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Gravity for Health: an Application to State Mental Hospital Admissions in Texas *

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Abstract

This paper discusses competing-destinations formulation of the gravity model for the flows of patients from their residential areas to health supplier regions. This approach explicitly acknowledges the interdependence of the patient flows between a set of alternative health supplier regions. This competing-destinations based approach may be implemented as a probabilistic demand function or conditional logit model, with a Poisson outcome. A Texas based case study of residential areas and State Mental Hospitals (SMHs) is presented. The results of the estimation do not lend support to the presence of scale effects in SMHs due to the size of population. This result, combined with the negative effect of average length of stay in hospitals (ALOS) and with the positive effect of the provision of forensic services on patient flows, highlights the problem of caseload growth in SMHs.

JEL Classification: C21, I11, R12.

Keywords: Gravity Model, Patients' Mobility, State Mental Hospital, Poisson Estimation

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1 Introduction

The central focus of the present work is modeling patient flows from their residential regions to health suppliers' regions. The basis for modeling flows is the gravity model: gravity models applied in contexts of human behavior involve a "mass" term for both the origin and destination, and incorporate the impact of distance on human spatial choices. In line with gravity modeling principles, patient flows from different residential regions (origins) to health suppliers' regions (destinations) reflect firstly, patterns of population demand as determined by the size of populations; second, the size and range of facilities in different health suppliers' regions; and third, the impact of economic and social separation on human spatial choices determined by distances or travel times from homes to health suppliers' regions.

Application of the gravity modeling to the issue of patient flows and hospital choice dates back to the late 1960s (see the early works of Morill and Earickson (1968), Studnicki (1975), Roghman and Zastowny (1979)). More recently, papers by Lowe and Sen (1996), Congdon (2001), Levaggi and Zanola (2004), Cantarero (2006), Fabbri and Robone (2010) adopt this framework to investigate patient mobility. Lowe and Sen (1996) use the gravity model to study the flows for acute inpatient hospital care from six-county metropolitan Chicago area to 92 hospitals in that same area in the year 1987. The model is used to forecast how potential changes in hospital financing policy can change patient flows. Congdon (2001) models patient flows to emergency units in 127 electoral wards in North East London and Essex and describes how such models may be adapted to allow for unit closures and expansion, or the opening up of other units. The estimation of the gravity model is based on simulation based Bayesian methods. Levaggi and Zanola (2004) study the net flows of people moving from one Italian region to another as determined by regional differences in the quality of healthcare and distance. The dataset they use is a sample of observations over the period 1994-1997. A similar analysis is developed by Cantarero (2006) working on patient mobility across Spanish regions during the period 1996-1999. Fabbri and Robone (2010) evaluate the extent to which the observed imbalances in the Italian geography of hospital admissions are due to scale effects or reflect the presence of other spatial factors in the distribution of healthcare resources.

We analyze patient mobility across Texas using data on hospital admissions that occurred in state-owned hospitals during the year 2006. In the reference year, the Texas State is partitioned into nine state-owned mental hospitals with the corresponding hospital service areas (HSA). The use of mental healthcare resources in Texas is highly localized. The Texas Department of State Health Services (DSHS) is responsible for managing the nine state-owned mental hospitals (SMH). The SMH are one component of the statewide mental health delivery system that includes inpatient care and community-based care. DSHS designates Local Mental Health Authorities (LMHA) that are responsible for achieving continuity of care in meeting a person's need for mental health services in the least restrictive environment. Within this continuum of care the SMH's primary purpose is to stabilize the patients admitted by providing inpatient mental health treatment. Admission to SMH can occur voluntarily or involuntary. Involuntarily admissions include civil and forensic commitments. There are also state provisions for the commitment of persons with intellectual disabilities experiencing acute psychiatric illness. Generally speaking, an LMHA screens persons who are self referred or referred by a community source, such as a police officer in the resident's service area. In collaboration with the judiciary, the LMHA has the duty of finding the least restrictive, most appropriate treatment setting for the patients, who may be referred to state mental hospitals. If a person seeks admission independently of an LMHA, the SMH by law must conduct an emergency psychiatric screening which may result in patient admission to the SMH. In consultation with the LMHA, the admissions physician has final authority for admitting persons consistent with the availability of hospital resources.

SMHs face managerial and fiscal challenges in meeting the needs of Texans with severe mental illness. Three significant challenges are addressing the growing forensic population, managing outside medical costs, and maintaining aging infrastructure. One of the major problems associated with the growing forensic population is the longer lengths of stay, often more than 90 days for forensic patients in SMH. These longer lengths of stay and the overall increase in the forensic population have led to longer wait times and waiting lists at SMHs for forensic beds.

Anderson and van Wincoop (2003) demonstrate that the traditional gravity equation is mis-specified and coefficient estimates are likely biased owing to omission of nonlinear multilateral resistance terms. These multilateral resistance variables capture the dependence of trade flows between trading countries on trade costs across all possible trading suppliers. Following Anderson and van Wincoop's (2003) seminal paper addressing omitted variables bias in the gravity equation, we include a variable to explain the spatial structure of patient flows in a geographical system. In general terms, destinations are viewed as competing with each other for interaction. One possible measure of destination competition is the competition factor, a composite variable that attempts to capture the gravity of the competing destinations (de Mello-Sampayo, 2009). The competing destinations gravity model represents a step forward in recognition of interdependencies in spatial choice (Fotheringham, 1983*a*,*b*, Thorsen and Gitlesen, 1998). Its main difference from the classic version stems from the fact that a competition factor encompassing the ability of third destinations to attract interaction flows is included as a dampening factor to inputs flowing to any potential destination.

The effect of several factors on the flow of patients from their residential area to SMHs is tested under the competing-destination gravity model implemented as a probabilistic demand function or conditional logit model, with a Poisson outcome. The flow of patients to the SMH is found to be increasing in the provision of forensic services, adjacency, institutional factors, and decreasing in average length of stay in hospitals (ALOS), road distance, gravity posed by other SMHs, and accessibility to other SMHs. This evidence suggests that county-specific spatial factors are very important determinants of the patient flows. These results, combined with the fact that the factor capturing the gravity of competing destinations, emerge with high significance and the correct sign, corroborating the use of the competing-destination formulation of the gravity model for the analysis of the patient flows to SMHs.

There is a long tradition in the literature of making a log-linearization of the gravity models and to estimate the parameters of interest using Ordinary Least Squares (OLS). However, it fails to work when no flow is observed between some pairs of origin and destination, thus making the dependent variable a true zero (Porell and Adams, 1995). Several methods have been adopted to deal with log-linearization of the zero observations. One view of zeros is that they stand for flows too small to report. Interpreting zeros in this way, it is legitimate to drop the zero observations from estimation because there is no economic significance to the zeros relative to the non-zero observations. In the presence of heteroskedastic errors, Santos-Silva and Tenreyro (2006) point out that inconsistent estimation arises from the usual econometric gravity practice using logarithmic transformation and estimated with Ordinary Least Squares (OLS). The expected value of the logarithm of a random variable depends both on its mean and on the higher-order moments of the distribution. Hence, if the variance of the error term in the gravity equation depends on the regressors, the expected value of the logarithm of the error term will also depend on the regressors, violating the condition of consistency of OLS. To address these two problems we follow the approach proposed by Santos-Silva and Tenreyro (2006) and estimate our model using a Poisson maximum likelihood estimator. Under the assumption that the conditional variance is proportional to the conditional mean, the parameters of the model can be estimated by solving a set of first-order conditions numerically equal to the Poisson pseudo-maximum likelihood estimator. All that is needed for this estimator to be consistent is the correct specification of the conditional mean. If the assumption that the conditional variance is proportional to the conditional mean does not hold (which is often the case), the estimator does not fully account for the heteroskedasticity in the model. For this reason, the inference has to be based on an Eicker-White robust covariance matrix estimator (Eicker, 1963; White, 1980).

The remainder of this paper is composed of four sections. In Section 2 we elaborate the theoretical model, and map the theoretical results into an empirical strategy in Section 3, where we also describe the data. We report and interpret the empirical findings in Section 4, and provide concluding comments in the closing section.

2 Theoretical Framework

Consider an economy divided into residential regions, $r = 1, 2, \ldots, R$, and health suppliers' regions, $s = 1, 2, \ldots, S$. Let $X = \sum_{irs} x_{irs}$ be defined as the total number of interactions in the economy, and we wish to model the interaction pattern in this economy, i.e. x_{irs}, the unknown amount of health service i consumed by residents of region r at region s. There are H+1 sectors in the economy. One sector produces a homogeneous good, while H sectors produce differentiated health service or goods. An exogenous fraction μ of income is spent on differentiated products of sector H, and the remaining fraction $1 - \mu$ on the homogeneous good, which is our numeraire. Now consider the particular sector H that produces differentiated health goods or services, i. We drop the index H, with the implicit understanding that all variables refer to sector H.

Preferences across varieties of goods have the standard constant elasticity of substitution (CES) form, with an elasticity of substitution σ. Let the utility function U_r be defined and calibrated over the consumers of region r in terms of quantities of each variety, $i = 1, 2, \ldots, I$, consumed at region s.

$$U_r = (\int_s \int_i x_{irs}^{\frac{\sigma-1}{\sigma}} dids)^{\frac{\sigma-1}{\sigma}}, \tag{1}$$

where x_{irs} stands for the amount of health service or good, i, consumed by residents of region r at region s. We assume monopolistic competition in the health sector so that each variety of the differentiated good is produced or supplied by only one firm. The price index in the differentiated health sector for region s is:

$$P_s = (\int_s \int_i p_{is}^{1-\sigma} dids)^{\frac{1}{1-\sigma}}. \tag{2}$$

Let y_r be the income of region r, which equals its expenditure level. Given the total demand μy_r on h in region r, the region r demand for each variety is given by:

$$x_{irs} = \mu y_r p_{is}^{-\sigma} P_s^{\sigma-1}. \tag{3}$$

Assume that the maximum optimum utility, U_r^*, emerging from the utility maximization will exceed the observed utility U_{ro} emerging from the observed flows x_{irso}. Thus, we investigate the entropy approach (Roy, 2004) to cope with this divergence. Let E be the number of ways that the observed number $X_{iso} = \sum_r x_{irso}$ of distinct good i ordered at each region s may be allocated to consumer regions r in groups x_{irso} times the number of ways the total of distinct goods orders $X_{ir} = \sum_s x_{irs}$ made from region r may be arbitrarily allocated to each of the N_r consumers there.

$$E = \frac{\prod_{is} X_{iso}!}{\prod_r x_{irs}!} \times \prod_{ir} N_r^{X_{ir}}. \tag{4}$$

The natural logarithm of Equation (4) is taken, the Stirling approximation[1] applied, and constant terms omitted. The entropy E then comes out as:

$$E = -\sum_{irs} x_{irs}[ln(\frac{x_{irs}}{N_r}) - 1]. \tag{5}$$

The maximization of Equation (5) is constrained by the model flows being induced to conform with certain aggregate base period quantities. If we have the total utility U_o based on the observed orders in all demand regions r, the following behavioral constraint is applied:

$$\sum_r U_r^* = U_o. \tag{6}$$

Let consumers of the differentiated product travel from their home region r to consumption region s to buy or consume the product, absorbing themselves the transport cost of iceberg type. Namely, τ_{rs} units of x_{irs} have to be bought by consumers of region r from suppliers of region s in order to obtain one unit of the differentiated product. Thus, τ_{rs} stands for the average cost of travel between r and s, and τ_o is the average generalized cost of travel over the entire economy. Reproducing the observed average generalized cost of travel τ_o in terms of the interzonal average cost, yields:

[1]The Stirling approximation is given by $x! = x(lnx - 1)$.

$$\sum_{rs} x_{irs}\tau_{rs} = X\tau_o. \tag{7}$$

Maximize Equation (5) subject to Equation (6) with multiplier λ, and Equation (7) with multiplier β to obtain:

$$x_{irs} = N_r e^{\frac{\lambda \frac{\sigma}{\sigma-1} U_r^*}{x_{irs}} + \beta\tau_{rs}}. \tag{8}$$

Substituting Equation (3) into Equation (8), and imposing that the predicted total interaction flow/volume leaving each origin should equal the observed value, i.e. $\sum_r x_{irs} = X_{iso}$, Equation (8) then becomes:

$$x_{irs} = \frac{X_{iso} N_r e^{\alpha(\frac{p_{is}}{P_s})^\sigma + \beta\tau_{rs}}}{\sum_r N_r e^{\alpha(\frac{p_{is}}{P_s})^\sigma + \beta\tau_{rs}}}, \tag{9}$$

which has a form similar to a conditional logit model (probabilistic demand function) and where $\alpha = \lambda\frac{\sigma}{\sigma-1}$, and β are parameters to be estimated. The parameters α, and β reflect the perception of the destination´s attractiveness and distance as determinants of interactions by the residents of region r. The balance of total flows is ensured by $X_{iso}/\sum_r N_r e^{\alpha(\frac{p_{is}}{P_s})^\sigma + \beta\tau_{rs}}$. The variable $(\frac{p_{is}}{P_s})^\sigma$ measures the quality of a health good or service i since the price of a specific health service relative to the price index of area s, weighted geometrically by the elasticity of substitution, gives an index performance of one good to another with a ratio chart. We expect α to be positive, indicating that as area s increases in quality, the volume of interactions between r and s increase. Conversely, we expect β to be negative: as the economic distance between region r and region s increases, the volume of interaction between them decreases.

The standard form of the gravity model as presented in Equation (9) contains an independence from the irrelevant alternatives (IIA) property: the ratio of flows to any two destinations is independent of any other destination (Fotheringham, 1984). The IIA axiom may be modified to reflect interdependencies in spatial choice. If these interdependencies are introduced into the gravity model, the ratios of predicted flows to remaining suppliers will be affected by the choice of a particular health supplier region (Fotheringham, 1984). Problems with the IIA principle occur in other choice modeling contexts, see for example Anderson and van Wincoop (2003) on trade and de Mello-Sampayo (2009) on FDI location choices.

2.1 Competing Destinations Model

In general terms, destination areas are viewed as competing with each other for interaction and when a variable measuring such competition is included in the gravity framework, the resulting interaction models are known as competing destinations model (Fotheringham, 1983*a*). One possible measure of destination competition is the competition factor, a composite variable that attempts to capture the gravity of the competing destinations (see de Mello-Sampayo, 2007, 2009):

$$c_{is} = \sum_{k \neq r,s} \alpha(\frac{p_{ik}}{P_k})^\sigma / \beta\tau_{rk}, \tag{10}$$

where c_{is} is the sum, weighted by economic distance, of all other destinations' characteristics (except destination s) in attracting patient flows from r. The variable $\frac{p_{ik}}{P_k}^{\sigma}$ represents the attractiveness of destination k; τ_{rk} represents the economic distance between origin r and destination k; α, and β are defined as in the gravity model given by Equation (9). Often they are set to one in the competition formulation (Roy, 2004). The competing destinations version of the gravity model in Equation (9) is given by:

$$x_{irs} = \frac{X_{iso} N_r e^{\alpha(\frac{p_{is}}{P_s})^{\sigma} + \beta\tau_{rs} + \gamma c_{is}}}{\sum_r N_r e^{\alpha(\frac{p_{is}}{P_s})^{\sigma} + \beta\tau_{rs} + \gamma c_{is}}}, \tag{11}$$

where α, β, and γ are parameters to be estimated. The parameters α and β are given as in Equation (9). A negative value of γ demonstrates the presence of competition or congestion forces. The above model structure clearly represents a great step forward in recognition of interdependencies in spatial choice. Its main difference from the classic version stems from the fact that a competition factor encompassing the ability of third destinations to attract interaction flows is included as a dampening factor to patients flowing to any potential destination.

In the context of same type origin-destination gravity models, Fotheringham (1983a) proposed a potential accessibility measure:

$$a_{is} = \sum_{k \neq r,s} \alpha(\frac{p_{ik}}{P_k})^{\sigma} / \beta\tau_{sk}, \tag{12}$$

where a_{is} represents the accessibility of destination s in relation to all other destinations. The higher the quality in destinations k, and the closer these destinations are to s (i.e., the smaller is τ_{sk}), the lower is the flow expected from r to s since there is a spatial concentration of opportunities in the neighborhood of s. In this situation the access measure a_{is} models competition effects since it will be high but the flow low, so that this type of accessibility has a negative impact on flows if several areas with large masses are close to each other. Alternatively stated, it may model agglomeration effects if the higher the quality in destinations k, and the closer these destinations are to s, the higher is the flow expected from r to s since there is a spatial concentration of opportunities in the neighborhood of s. In this situation the access measure a_{is} will be high and the flow high, so that this type of "accessibility" has a positive impact on flows if several areas with large masses are close to each other.

Earlier studies that attempt to control for geographical patterns, Santos-Silva and Tenreyro (2006), Fabbri and Robone (2010), Deardoff (1998), although it is an atheoretic measure, use the variable remoteness to account for the hypothesis that larger distances to all other locations might increase bilateral flows between two locations. The variable remoteness is defined as the mean distance of each destination from all other destinations, weighted by the population of each HSA. The variable remoteness allows us to test the hypothesis that larger distances to all other locations might increase bilateral flows between two locations, other things being equal. According to evidence in the empirical literature on trade, this variable affects flows positively (see Deardoff (1998)). This point is clarified by Santos-Silva and Tenreyro (2006) when they notice that the most remote locations will tend to trade more between each other because they do not have alternative trading partners. This relative distance measure is based on the premise that the origins are also potential destinations, and is beyond the scope of the present study, since it applies to gravity models where origins and destinations are both the same kind of unit. In this study the origins (areas of residence) differ from destinations (hospitals).

In health applications where origins and destinations are not of the same type, Congdon (2001) replaced the attractiveness of destinations and distance terms of the standard gravity model in Equation (8) by a function in relative accessibility. This relative accessibility amounts to a distance-weighted supply measure (for a given supply more distant hospitals are down weighted) or equivalently a supply-weighted distance measure (of two equally distant hospitals the one with the larger supply will receive larger patient flows). In particular, the introduction of this form of accessibility means that the IIA property no longer holds and that the ratios of predicted flows to remaining hospitals are affected by the closure of a particular unit or the opening of a new one. However, competition effects between nearby hospitals are not represented directly in this form of relative access measure, and it may not appropriate to combine separate access, distance and hospital mass terms in a single model.

3 Empirical Application

We analyze patient mobility across state-owned hospitals in Texas using data on hospital admissions that occurred during the year 2006. Patient flows are reported in the Texas Inpatient Public Use Data File (PUDF) provided by the Texas Department of State Health Services (DSHS). In the reference year, Texas is partitioned into 9 state-owned mental hospitals (SMH) with the corresponding hospital service areas (HSA) with a total resident population of 3.83 million. HSA are local health care markets for hospital care. An HSA is a collection of ZIP codes whose residents receive most of their hospitalizations from the hospitals in that area. HSAs were defined by assigning ZIP codes to the hospital area where the greatest proportion of their Medicare residents were hospitalized. In Figure 1, Texas is divided into 8 HSA, but our data are disaggregated into 9 SMH, since we also analyze Kerrville State Hospital, which offers statewide Forensic Services. Table 1 lists the counties served by each SMH.

(Insert Figure 1 here)

(Insert Table 1 here)

We focus our empirical work on the model's predictions concerning the determinants of the cross-county variation in choosing a particular SMH. The conditional logit model as given by Equation (11) for the matrix of patient flows, h_{rs}, from county r to hospital s may be specified in terms of Poisson sampling (Guimaraes, Figueiredo and Woodward, 2003):

$$h_{rs} \sim \text{Poisson}(\mu_{rs}),\ r = 1, 2, \ldots, 254;\ s = 1, 2, \ldots, 9, \tag{13}$$

where the Poisson mean is predicted by:

$$\widehat{\mu}_{rs} = k\ \text{ALOS}_s\ \text{FS}_s\ \text{D}_{rs}\ \text{ADJ}_{rs}\ \text{HSA}_{rs}\ \text{CF}_{rs}, \tag{14}$$

with the exposure variable as the population in county r, POP_r, which indicates the number of times the event could have happened. The dependent variable, h_{rs}, is the number of patients admitted to hospital that flow from each county of origin, r, to each possible SMH of destination, s; k is an overall constant; ALOS_s represents average length of stay in hospital s; FS_s is a dummy variable that indicates if the SMH provides forensic services; D_{rs} represents road distance between r and s; ADJ_{rs} is a dummy variable that indicates if county r has a border with the county where SMH is located; HSA_{rs} is a dummy variable that indicates if county r belongs to the SMH's HSA; and CF_{rs} is the competition factor or an index that yields the gravity faced by SMH s in attracting patients from r.

The benchmark model, given by equation (14), will be used primarily to test the validity of the gravity model as a relevant empirical framework for patient flows. Equation (14) provides a suitable testing ground for the competing gravity model because it groups the variables in (14) so as to match the terms of equation (11). In fact, POP_r, the exposure variable used in Equation (14), proxies N_r in equation (11). We can think of road distance, adjacency, and HSA in (14) to account for the economic distance between the county and the SMH. The variables proxying for SMH services' quality are ALOS and provision of forensic services. The remaining variable in equation (14), the competition factor, accounts for the competition exerted by alternative destinations. We will replace the CF_{rs} in equation (14) with the accessibility measure variable, AM_s, to fully test the competition-agglomeration hypothesis.

Further below, instead of using population as the exposure variable, we will add counties' population and income per capita to equation (14) as factors determining the push factors of the residential areas. We will also add HSA's population and average income per capita as factors determining the pull factors of the SMH. Population indicates the market demographic size of the county. This variable enters the model as a push factor when referred to the counties of origin, POP_r, and a pull factor when referred to the HSA, $\mathrm{POP}_{\mathrm{HSA}}$. We consider estimated population by county for the year 2006, provided by DSHS Center for Health Statistics. If we assume that the hospital utilization rate does not vary with the market demographic size, then population proxies the internal demand for hospital admissions arising at a given SMH. We expect that the larger this demand the greater the possibility of reaching scale economies in hospital production and that risk sharing among the patients should lead to economies of scale in insurance cost. This implication has found empirical support in the analysis of Wholey, Feldman, Christianson and Engberg (1996). Because of such scale effects, patients enrolled in larger HSAs are, other things being equal, more likely to receive high quality specialized mental hospital care. Therefore, our case study is particularly well suited to conducting an empirical test for the presence of scale effect due to the size of population. If there are scale effects, we expect that the larger the HSA population the larger the inflow of patients. If we reject the scale effects, we expect a negative effect due to the problem of shortage of state hospital beds in larger HSAs (Torrey, Kennardm, Eslinger, Lamb and Pavle, 2010).

Income per capita enters the model as a push factor when referred to the counties of origin, Y_r, and a pull factor when referred to the HSA, $\mathrm{Y}_{\mathrm{HSA}}$. The variable income per capita is measured as the after-tax income per capita available on average to individuals living in a given county. It is estimated using data from U.S. Census Bureau.

In the literature on hospital choice, income is shown to positively affect mobility, i.e. richer individuals are able to choose destinations further away. In our aggregate spatial interaction modeling, average income per capita is likely to capture broadly defined socio-economic factors operating at each county and HSA. Since people in low income or poverty levels are associated with several lifetime mental disorders (Bassuk, Buckner, Perloff and Bassuk, 1998), we expect to observe a negative relationship between counties' income per capita and patient flows to SMH. Conversely, we expect to observe, *ceteris paribus*, better quality of care in richer HSAs and therefore an emergent pattern of patient flows moving to richer HSAs.

We are interested in analyzing the effects on patient flows of some SMH specific variables. The regressors included in our specification are proxies capturing the broad concept of quality in the supply of hospital care. These variables enter the model as pull factors (i.e. referred to the SMH of destination). We included the average length of stay in hospitals, ALOS_s, that is often used as an indicator of quality of care and efficiency in hospitals (Thomas, Guire and Horvat, 1997, Borghans, Kleefstra, Kool and Westert, 2012). All other things being equal, a shorter stay will have a positive effect on flows of patients. The source of this variable is the DSHS Center for Health Statistics Utilization Review: Specific Inpatient Procedures by Texas Hospital Referral Region Reports on Health Maintenance Organizations (HMO) (Guide to Texas HMO Quality: 2006).

We also analyzed the provision of forensic services, FS_s, of Texas' SMH. According to DSHS, the forensic population in SMHs is increasing. The role of the SMH in the treatment of forensic patients has expanded in recent years as some SMHs have experienced a significant increase in the number of forensic patients they serve. A forensic patient is one who is admitted to an SMH by judicial order because he or she has been determined unfit to stand trial or found not guilty by reason of insanity. Forensic commitments generally involve longer lengths of stays in the SMHs. All other things being equal, the provision of forensic services will have a positive effect on flows of patients.

(Insert Table 2 here)

In the following subsections we discuss the variables used to proxy the separation factors between counties and SMHs and to characterize the geographical pattern of patients' flows. Table 2 provides some descriptive statistics for the regressors included in the empirical application.

3.1 Separation Factors

The gravity model emphasizes the significance of separation factors in determining the pattern of the economic interactions flows (Fujita, Krugman and Venables, 1999). Very often in empirical applications the physical distance between economic centers is used to proxy the separation factors in the gravity model (Santos-Silva and Tenreyro, 2006, Fabbri and Robone, 2010, Congdon, 2001).

The separation factors between each county and SMH have been calculated as the "road distance" and the "driving time" between the counties' centers required to travel from one county to a SMH. The "road distance" and the "driving time" between the county's center and the SMH were constructed from Google Maps. We assume that patients used the driving directions by car suggested by Google Maps. Google Maps use speed limits provided by data providers, which generally obtain the information from road signs or public records. The variables were expressed in kilometers and minutes, respectively. Other things being equal, road distance, D_{rs}, should capture the deterrence effect on patient flows due to direct and indirect cost of mobility.

Adjacency, ADJ_{rs}, is a dummy variable assuming a value of 1 when the county of origin and destination share a border, and 0 otherwise. This variable is often included in the gravity models as a flow facilitator. Another measure of separation has been adopted in our analysis. We considered a dummy variable assuming a value 1 when the county belongs to the same local health care markets for hospital care, HSA_{rs}, and 0 otherwise. This variable is intended as a control for the presence of institutional factors that positively affect patient mobility to the corresponding SMH.

3.2 Geographical Patterns

To control for geographical patterns, we use the competition factor as given by Equation (10), and a potential accessibility measure, as proposed by (Fotheringham, 1983*a*), see Equation (12). The competition factor, CF_{rs}, is a composite variable that seeks to capture the gravity of the competing destinations (de Mello-Sampayo, 2009) and it is the sum, weighted by economic distance of all other SMHs' characteristics (except SMH s) in attracting patients flows from each county. The potential accessibility measure, AM_s, represents the accessibility of destination s in relation to all other destinations. This type of access measure may model competition and agglomeration effects.

To proxy the SMH's overall quality in attracting patients'flows, we used average charge per patient relative to SMH's average price provided by the Texas DSHS. Decision makers observe and decide the viability, utility, and characteristics of health care goods and services only after using those products or services. Thus, the quality of health care good or service can only be ascertained upon their consumption. In such cases, a drop in price is often interpreted by the prospective consumer as a drop in quality or utility of the product or service. Indeed, it is possible for the demand curve for medical care to be upward sloping, even though medical care is a non-inferior good, a relationship that has some empirical support (Hoi and Robson, 1981, Hau, 2008, Dusansky and Cagatay, 2010). Relative price of health goods or services is thus, a good indicator of quality in SMH services. Further, relative price is correlated with the variable used in this study to analyze the quality of the Texas SMH (ALOS) and so is arguably able to capture the overall characteristics of the SMH. However, in order to avoid multicollinearity problems, the relative price and "driving time" will be used only to compute the competition factor and the accessibility measure.

4 Results

The results are presented for two separate cases. In the first case, presented in Table 3, the gravity equation as given by Equations (13) and (14) is estimated with counties' population as the exposure variable. The case where counties' population and income per capita enter the gravity model as push factors of the residential areas, and HSA's population and average income per capita as pull factors of the SMH is then presented in Table 4.

(Insert table 3 here)

Table 3 is arranged into two main sections. The first is composed of columns (1)–(2), which correspond to the random effects poisson model estimation, and the other composed of columns (3)–(4), which correspond to the population average poisson model estimation. As seen in Table 3, for every Poisson model, according to the Wald test the overall significance of the regressors is not rejected at the 1% significance level. The random effects specification is also not rejected with a highly significant likelihood ratio (LR) test. Columns (2) and (4) present the results for the estimation of the gravity equation when the competition factor, CF_{rs}, in columns (1) and (3) is replaced by the accessibility measure variable, AM_s, to test the competition-agglomeration hypothesis. The coefficient estimates all have the correct signs and are significant in columns (1) and (3) with the exception of adjacency, ADJ_{rs}, which is not significant in column (3). In columns (2) and (4) the coefficient estimates all have the expected sign. However, the accessibility measure variable, AM_s, is not significantly different from zero in either column, and adjacency, ADJ_{rs}, is not significant in column (4).

The results of the population average poisson model (column 3) suggest that, at sample means, changes in ALOS negatively affect the patient flows to SMH by 0.9, whereas the positive effect of provision of forensic services is approximately 0.8. Changes in distance negatively affect the patient flow to SMH by 0.6, adjacency positively affects by 0.2, and the HSA positively affects the patient flow by 2.5. Supported by the model's predictions, in this econometric application the competition factor, CF_{rs}, negatively affects the patient flows by 5.3.

Under the hypothesis of competition-agglomeration (columns 2 and 4), the data predict that at the sample means, the negative effect of variations in ALOS on the patient flow to SMH is approximately 0.7, whereas the positive effect of provision of forensic services on the patient flows is approximately 0.3. Changes in distance negatively affect the patient flow to SMH by 0.5, adjacency positively affects by 0.1, and the HSA positively affects the patient flow by 2.6. The patient flow to SMH is negatively affected by variations in the accessibility measure variable, AM_s, by 0.02 which suggests that the access measure models competition effects.

It is worth noting that although the qualitative response of patient flows to the different explanatory variables is similar, the quantitative impact differs under the two different geographical pattern variables. This discrepancy is explained not only by differences in the specification of the respective variable, but also by the underlying assumptions of each model. Therefore, the quantitative results obtained for each specification do not lend themselves to direct comparison. In fact, as opposed to the accessibility measure under the competition-agglomeration hypothesis, the competition factor is capturing the gravity of alternative SMHs. What can be drawn from the similarity of the qualitative results is that the predictions of the analytical model developed earlier are robust to both specifications.

(Insert Table 4 here)

Table 4 presents the results when we add to equation (14) counties' population and income per capita as push factors of the residential areas, and HSA's population and average income per capita as pull factors of the SMH. Table 4 is arranged into two main sections. The first is composed of columns (1)–(2), which correspond to the random effects poisson model and the other composed of columns (3)–(4), which correspond to the population average poisson model. The results of the model with the competition factor, CF_{rs}, characterizing the spatial pattern, is presented in columns (1) and (3) and with the accessibility measure variable, AM_s, to test the competition-agglomeration hypothesis, is presented in columns (2) and (4). Under both spatial patterns' characterizations we do not reject the overall significance of the regressors with the Wald test and we do not reject the random effects specification with a highly significant LR test.

The estimates of the gravity model under both spatial patterns' characterizations suggest, as expected, a positive and significant coefficient for counties' population, and since in our aggregate spatial interaction modeling, average income per capita is proxying socio-economic factors operating at each county, a negative and significant coefficient for the counties' income per capita is suggestive that low-income individuals are more likely to be the patients admitted in SMH's services. With regard to the variables that make up the push factors in the model, namely HSA's population and average income per capita, the results vary with the two spatial patterns' variables. Under the population average model estimation, when using the competition factor to characterize the geographical pattern (column 3), changes in HSA's population negatively affects the patients' flows by 0.5. This result does not give support to the presence of scale effect due to the size of population. However, the coefficient estimate for the HSA's population has the expected sign, but it is not significantly different from zero when using the accessibility measure to characterize the geographical pattern. HSA's income per capita positively affects, as expected, the patients' flow to SMH by 0.7. This estimated income effect is lower than under the accessibility measure's model, which stands at 1.3. For both spatial patterns' characterization, there is a pattern of patient flows to SMH in richer HSA, so as to get better quality of care in richer HSA.

At the sample means, we observe that when using the competition factor to characterize the geographical pattern (column 3), the patients' flow to SMH is affected negatively by the change in ALOS by around 0.5, and positively by the provision of forensic services by around 0.7. On the other hand, with respect to the spatial factors, the patient flow is negatively affected by the road distance and the competition factor and positively by the adjacency and HSA by around 0.7, 4.5, 0.03, and 2.6, respectively. When using the accessibility measure to characterize the geographical pattern (column 4), though not significant, ALOS, forensic services, adjacency, and the accessibility measure have the expected signs.

With respect to the variables that make up the geographical pattern in the model, namely competition factor and accessibility measure, the coefficient of the competition factor is significantly higher and different from zero. The estimated negative effect of the competition factor on patient flows reflects the fact that the higher the quality and the better localized the concurrent SMH, the fewer inflows one expects to occur to a particular SMH. The result by which the accessibility measure affects patient flows negatively is explained by the fact that the more accessible one SMH is to another raises the competition between SMH and the fewer inflows of patients we observe. However, the remarkable feature of the present results is the strong impact of the competition factor. The relevance of such a result in the present context is that, by highlighting the importance of the gravity of alternative SMH on patient flows, it lends overwhelming support to the analytical framework proposed in the first part of the paper.

5 Conclusion

This paper presents the micro-foundations for the gravity model with the aim of analyzing the flows of patients from their residential areas to the health service areas in a context of interdependence of the flows. With the goal of empirically testing the theoretical model, a discrete-variable econometric model that uses ALOS as the proxy for (the reciprocal) of the quality of hospital is estimated for a 2006 sample of US Texas counties' patient flows into SMHs. To control for the geographical pattern, we included in the gravity model a composite variable, the competition factor, capturing the gravity of alternative destinations. We also used an accessibility measure to test the competition-agglomeration hypothesis of alternative destinations.

The results of the econometric estimation suggest that the theoretical model can explain the patient flows from Texas' counties to SMHs under the hypothesis of interdependence of the flows. Indeed, as predicted, patient flows depend negatively on the ALOS, on road distance and on the gravity and accessibility of alternative SMH. Patient flows depend positively on the provision of forensic services, on adjacency, and on the institutional factors. By suggesting that patient flows depend not only on the push factors, pull factors and spatial factors but crucially on the geographical pattern, the overall empirical results corroborate the use of the competing-destinations of the gravity model.

Texas' patient flows are also found to be increasing in counties' population and HSA's income per capita, and decreasing in HSA's population and counties' income per capita. Thus, our results do not lend support to the presence of scale effects in SMHs due to the size of population. This result, combined with the negative effect of ALOS and with the positive effect of the provision of forensic services on patient flows, highlights the problem of caseload growth. One of the major problems associated with the growing forensic population is the longer lengths of stay. These longer lengths of stay and the overall increase in the forensic population has led to longer wait times and waiting lists at SMHs for forensic beds. Addressing all of these challenges to SMHs will require critical policy and fiscal decisions. One solution might be to reinforce the continuum of care or assisted outpatient treatment (Torrey et al., 2010), which requires selected seriously mentally ill persons to take medication under court order as a condition for living in the community.

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Figure and Tables to be Included in Main Text

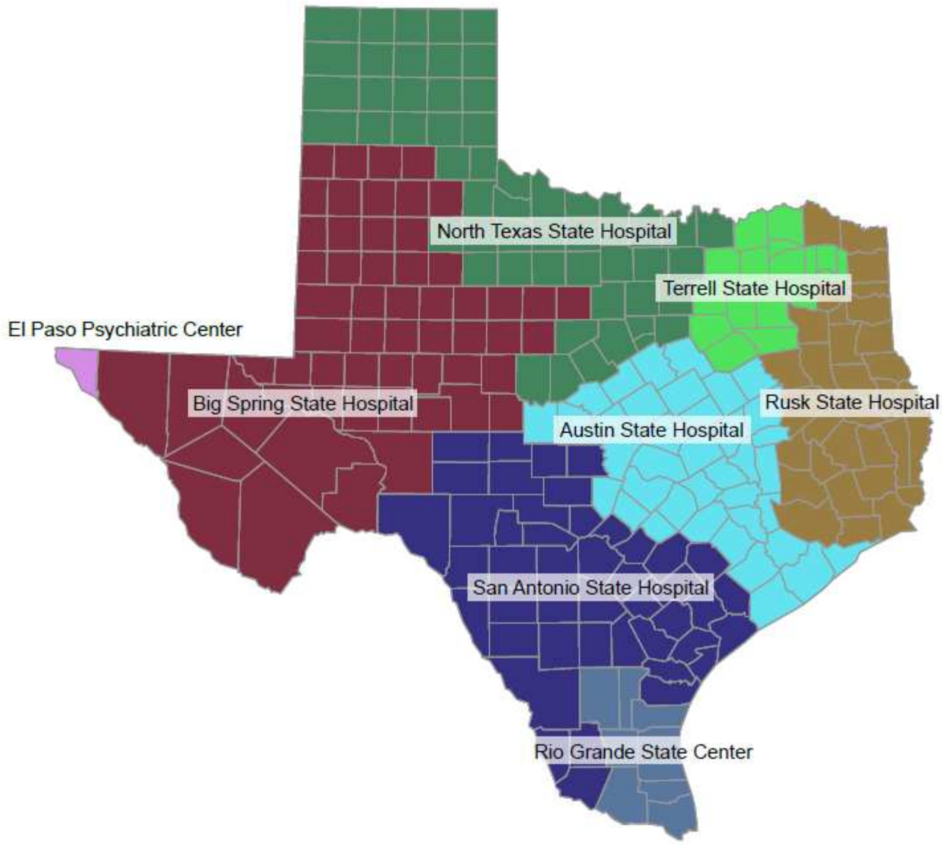

Figure 1: Texas State Hospital Service Areas

Table 1: Counties in State Mental Hospitals Services Areas

Hospitals Service Areas	Counties
North Texas State Hospital	Archer, Armstrong, Baylor, Brown, Carson, Childress, Clay, Coleman, Collingsworth, Comanche, Cooke, Cottle, Dallam, Deaf Smith, Denton, Dickens, Donley, Eastland, Erath, Foard, Gray, Grayson, Hall, Hansford, Hardeman, Hartley, Haskell, Hemphill, Hood, Hutchinson, Jack, Johnson, King, Knox, Lipscomb, Montague, Moore, Ochiltree, Oldham, Palo Pinto, Parker, Potter, Randall, Roberts, Sherman, Somervell, Stonewall, Tarrant, Throckmorton, Wheeler, Wichita, Wilbarger, Wise, and Young.
Terrell State Hospital	Camp, Collin, Dallas, Delta, Ellis, Fannin, Franklin, Henderson, Hopkins, Hunt, Kaufman, Lamar, Morris, Navarro, Rains, Titus, Van Zandt, and Wood.
Rusk State Hospital	Anderson, Angelina, Bowie, Cass, Chambers, Cherokee, Gregg, Hardin, Harris, Harrison, Houston, Jasper, Jefferson, Liberty, Marion, Montgomery, Nacogdoches, Newton, Orange, Panola, Polk, Red River, Rusk, Sabine, San Augustine, San Jacinto, Shelby, Smith, Trinity, Tyler, Upshur, and Walker.
Austin State Hospital	Austin, Bastrop, Bell, Blanco, Bosque, Brazoria, Brazos, Burleson, Burnet, Caldwell, Colorado, Coryell, Falls, Fayette, Fort Bend, Freestone, Galveston, Grimes, Hamilton, Hays, Hill, Lampasas, Lee, Leon, Limestone, Madison, Matagorda, McCulloch, McLennan, Milam, Mills, Robertson, San Saba, Travis, Waller, Washington, Wharton, and Williamson.
San Antonio State Hospital	Aransas, Atascosa, Bandera, Bee, Bexar, Calhoun, Comal, Dewitt, Dimmit, Edwards, Frio, Gillespie, Goliad, Gonzales, Guadalupe, Jackson, Jim Hogg, Karnes, Kendall, Kerr, Kinney, La Salle, Llano, Lavaca, Live Oak, Mason, Maverick, Medina, Menard, Nueces, Real, Refugio, San Patricio, Schleicher, Starr, Sutton, Uvalde, Val Verde, Victoria, Webb, Wilson, Zapata, and Zavala.
Kerrville State Hospital	Statewide Forensic Services.
Big Spring State Hospital	Andrews, Bailey, Borden, Brewster, Briscoe, Callahan, Castro, Cochran, Coke, Concho, Crane, Crockett, Crosby, Culberson, Dawson, Ector, El Paso, Fisher, Floyd, Gaines, Garza, Glasscock, Hale, Hockley, Howard, Hudspeth, Irion, Jeff Davis, Jones, Kent, Lamb, Loving, Lubbock, Lynn, Martin, Midland,Mitchell, Motley, Nolan, Parmer, Pecos, Presidio, Reagan, Reeves, Runnels, Scurry, Shackleford, Stephens, Sterling, Swisher, Taylor, Terrell, Terry, Tom Green, Upton, Ward, Winkler, and Yoakum.
Rio Grande State Center	Brooks, Cameron, Duval, Hidalgo, Jim Wells, Kenedy, Kleberg, Willacy.

Table 2: Descriptive Statistics

	Variables	Mean	Std. Dev.	Min.	Max.
Dependent Variable					
	Patient Flow	7.23	61.44	0	1843
Push Factors					
	Population County	92 550.33	329 826.10	60	3 830 130
	Income per capita County	21 521.11	5 049.17	10 180	42 220
Pull Factors					
	ALOS	132.22	230.07	18	777
	Forensic Services	0.67	0.47	0	1
Spatial Factors					
	Road Distance	542.69	286.84	2	1757
	Adjacency	0.02	0.14	0	1
	HSA	0.22	0.42	0	1
	Competition Factor	159.77	14.27	133.85	176.85
	Accessibility Measure	0.45	0.11	0.26	0.60
	Variables in Logs	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Push Factors					
	Log Population County	9.85	1.64	4.09	15.16
	Log Income per capita County	9.95	0.23	9.23	10.65
Pull Factors					
	Log Population HSA	14.68	0.69	13.52	15.62
	Log Income per capita HSA	9.85	0.26	9.22	10.14
	Log ALOS	3.76	0.60	2.89	4.73
Spatial Factors					
	Log Road Distance	6.14	0.68	0.69	7.47
	Log Competition Factor	5.06	0.09	4.90	5.18
	Log Accessibility Measure	-0.87	0.29	-1.34	-0.51

Table 3: Model Estimates

	Random Effects		Population Average	
	(1)	(2)	(3)	(4)
Pull Factors				
Log ALOS (ALOS$_s$)	-0.800***	-0.825***	-0.892***	-0.721***
	(0.057)	(0.284)	(0.094)	(0.239)
Forensic Services (FS$_s$)	0.733***	0.827*	0.751***	0,311
	(0.126)	(0.519)	(0.140)	(0.277)
Spatial Factors				
Log Road Distance (D$_{rs}$)	-0.587***	-0,587***	-0,560***	-0.517***
	(0.009)	(0.009)	(0.126)	(0.114)
Adjacency (ADJ$_{rs}$)	0.285***	0.287***	0.175	0.084
	(0.024)	(0.024)	(0.195)	(0.236)
HSA (HSA$_{rs}$)	2.321***	2.320***	2.510***	2.631***
	(0.027)	(0.027)	(0.358)	(0.344)
Log Competition Factor (CF$_{rs}$)	-5.277***	—	-5.301***	—
	(0.520)		(0.759)	
Log Accessibility Measure (AM$_s$)	—	-0,096	—	-0.022
		(0.778)		(0.416)
Constant	21.914***	-4,591***	22.041***	-5.459***
	(2.642)	(1.331)	(4.147)	(1.113)
Alfa	0.020	0.257	—	—
	(0.010)	(0.117)		
No. Observations	2286	2286	2286	2286
No. SMH	9	9	9	9
Wald Test	34438.50***	34061.50***	2140.37***	2222.60***
Degrees of Freedom	6	6	6	6
Likelihood-ratio Test	233.39***	2900.07***	—	—
Degrees of Freedom	1	1		

Exposure Variable: County's Population.
Standard errors in parentheses. Robust Standard errors in parentheses in columns (3) and (4).

* Rejects the null at the 10% level. ** Rejects the null at the 5% level. *** Rejects the null at the 1% level.

Table 4: Model Estimates with Push Factors

	Random Effects		Population Average	
	(1)	**(2)**	**(3)**	**(4)**
Push Factors				
Log Population County (POP_s)	0.816***	0.816***	0.850***	0.839***
	(0.006)	(0.006)	(0.060)	(0.072)
Log Income per capita County (Y_s)	-1.425***	-1,424***	-1.407***	-1.162**
	(0.043)	(0.043)	(0.502)	(0.533)
Pull Factors				
Log Population HSA (POP_{HSA})	-0.106	0.003	-0.455***	0.104
	(0.183)	(0.649)	(0.166)	(1.055)
Log Income per capita HSA (Y_{HSA})	0.385	1.420*	0.699	1.286**
	(0.326)	(0.781)	(0.461)	(0.572)
Log ALOS ($ALOS_s$)	-0.787***	-0.928	-0.453***	-0.798
	(0.204)	(0.625)	(0.129)	(0.764)
Forensic Services (FS_s)	1.166***	1.129	0.671**	0,709
	(0.270)	(0.750)	(0.298)	(0.759)
Spatial Factors				
Log Road Distance (D_{rs})	-0.651***	-0,650***	-0.654***	-0.591***
	(0.008)	(0.008)	(0.100)	(0.065)
Adjacency (ADJ_{rs})	0.054**	0.053**	0.032	0.051
	(0.024)	(0.024)	(0.238)	(0.294)
HSA (HSA_{rs})	2.387***	2.388***	2.550***	2.634***
	(0.027)	(0.027)	(0.361)	(0.382)
Log Competition Factor (CF_{rs})	-5.244***	—	-4.451***	—
	(0.811)		(0.859)	
Log Accessibility Measure (AM_s)	—	-0,040	—	-0.625
		(1.018)		(1.414)
Constant	28.610***	-9,158	24.843***	-13.657
	(6.478)	(10.423)	(6.820)	(14.419)
Alfa	0.036	0.203	—	—
	(0.017)	(0.093)		
No. Observations	2286	2286	2286	2286
No. SMH	9	9	9	9
Wald Test	63319.92***	63060.30***	2130.81***	300.65***
Degrees of Freedom	10	10	7	7
Likelihood-ratio Test	401.47***	2229.29***	—	—
Degrees of Freedom	1	1		

Standard errors in parentheses. Robust Standard errors in parentheses in columns (3) and (4).

* Rejects the null at the 10% level. ** Rejects the null at the 5% level. *** Rejects the null at the 1% level.