Theoretical Appendix.*

A.1.1 *Derivation of gravity equation for patient flows.* Starting from Equation (6) in the main text, we derive the gravity equation for patient flows as shown in Equation (7). We assume that $U_{kod} = U$. The probability that U_{kod} will be the highest utility is given by the probability that $U_{kos} \leq U$ for all $s \neq d$: $\Pi_{s\neq d} Pr(U_{kos} \leq U) = \Pi_{s\neq d} G_{kos}(U)$. Inserting the utility function (3) and using the Fréchet distribution (4) leads to

$$G_{kod}(U) = e^{-\Psi_{kod} U^{-\epsilon}}, \tag{A.1}$$

where $\Psi_{kod} = M_{od} A^{\epsilon}_{kod}$. In a next step, we use the Fréchet distribution to rewrite the joint probability

$$\Pi_{s\neq d} Pr(U_{kos} \leq U) = \Pi_{s\neq d} e^{-\Psi_{kod} U^{-\epsilon}} = e^{-\Psi_{ko} U^{-\epsilon}}, \tag{A.2}$$

where $\Psi_{ko} = \sum_{s\neq d} M_{os} A^{\epsilon}_{kos}$. The latter equation shows the joint probability that all other destination choices lead to a weakly smaller utility than $U_{kod} = U$. We take into account all possible realizations of U_{kod}, where the probability that $U_{kod} = U$ is given by

$$dG_{kod}(U) = \epsilon M_{od} A^{\epsilon}_{kod} U^{-\epsilon-1} e^{-M_{od} A^{\epsilon}_{kod} U^{-\epsilon}} dU. \tag{A.3}$$

This allows us to rewrite the probability of choosing destination d (when located in origin o) as follows:

$$\begin{aligned} \lambda_{kod} &= \int_0^{\infty} \Pi_{s\neq d} Pr(U_{kos} \leq U) dG_{kod}(U) \\ &= \int_0^{\infty} e^{-\Psi_{ko} U^{-\epsilon}} \epsilon M_{od} A^{\epsilon}_{kod} U^{-\epsilon-1} e^{-M_{od} A^{\epsilon}_{kod} U^{-\epsilon}} dU. \end{aligned} \tag{A.4}$$

Solving the integral leads to the following expression:

$$\lambda_{kod} = \frac{M_{od} A^{\epsilon}_{kod}}{\sum_s M_{os} A^{\epsilon}_{kos}}, \tag{A.5}$$

which simplifies to the gravity equation for patient flows as shown in Equation (7).

A.1.2 *Model variant with GP-specific accessibility.* Our model in the main text is based on accessibility that is aggregated to the regional level. In this section, we analyze a variant of our framework with a GP-specific accessibility measure. This variant takes into account that patients may have preferences regarding the accessibility of individual GPs. In this case, the accessibility measure is given by

$$A_{kol_d} = R_{l_d} f(dist_{kl_d}). \tag{A.6}$$

In contrast to Equation (2), we focus on accessibility of an individual GP instead of aggregating over all physicians in a destination. This implies that patients derive utility from seeing a specific GP:

$$U_{kol_d} = a_{kod} A_{kol_d}. \tag{A.7}$$

Note that the preference shock a_{kod} is unchanged compared to the main text, and captures that individual patients have different preferences regarding regions (e.g., differences in transportation costs).[44]

To simplify notation, we introduce $\Omega = \sum_s L_s$ as the set of all physicians. Analogous to the solution of the main model, patients choose the physician who offers the maximum utility:

$$U_k = \max\left\{U_{kol_d}; l_d \in \Omega\right\}. \tag{A.8}$$

The probability that choosing physician l in region d leads to the highest utility compared to all other physicians across all regions can be written as

$$\lambda_{kol_d} = Pr\left[U_{kol_d} \geq max\left\{U_{kol_s}; l_s \in \Omega^{-l_d}\right\}\right]. \tag{A.9}$$

Using the Fréchet distribution, we derive the probability that patient k from region o chooses physician l_d:

$$\lambda_{kol_d} = \frac{M_{od}(A_{kol_d})^{\epsilon}}{\sum_s M_{os} \sum_{l_s \in L_s} (A_{kol_s})^{\epsilon}}. \tag{A.10}$$

In this case, the probability to choose a GP depends on a region- as well as a physician-specific component. Conditional on regional differences, a patient is more likely to see a GP with a higher accessibility. Besides that, the probability of seeing that specific physician increases when located in a region with high average amenities. As we only observe the region where patients see a physician, we aggregate over all GPs in a particular destination. Hence, the probability of patient k from origin o to choose region d is given by:

$$\lambda_{kod} = \sum_{l_d} \lambda_{kol_d} = \frac{M_{od} \sum_{l_d} (A_{kol_d})^{\epsilon}}{\sum_s M_{os} \sum_{l_s \in L_s} (A_{kol_s})^{\epsilon}}. \tag{A.11}$$

This equation resembles the gravity equation of GP choice in the main text (see Equation 7). The difference is that the Fréchet shape parameter is attached to GP-specific accessibility measures. This implies that heterogeneity in accessibility across physicians within a region becomes more important. As $\epsilon > 1$, physicians with higher accessibility have a stronger weight and hence, have a larger impact on the probability to choose a particular region.

This model variant could also be used in a setting where price differences among physicians play a role. In this case, the utility in Equation (A.8) will include physician-specific prices such that indirect utility depends on a measure of price-adjusted accessibility. Conditional on accessibility, a higher price will then reduce the probability to see a specific physician. If prices for

[44] This amenity shock is consistent with the empirical observation that not all patients from one origin region choose the same destination. In principle, the shock could occur at the GP level as well. We abstract from this due to the lack of an empirical counterpart.

health-care services are identical within a region, they would enter the gravity equation as a regional fixed effect.

A.2 *Empirical Appendix.*

A.2.1 *Description and selection of distance decay.* In this section of the empirical appendix, we provide an empirical rationale for the choice of the distance decay function $f(dist_{lk})$ to derive the spatial accessibility measures based on the 2SFCA method.

Figure A.1 illustrates the nonparametric relationship between interregional patient flows and Euclidean distance. Intraregional patient mobility is suppressed for ease of exposition. The figure shows that patient flows decline quickly with distance, but the relationship flattens after a distance of about 50 km. Patient flows are not significantly different from zero after roughly 75 km distance between the patients' and the physicians' districts. Therefore, choosing a threshold distance of 100 km is a rather conservative estimate of the physicians' catchment areas.

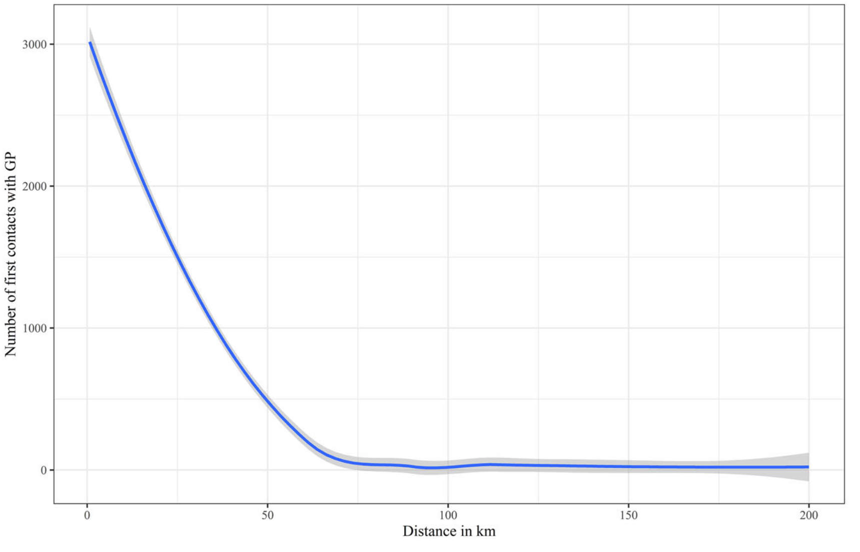
In order to select the distance decay parameter β for the distance decay function $f(dist_{lk}) = dist_{lk}^{-\beta}$, we estimate the regressions $\log(y_{od}) = \alpha + \gamma_1 \log(A_{od}) + \tau_o + \mu_d + \varepsilon_{od}$ and $\log(y_{od}) = \alpha + \gamma_1 \log(A^{r1}_{od}) + \tau_o + \mu_d + \varepsilon_{od}$, using a PPML regression, for different values of β. Table A.1 reports the goodness-of-fit statistics for these regressions, namely, the AIC, the BIC, and the value of the log-likelihood function. All three test statistics suggest using a value of $\beta = 2.8$ to calculate the regular accessibility measure A_{od} and a value of $\beta = 2.1$ to derive the simpler measure A^{r1}_{od}, under Restrictive Assumption 1 (i.e., when we abstract from intraregional heterogeneity for both physicians and patients).

A very high value of β results in a steep distance decay function, indicating that proximity is very important for patients. The Figures A.2(i) and (ii) show the spatial distribution of the accessibility measure at the individual level, $A_{ko} = \sum_d A_{kod}$, for $\beta = 2.8$ and $\beta = 0.3$. If β is low, proximity is less important, and spatial accessibility is rather evenly distributed across space, as illustrated by Figures A.2(ii).

TABLE A.1
GOODNESS-OF-FIT STATISTICS TO SELECT β FOR $f(dist_{lk}) = dist_{lk}^{-\beta}$

	in A^{r1}_{od}			in A_{od}		
β	**BIC**	**AIC**	**LL**	**BIC**	**AIC**	**LL**
2.0	49,516,152	49,517,882	−24,757,845	1,686,951	1,688,681	−843,244
2.1	**49,515,657**	**49,517,387**	**−24,757,598**	1,650,699	1,652,429	−825,118
2.2	49,518,296	49,520,026	−24,758,917	1,622,617	1,624,347	−811,077
2.3	49,523,130	49,524,860	−24,761,334	1,601,135	1,602,865	−800,336
2.4	49,529,460	49,531,190	−24,764,499	1,585,069	1,586,799	−792,303
2.5	49,536,766	49,538,496	−24,768,152	1,573,544	1,575,274	−786,541
2.6	49,544,663	49,546,394	−24,772,101	1,565,924	1,567,654	−782,731
2.7	49,552,870	49,554,600	−24,776,204	1,561,746	1,563,476	−780,642
2.8	49,561,178	49,562,908	−24,780,358	**1,560,674**	**1,562,404**	**−780,106**
2.9	49,569,440	49,571,170	−24,784,489	1,562,454	1,564,184	−780,996
3.0	49,577,548	49,579,278	−24,788,543	1,566,890	1,568,621	−783,214
3.1	49,585,430	49,587,160	−24,792,484	1,573,822	1,575,552	−786,680
3.2	49,593,036	49,594,766	−24,796,287	1,583,113	1,584,843	−791,326
3.3	49,600,335	49,602,065	−24,799,937	1,594,640	1,596,370	−797,089
3.4	49,607,311	49,609,041	−24,803,424	1,608,287	1,610,017	−803,912
3.5	49,613,954	49,615,684	−24,806,746	1,623,937	1,625,668	−811,738

NOTE: The statistics are based on the models $\log(y_{od}) = \alpha + \gamma_1 \log(A^{r1}_{od}) + \tau_o + \mu_d + \varepsilon_{od}$ and $\log(y_{od}) = \alpha + \gamma_1 \log(A_{od}) + \tau_o + \mu_d + \varepsilon_{od}$, respectively, estimated by a Poisson pseudo-maximum-likelihood (PPML) regression. The rows highlighted in bold indicate the model specifications with the best fit. A^{r1}_{od}: Accessibility measure after Restrictive Assumption 1. A_{od}: Accessibility measure based on the two-step-floating catchment area method. BIC: Bayesian information criterion. AIC: Akaike information criterion. LL: Log-likelihood value.



NOTES: The blue line depicts the locally weighted polynomial regression line for patient flows to public GPs, y_{od}, between the patients' region o and the physicians' district d, and the Euclidean distance between the population-weighted centroids (in km) of the respective district pairs. The gray area around the regression line illustrates the 95% confidence interval. The graph only includes out-of-own-district patient flows, that is, y_{od} with $o \neq d$.

FIGURE A.1

NONPARAMETRIC REGRESSION BETWEEN PATIENT FLOWS AND INTERREGIONAL DISTANCE

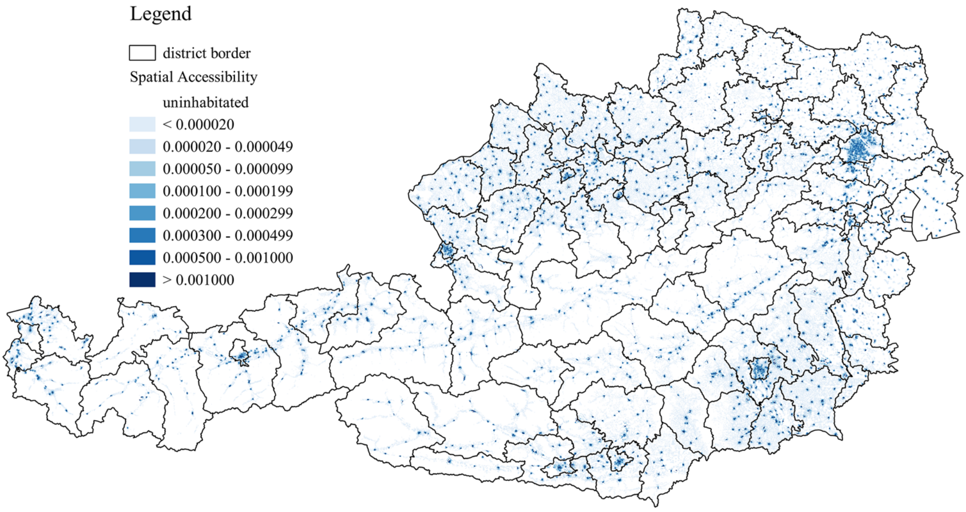
A.2.2 *Regression results with alternative distance decay parameters.*

TABLE A.2
SENSITIVITY ANALYSIS—ACCESSIBILITY BASED ON DISTANCE DECAY PARAMETER $\beta = 2.0$

	Model 2Aa	Model 3Aa	Model 3Ab	Model 3Ac	Model 3Ad
Accessibility of GPs, $\log(A_{od})$	0.980***	0.656***	0.656***	0.655***	0.601***
	(0.004)	(0.013)	(0.013)	(0.013)	(0.036)
Number of commuters, $\log(M_{od})$		0.522***	0.523***	0.526***	0.514***
		(0.018)	(0.017)	(0.018)	(0.019)
Population-weighted distance, $\log(dist_{od})$			0.004		
			(0.023)		
Accessibility of private GPs, $\log(A_{od}^{priv})$					0.038
					(0.025)
Constant	8.811***	5.497***	5.478***	5.504***	5.569***
	(0.027)	(0.127)	(0.145)	(0.128)	(0.145)
Origin fixed effects	Yes	Yes	Yes	Yes	Yes
Destination fixed effects	Yes	Yes	Yes	Yes	Yes
Dummy for same federal state	No	No	No	Yes	No
Number of obs.	13,225	13,225	13,225	13,225	13,225
Log-likelihood	−843,244	−573,918	−573,901	−573,550	−569,835
BIC	1,688,681	1,150,047	1,150,023	1,149,321	1,141,900
AIC	1,686,951	1,148,302	1,148,270	1,147,569	1,140,140

NOTE: All models estimate interregional patient flows by using a Poisson pseudo-maximum-likelihood (PPML) estimator and include origin- (patient-) and destination- (physician-) regional fixed effects. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

i) Based on distance decay function $f(dist_{lk}) = dist_{lk}^{-2.8}$



ii) Based on distance decay function $f(dist_{lk}) = dist_{lk}^{-0.3}$

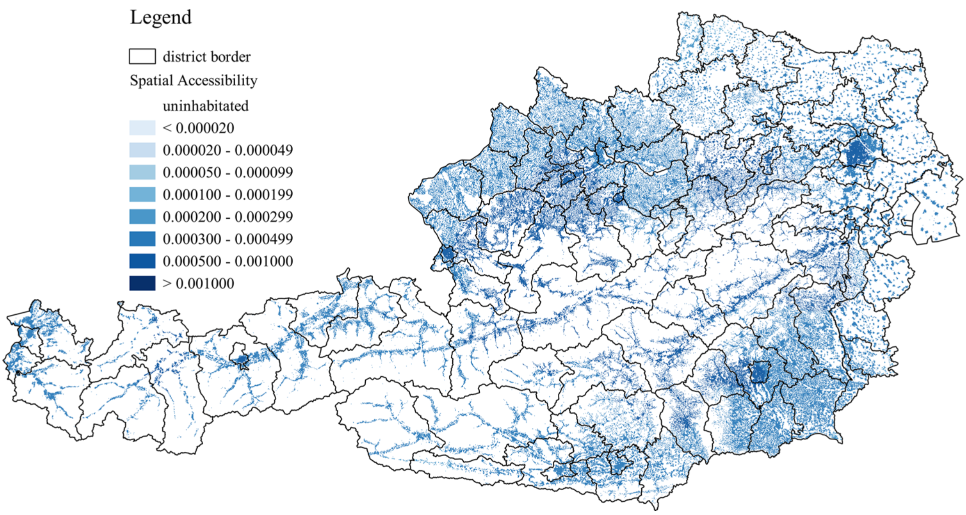


FIGURE A.2

SPATIAL ACCESSIBILITY MEASURE TO PUBLIC GPS AT THE INDIVIDUAL LEVEL $(A_k = \sum_d A_{kd})$

Table A.3
SENSITIVITY ANALYSIS—ACCESSIBILITY BASED ON DISTANCE DECAY PARAMETER $\beta = 3.5$

	Model 2Ab	Model 3Ae	Model 3Af	Model 3Ag	Model 3Ah
Accessibility of GPs, $\log(A_{od})$	0.464***	0.315***	0.315***	0.315***	0.291***
	(0.002)	(0.007)	(0.007)	(0.007)	(0.018)
Number of commuters, $\log(M_{od})$		0.507***	0.510***	0.506***	0.499***
		(0.021)	(0.021)	(0.021)	(0.021)
Population-weighted distance, $\log(dist_{od})$			0.015		
			(0.021)		
Accessibility of private GPs, $\log(A_{od}^{priv})$					0.035
					(0.024)
Constant	10.291***	6.624***	6.562***	6.624***	6.621***
	(0.064)	(0.161)	(0.169)	(0.161)	(0.158)
Origin fixed effects	Yes	Yes	Yes	Yes	Yes
Destination fixed effects	Yes	Yes	Yes	Yes	Yes
Dummy for same federal state	No	No	No	Yes	No
Number of obs.	13,225	13,225	13,225	13,225	13,225
Log-likelihood	−811,738	−556,930	−556,738	−556,928	−554,054
BIC	1,625,667	1,116,071	1,115,698	1,116,076	1,110,338
AIC	1,623,937	1,114,326	1,113,945	1,114,324	1,108,578

Note: All models estimate interregional patient flows by using a Poisson pseudo-maximum-likelihood (PPML) estimator and include origin- (patient-) and destination- (physician-) regional fixed effects. If explanatory variables are zero and the logarithm is undefined, dummy variables are included that take the value one in these cases and zero otherwise. Standard errors are reported in parenthesis and are based on a robust sandwich covariance matrix estimator. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

A.2.3 *Utilization rates of different sex–age cohorts.*

Table A.4
AVERAGE UTILIZATION RATES BY SEX–AGE COHORTS

Age Cohorts	0–9	10–19	20–29	30–39	40–49	50–59	60–69	70–79	80–89	≥ 90
Male	2.4	3.2	3.9	4.4	5.3	7.9	11.1	15.7	21.5	27.4
	(4.9)	*(5.2)*	*(6.7)*	*(6.7)*	*(7.2)*	*(7.6)*	*(5.2)*	*(3.8)*	*(1.5)*	*(0.2)*
Female	2.3	3.4	4.9	5.7	6.8	9.0	11.6	16.9	23.7	30.5
	(4.6)	*(4.8)*	*(6.4)*	*(6.6)*	*(7.2)*	*(7.6)*	*(5.7)*	*(4.6)*	*(2.5)*	*(0.7)*

Note: The figures denote the average number of consultations of public GPs in Austria in 2017. The numbers in parentheses (in italics) indicate the share of the respective sex-age cohort (in percent) in the total population.

A.2.4 *Simulation of counterfactual scenarios—Effects on accessibility and patient mobility.* Market exits or relocations of physicians in St. Veit influence the spatial accessibility of GPs and thus patient mobility. While the relative change in accessibility at the individual level, $A_{ko} = \sum_d A_{kod}$, is illustrated in Figure 4 in the main text for the four counterfactual scenarios under scrutiny, Table A.5 reports regional averages of these effects. The spatial accessibility for residents in St. Veit decreases between 33.3% and 54.9% in the first three scenarios, whereas these patients experience (on average) a gain in accessibility in scenario 4. The negative effects on accessibility for residents of other regions are generally largest in scenario 2 (i.e., when GPs in the south of the St. Veit district leave the market), in particular for regions in the south-west: Accessibility declines on average by 4.2% and 3.4% in the districts of Völkermarkt and of Klagenfurt Land, respectively.

The expected effects of these supply-side shocks on patient mobility are summarized by flow matrices, reported in Table A.6 to Table A.9. In order to derive these flow matrices, we first calculate the expected flow matrix in the baseline scenario, based on Equation (13) and the parameter estimates of Model 3, reported in Table 2. We then calculate the patient flow

TABLE A.5

RESULTS OF SIMULATION EXPERIMENTS—EXPECTED AVERAGE CHANGE IN SPATIAL ACCESSIBILITY

Scenario	1	2	3	4
St Veit	−33.32	−54.87	−36.52	15.15
Klagenfurt Stadt	−0.05	−0.85	−0.19	0.52
Feldkirchen	−0.46	−1.81	−0.79	0.69
Klagenfurt Land	−0.19	−3.42	−0.68	2.26
Villach Stadt	−0.01	−0.03	−0.01	0.02
Wolfsberg	−0.35	−0.83	−0.44	0.31
Murau	−1.33	−0.63	−0.65	0.67
Villach Land	−0.06	−0.19	−0.06	0.14
Völkermarkt	−0.46	−4.22	−1.81	1.07
Spittal	−0.06	−0.10	−0.04	0.08
Murtal	−0.13	−0.14	−0.08	0.11
Deutschlandsberg	−0.03	−0.07	−0.03	0.04
Voitsberg	−0.03	−0.06	−0.03	0.04
Tamsweg	−0.20	−0.24	−0.11	0.22
other districts	0.00	0.00	0.00	0.00

NOTE: Figures denote the average change in spatial accessibility (in %) relative to the baseline scenario. The change in accessibility is calculated at the individual (patient) level and averaged over all patients in the district.

TABLE A.6

FLOW MATRIX—EXPECTED CHANGE IN PATIENT MOBILITY UNDER SCENARIO 1

	SV	K	FE	KL	VI	WO	MU	VL	VK	SP	MT	DL	VO	TA	Other	$\sum$
SV	−5,860	1,078	1,767	610	349	280	453	195	296	172	162	48	23	16	410	0
K	−44	37	1	4	0	0	0	0	0	0	0	0	0	0	0	0
FE	−142	6	113	5	7	1	0	5	1	3	0	0	0	0	1	0
KL	−65	14	2	39	2	0	0	3	2	0	0	0	0	0	0	0
VI	−18	0	0	0	15	0	0	3	0	0	0	0	0	0	0	0
WO	−59	1	0	0	0	50	0	0	2	0	1	1	1	0	2	0
MU	−242	2	5	1	1	1	195	1	1	1	14	1	1	6	14	0
VL	−41	1	1	1	9	0	0	25	0	2	0	0	0	0	1	0
VK	−62	4	1	3	1	7	0	1	43	0	0	0	0	0	2	0
SP	−31	0	1	0	1	0	0	1	0	25	0	0	0	0	2	0
NT	−28	0	0	0	0	0	0	0	0	0	24	0	0	0	2	0
DL	−5	0	0	0	0	0	0	0	0	0	0	4	0	0	1	0
VO	−5	0	0	0	0	0	0	0	0	0	0	0	4	0	1	0
TA	−6	0	0	0	0	0	0	0	0	0	0	0	0	5	1	0
Other	−58	0	0	0	0	0	0	0	0	0	0	1	0	0	56	0
$\sum$	−6,666	1,144	1,893	665	386	340	650	236	344	205	202	54	29	27	492	

NOTE: Matrix reports the expected changes in patient flows under scenario 1, that is, when the 16 northern GPs leave the market. List of abbreviations: SV: St. Veit, K: Klagenfurt Stadt, FE: Feldkirchen, KL: Klagenfurt Land, VI: Villach, WO: Wolfsberg, MU: Murau, VL: Villach Land, VK: Völkermarkt, SP: Spittal, MT: Murtal, DL: Deutschlandsberg, VO: Voitsberg, TA: Tamsweg. All other districts are aggregated and labeled "Other."

matrix in each counterfactual scenario and report the difference to the flow matrix in the baseline scenario. Table A.6 to Table A.9 report the expected change in patient flows for all district pairs depicted in Figure 3 to Figure 5, whereas all other districts are aggregated for brevity (and labeled "other" in the respective tables).

The first row of Table A.6, for example, reports the expected change in patient flows under scenario 1 (i.e., when the 16 northern GPs leave the market) for residents of St. Veit (labeled SV). Due to the market exits, the expected number of inhabitants of St. Veit seeing a doctor

Table A.7
FLOW MATRIX—EXPECTED CHANGE IN PATIENT MOBILITY UNDER SCENARIO 2

	SV	K	FE	KL	VI	WO	MU	VL	VK	SP	MT	DL	VO	TA	Other	$\sum$
SV	−14,982	4,499	3,411	2,578	797	548	442	480	918	315	215	92	38	25	623	0
K	−1,240	1,024	27	131	15	5	1	13	13	4	1	1	0	0	5	0
FE	−551	33	418	31	26	2	2	22	3	8	1	1	0	1	3	0
KL	−1,293	314	46	774	36	11	2	49	39	7	2	2	1	1	9	0
VI	−69	1	1	0	55	0	0	11	0	1	0	0	0	0	0	0
WO	−188	3	1	1	1	161	0	1	6	0	3	2	2	0	7	0
MU	−141	1	3	0	1	0	114	1	0	1	7	0	0	4	7	0
VL	−155	4	5	4	34	0	0	100	0	5	0	0	0	0	2	0
VK	−734	61	9	43	10	67	1	8	507	4	2	3	1	0	18	0
SP	−54	0	1	0	2	0	0	2	0	45	0	0	0	0	2	0
NT	−36	0	0	0	0	0	0	0	0	0	32	0	0	0	3	0
DL	−17	0	0	0	0	0	0	0	0	0	0	13	0	0	3	0
VO	−12	0	0	0	0	0	0	0	0	0	0	0	9	0	2	0
TA	−8	0	0	0	0	0	0	0	0	0	0	0	0	6	1	0
Other	−109	0	0	0	1	0	0	1	0	1	1	2	1	0	104	0
$\sum$	−19,591	5,942	3,924	3,564	977	795	563	687	1,486	392	265	116	53	38	789	

Note: Matrix reports the expected changes in patient flows under scenario 2, that is, when the 16 southern GPs leave the market. List of abbreviations: SV: St. Veit, K: Klagenfurt Stadt, FE: Feldkirchen, KL: Klagenfurt Land, VI: Villach, WO: Wolfsberg, MU: Murau, VL: Villach Land, VK: Völkermarkt, SP: Spittal, MT: Murtal, DL: Deutschlandsberg, VO: Voitsberg, TA: Tamsweg. All other districts are aggregated and labeled “Other.”

in their districts of residence declines by 5,860. Of those, 1,078 residents see a GP in K (Klagenfurt Stadt), 1,767 in FE (Feldkirchen), and so on. The row sums up to zero, because every patient chooses exactly one physician. The column sums indicate the expected change in the number of patients choosing a physician in the respective region. For example, the expected number of patients opting for a GP in SV (St. Veit) declines by 6,666. Of those, 5,860 individuals are residents of SV (St. Veit), 44 are residents of K (Klagenfurt Stadt), and so on. These patients have to be admitted by physicians in other regions, as depicted by the other column sums in Table A.6. The expected effects on patient mobility in the three other counterfactual scenarios, reported in Table A.7, Table A.8, and Table A.9, can be interpreted analogously.

TABLE A.8
FLOW MATRIX—EXPECTED CHANGE IN PATIENT MOBILITY UNDER SCENARIO 3

	SV	K	FE	KL	VI	WO	MU	VL	VK	SP	MT	DL	VO	TA	Other	$\sum$
SV	−2,774	676	677	389	154	145	132	90	183	66	60	22	10	6	166	0
K	−150	123	4	16	2	1	0	2	2	0	0	0	0	0	1	0
FE	−146	9	112	7	7	1	1	6	1	2	0	0	0	0	1	0
KL	−167	39	6	100	5	1	0	7	5	1	0	0	0	0	1	0
VI	−16	0	0	0	13	0	0	2	0	0	0	0	0	0	0	0
WO	−77	1	0	1	0	66	0	0	2	0	1	1	1	0	3	0
MU	−93	1	2	0	0	0	75	1	0	0	5	0	0	2	5	0
VL	−36	1	1	1	8	0	0	23	0	1	0	0	0	0	0	0
VK	−195	17	3	11	3	20	0	2	131	1	1	1	0	0	5	0
SP	−18	0	0	0	1	0	0	1	0	15	0	0	0	0	1	0
NT	−17	0	0	0	0	0	0	0	0	0	15	0	0	0	1	0
DL	−5	0	0	0	0	0	0	0	0	0	0	4	0	0	1	0
VO	−5	0	0	0	0	0	0	0	0	0	0	0	3	0	1	0
TA	−3	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0
Other	−41	0	0	0	0	0	0	0	0	0	0	1	0	0	40	0
$\sum$	−3,743	866	806	525	193	234	208	133	324	88	83	30	15	11	226	

NOTE: Matrix reports the expected changes in patient flows under scenario 3, that is, when 16 randomly selected GPs leave the market. List of abbreviations: SV: St. Veit, K: Klagenfurt Stadt, FE: Feldkirchen, KL: Klagenfurt Land, VI: Villach, WO: Wolfsberg, MU: Murau, VL: Villach Land, VK: Völkermarkt, SP: Spittal, MT: Murtal, DL: Deutschlandsberg, VO: Voitsberg, TA: Tamsweg. All other districts are aggregated and labeled "Other."

TABLE A.9
FLOW MATRIX—EXPECTED CHANGE IN PATIENT MOBILITY UNDER SCENARIO 4

	SV	K	FE	KL	VI	WO	MU	VL	VK	SP	MT	DL	VO	TA	Other	$\sum$
SV	−727	182	123	103	40	58	30	23	65	15	19	8	3	1	55	0
K	387	−324	−8	−39	−4	−1	0	−4	−4	−1	0	0	0	0	−1	0
FE	192	−9	−149	−10	−9	−1	−1	−8	−1	−3	0	0	0	0	−1	0
KL	402	−96	−14	−243	−11	−3	−1	−16	−11	−2	−1	−1	0	0	−3	0
VI	32	0	0	0	−26	0	0	−5	0	0	0	0	0	0	0	0
WO	49	−1	0	0	0	−42	0	0	−1	0	−1	−1	0	0	−2	0
MU	120	−1	−3	0	−1	0	−98	−1	0	−1	−6	0	0	−3	−6	0
VL	71	−2	−2	−2	−16	0	0	−45	0	−3	0	0	0	0	−1	0
VK	143	−10	−1	−7	−2	−12	0	−1	−105	−1	0	−1	0	0	−3	0
SP	30	0	−1	0	−1	0	0	−1	0	−25	0	0	0	0	−1	0
NT	20	0	0	0	0	0	0	0	0	0	−17	0	0	0	−2	0
DL	6	0	0	0	0	0	0	0	0	0	0	−5	0	0	−1	0
VO	5	0	0	0	0	0	0	0	0	0	0	0	−4	0	−1	0
TA	5	0	0	0	0	0	0	0	0	0	0	0	0	−4	−1	0
Other	47	0	0	0	0	0	0	0	0	0	0	−1	0	0	−45	0
$\sum$	784	−260	−56	−199	−30	−2	−70	−58	−57	−21	−8	0	−2	−7	−12	

NOTE: Matrix reports the expected changes in patient flows under scenario 4, that is, when the number of GPs remains unaffected, but 16 randomly selected GP locations are dissolved. List of abbreviations: SV: St. Veit, K: Klagenfurt Stadt, FE: Feldkirchen, KL: Klagenfurt Land, VI: Villach, WO: Wolfsberg, MU: Murau, VL: Villach Land, VK: Völkermarkt, SP: Spittal, MT: Murtal, DL: Deutschlandsberg, VO: Voitsberg, TA: Tamsweg. All other districts are aggregated and labeled "Other."

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