Appendix To:

Healthcare Exceptionalism? Performance and Allocation in the U.S. Healthcare Sector

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Appendix A Analytical Framework

As mentioned in the text, models of reallocation mechanisms among heterogeneous-productivity producers have found applications in a number of fields, including industrial organization, trade, and macroeconomics. While these models differ considerably in their specifics, they share an archetypal mechanism that connects the extent of competition in the market (as reflected in consumers' willingness or ability to substitute among producers) to the shape of the productivity distribution among market producers. Here we sketch out a model with such a mechanism that fits the specific feature of the healthcare sector that consumers bear little if any of the financial costs of their firm choice.

We assume hospitals are heterogeneous in two dimensions: quality and costs. These two dimensions of heterogeneity may be correlated (e.g., higher quality hospitals might tend have higher costs on average), but this is not necessary for our results. While both quality and costs are likely to be at least in part affected by hospitals' choices, we follow the majority of the productivity literature and assume that they are exogenous and fixed.[34]

When choosing their hospital, we assume that patients care about quality but, conditional on quality, do not care about costs. The assumption that patients are not sensitive to hospital costs is a natural one, given that Medicare and supplemental insurance shields patients from paying for most of the care they receive, and likely all of the incremental cost associated with their hospital choice. Of course, while patients do not care about costs, a social planner does. A benevolent social planner would desire both high quality and low costs. The social planner would trade off between them based upon the parameters of the social welfare function. Thus there may be a wedge between the privately and socially optimal hospital choice.

Producers (indexed by h) earn profits which depend positively on their idiosyncratic quality levels q_h (higher quality firms earn higher profits because they draw more patients), negatively on their costs c_h, and negatively on the number (or mass, in models with a continuum of firms) of producers in the industry N.[35] Hence $\pi_h = \pi(q_h, c_h, N)$, with $\frac{\partial \pi}{\partial q_h} > 0$, $\frac{\partial \pi}{\partial c_h} < 0$, and $\frac{\partial \pi}{\partial N} < 0$. The monotonic relationship between quality and profits implies that, for any given N, there is locus of

[34] This model is a more generic and looser version of the type of multidimensional-heterogeneity-producer model in Foster, Haltiwanger and Syverson (2008).

[35] Standard presentations of these models consider profit-maximizing firms. Although we keep this terminology to be more familiar relative to the existing literature, we note that in the context of hospitals, it might be more appropriate to consider firms as earning (and maximizing) "surplus" rather than "profits". This more general terminology recognizes that many hospitals are legally structured as nonprofits. All that is required for the conceptual framework to carry over is for surplus to be increasing in quality (again because all else equal it increases the patient traffic at a hospital). Nonprofit hospitals are often modeled in the literature as having an objective function that is a convex combination of profits and other objectives; thus on the margin they should respond qualitatively the same way as for-profit hospitals to factors like competition. And indeed a large empirical literature finds essentially no evidence of differential behavior across for-profit and non-profit hospitals, calling into question whether the non-profit label has any substantive meaning for behavioral responses (see Sloan, 2000 for a review of this literature).

critical cutoff quality and cost levels at which hospital profits are zero. Along this locus, quality is a monotonically increasing function of costs, because higher costs require a higher quality level for a hospital to earn zero profit.

Call this locus $q^*(c,N)$, where we have expressed it as the critical value of quality necessary to earn zero profit as a function of costs and the number of hospitals in the market. Only producers with quality levels at or above $q^*(c,N)$ will operate in equilibrium.

The zero-profit cutoff locus is endogenously determined by a free entry condition, where ex-ante identical potential entrants consider whether to pay a sunk cost σ to take idiosyncratic quality and cost draws from a known joint distribution of q and c, $G(\cdot)$, with an upper bound quality of $\overline{q}$ and a lower and upper bound costs $\underline{c}$ and $\overline{c}$, respectively. The expected value of entry, which equals zero by the free entry condition, is:

$$V^e = \int_{\underline{c}}^{\overline{c}} \int_{q^*(c,N)}^{\overline{q}} \pi(q,c,N)\, g(q,c)\, dqdc - \sigma = 0$$

The expected profits from entry depend upon the equilibrium number of entrants N in two ways. First, an increase in N shifts upward the zero-profit cutoff quality level $q^*(c,N)$, reducing the probability that the entrant's quality and cost draws are high and low enough (respectively) to earn nonnegative profits, and thus making successful entry less likely. Second, a higher number of firms N also reduces the producer's profits if it does enter. Thus expected profits fall monotonically in N. In equilibrium, the number of firms choosing to pay the entry cost yields a number of entrants N that, through these two effects, exactly equates the expected profit from taking a quality and cost draw to the sunk entry cost.

The endogeneity of $q^*(c,N)$ means the industry quality and cost distribution observed in the data is determined in equilibrium. Specifically, it is a truncation of $G(\cdot)$, the underlying distribution from which potential entrants take quality and cost draws, where the truncation locus is $q^*(c,N)$. Changes in market primitives that shift the equilibrium location of $q^*(c,N)$ therefore shift the observed joint distribution of quality and costs.

The primitive that underlies these results is the extent to which patients are able or willing to substitute to alternate hospitals in order to obtain higher quality. The specific mechanism through which primitives map into substitutability may vary from, for example, the extent of information available to patients or their surrogates, to differences in travel costs. The particulars of the mechanism aren't important here; what matters are the effects on the equilibrium.

This framework has several predictions that we examine empirically. In equilibrium, if patients have some ability to substitute across alternate producers (hospitals), there is a robust prediction that the market will allocate patients to higher quality hospitals on average, so that there is a correlation between quality and market share at a point in time ("*static allocation*"). In addition, over

time higher quality hospitals will be more likely to grow in market share ("*dynamic allocation*"). Our empirical work in Section III focuses on examining these static and dynamic equilibrium allocations. The model also generates the comparative static prediction that these static and dynamic equilibrium allocation results will be stronger where patients have greater ability to substitute to alternate producers. In Section IV we test this comparative static prediction by comparing allocation results for patients admitted through the emergency department and patients admitted as non-emergency transfers from another hospital. Stratifying on the method of admission to the hospital offers one way to distinguish among patients with different abilities to substitute to alternate producers.[36]

Finally, we note that endogenous selection based on patients' preferences for quality also has implications for equilibrium cost levels. Even if quality and cost draws are uncorrelated in $G(\cdot)$, factors that tend to truncate the equilibrium quality distribution at a higher level will also raise average observed costs, because hospitals with higher quality can have higher costs before becoming unprofitable. Thus when patients are not sensitive to costs and choose based solely on quality, the equilibrium will tend to allocate toward both higher quality and higher cost firms. As noted, there may therefore be a wedge between the privately and socially optimal allocations.

[36]This model is static, so the effects of changes in competition on equilibrium should be thought of as comparing two different markets or the same market across different long-run steady states. However, several of the models in the literature are explicitly dynamic and have similar predictions about the effect of competition on the productivity of entrants and growth of incumbents (e.g. Hopenhayn, 1992; Asplund and Nocke, 2006).

Appendix B Quality Measures

This section provides details on the definition and construction of each of our four quality metrics.

B.1 Risk-adjusted survival

Risk-adjusted survival is arguably the key endpoint for emergent conditions and has been the health outcome of choice for a large economics and medical literature. CMS publicly reports risk-adjusted survival measures for heart attacks, heart failure and pneumonia for hospitals that treat at least 25 patients with the condition in the 3 year window it uses for the analysis. We calculate our own risk-adjusted survival scores for these conditions in order to have control over the regression model (we use a fixed effects linear regression while CMS uses a random effects logit), shrinkage approach (we use empirical Bayes adjustment while CMS uses the best linear unbiased predictors, or BLUPs, of the random effects), and risk adjustment (we test sensitivity to alternative sets of risk-adjusters while CMS only publishes one approach). The CMS data are also reported as ratios of observed mortality rates relative to expected mortality rates, which is a nonlinear transformation of the hospital random effects – and one that is not designed to produce unbiased coefficients when placed on the right-hand side of our allocation regressions.[37]

Mimicking the CMS measure, for each hospital with at least 25 patients with the condition between 2006 and 2008, we estimate a risk-adjusted survival rate – the probability that a Medicare patient would survive 30 days after being treated for the condition at the hospital. Specifically, we start with the patient-level sample of initial hospitalizations for the condition, or index events, from 2006-2008. Then, we regress 30-day survival (counting from the patient's hospital admission date) on a rich set of observable information about the patient, including age/race/sex interactions and indicators for being hospitalized for 25 conditions in the past year, as well as hospital fixed effects.[38] The inclusion of risk-adjusters is standard practice in the literature and is designed to minimize the impact of differences in patient health across hospitals on survival rates.

We extract the hospital fixed effects, which become the risk-adjusted survival rate estimates for the hospitals for a given condition. Since these estimates include measurement error, they may

[37] Since we use different regression models, shrinkage approaches, risk-adjustment approaches, and transformations of hospital effects, we do not expect the correlations between our measures and the CMS measures to be 100%. Still, in Appendix Table A19, we find that our risk-adjusted survival and readmission measures are highly correlated with the CMS measures, with correlation coefficients ranging from 0.66 to 0.82.

[38] The age groups are 66-69, 70-74, 75-79, 80-84, 85-89, 90-94, and 95+. The race and age groups are white/non-white and male/not male. The risk-adjusters are: heart failure, myocardial infarction, unstable angina, chronic atherosclerosis, respiratory failure, hypertensive heart disease, valvular heart disease, arrhythmia, hypertension, stroke, cerebrovascular disease, renal failure disease, dialysis, COPD, pneumonia, diabetes, protein calorie malnutrition, dementia, paralysis and disability, peripheral vascular disease, metastatic cancer, trauma, substance abuse, major psychiatric disorder, and chronic liver disease.

produce biased coefficients when included on the right hand side of our allocation regressions; for example, classical measurement error will cause attenuation bias toward zero. In Appendix C, we describe the empirical Bayes shrinkage approach we use to correct for measurement error bias. We discuss and show how the shrinkage method affects our results in Appendix Section C.5 and Appendix Table A2 – consistent with the presence of measurement error bias resulting in attenuation, the correction expands nearly all of our allocation gradients.

In our analyses studying risk-adjusted survival over the long horizon, we calculate the measure for 1996, 1999, 2002, and 2005 in addition to the baseline 2008 measure. As in the 2008 calculations, we aggregate over three years, e.g. the 1996 measure includes patients from 1994-1996. Results using this longer sample of risk-adjusted survival rates are presented in Section III.B.2.

B.2 Risk-adjusted readmission

This measure, defined and estimated similarly to risk-adjusted survival, indicates the probability that an average Medicare patient would be readmitted within 30 days after discharge from her initial hospital stay. It is widely used as a proxy for medical errors and inappropriate discharge. Mimicking the CMS measure, the sample of patients is the same as that for risk-adjusted survival, with the addition of the following exclusion criteria: if the patient dies during the initial hospital stay, is transferred from her initial hospital to another inpatient facility, or leaves the hospital against medical advice, the patient is removed from the sample. Per the CMS approach, these exclusions help to remove patients who either could not be readmitted or whose readmissions might not be due to the index hospital's quality of care. We then use the same regression, risk adjustment, and empirical Bayes method as in risk-adjusted survival. For hip and knee replacement, an indicator for whether the patient received a hip replacement is also included as a risk-adjuster to allow for differential readmission rates depending on which joint is being replaced.

B.3 Process of care

Publicly reported "process of care" measures give the shares of eligible patients who received certain evidence-based interventions. Hospitals report their utilization of these processes to CMS, which publishes the information online and uses it to adjust hospital payments.[39] The data pertain to all eligible patients irrespective of their insurer, and are not limited to patients covered by Medicare. Patients for whom the interventions are contraindicated are not counted in the numerator or denominator of the shares. We consider the process measures for specific inpatient conditions that were reliably reported from 2006 through 2008: 6 AMI measures, 4 heart failure measures, and 7 pneumonia measures.

[39]These data can be downloaded at https://data.medicare.gov/data/hospital-compare

The processes "were identified with respect to published scientific evidence and consistency with established clinical-practice guidelines" (Williams et al., 2005). The AMI measures have their origins in the Cooperative Cardiovascular Project, a large study of AMI among Medicare beneficiaries that was conducted in the 1990s; the metrics for heart failure and pneumonia can be traced back to the practice guidelines of professional organizations that focus on these conditions (Jencks et al., 2000). The AMI processes cover the administering of aspirin (one measure for arrival and another for discharge), ACE inhibitors, smoking cessation advice, β blockers, and angioplasty (percutaneous coronary intervention, or PCI).[40] The heart failure processes cover providing discharge instructions for care, evaluation of left ventricular systolic dysfunction, ACE inhibitors, and smoking cessation advice. The pneumonia processes cover providing oxygenation assessments, pneumococcal vaccines, blood cultures before antibiotics, smoking cessation advice, timely antibiotics, the most appropriate antibiotics for the particular infection, and influenza vaccines.

To reduce the dimensionality of the process measures before including them in our regressions, for each condition we generate a hospital-level composite measure of adherence to the condition's processes. We start with the publicly reported hospital-level data from 2006 to 2008; we combine 3 years to reduce measurement error. To further reduce measurement error in the composite score, we remove any individual process score for which the hospital had fewer than 50 eligible patients over the 3 year window (since each process has different contraindications, a hospital may have more than 50 patients in one score for a condition and fewer than 50 patients in another). We use a higher patient count threshold than for risk-adjusted survival and readmission because process scores are not empirical-Bayes-adjusted by CMS to account for measurement error; since the scores have all-payer coverage, the patient counts tend to be larger than for the risk-adjusted outcomes and this threshold is therefore less restrictive.

We standardize each process score (among the set of hospitals that reported it for at least 50 patients over the 3 years) to have mean 0 and standard deviation 1. For each condition, we average together the condition's individual process standardized scores to create a composite score, then standardize that composite score. The result is a condition-specific composite score with zero mean and unit variance defined on the set of hospitals that reported 50 or more patients for at least one process of care for that condition over 2006-2008.

The process of care data are only available at the hospital level so it is not possible to perform the kind of detailed risk adjustment when generating these quality metrics that we could for survival or readmission. However, one advantage of these metrics is that they are designed to measure interventions or experiences that the facility should deliver to essentially all of its patients; patients

[40] An additional AMI measure, Thrombolytics at Arrival, was missing for 60-80% of hospitals each year, and was removed from the analysis.

who are inappropriate for the intervention are excluded. As a result, risk adjustment is not obviously relevant or required for the process of care measures – while it may not be possible for a hospital to prevent all AMI deaths or readmissions, it is possible in theory for a facility to administer β blockers to all appropriate patients at discharge. Indeed, the study of processes of care has been justified by hospitals' ability to directly control these measures of quality, since quality scores based on clinical outcomes include factors like the hospital's patient population and patient compliance with post-discharge care that hospitals are less able to manage (Donabedian, 1966).

B.4 Patient satisfaction

Patient satisfaction is measured by the 2008 HCAHPS (Hospital Consumer Assessment of Healthcare Providers and Systems), which hospitals administer to their patients after discharge.[41] The survey is given to a sample of all of the hospital's patients, not just patients who were covered by Medicare; unlike our other quality measures, the public data covers all patients, and is not offered in a condition-specific manner. The survey results are processed and reported by CMS; the survey instrument is condensed into ten measures of the patient's experience and perceived quality of care. The ten measures are: communication with nurses, communication with doctors, responsiveness of hospital staff, pain management, communication about medicines, cleanliness of hospital environment, quietness of hospital environment, discharge information, overall hospital rating, and recommend the hospital. The average hospital reports scores for all 10 survey questions. CMS adjusts the results for interview mode (e.g. mail, telephone, etc.) and a set of patient characteristics. Its adjustment for mode uses data from a randomized trial comparing survey responses by mode, while the adjustment for patient characteristics comes from a model that is estimated quarterly from hospitals' submissions (Giordano et al., 2010; Elliott et al., 2009).

We generate a composite score of hospital performance on the patient survey by aggregating together the 10 questions into a measure with mean zero and unit variance. For all of the questions but one, the publicly reported data indicates the share of patients responding that the hospital provided high, medium or low quality. One question (discharge information) is reported as the shares of patients responding yes or no. We assign these responses to numeric values (3/2/1 for the three-level questions or 1/0 for the yes/no question, with higher values always better) and compute an average response for each hospital. Then, following the same method we use for process of care, we generate standardized scores for each question, average together the standardized scores, and standardize the result.

[41] For an overview of the design and implementation of HCAHPS, see Giordano et al. (2010).

Appendix C Empirical Bayes Adjustment

In this appendix we describe the empirical Bayes (EB) procedure we use to adjust our estimates of risk-adjusted survival, risk-adjusted readmission, risk-adjusted inputs, and input-adjusted risk-adjusted survival (which we call productivity) for measurement error. This procedure is based on Morris (1983). For another example see Jacob and Lefgren (2007).

For hospital h, its quality measure (risk-adjusted survival, risk-adjusted readmission, or input-adjusted risk adjusted survival; we also will refer to risk-adjusted inputs in this manner) is called q_h. These objects are the "true" quality values and their distribution is the "underlying" distribution of quality. We denote by $\hat{q}_h$ the estimate of quality; it equals quality plus an error term η_h:

$$\hat{q}_h = q_h + \eta_h$$

The goal of the EB procedure is to adjust the estimates of quality so that the presence of the error term does not introduce bias when the quality estimates are included as regressors in our allocation regressions (see equations 1 and 2). The procedure adjusts the estimates by shrinking them toward the mean of the true, underlying distribution. True quality is not observable, but we show in this appendix that its distribution is estimable. We also show how this shrinkage estimator fixes the attenuation bias that measurement error could otherwise introduce into our regressions.

In this appendix we use bold lowercase greek and roman letters to refer to vectors and uppercase greek and roman letters for matrices. Non-bold lowercase letters refer to scalars.

C.1 Background on Empirical Bayes Procedure

C.1.1 Statistical Background

We start with an overview of the EB procedure assuming that all parameters of the distributions are known, and refer to the EB-adjusted estimated quality as q_h^{EB}. We then describe the feasible EB-adjusted estimate, which we denote $q_h^{EB(f)}$.

Suppose that the estimated quality is independently normally distributed around the true quality with known variance π_h^2:

$$\hat{q}_h | q_h, \pi_h^2 \sim N\left(q_h, \pi_h^2\right) \text{ independently}$$

One can think of π_h^2 as the variance of the measurement error of the estimate.

We also assume that the true quality q_h is independently normal with underlying mean $\mathbf{x}_h'\boldsymbol{\lambda}$ (a known, linear function of the hospital's covariates) and underlying variance σ^2 (known and common across hospitals).

The *prior distribution* of quality q_h – the distribution before conditioning on the estimated

quality – is therefore:

$$q_h|\mathbf{x}_h, \boldsymbol{\lambda}, \sigma^2 \sim N\left(\mathbf{x}_h'\boldsymbol{\lambda}, \sigma^2\right) \text{ independently}$$

Conditioning on the estimated quality $\hat{q}_h$ produces the *posterior distribution* of q_h:

$$q_h|\hat{q}_h, \mathbf{x}_h, \boldsymbol{\lambda}, \sigma^2, \pi_h^2 \sim N\left(q_h^{EB}, \pi_h^2\left(1-b_h\right)\right) \tag{A1}$$

q_h^{EB} denotes the EB-adjusted quality. This object is the expected value of q_h conditional on the estimated value $\hat{q}_h$ and the parameters $\boldsymbol{\lambda}, \sigma^2$, and π_h^2 and is given by the formula:

$$q_h^{EB} = \left(1-b_h\right)\hat{q}_h + b_h\mathbf{x}_h'\boldsymbol{\lambda} \tag{A2}$$

$$b_h = \pi_h^2/\left(\pi_h^2+\sigma^2\right) \tag{A3}$$

The adjustment amounts to attenuating the estimate $\hat{q}_h$ toward the prior mean $\mathbf{x}_h'\boldsymbol{\lambda}$. As the variance of the measurement error π_h^2 rises, the EB correction increasingly disregards the value of the estimate and closes in on the prior mean.

C.1.2 Feasible Version of Procedure

This section describes how we implement the EB procedure when parameters must be estimated.

The value $\hat{q}_h$ is the estimated hospital fixed effect from the regression used to estimate quality (see Appendix B for a description of the regressions used to estimate risk-adjusted survival and readmission; see equation 9 for the regression used to estimate input-adjusted risk-adjusted survival, a.k.a. "productivity"). We estimate a standard error for the fixed effect assuming homoscedastic disturbances in the first-step patient-level regression; under the homoscedasticity assumption, the standard error is our estimate of the standard deviation of the asymptotic distribution of $\hat{q}_h$. We estimate π_h^2 by squaring the standard error and call this value $\hat{\pi}_h^2$.

We estimate the underlying parameters of the quality distribution, $\boldsymbol{\lambda}$ and σ^2, using the method outlined in section 5 of Morris (1983). We fix yearly estimates:

$$\begin{aligned}
\hat{\boldsymbol{\lambda}} &:= \left(X'WX\right)^{-1}X'WQ \\
\hat{\sigma}^2 &= \max\left\{0, \frac{\sum_h W_h\left\{\left(\frac{n_H}{n_H-n_X}\right)\left(\hat{q}_h-\mathbf{x}_h'\boldsymbol{\lambda}\right)^2-\hat{\pi}_h^2\right\}}{\sum_h w_h}\right\} \\
w_h &= \frac{1}{\hat{\pi}_h^2+\hat{\sigma}^2}
\end{aligned}$$

where X is the stacked $\mathbf{x}_h'$, W is a diagonal matrix of the w_h, and Q is the stacked $\hat{q}_h$ for year t. n_H is the number of hospitals, or equivalently the number of $\hat{q}_h$. n_X is the number of regressors,

i.e. the dimensionality of $\mathbf{x}_h$.

$\hat{\boldsymbol{\lambda}}$ is a WLS regression of the $\hat{q}_h$ on $\mathbf{x}_h$. $\hat{\sigma}^2$ is the weighted average of the squared deviations of $\hat{q}_h$ from $\mathbf{x}_h'\hat{\boldsymbol{\lambda}}$ less the weighted average of $\hat{\pi}_h^2$. The weights are w_h, giving more weight to observations with less measurement error. The max operator ensures that $\hat{\sigma}^2$ is always nonnegative in finite samples.

$\hat{\boldsymbol{\lambda}}$ and $\hat{\sigma}^2$ are simultaneously determined in these equations, so they are estimated by the following iterative procedure. We start by fixing $w_h = 1 \,\forall\, h$, then iterate the following to convergence:

1. Compute $\hat{\boldsymbol{\lambda}}$ and then a new estimate $\hat{\sigma}^2$
2. If this is the second or greater iteration and $\hat{\sigma}^2$ has converged, exit. Otherwise, fix new weights w_h and return to step 1

The (feasible) best estimate of the posterior mean $q_h^{EB(f)}$ is given in Morris (1983) by the formula of equations (A2) and (A3) with a degrees of freedom adjustment :

$$\begin{aligned} q_h^{EB(f)} &= \left(1-\hat{b}_h\right)\hat{q}_h + \hat{b}_h \mathbf{x}_h'\hat{\boldsymbol{\lambda}} \\ \hat{b}_h &= \left(\frac{n_H - n_X - 2}{n_H - n_X}\right)\left(\frac{\hat{\pi}_h^2}{\hat{\pi}_h^2 + \hat{\sigma}^2}\right) \end{aligned}$$

The variance of the quality distribution unconditional on covariates, called $\hat{\varsigma}^2$, is given by the following formula:

$$\text{(A4)} \qquad \hat{\varsigma}^2 = \max\left\{0, \frac{\sum_h w_h \left\{\left(\frac{n_H}{n_H-1}\right)(\hat{q}_h - \bar{q}) - \hat{\pi}_h^2\right\}}{\sum_h w_h}\right\}$$

$$\text{(A5)} \qquad \bar{q} = \frac{\sum_h w_h \hat{q}_h}{\sum_h w_h}$$

Where $\bar{q}$ is the weighted mean quality.

C.2 Implementation of Empirical Bayes Adjustment

We assume that the underlying mean of quality is equal to a market fixed effect, i.e. $\mathbf{x}_h'\boldsymbol{\lambda} = \tau_M$, where M indexes markets. Thus $\mathbf{x}_h$ becomes a vector of 306 indicators for whether hospital h was in each of the 306 markets and $\boldsymbol{\lambda}$ is a vector of the 306 market fixed effects. We then perform the EB procedure, producing estimates of the underlying market means $\hat{\boldsymbol{\lambda}}$ and conditional – i.e. within-market – variance $\hat{\sigma}^2$. Running the procedure also yields EB-adjusted estimated quality measures $q_h^{EB(f)}$ and also can be used to produce the unconditional – i.e. national – estimated

variance $\hat{\varsigma}^2$, as described above. When we compute quality metrics for multiple years, for example in the case of Appendix Table A13, we perform the EB adjustment separately for each year. That is, we allow each year to have its own market means $\hat{\boldsymbol{\lambda}}$ and conditional variance $\hat{\sigma}^2$.

Our procedure ensures that when the EB-adjusted quality is used in our main regressions (equations 1 and 2 in the main text), which have market fixed effects, all regressors are orthogonal to the measurement error term.

C.3 Reported Statistics Involving Quality Metrics

C.3.1 Standard Deviation

To estimate the standard deviation of quality in Table 2, we rely on the estimates of the underlying national variance of quality $\hat{\varsigma}^2$ that the procedure computes.[42] The root of these estimates is taken, forming $\hat{\varsigma}$.

The EB adjustment produces $\hat{\varsigma}^2$ by taking the weighted empirical variance of the $\hat{q}_h$ and subtracting the weighted average squared standard error $\hat{\pi}_h^2$ (see equations A4 and A5). Hospitals with larger standard errors receive lower weights. In effect, this process takes the variance of the noisy quality estimates and subtracts off the variance due to measurement error.

C.3.2 Correlations

In Table 3 and Appendix Table A4 we report correlations adjusted for measurement error. The raw correlation between two quality measures potentially suffers from two sources of bias. First, the variance terms in the denominator are upward-biased if either quality measure is estimated with measurement error, as in the fixed effects approach that we use for risk-adjusted survival and readmission. Second, the covariance term in the numerator may also be biased if the two quality metrics were estimated using the same samples of patients (e.g. risk-adjusted survival and readmission for the same condition), since the sampling error in one fixed effect may be correlated with the sampling error in the other.

Our empirical correlation estimate corrects for these two sources of bias, and is calculated as the following:

[42] While it might seem natural to instead estimate the standard deviation of the EB-adjusted values, this would cause us to erroneously under-estimate dispersion. True quality is composed of a best prediction (the EB-adjusted quality) and the prediction error. These two components are orthogonal. The variance of true quality is thus strictly greater than the variance of EB-adjusted quality (see Jacob and Lefgren, 2007).

$$
\begin{aligned}
\tilde{\text{Cor}}_h\left(\hat{q}_{A,h},\hat{q}_{B,h}\right) &= \frac{\tilde{\text{Cov}}_h\left(\hat{q}_{A,h},\hat{q}_{B,h}\right)}{\sqrt{\tilde{\text{Var}}_h\left(\hat{q}_{A,h}\right)\tilde{\text{Var}}_h\left(\hat{q}_{B,h}\right)}} \\
\tilde{\text{Cov}}_h\left(\hat{q}_{A,h},\hat{q}_{B,h}\right) &= \hat{\text{Cov}}_h\left(\hat{q}_{A,h},\hat{q}_{B,h}\right) - \hat{\mathbb{E}}_h\left[\pi_{AB,h}\right] \\
\tilde{\text{Var}}_h\left(\hat{q}_{X,h}\right) &= \hat{\text{Var}}_h\left(\hat{q}_{X,h}\right) - \hat{\mathbb{E}}_h\left[\pi^2_{X,h}\right]
\end{aligned}
$$

where $\hat{q}_{A,h}$ is one estimated quality score for hospital h and $\hat{q}_{B,h}$ is another, $\pi_{AB,h}$ is the estimate of the measurement error covariance between the two quality scores, and $\pi^2_{X,h}$ is the estimate of the measurement error variance for measure $X \in \{A,B\}$. Tildes indicate estimates that have been adjusted for measurement error and hats indicate raw sample averages and variances. In other words, we take the covariance of the two raw quality scores and subtract the average covariance of the measurement error, and we take the variance of each quality score and subtract its average measurement error variance.

When the two quality scores come from the same patient sample, $\pi_{AB,h}$ is derived by making a homoscedasticity assumption on the covariance of the error terms in the two first-step regressions that produce the quality measures. Each pair of patient error terms, one for each regression, is assumed to be drawn from a distribution with a common variance-covariance matrix; error terms across patients are uncorrelated. We then estimate the variance-covariance matrix of the two hospital fixed effects and $\pi_{AB,h}$ is set to the covariance. If the two quality scores are derived from different patient samples (i.e. risk-adjusted survival for AMI and heart failure) or if only one is estimated by us from patient data (i.e. risk-adjusted survival for AMI and process of care for AMI) $\pi_{AB,h}$ is set to 0.

$\pi^2_{X,h}$ is the squared standard error of the fixed effect for measure X, described in Appendix Section C.1.2. It is set to 0 if the measure is not estimated by us from patient data, like for process of care scores or the patient survey.

C.3.3 Static and Dynamic Allocation Regressions

The allocation metrics use noisy estimates of quality on the right-hand side of regressions, and they rely on EB adjustment to correct for measurement error. Jacob and Lefgren (2007) show that with the adjustment, these regressions are estimated consistently.

Suppose that there is a relationship between growth Δ_h, market fixed effects γ_M, and quality q_h:

$$\Delta_h = \gamma_M + \delta q_h + \varepsilon_h$$

where $\mathbb{E}\left[\varepsilon_h | x_h, q_h\right] = 0$ (x_h is a vector of indicators for the markets – the design matrix for the

market fixed effects). The left-hand side variable could alternatively be the number of patients as in the static allocation regression.

Since we do not observe true quality q_h, we use the estimate $\hat{q}_h = q_h + \eta_h$, where η_h is measurement error. Then substituting into the equation:

$$\Delta_h = \gamma_M + \delta \hat{q}_h + (\varepsilon_h - \delta \eta_h)$$

This regression generally produces a biased estimate of δ due to the correlation between $\hat{q}_h$ and η_h in the error term. We use the EB-adjusted quality q_h^{EB} to eliminate this correlation. Equation (A1) implies:

$$\mathbb{E}\left[q_h | \hat{q}_h, \mathbf{x}_h, \boldsymbol{\lambda}, \sigma^2, \pi_h^2\right] = q_h^{EB}$$

We represent the prediction error of the EB procedure as v_h:

$$q_h = q_h^{EB} + v_h$$

By construction the prediction error is orthogonal to q_h^{EB} and any regressor included in x_h – i.e. the market fixed effects:

$$\mathbb{E}\left[v_h | q_h^{EB}, \mathbf{x}_h, \boldsymbol{\lambda}, \sigma^2, \pi_h^2\right] = 0$$

($\hat{q}_{ht}$ is replaced by q_h^{EB} because given the parameters, knowing one determines the other)

The regression of Δ_h on market effects and q_h^{EB} adds only δv_h to the original error term ε_h:

$$\Delta_h = \gamma_M + \delta q_h^{EB} + (\varepsilon_h - \delta v_h)$$

Therefore there is no correlation between any of the regressors and the new error term. The unbiasedness of δ follows.

C.4 Multivariate Empirical Bayes Procedure

In some cases we run regressions with multiple imprecisely measured quality metrics on the right-hand side, each estimated from the same sample of patients. In these cases, the measurement error across the quality metrics is likely to be correlated, making the EB procedure we used for a single quality metric insufficient to restore unbiasedness to the regression estimates – one EB-adjusted quality metric is uncorrelated with its own prediction error, but it may be correlated with the prediction error of the other EB-adjusted quality metric. For these regressions, the quality metrics must be EB-adjusted jointly.

Let $\mathbf{q}_h$ be the "true" vector of quality for hospital h and let $\hat{\mathbf{q}}_h$ be the estimate of the vector. The multivariate method assumes that the two quality estimates are distributed jointly normal around

true quality with covariance matrix Π_h:

$$\hat{\mathbf{q}}_h|\mathbf{q}_h,\Pi_h \sim \mathrm{N}(\mathbf{q}_h,\Pi_h) \text{ independently} \tag{A6}$$

The underlying, or prior, distribution of quality is also jointly normal:

$$\mathbf{q}_h|\mathbf{x}_h,\Lambda,\Sigma \sim \mathrm{N}(\Lambda\mathbf{x}_h,\Sigma) \text{ independently} \tag{A7}$$

Conditioning on the estimated quality vector yields the posterior distribution (we present the formula given in Murphy, 2007 after some algebraic manipulation):

$$\mathbf{q}_h|\hat{\mathbf{q}}_h,\mathbf{x}_h,\Lambda,\Sigma \sim \mathrm{N}\left(\mathbf{q}_h^{EB},(I-B_h)\Pi_h\right) \tag{A8}$$

Where:

$$\mathbf{q}_h^{EB} = (I-B_h)\hat{\mathbf{q}}_h + B_h\Lambda\mathbf{x}_h \tag{A9}$$

$$B_h = \Pi_h(\Pi_h+\Sigma)^{-1} \tag{A10}$$

One can think of $\mathbf{q}_h$ as the hyperparameter for the mean of $\hat{\mathbf{q}}_h$. The above formulas give the posterior distribution of the hyperparameter after conditioning on realization $\hat{\mathbf{q}}_h$.

C.4.1 Feasible Version of Procedure

To implement the EB adjustment, we begin by fixing values of $\hat{\mathbf{q}}_h$. Each member of the vector equals the estimated fixed effect from a patient-level quality regression, e.g. for $\hat{\mathbf{q}}_h = \left(\hat{q}_{A,h},\hat{q}_{B,h}\right)'$, $\hat{q}_{A,h}$ could be hospital h's fixed effect from the risk-adjusted survival patient-level regression while $\hat{q}_{B,h}$ could be the fixed effect from the readmission regression.

To construct $\hat{\Pi}_h$ (the estimate of Π_h), we assume homoscedastic disturbances in each first-step quality regression, but we extend the assumptions to account for multiple measures. We treat the set of first-step regressions as a SUR and assume that each patient's disturbances are drawn from a distribution with a common covariance matrix. That is, we allow a patient's disturbance term in one quality regression to be correlated with her disturbance term in another. Disturbances across patients are assumed to be uncorrelated. (We make the same assumption in Appendix Section C.3.2 to estimate correlations between quality measures.)

Under these assumptions, we extract hospital-level estimates of the covariance of the measure-

ment error between the quality measures, for example between the hospital's risk-adjusted survival score and its risk-adjusted readmission score. These estimates become the off diagonal values of $\hat{\Pi}_h$. We also estimate standard errors on the hospital fixed effects in each regression – under our homoscedasticity assumption these standard errors are the same as in the single quality-metric approach. The squared standard errors are estimates of the variance of the measurement error of each quality metric; these values become the diagonals of $\hat{\Pi}_h$.

Next we must estimate Σ and Λ. Combining equations (A6) and (A7) we have the distribution of $\hat{\mathbf{q}}_h$ unconditional on $\mathbf{q}_h$ (in Bayesian terms called the prior predictive distribution):

$$\hat{\mathbf{q}}_h|\mathbf{x}_h,\Lambda,\Sigma,\Pi_h \sim \mathrm{N}\left(\Lambda\mathbf{x}_h,\Sigma+\Pi_h\right) \text{ independently}$$

The full vector of measured quality $\hat{\mathbf{q}}$ – the stacked $\hat{\mathbf{q}}_h$ – therefore follows a multivariate normal distribution as well. We now show how to represent this joint distribution so that we can build its likelihood function.

For the simultaneous EB adjustment of k quality measures at once, we define X as the stacked $I_k \otimes \mathbf{x}_h'$, $\boldsymbol{\lambda}$ as the rows of Λ transposed to column vectors and stacked to create one vector of coefficients, and Π as the block diagonal matrix formed with Π_h on the diagonals. Then $\hat{\mathbf{q}}$ is distributed:

$$\hat{\mathbf{q}}|X,\Lambda,\Sigma,\Pi \sim \mathrm{N}\left(X\boldsymbol{\lambda},I_{n_h}\otimes\Sigma+\Pi\right)$$

In our model, the number of parameters in $\boldsymbol{\lambda}$ is large relative to the sample size – 306 market fixed effects per quality measure and about 3,000 hospitals per measure. An ML estimate of Σ would therefore have significant bias in finite samples due to the loss of degrees of freedom from estimating $\boldsymbol{\lambda}$. We estimate Σ by REML instead of MLE to avoid this bias.

The REML likelihood function is:[43]

$$\text{(A11)} \qquad \mathscr{L}\left(\tilde{\Sigma};\Pi\right) = -\frac{1}{2}\ln\left|\tilde{\Theta}\right| - \frac{1}{2}\ln\left|X'\tilde{\Theta}^{-1}X\right| - \frac{1}{2}\left(\hat{\mathbf{q}}-X\tilde{\boldsymbol{\lambda}}\right)'\tilde{\Theta}^{-1}\left(\hat{\mathbf{q}}-X\tilde{\boldsymbol{\lambda}}\right)$$

$$\text{(A12)} \qquad \tilde{\boldsymbol{\lambda}}\left(\tilde{\Theta}\right) = \left(X'\tilde{\Theta}^{-1}X\right)^{-1}X'\tilde{\Theta}^{-1}\hat{\mathbf{q}}$$

$$\text{(A13)} \qquad \tilde{\Theta}\left(\tilde{\Sigma};\Pi\right) = I_{n_h}\otimes\tilde{\Sigma}+\Pi$$

$\hat{\Sigma}$ is the maximizer of the likelihood function (with unknown Π replaced by the known $\hat{\Pi}$) and $\hat{\boldsymbol{\lambda}}$ is given by equation (A12):

[43] This likelihood function is derived and given in Diggle et al. (2002). The MLE likelihood function is defined identically but omits the $\frac{1}{2}\ln\left|X'\tilde{\Theta}^{-1}X\right|$ term. Maximizing this likelihood would yield unbiased estimates of λ but not Σ.

$$\begin{aligned}\hat{\tilde{\Sigma}} &= \arg_{\tilde{\Sigma}} \max \mathscr{L}\left(\tilde{\Sigma};\hat{\Pi}\right) \\ \hat{\boldsymbol{\lambda}} &= \tilde{\boldsymbol{\lambda}}\left(\tilde{\Theta}\left(\hat{\tilde{\Sigma}};\hat{\Pi}\right)\right)\end{aligned}$$

The feasible estimate of the posterior quality vector is given by equations (A9) and (A10) with unknown parameters replaced by their estimates ($\hat{\Lambda}$ is constructed from $\hat{\boldsymbol{\lambda}}$ by splicing the vector back into matrix form):

$$\begin{aligned}\mathbf{q}_h^{EB(f)} &= \left(I-\hat{B}_h\right)\hat{\mathbf{q}}_h + \hat{B}_h\hat{\Lambda}\mathbf{x}_h \\ \hat{B}_h &= \hat{\Pi}_h\left(\hat{\Pi}_h+\hat{\Sigma}\right)^{-1}\end{aligned}$$

C.4.2 Implementation

We perform bivariate EB adjustment in two cases. The first is our multivariate allocation regressions, where we regress hospital size and growth on risk-adjusted survival and readmission simultaneously (see the discussion of Section III.A and Appendix Table A6). The second is our regressions that study allocation with respect to productivity decomposed into risk-adjusted survival and risk-adjusted spending (see Section III.C and Table 7). In these cases, we allow the underlying mean of each quality measure to equal a market fixed effect, so e.g. $\Lambda\mathbf{x}_h = \begin{pmatrix}\tau_M^1 \\ \tau_M^2\end{pmatrix}$. As in the approach with a single quality metric, $\mathbf{x}_h$ is a vector of 306 indicators for whether a hospital is in each of the 306 markets.

We perform the EB procedure, extracting the matrix of underlying market means $\hat{\Lambda}$ and underlying variance $\hat{\Sigma}$, then producing EB-adjusted quality vectors $\mathbf{q}_h^{EB(f)}$. The $\mathbf{q}_h^{EB(f)}$ become regressors in the multivariate allocation and decomposed productivity regressions replacing the noisy estimates $\hat{\mathbf{q}}_h$. By the result given in section C.3.3 (replacing scalars q_h and η_h with vectors $\mathbf{q}_h$ and $\boldsymbol{\eta}_h$), the EB adjustment restores consistency to the coefficients of interest in these regressions.

C.5 Comparison of estimates

We run all of our baseline regression analyses with the EB-adjusted productivities $q_h^{EB(f)}$. Appendix Table A2 explores the impact of the EB correction on our main results, reproducing the EB-adjusted main results from Table 4 without the EB correction.

To produce the uncorrected allocation metrics, we use the estimates $\hat{q}_h$ rather than $q_h^{EB(f)}$ in our regressions. Due to measurement error in the estimates, we generally expect the allocation

metrics computed without the EB correction to be attenuated. The attenuation result is well-known under classical measurement error, though when measurement error is non-classical it is possible for coefficients to be expanded rather than attenuated. Our EB approach allows each hospital's measurement error to be different (based on the squared standard error of the hospital fixed effect from the first-step regression), so it is robust to this violation of the classical measurement error assumption.

The results show that the EB correction has a substantial effect on our baseline estimates, and our findings are consistent with measurement error causing attenuation. Comparing our baseline (EB-adjusted) estimates to the un-adjusted versions, we see that the allocation gradients are substantially greater with the correction. For example, in column 1 of Appendix Table A2, a 1 percentage point rise in risk-adjusted AMI survival is associated with 17% more patients when the EB correction is used, but only 7% more patients when we use the raw quality metric. The expansion of the coefficient is more substantial for some of the other metrics – e.g. a 1 percentage point fall in risk-adjusted HF readmission is associated with 10% more patients in our baseline analysis, but only 1% more patients when we drop the EB correction.

A quantitatively large impact of the EB correction (i.e. a large amount of measurement error, to the extent that it is classical) is not surprising in light of results from other applications. For example, looking at estimates of teacher fixed effects in value added regressions, Jacob and Lefgren (2007) estimate a ratio of the unadjusted standard deviation to the EB-adjusted estimate of the standard deviation of about 1.3 to 1.6. We find ratios ranging from 1.5 to 2.1.

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Tables (Additional for Appendices)

Table A1 - Sensitivity of Static Allocation Results to Truncation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Condition	AMI			Heart Failure			Pneumonia			Hip/Knee Replacement		
Measure \ Model	Baseline	Trunc OLS	Trunc MLE	Baseline	Trunc OLS	Trunc MLE	Baseline	Trunc OLS	Trunc MLE	Baseline	Trunc OLS	Trunc MLE
Risk-Adjusted Survival	17.496	10.075	14.050	15.360	11.714	16.950	5.140	4.299	5.748			
	(0.995)	(0.750)	(1.085)	(1.320)	(1.120)	(1.713)	(0.777)	(0.654)	(0.884)			
Hospitals	2,890	1,910	1,910	4,023	2,918	2,918	4,325	3,578	3,578			
Risk-Adjusted Readmission	-9.162	-7.639	-10.556	-10.346	-9.993	-13.895	0.499	-1.093	-1.410	-21.037	-16.078	-22.119
	(1.621)	(1.449)	(2.037)	(1.782)	(1.617)	(2.335)	(1.575)	(1.302)	(1.680)	(2.027)	(1.781)	(2.536)
Hospitals	2,322	1,909	1,909	3,904	2,918	2,918	4,264	3,575	3,575	2,632	2,108	2,108
Process of Care Z-Score	0.319	0.285	0.493	0.332	0.230	0.378	0.211	0.151	0.217			
	(0.026)	(0.022)	(0.035)	(0.016)	(0.015)	(0.030)	(0.015)	(0.014)	(0.019)			
Hospitals	2,398	1,893	1,893	3,666	2,892	2,892	3,920	3,450	3,450			
Patient Survey Z-Score	-0.321	0.054	0.077	-0.252	-0.064	-0.088	-0.210	-0.092	-0.112	0.057	0.071	0.102
	(0.052)	(0.027)	(0.040)	(0.038)	(0.026)	(0.035)	(0.030)	(0.023)	(0.029)	(0.051)	(0.029)	(0.042)
Hospitals	3,498	1,901	1,901	3,598	2,808	2,808	3,610	3,197	3,197	3,061	2,104	2,104

This table repeats the static allocation analysis of Table 4 and shows its sensitivity to truncation in patient counts. For each condition, the left column ("Baseline") repeats our baseline results. The middle column ("Trunc OLS") shows static allocation limiting to hospitals with at least 25 patients in 2008, i.e. truncating at 25 patients; this specification attenuates results, as is generally the case when outcomes are truncated. The right column ("Trunc MLE") shows results from running a Tobit-style maximum-likelihood truncated regression on the "Trunc OLS" sample. This model adjusts for the truncation under a normality assumption; as expected, this correction always expands coefficients beyond the truncated OLS model and often beyond our baseline results. Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A2 - Sensitivity of Allocation Results to Empirical Bayes Adjustment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Static Allocation				Dynamic Allocation			
Condition	AMI	HF	Pneu	Hip/Knee	AMI	HF	Pneu	Hip/Knee
Panel A - Risk-Adjusted Survival								
Baseline (EB-Adjusted)	17.496	15.360	5.140		1.533	0.774	1.220	
	(0.995)	(1.320)	(0.777)		(0.379)	(0.501)	(0.354)	
Raw (No EB Adjustment)	6.833	3.761	1.957		0.645	0.084	0.340	
	(0.342)	(0.425)	(0.403)		(0.175)	(0.199)	(0.175)	
Hospitals	2,890	4,023	4,325		2,890	4,023	4,325	
Raw SD / Corrected SD	1.597	1.788	1.547		1.597	1.788	1.547	
Panel B - Risk-Adjusted Readmission								
Baseline (EB-Adjusted)	-9.162	-10.346	0.499	-21.037	-1.428	-2.300	-1.138	-1.112
	(1.621)	(1.782)	(1.575)	(2.027)	(0.611)	(0.651)	(0.679)	(0.836)
Raw (No EB Adjustment)	-1.699	-1.043	0.755	-6.492	-0.307	-0.217	-0.189	-0.431
	(0.395)	(0.346)	(0.427)	(0.727)	(0.197)	(0.162)	(0.195)	(0.382)
Hospitals	2,322	3,904	4,264	2,632	2,322	3,904	4,264	2,632
Raw SD / Corrected SD	1.870	2.132	1.864	1.794	1.870	2.132	1.864	1.794

This table shows the sensitivity of the allocation results of Table 4 to the empirical Bayes adjustment procedure. In each panel, we first repeat the baseline allocation results in which the quality metric is empirical-Bayes-adjusted. We then show the same allocation models using the raw quality metric without empirical Bayes adjustment. Lastly, we show the ratio of the raw standard deviation of the quality measure to its standard deviation after correcting for measurement error (see Appendix Section C.3.1). Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A3 - Distance Traveled across Conditions

	(1)	(2)	(3)	(5)
Condition	AMI	Heart Failure	Pneumonia	Hip Fracture
Median miles traveled	7.0	5.4	5.2	9.1
Mean miles traveled	45.0	33.7	35.8	41.9
Share treated at nearest hospital	0.43	0.52	0.56	0.38
Share staying in market	0.87	0.89	0.90	0.84
Index Events	190,189	308,122	354,319	267,557
Hospitals	2,890	4,023	4,325	2,632

Distances are miles from the centroid of the patient's ZIP code to the centroid of the hospital's ZIP code. The sample is patients in 2008 at hospitals that had a valid risk-adjusted survival rate (risk-adjusted readmission for hip/knee replacement).

Table A4 - Correlation of Measures Across Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Risk-Adjusted Survival			Risk-Adjusted Readmission			
Condition	AMI	HF	Pneu	AMI	HF	Pneu	Hip/Knee
AMI	1.00			1.00			
	[2,890]			[2,322]			
HF	0.58	1.00		0.76	1.00		
	[2,888]	[4,023]		[2,320]	[3,904]		
Pneumonia	0.45	0.70	1.00	0.66	0.94	1.00	
	[2,883]	[4,006]	[4,325]	[2,313]	[3,880]	[4,264]	
Hip/Knee Replacement				0.44	0.51	0.44	1.00
				[2,020]	[2,524]	[2,544]	[2,632]

	Process of Care		
Condition	AMI	HF	Pneu
AMI	1.00		
	[2,398]		
HF	0.59	1.00	
	[2,397]	[3,666]	
Pneumonia	0.44	0.63	1.00
	[2,386]	[3,637]	[3,920]

Hospitals used to calculate correlation in brackets. Correlations involving survival or readmission are adjusted for measurement error (see Appendix Section C.3.2).

Table A5 - Correlation of Management Scores and Quality

Measure \ Condition	(1) AMI	(2) HF	(3) Pneu	(4) Hip/Knee
Risk-Adjusted Survival	0.19	0.21	0.17	
	[198]	[274]	[289]	
Risk-Adjusted Readmission	0.09	-0.09	0.45	0.21
	[158]	[267]	[288]	[190]
Process of Care Z-Score	0.12	0.35	0.28	
	[162]	[244]	[263]	
Patient Survey Z-Score	-0.01	-0.02	-0.02	0.05
	[227]	[233]	[233]	[202]

Each cell shows the correlation between our measure and the Bloom-Van Reenen average management score at the hospital. Hospitals used to calculate correlation in brackets. Correlations involving survival or readmission are adjusted for measurement error (see Appendix Section C.3.2).

Table A6 - Allocation across Conditions - Multivariate Approach to Measuring Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Static Allocation				Dynamic Allocation			
Measure \ Condition	AMI	HF	Pneu	Hip/Knee	AMI	HF	Pneu	Hip/Knee
Risk-Adjusted Survival	12.866	17.839	4.237		0.217	1.827	1.269	
	(1.421)	(1.902)	(0.764)		(0.600)	(0.586)	(0.357)	
Risk-Adjusted Readmission	-6.108	-14.155	-1.120	-20.716	-0.814	-2.264	-0.580	-0.757
	(1.983)	(2.214)	(1.552)	(2.108)	(0.745)	(0.668)	(0.644)	(0.845)
Process of Care Z-Score	0.196	0.188	0.196		0.036	0.014	0.015	
	(0.027)	(0.022)	(0.014)		(0.011)	(0.010)	(0.009)	
Patient Survey Z-Score	-0.113	-0.292	-0.166	-0.022	0.002	-0.014	-0.004	0.025
	(0.040)	(0.028)	(0.022)	(0.034)	(0.013)	(0.009)	(0.009)	(0.016)
Hospitals	2,193	3,316	3,454	2,542	2,193	3,316	3,454	2,542

This table repeats the analysis of Table 4 but uses all available quality measures for the condition at once (plus the patient survey, which is not condition-specific). The allocation sample for each regression is all hospitals with the displayed quality measures and at least one patient in 2008. Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A7 - Allocation across Conditions - Constant Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Static Allocation				Dynamic Allocation			
Measure \ Condition	AMI	HF	Pneu	Hip/Knee	AMI	HF	Pneu	Hip/Knee
Risk-Adjusted Survival	12.082	13.870	4.192		0.526	1.364	1.170	
	(0.929)	(1.296)	(0.745)		(0.401)	(0.452)	(0.323)	
Hospitals	2,193	3,316	3,454		2,193	3,316	3,454	
Risk-Adjusted Readmission	-9.909	-10.519	-1.372	-20.742	-1.127	-1.969	-0.733	-0.988
	(1.600)	(1.686)	(1.562)	(2.097)	(0.567)	(0.531)	(0.561)	(0.835)
Hospitals	2,193	3,316	3,454	2,542	2,193	3,316	3,454	2,542
Process of Care Z-Score	0.327	0.300	0.185		0.045	0.030	0.018	
	(0.023)	(0.018)	(0.015)		(0.009)	(0.008)	(0.008)	
Hospitals	2,193	3,316	3,454		2,193	3,316	3,454	
Patient Survey Z-Score	0.074	-0.172	-0.121	0.068	0.017	0.004	0.004	0.029
	(0.030)	(0.031)	(0.028)	(0.035)	(0.012)	(0.007)	(0.008)	(0.015)
Hospitals	2,193	3,316	3,454	2,542	2,193	3,316	3,454	2,542

This table repeats the analysis of Table 4 but uses a constant sample of hospitals across the quality metrics. The sample for each regression is all hospitals with a risk-adjusted survival rate (if calculated for that condition), risk-adjusted readmission rate, process of care score (if calculated for that condition), patient survey score, and at least one patient in 2008. Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A8 - Allocation with Respect to All Condition-Specific Quality Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Static Allocation				Dynamic Allocation			
Measure \ Condition	AMI	HF	Pneu	Hip/Knee	AMI	HF	Pneu	Hip/Knee
Risk-Adjusted Survival Z-Score								
AMI	0.553	0.335	0.183		0.048	0.014	0.031	
	(0.030)	(0.022)	(0.021)		(0.014)	(0.009)	(0.010)	
HF	0.198	0.124	0.031		-0.001	0.010	0.004	
	(0.036)	(0.030)	(0.026)		(0.017)	(0.011)	(0.012)	
Pneumonia	0.034	0.080	0.052		0.014	0.010	0.032	
	(0.034)	(0.024)	(0.019)		(0.014)	(0.013)	(0.011)	
Hospitals	2,882	2,882	2,882		2,882	2,882	2,882	
Risk-Adjusted Readmission Z-Score								
AMI	-0.171	-0.112	-0.122	-0.265	-0.031	-0.035	-0.018	-0.001
	(0.047)	(0.038)	(0.035)	(0.056)	(0.019)	(0.014)	(0.015)	(0.023)
HF	-0.215	-0.146	-0.086	-0.282	-0.027	-0.043	-0.028	-0.007
	(0.044)	(0.031)	(0.030)	(0.054)	(0.019)	(0.017)	(0.015)	(0.021)
Pneumonia	0.104	0.084	0.041	-0.055	-0.006	-0.014	-0.018	-0.008
	(0.042)	(0.031)	(0.027)	(0.050)	(0.019)	(0.017)	(0.015)	(0.024)
Hip/Knee Replacement	-0.079	-0.067	-0.086	-0.284	-0.010	-0.016	0.002	-0.024
	(0.034)	(0.024)	(0.021)	(0.041)	(0.013)	(0.012)	(0.012)	(0.016)
Hospitals	2,018	2,018	2,018	2,018	2,018	2,018	2,018	2,018
Process of Care Z-Score								
AMI	0.336	0.209	0.165		0.058	0.046	0.014	
	(0.031)	(0.021)	(0.020)		(0.013)	(0.011)	(0.011)	
HF	-0.054	-0.103	-0.219		-0.061	-0.027	0.001	
	(0.049)	(0.040)	(0.042)		(0.025)	(0.020)	(0.018)	
Pneumonia	0.001	0.094	0.205		0.036	0.026	0.025	
	(0.051)	(0.041)	(0.037)		(0.020)	(0.020)	(0.016)	
Hospitals	2,386	2,389	2,390		2,386	2,389	2,390	

This table repeats the analyses of Table 4 but rather than using the one (non-standardized, except for process of care) quality measure for the left-hand side condition, it uses Z-scores of all condition specific quality measures. Each column in a panel represents one regression, e.g. the top panel of column (1) regresses hospital size for AMI on risk-adjusted survival Z-scores for AMI, HF, and pneumonia. Standard errors are analytic and clustered at the market level.

Table A9 - Sensitivity of Static Allocation to Poisson Regression Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Condition	AMI		HF		Pneumonia		Hip/Knee	
Measure \ Model	Baseline	Poisson	Baseline	Poisson	Baseline	Poisson	Baseline	Poisson
Risk-Adjusted Survival	17.496	18.631	15.360	17.532	5.140	6.478		
	(0.995)	(1.109)	(1.320)	(1.504)	(0.777)	(0.829)		
Hospitals	2,890	2,881	4,023	4,023	4,325	4,325		
Risk-Adjusted Readmission	-9.162	-10.685	-10.346	-13.145	0.499	-1.922	-21.037	-25.811
	(1.621)	(2.086)	(1.782)	(2.175)	(1.575)	(1.756)	(2.027)	(3.466)
Hospitals	2,322	2,304	3,904	3,903	4,264	4,264	2,632	2,626
Process of Care Z-Score	0.319	0.422	0.332	0.332	0.211	0.199		
	(0.026)	(0.024)	(0.016)	(0.020)	(0.015)	(0.014)		
Hospitals	2,398	2,379	3,666	3,665	3,920	3,920		
Patient Survey Z-Score	-0.321	-0.131	-0.252	-0.123	-0.210	-0.114	0.057	0.130
	(0.052)	(0.035)	(0.038)	(0.030)	(0.030)	(0.023)	(0.051)	(0.057)
Hospitals	3,498	3,498	3,598	3,598	3,610	3,610	3,061	3,059

This table shows the baseline static allocation results of Table 4 in comparison to the same model run as a fixed effects Poisson regression. To make the models analogous, the Poisson regressand is the count of patients, not its logarithm. Standard errors are bootstrapped with 300 replications and are clustered at the market level.
The baseline sample is used; hospital counts can be smaller for the Poisson models because they exclude markets with only one hospital.

Table A10 - Sensitivity of Allocation Results to Risk Adjustment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Static Allocation				Dynamic Allocation			
Condition	AMI	HF	Pneu	Hip/Knee	AMI	HF	Pneu	Hip/Knee
Panel A - Risk-Adjusted Survival								
Baseline Risk-Adjustment	17.496	15.360	5.140		1.533	0.774	1.220	
	(0.995)	(1.320)	(0.777)		(0.379)	(0.501)	(0.354)	
Age/Race/Sex Only	16.898	14.798	3.209		1.565	0.654	1.065	
	(0.847)	(1.377)	(0.764)		(0.337)	(0.508)	(0.361)	
No Risk Adjustment	14.896	13.763	3.625		1.520	0.765	1.315	
	(0.571)	(1.192)	(0.713)		(0.241)	(0.420)	(0.332)	
Hospitals	2,890	4,023	4,325		2,890	4,023	4,325	
Panel B - Risk-Adjusted Readmission								
Baseline Risk-Adjustment	-9.162	-10.346	0.499	-21.037	-1.428	-2.300	-1.138	-1.112
	(1.621)	(1.782)	(1.575)	(2.027)	(0.611)	(0.651)	(0.679)	(0.836)
Age/Race/Sex Only	-10.358	-6.466	3.152	-20.023	-1.556	-1.621	-0.547	-1.048
	(1.212)	(1.457)	(1.280)	(1.859)	(0.475)	(0.528)	(0.482)	(0.767)
No Risk Adjustment	-10.909	-5.596	2.753	-20.710	-1.601	-1.514	-0.585	-1.140
	(1.096)	(1.441)	(1.272)	(1.819)	(0.435)	(0.511)	(0.465)	(0.732)
Hospitals	2,322	3,904	4,264	2,632	2,322	3,904	4,264	2,632

This table shows the sensitivity of the allocation results of Table 4 to the risk-adjustment procedure. In each panel, we repeat the baseline allocation results with full risk adjustment, followed by identical specifications under two alternative measures. First, we risk-adjust using only age-race-sex interactions. Second, we perform no risk-adjustment. Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A11 - Static Allocation Restricted to Patients Treated in Market of Residence (Choice Model Subsample)

	(1)	(2)	(4)	(5)	(7)	(8)	(10)	(11)
Condition	AMI		Heart Failure		Pneumonia		Hip/Knee	
Sample	Baseline	Choice	Baseline	Choice	Baseline	Choice	Baseline	Choice
Share Baseline Patients in Sample	1.00	0.87	1.00	0.89	1.00	0.90	1.00	0.84
Risk-Adjusted Survival	17.496	16.769	15.360	15.184	5.140	5.402		
	(0.995)	(0.988)	(1.320)	(1.341)	(0.777)	(0.808)		
Hospitals	2,890	2,889	4,023	4,023	4,325	4,324		
Risk-Adjusted Readmission	-9.162	-9.447	-10.346	-10.561	0.499	-0.233	-21.037	-20.794
	(1.621)	(1.600)	(1.782)	(1.823)	(1.575)	(1.590)	(2.027)	(2.014)
Hospitals	2,322	2,322	3,904	3,904	4,264	4,263	2,632	2,632
Process of Care Z-Score	0.319	0.317	0.332	0.332	0.211	0.210		
	(0.026)	(0.026)	(0.016)	(0.016)	(0.015)	(0.016)		
Hospitals	2,398	2,397	3,666	3,662	3,920	3,918		
Patient Survey Z-Score	-0.321	-0.316	-0.252	-0.261	-0.210	-0.217	0.057	0.041
	(0.052)	(0.051)	(0.038)	(0.039)	(0.030)	(0.030)	(0.051)	(0.048)
Hospitals	3,498	3,480	3,598	3,594	3,610	3,608	3,061	3,046

This table repeats the static allocation analysis of Table 4 and shows how it is affected by restricting to patients who were treated in their market of residence, which is the patients who were included in the choice model. For each condition, the left column (Baseline) repeats our baseline results. The right column (Choice) runs the same regression but only counts patients residing in the hospital's market. Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A12 - Choice Model of Patient Allocation - Raw Logit Coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Condition	AMI	AMI	AMI	AMI	HF	HF	HF	HF
Mean miles to chosen hospital	12.48	12.67	12.65	12.45	8.27	8.27	8.30	8.35
SD miles to chosen hospital	20.06	20.27	20.27	20.31	13.25	13.25	13.27	13.33
Distance	-0.111	-0.128	-0.137	-0.099	-0.159	-0.163	-0.160	-0.159
	(0.006)	(0.007)	(0.007)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)
Distance^2	0.00019	0.00032	0.00034	0.00012	0.00018	0.00026	0.00013	0.00013
	(0.00003)	(0.00003)	(0.00003)	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00001)
Risk-Adjusted Survival	19.004				16.041			
	(1.147)				(1.728)			
Risk-Adjusted Readmission		-13.626				-16.491		
		(2.007)				(1.808)		
Process of Care Z-Score			0.568				0.353	
			(0.036)				(0.028)	
Patient Survey Z-Score				-0.031				0.015
				(0.037)				(0.032)
Patients	165,005	158,086	158,032	167,429	275,671	274,667	270,773	266,915
Observations	2,869,091	2,321,684	2,427,869	3,359,387	6,241,586	6,103,120	5,811,375	5,532,403
Avg Hospital Choices/Patient	17.39	14.69	15.36	20.06	22.64	22.22	21.46	20.73

This table shows the raw logit coefficients (log odds ratios) from the models of Table 5. See that table for sample restrictions. Standard errors are analytic and clustered at the market level.

Table A12 Continued - Choice Model of Patient Allocation - Raw Logit Coefficients

	(9)	(10)	(11)	(12)	(13)	(14)
Condition	Pneu	Pneu	Pneu	Pneu	Hip/Knee	Hip/Knee
Mean miles to chosen hospital	7.49	7.49	7.50	7.54	13.16	13.09
SD miles to chosen hospital	11.92	11.91	11.77	11.77	18.85	18.80
Distance	-0.178	-0.178	-0.181	-0.185	-0.105	-0.101
	(0.006)	(0.006)	(0.006)	(0.007)	(0.004)	(0.004)
Distance^2	0.00013	0.00013	0.00013	0.00013	0.00017	0.00012
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00001)
Risk-Adjusted Survival	6.647					
	(0.962)					
Risk-Adjusted Readmission		-7.927			-24.091	
		(1.979)			(2.570)	
Process of Care Z-Score			0.238			
			(0.018)			
Patient Survey Z-Score				-0.007		0.157
				(0.028)		(0.039)
Patients	317,904	317,374	309,623	298,185	222,673	224,451
Observations	7,766,357	7,666,146	6,997,264	6,233,133	3,422,903	4,017,558
Avg Hospital Choices/Patient	24.43	24.15	22.60	20.90	15.37	17.90

This table shows the raw logit coefficients (log odds ratios) from the models of Table 5. See that table for sample restrictions. Standard errors are analytic and clustered at the market level.

Table A13 - Static and Dynamic Allocation over Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	AMI					HF				
Measure \ Year	1996	1999	2002	2005	2008	1996	1999	2002	2005	2008
Static Allocation	11.463	13.759	14.201	16.082	17.496	2.741	2.389	1.118	9.222	15.360
	(0.838)	(1.008)	(1.058)	(0.815)	(0.824)	(1.117)	(1.423)	(1.580)	(1.369)	(1.348)
Dynamic Allocation	0.536	0.875	0.787	1.103	1.533	0.609	-0.095	0.580	0.839	0.774
	(0.341)	(0.475)	(0.422)	(0.322)	(0.380)	(0.525)	(0.544)	(0.596)	(0.420)	(0.483)
Hospitals	3,708	3,558	3,487	3,267	2,890	4,361	4,254	4,176	4,130	4,023
	Pneumonia									
Measure \ Year	1996	1999	2002	2005	2008					
Static Allocation	-2.423	-2.723	-2.690	3.763	5.140					
	(0.750)	(0.778)	(0.845)	(0.800)	(0.768)					
Dynamic Allocation	-0.143	-0.608	0.181	-0.124	1.220					
	(0.314)	(0.365)	(0.288)	(0.331)	(0.363)					
Hospitals	4,565	4,496	4,403	4,375	4,325					

This table shows the allocation relationships with respect to risk-adjusted survival over time. Risk-adjusted survival is calculated from a regression of survival on hospital fixed effects and patient risk-adjusters. A separate regression is run for each of the year groups 1994-1996, 1997-1999, 2000-2002, 2003-2005, and 2006-2008. The empirical-Bayes-adjusted hospital effects are considered the hospital's quality metric for the year group's terminal year, the static allocation analysis is based on patient allocation in the terminal year, and the dynamic allocation is based on growth between the terminal year and the subsequent 2 years. Thus, for example, the "1996" analysis measures quality over 1994-1996, static allocation in 1996, and dynamic allocation based on growth between 1996 and 1998. Standard errors are analytic and clustered at the market level.

Table A14 - Allocation for Non-ED Non-Transfer Patients across Conditions

	(1)	(2)	(3)	(4)	(5)	(6)
	Static Allocation			Dynamic Allocation		
Measure \ Condition	AMI	HF	Pneu	AMI	HF	Pneu
Risk-Adjusted Survival	14.840	19.870	3.440	5.381	-0.125	0.637
	(1.215)	(2.093)	(1.159)	(1.071)	(0.993)	(0.720)
Hospitals	2,879	4,023	4,325	2,320	3,924	4,246
Risk-Adjusted Readmission	-6.086	-17.273	-3.285	-6.180	-0.828	0.330
	(3.831)	(2.469)	(1.900)	(1.695)	(1.324)	(1.173)
Hospitals	2,302	3,903	4,264	1,953	3,811	4,191
Process of Care Z-Score	0.317	0.173	0.015	0.151	0.038	0.023
	(0.046)	(0.018)	(0.017)	(0.028)	(0.015)	(0.012)
Hospitals	2,377	3,665	3,920	1,944	3,541	3,819
Patient Survey Z-Score	-0.039	-0.057	0.001	-0.103	0.001	-0.001
	(0.037)	(0.027)	(0.023)	(0.035)	(0.020)	(0.018)
Hospitals	3,498	3,598	3,610	2,653	3,472	3,513

This table repeats the analysis of Table 4 but considers hospital size and growth counting only non-ED non-transfer patients (the omitted category of patients from the analysis of Table 9). Static allocation uses the Poisson model (see Appendix Table A9) and the baseline allocation sample. Dynamic allocation uses the subset of hospitals with at least one non-ED non-transfer patient in 2008. Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A15 - Sensitivity of ED and Non-ED Transfer Patient Static Allocation to Poisson Regression Model

	(1)	(2)	(3)	(4)	(5)	(6)
Condition	AMI		Heart Failure		Pneumonia	
Source of Admission	ED	Transfer	ED	Transfer	ED	Transfer
Risk-Adjusted Survival						
Baseline Static Allocation	14.377	29.264	15.254	24.036	7.720	5.658
	(0.878)	(2.184)	(1.693)	(2.566)	(1.387)	(1.658)
P-value of test for equality	0.000		0.001		0.222	
Hospitals	2,742	1,408	3,329	1,563	3,513	1,601
Poisson Static Allocation	14.489	42.532	15.727	50.673	7.168	14.049
	(1.022)	(2.609)	(1.586)	(4.664)	(0.983)	(2.941)
P-value of test for equality	0.000		0.000		0.009	
Hospitals	2,881	2,881	4,023	4,011	4,325	4,275
Risk-Adjusted Readmission						
Baseline Static Allocation	-7.903	-13.315	-10.690	-16.527	0.204	2.008
	(1.295)	(3.904)	(1.775)	(3.483)	(2.314)	(3.107)
P-value of test for equality	0.109		0.062		0.585	
Hospitals	2,276	1,361	3,277	1,550	3,488	1,592
Poisson Static Allocation	-8.128	-25.550	-11.265	-37.988	-1.647	1.089
	(1.730)	(5.921)	(2.329)	(6.744)	(2.021)	(6.252)
P-value of test for equality	0.001		0.000		0.653	
Hospitals	2,304	2,304	3,903	3,892	4,264	4,214
Process of Care Z-Score						
Baseline Static Allocation	0.272	0.874	0.370	0.325	0.307	0.078
	(0.023)	(0.062)	(0.024)	(0.036)	(0.030)	(0.035)
P-value of test for equality	0.000		0.233		0.000	
Hospitals	2,369	1,376	3,245	1,520	3,389	1,548
Poisson Static Allocation	0.326	1.179	0.377	0.754	0.262	0.214
	(0.021)	(0.090)	(0.025)	(0.058)	(0.018)	(0.043)
P-value of test for equality	0.000		0.000		0.261	
Hospitals	2,379	2,379	3,665	3,653	3,920	3,869
Patient Survey Z-Score						
Baseline Static Allocation	-0.234	0.232	-0.227	0.045	-0.218	-0.087
	(0.049)	(0.067)	(0.041)	(0.046)	(0.041)	(0.039)
P-value of test for equality	0.000		0.000		0.008	
Hospitals	3,116	1,438	3,214	1,496	3,257	1,484
Poisson Static Allocation	-0.157	-0.034	-0.141	-0.090	-0.137	-0.203
	(0.035)	(0.072)	(0.032)	(0.060)	(0.028)	(0.057)
P-value of test for equality	0.051		0.349		0.170	
Hospitals	3,498	3,498	3,598	3,586	3,610	3,559

This table shows the static allocation results for ED and non-ED transferred patients using Poisson regression (as in Table 9) and linear regression. The left hand side of these regressions considers hospital size counting only ED patients in the odd-numbered columns and only non-ED transferred patients in the even-numbered columns. To make the linear and Poisson models analogous, the Poisson regressand is the count of patients, not its logarithm. Both approaches include market fixed effects. Hospital counts can be smaller for the Poisson models because they exclude markets with only one hospital. In addition, in the Poisson models, hospital counts may differ between ED and non-ED transfers for the same condition and quality measure because the counts also exclude markets with no variation in the outcome (e.g. all zeroes). Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A16 - Choice Model of Patient Allocation for ED and Non-ED Transfer Patients across Conditions

	(1)	(2)	(3)	(4)	(5)	(6)
Condition	AMI		Heart Failure		Pneumonia	
Source of Admission	ED	Transfer	ED	Transfer	ED	Transfer
Share of patients in 2008	0.79	0.14	0.76	0.02	0.77	0.01
Median miles to chosen hospital	4.7	29.8	4.4	26.3	4.4	21.1
Mean miles to chosen hospital	8.2	36.8	7.1	32.3	7.1	27.7
Share treated at nearest hospital	0.57	0.04	0.58	0.09	0.60	0.15
Risk-Adjusted Survival						
MRS(1 pp risk-adjusted survival, miles)	-0.744	-16.061	-0.623	-16.642	-0.317	-4.014
	(0.075)	(1.423)	(0.103)	(1.601)	(0.054)	(0.777)
P-value of test for equality	0.000		0.000		0.000	
Patients	129,889	23,185	209,094	6,130	244,358	4,097
Risk-Adjusted Readmission						
MRS(1 pp risk-adjusted readmission, miles)	0.527	10.818	0.734	12.774	0.410	1.303
	(0.086)	(2.097)	(0.104)	(2.193)	(0.102)	(1.713)
P-value of test for equality	0.000		0.000		0.598	
Patients	124,707	22,947	208,842	6,115	244,181	4,088
Process of Care Z-Score						
MRS(1 SD process of care, miles)	-2.024	-36.431	-1.712	-25.332	-1.392	-6.321
	(0.191)	(3.468)	(0.212)	(2.521)	(0.122)	(1.545)
P-value of test for equality	0.000		0.000		0.001	
Patients	124,989	22,913	208,503	6,083	243,368	4,025
Patient Survey Z-Score						
MRS(1 SD patient survey, miles)	-0.052	0.090	-0.179	2.178	-0.024	4.896
	(0.217)	(3.591)	(0.172)	(2.092)	(0.144)	(1.682)
P-value of test for equality	0.968		0.250		0.002	
Patients	131,603	23,281	207,472	6,059	241,158	3,948
Distance MRSs were evaluated at	12.48	12.48	8.27	8.27	7.49	7.49

These regressions repeat the conditional logit choice models of Table 5 but are restricted to ED patients (in odd columns) and non-ED transfer patients (in even columns). Standard errors are analytic and clustered at the market level.

This table reports the marginal rates of substitution (MRSs) of quality for distance derived from the conditional logit model (see equation 6). For the survival and readmission rates, the MRS given by equation (6) is divided by 100 to put it into percentage point terms. MRSs for a condition are evaluated at the same distance that was used for the condition in Table 5.

The sample is ED patients (odd columns) or non-ED transfer patients (even columns) with the condition in 2008 who stayed in their market of residence for treatment. The choice set for a patient is all hospitals in his market with the quality measure available that treated at least one patient in 2008.

Table A17 - Static Allocation with Patients Mechanically Allocated to Nearest Hospital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Condition	AMI		HF		Pneumonia		Hip/Knee	
Measure \ Method	Baseline	Mech	Baseline	Mech	Baseline	Mech	Baseline	Mech
Share truly going to closest	0.44		0.52		0.56		0.38	
Risk-Adjusted Survival	17.496	2.309	15.360	2.507	5.140	0.685		
	(0.995)	(0.577)	(1.320)	(1.115)	(0.777)	(0.653)		
Hospitals	2,890	2,888	4,023	4,021	4,325	4,322		
Risk-Adjusted Readmission	-9.162	-0.470	-10.346	-0.660	0.499	-0.328	-21.037	-2.783
	(1.621)	(1.111)	(1.782)	(1.305)	(1.575)	(1.130)	(2.027)	(1.140)
Hospitals	2,322	2,320	3,904	3,902	4,264	4,261	2,632	2,630
Process of Care Z-Score	0.319	0.018	0.332	0.158	0.211	0.099		
	(0.026)	(0.015)	(0.016)	(0.012)	(0.015)	(0.010)		
Hospitals	2,398	2,396	3,666	3,664	3,920	3,918		
Patient Survey Z-Score	-0.321	-0.203	-0.252	-0.238	-0.210	-0.182	0.057	-0.101
	(0.052)	(0.024)	(0.038)	(0.023)	(0.030)	(0.021)	(0.051)	(0.018)
Hospitals	3,498	3,496	3,598	3,595	3,610	3,607	3,061	3,058

This table shows our baseline static allocation results from Table 4 in comparison to an alternative allocation constructed by mechanically assigning each patient to his closest hospital. Only hospitals that treated at least one patient with the condition in 2008 are eligible for mechanical assignment. Distance is measured from the ZIP code centroid of the patient's residence to the ZIP code centroid of the hospital. The sample for each regression is all hospitals with the relevant quality measure and at least one mechanically allocated patient in 2008. Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A18 - Dynamic Allocation with Patients Mechanically Allocated to Nearest Hospital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Condition	AMI		HF		Pneumonia		Hip/Knee	
Measure \ Method	Baseline	Mech	Baseline	Mech	Baseline	Mech	Baseline	Mech
Share truly going to closest	0.44		0.52		0.56		0.38	
Risk-Adjusted Survival	1.533	-0.297	0.774	0.378	1.220	0.842		
	(0.379)	(0.250)	(0.501)	(0.497)	(0.354)	(0.356)		
Hospitals	2,890	2,888	4,023	4,021	4,325	4,322		
Risk-Adjusted Readmission	-1.428	-0.076	-2.300	-1.358	-1.138	-0.988	-1.112	-0.378
	(0.611)	(0.585)	(0.651)	(0.565)	(0.679)	(0.562)	(0.836)	(0.747)
Hospitals	2,322	2,320	3,904	3,902	4,264	4,261	2,632	2,630
Process of Care Z-Score	0.048	0.015	0.043	0.027	0.026	0.019		
	(0.010)	(0.010)	(0.009)	(0.008)	(0.009)	(0.009)		
Hospitals	2,398	2,396	3,666	3,664	3,920	3,918		
Patient Survey Z-Score	-0.065	-0.041	-0.003	0.000	0.007	-0.004	0.037	0.014
	(0.015)	(0.012)	(0.011)	(0.009)	(0.011)	(0.008)	(0.022)	(0.016)
Hospitals	3,498	3,496	3,598	3,595	3,610	3,607	3,061	3,058

This table shows our baseline dynamic allocation results from Table 4 in comparison to an alternative allocation constructed by mechanically assigning each patient to his closest hospital. Only hospitals that treated at least one patient with the condition in 2008 are eligible for mechanical assignment. Distance is measured from the ZIP code centroid of the patient's residence to the ZIP code centroid of the hospital. The sample for each regression is all hospitals with the relevant quality measure and at least one mechanically allocated patient in 2008. Standard errors are bootstrapped with 300 replications and are clustered at the market level.

Table A19 - Correlation with CMS Quality Measures

Measure \ Condition	(1) AMI	(2) HF	(3) Pneu
Risk-Adjusted Mortality	0.79	0.73	0.82
	[2,802]	[3,788]	[3,994]
Risk-Adjusted Readmission	0.66	0.67	0.71
	[2,254]	[3,681]	[3,924]

Each cell shows the correlation between our 2008 empirical-Bayes-adjusted quality measure and the CMS 2008 risk-standardized quality measure. We produce our risk-adjusted survival measure as risk-adjusted mortality to match the CMS measure. Hospitals used to calculate correlation in brackets.