Why is Distance Important for Hospital Choice? Separating Home Bias from Transport Costs*

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Abstract

In retail and health care markets, demand declines with geographic distance to the establishment, but either transport costs or preferences correlated with distance ("home bias") could cause this decline. Using hospital choices for childbirth, we find that, after controlling for home bias using fixed effects, estimates of the transport cost disutility fall by 50% relative to a standard logit model. We show that referrals are a likely source of home bias. Through two examples – a simulated merger and a planned hospital move – we demonstrate that controlling for home bias can imply greater substitution between geographically distant hospitals.

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1 Introduction

As economists have known since Hotelling (1929), demand declines rapidly with distance in retail and health care markets. For example, Gowrisankaran et al. (2015) find that a five minute increase in travel time to a hospital reduces demand between 17 and 41 percent. Holmes (2011) finds that an increase in consumer distance to a Wal-Mart from zero to five miles can decrease demand by 80 percent. In addition, perhaps the most robust empirical relationship in economics is the gravity equation, which predicts that the distance between trading partners engaged in international trade is roughly inversely proportional to their trade flow. In this paper, we examine the role of distance in the context of health care markets.

Researchers typically interpret distance effects as due to transport costs. However, as Doane et al. (2012) note, travel time matters far more relative to hospital quality than would be expected from the opportunity cost of time. An alternative explanation for distance effects is that distance is correlated with unobserved consumer preferences, a correlation we refer to as "home bias". When distance effects also reflect differences in preferences, counterfactual policy analysis may understate consumers' willingness to travel. For example, a main area of focus in the welfare analysis of hospital mergers has been estimates of patients' willingness to travel to obtain medical care, which can determine both the likely price effects and the proper antitrust market definition for a given merger.

In this paper, we employ a panel data fixed effects approach from Chamberlain (1980) to control for potential home bias effects in the context of patients' choice of hospital for childbirth.[1] We define home bias as patient-hospital interactions that are persistent across births and larger on average for hospitals that a patient lives close to. The fixed effects approach uses women who move and switch hospitals between their first two births. Women moving between births identify transport costs independently from persistent unobserved hospital preferences, because patients' distance to hospital providers changes over time.[2] This

[1] Childbirth is a good context to study this question because the services that the patient needs are similar across multiple childbirths, but patients do not typically need to return to the same hospital where they previously received care.

[2] Our use of migrants is similar in spirit to Finkelstein et al. (2016), who use migrants to separate supply and demand side effects in health care utilization.

estimator also provides consistent estimates of the effect of transport costs when switching hospitals is costly for women.

We use data on inpatient childbirths in Florida between 2006 and 2014, and compare our fixed effects estimates to the common approach in the literature – a logit model using patient choices that does not control for individual patient-hospital interactions. The disutility of transport costs derived from the fixed effects estimator falls by about half compared to those derived from the standard logit approach. For example, the standard discrete choice framework implies that demand falls by 9.7% for a 1 minute increase in travel time for a hospital with a 20% share of the market, compared to a 5.4% fall in demand using the fixed effects estimator. Thus, without controlling for home bias, one will substantially overestimate the disutility of transport costs.

One possible concern with our estimates is that the disutility of transport costs is different for women who move and switch hospitals compared to the full sample of women giving birth in Florida. However, we find similar estimates for the standard logit estimator for both datasets. In addition, we also consider changes in consideration sets post-move, time-varying unobservables correlated with changes in distance, and measurement error in distance, and conclude that none of these factors can explain our findings.

We next find that referral patterns are likely an important determinant of home bias. If patients' hospital choices depend on their physicians, physicians' offices are located near their patients, and physicians refer to hospitals near their offices, referral networks would magnify any effect of distance.[3] We empirically examine how physician referrals affect our results by including an indicator variable for hospitals at which patients' obstetricians practice, and find that doing so explains half of the gap between the standard logit and fixed effect estimates. In contrast, we do not find evidence that switching costs or catering to local demand can explain our home bias effects.

We then examine three applications for which controlling for home bias changes the conclusions of counterfactual policy analysis. First, we decompose the referral function of Ho and Pakes (2014a), and show that accounting for referral patterns affects both estimates

[3] A similar argument applies for a patient's network of friends. We present a simple model that illustrates that the social multiplier from peers required to match the gap between our standard logit and fixed effects estimates is within estimates found in the peer effects literature in other contexts (Glaeser et al., 2003).

of patients' willingness to travel and predicted harm from mergers. In particular, we assume that both patients and clinicians have a disutility for traveling and that patients' choice of hospitals depends both on their own and their clinician's disutility for travel. In this context, the clinician's disutility for travel can generate home bias. In a simulation, we replicate our findings that failing to account for home bias overstates consumers' disutility of travel. Further, if insurance companies only care about patient preferences, we find that ignoring home bias understates merger harm by a magnitude that could lead to permitting a problematic merger. More broadly, our simulated results thus show that, under realistic parameter values, failing to account for home bias could lead to inefficient merger policy.

In our second application, we examine changes in demand for different geographic areas after the proposed relocation of a Hospital Corporation of America (HCA) hospital. In a Certificate of Need (CON) filing, several hospital systems opposed this relocation. A major point of contention was the definition of the hospital's new service area. Opposing hospitals claimed that patients living close to the old location, but far from the new location, would be harmed because they would be unwilling to travel to the new location. The fixed effects estimates imply that the new hospital would lose a much smaller share of patients that lived far from the new hospital site but close to the old one compared to the standard logit estimates, because patients are much more willing to travel under the fixed effects model.[4] Thus, evaluations of product repositioning or entry have to account for home bias effects in order to predict the spatial distribution of demand.

In addition, our results on home bias will affect researchers that use distance as a welfare metric. For example, Capps et al. (2010) use patient's disutility for distance to dollar denominate the welfare loss of hospital closures. Gowrisankaran et al. (2017) measure patient's valuation of Critical Access Hospitals in Medicare's Rural Hospital Flexibility Program in terms of distance. In addition, previous work has used distance to determine patients' valuation of quality (Romley and Goldman, 2011; Chandra et al., 2016; Gaynor et al., 2016). In our third application, we recalculate patients' marginal rate of substitution between quality and distance and find that patients may be more sensitive to hospital quality than previously

[4] In this counterfactual, we assume that patient-hospital interactions remain constant immediately following the move, which could reflect that referral patterns take time to adjust.

thought.

A large literature finds that a consumer's demand declines with distance for industrial organization markets, and that consumers' aversion to travel is critical to understand where retailers set up stores and how they respond to changes in competition (Holmes (2011), Houde (2012), Thomadsen (2005)).[5] In healthcare markets, distance to medical provider is one of the most important predictors of provider choice (Capps et al. (2003), Gowrisankaran et al. (2015), Ho (2006), Raval et al. (2017a)).

Three recent papers demonstrate how distance can affect demand other than through transport costs in other contexts. In the setting closest to ours, Beckert and Collyer (2017) find that distance elasticities fall by over 50% after accounting for physician referrals in a population of UK patients choosing hospitals for elective surgeries. Moraga-González et al. (2017) derive a search model for automobile purchase in which distance affects search frictions rather than consumer utility. Chaney (2018) develops a model of international trade in which the social network of entrepreneurs can lead to gravity effects without direct transportation costs from trade.

This paper proceeds as follows. In Section 2, we outline a model of provider choice and our approaches to identification. In Section 3, we describe the data. In Section 4, we estimate the disutility of transport costs. In Section 5, we examine several mechanisms for home bias. In Section 6, we show the implications of controlling for home bias for three counterfactual policy applications. We conclude in Section 7.

2 Identification of Consumer Choice Model

We begin by reviewing a workhorse model of a patient's hospital choice used in many recent papers as the cornerstone of a broader empirical model of hospital and insurer bargaining (Capps et al. (2003), Gowrisankaran et al. (2015), Ho and Lee (2017)). We then show how to use panel data to identify the disutility of transport costs in the presence of home bias.

[5] In addition, the gravity equation in trade arises naturally out of several economic models (Bergstrand (1985), Head and Mayer (2013)). Anderson and Van Wincoop (2004) and Anderson (2011) provide surveys of the empirical evidence in international trade. A gravity equation has been documented by Hortaçsu et al. (2009) for online commerce, Grogger and Hanson (2011) for migration, Helpman et al. (2004) for FDI, and Wolf (2000) for domestic trade.

2.1 Baseline Model

Patient i becomes pregnant at time t in market m. She chooses hospital j from a set of hospitals H ($j = 1, ..., N$) that are available to her based on the utility from receiving care there. She can also choose an outside option $j = 0$. Patient i's utility from care at hospital j at time t is given by:[6]

$$u_{ijt} = \delta_{ijt} + \epsilon_{ijt}. \tag{1}$$

The mean utility of hospital j for patient i at time t is δ_{ijt}, while ϵ_{ijt} is a Type-I extreme value distributed patient-hospital-time i.i.d error term that reflects a patient's idiosyncratic hospital preferences. We normalize the mean utility of the outside option to zero.

A patient's ex-ante probability of choosing hospital j at time t is given by:

$$Pr(h_{it} = j) = \frac{\exp(\delta_{ijt})}{\sum_{k \in 0,...,N} \exp(\delta_{ikt})}. \tag{2}$$

We then parametrize δ_{ijt} to include distance, switching costs, and observed and unobserved components of a patient's tastes for hospitals:

$$u_{ijt} = \alpha d_{ijt} + \beta x_{ijt} + \gamma I[j = H_{it-1}] + \xi_{ij} + \epsilon_{ijt}, \tag{3}$$

where

$$H_{it-1} = \arg \max_{k=0,...,N} u_{ikt-1}.$$

In equation (3), d_{ijt} is the distance from patient i's residence to hospital j at time t, while ξ_{ij} represents persistent patient preferences for a given facility. These persistent preferences could be the result of persistent doctor or friend referral patterns, patient specific preferences for hospital amenities, or proximity to another location to which the patient frequently travels such as a workplace.

Since we focus on young women with childbirths, a fairly clinically homogeneous pop-

[6] As Ho and Pakes (2014a) note, a patient's decision of where to go to the doctor is the result of a combination of preferences of the woman, her physician, and her insurer. In the first sections of this paper, as in Gowrisankaran et al. (2015), Ho and Lee (2017), and other papers in this literature, we give this function a welfare interpretation. In Section 6, we decompose this function in such a way that some components affect welfare, but others do not.

ulation, we suppress observable time-varying characteristics x_{ijt} in the utility function.[7] $I[j = H_{it-1}]$ is a dummy variable indicating whether the patient visited hospital j on her previous visit. Therefore, γ represents the switching costs of visiting a different hospital on different visits.

The semi-elasticity of demand for hospital j with respect to transport costs depends both upon the transport cost parameter α and hospital j's share of the market. As a hospital's share rises, the effect of transport costs on demand falls. The transport cost semi-elasticity is the coefficient on distance, α, multiplied by the probability that the patient goes to any other hospital $1 - Pr(h_{it} = j)$:

$$\frac{d \log(Pr(h_{it} = j))}{d(d_{ijt})} = \alpha(1 - Pr(h_{it} = j)). \tag{4}$$

2.2 Identification

The identification approach used in previous research estimating patient demand for health care providers typically makes two implicit assumptions (Gowrisankaran et al., 2015; Ho and Lee, 2017; Ho and Pakes, 2014a; Raval et al., 2017a). First, individual preferences for hospitals only vary with patient observable characteristics, which is equivalent to restrictions on the form of ξ_{ij}. Second, switching costs γ are assumed to be zero.[8] These two assumptions have important implications for the interpretation of distance estimates, since they both rule out the possibility for home bias. Consumer preferences exhibit home bias when unobserved tastes ξ_{ij} are, on average, larger for individuals living closer to hospital j.

For consistent estimates of the disutility of transport costs in this framework, unobservable patient preferences for hospitals ξ_{ij} must be independent of a patient's distance from the hospital d_{ijt}. For example, given home bias of preferences, logit estimates will overestimate the effect of distance. Further, for patients who do not move residential location, the patient's previous choice will also be a function of her distance to the hospital. In that case,

[7] If there is variation over time within individuals in other variables, we could identify β for those characteristics as well. For example, see Raval and Rosenbaum (2016) for steering effects of Medicaid MCOs.

[8] One recent exception is Shepard (2016), who estimates a demand model which allows for state dependence (i.e., $\gamma \neq 0$), although he acknowledges that he is unable to separately identify preference heterogeneity from structural state dependence.

when there are switching costs (so $\gamma > 0$), the error term when switching costs are excluded will be a function of distance d_{ijt} and unobserved preferences ξ_{ij}.

We address these endogeneity issues by using the fixed effects logit approach of Chamberlain (1980) to identify the transport cost parameter α. This approach conditions on the sum of an individual's choices over time, and identifies the parameters of interest from variation in the sequence of choices over time.

For intuition, consider Figure 1, which shows a woman who has hospitals A, B, and C in her choice set for both her first and second birth. For her first birth, she lived closer to hospital A than hospital B. Between the two births, she moves residences, such that for her second birth she is closer to hospital B than hospital A. The conditional logit estimator is based upon the probability that she went to hospital A for the first birth, and then hospital B for the second birth, compared with the opposite order. Since hospital A is located closer to her for the first birth, and hospital B is located closer to her for the second birth, her likelihood of going to A for the first birth and B for the second birth increases as the disutility of transport costs α rises.

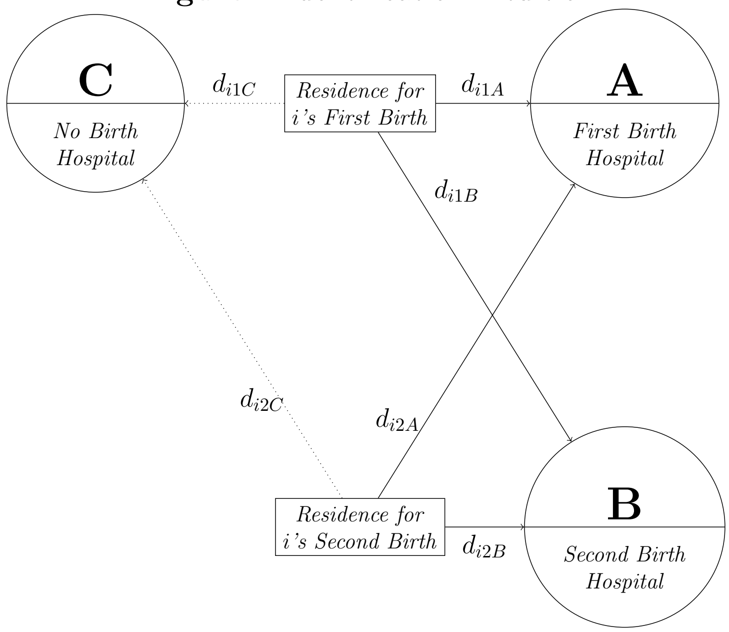
Since both hospitals A and B were options each time, the fixed effects approach differences out any time-invariant hospital-patient interactions. Switching costs are also differenced out, because in either case the patient incurs a switching cost γ in the second period. We are then able to identify the marginal impact of changing d_{ijt} using the conditional likelihood.

Consider women that went to hospital A for one birth and hospital B for the other birth. Then, if ϵ_{ijt} is distributed Type-I extreme value, Chamberlain (1980) shows that the conditional probability that these women went to A first and B second is a function of the "difference in difference" in distance: the difference in distance in the second period between hospital B and hospital A, minus the difference in the first period between hospital B and hospital A. As the transport cost parameter α gets larger, the probability that the women went to the hospital that became relatively closer in the second period rises.

Formally, the expression for the conditional probability is:

$$\Pr[(A,B)|(A,B) \text{ or } (B,A)] = \frac{\exp(\alpha z)}{1+\exp(\alpha z)},$$

Figure 1 Identification Intuition



where

$$z = (d_{2B} - d_{2A}) - (d_{1B} - d_{1A})$$

and

$$Pr(j,k) = Pr(h_{i1} = j, h_{i2} = k).$$

Since the ξ_{ij} terms and switching costs γ are differenced out from the expression, we can consistently estimate α. However, only patients that move residences between their births and go to different hospitals for each birth provide identifying variation under this approach.[9]

To see how this identification works, take the choice behavior of the woman in Figure 1. Let hospital A be ten miles from her residence at first birth, and twenty miles from her residence at second birth, while hospital B is twenty miles from her residence at first birth and ten miles from her residence at second birth. In that case, if the transport cost parameter α is -0.1, her likelihood of going to hospital A for her first birth and then B for the second birth is 88%. If the transport cost parameter falls by half to -0.05, her likelihood of going to A first and then B falls to 73%. Thus, the likelihood that she goes to A first and then B is informative of the degree of disutility of transport costs. Her distance to hospital C

[9]If patients do not move, it would be impossible under this approach to estimate patients' travel preferences, since there would be no variation in z.

plays no role in this identification approach, as only the hospitals that she went to enter the conditional likelihood.

2.3 Threats to Identification

Our identification approach assumes that unobserved preferences for hospitals are fixed, and so only takes account of time-invariant correlations between unobserved patient preferences for a specific facility and distance. In this section, we examine the implications of potential time-varying changes in unobserved preference due to patient learning about quality, changes in patient consideration sets due to the move, and income shocks that affect both patient location and hospital preference. In general, these threats to our identification strategy will bias our estimates away from a zero effect of distance.

If patients learn about hospital quality after their hospital visit, the assumption of fixed unobserved preferences will be violated. While the overall change in hospital quality for the hospital the patient visited previously across all hospitals and patients will be captured in the switching costs γ, the update in belief about quality could vary across hospitals and patients depending on the patient's experience. However, because our focus is on the role of distance, our main requirement is that any update to the patient's belief about hospital quality is independent of the change in distance from the move, just as the logit error shock is independent of distance. In our view, this assumption is reasonable.

A second threat to identification is that the hospitals that patients consider when they make their hospital choice change with the move. In our model, the patient considers both hospitals in each location; a hospital entering the patient's consideration set after the move would have a large increase in the patient-hospital quality ξ_{ij}, which would break our identification approach. If consideration sets change such that hospitals that become closer enter the consideration set, or hospitals that become farther away leave the consideration set, we will overstate the effect of transport costs. In this scenario, the change in consideration sets implies that patients move closer to hospitals for which they have a positive preference shock, and away from hospitals for which they have a negative preference shock, so the change in distance is negatively correlated with the change in quality. We examine this threat to identification empirically by comparing small moves to large moves; larger moves are more likely to change the patients' consideration set. We find fairly similar estimates for both types of moves, indicating that major bias in our transport cost coefficients from changes in consideration set is unlikely.

A third possibility is that a shock both affects a patient's residence and her hospital preferences. For example, if a patient has a positive income shock and so both moves to a more upscale neighborhood and increases her valuation of hospital quality, the fixed effects estimator will overstate the effects of transport costs so long as higher quality hospitals are located in more upscale neighborhoods. In order to examine this possible threat to our identification strategy, we examine only women for whom the difference in zip code median household income between locations is less than $10,000, and find similar estimates to our baseline results.

3 Data

We use hospital discharge data obtained from the Florida Agency for Health Care Administration (AHCA) from 2006 to 2014.[10] The data includes the zip code of residence for each patient, which allows us to compute the travel time from the patients' residence to each hospital. Patient identifiers allow us to match births by the same woman over time.

In order to difference out switching costs in our structural estimates, we need to know the first birth of women in our sample. However, we only have data going back to 2006, so we do not know of women's births prior to that date. Because of this initial conditions problem, we only include women who were at most 21 in 2006. This restriction eliminates the initial conditions problem for most of the women.[11]

We report summary statistics in Table I for the full sample of all births in Florida, all births for women that meet our age restriction, and births for women who meet our age restriction and contribute to the likelihood of the Chamberlain estimator. The latter set of women switch both residence and hospital between their first and second birth. Imposing

[10]The limited data set was obtained from the AHCA, but that agency bears no responsibility for any analysis, interpretations, or conclusions based on this data.

[11]Nationwide, about 87 percent of first births are of mothers age 20 and above and 96 percent of first births are of mothers age 18 or above (Hamilton et al. (2015)).

the age restriction leaves about 35 percent of the women from the full sample of all births in Florida and about 37 percent of total births. The women in the Chamberlain sample make up 3.8 percent of the women that meet the age restriction, and their births comprise 5.9 percent of the births of the women that meet the age restriction.

The average age is much higher for the full sample, at 27.6 years, than for the other datasets that impose the age restriction, all of which have an average age of about 21.7. As we impose more restrictions, the fraction of admissions that are white falls, from 66 percent for the full sample of births to 52 percent for the Chamberlain dataset, while the fraction of admissions that are black rises from 23 percent for the full sample to 40 percent for the Chamberlain dataset. The fraction of admissions that are Hispanic remains constant at about 20 percent. The fraction of admissions from patients on Medicaid rises from 51 percent for all births, to 72 percent for births of women that meet the age restriction, to 79 percent for the Chamberlain sample. Almost all births are of women living in metropolitan areas.

Table I Summary Statistics

	All	Age Restriction	Chamberlain
Age	27.58	21.73	21.70
White	0.66	0.61	0.52
Black	0.23	0.30	0.40
Hispanic	0.20	0.20	0.19
Medicaid	0.51	0.72	0.79
Metro	0.94	0.92	0.98
N Births	1,794,598	667,310	39,462
N Women	1,247,610	439,636	16,718

Note: All datasets are as described in the text.

We define the choice set for each patient as all hospitals within 45 minutes driving time of her zip code centroid.[12] All hospitals not within this choice set are included together as the "outside option". For the Chamberlain sample, we require the hospital chosen for each birth to be in the choice set for both births. This restriction would remove, for example, women who choose a hospital in Jacksonville at first birth and in Miami at second birth.

Since the data includes the zip code of residence for each patient, the measure of distance

[12]See Ho and Pakes (2014a) for a similar choice set restriction.

that we use is the travel time from the centroid of the patient's zip code to each hospital's address.[13] Figure 2 displays the density for the post-move change in distance for both the hospital of first birth and hospital of second birth for women in the Chamberlain sample. It is reassuring that these graphs are close to mirror images of each other; there do not seem to be systematic differences between changes for the first birth hospital and second birth hospital. Patients do tend to move closer to their hospital of second birth, and farther away from their hospital of first birth. On average, the hospital of first birth becomes 3.2 minutes farther away, and the hospital of second birth becomes 2.7 minutes closer, after the move, but there is a wide range of changes in distance.

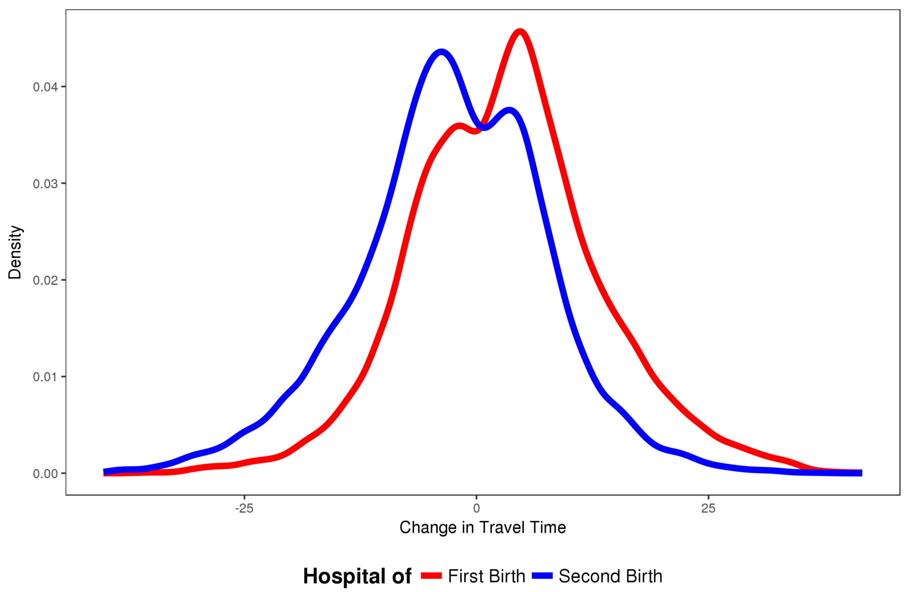


Figure 2 Density of Change in Travel Time after Patient Move for Hospitals of First and Second Birth

Note: The red line is the smoothed density curve for the change in distance to the hospital of first birth after the patient's move in residential location between her first and second birth for the Chamberlain sample; the blue line is the density for the change in distance to the hospital of second birth.

[13]It is standard to use zip code centroid to calculate distance in hospital choice models; for example, see Gowrisankaran et al. (2015) and Ho and Lee (2017). We use ArcGIS to construct these travel times based on historic travel time for 8am on Wednesdays.

4 Estimates

In this section, we show that fixed effect estimates of the transport cost parameter α are much lower than estimates from a patient level discrete choice framework that does not separate unobserved preferences from transport costs.

Using equation (2), we estimate a standard logit model using the disaggregated patient discharge data that includes hospital indicators and travel time as covariates, but does not include patient-hospital interactions.[14] We examine these estimates under both the sample meeting the age restriction and the Chamberlain sample to examine whether the magnitude of the transport cost coefficient varies between the two populations.

Figure 3 depicts the absolute value of estimates of α,the transport cost parameter, from the standard and fixed effect logit models. Both standard logit estimates are of similar magnitude, with an estimate of -0.121 using the full sample meeting the age restriction and -0.116 using the Chamberlain sample.[15] Thus, for a hospital with a 20% share of the market, the standard logit estimator predicts a one minute increase in distance will decrease demand from 9.3 to 9.7%.

The transport costs parameter α from the fixed effects specification is -0.068, approximately half that of the standard logit approaches. The fixed effects approach thus implies that people are much more willing to travel long distances than is implied by the standard logit approach. As the 95% confidence intervals make clear, the statistical difference between these coefficients is well beyond that which can be explained by sampling variation.

To demonstrate how our identification approach works, we show how the conditional choice probability of women choosing a given sequence of hospitals varies with the double difference in distance, as this relationship is the conditional probability used in the fixed effects estimator. Since it is arbitrary which conditional probability is used (i.e., which

[14] While much of the literature on hospital choice includes more detailed controls for the type of patient, our sample is extremely homogeneous in that it consists of young women entering the hospital for the identical procedure. We discuss below a robustness check in which we include a large set of interactions, and find little change in our estimate of distance.

[15] In our main estimates, we restrict the choice set to only include hospitals within 45 minutes drive time for each birth. We have conducted a robustness check in which we include all hospitals within 45 minutes driving time for either birth in the choice set using the Chamberlain sample, so the patients' choice set does not vary over time, and get an estimate of -0.125, similar to our baseline estimates.

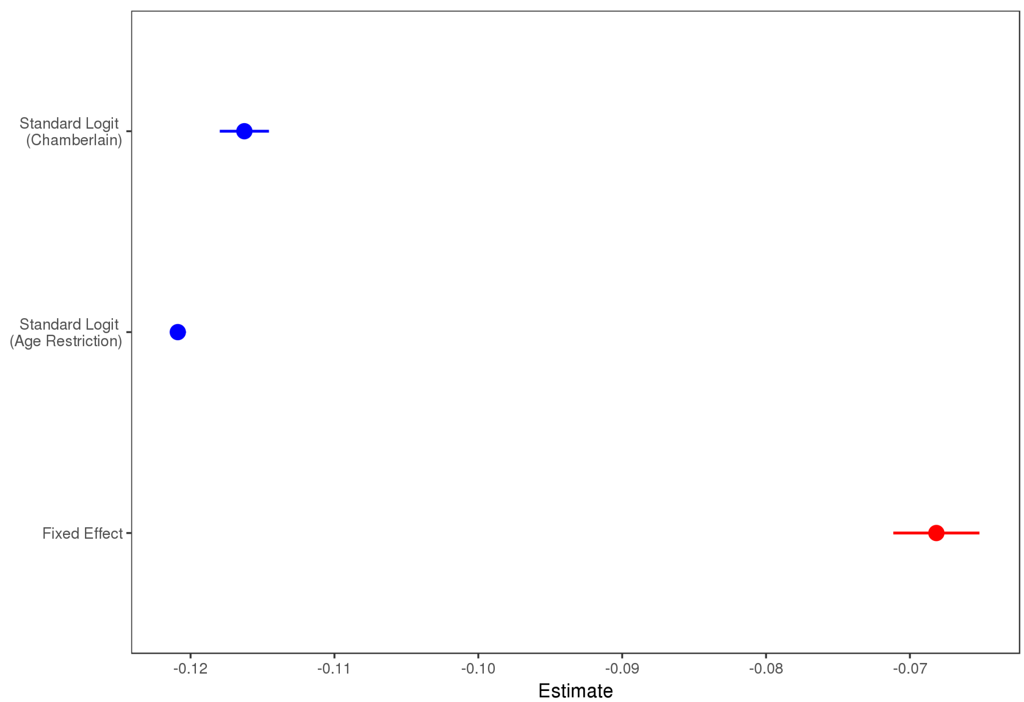


Figure 3 Estimates of the Transport Cost Coefficient

Note: The standard logit, age restriction sample specification is based on all women meeting our age restriction, while the standard logit, Chamberlain sample is based on women in the "Chamberlain" sample. For each specification, the dot is the point estimate and the lines are the 95% confidence interval. Logit estimates reflect the transport cost parameter α; the semi-elasticity with respect to transport costs is α multiplied by one minus the probability of going to the hospital. See Table IV for a table of the estimates and standard errors used to generate this figure.

hospitals are "A" and "B" in Section 2.2), we randomize which hospital is labeled A and B and display the conditional probability that B is chosen second.

The red line in Figure 4 is the nonparametric relationship between the conditional probability and the double difference in distance for the women in the Chamberlain sample. The blue points in the figure represent the implied conditional probabilities using the distance estimates from the standard logit model estimated on all women meeting the age restriction. Thus, Figure 4 illustrates the difference between the standard and fixed effect logit estimates. The nonparametric estimates of the conditional probability decline much less steeply with distance, which implies a much lower disutility from transport costs.

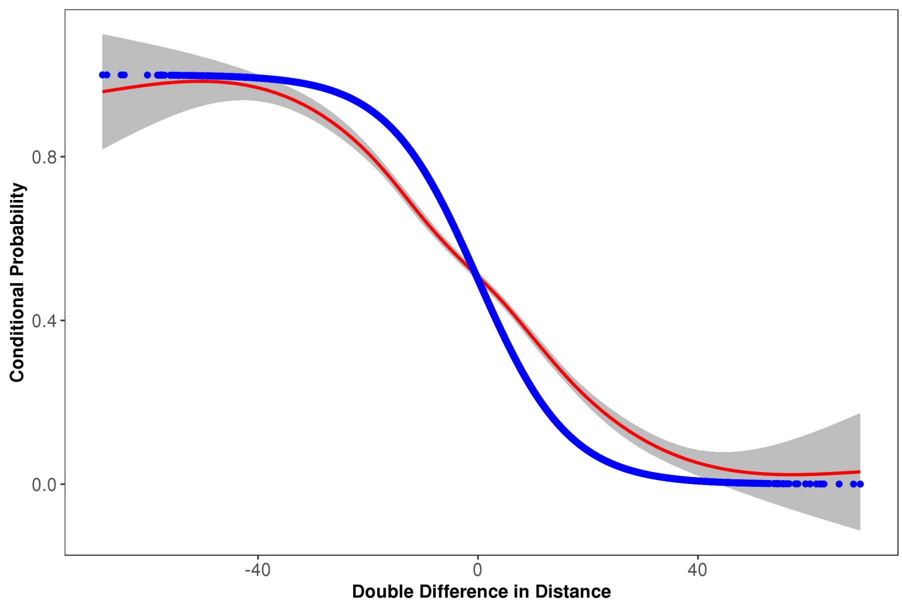


Figure 4 Distance and Conditional Probability of Choice

Note: The red line depicts the nonparametric relationship between the conditional probability and the double difference in distance, and the shading the 95% confidence interval around this relationship, while the blue points depict the implied probabilities under the standard logit model estimated on all women meeting the age restriction.

Our results remain robust to a variety of alternative specifications that relax some of the assumptions of our model. Our baseline model assumes that all patients have the same ex-ante treatment complexity, that all patients can visit both hospitals in both periods, that we observe all births of the women, that there is no time-varying patient/provider unobservable correlated with the change in distance, and that there is no measurement error in our estimate of distance.

To address the concern that patients may vary in treatment complexity, we restrict our attention to women that had a normal labor and delivery. We also examine normal vaginal and normal C-section births separately, as well as full term births separately. To address the concern that some women may have had births prior to 2006, the start of our dataset, we further restrict our sample to women who were 18 and under in 2006. To address concerns about heterogeneity across different patient populations, we examine commercial patients separately, as most of the women in the sample are on Medicaid. While we estimate the fixed effects model on different subsamples, we recognize that the patient population in these subsamples is still younger and possibly poorer than the population as a whole.

We also examine multiple reasons that a time-varying patient/hospital unobservable could arise. Women could shift delivery physician after the move to one closer to her new home, which could change her preferences for each hospital because the new doctor has different preferences over hospitals for delivery than the previous doctor. We thus estimate a specification where we only include women who have the same delivery physician for each birth. We also examine only women for whom the difference in median household income between zipcodes is less than $10,000, in order to avoid women who might experience a large income or other preference shock between births. Finally, in order to examine concerns of changes in consideration set, we estimate our specifications separately for women with moves less than and greater than 15 minutes. Inference using smaller moves should be less prone to bias from changes in consideration sets over time.

Figure 5 depicts the results from these alternate specifications.[16] While there is some variation around our main coefficient estimates, in general the estimates of transport costs are close to the estimates from the baseline fixed effects approach, and much lower than the estimates from the standard logit. The only major deviation is for the same clinician specification for transport costs, for which the transport cost coefficient is -0.04, about 40% lower than the baseline fixed effects estimate. While the coefficient for the same clinician specification is measured with considerable error, the estimate is consistent with time-varying

[16] Figure 12 in Appendix D examines several of these same specifications using the standard logit estimator, and finds similar point estimates to the baseline estimates.

unobservables causing the Chamberlain estimator to *overstate* transport costs. These robustness checks thus reinforce the paper's main message: approaches that do not control for home bias will overestimate the disutility of transport costs.

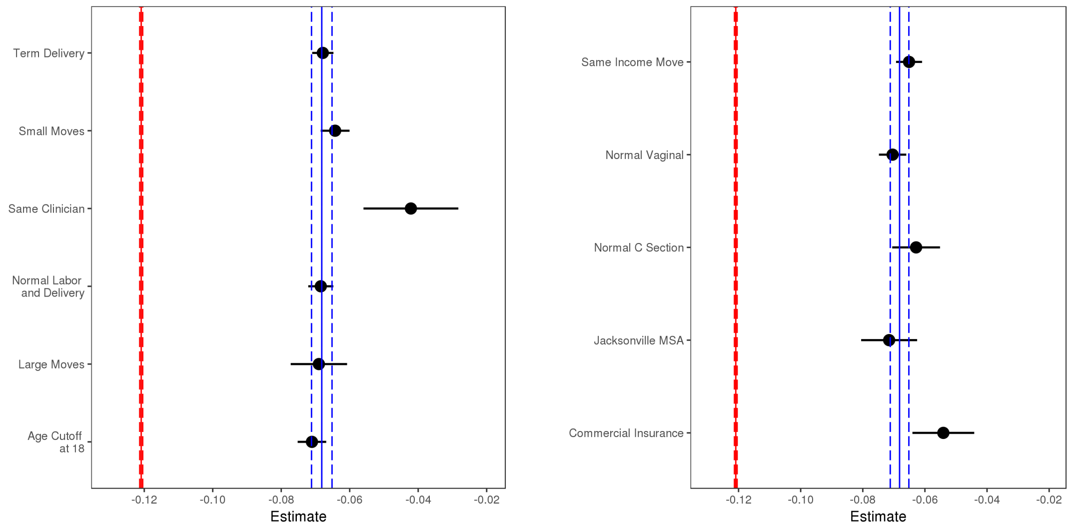


Figure 5 Robustness Checks for Estimates of the Transport Cost Coefficient

Note: The red lines are the coefficient estimates from the standard logit model while the blue lines are the coefficient estimates from the fixed effects model. The solid lines are the point estimates while the dashed lines are the 95% confidence interval. The black horizontal lines are the coefficient estimates from our robustness checks. The dot is the point estimate and the lines are the 95% confidence interval. Logit estimates reflect the transport cost parameter α; the semi-elasticity with respect to transport costs is α multiplied by one minus the probability of going to the hospital. See Table V for a table of the estimates and standard errors used to generate this figure.

Our main standard logit specification only includes travel time and hospital fixed effects. We examine whether including additional interactions would control for home bias in distance estimates by generalizing the choice models used in Ho (2006) and Gowrisankaran et al. (2015) through the inclusion of interactions of hospital indicators with whether the delivery was vaginal or C-section (to account for severity of procedure), whether the delivery was term or pre-term, zip code median income of the patient, and whether the patient was on commercial insurance.[17] Using normal deliveries in Florida, we estimate a distance coefficient of -0.126, compared to -0.122 without the interactions, so additional interactions of

[17]The models in Ho (2006) and Gowrisankaran et al. (2015) also include interactions with teaching hospital status and other variables that are subsumed within hospital fixed effect interactions, as well as interactions irrelevant for obstetrics and interactions with travel time which measure heterogeneous effects of travel time.

observed patient and hospital characteristics cannot account for home bias effects.

In order to ensure that mismeasurement of patient travel time is not driving our results, we conduct an additional robustness check. Since we only have data on patients' location at the zip code level, we examine patients in the Chamberlain sample and construct a distribution of potential travel times by drawing a travel time for each patient from all census blocks in the zip codes that she lived in. We then randomly draw a travel time from this sample of travel times for each patient, and randomly draw a sequence of hospital choices from the conditional likelihood given that the fixed effect estimate of distance is the truth. We then reestimate our model for these patients using the mismeasured zip code centroids. This Monte Carlo simulation thus allows us to examine how much the distance coefficient would change for the fixed effect estimates due to mismeasurement of distance.

We conduct this exercise for the Jacksonville metro area; as Figure 5 demonstrates, the Chamberlain estimate for Jacksonville is similar to that for the overall sample. Figure 6 plots the distribution of transport cost coefficients from this exercise, which is shifted slightly to the right of the "true" value, with the modal value implying a small amount of mismeasurement of about 0.006, or 9 percent of the fixed effects estimate. This amount of mismeasurement is much smaller than the difference between the fixed effect and standard logit estimates in Figure 3. Thus, the probability that more precise data on location would overturn our results is extremely small.

5 Mechanisms

We now explore three possible drivers for home bias: switching costs, hospitals' catering to local demand, and referrals from physicians or peers. All of these mechanisms could increase demand for nearby hospitals, and so bias the transport cost coefficient. We then examine whether the estimated effect of distance falls after controlling for these mechanisms for home bias by estimating the standard logit model after including different proxy variables for home bias confounders. We present these results in Figure 7 across different specifications, together with the estimates for the standard logit and fixed effects models from Section 4 in red and blue respectively. We find evidence that referrals are a likely mechanism for home bias.

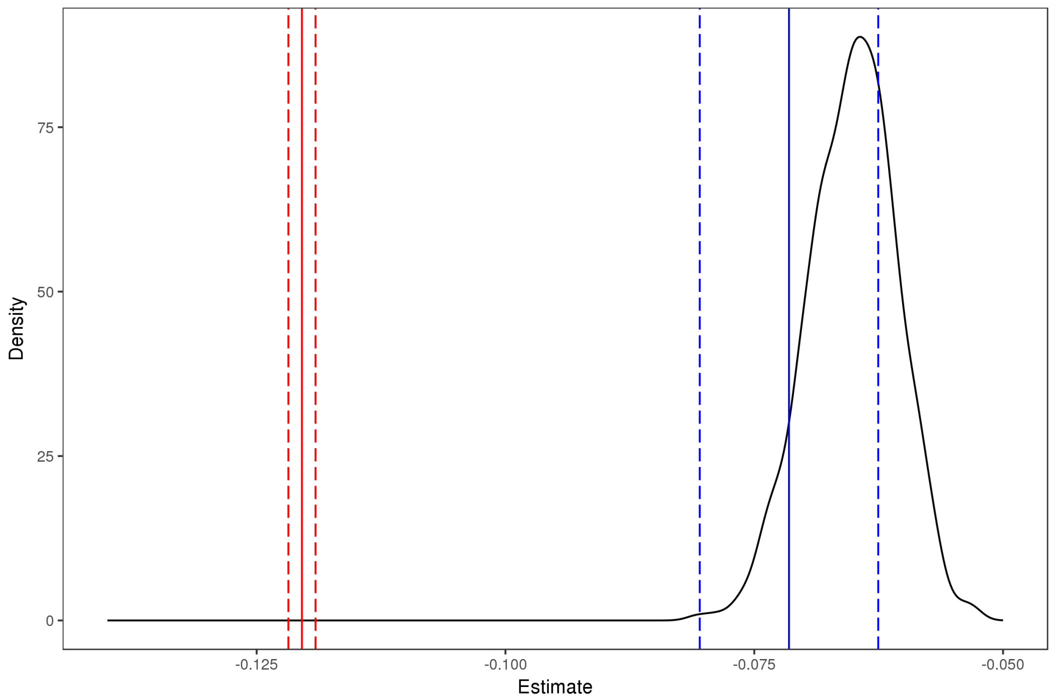


Figure 6 Monte Carlo of Transport Cost Coefficients for Jacksonville Metro Area

Note: The red solid and dashed lines are the point estimate and 95% confidence intervals for the standard logit estimate of the distance coefficient for the Jacksonville metro area, while the blue solid and dashed lines are the point estimate and 95% confidence intervals for the Chamberlain estimate of the distance coefficient for the Jacksonville metro area. The density curve is based on 1000 estimates of the fixed effects logit model using zip code centroids as data and random draws from the census block - hospital travel time distribution as the truth.

5.1 Switching Costs

One possible source of home bias is the presence of switching costs from switching from one hospital to another between births. These switching costs could be pecuniary, such as record switching, or non-pecuniary, such as the need to acclimate to a new medical facility.

However, switching costs should only affect our estimates for births after a woman's first birth. Therefore, we reestimate our standard logit specification for women's first births to test whether switching costs drive the lower estimate of transport costs in the fixed effects estimator. If switching costs are a main driver of home bias, we should expect to see a lower coefficient on transport costs for women's first births.

In addition, we include a specification where we explicitly include switching costs. In Raval and Rosenbaum (forthcoming), we structurally estimate switching costs using a panel data estimator from Honoré and Kyriazidou (2000) and information on the third births of women in the Chamberlain sample. For this paper, we use that estimate of switching costs to reestimate a standard logit model including a switching cost parameter.

These results, in Figure 7, show that the distance coefficients for first births ("First Birth"), and for all births including a calibrated switching cost parameter ("Switching Cost"), are nearly identical to the distance coefficient in our baseline standard logit specification. Therefore, we find little evidence that switching costs are a major factor for home bias in this context.

5.2 Catering to Local Demand

Another reason why patients could prefer to visit hospitals located nearby them is that hospitals set their quality to cater to local demand preferences. Health care providers can cater to local demand in a number of ways. First, hospitals could invest in specialty centers that match the needs of the local patient population (Devers et al. (2003)). In the case of obstetrics, for example, hospitals could build or expand labor and delivery rooms and neo-natal intensive care units, or improve their obstetrics facilities, if the local population around them values these attributes. Second, many hospitals are affiliated with a religious denomination – one in six patients in the US are treated by a Catholic hospital alone. While

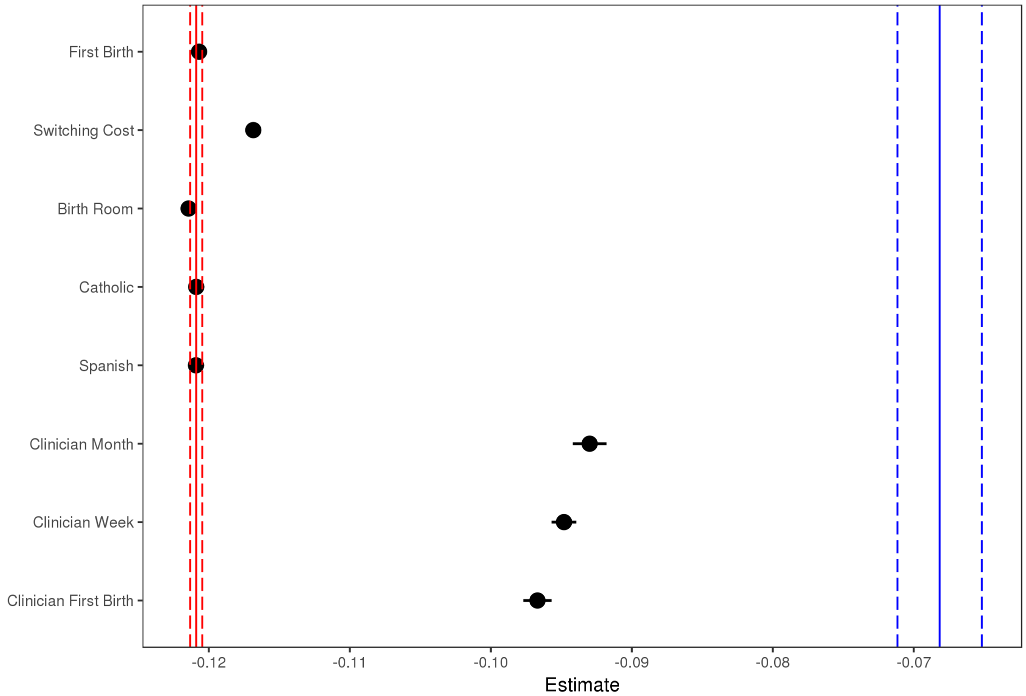


Figure 7 Potential Mechanisms for Home Bias

Note: The red lines are the coefficient estimates from the standard logit model while the blue lines are the coefficient estimates from the fixed effects model. The solid lines are the point estimates while the dashed lines are the 95% confidence interval. The black horizontal lines are the coefficient estimates from our robustness checks. The dot is the point estimate and the lines are the 95% confidence interval. Logit estimates reflect the transport cost parameter α; the semi-elasticity with respect to transport costs is α multiplied by one minus the probability of going to the hospital. See Table VII, Table VIII, and Table IX for tables of the estimates and standard errors used to generate this figure for the Referral, Switching Cost, and Catering to Local Demand mechanisms.

there is considerable evidence from the older literature on patient choice that patients are more likely to go to a hospital that shares their religious denomination (Schiller and Levin (1988)), it is unclear whether patients still consider the religious affiliation of a hospital. If religiously affiliated hospitals are more likely to be located in neighborhoods whose residents share their religious affiliation, then local demand based on religious preferences would be correlated with hospital distance. Third, the medical literature has documented that patients are more likely to select physicians that share their race, ethnicity, or language (Saha et al. (2000)). Thus, hospitals could cater to local demand by employing physicians that have similar demographic characteristics to their patient population, or investing in services valued by those demographics, such as Spanish language translation services.

We examine the hypothesis of hospitals catering to local demand in three ways. We first examine whether interactions between hospital religious affiliation and patients' religious beliefs affect the distance coefficient. To do so, we include interactions between whether a zip code has a Catholic school, a proxy for the Catholic proportion of the neighborhood, and whether a hospital is affiliated with the Catholic Church. Second, we examine whether Hispanics are more likely to go to hospitals with greater Spanish language proficiency. We thus add interactions between whether the patient is Hispanic and the fraction of obstetricians with admitting privileges at the hospital that speak Spanish. Third, to examine catering to local demand for labor and delivery rooms, we include an interaction between zip code median income and whether the hospital has a labor and delivery room.[18] Figure 7 contains the results from these three specifications as "Catholic", "Spanish", and "Birth Room", respectively. Since the estimates from all three specifications remain close to our baseline standard logit estimates, we find very little evidence that catering to local demand can explain much of the home bias that we document.

5.3 Referrals

5.3.1 Clinician Referrals

Clinician referrals could create home bias because patients choose clinicians that are near their residence and rely on their referral to determine the hospital they go to, and clinicians admit patients at hospitals near their offices. The literature has found that clinicians have an important role in helping patients decide which hospital to go to. For example, Ho and Pakes (2014a) find that physician incentive payments can affect patients' choice of hospital for labor and delivery, while Burns and Wholey (1992) shows that the distance from an admitting physician's office to a hospital is a larger factor in hospital choice than the distance from a patient's residence to the hospital. In the context of elective surgeries, Beckert and Collyer (2017) find that the distance from a physician's office is an important determinant of hospital choice for patients and that, after accounting for this distance, patients' estimated

[18]We obtain data on Catholic Schools from http://www.floridaschoolchoice.org/information/privateschooldirectory/DownloadExcelFile.aspx (downloaded on 12/16/16) and physician language proficiency from the Florida State Hospital Licensure Database.

distance elasticity for their hospital choice falls by over 50%.

We test the possibility that clinician preferences for hospitals, or admitting privileges, drive our results by including binary variables in our standard logit specification based on the hospitals that the operating clinician practices at. We first include either whether a clinician delivers an average of more than one baby per week at a hospital in that year ("Clinician Week"), or whether a clinician delivers an average of more than one baby per month at a hospital in that year ("Clinician Month"). However, if patients first choose their hospital and then their doctor, these specifications can mechanically explain choices. Thus, we also include a third specification: looking only at second births, whether the operating clinician for the *first birth* delivers an average of more than one baby per month at a hospital in that year ("Clinician First Birth"). If home bias primarily operates through clinician referrals, these variables should control for that – leading to a coefficient on distance more similar to that in the fixed effects specification.

Our results, in Figure 7, show that the distance coefficient falls substantially in these specifications, explaining about half of the gap between our fixed effects and standard logit estimates. Thus, clinician referrals are likely important in explaining some, but not all, of the correlation between distance and unobserved patient preferences for facilities. These results are consistent with our findings earlier that conditioning on women who had the same attending clinician for both her first and second birth sharply lowers the estimated distance coefficient.

5.3.2 Peer Referrals

In addition, social networks could magnify the effect of transportation costs because patients rely on recommendations from friends and family located close to them. When building a model of patient choice, Satterthwaite (1985), for example, states that "consumers when they are seeking a new physician who fits their idiosyncratic needs generally rely on the recommendations of trusted relatives, friends, and associates." Hoerger and Howard (1995) study patient choice of prenatal care physician and find that 51% report using a friend or colleague as a source of information, and 27% a relative. Harris (2003) also find that 51% of patients report using family and friends as a source of information to choose their physician.

Recommendations from family and friends can magnify the role of distance if they are located near the patients' own location. Goldenberg and Levy (2009) and Backstrom et al. (2010) both find using data on Facebook friends that the likelihood of being someone's Facebook friend is decreasing in distance. In addition, friends that live close by may have a greater influence on a patient's decisions.

We develop a simple social network model of patient choice based on the economic literature on social multiplier effects (Glaeser et al., 2003), which has found substantial peer effects in several settings (Sacerdote, 2011). Appendix B details the model; a patient's utility from each hospital depends upon both physical distance and the average of all of her friends' utilities for the hospitals. This model reduces to one in which her utility for a hospital is based both upon her distance to the hospital as well as her friends' average distance to the hospital. If all of her friends live at the same location as the patient, then the full effect of distance is a combination of the patient's own disutility of distance and the weight that she places on her friends' utility. If her friends do not all live at the same location, the correlation between her distance between two hospitals and her friends' average distance between the two hospitals also matters; when her friends' distances are less correlated with her distances, the multiplier effect of the social network falls.

A social multiplier can plausibly explain much of the difference between the standard and fixed effect logit estimates. If all of the difference between the standard and fixed effect logit estimates of distance reflects a social multiplier, the social multiplier would be 2 in the context of our model. The social multiplier literature has found multipliers of similar magnitude for fraternity and sorority membership based on random assignment of Dartmouth undergraduate roommates, as well as for schooling and earnings from local area effects (Glaeser et al., 2003).

6 Applications

In this section, we examine three applications of our estimates of distance effects that show how accounting for home bias affects policy counterfactuals. In the first application, we examine a simulated hospital merger and show how accounting for referral patterns, one possible source of home bias, can affect both estimates of patients' willingness to travel and merger harm. In the second application, we analyze a hospital after its repositioning through a contentious planned move, and show that our fixed effects estimates imply much greater demand for the relocated hospital in areas close to the old location, but farther from the new location. In the third application, we take an example of using distance as a welfare metric, and show that accounting for home bias implies that patients are substantially more willing to travel to receive higher quality care.

6.1 Hospital Merger Analysis

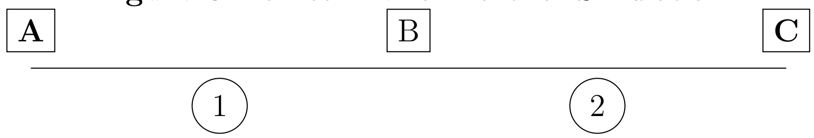
A main area of focus in the academic and legal analysis of hospital mergers has been patient's willingness to travel to obtain medical care. In particular, market definition has been critical in courts' rulings on FTC challenges of hospital mergers (Capps, 2014; Gaynor and Pflum, 2017). Farther hospitals are more likely to be substitutes for patients at the time they need medical care when patients are willing to travel farther. Therefore, patients' willingness to travel can determine both the likely price effects of a merger and the proper market definition to analyze it.

In Section 5, we showed evidence that the estimates of patients' disutility of travel to obtain medical care falls after accounting for the home bias generated by physician referral patterns. In this section, we build a stylized model that illustrates how accounting for referral patterns affects estimates of patients' willingness to travel and the estimated harm from mergers. Provided that patients suffer more disutility from travelling to their doctor than their hospital and that physicians are more likely to refer to hospitals close to them, we can replicate our findings that controlling for home bias reduces the estimated distance coefficient. In addition, hospitals located relatively far away from each other are closer substitutes for patients, which increases estimates of harm from a merger of such hospitals.

6.1.1 Model

Patients are uniformly distributed over a line and can choose between three hospitals and two clinicians. Hospitals A and C are located at either end of the line, while hospital B is

Figure 8 Market Environment for Simulation



in the middle. Clinician 1 is located halfway between A and B, while clinician 2 is halfway between B and C. A diagram is in Figure 8.

We consider a hypothetical merger of hospital A and hospital C, both of which are marked in bold in the figure. The other hospitals and clinicians are assumed to be independently owned. While clinicians are assumed to have privileges in all of the hospitals, they refer more patients to the two hospitals that are closest to them. Therefore, clinician 1 disproportionately refers to hospitals A and B and clinician 2 disproportionately refers to hospitals B and C.

Patients first choose a clinician and then a hospital.[19] A patient i's choice of clinician c reflects her utility for that clinician,

$$u_{ic} = \alpha_c d_{ic} + \epsilon_{ic}, \tag{5}$$

where d_{ic} is the distance from the patient to the clinician and ϵ_{ic} is an iid logit error draw.

We then decompose the notion of a referral function (Ho and Pakes (2014b)). The referral function drives choices, but is a combination of the preferences of a patient and a doctor and so does not represent the patient's utility function.[20] Conditional on choosing clinician c, patient i's referral function for hospital h is given by:

$$r_{ih|c} = \underbrace{\alpha_h d_{ih} + \epsilon_{ih}}_{u_{ih}} + \rho d_{ch}, \tag{6}$$

where d_{ih} is the distance from the patient to the hospital, ϵ_{ih} is an iid logit error draw, and d_{ch} is the distance from the clinician to the hospital.

Summarizing, the three main parameters in this model are:

[19]There is no outside option, so all patients choose both a doctor and a hospital.

[20]A consideration set approach, where doctors choose the consideration set and patients choose from that set, has also been used to model this joint decision problem (Gaynor et al., 2016; Beckert and Collyer, 2017).

1. patients' disutility of travel to hospitals α_h,

2. patients' disutility of travel to doctors α_c,

3. doctors' disutility of travel to hospitals ρ.

We assume that customer utility is given by u_{ih}, but that a woman's choice of hospital is affected by both u_{ih} and ρd_{ch}. In particular, women will choose a hospital that maximizes $r_{ih|c}$, the referral function, but they will receive utility u_{ih} for making that choice. Therefore, conditional on choosing doctor c, the probability of a woman choosing hospital h is given by the usual logit form:

$$Pr_{ih|c} = \frac{\exp(\alpha_h d_{ih} + \rho d_{ch})}{\sum_{h'} \exp(\alpha_h d_{ih'} + \rho d_{ch'})}$$

We measure the welfare effects of a merger of hospitals A and C by using the WTP measure of Capps et al. (2003), which measures patients' willingness to pay to have access to a given hospital, and therefore a hospital's relative leverage when negotiating with an insurer. This measure has been used to predict post-merger harm following hospital mergers (Capps et al., 2003; Gowrisankaran et al., 2015; Garmon, 2017). We look at the percent change in WTP, which has been suggested as a screen for hospital mergers (Garmon, 2017).[21]

When choice probabilities reflect consumer utility alone, WTP is a function of patient choice probabilities (Raval et al., 2017b). However, if physician referrals affect consumers' choice probabilities for hospitals, but not their utility from using that hospital, one cannot use choice probabilities to determine the post-merger change in WTP. Rather, one must use the utility parameters to construct choice probabilities that would hold *in the absence of any physician referrals*. In our context, this is the difference between using $r_{ih|p}$ and u_{ih} to compute WTP.[22]

[21] See Appendix C for further details on the percent change in WTP measure.

[22] In the framework above, women's expected utility from being referred to different hospitals does not affect her choice of clinician. This is due to two assumptions we make: a) logit errors and b) that the true value of ϵ_{ih} is realized following the woman's choice of doctor. Under those two assumptions, the expected utility of going to all chosen hospitals is equal, and therefore has no bearing on the choice of doctor (Anas and Feng, 1988). While this may be a strong assumption for empirical work, we maintain it here for two reasons. First, it is the implication of the logit, the most commonly used distributional assumption in this literature. Second, it simplifies the calculations and the exposition.

6.1.2 Simulation Results

For our simulation, we parameterize the disutility of travel for hospitals α_h to our fixed effects parameter estimate of 0.06 and set the length of our line to be 20 miles. We allow both patients' disutility of travel for doctors α_c and doctors' disutility of travel to hospitals ρ to vary from zero to five times the patient disutility of travel to hospitals α_h. We simulate 10 different datasets of 10,000 patients for each of the parameterizations we consider, and average across simulations.

In Figure 9, we depict the estimated disutility of travel to a hospital estimated from a logit model that only includes distance to the hospital as a covariate, which is analogous to the standard logit model discussed earlier in the paper. The true disutility of travel is shown as a black horizontal line and the standard logit estimate estimated from the Florida data is shown as a dashed line. We show the estimated patient disutility of travel to the hospital as a function of patients' disutility of travel to doctors α_c, shown on the x-axis, and doctors' disutility of travel to hospitals ρ, shown in the different colors, both in multiples of the true patient disutility of travel to hospitals.

Patient disutility of travel to a hospital is overstated by a standard logit model when patients have greater disutility to travel to a doctor than a hospital. The magnitude of this effect increases in the doctor's disutility from traveling to hospitals. Since the colored lines intersect with the dashed line, physician referral effects could generate the magnitude of the bias that we observe in the data.

In Figure 10, we depict the percent change in WTP from the standard approach that ignores physician referrals; the black horizontal line is the true percent change in WTP, which we have set to 25%. As Figure 9 shows, the bias in the distance coefficient can be obtained by a variety of different parameterizations, so we bold each line in areas that reflect parameterizations consistent with the bias that we observe in the data. In those areas, the estimated WTP from the standard approach ranges from 12% - 14%, and thus understates the estimated harm from the simulated merger. The standard approach overstates competition between the middle and corner hospitals, and understates the competition between the corner hospitals. In the absence of a referral, the farthest hospital would be many patients' second choice, if either of the closer ones became unavailable. However, due to the referrals, many fewer people go there than if people were making choices purely on the basis of their own welfare. Therefore, in this case, the competitive effects of the merger are understated.

We map these percent changes in WTP to hospital prices using the estimated elasticity of 0.2 between WTP and hospital prices of Garmon (2017).[23] Given this elasticity, we find that a merger of distant hospitals would lead to a predicted price increase of approximately 5% under the true model, but only 2-2.5% under the standard logit model. If a 5% price threshold for a merger screen is being used, as has been contemplated in other literature (Miller et al., 2017; Balan and Brand, 2018), using a standard logit model could lead to incorrectly permitting a problematic merger.[24]

Our simulations show that in order to measure mergers' effect on welfare, it can be important to recover patients' willingness to travel unconfounded by referral patterns. When physician referrals play an important role in predicting hospital choice, the only way to measure patient welfare is to estimate patient preferences, including patients' true willingness to travel to the hospital. While our conclusions about the direction of bias in welfare effects are specific to our stylized setting, our results show that it is potentially important to consider the extent to which this is an issue in a given merger.[25]

In this simulation, we considered a case where the doctor referral preferences are fixed before and after the merger. However, if physician practices are owned by merging hospitals it is possible that the referral patterns of the merging hospitals would change following a merger.[26] Baker et al. (2016) show physician practices owned by a hospital are much more likely to refer to the hospital that owns them. Therefore, when hospitals own local physician practices, it may be important in merger analysis to separately identify the distance and referral parameters *and* to modify the referral parameter to reflect the change in ownership.

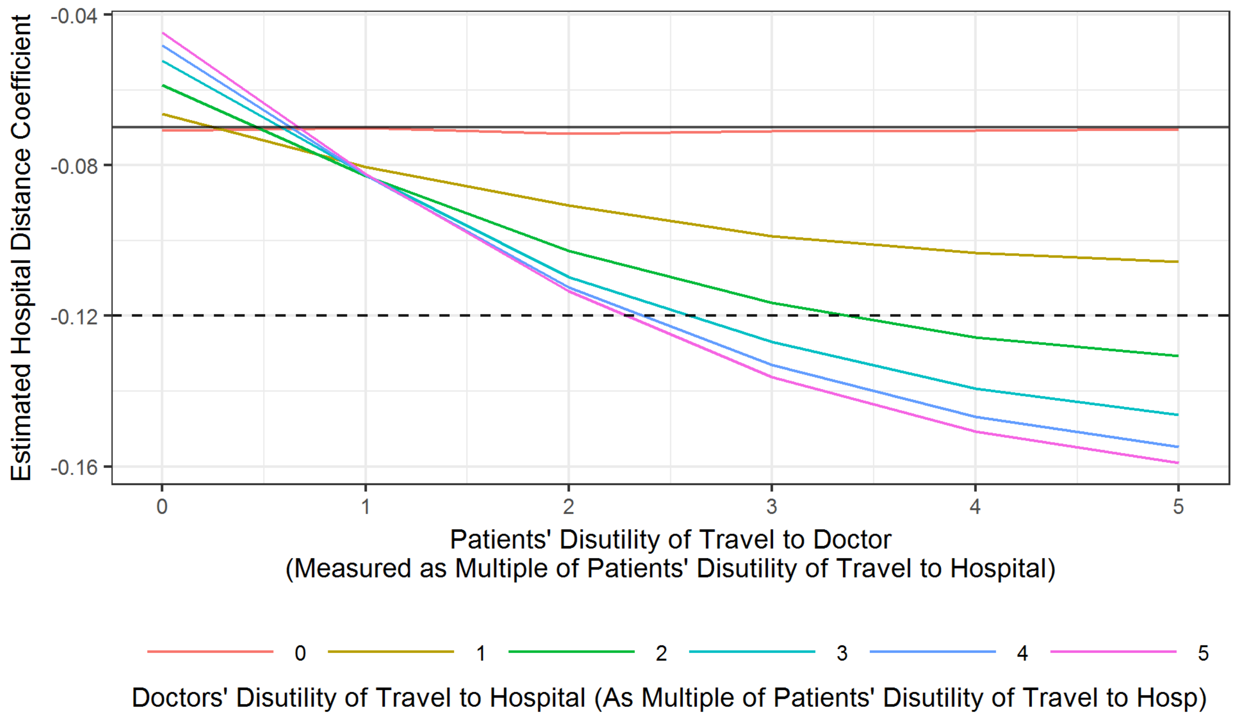
[23]We use his estimates from a set of 16 hospital mergers that did not have variable cost savings.

[24]Garmon (2017) recommends a threshold of a 6% change in willingness to pay in order to flag problematic mergers, which is different than what we use here. Our point is not to advocate a specific threshold, but rather to show how policy decisions can change as a result of not accounting for referrals in one's estimation procedure.

[25]We assume in this section that patients do not value the physician's preferences for different hospitals. If, alternatively, one assumes that patients fully value their physicians' preferences, there remains a bias that goes in the opposite direction.

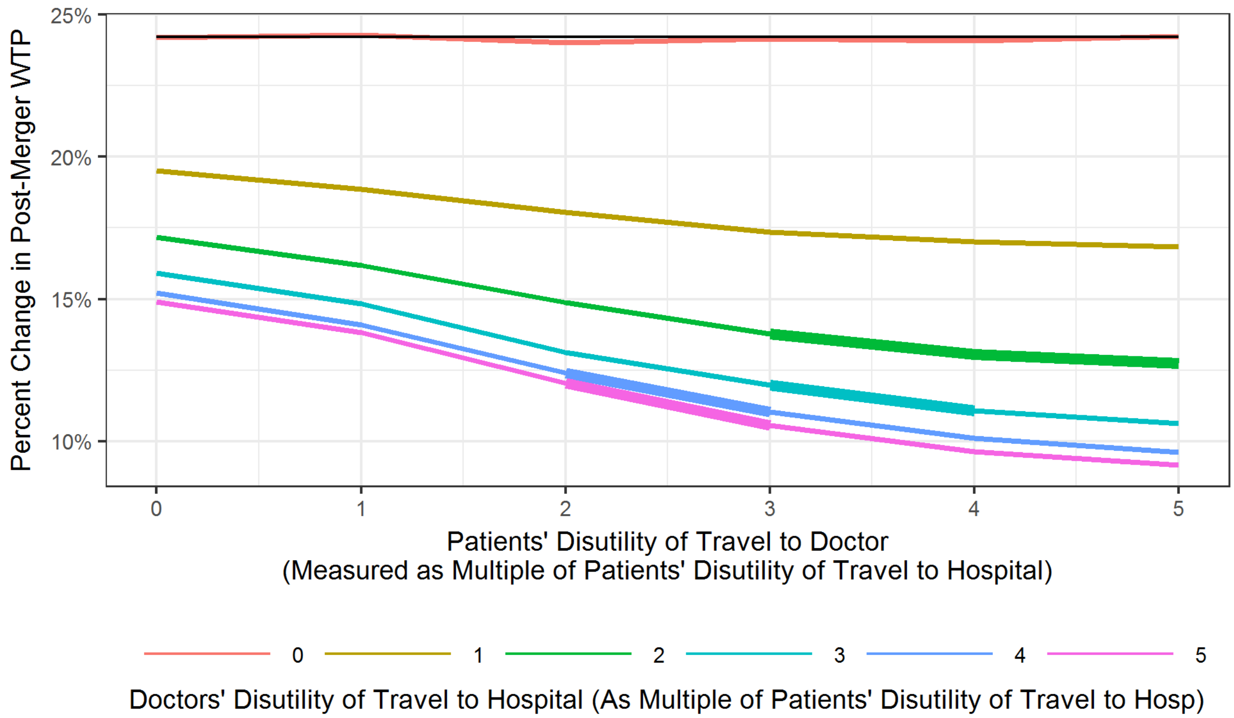
[26]According to a survey by the American Medical Association, 33% of physicians were either owned or employed by a hospital in 2016 (Kane, 2017).

Figure 9 Estimated Disutility of Travel to Hospital from Simulations



Note: The estimated patient disutility of travel to the hospital from a standard logit model is on the y-axis, and is shown as a function of patients' disutility of travel to doctors α_c, shown on the x-axis, and doctors' disutility of travel to hospitals ρ, shown in the different colors, both of which are expressed in multiples of the true patient disutility of travel to hospitals. The true disutility of travel is shown as a black horizontal line and the standard logit estimate estimated from the Florida data is shown as a dashed line.

Figure 10 Percent Change in WTP Following Simulated Merger



Note: The percent change in WTP from a merger of the two corner hospitals based on the distance coefficient from a standard logit model is depicted on the y-axis, and is shown as a function of patients' disutility of travel to doctors α_c, shown on the x-axis, and doctors' disutility of travel to hospitals ρ, shown in the different colors, both of which are expressed in multiples of the true patient disutility of travel to hospitals. We bold each line in areas that reflect parameterizations consistent with the bias in the transport cost coefficient that we observe in the data. The black horizontal line is the true percent change in WTP, which we have set to 25%.

6.2 Product Repositioning: A Planned Hospital Move

The importance of "home bias" in demand can affect how consumers react to hospital entry, product repositioning, and quality upgrading. In this section, we examine these issues through one type of product repositioning: a controversial planned move of a hospital evaluated by the state regulator. With the move, the hospital changes its distance to all potential patients, and thus becomes much more attractive to some patients and less attractive to others. We examine how demand predictions change after distinguishing between unobserved heterogeneity and distance.

In 2014, HCA proposed to relocate its existing Plantation General Hospital (PGH) to the campus of Nova Southeastern University (NSU) in the town of Davie in Broward County, Florida. It would have become the nucleus of a new academic medical center after being integrated into the research and clinical programs of NSU, including its colleges of Osteopathic Medicine and Nursing and 20 health care clinics. In Figure 11, the existing hospital is hospital number one and the proposed new hospital the purple star. The relocated hospital would have 200 beds after the move, including 32 dedicated OB beds, down from 264 at the original hospital site, and would be 6.7 miles or 13 to 20 minutes drive from the original hospital site.

Since Florida has a Certificate of Need (CON) Law, the construction of a new hospital required approval from the Florida Agency for Health Care Administration (AHCA), which had rejected an earlier plan by HCA to build a new 100 bed hospital at the same site after five hospital systems in the area filed statements of opposition. While three hospital systems objected to the new plans, the ACHA recommended approval of the new application. Memorial Health and the Cleveland Clinic then sued in court to stop the move of the new hospital, although they lost in court.[27]

As part of the CON application process, HCA defined a service area consisting of 17 zip codes for the relocated hospital and provided market share predictions for three sets of zip codes: those closer to the new hospital location, farther from the new location, and at a constant distance. Figure 11 displays these zip code areas, with the closer areas in yellow,

[27]See http://touch.sun-sentinel.com/#section/-1/article/p2p-82533665/ and http://www.sun-sentinel.com/local/broward/fl-plantation-general-hospital-nova-20160516-story.html.

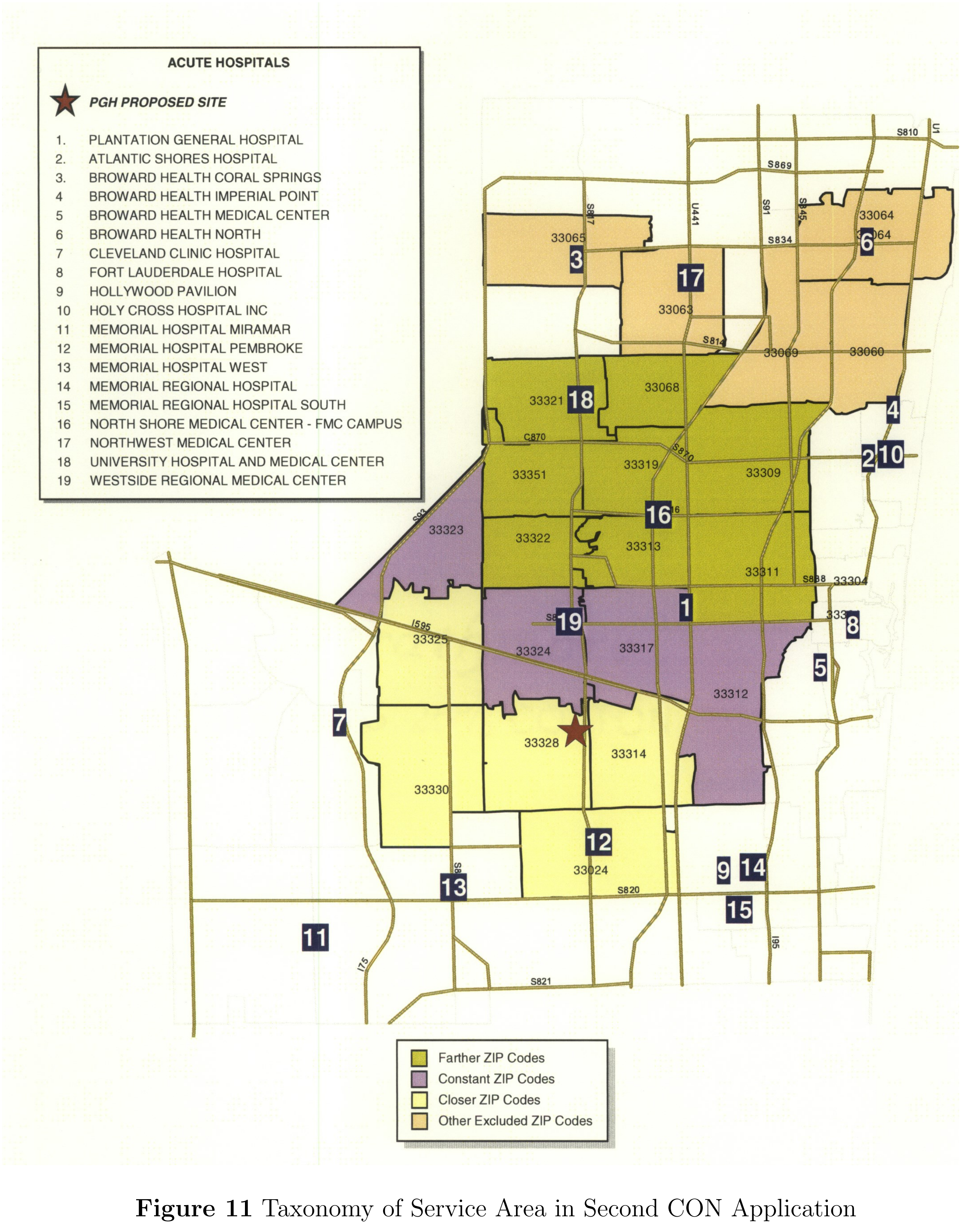


Figure 11 Taxonomy of Service Area in Second CON Application

Note: Source is the opposition statement of North Broward Medical District to CON Application No. 10235.

constant areas in purple, and farther areas in green.

The three health care systems opposing the hospital relocation criticized HCA's definition of the service area and its market share projections. The Cleveland Clinic stated, for example, that "It is obvious from the above statistics that those zip code areas to the north [the farther zip codes] are not within the primary service area of the Replacement Hospital ... Data analysis concludes such service area is between seven and nine zip code areas in and immediately surrounding zip code area 33328 [the zip code of the new location]". The closer zip codes also differed from the farther zip codes demographically, raising equity concerns. As Broward Health noted, "In essence, PGH is moving from a heavily minority population towards a much less diverse population ... Many patients in these abandoned areas will find it difficult to use PGH if it is permitted to move ... which could leave a large number of Medicaid and self pay/non-pay patients without ready access to the hospital they historically depended upon."

We examine how HCA's predictions in its CON application compare to predictions based upon the distance estimates from the standard logit and fixed effects models.[28] We allow ξ to vary at the zip code-hospital level using market shares for first-time mothers, for whom switching costs are not relevant, and estimate these given the distance estimates from both the standard logit and fixed effects models.

In order to simulate demand post-move, we need to make an assumption on how the distribution of ξ changes after the hospital moves.[29] We assume a uniform 10 percent increase in ξ across zip codes after the hospital moves, after computing ξ for each model based upon the current location of the PGH hospital. This assumption is strong in that it assumes a 10%, uniform increase in ξ after the move. However, this assumption has some justification in our context. We view an increase in ξ as a reasonable assumption since the hospital is moving into a new building and obtaining an academic affiliation, which we assume that all patients value. Further, as we show below, a 10% increase in ξ makes the geographic distribution of share changes for the standard logit model similar to the CON predictions.

[28]The CON application defined OB admissions slightly more broadly, including non-birth DRGs such as abortions that we excluded in our sample.

[29]This is always an issue in estimating the effects of a product's entry or repositioning. The econometrician must make an assumption on consumers' taste for that product.

The assumption of a uniform increase in quality implies that referral patterns do not change post-move. This assumption may be reasonable because the doctors and staff at the relocated hospital should be similar to those at the previous location, as should admitting privileges. Thus, the relationships between doctors and the hospital that underlie referral patterns may not change much post-move, at least in the short run.

Table II Percent Change in OB Admissions by Service Area Divisions

Model	Overall	Closer	Constant	Farther
CON Application Predictions	0.4	178.6	-0.4	-19.1
Standard Logit	-5.1	170.5	2.2	-20.2
Fixed Effects	3.9	83.8	7.8	-3.1

Note: CON Application Predictions are based upon Exhibit 18 in CON Application No. 10235, comparing 2020 predictions to 2013 actual shares. Standard logit and fixed effects estimates are based upon an increase in ξ of 10 percent across zip codes. We adjust the number of admissions in each zip code based on predictions of demand growth between 2013 and 2020 in the CON Application.

Table II reports predictions on the percent growth in OB admissions for the relocated hospital by the different zip code areas. Looking at the shares across zip codes, the standard logit predictions are strikingly close to the CON application predictions: a large increase in the closer areas (178.6% in the CON application vs. 170.5% in the standard logit estimates) and a large fall in admissions in the farther area (-19.1% in the CON application vs. -20.0% in the standard logit estimates). The fixed effects estimates are quite different, with about half the share growth in the closer areas (83.8%) and a much smaller decline in share in the farther areas (-3.1%).

The reason for the difference between the two models is the relative weighting given to travel costs and differential preferences between the standard logit and fixed effects approaches. While the standard logit estimates predict that the patients from the farther areas are unlikely to travel to the hospital after it is moved, the fixed effects estimates suggest that patients are less reluctant to do so. Thus, the fixed effects model does not predict the large share declines for the PGH hospital for the farther area that the opposing hospital systems alleged. Our results suggest that HCA likely underestimated demand from patients in the farther areas post-hospital move. In general, firms that predict spatial demand without accounting for home bias effects may make systematic errors in their projections.

6.3 Tradeoffs between Distance and Quality

The incentives that health care providers have to improve quality depend upon the degree to which patients are willing to substitute towards higher quality facilities. Because patient distance to facility is typically the most important variable explaining patient choices, researchers have typically examined the marginal rate of substitution (MRS) between quality and distance (Tay, 2003; Romley and Goldman, 2011; Chandra et al., 2016; Gaynor et al., 2016). In general, the literature has found that patients are not willing to travel very far to go to a higher quality hospital. For example, Romley and Goldman (2011) find that a baseline pneumonia patient in the LA area would be willing to travel 2.9 miles farther to go from a hospital at the 25th percentile of quality to one at the 75th percentile of quality, and Chandra et al. (2016) find that the average heart attack (AMI) patient will travel 1.8 miles for a hospital with a 1 percentage point higher risk-adjusted survival rate. As Doane et al. (2012) point out, these distances are small compared to the decrease in mortality from going to a higher quality hospital. However, these results implicitly assume that distance effects on demand reflect transport costs.

We re-examine the quality-distance tradeoff in light of our results, using the "revealed quality" of the hospital based on patient choices as in Romley and Goldman (2011). For both the standard logit and fixed effect distance estimates, we estimate multinomial logit models of patient choice and include hospital indicators to measure hospital quality. These hospital indicators can be thought of as averages of ξ_{ij} across patients. We then compare the utility gain from an increase in hospital quality from the 25th to 75th percentile of quality to the utility loss from increasing distance. Table III contains the marginal rate of substitution between quality and distance for both all hospitals in Florida and those in the Jacksonville metro area.

Examining all the hospitals in Florida, an increase in quality from the 25th to the 75th percentile is equivalent to increasing travel time by 8 minutes under the standard logit specification, compared to 13 minutes under the fixed effects specification. Thus, under the fixed effects estimates, the MRS between quality and distance is about 50 percent larger than under the standard logit estimates. We also examine the Jacksonville metro area separately, for which the differences across hospitals in quality are smaller than across the entire state of Florida. For Jacksonville, an increase in quality from the 25th to the 75th percentile is equivalent to increasing travel time by 5 minutes under the standard logit specification, compared to 9 minutes under the fixed effects specification. Thus, patients are considerably more willing to tradeoff distance for quality than previous results have suggested.

Table III Quality Tradeoffs with Distance

Geographic Area	Standard Logit	Fixed Effects
Florida	-8.3	-12.6
Jacksonville	-5.1	-9.4

Note: The marginal rate of substitution is the difference in quality between the 75th percentile hospital and 25th percentile hospital divided by the distance parameter α. For Jacksonville, we use coefficients and quality estimates for the Jacksonville metro area alone.

7 Conclusion

Using variation from women that move location over time to difference out home bias, we found that estimates of disutility of transport costs using common approaches greatly overstate patients' aversion to travel to a hospital for childbirth. For hospitals with a 20% share, a one minute increase in travel time decreases demand by 9.7% under a standard logit framework, compared to 5.4% under a fixed effect model that accounts for home bias. We then showed that referral patterns could explain a substantial part of the difference between the fixed effect and standard logit estimates.

We then examined three applications that demonstrate the importance of controlling for home bias. In our first application, we showed that, when patients dislike travelling to doctors more than travelling to hospitals, and doctors also dislike travelling to hospitals, we can replicate our results on the impact of home bias on estimates of transportation costs. In addition, a standard approach can greatly underestimate the extent to which two distant hospitals are substitutes. In our second application, we examined a contested hospital move and show that our fixed effect estimates imply much more demand for the hospital from patients that live farther from the new location than the old location, compared to standard models. Thus, the relocated hospital remains a relevant substitute for patients living far from the new location. In our third application, we found that patients are more sensitive to quality, and so are more willing to travel farther to visit a higher quality hospital, under the fixed effect estimates than under a standard logit.

In this paper, we found evidence that referral patterns are a likely source of home bias, and accounting for these patterns can change estimates of welfare effects from policy changes such as mergers. Since this is true even when there is no change in referral patterns post-merger, understanding referral patterns can be important to predict the welfare consequences of policy changes. In addition, referral patterns themselves may change with a major change in the economic environment, such as vertical mergers between physicians and hospitals, or managed care, in ways that could substantially affect welfare. Thus, more research is needed both in how physician incentives affect referral patterns, and how referral patterns affect consumer welfare.

For future research, it would be useful to examine the generalizability of our results. In this paper, we have only examined the choices of pregnant women. Transport costs themselves may be more burdensome for pregnancy than other conditions, because pregnant women need to get to the hospital quickly after labor begins, compared to more schedulable procedures. In addition, referrals may be more salient in patient choice for some conditions and less salient for others. Both of these channels would affect estimated distance coefficients and the potential effect of not accounting for home bias.

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A Parametrization of Patient Heterogeneity

For our counterfactual experiments, we have to place further restrictions on patients' unobserved preferences for hospitals. We assume that ξ_{ij} only varies with the zip code where women live at the time of their first birth. Therefore, we can rewrite $\xi_{ij} = \mu_{zj}$, where μ_{zj} is the mean within woman i's zip code z at the time of their first birth.

Using this assumption, we recover μ_{zj} by focusing on the full population of first time mothers. Rewriting equation (3) for this population of women, we obtain:

$$u_{ij1} = -\alpha d_{ij1} + \mu_{zj} + \epsilon_{ij1}.$$

Since we only observe distance at the zip code level, we can write this as:

$$u_{ij1} = \underbrace{-\alpha d_{zj1} + \mu_{zj}}_{\tilde{\mu}_{zj}} + \epsilon_{ij1}.$$

Since ϵ_{ij1} is distributed type I extreme value, we obtain:

$$Pr_{ij1} = \frac{\exp(\tilde{\mu}_{zj})}{\sum_j \exp(\tilde{\mu}_{zj})}.$$

Using the transformation discussed in Berry (1994), we can recover:

$$\tilde{\mu}_{zj} = \log(s_{zj1}) - \log(s_{0z1}),$$

where s_{zj} is the share of first time mothers in zip code z giving birth in hospital j, and s_{0z1} is the share of women giving birth outside of their service area.

B Social Multiplier Model

In this section, we develop a model in which a patient's utility for a hospital depends both upon distance and the average of her friends' utilities, similar to models used in the social multiplier literature (Glaeser et al., 2003).

Deterministic utility δ_{ij} for individual i and hospital j is:

$$\delta_{ij} = \alpha d_{ij} + \frac{\gamma}{N-1} \sum_{f \in F_i} \delta_{fj},$$

where F_i is the set of i's friends and $N-1$ is the number of friends. The parameter γ determines how important average friend utility is for individual i's utility. For simplicity, we assume that everyone is friends with everyone else. In that case, we can solve for δ_{ij} as a function of individual i's own distance and the average friend distance:

$$\delta_{ij} = \alpha d_{ij} + \alpha \frac{\gamma}{1-\gamma} \frac{1}{N-1} \sum_{f \in F_i} d_{fj}.$$

First take the case in which all of the friends live in the same location, so, $\forall f \in F_i, d_{ij} = d_{fj}$. In that case, we have that:

$$\delta_{ij} = \alpha \frac{1}{1-\gamma} d_{ij}.$$

Here, $\frac{1}{1-\gamma}$ is the social multiplier of the effect of distance; it collapses to 1 when γ is zero, and is 2 when γ is 0.5.

Now take the case in which friends do not live at the same location. In that case, we have that the ratio in individual i's probability of visiting hospitals j and l is:

$$\frac{Pr_{ij}}{Pr_{il}} = \frac{\exp(\delta_{ij})}{\exp(\delta_{il})} = \exp(\alpha(d_{ij} - d_{il}) + \alpha \frac{\gamma}{1-\gamma} (\frac{1}{N-1} \sum_{f \in F_i} (d_{fj} - d_{fl})).$$

Thus, the relative probability of going to hospital j over hospital l depends both upon the difference in i's distance, and the average difference in all of the friends' distance. We can always partition the average difference in all of the friends' distance into a component correlated with i's distance and a part uncorrelated with i's distance:

$$\frac{1}{N-1} \sum_{f \in F_i} (d_{fj} - d_{fl}) = \beta_{jl}(d_{ij} - d_{il}) + \epsilon,$$

where the coefficient β_{jl} is the regression coefficient of the average friends' difference in distance on individual i's difference in distance:

$$\frac{Cov(d_{ij} - d_{il}, \frac{1}{N-1} \sum_{f \in F_i} (d_{fj} - d_{fl}))}{Var(d_{ij} - d_{il})},$$

and ϵ is uncorrelated with $d_{ij} - d_{il}$ by definition. In that case, we can rewrite the relative probability of going to hospital j over hospital l as

$$\frac{Pr_{ij}}{Pr_{il}} = \exp(\alpha(1 + \beta_{jl} \frac{\gamma}{1-\gamma})(d_{ij} - d_{il}) + \epsilon),$$

which collapses to the formula in which all friends live in the same location, so β_{jl} is one and ϵ always zero. Thus, when friends do not all live in the same location, how close each of the friends lives will affect the social multiplier – the closer they live, so their distances to providers are more highly correlated, the higher the social multiplier.

C Ex-Ante Utility and WTP

In the logit model, the expected decline in patient i's welfare from excluding a set of hospitals $S \subset J$ is as follows:

$$WTP_{iS} = -\ln(1 - \sum_{j \in S} s_{ij}). \tag{7}$$

A patient's WTP is an increasing function of the probability she will select a hospital in set S, and equals zero when that probability is zero. Overall WTP is obtained by adding up patient-level WTP across all patients.

The antitrust agencies have used WTP to assess the expected harm from a merger of two hospital systems (Farrell et al. (2011)). The combined system's bargaining position changes post-merger, since it can now threaten to exclude both systems simultaneously from the provider's network. Let WTP_{12} represent the WTP for the combined system, and WTP_1 and WTP_2 for System 1 and System 2 individually. If the two systems are substitutes, then the loss in welfare from simultaneously excluding both systems exceeds the sum of the losses from individually excluding each system. The percentage increase in WTP resulting from a merger between the two systems can then be calculated as follows:

$$\Delta WTP_{12} = \frac{WTP_{12}}{WTP_1 + WTP_2} - 1. \tag{8}$$

This measure has the property that it equals zero when the two systems are not substitutes, and is an increasing function of the level of substitution between the two systems.

D Additional Graphs and Tables

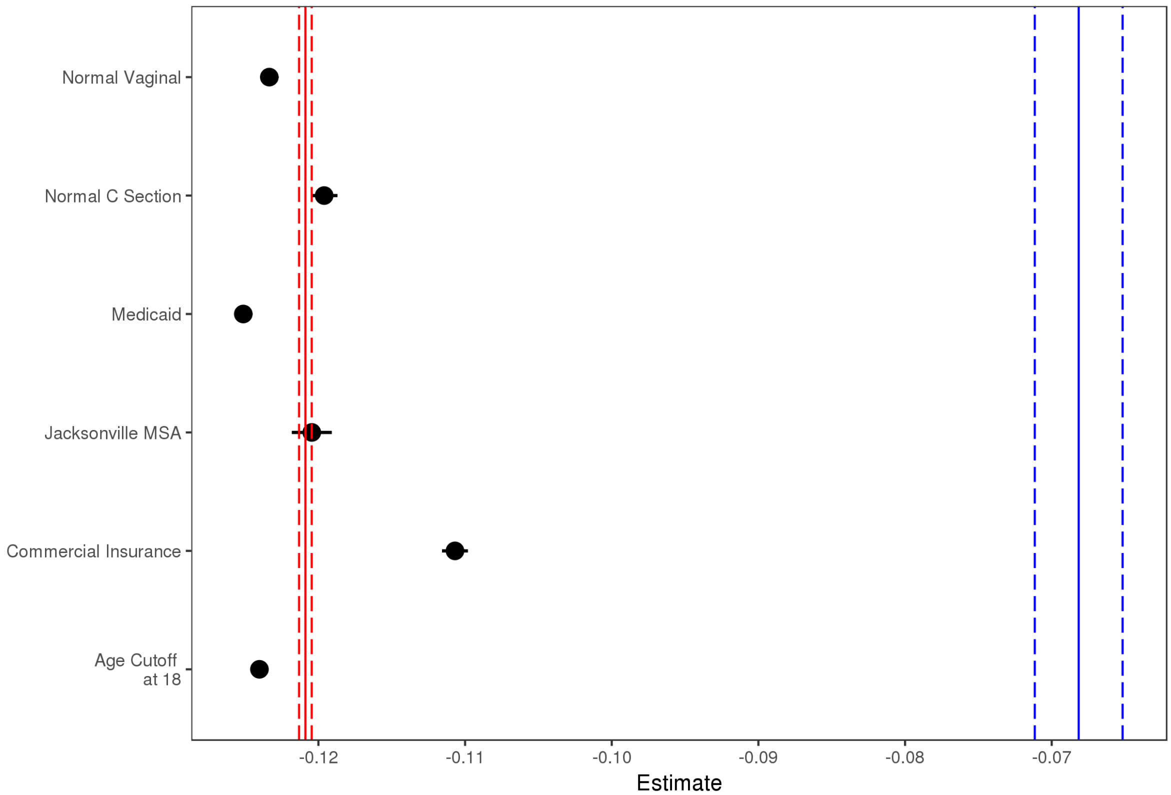

Figure 12 Robustness Checks for Estimates of the Transport Cost Coefficient Using the Standard Logit Model

Note: The red lines are the elasticity estimates from the standard logit model while the blue lines are the elasticity estimates from the fixed effects model. The solid lines are the point estimates while the dashed lines are the 95% confidence interval. The black horizontal lines are the elasticity estimates from our robustness checks conducted under the standard logit specification. The dot is the point estimate and the lines are the 95% confidence interval. Logit estimates reflect the transport cost parameter α; the semi-elasticity with respect to transport costs is α multiplied by one minus the probability of going to the hospital. See Table VI for a table of the estimates and standard errors used to generate this figure.

Table IV Parameter Estimates: Main Results

	Standard Logit (Age Restriction)	Standard Logit (Chamberlain)	Fixed Effect
Time	-0.121	-0.116	-0.068
	(0.000)	(0.001)	(0.002)
Hospital/Patient Fixed Effects			X
N	626,738	38,591	16,718

Note: All specifications include time invariant hospital indicator variables. N gives the units of observation used to compute the asymptotics. For the models that include hospital/patient fixed effects, this is the number of women, while for the other discrete choice models this is the number of admissions. The age restriction sample includes all women in Florida that were of age 21 or less in 2006. The Chamberlain sample only includes women in the age restriction sample who move houses and switch hospitals between their first and second birth.

Table V Parameter Estimates: Main Results Robustness

	Point Estimate (Std. Error)	N
Normal Delivery	-0.068 (0.002)	11,031
Normal Vaginal	-0.070 (0.002)	7,797
Normal C Section	-0.063 (0.004)	2,409
Term Delivery	-0.068 (0.002)	15,433
Age Cutoff at 18	-0.071 (0.002)	8,996
Same Income Move	-0.065 (0.002)	8,835
Jacksonville MSA	-0.072 (0.005)	2,168
Same Clinician	-0.042 (0.007)	937
Commercial Insurance	-0.054 (0.005)	1,340
Large Moves	-0.069 (0.004)	1,136
Small Moves	-0.064 (0.002)	12,878

Note: All specifications include time invariant hospital/patient fixed effects. N gives the units of observation used to compute the asymptotics - the number of women. The samples for each regression are restricted as follows. "Normal Delivery" only includes patients with a normal labor and delivery for both births, while "Normal Vaginal" and "Normal C-Section" further restricts to patients with two normal vaginal or C-Section deliveries respectively, and "Term Delivery" restricts to patients with a term delivery. "Same Clinician" only includes patients with the same operating physician for both births. "Large Moves" and "Small Moves" only include women whose distance to both hospitals changes by more than 15 minutes, or less than 15 minutes, respectively. "Age Cutoff at 18" only includes women who were at most 18 in 2006. "Same Income Move" only includes women for whom the zip code median household income changes by less than $10,000 between births. "Commercial Insurance" only includes women using commercial insurance for both births. Finally, "Jacksonville MSA" only includes women residing in the Jacksonville MSA for both births.

Table VI Parameter Estimates: Standard Logit Results Robustness

	Point Estimate (Std. Error)	N
Age Cutoff at 18	-0.124 (0.000)	359,416
Commercial Insurance	-0.111 (0.000)	142,141
Jacksonville MSA	-0.120 (0.001)	56,726
Medicaid	-0.125 (0.000)	452,974
Normal Vaginal	-0.123 (0.000)	363,681
Normal C Section	-0.120 (0.000)	135,651

Note: All specifications include hospital indicator variables, but do not include time invariant hospital/patient fixed effects. N gives the units of observation used to compute the asymptotics - the number of admissions. The samples for each regression are restricted as follows."Normal Vaginal" and "Normal C-Section" further restricts to patients with normal vaginal or C-Section deliveries respectively. "Age Cutoff at 18" only includes women who were at most 18 in 2006. "Commercial Insurance" only includes women using commercial insurance, while "Medicaid" only includes women on Medicaid insurance. Finally, "Jacksonville MSA" only includes women residing in the Jacksonville MSA.

Table VII Parameter Estimates: Referral Mechanism

	Clinician Month	Clinician Week	Clinician First Birth
Time	-0.093	-0.095	-0.097
	(0.001)	(0.000)	(0.001)
Clinician/Hosp Use	7.793	5.352	1.362
	(0.020)	(0.010)	(0.008)
N	626,738	626,738	147,661

Note: All specifications include hospital indicator variables, but do not include time invariant hospital/patient fixed effects. N gives the units of observation used to compute the asymptotics - the number of admissions. The second column includes an indicator for every hospital for which the obstetrician delivers an average of more than one baby per month, the third column includes an indicator for every hospital for which the obstetrician delivers an average of more than one baby per week, and the fourth column only includes second births and includes an indicator for every hospital for which the obstetrician at first birth delivers an average of more than one baby per month.

Table VIII Parameter Estimates: Switching Cost Mechanism

	Switching Cost	First Birth
Time	-0.117	-0.121
	(0.000)	(0.000)
N	626,738	432,390

Note: All specifications include hospital indicator variables, but do not include time invariant hospital/patient fixed effects. N gives the units of observation used to compute the asymptotics - the number of admissions. The second column includes an indicator for the hospital previously chosen by the patient calibrated using the switching cost parameter estimated in Raval and Rosenbaum (forthcoming), while the third column only examines first births.

Table IX Parameter Estimates: Catering To Local Demand Mechanism

	Catholic	Spanish	Birth Room
Time	-0.121	-0.121	-0.121
	(0.000)	(0.000)	(0.000)
Cath School X Cath Hosp	0.002		
	(0.011)		
Hispanic Pat X Spanish Hosp		0.122	
		(0.020)	
Median Income X Birth Rm			0.790
			(0.284)
N	626,738	626,738	622,212

Note: All specifications include hospital indicator variables, but do not include time invariant hospital/patient fixed effects. N gives the units of observation used to compute the asymptotics - the number of admissions. The second column interacts whether the hospital is affiliated with the Catholic Church with whether the patient's zip code has a Catholic school, the third column interacts whether the patient is Hispanic with the fraction of obstetricians with admitting privileges at the hospital that speak Spanish, and the fourth column interacts zip code median income with whether the hospital has a birthing room.