Quality vs. Familiarity: An Equilibrium Analysis of Physician Referrals

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Referrals among providers are a central feature in markets for advanced medical services. In a nationwide estimate for 2009, over 100 million patient visits resulted in a referral to another physician (Barnett, Song, and Landon 2012). Yet despite the importance of referrals in medical markets, the literature on this topic is quite limited. Most studies are purely descriptive, and often are focused on issues of appropriateness or coordination in specific clinical contexts. Few, if any, studies consider the incentives and behavior of both the referring physician and the specialist, who jointly determine which referrals occur in equilibrium.

In this paper we apply a simple equilibrium model to examine referrals for heart surgery in the state of Pennsylvania. This is an unusually good context to study referrals for a number of reasons. First, the referring physician, a cardiologist, can be identified with reasonable accuracy from health insurance claims data. Second, this is a focused area of medical care, so we might expect cardiologists to be aware of the available surgeons in their market. Third, specific and highly relevant quality measures—patient mortality rates—are publicly available through "report cards" on individual surgeons in Pennsylvania. This enables us to compare the importance of a quality measure against other factors that influence the choice of surgeon.

The first basic question we address is, how and to what extent does the referring physician affect the choice of specialist? Broadly speaking, the economic purpose of referrals is to address informational frictions. However the referring physicians themselves may not be fully informed about the quality of all the available specialists in their market, even if they do serve as perfect agents for their patients. To quantify this friction, we compare the effects of the reported mortality rates and other determinants of patient utility (e.g., distance to the surgeon) against additional factors that could make a cardiologist more familiar with a particular surgeon without necessarily relating to quality or patient well-being. Specifically we consider the distance between the cardiologist's and surgeon's offices, and whether they attended the same medical school. We find that proximity between the two offices is a substantial predictor of surgeon choice, with a stronger effect than the distance between the patient's residence and the hospital where the surgery is performed.

In addition, we offer a potentially important improvement for assessing the effects of publicly reported quality measures. A large literature evaluates the impacts of report cards in health care decisions and outcomes (see Dranove 2012 for a review). Many of these analyses apply a consumer choice model to estimate the effect of a reported quality measure on the demand for providers (e.g., Dranove and Sfekas 2008, Epstein 2010).[1] However these models do not account for the role of the supply side in determining equilibrium outcomes and, as we note, may produce biased estimates as a consequence.[2] The intuition is simple: if more patients want to see providers with better scores, but providers are constrained in the number of patients they can take, then a better score makes a provider marginally harder to see. This negative spillover among patients generates a downward bias in the estimate of the effect of a report card quality measure on demand (or the effect any other desirable characteristic, for that matter).

When applied in other industries, models of consumer choice typically incorporate the role of supply in equilibrium very naturally by including a price. In the case of medical services, however, the price (as listed or as paid) may not be an important determinant of demand because patients and referring physicians face it indirectly at best. Patient out-of-pocket payments depend mainly on insurance plan characteristics, not the quality or desirability of the provider. Instead we account for the negative spillover among patients, which arises from constraints on the supply side, in a general manner by including a congestion effect in the model. In other words, the choice probabilities are partly a function of the number of other patients in the market who see each provider (somewhat like a negative peer effect). This applies the approach developed in Bayer and Timmins (2007), which extends Berry, Levinsohn, and Pakes (1995) to include non-price spillovers among consumers based on the number or proportion of individuals who purchase each product. The estimation procedure involves the use of instruments based on distances to providers, in order to address the bias that would otherwise arise from unobserved quality and demand factors. Our results indicate a substantial congestion effect among patients, and they show that the estimated effect of the report card mortality rate on demand is biased downward by perhaps 20% if this is not accounted for.

[1] Other papers use a choice model to estimate the effects of report card quality measures on the demand for health insurance plans, for example Jin and Sorensen (2006) and Chernew, Gowrisankaran, and Scanlon (2008). The bias we describe is not an issue there because equilibrium prices are observed in the form of health insurance premiums.

[2] Mukamel, Weimer, and Mushlin (2007) and Epstein (2010) also note that the models of demand in this literature do not account for equilibrium supply and may therefore produce biased estimates. However they do not propose a method to incorporate the supply side.

The preliminary draft that follows contains four main sections. We first lay out the model, where we show how the usual consumer choice framework is extended to include a congestion effect as well as characteristics of the referring physician. Section 2 then describes the estimation procedure. Section 3 describes our data and the specific measures used in the model, and Section 4 presents the results.

1. Model

Our market consists of three sets of individuals: patients, referring physicians (cardiologists), and specialists (surgeons). We assume that referring physicians act as perfect agents for their patients, so these two can be treated interchangeably for most purposes. The specialists are not modeled explicitly, but we assume that they have increasing marginal costs which lead to the congestion effect among patients. In the background we have in mind a matching process, where the equilibrium probability that a patient sees a particular specialist depends on the preferences on both sides, and so we refer to these outcomes as matches and match probabilities.

We use the standard approach of modeling consumer demand by specifying a choice model over differentiated products or services. The utility that patient p would obtain from specialist j is a function of the public quality measure Q_j, other specialist characteristics Z_j, and attributes of the patient-specialist pair X_{pj} such as distance along with an unobservable term ϵ_{pj}. The typical utility specification is then as follows:

$$U_{pj} = \beta_1 Q_j + Z_j' \beta_2 + X_{pj}' \beta_3 + \epsilon_{pj}.$$

We extend this basic model by incorporating information about the referring physician i, specifically by including attributes of the pair of physicians X_{ij} such as the distance between their offices.[3] We also allow for an unobserved factor affecting the demand for specialist j, denoted ξ_j (e.g., unobserved quality factors). Our specification of utility is thus

[3] A "main effect" of characteristics of the referring physician or the patient cannot be included because it would affect the utility derived from all specialists equally; hence it drops out from the differences in utility that determine the choice of specialist.

$$U_{pij} = \beta_1 Q_j + Z_j' \beta_2 + X_{pj}' \beta_3 + X_{ij}' \beta_4 + \xi_j + \epsilon_{pij}. \qquad (1)$$

This can be interpreted as the utility that the referring physician *i* expects patient *p* to receive from specialist *j*. The presence of attributes of the referring physician in relation to the surgeon (i.e., X_{ij}) does not necessarily mean that the referring physician is not acting as a perfect agent for the patient. Instead, we interpret these factors as relating to informational frictions in the market. Because cardiologists do not have perfect information about the performance and capabilities of all the surgeons in their market, their beliefs about patient utility are influenced by their familiarity with each surgeon. Accordingly X_{ij} contains factors that would tend to increase cardiologist *i*'s familiarity with surgeon *j*, such as training at the same institution or having nearby offices.

Specification (1) yields a probabilistic choice model, given some distribution for ϵ. Assuming independent extreme value shocks yields the common multinomial logit model:

$$\Pr\left(j \middle| \left\{Q_k, Z_k, X_{pk}, X_{ik}, \xi_k\right\}_{k \in M}\right) = \frac{\exp\left(\beta_1 Q_j + Z_j' \beta_2 + X_{pj}' \beta_3 + X_{ij}' \beta_4 + \xi_j\right)}{\sum_k \exp\left(\beta_1 Q_k + Z_k' \beta_2 + X_{pk}' \beta_3 + X_{ik}' \beta_4 + \xi_k\right)}$$

where the set *M* collects the surgeons available in patient *p*'s market. However this model only represents the demand for specialists. Notably absent, especially in comparison with similar models applied in other industries, is a price or any other equilibrating factor. Prices may not be highly relevant for consumer choices here, but it is nevertheless important to incorporate the role of the supply side in determining equilibrium match probabilities. To do this, a fully developed model would specify the utility that surgeons receive from treating patients and would then apply an equilibrium concept to predict market outcomes. We do not specify the model to that extent, but rather we motivate an extension to the choice model above based on a simple notion of surgeon utility. This is intended to account for the role of the supply side in a flexible manner.

We suppose that surgeon utility depends only on the payment received for performing a procedure and the marginal cost of providing this treatment. Additionally we assume that the marginal cost is increasing in the number of patients seen over a given time period. This could take the extreme form of a fixed capacity constraint (a supply curve that is initially flat until the capacity is reached, and then is infinite) or appear as a more standard upward sloping supply curve. As a consequence, the probability that an individual patient is matched to a given surgeon would be decreasing in the number of patients that surgeon has in total. (Intuitively, it is harder to see a more popular provider.) We incorporate this into the model by including a measure of the patient volume for each surgeon, Y_j.[4] In other words, the model allows for a congestion effect among patients, which is interpreted as reflecting the diminishing availability of a surgeon due to increasing marginal costs.

The other factor in this notion of surgeon utility is the payment. Our sample consists only of Medicare and Medicaid beneficiaries, so we can assume that payments are fairly uniform from each payor within each market. (Indeed we see this in our data on the payment amounts.) Therefore we can account for the effect of the different reimbursement amounts in our sample simply with an indicator for Medicaid patients, I_p. The main effect of this variable drops out because it is constant within each patient, but its interactions with other variables are identifiable. Specifically we include the interaction of the Medicaid indicator with the surgeon's volume, $I_p Y_j$, because we would expect surgeons facing higher demand to be less likely to see patients whose insurance offers substantially lower payments.[5]

Given these extensions, the model we estimate is as follows:

$$\Pr(j|p,i,M) = \frac{\exp\left(\beta_1 Q_j + Z_j'\beta_2 + X_{pj}'\beta_3 + X_{ij}'\beta_4 + \gamma_1 Y_j + \gamma_2 I_p Y_j + \xi_j\right)}{\sum_k \exp\left(\beta_1 Q_k + Z_k'\beta_2 + X_{pk}'\beta_3 + X_{ik}'\beta_4 + \gamma_1 Y_k + \gamma_2 I_p Y_k + \xi_k\right)} \qquad (2)$$

(here "p, i, M" is shorthand for the characteristics of the patient, cardiologist, and all the surgeons in the market).

2. Estimation

To estimate the model in (2) we apply methods developed in Bayer and Timmins (2007). This extends the approach for differentiated products from Berry, Levinsohn, and Pakes (1995) to incorporate general non-price spillovers in demand. In our case, the spillover effect is the crowding out of a surgeon's available capacity as described in the previous section.

[4] We consider two alternative measures of patient volume, described in Section 3.
[5] Medicaid generally pays about 2/3 as much as Medicare (http://kff.org/medicaid/state-indicator/medicaid-to-medicare-fee-index/).

The estimation proceeds in two steps. First a conditional logit is estimated that includes fixed effects for each surgeon. Denoting these as δ_j, the model is

$$\Pr(j|p,i,M) = \frac{\exp\left(\delta_j + X_{pj}'\beta_3 + X_{ij}'\beta_4 + \gamma_2 I_p Y_j\right)}{\sum_k \exp\left(\delta_k + X_{pk}'\beta_3 + X_{ik}'\beta_4 + \gamma_2 I_p Y_k\right)}. \qquad (3)$$

The remaining parameters are then estimated using the identity

$$\delta_j = \beta_1 Q_j + Z_j'\beta_2 + \gamma_1 Y_j + \xi_j. \qquad (4)$$

This provides a simple linear model for the surgeon fixed effects.

Because surgeon volume (Y_j) is endogenous to unobserved demand factors (ξ_j), the linear model in (4) is estimated via two-stage least squares.[6] Following Bayer and Timmins (2007), the instrument is the predicted market share for each surgeon, using a logit model with only the exogenous variables: Q_j, Z_j, X_{pj}, and X_{ij}. The crucial exogenous variation comes from the distances between each patient and surgeon and between each cardiologist and surgeon in the market. All else equal, these distances predict different patient volumes for each surgeon. Thus the key assumption is that the locations of patients, surgeons, and cardiologists are exogenous.

3. Data and Measures

Our data come from Pennsylvania, a state that has published heart surgeon report cards since 1992. We use the report card quality measures for 2008-09, combined with data on coronary artery bypass graft (CABG) and heart valve repair surgeries performed in 2010-11. The patient sample consists of Medicare fee-for-service (FFS) beneficiaries with Part D coverage and Medicaid beneficiaries in the fee-for-service program or enrolled in managed care plans. From their insurance claims, we identify those beneficiaries who underwent one of the relevant surgeries in 2010-11, using the same procedure list as the report card. The surgeon who

[6] Note that, if the additive specification of the index within the probability model is correct, the endogeneity of the interaction term $I_p Y_j$ is addressed by the surgeon fixed effects. Hence γ_2 can be consistently estimated in the first step where there are no instruments.

performed the procedure is identified on these claims records. The referring physician is then inferred by searching through the patient's claims records for a specific diagnostic procedure prior to the surgery: the cardiologist who provides a left heart catheterization to the patient most recently before the surgery (and within 180 days) is treated as the referring physician. This procedure is required before a CABG or valve repair surgery, in order to determine which vessels are to be repaired.

For the present analysis we restrict to two Hospital Referral Regions (HRRs), Pittsburgh and Harrisburg. These markets are relatively self-contained, in the sense that most patients residing in these HRRs have heart surgery in their home HRR.[7] Appendix Table 1 describes the samples from these two markets. There are 792 patients in Pittsburgh and 466 in Harrisburg, about three-quarters of whom are Medicare beneficiaries. Among the Medicare beneficiaries, our final sample contains approximately 80% out of the initial pool of patients we identify in our claims data as residing in these two HRRs and having a CABG or valve repair anywhere in Pennsylvania in 2010 or 2011. From this initial pool, about 10% cannot be matched to a claim for left heart catheterization or to an inpatient claim for the surgery (needed for its location), and a further 10% are observed to have their surgery outside their home HRR. Among the Medicaid beneficiaries, the match rate for catheterizations is lower (we lose about 30% of the initial pool), and so there our sample consists of about 60% of the initial pool of patients identified in our claims data. In total our final sample contains 71% of the initial pool.

The characteristics of the surgeons, patients, and cardiologists in our sample are described in Table 1. There are 52 surgeons, 48 of whom see at least one Medicare patient in our sample and 47 of whom see at least one Medicaid patient. On average these surgeons treat 24 patients from our sample. To find the total number of heart surgeries performed by each surgeon, beyond our sample patients, we also obtained hospital discharge records from the Pennsylvania Health Care Cost Containment Council (PHC4). Over the two-year period (2010-11) these surgeons performed an average of 180 CABG and/or valve repair surgeries. Most of the additional patients either have private insurance or are Medicare beneficiaries in managed care (40% of Medicare beneficiaries in PA) and/or without Part D coverage (about 30%

[7] We considered the Scranton and Philadelphia HRRs as well, which are also relatively self-contained. However our key instruments, patient-surgeon distance and cardiologist-surgeon distance, are not effective in these markets. In Scranton all heart surgeons are located at a single hospital, and in Philadelphia the predicted market shares based on distance are not sufficiently predictive of the actual market shares. We hope to expand the sample to other HRRs in Pennsylvania by combining other HRRs with substantial patient flows among them.

nationally).[8] Also some patients are excluded from our sample because they cannot be matched to a cardiologist or because they have the surgery outside their home HRR, as described above.

The market share of each surgeon is computed using all heart surgeries from the hospital discharge data. The average market share is 3.8%, with a range from 0.1% to 6.9% in Pittsburgh and 1.2% to 23.1% in Harrisburg. The market share serves as one measure of the patient volume for each surgeon, Y_j. This is essentially equivalent to using the number of patients because, within each HRR, the market shares are directly proportional to the number of patients. The other measure we consider is an index of capacity utilization. This index is computed by first finding the number of unique days each month that the surgeon performs heart surgery on a patient in our claims data (i.e., Medicare FFS and Medicaid).[9] For each surgeon we then take the 75th percentile of the number of days per month, and use that as a proxy for the number of days they are available to operate per month. Finally we multiply this by the 24 months in our time period to represent the surgeon's overall capacity, and then take the ratio of the total number of surgeries in the discharge data over this capacity. Thus our index of capacity utilization is:

$$Y_j = \frac{\text{\# heart surgeries in 2010-11 (from discharge records on all patients)}}{\text{24 x 75}^{\text{th}}\text{ percentile of \# days per month with a surgery (from our claims data)}}$$

The index has an average of 1.2 and ranges up to 3.6 and 2.7 in Pittsburgh and Harrisburg respectively. Conceptually, the main difference between this and the raw market shares is that the index attempts to adjust for differences across surgeons in the number of days they are available to operate (vs. conduct research, for example, for those at academic centers).

The other important measure for our model is the public quality signal from the report card, Q_j. For this we use a risk-adjusted mortality rate (RAMR) that is derived from the 30-day mortality rates provided in the report card. The report card dataset lists the raw mortality rates for CABG and valve repair surgeries separately for each surgeon, along with the expected mortality rates for each surgeon based on a risk adjustment model. We construct a combined RAMR for CABG and valve repair by first subtracting the expected mortality rates from the raw rates for each type of surgery, and then taking a weighted average of the two using the number of surgeries of each type. If the report card does not list a mortality rate for one type of surgery

[8] See http://kff.org/medicare/state-indicator/enrollees-as-a-of-total-medicare-population/ and Donohue (2014).

[9] We cannot use the discharge data with all surgeries because only the calendar quarter is reported in those data.

(because a surgeon has too few cases), we simply use the risk-adjusted mortality rate for the type that is reported. Of the 52 surgeons, 43 have CABG mortality rates and 37 have valve repair mortality rates listed in the report card, and 44 have at least one of the two. (We include two indicator variables to account for surgeons without either one of the mortality rates in the report card.) The average RAMR in our sample is 0.5 per 100 for CABG, 0.3 per 100 for valve repair, and 0.5 per 100 for the weighted combination that we use in the model. The standard deviation of the combined RAMR is 2.4 per 100, and it ranges from -2.5 to 11.2.

There are 1,258 patients in the current sample and a total of 36,294 possible patient-surgeon pairs (= num. patients x num. surgeons, within each HRR). We use the Elixhauser index as a measure of overall health status of patients. This counts the number of certain comorbidities observed using diagnosis codes in health insurance claims over the 365 days prior to the surgery. The average of this index is 5.2, with slightly more comorbidities observed among Medicare FFS beneficiaries than among Medicaid beneficiaries. Also, each patient is associated with a referring cardiologist as described earlier, and there are 181 unique cardiologists in the sample.

The distances between patients and surgeons, and between cardiologists and surgeons, are measured using zip code centroids. The distances between patients and surgeons use the patient's residence and the hospital where the surgery takes place, to reflect travel costs. The distances between cardiologists and surgeons instead use their office locations, inferred from professional claims, in order to capture the likelihood of professional interactions. The average distance between a patient and any of the surgeons in their HRR is 43 miles and the median is 38 miles. The distances between each patient's cardiologist and the surgeons are somewhat less, with an average of 34 miles and a median of 24 miles. (The latter measures are also taken over patients to reflect how they enter into the estimation of the model.)

4. Results

We first present the estimates of our main empirical specification, equation (2), in Table 2. The model is estimated separately for the Pittsburgh and Harrisburg HRRs and then with the two HRRs combined. This lets us see the precision available from each HRR and the extent to which either one is driving our results.

First, the estimates of the effect of the RAMR on demand have the expected sign and typically have plausible magnitudes as well, but they are not statistically significant. This indicates a need to expand our sample to other HRRs. We discuss these point estimates below, but with the caveat that they are imprecise.[10] Second, the two-step estimation procedure appears to be successful even in this limited sample, when the patient volume of surgeons is measured using their market shares. With both HRRs combined the first-stage *F* statistic just satisfies the conventional threshold of 10, and in all cases we obtain the expected sign for a congestion effect. The separate estimates from each HRR indicate that much of the predictive power of the instrument is in Harrisburg, although we see good correlation between the predicted and observed market shares in both HRRs (see Appendix Figure 1). Third, by contrast, when the index of capacity utilization is used estimation fails because the instrument is not sufficiently predictive ($F < 10$).

The coefficients in this conditional logit model can be interpreted roughly as semi-elasticities.[11] For example, a 1-mile increase in the distance to the surgeon's hospital reduces the probability that a patient would see this surgeon by about 8% (in relative terms). Also, as predicted, we find that Medicaid patients are less likely to see high-volume surgeons. For a surgeon with a market share of 5% (the 75th percentile), for example, the match probability for a Medicaid patient is 22% lower than for a Medicare patient (see footnote 10 regarding the computation). The point estimate of the overall congestion effect is quite large: each percentage point of market share reduces an individual patient's probability of matching with a surgeon by 44% (again, in relative terms). This indicates substantial crowding out of the capacity of popular surgeons who have low mortality rates. The point estimate of the effect of the RAMR from the report card is similar: having one less death per 100 patients increases demand by 45%. However this estimate is imprecise and cannot be statistically distinguished from zero.

This model also indicates the importance of the referring cardiologist in shaping the choice of surgeon. Specifically, the distance between the cardiologist's and surgeon's offices has a stronger effect on the match probability than the distance between the patient's residence

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[10] Our analysis with an expanded geographic sample is in fact complete and addresses the power issues, but a review by the state Medicaid office is required prior to dissemination.

[11] In a general conditional logit model where the index for each alternative is $x'\beta$, the marginal effect of variable x_k on outcome j is $P_j(1 - P_j)\beta_k$, and so the semi-elasticity is $(1 - P_j)\beta_k$. For small values of P (recall our average market share is 3.8%) this is roughly β_k. For larger values of P, or when the coefficient is multiplied by another quantity like a mean or standard deviation, we include the adjustment of $(1 - P)$.

and the hospital where the surgery is performed. Each additional mile between the physicians' offices reduces the match probability by roughly 17%. We interpret this as reflecting the influence of the greater familiarity that a cardiologist would have with nearby surgeons.[12]

Then, to assess the bias that occurs in demand models that do not account for equilibrium supply, we compare estimates from a model that omits the congestion effect among patients. Table 3 shows the estimated effects of the RAMR from such a model, along the results from our baseline specification and from two alternative estimation procedures (discussed below). The point estimate of the effect of the report card quality measure in the model without a congestion effect is -0.36. This is 20% lower in magnitude than the estimate from our equilibrium model (although both are imprecise). Thus we see evidence of the negative bias predicted earlier.

The last two columns of Table 3 present estimates of the effects of the RAMR and surgeon volume in equation (4) using the reduced form (where the predicted market shares are directly included) and using OLS (where the observed market shares are used) rather than 2SLS. The predicted market shares in the reduced form have a similar negative effect as their IV estimate, while the OLS estimates show the expected positive bias due to unobserved demand factors ξ. The estimated effect of the RAMR in the reduced form is similar to the IV estimate, but with OLS estimation it is lower as in the model without the congestion effect.

5. Conclusion

Our analysis of referrals for heart surgery in Pennsylvania suggests that referring cardiologists affect the choice of surgeon, such that the same patient might see a different surgeon depending on the cardiologist initially consulted. This has implications for patient welfare, whether it arises from informational frictions or another source.

The analysis employs a simple equilibrium model that accounts for constraints in the supply available from each surgeon. This framework would be applicable for demand estimation in other health care markets, wherever a congestion effect among patients is a concern. The model is easily estimated in two steps using pre-programmed commands available in software

[12] There are other interpretations of course. Cardiologists and surgeons with closer offices are more likely to be part of the same health system, for example. This could foster greater familiarity, but it may also involve the benefits of integrated health records or possible incentives for internal referrals.

like Stata. Our approach may therefore be useful to assess the effects of provider report cards and other quality measures more generally.

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Table 1. Sample Descriptive Statistics

	Total (Medicare & Medicaid)
Number of surgeons (N)	52
Surgeries performed 2010-11 (Mean ± STD)	
Using our Medicare and Medicaid claims data	24.2 ± 21.2
Using PHC4 hospital discharge data	179.8 ± 128.8
Market share 2010-11 (Mean ± STD)	3.8% ± 3.8%
Index of capacity used 2010-11 (Mean ± STD)	1.2 ± 0.9
CABG mortality rate 2008-09* (Mean ± STD)	0.5 ± 2.4
N with CABG mortality (N)	43
Valve mortality rate 2008-09* (Mean ± STD)	0.3 ± 3.3
N with valve mortality (N)	37
Combined mortality rate* (Mean ± STD)	0.5 ± 2.4
N with combined mortality rate (N)	44
Number of patients (N)	1,258
Age (Mean ± STD)	67.4 ± 12.5
Sex (# (%) female)	551 (43.8%)
Elixhauser index (Mean ± STD)	5.2 ± 3.0
Number of patient/cardiologist and surgeon pairs (N)	36,294
Patient-surgeon distance (Mean ± STD)	42.8 ± 30.4
Cardiologist-surgeon distance (Mean ± STD)	34.2 ± 33.9
Card. and surg. attended same medical school (Mean)	0.02
Number of unique cardiologists (N)	181

* Risk-adjusted by subtracting the expected mortality rates listed in the report card.

Table 2. Main Model Estimates

	PIT	HBG	PIT & HBG	PIT	HBG	PIT & HBG
Surgeon quality						
Risk-adjusted mortality rate	-0.758	-0.270	-0.448	-1.472	-0.478	-2.737
	(0.626)	(0.232)	(0.396)	(1.105)	(0.511)	(4.296)
Surgeon volume						
Market share	-3.240	-0.059	-0.443			
	(2.575)	(0.053)	(0.221)			
Capacity utilization				-6.091	-1.557	-19.034
				(5.229)	(1.819)	(34.821)
Patient-surgeon interactions						
Distance (patient-surgeon)	-0.091	0.038	-0.081	-0.091	0.038	-0.081
	(0.006)	(0.021)	(0.005)	(0.006)	(0.021)	(0.005)
Elixhauser x mortality rate	0.003	-0.038	-0.007	0.003	-0.038	-0.007
	(0.006)	(0.012)	(0.005)	(0.006)	(0.012)	(0.005)
Medicaid x volume	-0.030	-0.044	-0.046	-0.151	-0.405	-0.224
	(0.054)	(0.021)	(0.019)	(0.101)	(0.179)	(0.086)
Cardiologist-surgeon interactions						
Distance (card.-surgeon)	-0.169	-0.218	-0.170	-0.169	-0.219	-0.170
	(0.012)	(0.023)	(0.010)	(0.012)	(0.023)	(0.010)
Same medical school	0.126	-0.001	0.131	0.125	-0.012	0.124
	(0.283)	(0.499)	(0.244)	(0.282)	(0.500)	(0.244)
First-stage *F* statistic	2.8561	46.5124	10.24	2.6569	1.1881	0.2704

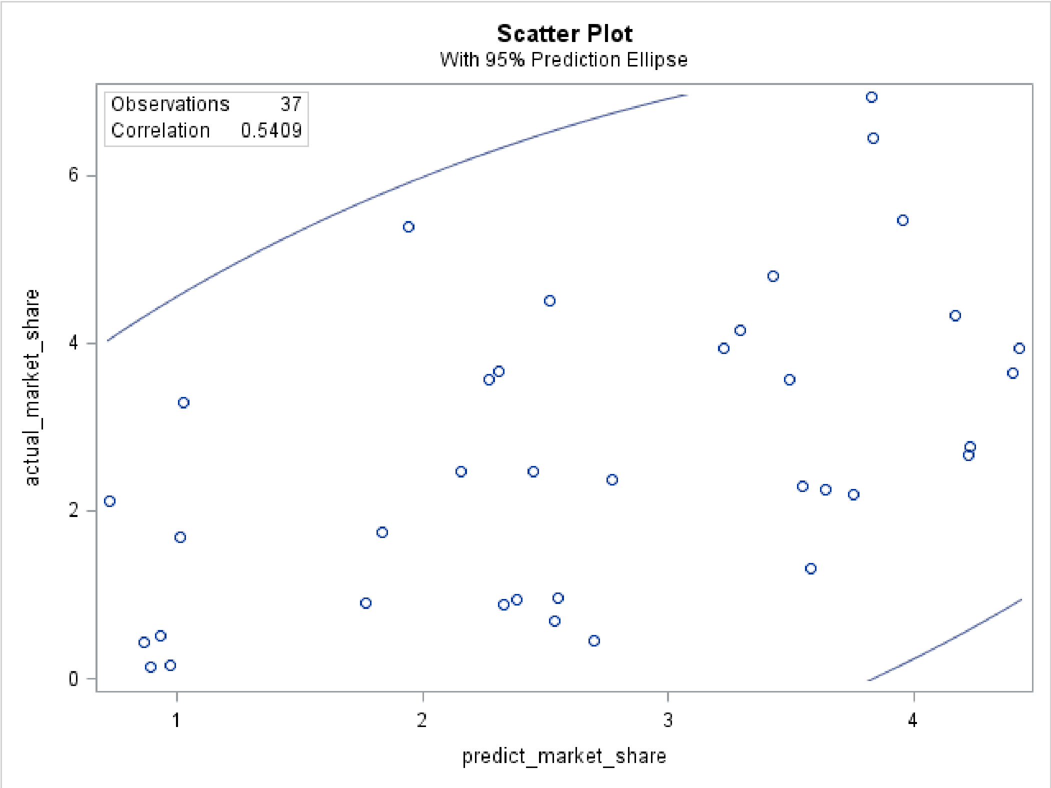
Each column is a separate model. Standard errors shown in parentheses.

Table 3. Effects of Surgeon Quality in Alternative Models

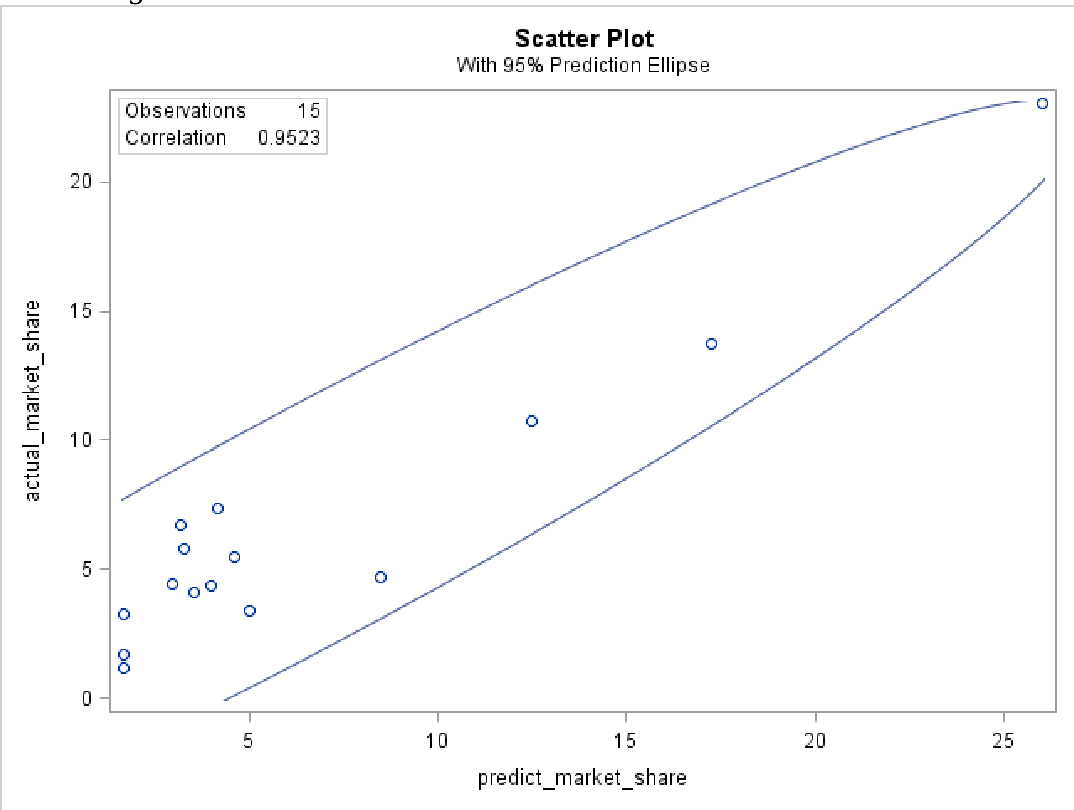
	IV (main)	Omit Volume	Reduced Form	OLS
Surgeon quality				
Risk-adjusted mortality rate	-0.448	-0.363	-0.414	-0.352
	(0.396)	(0.347)	(0.345)	(0.353)
Surgeon volume				
Market share	-0.443		-0.312	0.057
	(0.221)		(0.220)	(0.218)

Table presents estimates of equation (4) in the main specification and alternative specifications or estimation procedures. Standard errors shown in parentheses.

Appendix Figure 1. Actual and Predicted Market Shares
Pittsburgh HRR:



Harrisburg HRR:



Appendix Table 1. Construction of the Patient Sample

	Pittsburgh	Harrisburg
Number of beneficiaries who live in Pittsburg or Harrisburg HRRs and have CABG or valve repair anywhere in PA	1,118	648
+ who had left catheterization in home HRR within 180 days before surgery	918 (82%)	563 (87%)
+ who had CABG or valve repair in home HRR	811 (73%)	477 (74%)
+ whose surgeon appears in a report card (either 2008-2009 or 2011-2012)	794 (71%)	469 (72%)
+ who are enrolled for 365 days prior to surgery (to construct Elixhauser idx) and whose cardiologist is not both outside home HRR and farther from the chosen surgeon than the distance between any cardiologist-surgeon pair within the HRR	792 (71%)	466 (72%)