Measuring Quality Effects in Equilibrium*

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Abstract: In certain applications, such as markets for healthcare services, models of demand often omit a price that reflects the scarcity of quality in equilibrium. Estimates of the demand response to quality may consequently be attenuated, due to the limited availability of high-quality options. We propose a tractable method to address this problem by adding a congestion effect to standard discrete-choice models, which improves forecasts of the market response to quality changes. We apply this method to the market for heart surgery, and find that the attenuation bias in estimated quality effects can be important empirically.

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How demand responds to quality is an important concern in many markets. The issue has received particular attention in healthcare markets, where the economics literature often points to low responsiveness to quality as a source of inefficiency, and a variety of public quality measures have been adopted in attempts to improve market allocations.[1] However, healthcare markets are unusual in that consumers often do not face the full prices of the products or services they acquire, and this has important implications for demand estimation. Without a price or other equilibrating factor in consumer utility, estimates of the effect of quality on demand are biased toward zero and demand forecasts are similarly attenuated, when standard discrete-choice models are employed.

Consider a simple example: patients $i = 1 \dots I$ choose among physicians $j = 1 \dots J$ to receive a one-time service. Physicians have an observable quality attribute, Q_j, and patient i's utility of the service from physician j is $\beta Q_j + \epsilon_{ij}$, where ϵ_{ij} reflects other demand factors that are not included in the analysis. A standard discrete-choice model would specify the probability that patient *i* sees physician *j* as a function of *i*'s potential utility from each physician in the market. However, without a price or other equilibrating factor, this model ignores any role of the supply side in determining equilibrium outcomes, which may result in biased estimates. The intuition is simple: if more patients want to see physicians with higher quality ($\beta > 0$), but physicians have limits on the number of patients they can treat, then higher quality physicians may be harder to see. This congestion effect among patients generates a downward bias in the estimate of the effect of a quality measure on demand (or the effect any desirable characteristic, for that matter), absent an equilibrating factor such as price or wait times in the demand model. Such a bias would be present any time the supply *from individual physicians* is not perfectly elastic, because the negative spillover from the congestion effect would be larger for higher quality physicians. Having imperfect elasticity of supply is natural for individual producers of skilled services, whether from fixed capacity or time constraints, or more generally from increasing marginal costs.

[1] Surveys by Dranove (2011) and Skinner (2011) discuss the limited response to quality in healthcare markets, although recent work by Chandra et al. (2016) provides important evidence of the relationship between hospital quality and market shares. Public "report cards" have been issued on hospitals, physicians, and insurance plans since the 1990s (e.g., surgeon report cards in Pennsylvania and New York, Medicare's "Hospital Compare," and National Committee for Quality Assurance ratings).

Because of this congestion effect, models without an equilibrating factor cannot be interpreted as representing demand.[2] Instead these models fit the equilibrium probabilities that patients with certain characteristics receive services from physicians with certain characteristics. Fitting and forecasting these probabilities is important, for example to measure the responsiveness to quality in equilibrium and to predict the effect of quality improvements on patient outcomes. However, without accounting for the congestion effect, forecasts of changes in equilibrium outcomes given changes in the quality or number of physicians in a market are also systematically biased. As an extreme example, suppose that each physician in the market is "cloned" (i.e., now $j = 1 \dots 2J$ and $Q_{j+J} = Q_j$). A standard multinomial logit would predict that the market share for each original physician would be cut in half, and the clones would have the same market shares as their originals.[3] There would be no aggregate shift toward higher quality physicians, even though there is a large increase in supply relative to demand. This is clearly contrary to economic intuition. Our goal in this paper is to understand and address this problem.

We propose a relatively simple and tractable way to incorporate a congestion effect among consumers into discrete-choice models of provider choice, and thereby to obtain more accurate estimates of the effects of quality measures on equilibrium outcomes. The approach is to include the number or proportion of patients treated by each provider in a market as variables in the model. This is an application of the method developed in Bayer and Timmins (2007), originally for location choices, which extends the demand model from Berry, Levinsohn, and Pakes (1995) to include a peer effect that reflects various possible spillovers (positive or negative) among individuals at the same location. Their two-step estimation procedure can be implemented using standard commands in econometric software such as Stata, and in healthcare applications such as ours the distances between all patients and physicians in a market provide the exogenous variation needed for a credible instrument.

We then use this method to examine the role of quality in the market for heart surgery, a topic of substantial interest to both policy-makers and researchers. Several important studies in economics have applied discrete-choice models to estimate the effect of publicly-reported quality

[2] Consequently, for example, such models should not be used to compute consumer welfare.
[3] This is not simply a consequence of the IIA assumption; we find the same result in simulations with a mixed logit model in Section 2.3.

measures on the demand for heart surgeons (e.g., Dranove and Sfekas 2008, Epstein 2010, Wang et al. 2011, Kolstad 2013, Gaynor et al. 2016).[4] With the exception of Gaynor et al. (2016), which includes a measure of wait time, none of the demand models in these papers include an equilibrating factor. Certain results in this literature could therefore be driven by the attenuation bias described above. For example, Dranove and Sfekas (2008) and Wang et al. (2011) estimate negative effects of low quality on market share but insignificant effects of high quality on market share, which would be consistent with, for example, capacity constraints limiting the ability of high-quality providers to increase their supply. Also, Kolstad's (2013) insightful decomposition of incentives for quality improvement into intrinsic and extrinsic motives would be biased toward intrinsic motives if the demand model is subject to attenuation bias in the estimated response to quality. On the other hand, Chandra et al. (2016) recover a non-trivial relationship between hospital quality and market share in cardiac care, which would be consistent with a smaller congestion effect for hospitals compared to individual physicians.

Our empirical analysis finds a substantial congestion effect for heart surgeons and shows that the attenuation bias in estimates of the market response to quality can be economically important. In one regional market in Pennsylvania, for example, the estimated quality parameter is biased downward by 40% to 80%, and the standard model underpredicts the aggregate impact of surgeon quality improvements by 25% or more. This suggests that the returns to investments in provider quality may be substantially greater than what is indicated by standard models.

We are not the first to recognize the potential importance of supply constraints in this context. Mukamel, Weimer, and Mushlin (2007) and Epstein (2010) also note that typical models of demand for heart surgery do not account for supply constraints and may therefore produce biased estimates. However, they do not propose a method to address the potential bias. Conlon and Mortimer (2013) study incomplete product availability ("stock outs") in a different context and develop a method to account for that form of supply restriction in a discrete-choice framework. Last, although not on demand estimation, Cutler, Huckman, and Kolstad (2010) consider the impact of the supply of heart surgeons on hospital entry into the heart surgery market, and they find evidence that the relatively inelastic supply of surgeons has affected entry.

[4] Other important studies such as Dranove, Kessler, McClellan, and Satterthwaite (2003) do not involve demand estimation or forecasts and are not subject to the bias considered here. Also, to be clear, our concern is with the market response to quality, not the informational value of report cards.

In what follows, there are two main sections. The first develops the model, where the usual discrete-choice framework is extended to include a congestion effect, then analyzes the potential attenuation bias in forecasts from standard models, and finally describes the estimation procedure. The second presents the empirical analysis, which uses data on heart surgeries in Pennsylvania in 2010 and 2011.

1. Model and Estimation

The market in our application consists of three sets of individuals: patients, referring physicians (cardiologists), and specialists (surgeons). However, for simplicity we assume that referring physicians act as perfect agents for their patients, so these two are treated interchangeably. The specialists are the surgeons being chosen. Their supply decisions are not modeled, but we assume that specialists have increasing marginal costs, so their supply is not perfectly elastic and hence a congestion effect is present. Also, in the background we have in mind a matching process, where the equilibrium probability that a patient sees a particular specialist depends on the payoffs on both sides, and so we refer to outcomes in terms of matches and match probabilities.

To develop the model we start with a standard discrete-choice framework. The utility that patient *i* would obtain from specialist *j* is a function of a quality measure, Q_j, other specialist characteristics, Z_j, and observable attributes of the patient-specialist pair, X_{ij}, such as distance, along with an unobservable term, ϵ_{ij}. We also incorporate information about the referring physician *r* by including attributes of the pair of physicians, X_{rj}, such as the distance between their offices and whether they attended the same medical school.[5] Last, we allow for a common unobserved factor affecting the demand for specialist *j*, denoted ξ_j (e.g., quality factors that are unobserved to the analyst). With the standard linear specification, utility is thus

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

[5] Under the assumption that referring physicians are perfect agents for their patients, these pairwise attributes capture the effects of informational frictions.

This can be interpreted as the utility that the referring physician *r* expects patient *i* to receive from specialist *j*.

Specification (1) yields a probabilistic choice model, given some distribution for ϵ. Assuming independent extreme value shocks yields the common multinomial logit model:[6]

$$\Pr(j|\{Q_k, Z_k, X_{ik}, X_{rk}, \xi_k\}_{k\in M}) = \frac{\exp(\beta_1 Q_j + Z_j'\beta_2 + X_{ij}'\beta_3 + X_{rj}'\beta_4 + \xi_j)}{\sum_k \exp(\beta_1 Q_k + Z_k'\beta_2 + X_{ik}'\beta_3 + X_{rk}'\beta_4 + \xi_k)}, \qquad (2)$$

where the set *M* collects the specialists available in patient *i*'s market. However, this model only captures demand-side factors. Notably absent, especially in comparison with similar models applied to other industries, is a price or any other equilibrating factor. The insurance payments to heart surgeons, for example, are not highly relevant for consumer choices. Nevertheless, as discussed in the introduction, it is important to account for 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 model the supply side in this way, but rather we extend the discrete-choice model above to allow for a congestion effect among patients. This is intended to capture the effects of physician labor supply decisions and other capacity constraints on equilibrium match probabilities in a simple and flexible manner.[7]

The congestion effect is incorporated by adding a measure of the specialist's patient volume, Y_j, to the model. This can be specified as the number or proportion of patients treated in a given time period, or with a more complex measure that accounts for heterogeneity in capacity (e.g., due to academic or administrative responsibilities). In the empirical analysis we use the proportion of patients treated by each surgeon (i.e., the market shares), because it is a common and easily interpreted measure.[8]

Other factors that influence specialist utility and supply decisions may also be included in this extended model. Particularly, because models of physician utility often include

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[6] We also use a mixed logit model in the empirical analysis.
[7] As we discuss below, this is no longer a structural model by design.
[8] When estimation is done within a single market, as in our empirical analysis, the proportion equals the number of patients divided by a constant (i.e., the total number of patients in the market), so the two are essentially equivalent.

compensation (e.g., Ellis and McGuire 1986, Chandra, Cutler, and Song 2011), it would be natural to include the insurance payment to the specialist. In our empirical application, the sample consists entirely of Medicare and Medicaid beneficiaries, so we can assume that payments are fairly uniform from each payer within each market.[9] Therefore we can roughly account for the effect of different insurance payment amounts on the match probabilities by including indicator(s) for insurance type—here we use an indicator for Medicaid coverage, I_i. The main effect of this variable drops out, but its interactions with other variables are identifiable. Specifically, we include the interaction of the Medicaid indicator with the surgeon's volume, $I_i Y_j$, because we expect surgeons facing higher demand to be less likely to see patients whose insurance offers lower payments.[10]

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

$$\Pr(j|i,r,M) = \frac{\exp\left(\beta_1 Q_j + Z_j'\beta_2 + X_{ij}'\beta_3 + X_{rj}'\beta_4 + \gamma_1 Y_j + \gamma_2 I_i Y_j + \xi_j\right)}{\sum_k \exp(\beta_1 Q_k + Z_k'\beta_2 + X_{ik}'\beta_3 + X_{rk}'\beta_4 + \gamma_1 Y_k + \gamma_2 I_i Y_k + \xi_k)} \qquad (3)$$

(here "i, r, M" is shorthand for the characteristics of the patient, cardiologist, and all the surgeons in the market). To be clear, the terms inside the exponents do not have a structural interpretation as patient utility, so this is not a model of demand. Instead, this model is designed to measure and forecast the effect of quality on equilibrium match probabilities more accurately than models without an equilibrating factor. The next section demonstrates how the standard models can produce systematically biased forecasts and discusses when this issue is relevant.

1.1. Forecast bias in standard models

Intuitively, the market shares of providers with substantial congestion (e.g., surgeons working at full capacity) should be less sensitive to changes in their competitive environment, because they have a surplus of potential customers. We formalize this idea in the context of the model above, by showing that the (negative) substitution effect from quality improvements at other providers is smaller for providers with larger market shares, compared to the substitution effect predicted by a model without congestion. This implies that the market shares of higher

[9] We have verified this with our available data on payment amounts.
[10] Medicaid generally pays about 70% as much as Medicare (http://kff.org/medicaid/state-indicator/medicaid-to-medicare-fee-index/).

quality providers would remain larger than predicted by a standard model, because higher quality providers tend to have larger market shares initially. As a consequence, forecasts from a standard model may underpredict the increase in the aggregate consumption of quality, given an increase in the quality of one or more individual providers in a market.

To focus this analysis, we use a simple version of model (3) where the quality measure (Q) is the only exogenous variable, and we assume the market shares (Y) are known. Accordingly, suppose the data are generated by the following model:[11]

$$Y_j = \frac{\exp(\beta Q_j + \gamma Y_j)}{\sum_k \exp(\beta Q_k + \gamma Y_k)}, \qquad (4)$$

where $\beta > 0$ and $\gamma < 0$, and Y_j is the market share of provider j. However a standard model without a congestion effect is fit to the data:

$$Y_j = \frac{\exp(\hat{\beta} Q_j)}{\sum_k \exp(\hat{\beta} Q_k)}. \qquad (5)$$

We will show that the substitution effect from quality improvements at other providers ($\frac{\mathrm{d}Y_j}{\mathrm{d}Q_k}$) is relatively smaller for providers with larger market shares, in model (4) compared to model (5). Appendix A provides a similar analysis about the effect of entry, showing that the substitution away from providers with larger market shares is relatively smaller in the congestion model.

First, a useful closed-form expression for $\hat{\beta}$ can be obtained from a linear regression of the log-ratio of market shares, $\ln(Y_j/Y_1)$, on quality differences, $Q_j - Q_1$. (This would be a consistent estimator if the standard model were correct.) Denote the quality differences as $\Delta Q_j \equiv Q_j - Q_1$, and similarly define $\Delta Y_j \equiv Y_j - Y_1$. Then, in the true congestion model, we have $\ln(Y_j/Y_1) = \beta \Delta Q_j + \gamma \Delta Y_j$. The value of $\hat{\beta}$ recovered using the standard model is therefore

$$\hat{\beta} = \frac{\sum_j \Delta Q_j \cdot \ln(Y_j/Y_1)}{\sum_j (\Delta Q_j)^2} = \frac{\sum_j \Delta Q_j \cdot (\beta \Delta Q_j + \gamma \Delta Y_j)}{\sum_j (\Delta Q_j)^2} = \beta + \gamma \frac{\sum_j \Delta Q_j \Delta Y_j}{\sum_j (\Delta Q_j)^2}. \qquad (6)$$

[11] In Appendix A we show that this specification could arise from a structural model with wait times.

This is the true value, β, plus γ times the slope of the regression of market shares on quality differences. Hence $\hat{\beta}$ is less than β, because γ is negative while the covariance of *Y* and Q is positive. In addition, this indicates that $\hat{\beta}$ is not invariant to changes in the distribution of provider quality, so it should not be interpreted as representing consumer preferences.

Rather than the value and interpretation of the quality parameter, however, our main interest is in the model's forecasts of changes in market shares given changes in the quality or number of providers in a market. To analyze this, we consider the marginal substitution effect of competitor quality on own market share. As shown in Appendix A, this is

$$\frac{\mathrm{d}Y_j}{\mathrm{d}Q_k} = -Y_j Y_k \left(\beta + \gamma \frac{\mathrm{d}Y_k}{\mathrm{d}Q_k}\right) \cdot \left(1 - \gamma Y_j\right)^{-1}. \qquad (7)$$

By comparison, in the standard model, we have the usual result for a multinomial logit: $\frac{\mathrm{d}Y_j}{\mathrm{d}Q_k} = -Y_j Y_k \hat{\beta}$.

Now we can examine the differences in the predicted substitution effect between models (4) and (5). Using the expression for $\hat{\beta}$, the prediction from the standard model is

$$\frac{\mathrm{d}Y_j}{\mathrm{d}Q_k} = -Y_j Y_k \left(\beta + \gamma \frac{\sum_l \Delta Q_l \Delta Y_l}{\sum_l (\Delta Q_l)^2}\right), \qquad (8)$$

while the actual substitution effect is as expressed in (7). One difference is that the standard model uses the average marginal effect of own quality on market share (i.e., the regression slope, $\frac{\sum_l \Delta Q_l \Delta Y_l}{\sum_l (\Delta Q_l)^2}$) where the congestion model uses the individual marginal effect for provider *k* ($\frac{\mathrm{d}Y_k}{\mathrm{d}Q_k}$). But the key difference is that, given any provider *k*, the effect on provider *j* is deflated by $\left(1 - \gamma Y_j\right)^{-1}$ in the congestion model. Hence the (negative) substitution effect is smaller in magnitude for providers with larger market shares (because $\gamma < 0$). Therefore, because market shares are larger when quality is higher (because $\beta > 0$), the market share losses are smaller for higher quality providers. This makes it possible for the congestion model to have larger market shares for higher quality providers, compared to the predictions from the standard model, in a counterfactual where quality increases for one provider (or more).

This result, and the result on entry in Appendix A, indicate that a model without an equilibrating factor *could* underpredict the increase in the aggregate consumption of quality, given an increase in the quality or number of providers in a market. The empirical analysis demonstrates that this is indeed the case in a salient application. Below we first provide a simple numerical example to illustrate these results.

Figure 1 shows a simulation of models (4) and (5) using parameter values $\beta = +1$ and $\gamma = -1$. The baseline scenario has three providers with quality levels 0, 1, and 2. Panel A plots the log-ratio of market shares ($\ln(Y_j/Y_1)$) against provider quality differences ($Q_j - Q_1$) from the true congestion model, along with the fitted values from the misspecified standard model. (The log-ratios and quality differences are useful quantities because the standard model assumes they have an invariant linear relationship: $\ln(Y_j/Y_1) = \hat{\beta}(Q_j - Q_1)$, as indicated in the plots.) Panel B then shows a scenario where the quality of provider two increases from 1 to 1.5. The standard model predicts the new log-ratios to be on the same line as in the baseline, because $\hat{\beta}$ is invariant, but the congestion model shows that the true log-ratios for the higher quality providers are above this line. Hence the aggregate consumption of quality would be higher than is predicted by the standard model. Panels C and D show the results of entry by a relatively low (panel C) or high (panel D) quality provider. These add a fourth provider with $Q_4 = 0.5$ or 1.5, respectively. In both cases the true log-ratios for the higher quality providers are above the predictions from the standard model, again showing that the aggregate consumption of quality would be higher than is predicted by the standard model.

We finish this section with a more general discussion of why the forecast bias occurs, which stems from how the model is recovered and then used to generate counterfactual forecasts. First, if data were available from many markets, where many different distributions of provider quality are observed, this issue would be irrelevant. A nonparametric model could be estimated, at least in concept, and the desired marginal effects and counterfactual forecasts could be computed simply by comparing outcomes between markets with the appropriate realizations of the distribution of provider quality. This is not the usual empirical setup, however. The analyst typically has data from one or a limited number of markets, and must rely on a parametric model

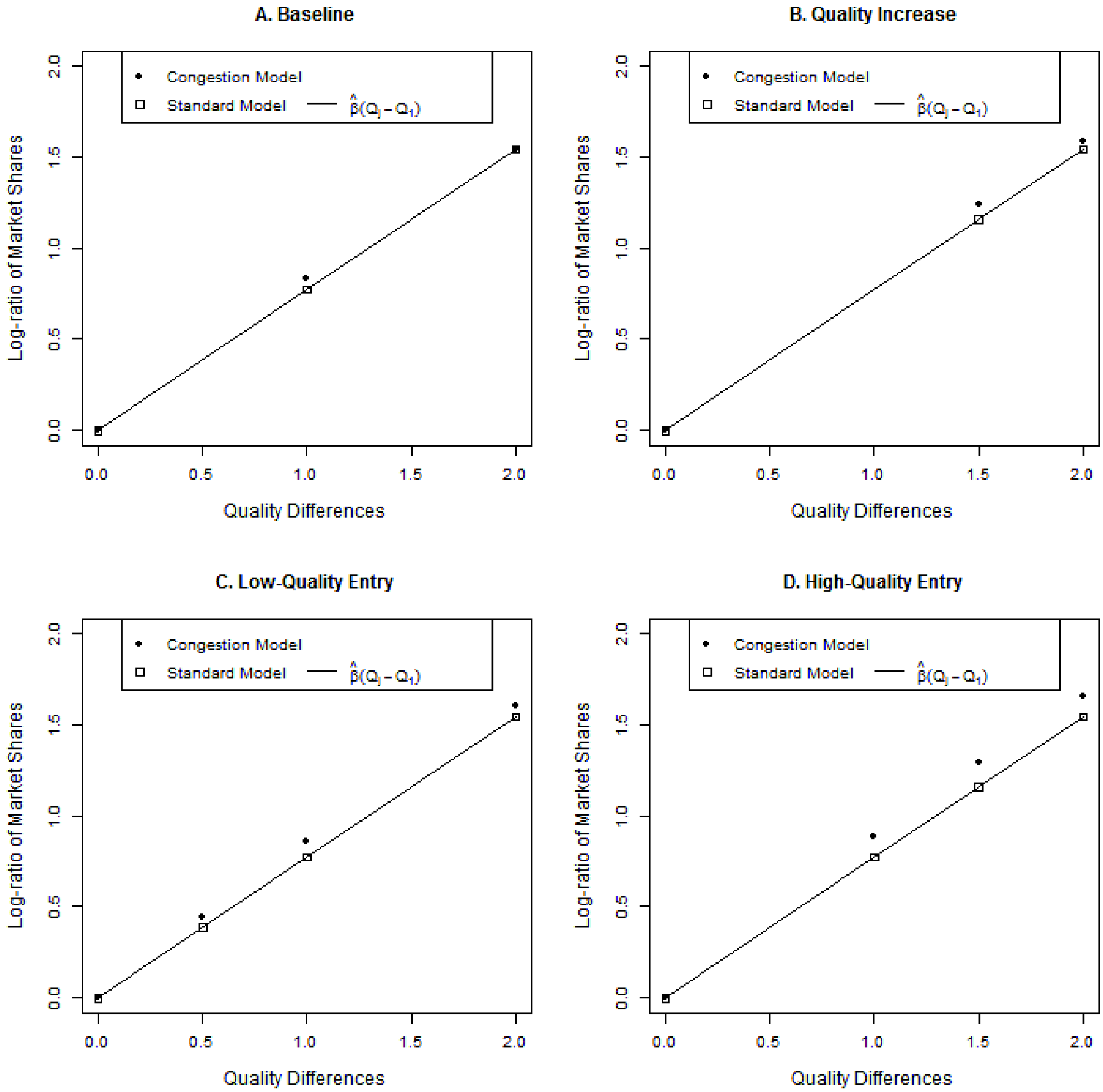

Figure 1. Numerical Example of Differences in Forecasts

Notes: Figure shows the log-ratio of market shares, $\ln(S_j/S_1)$, from the congestion model (filled circles) and the standard model (open squares) in an example with three providers at baseline. Predictions from the standard model fall on the line $\hat{\beta}(Q_j - Q_1)$, where $\hat{\beta}$ is recovered from the baseline market shares.

to compute the quantities of interest. In this setup, quality parameters are recovered from observed differences in quality and market shares across providers within a market, which holds fixed the market-wide distribution of quality. But even a basic counterfactual forecast, such as the marginal effect of increasing the quality of one provider while holding the others constant, typically contemplates a change in the aggregate supply of quality. Without an equilibrating factor, a standard model misses how this can affect all the alternatives. By contrast, a model with prices (e.g., Berry, Levinsohn, and Pakes 1995) would allow for changes in the prices of all alternatives when one alternative is improved. The congestion effect is like a price in that it can incorporate such spillovers across alternatives—in this case, how an increase in quality of one provider reduces congestion at another provider.

1.2. Estimation with a congestion effect

We now describe the estimation of model (3), which follows the method developed in Bayer and Timmins (2007). The procedure involves two steps. First a multinomial logit model is estimated that includes fixed effects for each provider. Denoting these as δ_j, the model is

$$\Pr(j|i,r,M) = \frac{\exp\left(\delta_j + X'_{ij}\beta_3 + X'_{rj}\beta_4 + \gamma_2 I_i Y_j\right)}{\sum_k \exp(\delta_k + X'_{ik}\beta_3 + X'_{rk}\beta_4 + \gamma_2 I_i Y_k)}. \qquad (9)$$

The remaining parameters are then estimated using the identity

$$\delta_j = \beta_1 Q_j + Z'_j\beta_2 + \gamma_1 Y_j + \xi_j. \qquad (10)$$

This defines a linear regression model for the provider fixed effects, which is estimated via two-stage least squares because the measure of surgeon volume (Y_j) is endogenous to the unobserved demand factors (ξ_j) by construction.[12]

Following Bayer and Timmins (2007), the instrument for Y_j is a predicted market share, generated using a multinomial logit model with only the exogenous variables. In other words,

[12] 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. This also follows Bayer and Timmins (2007).

we estimate a logit like (2) without the unobserved factor (ξ_j), and use it to generate a predicted market share for each provider (e.g., $\hat{Y}_j$). In our application, the crucial exogenous variation for the instrument comes from the distances between all the patients and providers in the market. While the distance between the reference patient *i* and provider *j* is included in the main model (3), the distances between all other patients and provider *j* are excluded and therefore can provide identifying variation.[13] The key assumption is that the locations of patients and providers are exogenous.

We also estimate an alternative specification of (9) as a mixed logit model, where the distance variables have random coefficients.[14] For both specifications, the estimation of (10) uses weights that account for the variance of the estimated surgeon fixed effects. These procedures are all readily available in Stata. Last, to generate predictions and counterfactuals from the estimated model, we wrote a simple program in Stata that iterates on the vector of predicted market shares until convergence is achieved.

2. Empirical Application

2.1 Data and Measures

The data for our empirical application come from Pennsylvania, where highly relevant quality measures are available in heart surgeon "report cards" published every one or two years. The patient sample consists of Medicare fee-for-service beneficiaries with Part D coverage and Medicaid beneficiaries with any plan type (but not dually eligible for Medicare). We identify those beneficiaries who underwent coronary artery bypass graft (CABG) or heart valve repair surgeries in 2010 and 2011, using the same procedure list as the report card. The surgeon who performed the procedure is identified on the insurance claim. The referring physician is then inferred by searching through the patient's claims records for a specific diagnostic procedure: the cardiologist who provides a left heart catheterization to the patient most recently before the

[13] These distances between other patients and the providers in the market represent additional information used by the congestion model over the standard model. Hence the differences between the forecasts from the two models are driven by this additional information, not simply functional form.
[14] We also evaluated a version of (9) with random coefficients on all variables, but most of the estimated standard deviations for the random coefficients on the other variables were not statistically significant.

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.

Using data on patient flows, specifically the zip codes of residence and of the hospital where surgery occurred, we construct three regional markets in Pennsylvania: Central, Southeastern, and Western.[15] These markets are largely self-contained: about 90% of the patients residing in these regions have heart surgery in their home regions. Our main results come from the Central region, as discussed in Section 2.2, but we describe all three regions to show how they are broadly comparable.

The characteristics of the surgeons, patients, and cardiologists in our sample are summarized in Table 1, separately by region. There are respectively 22, 71, and 49 heart surgeons in the Central, Southeastern, and Western regions. On average, these surgeons treated about 33 patients each from our sample of Medicare and Medicaid beneficiaries in 2010 and 2011. To find the total number of heart surgeries performed by each surgeon (across all payers), we also obtained hospital discharge records from the Pennsylvania Health Care Cost Containment Council (PHC4). Over the two-year period each of these surgeons performed an average of about 175 CABG and/or valve repair surgeries in total.[16]

The key variable of interest in our model is the quality measure, 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, based on surgeries performed in 2008 and 2009. The summary dataset released with the report card lists the raw mortality rates for CABG and valve repair surgeries separately for each surgeon, along with the expected mortality rates for each surgeon derived from a risk-adjustment model.[17] 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 mortality rate for one type of surgery is not listed (because a surgeon has too few cases), we simply use the RAMR for the type that is reported. Of the 142 surgeons in our sample, 115 have CABG

[15] Parts of the state, such as the Scranton HRR, are omitted.

[16] 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% nationally). See http://kff.org/medicare/state-indicator/enrollees-as-a-of-total-medicare-population/ and Donohue (2014). Also patients are excluded from our analytic sample if they cannot be matched to a cardiologist or if they have surgery outside their home region.

[17] Available at: http://www.phc4.org/reports/cabg/09/download.htm

mortality rates and 91 have valve repair mortality rates listed in the report card, and 119 have at least one of the two. (We also include two indicator variables for surgeons without each of the mortality rates in the report card.) The average of the observed 30-day mortality rate is 3.15 per 100, while the average of the combined RAMR is 0.2 per 100.

The other key variable in our model is the measure of patient volume, Y_j. We use the market share, computed from all CABG and/or valve repair surgeries in the hospital discharge data. This is equivalent to using the number of patients because the models are estimated within market (see footnote 8).

There are 4,690 patients in the sample (including 856 in Central PA). We use the Elixhauser index (Elixhauser et al. 1998) as a measure of the 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. Also, each patient is associated with a referring cardiologist as described earlier, and there are 479 unique cardiologists in the sample. The distances between patients and surgeons, and between cardiologists and surgeons, are measured using zip code centroids. We also collect data on the medical schools and current hospital affiliations of the cardiologists and surgeons in our sample, and include indicators for whether a cardiologist and surgeon attended the same school or work at the same hospital.

2.2. Model Estimates

Key parameter estimates from the standard model (2) and the congestion model (3) are presented in Table 2. The table shows the coefficients on the RAMR and market share variables estimated for the Central region using multinomial logit and mixed logit specifications. (The full sets of parameters for all three regions appear in supplemental tables B1-B3). We focus on this region because in the other regions the predicted market share is too weak as an instrument (F-stat < 10, see column 8 of tables B2 and B3). Also our model specifications recover insignificant coefficients on the RAMR in the other regions, which makes a discussion of bias difficult. However most other variables have qualitatively similar estimated coefficients as those for Central PA.

The coefficient on the surgeon's market share in either specification of the congestion model (columns 5 and 6) indicates a substantial congestion effect among patients. These coefficients can be interpreted roughly as semi-elasticities, so for example the estimate in column

5 implies that a one percentage-point increase in a surgeon's market share reduces an individual patient's probability of seeing that surgeon by 20% (in relative terms). The congestion effect is even greater for Medicaid beneficiaries, whose insurance offers surgeons a lower payment, which implies that Medicaid beneficiaries are less likely to see high-volume surgeons, all else equal.

Comparing the estimates in the first two columns with the last two columns, we see that the standard model has a substantial attenuation bias in the estimate of β_1 (the parameter on quality). In columns 1 and 2 the coefficient on the RAMR is five or six times smaller in magnitude than in columns 5 and 6. To examine whether this is a consequence of the different estimation procedures, columns 3 and 4 show the results from estimating the standard model using the two-step procedure (with OLS rather than 2SLS in the second step). The coefficient on the RAMR is still much smaller in magnitude than in columns 5 or 6, with a bias toward zero of over 40%.

Figure 2 plots the observed and predicted market shares for each surgeon in the Central region against their RAMR. This is useful to show the baseline distributions that will be manipulated in the simulations below, and to illustrate the fit of the estimated models. The predicted market shares from both the standard and congestion models are quite close to the observed shares for most surgeons (the predictions have the same horizontal position as the observed share for each surgeon because they use the same RAMR), and their correlations with the observed shares are above 0.85 for both models.

2.3 Effects of Quality Improvements

As discussed in the introduction and Section 1, our focus is not on the attenuation bias in the parameter estimates themselves, but rather in the predicted effects of quality changes on equilibrium match probabilities and the aggregate consumption of quality. Here we present two simulation exercises that empirically demonstrate the extent of the bias in such forecasts from the standard model. One simulates entry by duplicating surgeons in the market, the other simulates quality improvements by decreasing the historical RAMRs (i.e., from 2008-09) of the existing surgeons. Each exercise consists of a sequence of simulations, where first one surgeon is duplicated or improved, then two, then three, and so on.

The first exercise starts by duplicating the surgeon with the lowest RAMR, meaning that there is an additional alternative with the same characteristics as this surgeon. New match probabilities are computed, which is immediate for the standard model and involves converging to a new vector of market shares for the congestion model.[20] Then going in sequence of increasing RAMR, the other surgeons are duplicated and the match probabilities are recomputed.[21] The second exercise uses the original set of surgeons, but decreases the historical RAMRs by one standard deviation (1.32) for surgeons in the middle range of quality, whose original RAMRs were within one standard deviation from 0.[22] In relation to Figure 2, this would appear as a leftward shift of the points that are currently between -1.32 and +1.32 on the x-axis (and with new predicted market shares for all surgeons).

Figure 3 shows the forecasted changes in the average quality consumed in these two exercises. Each panel plots the change in quality (y-axis), measured as the average historical RAMR of the chosen surgeons, against the combined baseline market share of the surgeons who were duplicated or improved at that point in the sequence of simulations (x-axis).[23] For example in the first exercise, the first surgeon duplicated has a market share of 14% at baseline. In Panel A, the values of the plotted lines below that point on the x-axis show that the standard model predicts the RAMR of chosen surgeons decreases by 0.22 on average while the congestion model predicts it decreases by 0.27. With more entry, the difference between these forecasts grows larger, ultimately exceeding 0.15. Also, as discussed in the introduction, when all surgeons are duplicated the standard model predicts the same average quality consumed as at baseline, which entirely fails to reflect the increase in the aggregate supply of quality.

Similar differences between the forecasts are seen in the in exercise that decreases the historical RAMRs (Panel B). For example, when four surgeons (with 24% baseline market share) have their RAMRs improved, the standard model predicts the RAMR of chosen surgeons

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[20] Equilibrium is unique in the congestion model because the spillover is negative (see Bayer and Timmins 2007).
[21] The five surgeons without an observed RAMR are duplicated last.
[22] We do not change the RAMR of surgeons who are already more than one standard deviation below zero because that may be unrealistic, and for symmetry we do not change the RAMR of surgeons who are more than one standard deviation above zero.
[23] The average historical RAMR of the chosen surgeons equals $\sum_i \sum_j \hat{p}_{ij} Q_j / N$, where $\hat{p}_{ij}$ is the predicted match probability and N is the number of patients. The combined baseline market share is the same as the weighted proportion of surgeons who are altered, using their baseline market shares as weights. This is better than the simple proportion because it reflects differences in surgeon market shares due to location and other factors.

decreases by 0.38 on average while the congestion model predicts it decreases by 0.47. This reflects the smaller market share losses for higher quality surgeons, discussed in Section 2.1.

The differences between the forecasts from the standard model and the congestion model in these exercises are roughly 10% of a standard deviation of the quality measure (i.e., 0.10-0.15 vs. 1.32). Although somewhat small relative to the variation across surgeons, these differences nevertheless have substantial economic value. For example, assuming the current RAMR is close to the historical RAMR, a decrease of 0.1 in the average RAMR of the chosen surgeons means a difference of 1 per 1000 in the 30-day mortality risk. Even with a conservative value of statistical life of $2 million, this is worth $2,000 per patient—or $2 million total in a market with 1,000 patients.

3. Conclusion

We have shown that discrete-choice models of demand are subject to attenuation bias if they omit an equilibrating factor, and we have proposed a straightforward way to address the bias by allowing for a congestion effect among consumers. Empirically we find that the congestion effect is substantial in the market for heart surgery, and the resulting biases in predicted responses to quality improvements can be economically important.

Our approach could be applicable to many healthcare services, because the relevant equilibrating factors are often difficult to define or observe. The method requires an instrument that is sufficiently predictive of provider market shares. This can be a limitation in some markets, as we have seen, but the distances between patients and providers offer good candidate instruments and are typically available in research datasets. The method is easy to implement in econometric software such as Stata, and so our hope is that it may be useful for applied researchers studying the market response to quality in healthcare and possibly other industries.

References

Bayer, Patrick, and Christopher Timmins. 2007. "Estimating Equilibrium Models of Sorting Across Locations." *The Economic Journal*, 117: 353-374.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica*, 63: 841-890.

Chandra, Amitabh, Amy Finkelstein, Adam Sacarny, and Chad Syverson. 2016. "Health care exceptionalism? Performance and allocation in the US health care sector." *American Economic Review*, 106: 2110-44.

Chandra, Amitabh, David Cutler, and Zirui Song. 2011. "Who Ordered That? The Economics of Treatment Choices in Medical Care." In *Handbook of Health Economics*, vol. 2: 397-432.

Conlon, Christopher T., and Julie Holland Mortimer. 2013 "Demand estimation under incomplete product availability." *American Economic Journal: Microeconomics*, 5: 1-30.

Cutler, David M., Robert S. Huckman, and Jonathan T. Kolstad. 2010. "Input constraints and the efficiency of entry: Lessons from cardiac surgery." *American Economic Journal: Economic Policy*, 2: 51-76.

Donohue, Julie M. 2014. "Impact and Evolution of Medicare Part D." *New England Journal of Medicine*, 371: 693-5.

Dranove, David. 2011. "Health care markets, regulators, and certifiers." In *Handbook of Health Economics*, vol. 2: 639-690.

Dranove, David, Daniel Kessler, Mark McClellan, and Mark Satterthwaite. 2003. "Is more information better? The effects of "report cards" on health care providers." *Journal of Political Economy*, 111: 555-588.

Dranove, David, and Andrew Sfekas. 2008. "Start Spreading the News: A Structural Estimate of the Effects of New York Hospital Report Cards." *Journal of Health Economics*, 27: 1201-1207.

Elixhauser, Anne, Claudia Steiner, D. Robert Harris, and Rosanna M. Coffey. 1998. "Comorbidity measures for use with administrative data." *Medical Care*, 36: 8-27.

Ellis, Randall P., and Thomas G. McGuire. 1986. "Provider Behavior under Prospective Reimbursement: Cost Sharing and Supply." *Journal of Health Economics*, 5: 129-151.

Epstein, Andrew J. 2010. "Effects of Report Cards on Referral Patterns to Cardiac Surgeons." *Journal of Health Economics*, 29: 717-731.

Gaynor, Martin, Carol Propper, and Stephan Seiler. 2016. "Free to choose? Reform, choice, and consideration sets in the English National Health Service." *American Economic Review*, 106: 3521-57.

Kolstad, Jonathan T. 2013 "Information and quality when motivation is intrinsic: Evidence from surgeon report cards." *American Economic Review*, 103: 2875-2910.

Mukamel, Dana B., David L. Weimer, and Alvin I. Mushlin. 2007. "Interpreting Market Share Changes as Evidence for Effectiveness of Quality Report Cards." *Medical Care*, 45: 1227-32.

Skinner, Jonathan. 2011. "Causes and consequences of regional variations in health care." In *Handbook of Health Economics*, vol. 2: 45-93.

Wang, Justin, Jason Hockenberry, Shin-Yi Chou, and Muzhe Yang. 2011. "Do bad report cards have consequences? Impacts of publicly reported provider quality information on the CABG market in Pennsylvania." *Journal of Health Economics*, 30: 392-407.

Table 1. Sample Descriptive Statistics

	Region		
	Central PA	Southeastern PA	Western PA
Surgeons *(N)*	22	71	49
Surgeries performed (2010-11):			
Analytic sample (Medicare/Medicaid)	38.9 ± 35.6	33.5 ± 25.3	29.6 ± 18.3
Discharge data (all payers)	219 ± 162	162 ± 138	182 ± 109
Market share (pct., discharge data)	4.5 ± 3.4	1.4 ± 1.2	2.0 ± 1.2
Risk-adj. mortality rate (pct., 2008-09)	0.1 ± 1.3	0.2 ± 2.4	0.2 ± 2.3
Cardiologists *(N)*	74	217	188
Number of patients in sample	11.6 ± 10.4	11.0 ± 10.1	7.7 ± 7.7
Number of surgeons referred to	2.9 ± 1.8	3.3 ± 1.9	2.6 ± 1.5
Patients *(N)*	856	2382	1452
Elixhauser comorbidity index	5.2 ± 2.9	5.5 ± 2.9	5.5 ± 3.0
Age	69.7 ± 11.7	70.0 ± 11.4	67.3 ± 12.3
Female (pct.)	43.9	41.3	43.9
Patient/Cardiologist – Surgeon Pairs (*N*)*	17,601	143,613	67,039
Patient-surgeon distance	55.9 ± 32.7	48.1 ± 28.7	83.3 ± 50.7
Cardiologist-surgeon distance	49.6 ± 33.4	45.9 ± 27.2	77.8 ± 55.3
Cardiologist and surgeon:			
Attended same medical school (pct.)	1.5	1.9	1.3
Admit to same hospital (pct.)	11.2	7.9	11.2
Work in same hospital system (pct.)	15.4	13.3	23.3

Notes: Data from Medicare and Medicaid insurance claims, hospital discharge records, Healthcare Organization Services from IMS Health, and the AMA Physician Masterfile. Standard deviations are shown after ± where appropriate.

* Surgeons without any surgeries in the quarter when a patient has surgery are excluded.

Table 2. Key Parameter Estimates, Central PA Market

	Standard Model				Congestion Model	
	ML / MSL Estimation		2-Step Estimation		2-Step Estimation	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Risk-adjusted mort. rate	-0.110	-0.136	-0.379	-0.396	-0.661	-0.716
	(0.061)	(0.063)	(0.263)	(0.261)	(0.303)	(0.283)
Elixhauser x RAMR	-0.037	-0.039	-0.038	-0.039	-0.035	-0.037
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
Surgeon's market share					-0.198	-0.238
					(0.083)	(0.088)
Medicaid x mkt. share					-0.073	-0.074
					(0.031)	(0.032)
Specification	*MNL*	*Mixed*	*MNL*	*Mixed*	*MNL*	*Mixed*

Notes: Models are defined in equations (2) and (3), for multinomial logit (MNL) specifications. Mixed logit specifications include random coefficients on distance variables. All models include: distance between patient and surgeon, distance between cardiologist and surgeon, indicators for cardiologist and surgeon attending same medical school, working at same hospital, and working in same hospital system, and two indicators for surgeons without CABG mortality rates or without valve repair mortality rates listed in the report card. Standard errors shown in parentheses. Full results are presented in Appendix Tables B1-B3.

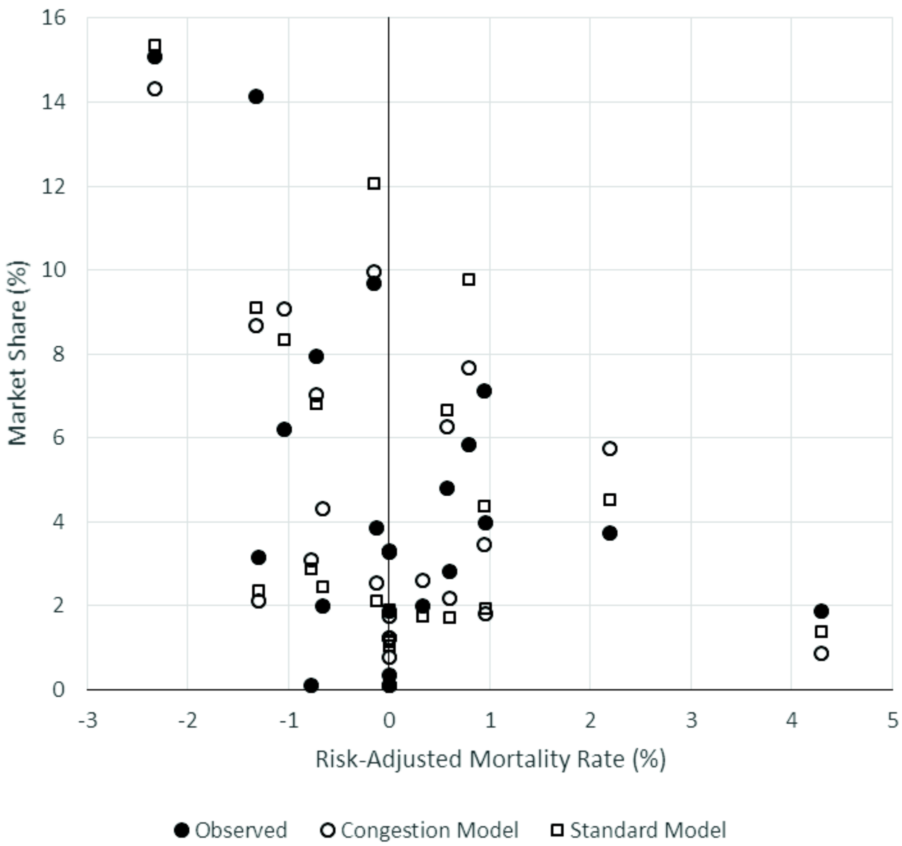
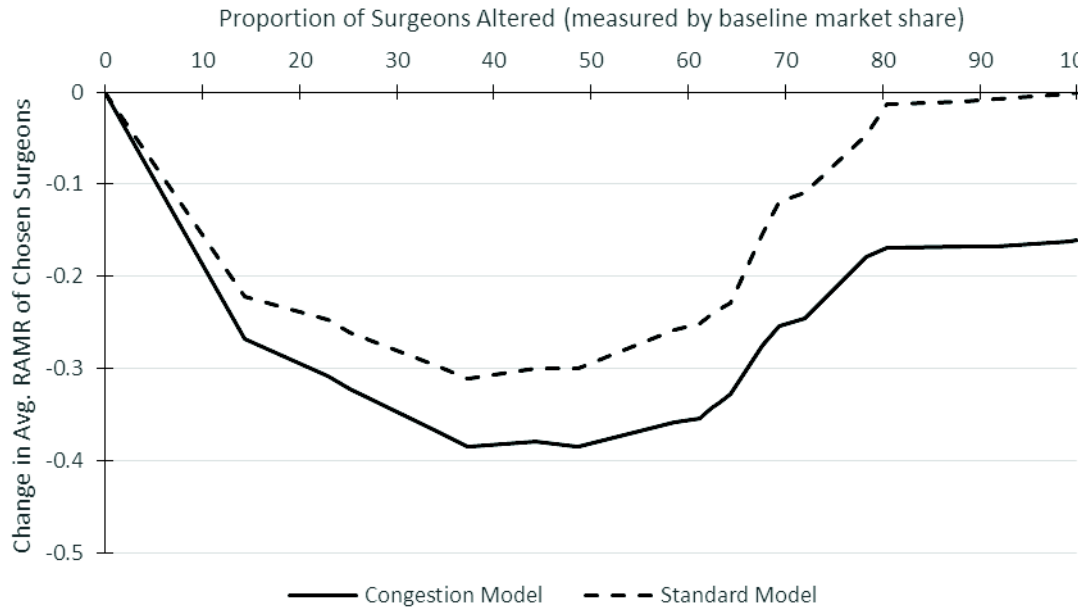


Figure 2. Surgeon Market Shares and Risk-Adjusted Mortality Rates, Central PA Market

Notes: Observed market shares are computed from the analytic sample of Medicare and Medicaid beneficiaries. Predicted market shares are generated from the mixed logit specifications of the models. The prediction from the congestion model is in equilibrium (i.e., the predicted vector of shares has converged). Five surgeons without an observed RAMR are plotted at a RAMR of 0.

Panel A. Entry simulation by duplicating surgeons



Panel B. Quality improvement simulation by decreasing historical RAMRs

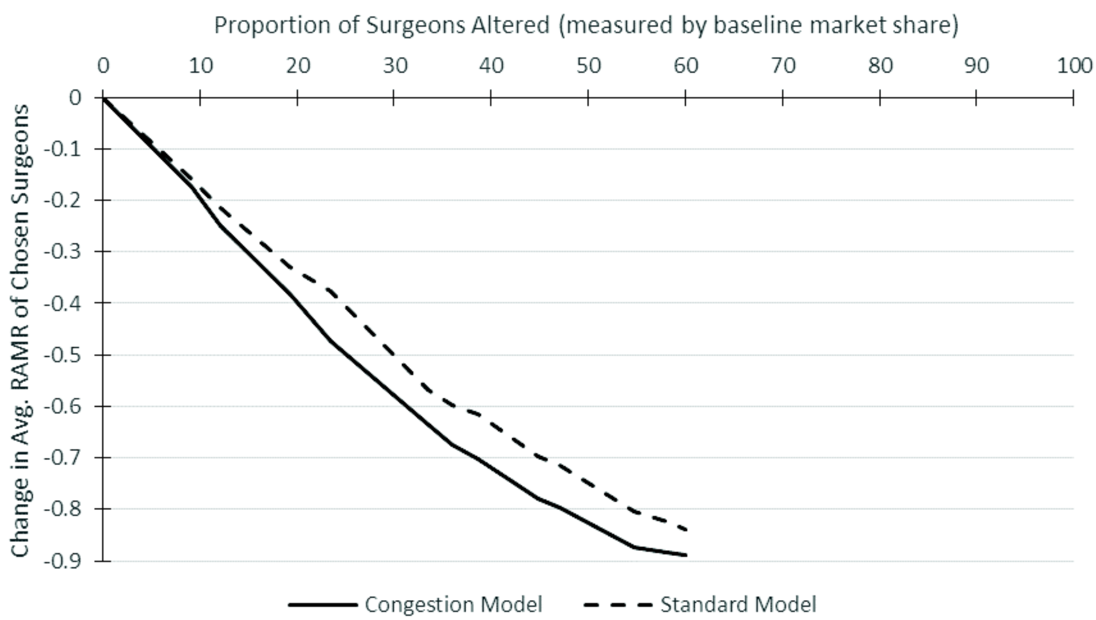


Figure 3. Forecasts of Quality Improvements

Notes: This figure plots differences in the average quality consumed between simulated markets and the baseline market, in a sequence of simulations. The average quality consumed in each scenario equals $\sum_i \sum_j \hat{p}_{ij}\, Q_j / N$, where $\hat{p}_{ij}$ is the predicted match probability, Q_j is the 2008-09 RAMR, and N is the number of patients. The predicted quality differences (y-axis) are plotted against proportion of surgeons who were altered in each simulation, weighted by their baseline market shares (x-axis).

Appendix A. Analysis of Forecast Bias

Here we provide the derivation of one result presented in Section 1.1 and develop a related result on entry. The marginal effect of the quality of provider *k* on the market share of provider *j*, reported in equation (7), is found as follows:

$$\frac{\mathrm{d}Y_j}{\mathrm{d}Q_k} = \frac{\exp(\beta Q_j + \gamma Y_j)\,\gamma \frac{\mathrm{d}Y_j}{\mathrm{d}Q_k}}{\sum_l \exp(\beta Q_l + \gamma Y_l)} - \frac{\exp(\beta Q_j + \gamma Y_j)\exp(\beta Q_k + \gamma Y_k)\left(\beta + \gamma \frac{\mathrm{d}Y_k}{\mathrm{d}Q_k}\right)}{[\sum_l \exp(\beta Q_l + \gamma Y_l)]^2}$$

$$= \gamma Y_j \frac{\mathrm{d}Y_j}{\mathrm{d}Q_k} - Y_j Y_k \left(\beta + \gamma \frac{\mathrm{d}Y_k}{\mathrm{d}Q_k}\right)\ ; \qquad (A1)$$

hence,

$$\frac{\mathrm{d}Y_j}{\mathrm{d}Q_k} = -Y_j Y_k \left(\beta + \gamma \frac{\mathrm{d}Y_k}{\mathrm{d}Q_k}\right) \cdot \left(1 - \gamma Y_j\right)^{-1}. \qquad (A2)$$

To analyze entry with a similar approach, we include distance in the simple model so that entry can be represented as a (substantial) decrease in the distance between provider *k* and the patients in the market. Suppose that all the patients and all the providers, except provider *k*, are at the same location, and let the variable X_j be the distance between provider *j* and all the patients ($X_j = 0$ for all providers except *k*). The model is now:

$$Y_j = \frac{\exp(\beta Q_j + \delta X_j + \gamma Y_j)}{\sum_l \exp(\beta Q_l + \delta X_l + \gamma Y_l)}, \qquad (A3)$$

with $\beta > 0$, $\delta < 0$, and $\gamma < 0$. The marginal effect of the distance between provider *k* and the patients in the market, on the market share of some provider $j \neq k$, is found as follows:

$$\frac{\mathrm{d}Y_j}{\mathrm{d}X_k} = \frac{\exp(\beta Q_j + \delta X_j + \gamma Y_j)\,\gamma \frac{\mathrm{d}Y_j}{\mathrm{d}X_k}}{\sum_l \exp(\beta Q_l + \delta X_l + \gamma Y_l)} - \frac{\exp(\beta Q_j + \delta X_j + \gamma Y_j)\exp(\beta Q_k + \delta X_k + \gamma Y_k)\left(\delta + \gamma \frac{\mathrm{d}Y_k}{\mathrm{d}X_k}\right)}{[\sum_l \exp(\beta Q_l + \delta X_l + \gamma Y_l)]^2}$$

$$= \gamma Y_j \frac{\mathrm{d}Y_j}{\mathrm{d}X_k} - Y_j Y_k \left(\delta + \gamma \frac{\mathrm{d}Y_k}{\mathrm{d}X_k}\right)\ ; \qquad (A4)$$

hence,

$$\frac{\mathrm{d}Y_j}{\mathrm{d}X_k} = -Y_j Y_k \left(\delta + \gamma \frac{\mathrm{d}Y_k}{\mathrm{d}X_k}\right) \cdot \left(1 - \gamma Y_j\right)^{-1}. \qquad (A5)$$

By contrast, in a model without a congestion effect, the predicted marginal effect would be: $\frac{\mathrm{d}Y_j}{\mathrm{d}X_k} = -Y_j Y_k \hat{\delta}$, where $\hat{\delta}$ is the estimated coefficient on distance. As with the substitution effect discussed in Section 1.1, the key difference between these marginal effects in the standard model and the congestion model is the factor $\left(1 - \gamma Y_j\right)^{-1}$ in (A5). Given some provider k, (i.e., the one entering the market), this factor makes the magnitude of the substitution effect be relatively smaller for providers with larger market shares. Thus when a new provider "enters" the market (i.e., gets closer to the market) the substitution away from higher quality providers, which have larger market shares, is relatively smaller in the congestion model, compared to what is predicted by the standard model.

Last, we briefly note how the simple model (4) in Section 1.1 can be obtained from a structural model with wait times. Suppose that all patients enter the market in period 0, and surgeons can treat one patient per period from $t = 1$ to T. Patients choose a surgeon and are then treated in random order. Hence if the number of patients who choose surgeon j is N_j, the expected wait time for surgeon j is $N_j/2$. (This assumes $N_j < T$, for all j, and the choice of surgeon is irrevocable.) Patient utility is a linear combination of surgeon quality, Q_j, wait time, W_{ij}, and idiosyncratic factors, ϵ_{ij}, as follows: $U_{ij} \equiv \beta Q_j + \alpha W_{ij} + \epsilon_{ij}$, with $\beta > 0, \alpha < 0$. However the realized wait times are not known when patients select surgeons, so their choices are based on the expected utilities: $V_{ij} \equiv \beta Q_j + \alpha\, N_j/2 + \epsilon_{ij}$. Then defining N as total the number of patients in the market, Y_j as the market share of surgeon j, and $\gamma = \alpha\, N/2$, we have $V_{ij} = \beta Q_j + \gamma Y_j + \epsilon_{ij}$. A pure-strategy Nash equilibrium among patients is characterized by $j_i^* = \arg\max_k \{V_{ik}\}$. (Note that surgeon behavior is exogenous in this simple model.) Finally, if the shocks (ϵ_{ij}) have independent type I extreme value distributions, this yields model (4).

Appendix B. Supplemental Tables

The tables that follow contain the full sets of parameter estimates for the multinomial logit and mixed logit models estimated in each regional market.

Table B1. Parameter Estimates, Central PA Market

	ML/MSL Estimation			2-Step Estimation			2-Step Estimation		
	Mult.	Mixed Logit		Mult.	Mixed Logit		Mult.	Mixed Logit	
Variables	Logit	Mean	Std. Dev.	Logit	Mean	Std. Dev.	Logit	Mean	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk-adjusted mort. rate	-0.110	-0.136		-0.379	-0.396		-0.661	-0.716	
	(0.061)	(0.063)		(0.263)	(0.261)		(0.303)	(0.283)	
Elixhauser x RAMR	-0.037	-0.039		-0.038	-0.039		-0.035	-0.037	
	(0.010)	(0.010)		(0.010)	(0.011)		(0.010)	(0.011)	
Surgeon's market share							-0.198	-0.238	
							(0.083)	(0.088)	
Medicaid x mkt. share							-0.073	-0.074	
							(0.031)	(0.032)	
Patient-surgeon dist.	-0.058	-0.075	-0.032	-0.017	-0.032	0.020	-0.017	-0.032	0.020
	(0.006)	(0.008)	(0.018)	(0.010)	(0.012)	(0.011)	(0.010)	(0.012)	(0.011)
Card.-surgeon dist.	-0.095	-0.178	0.091	-0.145	-0.202	-0.067	-0.144	-0.202	-0.067
	(0.007)	(0.017)	(0.014)	(0.012)	(0.019)	(0.011)	(0.012)	(0.019)	(0.011)
Card.-surg. same med. sch.	-0.171	0.066		0.202	0.230		0.219	0.250	
	(0.492)	(0.485)		(0.484)	(0.491)		(0.484)	(0.492)	
…same hospital	0.413	0.221		0.585	0.601		0.585	0.601	
	(0.223)	(0.234)		(0.240)	(0.253)		(0.241)	(0.254)	
…same hospital sys.	-0.171	-0.280		0.421	0.203		0.417	0.196	
	(0.203)	(0.207)		(0.261)	(0.265)		(0.261)	(0.265)	
CABG mort. not reported	-0.478	-0.255		-1.270	-1.084		-1.912	-1.802	
	(0.167)	(0.176)		(0.725)	(0.766)		(0.683)	(0.655)	
Valve mort. not reported	-0.264	-0.272		0.757	0.675		0.580	0.393	
	(0.151)	(0.152)		(0.666)	(0.705)		(0.476)	(0.478)	
First-stage F-stat.							49.94	36.46	
Observations	17,601	17,601		17,601	17,601		17,601	17,601	

Notes: Estimated standard deviations of random coefficients in mixed logit models are reported in separate columns, as indicated. First-stage F-statistics refer to 2SLS estimation of equation (6). Standard errors shown in parentheses.

Table B2. Parameter Estimates, Southeastern PA Market

	ML/MSL Estimation			2-Step Estimation			2-Step Estimation		
	Mult.	Mixed Logit		Mult.	Mixed Logit		Mult.	Mixed Logit	
Variables	Logit	Mean	Std. Dev.	Logit	Mean	Std. Dev.	Logit	Mean	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk-adjusted mort. rate	0.057	0.057		0.098	0.044		0.116	0.070	
	(0.024)	(0.026)		(0.090)	(0.090)		(0.156)	(0.168)	
Elixhauser x RAMR	-0.005	-0.005		-0.010	-0.008		-0.009	-0.008	
	(0.004)	(0.004)		(0.005)	(0.005)		(0.005)	(0.005)	
Surgeon's market share							-1.852	-2.389	
							(0.750)	(1.076)	
Medicaid x mkt. share							-0.285	-0.302	
							(0.052)	(0.055)	
Patient-surgeon dist.	-0.083	-0.125	0.085	-0.079	-0.136	-0.077	-0.080	-0.137	-0.078
	(0.004)	(0.006)	(0.009)	(0.005)	(0.009)	(0.016)	(0.005)	(0.009)	(0.016)
Card.-surgeon dist.	-0.081	-0.148	-0.081	-0.117	-0.208	-0.119	-0.116	-0.207	-0.119
	(0.003)	(0.007)	(0.007)	(0.005)	(0.011)	(0.010)	(0.005)	(0.011)	(0.010)
Card.-surg. same med. sch.	-0.057	-0.094		-0.300	-0.322		-0.282	-0.305	
	(0.133)	(0.139)		(0.139)	(0.143)		(0.139)	(0.144)	
…same hospital	0.706	0.482		0.779	0.538		0.785	0.541	
	(0.086)	(0.093)		(0.112)	(0.127)		(0.112)	(0.127)	
…same hospital sys.	0.616	0.700		1.160	1.292		1.149	1.282	
	(0.089)	(0.093)		(0.122)	(0.136)		(0.121)	(0.136)	
CABG mort. not reported	0.160	0.238		1.191	1.052		1.781	1.623	
	(0.076)	(0.079)		(0.389)	(0.460)		(0.868)	(1.047)	
Valve mort. not reported	-0.589	-0.751		-0.305	-0.641		-3.089	-4.260	
	(0.060)	(0.066)		(0.442)	(0.447)		(1.361)	(1.870)	
First-stage F-stat.							11.43	6.95	
Observations	143,613	143,613		143,613	143,613		143,613	143,613	

Notes: Estimated standard deviations of random coefficients in mixed logit models are reported in separate columns, as indicated. First-stage F-statistics refer to 2SLS estimation of equation (6). Standard errors shown in parentheses.

Table B3. Parameter Estimates, Western PA Market

	ML/MSL Estimation			2-Step Estimation			2-Step Estimation		
	Mult.	Mixed Logit		Mult.	Mixed Logit		Mult.	Mixed Logit	
Variables	Logit	Mean	Std. Dev.	Logit	Mean	Std. Dev.	Logit	Mean	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk-adjusted mort. rate	-0.014	0.007		-0.006	0.055		0.020	0.092	
	(0.032)	(0.033)		(0.074)	(0.096)		(0.143)	(0.131)	
Elixhauser x RAMR	0.001	-0.001		0.001	-0.003		0.001	-0.003	
	(0.005)	(0.005)		(0.005)	(0.006)		(0.005)	(0.006)	
Surgeon's market share							-1.160	-0.705	
							(0.749)	(0.459)	
Medicaid x mkt. share							-0.072	-0.069	
							(0.065)	(0.069)	
Patient-surgeon dist.	-0.042	-0.066	-0.049	-0.051	-0.109	0.064	-0.051	-0.109	0.064
	(0.003)	(0.005)	(0.006)	(0.004)	(0.009)	(0.010)	(0.004)	(0.009)	(0.010)
Card.-surgeon dist.	-0.042	-0.084	-0.047	-0.050	-0.126	-0.076	-0.050	-0.126	-0.076
	(0.002)	(0.006)	(0.006)	(0.003)	(0.012)	(0.010)	(0.003)	(0.012)	(0.010)
Card.-surg. same med. sch.	-0.084	-0.194		-0.343	-0.278		-0.346	-0.283	
	(0.255)	(0.266)		(0.272)	(0.288)		(0.272)	(0.288)	
…same hospital	1.149	1.075		1.425	1.314		1.426	1.315	
	(0.107)	(0.113)		(0.127)	(0.137)		(0.127)	(0.137)	
…same hospital sys.	0.411	0.620		0.712	0.797		0.713	0.798	
	(0.106)	(0.116)		(0.140)	(0.156)		(0.140)	(0.156)	
CABG mort. not reported	-0.192	-0.113		-0.757	-0.714		-1.187	-0.863	
	(0.185)	(0.187)		(0.905)	(1.146)		(1.464)	(1.431)	
Valve mort. not reported	-0.904	-0.914		-0.524	-0.481		-1.799	-1.449	
	(0.139)	(0.141)		(0.600)	(0.645)		(1.217)	(0.956)	
First-stage F-stat.							3.98	6.57	
Observations	67,039	67,039		67,039	67,039		67,039	67,039	

Notes: Estimated standard deviations of random coefficients in mixed logit models are reported in separate columns, as indicated. First-stage F-statistics refer to 2SLS estimation of equation (6). Standard errors shown in parentheses.