Quality Information Disclosure and Patient Reallocation in the Healthcare Industry: Evidence from Cardiac Surgery Report Cards

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Abstract

In a healthcare industry with capacity constraints, the best healthcare providers are often congested after quality information disclosure. This congestion can lead to the reallocation of urgent patients to low-quality healthcare providers. The reallocation can have a detrimental impact on the overall patient survival rate if sicker patients benefit more from the best providers. This paper provides the first empirical evidence regarding this problem in the context of the publication of cardiac surgery report cards. I find that these report cards can have a negative impact on positive assortative matching between patients and surgeons due to a reallocation of high-risk patients to low-quality surgeons. Despite the quality improvement in response to these report cards, such patient reallocation can still be a problem, conditional on the improved quality, and thus should not be ignored.

Keywords: quality information disclosure, assortative matching, patient reallocation, capacity constraint, quality improvement, hospital and surgeon report cards

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1. Introduction

Quality information disclosure about healthcare providers enables patients to obtain information on physicians and hospitals. For example, Medicare Hospital Compare[1] provides quality information about hospitals, including patient surveys, infection rates, and death rates, and Healthgrades[2] offers patients' reviews and ratings of physicians and quality information about hospitals. These sources of information reduce information asymmetry between patients and healthcare providers and ideally allow patients to choose the best healthcare providers on the market (Dranove and Jin 2010; Dranove and Sfekas 2008). However, the demand from informed patients means that high-quality physicians and hospitals are often overbooked, have long wait lists, or are not taking on new patients, due to capacity constraints. As a result, patients with urgent needs who cannot plan in advance or wait longer than others are reallocated to low-quality physicians. As urgent patients are relatively sicker and would benefit more from high-quality healthcare providers, this reallocation can run counter to the expected impacts of positive assortative matching (Becker 1973). Nevertheless, few studies have examined this problem.

The primary aim of this study is to investigate the impact of quality information disclosure on the reallocation problem. I use a novel dataset from the cardiac surgery industry in the U.S. state of New Jersey that provides an ideal setting for examining patient reallocation. In November 1997, the New Jersey Department of Health (NJDOH) began publishing coronary artery bypass graft (CABG) surgery report cards every one or two years. These report cards provide risk-adjusted mortality rates (RAMRs) by surgeon and hospital. Using this exogenous policy shock, I find that after the publication of these report cards, urgent patients were less likely to choose low-quality hospitals. This finding on between-hospital reallocation is in line with previous empirical evidence on the impact of quality information disclosure on vertical sorting in the healthcare industry (e.g. Dafny and Dranove 2008; Wang et al. 2011) and other industries (e.g. Chevalier and Mayzlin 2006; Reinstein and Snyder 2005; Zhu and Zhang 2010).

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[1] www.medicare.gov/hospitalcompare/search.html
[2] www.healthgrades.com

Within hospitals, however, I find that after the release of the report cards, elective patients were more likely to be operated on by high-quality surgeons, while urgent patients were more likely to be operated on by low-quality surgeons. Regarding this within-hospital reallocation effect, this paper argues that changes in patient–surgeon matching following the policy shock occurred mainly because high-quality surgeons could not meet the higher demand, due to their capacity constraints. I also examine whether this phenomenon was due to surgeon gaming behavior (Dranove et al. 2003; Schneider and Epstein 1996; Zhang 2011), in which high-quality surgeons with sufficient patient volumes might strategically turn away urgent patients, who are more likely to be severely ill, to improve the RAMRs in their report cards. If this was the case, they might have had greater incentives to turn away more risky patients even among the urgent patients. However, this paper shows that there is no evidence for this, and thus gaming behavior does not seem to have driven the within-hospital patient reallocation in New Jersey. Additionally, to prove that surgeons' capacity constraints played a role in within-hospital patient reallocation, I show that after the publication of the first report cards, patient waiting times for high-quality surgeons increased and the number of patients in these surgeons' capacity slots increased before urgent patients were scheduled.

Based on these findings, I argue that there are striking implications for within-hospital patient reallocation. Nallamothu et al. (2001) suggest that there is an interaction between provider quality[3] and the severity of patient illness in the outcomes of CABG surgeries. In this paper, I find in addition that high-quality healthcare providers provide better treatment to urgent patients who are more likely to be severely ill. This suggests that the report-card system can not only be detrimental to the reallocated urgent patients, but it can also reduce the overall patient survival rate for CABG surgeries because it can interrupt the positive assortative matching between patients and surgeons. In particular, this paper argues that before the publication of the report cards in New Jersey, vertical sorting was more efficient because urgent patients in New Jersey were more likely to be referred to high-quality surgeons while elective

[3] Nallamothu et al. (2001) measure provider quality using hospital-level surgical volume, not risk-adjusted mortality rates.

patients were not. This implies that the information in the report cards was not new to the cardiologists, as suggested by Dranove and Sfekas (2008), and that the report cards changed how this information was used within hospitals. That is, cardiologists already knew who the high-quality surgeons were prior to the release of the report cards, and they used this information for urgent patients who could benefit more from the best surgeons; but after the policy change, the report-card system induced cardiologists to use the information for more patients, and patients could also use the report cards as newly available information. Thus, after the report-card publication, elective patients were referred to high-quality surgeons more frequently than before. This paper suggests that this excess demand was not socially optimal within hospitals.

Although this within-hospital reallocation can have a negative impact on patient survival, the report-card system can also benefit patients by fulfilling another goal, namely, stimulating healthcare providers to improve the quality of their care. Several previous studies on quality information disclosure have found that sellers subsequently improved the quality of their service (Chassin 2002; Cutler et al. 2004; Hannan et al. 1994; Jin and Leslie 2003). Similarly, hospitals and cardiac surgeons may have improved the quality of their care after the report cards were published. I report evidence for this by showing that surgeons improved their quality, poor surgeons left the market, and better surgeons entered the market.

Although this quality improvement in New Jersey increased the overall patient survival rate for CABG surgeries, this paper argues that the within-hospital patient reallocation effect induced by quality information disclosure should not be ignored because this reallocation can be generalized to many situations in healthcare markets. Top hospitals and physicians are often overwhelmed with patients. If the amount of governmental mandatory quality disclosure in the healthcare industry is more than is socially optimal[4], then a reallocation problem due to capacity constraints can occur. It can also become

[4] An amount of disclosure about healthcare providers' quality is socially optimal for patient sorting if disclosing more or less information has a negative impact on positive assortative matching between patients and healthcare providers. This amount is usually unknown to policy makers ex ante. However, investigating the current status of patient sorting and healthcare providers' capacity can help them determine an appropriate level of mandatory disclosure.

more critical when the quality improvement in the market in response to the disclosure is not sufficient.

This paper contributes to the literature on quality information disclosure by empirically showing why providing this information about capacity-constrained healthcare providers can cause an undesirable effect. To the best of my knowledge, this is the first paper to document empirical evidence on patient reallocation and its implications for assortative matching. A substantial amount of work on the CABG report cards finds that their impact on market shares may be small or even non-existent (Chassin 2002; Epstein 2006; Jha and Epstein 2006; Mukamel and Mushlin 1998; Mukamel et al. 2007). The present paper suggests that when surgeons are already at or near capacity, the market share may not change. However, the report-card system can significantly affect patient welfare through a change in surgeons' patient mix.

The rest of this paper is structured as follows. Section 2 provides institutional background information regarding CABG surgery and its market in New Jersey. Section 3 presents the data and key metrics in detail. Section 4 provides initial evidence of patient reallocation. Section 5 presents the empirical models and results. Section 6 shows evidence of surgeon quality improvement. Section 7 concludes the paper.

2. Institutional Background

CABG Surgery: Definition, Referral Steps, and Scheduling

CABG surgery is open-heart surgery that treats patients who have an impaired blood supply to their heart muscles. If the coronary artery narrows, then the blood supply to the heart muscles is impaired. This can cause anginal pain or a heart attack (more formally known as acute myocardial infarction (AMI)), both of which are classified as coronary heart disease (CHD). The average annual mortality rate from CABG operations across hospitals in the US was about 3–4% in the 1990s, but it is now around 2% (Li et al. 2010). This average mortality rate after CABG surgery is significantly higher than the mortality rates for other types of common surgical procedures, and thus CABG surgery is regarded as one of the riskiest surgical procedures.

The steps for patient diagnosis and referral for CABG surgery are as follows. There are two referral steps. The first referral is from referring physicians to cardiologists: Patients who have chest pain are referred to a cardiologist by their physician. If the patient's symptom is mild, the cardiologist will begin treatment with medicine. However, if the cardiologist suspects that the patient is suffering from a severe CHD, then an interventional cardiologist[5] will perform a catheterization of the coronary vessels to see how many coronary arteries have narrowed. Based on the catheterization results, the cardiologist will decide whether the patient requires a percutaneous transluminal coronary angioplasty (PTCA) or CABG surgery. If they opt for PTCA, the interventional cardiologist can immediately insert balloons or stents along with the catheter during the catheterization. If they choose CABG surgery, a second referral is made: Soon after the catheterization is complete, the patient is referred to a cardiac surgeon, who then schedules the CABG.

Although cardiac surgeons are not chosen during the first referral step, the referral decision during this step can significantly limit the choice set of hospitals and cardiac surgeons in the second referral step, because most cardiologists in the US are affiliated with only a small number of CABG-capable hospitals. Therefore, after referral to a cardiologist, patients' surgeon choice sets are limited to surgeons in one or two hospitals because patients usually follow their cardiologist's recommendations. Referring physicians also have hospital affiliations. However, since many referring physicians are not directly affiliated with CABG-capable hospitals, they usually have more choices of hospitals than do cardiologists. Thus, in most cases, the hospital choice set is determined in the first step. This implies that if referring physicians refer their patients to a cardiologist in a high-quality CABG-capable hospital, those patients are more likely to receive better surgical treatments.

In the second referral step, cardiologists consider the patient's urgency status as well as which cardiac surgeons are available. All patients who receive CABG surgery are basically in a severely ill condition and will need to have the operation performed in the near future (in most cases, within two

[5] Interventional cardiologists can be patients' attending cardiologists or they can be other cardiologists who work in the same hospital and have intervention skills.

months after catheterization). Thus, most patients schedule their surgery soon after the catheterization. However, how soon the operation should be done depends on the level of urgency, which classifies CABG surgeries into three categories: elective, urgent, and emergent. In elective and urgent cases, patients generally meet their surgeons through their cardiologists' referral. For elective patients, the surgeons' availability for operations within a short period (e.g., within a week) is not always necessary because elective patients' condition is less severe, so they can wait and schedule their operations when their preferred surgeon becomes available. For urgent cases, however, cardiologists need to seriously consider the surgeons' availability. Urgent patients' unstable conditions cannot be addressed through medical or interventional treatments, and thus, they cannot be discharged before undergoing surgery. Rather, they should meet their surgeons and schedule their operations on an urgent basis immediately after catheterization and during the same hospitalization. Emergent patients have conditions that are more severe than those of urgent patients, and usually, only a small number of CABG operations are performed on an emergent basis. Due to the nature of the emergency, operating surgeons are determined by who is on call on a particular day in each hospital rather than being chosen by the patient or the referring cardiologist.

In addition to surgeon availability, cardiologists may also consider the quality of surgeons when making patient referrals. One New Jersey cardiologist whom I interviewed said that cardiologists consider surgeon quality when referring severely ill patients, but many cardiologists simply refer their patients to cardiac surgeons with whom they have a good relationship. However, some patients do not follow their cardiologists' initial recommendation. The survey of Schneider and Epstein (1996) reports that for 56% of the cardiologists who participated in the survey, 1–10% of their patients did not follow their initial recommendation, which suggests that patients' own preferences can also affect the choice of cardiac surgeons. However, even when patients choose an alternative surgeon, the alternative surgeon is usually chosen from among the cardiac surgeons who are affiliated with their cardiologist.

Once patients are referred to a cardiac surgeon, the surgeon generally schedules operations immediately. When cardiac surgeons schedule elective patients, they are not so limited by their capacity status because elective patients can wait. However, when they schedule urgent patients, their capacity status becomes important. One cardiac surgeon whom I interviewed for this research said that when their capacity is full, new urgent patients should find an available alternative surgeon because it is unusual for a surgeon to move an already scheduled elective operation to another day due to a new urgent case. Thus, a surgeon's capacity status plays an important role in scheduling urgent patients.

New Jersey CABG Market and Report Cards in the Late 1990s

About 9,000 patients each year had CABG surgeries in New Jersey during the late 1990s. By the end of 1997, only 13 hospitals in New Jersey could perform open-heart surgery. St. Francis and St. Barnabas Medical Centers were licensed to perform open-heart surgery in 1998 and 1999. Figure 1 shows each cardiac surgery hospital's location in the late 1990s. In addition to these CABG-capable hospitals, approximately 50 other hospitals in New Jersey could perform catheterizations to determine whether patients needed a CABG.

In November 1997, the New Jersey Department of Health (NJDOH) released the state's first cardiac surgery report cards for isolated CABG surgeries performed in 1994 and 1995. The report cards provided the public with hospital-level and surgeon-level quality information on CABG surgery. They reported the risk-adjusted mortality rates (RAMRs), the observed mortality rates (OMRs), the expected mortality rates (EMRs), the number of surgical cases, and the number of patient deaths after surgery for the 13 hospitals and the 48 cardiac surgeons in the state who performed at least 100 isolated CABG surgeries during 1994 and 1995. New Jersey's second cardiac surgery report cards were published in March 1999, for isolated CABG surgeries performed during 1996 and 1997. Since 2000, the NJDOH has released cardiac surgery report cards every one or two years.[6]

All of the report cards and their technical reports were published on the NJDOH website, and hard copies were sent to all of the hospitals and public libraries in the state. In addition, on November 19,

[6] See http://www.state.nj.us/health/healthcarequality/health-care-professionals/cardiac-stroke-services/cardiac-surgery/ for recent report cards.

1997, the NJDOH held a press conference on the first report cards. On November 20, 1997, major newspapers and media in New Jersey published articles about the report cards on their front pages, some with a link to the NJDOH website so that readers could refer to the entire report cards.[7] The media also published follow-up articles in 1998, 1999, and 2000. From these sources, patients and physicians could access the information provided on the report cards. I interviewed a NJDOH research scientist who had managed the report card system from the beginning. She said that patients and their families had called the NJDOH to ask for more information about the cardiac surgery hospitals and surgeons. This suggests that patients actually used the information in the report cards.

Although the first report cards were published in November 1997, the impact of the first report cards may have started between January 1997 and November 1997, because both cardiologists and cardiac surgeons as well as hospitals were aware at the beginning of the year that the first report cards would be released in November. Between January 1997 and November 1997, all of the CABG-capable hospitals and their doctors were working with the NJDOH on data cleaning, validation, feedback, and final data sign-offs. Since cardiologists could have information about hospital and surgeon quality from this report-card preparation step as well as their own experience, the incoming report-card system may have pushed them to make more use of such information for their patient referrals, even before the official report-card publication.

3. Data

I use two primary datasets in this paper. The first comprises patient-level hospital discharge data for New Jersey for the period 1994 to 1999, inclusive. This dataset includes patient-level diagnoses, procedure codes, admission sources, in-hospital deaths, hospital charges, and demographics (age, gender, race, and zip code). It also includes identifiers for patients, hospitals, attending physicians, and surgeons. The diagnosis and procedure codes were based on the International Classification of Diseases,

[7] See, for example, "Cardiac surgery stats put heat on hospitals: State hopes report card will spur improvement", *Star-Ledger*, November 20, 1997, and "Death rate for bypasses less than 4%", *Asbury Park Press*, November 20, 1997.

Ninth Revision, Clinical Modification. Using these codes, I extract from the data those patients who underwent CABG operations between 1994 and 1999. I also identify the dates patients underwent catheterizations and the CABG surgeries, based on the procedure codes and dates provided in the data.

The second dataset comes from the New Jersey Open Heart Surgery (OHS) Registry, also for the period 1994 to 1999, inclusive. This dataset includes information about patients who underwent open heart surgeries in New Jersey. I identify patient risk factors, patient urgency statuses, street-level patient addresses, and cardiac surgery types—such as isolated CABG or CABG plus cardiac valve replacement—from the dataset. The dataset provides identifiers for both the cardiac surgeons and the referring cardiologists.

I merge the two datasets, using patient demographics and date information such as birthdates, admission dates, and surgery dates. The merged data consists of a total of 43,579 patients who underwent CABG surgeries between 1994 and 1999. However, as this paper's main study period is 1995 to 1999, inclusive, I use data for the year 1994 to calculate time-varying quality measures not provided in the report cards, such as surgical cases and observed mortality rates for one year prior to the operation dates. I also use this data to measure the severity of patient illness with the patient risk model.

From the merged data, I extract two subsamples. For the first subsample, I extract the 35,031 patients who had CABG surgeries between 1995 and 1999 and whose referring cardiologists and catheterization dates could be identified. This subsample includes a total of 87 cardiac surgeons across 14 hospitals.[8] Forty-five of these cardiac surgeons were included in the 1994–95 report cards.[9] I use this subsample to examine surgeons' entering and exiting the market, their quality improvement, and patient reallocations across all surgeons in New Jersey. However, since many surgeons either exited or entered the market during the study period, this subsample is inappropriate for an investigation into patient reallocation across the same set of surgeons who practiced before and after the report-card publication.

[8] See the top graph of Figure A1 in Online Appendix A for the distribution of the number of surgeons per hospital for the 87 surgeons.
[9] Of the 48 cardiac surgeons on the 1994–95 report cards, three surgeons had already exited the market in 1994.

Thus, of the 87 cardiac surgeons, I exclude 12 who appeared on the first report cards but left the market after 1994. I also exclude 42 surgeons who were not rated on the first report cards because their patient volume was too small or they had entered the CABG market after the publication of the first report cards. This leaves a total of 23,922 patients, 33 cardiac surgeons across 14 hospitals,[10] and 735 referring cardiologists in the second (final) subsample. Table 1 presents the descriptive statistics of patient and surgeon characteristics for the final subsample. In this paper, I use this final subsample as a basis for examining patient reallocation across the surgeons whose quality was evaluated in the first report cards.

In the final subsample, about 79% of the patients were referred to cardiac surgeons who worked in the same hospital where they underwent their catheterizations. About 16% of the patients had catheterizations in CABG-incapable hospitals and were then referred or transferred to cardiac surgeons at the CABG-capable hospitals with which the referring cardiologists were affiliated. In contrast, about 5% of the patients were referred or transferred to CABG-capable hospitals that the referring cardiologists were not affiliated with. This suggests that once patients choose their cardiologists, their choice of cardiac surgeons is limited to those with whom their cardiologists are affiliated, as explained in Section 2—that is, once the patients have received their catheterizations, most of them are sorted across the surgeons within the same hospital.

Finally, I use a secondary dataset in Section 5.3 of this paper to examine the border effect. The number of patients in New Jersey who received CABG surgery in New York and vice versa are important pieces of information for understanding an institutional fact about the CABG market near the border. However, the primary dataset in this paper does not have information about patients who received treatments in neighboring states. Therefore, I use the New Jersey and New York State Inpatient Databases (SIDs) from the Healthcare Cost and Utilization Project (HCUP) for the years 1995, 1997, 1998, and 1999.[11] These are hospital discharge datasets, but all direct patient- or doctor-identifiable

[10] See the bottom graph of Figure A1 in Online Appendix A for the distribution of the number of surgeons per hospital for the 33 surgeons.

[11] For reasons that I do not know, half of the total inpatient records in the NY SID for the year 1996 are missing. Thus, I do not use either the NJ or the NY SIDs for the year 1996. In addition, an SID for Pennsylvania is not

information is de-identified. However, they provide patients' zip codes. Using the zip code information, I determine the proportion of patients who left their state to have CABG surgeries in the neighboring state.

Patient Severity of Illness

The severity of a patient's illness is measured as the probability of patient death during the hospitalization following surgery. I predict this by using a risk model that is based on the Society of Thoracic Surgeons' (STS) 2008 cardiac surgery risk models. Their cardiac surgery registry is the largest in the world and includes records for more than 3.6 million operations (Shahian et al. 2009). Their model includes much more detailed patient risk factors than the model that was used to calculate hospitals' or surgeons' risk-adjusted mortality rates (RAMRs) in New Jersey's report cards. However, the STS models do not control for quality differences across cardiac surgeons. Even if two patients have the same risk factors, a patient who is treated by a better surgeon may have a lower probability of death. Thus, to control for surgeon quality, I include the surgeon fixed effects in the risk model. I also include the half-year fixed effects in the model to control for technological developments. The risk model that I use in this paper is:

$$logit\left(prob\left(death_{ijt}\right)\right) = \boldsymbol{Z}_{\boldsymbol{i}}'\beta + S_j + Y_t + \varepsilon_{ijt}, \qquad (3.1)$$

where $\boldsymbol{Z_i}$ is a vector of risk factors for patient *i*, S_j is surgeon *j*'s fixed effect, and Y_t is half-year *t*'s fixed effect. The dependent variable is a binary variable that indicates a patient death in the hospital discharge data. Patient risk factors are identified from the risk variables in the New Jersey OHS registry or the diagnosis or procedure codes found in the hospital discharge data. I estimate this model using the 1994 to 1999 data for the 87 cardiac surgeons. Table 2 shows the estimation results. This risk model is more

available from the HCUP.

precise (c-statistics: 0.87) than the New Jersey model (c-statistics: 0.78) that was used for the first report cards. Also, it indicates that renal failure, cardiogenic shock, previous cardiac operations, and cerebrovascular accidents are highly correlated with patients' probability of death. Using the estimated parameters, I predict the intrinsic patient severity of illness (expected patient mortality after surgery) as $\boldsymbol{Z}_i'\hat{\beta}$.

One limitation of this paper's risk model should, however, be noted: if surgeons systematically select patients with unobservable factors that are positively (negatively) correlated with the probability of death in the risk model, then the patient severity of illness is underestimated (overestimated), and thus Equation (3.2) underestimates (overestimates) surgeon quality.

Surgeon Quality

The New Jersey report cards measure hospital and surgeon quality by their RAMRs. Equation (3.2) shows how this measure is calculated:

$$RAMR_j = \frac{OMR_j}{EMR_j} \times State\ Average\ OMR, \tag{3.2}$$

where OMR_j is surgeon j's observed mortality rate and EMR_j is the expected mortality rate for surgeon j's patients. In the report cards, EMR_j is calculated by using the New Jersey risk model to predict the patient mortality rate. Since the state average *OMR* is invariant across all surgeons, $\frac{OMR_j}{EMR_j}$ determines surgeon quality as measured by $RAMR_j$. In the following analysis, $RAMR_j$ in the 1994–95 report cards is the quality measure of surgeon j. This paper examines how patient–surgeon matching changed in response to the publication of this measure.

Additionally, I calculate another quality measure that is based on Equation (3.2), using the prediction of patient severity of illness, $\boldsymbol{Z}_i'\hat{\beta}$, from the risk model Equation (3.1). I calculate my own

EMR_j by summing the predicted severity of patient illness across all patients of surgeon j. I also calculate my own OMR_j and $State\ Average\ OMR$ during the study period using the number of surgeon j's patient deaths and the total number of patient deaths in the data, respectively. This quality measure is used to examine surgeons' quality improvement in response to the report-card publication because unrated surgeons' quality is not reported in the report cards.

Interaction of Patient Severity of Illness and Surgeon Quality

A finding of Nallamothu et al. (2001) suggests that there is an interaction between provider quality and patient severity of illness in the outcomes of CABG surgeries: sicker patients can benefit more from high-quality healthcare providers. Figure 2 shows that there is such an interaction. In Figure 2, I divide the surgeons in the final subsample into two groups (17 high-quality surgeons vs. 16 low-quality surgeons), based on the reported RAMRs, and I plot the relationship between the patient severity of illness as measured by $\boldsymbol{Z_i'}\hat{\beta}$ in Equation (3.1) and the observed death rate for each group using local polynomial smoothing with an Epanechnikov kernel function. As Figure 2 shows, the surgical outcomes for patients whose condition is relatively mild (patient severity < 0.046) may not differ between low- and high-quality surgeons. In Figure 3, 79.8% of the patients in the final subsample belong to this group. However, for more severely ill patients, those whose severity of illness is between 0.046 and 0.247 (17.2% of the patients in Figure 3), the observed patient death rates are higher for low-quality surgeons. This means that severely ill patients can be better off when they are treated by high-quality surgeons. This interaction of patient severity of illness and surgeon quality suggests that the reallocation of urgent patients to low-quality surgeons can have a negative impact on patient welfare, because urgent patients are more likely to be severely ill than elective patients. However, for very severely ill patients, those whose severity is greater than 0.247 (3.1% of the patients in Figure 3), Figure 2 shows that their surgical outcomes do not differ between low- and high-quality surgeons, potentially suggesting that their condition is so severe that even high-quality surgeons cannot perform better than low-quality surgeons.[12]

4. Initial Evidence on Patient Reallocation

Propensity Score Matching

As initial descriptive evidence on patient reallocation, the patient mix along the urgency dimension across cardiac surgeons can be compared before and after the report-card publication. However, one obstacle is that the distribution of the patient urgency status during the study period changed significantly. Table 3 shows that the number of elective cases decreased over time, from 56% in 1995 to 35% in 1999, while the number of urgent cases increased from 38% in 1995 to 61% in 1999. This change occurred because the definition of patient's urgency status changed during the study period. When the NJDOH was collecting the 1994–1995 OHS registry data, some hospitals reported their patient urgency statuses based on the STS definition, while other hospitals reported it using their own criteria. For the 1996–1997 OHS registry data, a few more hospitals began to use the STS definition. For the 1998–1999 OHS registry data, the NJDOH created their own patient urgency definition. After examining all of the data-collection forms from those years, I found that the NJDOH definition explicitly specifies that patients who have acute myocardial infarction (AMI), an intra-aortic balloon pump (IABP), or unstable angina with intravenous nitroglycerin are considered "urgent", but the STS definition that was used before 1998 does not define urgent patients as such. Consequently, patients with AMI, IABP, and unstable angina were more likely to be classified as urgent patients beginning with the 1998–1999 OHS registry data.[13]

This measurement inconsistency, due to the change in the definition of urgency, makes it difficult to compare the elective–urgent patient mix before and after the report-card publication. In addition, this problem could cause bias in the estimates of the empirical models presented in the next section. For example, if patients who would have been classified as "elective" based on the 1995 criteria were

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[12] Another reason may be that there are not enough "very severely ill" patients in the data to make a statistical comparison. The confidence intervals in Figure 2 widen as patient severity of illness increases.
[13] Table A1 in Online Appendix A provides evidence for this.

classified as “urgent” in the 1999 data and if these patients were insensitive to surgeon quality, then the urgent cases in the 1999 data may appear more insensitive to surgeon quality than the urgent cases in the 1995 data. Therefore, the potential endogeneity from this measurement inconsistency should be controlled for.

To control for this potential endogeneity, I use a one-to-one (without replacement) propensity-score matching method. For each patient urgency group (elective patients and urgent patients), I match each year’s patients to the base year’s patients, based on the estimated propensity score, by running logistic regressions with patient risk factors.[14] In the logistic regressions, the dependent variables are binary variables that indicate whether patients received CABG operations in the base year. The base year for the elective cases is 1999 and the base year for the urgent cases is 1995; this is because 1995 and 1999 have the smallest number of urgent and elective patients, respectively (see Table 3), and thus represent more reliable elective and urgent samples. Regarding this matching, Table 4 reports the results from the logistic regressions. Column (1) shows which risk factors distinguish the year 1995 from the year 1999 for urgent cases. Congestive heart failure, cardiogenic shock, and AMI, which represent patient urgency better than other risk factors, are more likely to be related to the urgent patients in the base year 1995. On the other hand, column (2) shows that IABP, unstable angina, and AMI, which represent patient urgency, are less likely to be related to the elective patients in the base year 1999, compared to the elective patients in 1995. This implies that the urgent patient population was more urgent in 1995 than in the other years. Similarly, the elective patient population in 1999 was less urgent than in the other years. After one-to-one propensity-score matching, the risk characteristics of both types of patients are balanced, as shown in Figure 4. For matching (1) in Table 4, Rubin’s R is 1.05 and Rubin’s B is 9.7. For matching (2) in Table 4, Rubin’s R is 1.52 and Rubin’s B is 16.8. These suggest that the quality of balancing is sufficient, given Rubin (2001)’s criteria.

[14] Propensity score matching is not applied to the emergency cases because the definition of emergency CABG surgery did not change during the study period and the proportion of the emergency cases in Table 3 does not show abrupt changes from 1995 to 1999.

Model-Free Evidence on Patient Reallocation

Table 5 shows how the patient volume and mix changed after the publication of the first report cards. I compare two time periods before and after the publication of the first report cards (1995–1996 and 1998–1999). I exclude patients from the year 1997 in this analysis, because this was a transition period from hospitals and physicians having an awareness of the upcoming report cards to the actual report-card publication in November 1997. I divide the 33 cardiac surgeons in the final subsample into two groups (17 high-quality surgeons vs. 16 low-quality surgeons) based on their risk-adjusted mortality rates in the first report cards.

The top panel of Table 5 for the non-matched final subsample shows that the patient volume of each group barely changed after the report-card publication This result also holds for the propensity-score matched final subsample. However, the bottom panel of Table 5 for the propensity-score matched final subsample shows that the patient mix changed.[15] For the high-quality surgeon group, the number of elective patients increased by 220 but the number of urgent patients decreased by 251 after the publication of the first report cards. In contrast, for the low-quality surgeon group, the number of elective patients decreased by 220 and the number of urgent cases increased by 251. These results indicate that the report-card publication reallocated 7.2% of the total number of urgent patients to low-quality surgeons and 6.8% of the total elective patients to high-quality surgeons. The two rightmost columns in the bottom panel of Table 5 show the observed death rates for elective and urgent patients during the pre- and post-publication periods. In both periods, the observed death rates for urgent patients were higher than the rates for elective patients for both groups of surgeons, indicating that urgent patients are more complex (severe) cases. In addition, those two columns show that there is an interaction of patient severity of illness and surgeon quality in the outcomes of the CABG surgeries. In both periods, the difference in the death rates between high- and low-quality surgeons is greater for urgent cases, which, again, are more complex. Also, these two columns show that, after the report-card

[15] I do not use the non-matched final subsample to examine a change in the patient mix because of the measurement inconsistency of the patient urgency status.

publication, both high- and low-quality surgeons improved their quality for both types of patients.

Two implications can be drawn from this table. One is that the report cards were detrimental to the reallocated urgent patients. Although the death rate of patients of low-quality surgeons declined from 6.81% to 4.21% after the report-card publication, this rate (4.21%) was still higher than that for high-quality surgeons (3.17%) during the pre-publication period. The other implication is that overall patient welfare after the report-card release may have decreased if there had been no quality improvement during the post-publication period, because there were more additional deaths of urgent patients (251 patients × (6.81% - 3.17%)) due to reallocations to low-quality surgeons than additional survivals of elective patients (220 patients × (3.23%-2.81%)) due to reallocations to high-quality surgeons. However, because surgeon quality improved during the post-publication period, the report cards might have benefited both types of patients. It is noteworthy that this implies that although cardiac surgery report cards can have a negative impact on positive assortative matching between patients and surgeons, they can also benefit most patients by stimulating improvements in the surgeons' quality.[16]

5. Empirical Model Analysis

In this section, I use empirical models to examine whether the patient reallocation induced by the report cards (as shown in Section 4) was statistically significant and how patients were reallocated within and between hospitals. In addition, based on the results from estimating the empirical models, I explain the underlying mechanism behind the patient reallocation.

5.1 Between-Hospital Patient Reallocation

First, I use the following conditional logit model to examine whether there was a change in patient preferences across surgeons in response to the publication of the report cards. Let patient i's utility derived from being treated by cardiac surgeon j in hospital h on date t be as follows:

[16] The quality improvement in Table 5 could have partially been due to surgeons' surgical skill improvements or technological improvements over time that were not necessarily induced by the report cards. However, the discussion in Section 6 suggests that the quality improvement was mainly due to the report-card publication.

$$u_{ijht} = \boldsymbol{\alpha}'(q_j \boldsymbol{T_t}) + \boldsymbol{\beta}' D_{ih}[1\ UR_i\ EM_i]' + \boldsymbol{\gamma}'\big(\boldsymbol{X_{jt}} \otimes [1\ UR_i\ EM_i]'\big) + H_h \times \boldsymbol{T_t} + H_h \times age_i + H_h \times gender_i + \varepsilon_{ijht}, \qquad (5.1)$$[17]

where ε_{ijht} is an error term with a type-I extreme value distribution. Therefore, in this conditional logit model (also in the following conditional logit models, Equations (5.2)–(5.5)), the dependent variable is the probability of choosing surgeon *j* in hospital *h* on date *t*. As explained in Section 2, patients' choice set of surgeons between hospitals (in Equations (5.1) and (5.2)) is determined by the hospital choices of their referring physicians. The choice set for patients whose referring physicians were affiliated with CABG-capable hospitals consists of all the cardiac surgeons in the affiliated hospitals, while the choice set for patients whose referring physicians were not affiliated with any of the CABG-capable hospitals consists of all available cardiac surgeons in New Jersey. Given these choice sets, on average, patients in the final subsample chose their surgeon from 15.3 surgeons across 6.3 hospitals.

In Equation (5.1), q_j denotes surgeon *j*'s quality as measured by surgeon *j*'s RAMR listed in the first report cards, and $\boldsymbol{T_t'} = [1\ Post1_t\ Post2_t\ Post3_t]$ is a vector of dummy variables that indicate pre- and post-publication time periods (Figure 5). The baseline period is 1995 to 1996, the period before the publication of the first report cards, and *Post*1 denotes the transition period from January 1, 1997 to November 20, 1997. During this period, hospitals, cardiologists, and cardiac surgeons knew that the first report cards would be published in November 1997. *Post*2 indicates the period (November 21, 1997 to March 7, 1999) after the publication of the first report cards and before the publication of the second report cards. *Post*3 is the period after the publication of the second report cards and before the year 2000 (March 8, 1999 to December 31, 1999). $[1\ UR_i\ EM_i]$ is a vector of dummy variables to indicate patient *i*'s urgency: baseline, urgent, and emergent. D_{ih} denotes the traveling distance between patient *i*'s location and hospital *h*. $\boldsymbol{X_{jt}}$ is surgeon *j*'s observed death rates and number of CABG surgery cases[18] for the year before date *t*, which represents time-varying quality information that is not contained in the

[17] Henceforth, the operator notation "⊗" denotes a tensor product of two vectors.

[18] The volume–outcome relationship has been documented in many studies (Halm et al. 2002).

report cards. D_{ih} and $\boldsymbol{X_{jt}}$ are interacted with $[1\ UR_i\ EM_i]$ to control for the different preferences according to patient *i*'s urgency status. H_h denotes the hospital fixed effects that control for the observed and unobserved characteristics of hospitals; this variable is interacted with pre and post time periods to control for time-variant hospital fixed effects. It is also interacted with patient age groups and gender. In Equation (5.1), $\boldsymbol{\alpha}$ is the parameter of main interest and shows how patient–surgeon matching changed compared to the baseline patient allocation during the years 1995–1996.

The coefficients for RAMR (baseline) in Columns (1) and (2) of Table 6 show that patients preferred high-quality surgeons even before the pre-publication period. This suggests that some of the report-card information already existed in the market. This preference did not change after the report-card publication (during Post1, Post2, and Post3). However, Table 7 shows that there was a demand shift from low- to medium-quality hospitals during the years 1998–1999.[19] In addition, Figure 6 shows that this demand shift occurred mainly because many urgent patients in the low-quality hospital group were reallocated to the medium-quality hospital group. From the fourth quarter of 1997, when the report cards were published, there was a significant decrease in the proportion of urgent patients in the low-quality group, but the proportion of urgent patients in the medium-quality group increased. To statistically examine this between-hospital patient reallocation along the urgency dimension and to distinguish it from the surgeon-level patient reallocation, I demean the surgeons' RAMRs using the hospitals' RAMRs and construct the following model:

$$u_{ijht} = \boldsymbol{\alpha_1'}(q_j - q_h)(\boldsymbol{T_t} \otimes [EL_i\ UR_i\ EM_i]') + \boldsymbol{\alpha_2'} q_h(\boldsymbol{T_t} \otimes [EL_i\ UR_i\ EM_i]') +$$
$$\boldsymbol{\beta}' D_{ih}[1\ UR_i\ EM_i]' + \boldsymbol{\gamma}'\left(\boldsymbol{X_{jt}} \otimes [1\ UR_i\ EM_i]'\right) + \varepsilon_{ijht}, \quad (5.2)$$

where q_h indicates hospital *h*'s reported RAMR in the first report cards. $\boldsymbol{\alpha_1}$ shows within-hospital patient sorting and $\boldsymbol{\alpha_2}$ shows between-hospital patient sorting based on the 1994–95 report card information, $[EL_i\ UR_i\ EM_i]$ is a row vector in which EL_i, UR_i, and EM_i are patient *i*'s urgency: elective, urgent, and

[19] The report cards report both hospital RAMRs and surgeon RAMRs. I divide the 13 hospitals appearing on the 1994–95 report cards into three groups (four high-quality hospitals, four medium-quality hospitals, and five low-quality hospitals) based on their RAMRs.

emergent. The other variables are the same as the corresponding variables in Equation (5.1).

Column (1) in Table 8 presents the results using the propensity-score matched final subsample. The coefficients for Hospital RAMR (baseline) show that urgent and emergent patients were choosing high-quality hospitals before the report-card publication date. This implies that there was some information about hospitals in the market before the report cards were available and this information was used for more severely ill patients, who were more likely to have CABG surgeries. However, in Column (1), it is unclear whether the report cards changed patients' choice of hospitals after their publication. The coefficients for Hospital RAMR during Post1, Post2, and Post3 show that, for both elective and urgent patients, there was no consistent pattern during the post-publication periods. However, if the analysis is limited to the medium- and low-quality hospitals in the propensity-score matched final subsample, the coefficients for Hospital RAMR for urgent patients in Column (2) show that urgent patients were statistically significantly reallocated from the low-quality hospitals to the medium-quality hospitals during Post2 and Post3. For both of these hospital groups, elective patients were not more likely to choose better-quality hospitals after the report-card publication. Rather, the coefficient for Hospital RAMR × Post3 for elective patients in Column (2) shows that they were more likely to be treated in low-quality hospitals during Post3. However, it is unlikely that they chose low-quality hospitals based on the report-card information. A capacity issue more likely played a role in sorting elective patients into low-quality hospitals. As shown in Table 7, the patient volume of the medium-quality hospital group was much higher during the post-publication period than before. For urgent patients, the coefficient (-0.72) for Hospital RAMR × Post3 in Column (2) is much larger in magnitude than the coefficients for Hospital RAMR during the previous periods (baseline, Post1, and Post2). This implies that urgent patients chose medium-quality hospitals during Post3 more frequently than before, which made the capacity of these hospitals binding, so that elective patients had to choose low-quality hospitals.[20]

[20] The reallocation of urgent patients to medium-quality hospitals during Post2 might not have caused this capacity problem because the effect size was smaller during Post2 than during Post3. This seems reasonable since more patients and referring physicians could use the information in the report cards over time.

There are two possible explanations for urgent patients' between-hospital reallocations. The first possibility is that, after the report-card publication, the low-quality hospitals systematically turned away urgent patients who were more likely to be risky cases and consequently increased their RAMRs. In other words, there might have been gaming behavior on the part of the low-quality hospitals. The other possible explanation is that urgent patients with a higher chance of having CABG operations were more interested in the quality of the CABG surgery and chose better-quality hospitals based on the report cards. Both of these responses to the report cards may have occurred, but the impact of the demand-side response might have been much larger. Compared to the years 1995–1997, more than 500 patients were reallocated from the low-quality hospital group to the medium-quality hospital group during the years 1998–1999 (see Table 7); furthermore, these were largely urgent patients. It would be unreasonable for hospitals to actively turn away this number of patients (roughly more than 20% of their patient volume in 1996 or 1997),[21] thereby sacrificing their profits, while not selectively turning away the more severely ill patients among these urgent cases.[22] In addition, in early 1998, the NJDOH proposed a new regulation under which all hospitals would have to perform at least 350 CABG surgeries per year and each surgeon would have to operate on at least 100 patients per year (Becker 1998). Therefore, it might not have been easy for hospitals to turn away many urgent patients. Also, the fact that this effect occurred immediately after the report-card publication (the fourth quarter of 1997), and not between January 1997 and the publication, supports the notion that this reallocation might be due to a demand-side response.

Therefore, the results in Column (2) of Table 8 imply that referring physicians likely used the first report cards' information on hospital quality when they chose hospitals for their urgent patients. However, they might not have referred these patients to high-quality hospitals because the high-quality hospitals were capacity constrained, and therefore they chose medium-quality hospitals. Although the final classification regarding operation urgency is determined after catheterizations, most of the patients

[21] Note that no surgeons in the sample for this analysis left the market during the study period. Therefore, the demand shift was not due to the exiting of low-quality surgeons.

[22] Table A2 in Online Appendix A shows that urgent patients were reallocated to the medium-quality hospitals from the low-quality hospitals regardless of the severity of their illness.

who eventually receive urgent operations would show urgent symptoms when they first met their referring physicians, and the referring physicians could therefore conjecture that these patients were more likely to have CABG surgeries. On the other hand, the elective patients and their referring physicians in the final subsample were less affected by the report cards when they chose their hospitals. The referring physicians for elective patients usually do not know whether they need CABG surgery. Because elective patients' symptoms are mild, their referring physicians would usually expect them to begin their treatments with medicine. Therefore, the between-hospital effect of the report-card publication likely benefited urgent patients more than elective patients.

5.2 Within-Hospital Patient Reallocation

The coefficients for dRAMR in both columns of Table 8 show that, after the report-card publication, elective patients were more likely to choose high-quality surgeons within hospitals, while urgent patients were more likely to be treated by low-quality surgeons within hospitals. Compared to Column (2) of Table 6, this implies that many surgeons might already have been working at or near capacity, and thus the report cards did not affect these surgeons' patient volumes, but their patient mix.

To examine this within-hospital reallocation in more detail, I use the following conditional logit model:

$$u_{ijht} = \boldsymbol{\alpha}' q_j(\boldsymbol{T_t} \otimes [EL_i\ UR_i\ EM_i]') \times severity_i + \boldsymbol{\beta}' D_{ih}[1\ UR_i\ EM_i]' + \boldsymbol{\gamma}'\left(\boldsymbol{X_{jt}} \otimes [1\ UR_i\ EM_i]'\right) + H_h \times \boldsymbol{T_t} + H_h \times age_i + H_h \times gender_i + \varepsilon_{ijht}, \qquad (5.3)$$

In Equation (5.2), patients' choice set of cardiac surgeons is determined by the hospital affiliations of their referring physicians, and thus it is relaxed to include many surgeons across multiple hospitals for the examination of between-hospital reallocations. However, for a further investigation of the within-hospital patient reallocation, the size of the choice set needs to be limited in Equation (5.3) (and also in the following Equations (5.4) and (5.5)) based on the hospital affiliations of the referring cardiologists because they, not the referring physicians, determined the choices of surgeons after catheterizations, and most of them were affiliated with one or two CABG hospitals.[23] Because of this formation of choice sets, on average, patients in the final subsample choose their surgeon out of 5 surgeons across 1.8 hospitals.

In Equation (5.3), I drop the hospital RAMRs and do not demean the surgeon RAMRs since Equation (5.2) cannot control for hospital characteristics other than hospitals' RAMRs in the first report cards. Instead, I include the hospital fixed effects and interact them with the time fixed effects to control for the time-variant hospital characteristics. The hospital fixed effects are also interacted with patient age groups and gender. In addition, for each urgency type, I use three-way interactions between surgeon quality q_j, time periods $\boldsymbol{T_t}$, and patient severity of illness $severity_i$, to investigate whether high-quality surgeons selectively turned away more risky (severely ill) patients among urgent patients after the report-card publication. $severity_i$ is measured as described in Section 3. The parameter $\boldsymbol{\alpha}$ shows within-hospital patient sorting before and after the report-card publication.

Table 9 shows that the results for within-hospital reallocation are consistent with the results in Table 8. Column (1) in Table 9 shows that urgent patients were more likely to choose high-quality surgeons during the pre-publication (baseline) period. However, urgent patients were less likely to be treated by high-quality surgeons during the post-publication periods (Post1, Post2, and Post3). Instead, elective patients, who did not show preferences for high-quality surgeons during the pre-publication period, were more likely to be treated by high-quality surgeons during the post-publication periods.

This implies that, to some extent, cardiologists already knew each surgeon's quality and used this information to refer urgent patients even before the publication of the report cards. However, it seems that cardiologists did not consider surgeon quality when they referred less severe patients, such as elective patients, before the report-card publication. As the cardiologist I interviewed noted (see section 2), they might simply have referred such patients to surgeons with whom they had good relationships. This suggests that, before the introduction of the report cards, there was efficient vertical sorting of patients

[23] As explained in Section 3, the cardiologists for 5% of the patients in the final subsample were not affiliated with any CABG-capable hospitals. I assume that these cardiologists' choice set consisted of all available cardiac surgeons in New Jersey.

through referrals, which led to positive assortative matching between severely ill patients and high-quality surgeons.

This tendency changed during the post-publication periods. During these periods, cardiologists seem to have been affected by the report-card publication. In surveys of cardiologists in New York and Pennsylvania, approximately 38% said the report cards had affected their referrals (Hannan et al. 1997; Schneider and Epstein 1996). Cardiologists in New Jersey might also have felt under pressure to refer more patients to better surgeons, based on the information on surgeon quality, and thus more elective patients might have been referred to high-quality surgeons than before. They might have felt this pressure even during Post1, because CABG hospitals and physicians knew in January that the report cards would be published in November and they were also working with the NJDOH to process the data for the first report cards.[24] Further, during Post2 and Post3, the report-card information became available to the public, and thus patients could use this information when consulting with their cardiologists and for making more informed decisions. This might explain why the absolute values of the estimated coefficients for RAMR during Post1, Post2, and Post3 in Table 9 increased for elective cases over time, even though the differences were not statistically significant.[25]

For urgent patients, the positive coefficients for RAMR in Table 9 during the post-publication periods do not mean that urgent patients preferred low-quality surgeons. It is likely that both elective and urgent patients wanted to choose high-quality surgeons, but because elective patients chose high-quality surgeons more than before, these surgeons would not have been available to operate on urgent patients who could not wait. Therefore, urgent patients were reallocated to low-quality surgeons as a consequence of the report-card publication.

An alternative explanation for this reallocation phenomenon is that, regardless of the surgeons' capacity status, urgent patients could have been reallocated to low-quality surgeons because high-quality

[24] I examined when elective patients actually began to be referred to high-quality surgeons during Post1. Table A3 in Online Appendix A shows that this change started around July 1997.

[25] Table A3 shows that the ordered coefficients from Post1 to Post3 are not due to continuation of a certain trend from the pre-publication periods before Post1.

surgeons had more patient volume and thus could easily turn away risky (severely ill) patients to improve their report card scores. If this were the case, then more severely ill patients even among the urgent patients might have been turned away more often because the risk-adjustment scheme in the report cards was not perfect, and one additional death due to a mistake could significantly increase a surgeon's RAMR (Lee et al. 2007). However, the coefficients for Severity × RAMR in Column (2) of Table 9 show that high-quality surgeons did not turn away the more severely ill patients among urgent patients after the report-card publication. Rather, they accepted more severely ill patients among the urgent patients during Post1. Therefore, it is likely that the within-hospital reallocation of urgent patients was driven by surgeons' capacity constraints rather than surgeons' gaming behavior.

The findings in this subsection suggest that the change in the patient mix across surgeons after the report-card publication in Table 5 was mainly due to the within-hospital patient reallocation. As reported in Section 5.1, the report-card publication induced urgent patients to choose a better hospital. However, once the urgent patients chose their hospital, they were more likely to be referred to low-quality surgeons within their hospital.

5.3 The Border Effect on Patient Reallocation

In Section 5.2, the empirical setting is a before-and-after design using an exogenous policy shock to publish cardiac surgery report cards in New Jersey. One limitation of this approach is that the within-hospital patient reallocation might have been due to some factors other than the report cards. Using a difference-in-difference design might have been a reasonable approach to address this problem if I had obtained data from other states as a control group. However, such data were not available to me. Instead, I tackle this problem by showing that there were heterogeneous responses to the report cards between New Jersey's border and non-border hospitals. This border/non-border comparison is a useful approach to identifying the capacity issue induced by the report cards. This is because patients near the border in New Jersey could choose alternative surgeons in a neighboring state more easily than patients living far from the border, and thus the capacity and within-hospital patient reallocation issues might not have been critical in hospitals near the border. In this subsection, I use this geographical difference to increase the validity of the main argument of this paper: that the underlying mechanism behind the within-hospital reallocation was a capacity problem.

For the border/non-border comparison, I divide the CABG hospitals in New Jersey into two groups. One group consists of the nine hospitals that were located within 20 miles of Manhattan, New York, or Philadelphia, Pennsylvania, and the other group consists of the five hospitals that were located more than 20 miles away from the two cities.[26] In the final subsample, 13,092 and 10,830 patients had CABG surgeries in the border and non-border hospitals. The RAMR (4.48%) of the border hospitals was lower than that (4.63%) of the non-border hospitals during the pre-publication period (1995–1996). However, the 95% confidence intervals of their RAMRs overlap. During the post-publication period (1997–1999), the average RAMR (2.89%) of the non-border hospitals was lower than that (3.49%) of the border hospitals, but those are not statistically significantly different either. The average number of surgeons per hospital was 2.6 in the border hospitals and 2.8 in the non-border hospitals. The variations in surgeon quality (measured by the standard deviation of RAMRs) within a hospital were 0.92% in the border hospitals and 1.36% in the non-border hospitals.

There are two notable institutional facts that could have affected the hospitals near the border: 1) the average quality of surgeons and hospitals was better in New York and Pennsylvania than in New Jersey during the study period,[27] and 2) the CABG market near the New Jersey–Manhattan or New Jersey–Philadelphia border was competitive because there were many hospitals, as shown in Figure 1. Because of these facts, the New Jersey report cards might not have reallocated patients in the border hospitals.

The state health departments of New York and Pennsylvania had published surgeon-level cardiac surgery report cards earlier (since 1992) than the NJDOH, and thus even patients and physicians in New Jersey had been able to see the quality of surgeons and hospitals in New York and Pennsylvania since the

[26] Hereafter, I refer to the former group as the border hospitals and the latter group as the non-border hospitals.
[27] The average death rate for the CABG surgeries was 2.57% in the 1993–1995 New York report cards. It was 3.1% in the 1994–1995 Pennsylvania report cards. However, New Jersey's death rate was 3.75% during the years 1994–1995, as reported in their first report cards.

early 1990s. Therefore, it is questionable whether, near the border, the report cards in New Jersey would have induced more patients to choose high-quality surgeons than before the report-card publication. It is likely that, near the border, patients in New Jersey who sought information about the quality of surgeons might already have travelled to hospitals in Manhattan or Philadelphia for their surgeries, even after the report-card publication in New Jersey, because they could find better surgeons in those two cities.

Figure 7 shows the locations of patients in New Jersey and New York who crossed the border to have CABG surgeries in the other state during the years 1995, 1997, 1998, and 1999. As explained in Section 3, I use the New Jersey and New York SIDs from the HCUP for this figure. Each circle shows how many patients from that zip code location crossed the border. Near the New Jersey–Manhattan border, 8.3% of the New Jersey patients in Bergen, Essex, Hudson, and Passaic Counties had CABG surgeries in hospitals in New York, and 92% of these patients had CABG surgeries in Manhattan. In contrast, fewer than 1% of the New York patients in New York (Manhattan), Bronx, Kings, Richmond (Staten Island), Queens, and Westchester Counties had their CABG operations in hospitals in New Jersey.[28]

This is strong evidence that many patients in New Jersey preferred surgeons in Manhattan. Also, it suggests that this competitive market environment might already have encouraged cardiologists in New Jersey's border hospitals to refer more patients to high-quality surgeons within their hospital, even before the report-card publication, in order not to lose their patients to the hospitals in Manhattan. Therefore, it is likely that the New Jersey report cards did not change patients' or cardiologists' choices of surgeons near the state's border, which suggests that the within-hospital reallocation effect shown in Section 5.2 might not have appeared in the border hospitals.

To test this border effect, I separate the patient reallocation within the border hospitals from the patient reallocation within the non-border hospitals using the following conditional logit model:

[28] As Figure 7 shows, many patients from Orange and Rockland Counties in New York had CABG operations in New Jersey. This was because there were no CABG-capable hospitals in those counties and the closest CABG-capable hospitals were in New Jersey (see Figure 1). It is unclear why more than 70 patients from only one zip code in Queens County also had their surgeries in New Jersey (see Figure 7).

$$u_{ijht} = \boldsymbol{\alpha}_{\mathbf{1}}' q_j(\boldsymbol{T_t} \otimes [EL_i\ UR_i\ EM_i]') \times border_i + \boldsymbol{\alpha}_{\mathbf{2}}' q_j(\boldsymbol{T_t} \otimes [EL_i\ UR_i\ EM_i]') \times non_{border_i} + \boldsymbol{\beta}' D_{ih}[1\ UR_i\ EM_i]' + \boldsymbol{\gamma}'(\boldsymbol{X_{jt}} \otimes [1\ UR_i\ EM_i]') + H_h \times \boldsymbol{T_t} + H_h \times age_i + H_h \times gender_i + \varepsilon_{ijht}, \tag{5.4}$$

where $border_i$ and non_border_i are dummy variables that indicate whether or not patient *i* chose a hospital in New Jersey that was located within 20 miles of Manhattan or Philadelphia. The definition of the other variables is the same as in the previous models.

Table 10 presents the results. It shows that the report cards induced within-hospital reallocation only in the non-border hospitals. Both elective and urgent patients in the border hospitals were already more likely to be referred to high-quality surgeons before the report-card publication. This result supports the hypothesis that the competitive market environment already encouraged cardiologists affiliated with border hospitals to refer their patients to high-quality surgeons before the publication of the report cards. But the report cards did not change this tendency within those hospitals. Since they were already referring both elective and urgent patients based on surgeon quality, the report cards could not have affected their referral decisions. Furthermore, the remaining patients in the border hospitals might have been less quality-sensitive than the patients who had already left New Jersey, and thus they might not have responded to the report-card publication. Therefore, the report cards could not have induced additional patients to choose high-quality surgeons in the border hospitals, and the capacity status of these surgeons did not change.

In conclusion, the findings in this subsection suggest that the within-hospital reallocation problem that this paper finds in Section 5.2 only occurred when there were no outside options that patients or their cardiologists could alternatively choose, and thus the surgeon's capacity constraint can explain the underlying mechanism of the within-hospital patient reallocation.

5.4 Robustness Check

In this subsection, I show that the patient reallocation effect is robust to including all of the surgeons who were unrated in the first report cards due to their small number of CABG cases, or exited or entered the New Jersey CABG market during the study period. In this test, I use the subsample of 35,031 patients of 87 cardiac surgeons (see Section 3). For this subsample, I also do one-to-one propensity-score matching, which leaves a total of 25,541 patients. Next, I use the following conditional logit model:

$$u_{ijht} = \boldsymbol{\alpha_1'} q_j(\boldsymbol{T_t} \otimes [EL_i\ UR_i\ EM_i]') \times rated_j + \boldsymbol{\alpha_2'}(\boldsymbol{T_t} \otimes [EL_i\ UR_i\ EM_i]') \times unrated_i\ + \boldsymbol{\beta}' D_{ih}[1\ UR_i\ EM_i]' + \boldsymbol{\gamma}'\left(\boldsymbol{X_{jt}} \otimes [1\ UR_i\ EM_i]'\right) + H_h \times \boldsymbol{T_t} + H_h \times age_i + H_h \times gender_i + \varepsilon_{ijht}, \quad (5.5)$$

In Equation (5.5), $rated_j$ and $unrated_i$ are dummy variables that indicate whether surgeon j was rated in the first report cards. Because there is no reported quality rating for unrated surgeons, $unrated_i$ is interacted only with the time periods for each urgency type, without a quality variable. $\boldsymbol{\alpha_2}$ shows whether patients were more likely to choose unrated surgeons during each time period. The definition of the other variables is the same as in the previous models.

Table 11 shows that the within-hospital patient reallocation effect is consistent, even after including all of the other surgeons. The table also shows that both elective and urgent patients were less likely to choose unrated surgeons during the pre-publication period. Unrated surgeons had lower patient volumes, and thus their quality was more likely to be low. Therefore, it is possible that relatively few patients chose them. This tendency was reinforced for elective patients during the post-publication period. For the elective cases, the negative coefficients for “unrated” during Post 2 and Post 3 imply that elective patients chose unrated surgeons less than before. But urgent patients were more likely to be treated by unrated surgeons than before. This suggests that the report-card publication also affected patient reallocation across rated and unrated surgeons. Urgent patients might have been reallocated to unrated surgeons because elective patients were more likely to choose rated surgeons.

5.5 Patient Reallocation and the Role of Capacity

The findings on patient reallocation presented in the previous subsections suggest that urgent patients were reallocated to low-quality surgeons within hospitals due to the capacity constraints of high-quality surgeons. According to the data, elective patients had their CABG surgery approximately

13 days, on average, after catheterization, while urgent patients had it four days, on average, after catheterization. This means that, after the report-card publication, elective patients could schedule their surgeries with high-quality surgeons ahead of the urgent patients because they could wait. However, the results in the previous subsections have a limitation in that the status of surgeon capacity is not directly controlled for because it was not collected in the data. Therefore, I provide additional evidence on the role of capacity in this subsection.

First, I use the following linear regression model to test whether patients' waiting time for high-quality surgeons increased after the report-card publication:

$$waiting_{ijht} = \boldsymbol{w}'(q_j \boldsymbol{T_t}) + H_h \times \boldsymbol{T_t} + \varepsilon_{ijht}, \tag{5.6}$$

In Equation (5.6), $waiting_{ijht}$ denotes patient i's waiting time for the operation with surgeon j in hospital h on date t. q_j denotes surgeon j's quality as measured by the RAMR in the first report cards, and $\boldsymbol{T'_t} = [1\ Post1_t\ Post2_t\ Post3_t]$ is a vector of dummy variables that indicate the pre- and post-publication time periods. H_h denotes the hospital fixed effects; this is interacted with pre and post time periods to control for time-variant hospital fixed effects. To measure $waiting_{ijht}$, it is important to know when the patients were scheduled for their CABGs. However, there is no direct information about this in the data. Instead, I use the catheterization and operation dates in the data, assuming that patients were scheduled for CABG surgery on their catheterization dates. Thus, regardless of their operation dates, I assume that patients who received their catheterizations first were scheduled first. This is a reasonable assumption because cardiologists decide whether patients need to receive CABG operations based on the results of their catheterizations and therefore refer these patients to cardiac surgeons soon after this procedure. Based on this assumption, $waiting_{ijht}$ is defined as the number of days from patient i's catheterization date to patient i's operation date. The parameter $\boldsymbol{w}$ shows how the surgeons' RAMR in the first report cards affected the waiting time.

In addition, in the following model, I test whether high-quality surgeons had more patients in their capacity slot when they were scheduling urgent patients:

$$y_{ijht} = \boldsymbol{v}'(q_j \boldsymbol{T_t}) + H_h \times \boldsymbol{T_t} + \varepsilon_{ijht}, \tag{5.7}$$

In Equation (5.7), y_{ijht} denotes surgeon *j*'s capacity status when this surgeon is accepting patient *i* for an operation in hospital h on date t. The definitions of the other variables are the same as those for Equation (5.6). In this model, y_{ijht} is defined as the number of patients who were scheduled ahead of patient *i* in surgeon *j*'s two-week capacity slot (from seven days before patient *i*'s operation date to six days after patient *i*'s operation date) around patient *i*'s operation date *t* in hospital h. The parameter $\boldsymbol{v}$ shows how the surgeons' RAMR in the first report cards affected their capacity status.

Table 12 presents the results from estimating Equations (5.6) and (5.7) for the non-border hospitals because the within-hospital reallocation effect only occurred in non-border hospitals, as shown in Section 5.3.[29] The coefficients for RAMR during Post2 and Post3 in Column (1) of Table 12 show that, after the report-card publication, patients who chose high-quality surgeons in the non-border hospitals waited longer for their operations. This result suggests that the information provided on the report cards induced more patients to choose high-quality surgeons in the non-border hospitals, but the patients had to wait longer because these surgeons' capacities were binding. Therefore, urgent patients who could not wait might not have been treated by high-quality surgeons. In Column (1) of Table 12, the coefficient for RAMR during Post1 is not statistically significant, but its sign is negative, as are the signs for the coefficients for RAMR during Post2 and Post3.

Column (2) in Table 12 adds more evidence. It shows that, during the post-publication period (Post1, Post2, and Post3), the coefficients for RAMR are statistically significantly negative for urgent patients in the non-border hospitals. This means that, compared to the baseline (the years 1995 and 1996), high-quality surgeons in the non-border hospitals had more scheduled patients in their capacity slot when they were scheduling urgent patients during the post-publication period. Also, as shown in Column (3) of Table 12, when elective patients were scheduled, it does not appear that high-quality surgeons had more

[29] Table A4 in Online Appendix A reports the results for the border hospitals.

scheduled patients in their slot during the post-publication period. This means that elective patients replaced urgent patients in the capacity slots of high-quality surgeons during the post-publication period, because they were more likely to be scheduled earlier than urgent patients.

These results explain why urgent patients were more likely to be reallocated to low-quality surgeons in the non-border hospitals. It would be ideal to directly show that urgent patients were turned away because high-quality surgeons had more patients. However, the data do not allow me to observe when urgent patients were turned away. But considering that surgeons' capacity is limited, the fact that high-quality surgeons had more scheduled patients when they scheduled urgent patients during the post-publication period means that the number of their urgent patients decreased. Therefore, the results in this subsection strongly support the role of surgeon capacity constraints in the within-hospital patient reallocation.

6. Quality Improvement

In the preface to the NJDOH's first report cards, State Commissioner of Health and Senior Services Len Fishman mentioned two goals for the report cards (New Jersey Department of Health and Senior Services 1997). One of the goals was to provide more information to patients and their families, and the other was to improve the overall quality of CABG surgeries. In the previous sections, I examine the impact of the report-card publication on the first goal and find that the information on the report card not only induced more patients to choose better surgeons, but it also caused a within-hospital reallocation problem. In this section, I examine whether the report cards improved the quality of cardiac surgeons and discuss the overall effect of the New Jersey's first report cards on patient welfare.

Figure 8 provides evidence of quality improvement. In this figure, I measure surgeons' quality using their RAMRs during the pre-publication (1994–1996) and post-publication periods (1997–1999). The figure shows that both high- and low-quality surgeons (the 17 high-quality and 16 low-quality surgeons who were reported in the first report cards) and the six unrated surgeons who had not exited the market since 1994 improved their quality from the pre-publication period to the post-publication period.

Table 2 adds more evidence for the quality improvement. In Table 2, the estimated coefficients for the half-year fixed effects show that the patients' probability of death suddenly dropped beginning with the first half of 1997, compared to the previous half-year time periods. This change was statistically significant and consistent during the post-publication periods (see Table A5 in Online Appendix A for the statistical test results). This implies that the overall quality of CABG surgery in New Jersey improved since the first half of 1997. As explained in Section 2, hospitals and surgeons were notified in January 1997 that the report cards would be published in November 1997. Since the magnitudes of the coefficients for the half-year fixed effects do not seem to be ordered going from the pre-publication period to the post-publication period, this sudden improvement in quality cannot be explained by continuous technological development. This suggests that the quality improvement was due to the report-card publication. The cardiologist I interviewed in New Jersey said that hospitals and surgeons in New Jersey could have improved their quality over a short time by examining all of their procedures related to CABG surgery and improving their post-operation management.

I also examine whether, after the report-card publication, cardiac surgeons' entry into or exit from the market improved the overall quality of CABG surgery in New Jersey. There is anecdotal evidence that hospitals in New Jersey started to watch each surgeon's performance after the publication of the report cards and dismissed low-quality surgeons and hired high-quality ones (Leusner 1999). If new surgeons operated on patients as substitutes for the low-quality surgeons who exited the market, then patient welfare might have increased. Figure 8 shows evidence of such substitution. Compared to the pre-publication period RAMR of the 17 high-quality surgeons who were reported on the first report cards, surgeons (both reported and unrated) who exited the market during the post-publication period had significantly higher RAMRs during the pre-publication period. Comparing the surgeon groups who exited during the pre-publication period and the surgeon groups who exited during the post-publication period, more surgeons (9 surgeons during the post-publication period vs. 3 surgeons during the pre-publication period for both the unrated group and the reported group) exited during the post-publication period. In addition, the point estimates of their RAMRs show that the surgeons who exited during the post-publication period had higher RAMRs during the pre-publication period than the surgeons who exited during the pre-publication period, even though the confidence intervals overlap.

Turning to the entry of surgeons, Figure 8 shows that good surgeons entered the CABG market regardless of whether it was during the pre- or post-publication period. However, more surgeons (17 surgeons during the post-publication period vs. 10 surgeons during the pre-publication period) entered during the post-publication period. The post-publication period RAMRs of the surgeons who entered during the pre- or post-publication period are better than the pre-publication period RAMRs of the surgeons who exited during the post-publication period.

These findings suggest that the entry and exit of surgeons as well as the improvement in surgeon quality in response to the report-card publication significantly improved the overall quality of CABG surgery and thus might have benefited all patients in New Jersey. In Figure 8, except for the six unrated surgeons who had not exited since 1994, the post-publication period RAMRs of all the surgeon groups were statistically significantly lower than the statewide death rate (4.75%; the blue dashed line in Figure 8) during the pre-publication period.

Although a detailed welfare analysis is beyond the scope of this paper, a simple calculation using the bottom panel of Table 5 shows that if surgeon quality had not improved after the report-card publication, there might have been 8.2 additional patient deaths due to the within-hospital reallocation.[30] However, for the same patients in the bottom panel of Table 5, the average surgeon quality (measured by patients' death rates) improved from 3.92% to 2.77% from the years 1995–1996 to the years 1998–1999. This means that 76.8 additional patients could have survived due to the quality improvement.[31] Therefore, the net impact of the New Jersey's first report cards on patient survival was positive.

Nonetheless, the negative impact of within-hospital reallocation should not be disregarded, because the reallocation problem can occur, conditional on the improved surgeon quality level. Table 2 and Table

[30] 251 patients x (6.81 - 3.17)% - 220 patients x (3.23 - 2.81)%.

[31] (3.92-2.77)% x 6682 patients (the total number of patients during the period 1998–1999 in the bottom panel of Table 5).

A5 in Online Appendix A show that surgeon quality improved immediately after the report-card publication, but there was no further improvement in surgeon quality, during the post-publication period, beyond the initial improvement. In addition, Figure 8 shows that, even during the post-publication period, the quality of the 16 low-quality surgeons who were rated in the report cards was still statistically significantly lower than that of the 17 high-quality surgeons. Therefore, the reallocation of urgent patients to the low-quality surgeon group may still have hurt them.

7. Conclusion

A key question about healthcare report cards is: what happens if they overwhelm the best providers' capacity and consequently cause the sickest patients to be turned away, when these patients would have benefited the most from these providers? This question and the patient reallocation problem it raises are of first-order importance in the healthcare industry but have been little studied. If patients' illness severity is correlated with their urgency status, then this problem becomes more critical because urgent patients do not have sufficient time to search for quality information or to wait for the best providers to become available.

In this paper, I investigate this question based on a policy change in New Jersey, which was the publication of cardiac surgery report cards. I find that these report cards changed the patient mix along the patient-urgency dimension across surgeons between and within hospitals in New Jersey. Between hospitals, urgent patients with a high chance of needing CABG surgery were less likely to choose low-quality hospitals based on the report-card information. Thus, using these report cards in between-hospital sorting might benefit urgent patients. However, once urgent patients chose their hospital, they were more likely to receive treatment from low-quality surgeons within their hospital because elective patients filled the capacity of the high-quality surgeons ahead of the urgent patients based on the report-card information. Such within-hospital reallocation hurt urgent patients who would have benefited more from high-quality surgeons, due to the interaction of patient severity and surgeon quality in CABG surgery outcomes.

This finding is striking because these report cards could have reduced the overall patient survival rate, depending on the magnitude of the negative impact of within-hospital reallocations on urgent patients. However, this paper also finds that the overall post-CABG patient survival rates increased in New Jersey during the study period because the report cards encouraged surgeons to improve their quality and induced hospitals to dismiss poor surgeons and hire better ones.

Nonetheless, the negative impact of patient reallocation should not be ignored, because this problem can be generalized to many situations in the healthcare industry. For example, emergency departments in high-quality hospitals are always crowded. Because of the many mildly ill patients in emergency departments, ambulances that are transferring severely ill patients are often turned away. The cancer surgery centers of top-notch hospitals are also overwhelmed by many patients, and urgent patients who would benefit more from these hospitals are often forced to choose other hospitals because of waiting times. Even if report cards can improve the overall quality of healthcare, the reallocation problem may still exist, conditional on the improved quality. This problem also becomes more critical when the rate of quality improvement begins to decrease.

Therefore, this paper suggests that health policymakers and hospital administrators may need to redesign their healthcare report-card systems or take complementary measures in order to achieve both quality improvement of healthcare providers and positive assortative matching between patients and healthcare providers. One possible measure would be to adjust the disclosure level of quality information to a socially optimal level. For example, for cardiac surgery report cards, it might be better not to report surgeons' RAMRs. If patients cannot see the information on surgeon-level quality, the reallocation of urgent patients to low-quality surgeons might be lessened. Instead, reporting only hospitals' RAMRs might be sufficient to encourage hospitals and surgeons to improve their quality. Another measure would be for hospital administrators to adopt a policy of assigning more urgent patients to high-quality providers within their hospital. The cardiac surgery report cards would give them an incentive to adopt such a policy because their hospital's RAMR can improve when high-quality surgeons treat more urgent patients. In practice, such a policy means that high-quality surgeons should reserve some of their operation slots for urgent patients. Just as the U.S. Emergency Medical Treatment and Labor Act requires hospitals to maintain a list of on-call physicians for emergency patients, hospitals need to arrange a list of high-quality surgeons for urgent patients. Insurance companies also need to create new incentive plans to make these surgeons more willing to accept urgent patients, because a mismatch between patients and surgeons can lead to bad surgical outcomes, which might require insurance companies to cover additional treatment costs for such a surgical case.

This paper has two limitations. First, the reduced-form models in this paper cannot disentangle demand-side (patients and referring cardiologists) responses from supply-side (surgeons) responses. Although I used alternative tests to identify surgeons' capacity status and rule out surgeon gaming behavior, supply-side responses might still have affected the results in this paper. In addition, it is difficult to do a detailed welfare analysis using these reduced-form models. Second, the quality improvement documented in this paper could be overestimated if there were nationwide technological improvements in CABG surgery during the study period. Although the magnitude of the decrease in the observed death rate in New Jersey from the period 1994–1995 to the period 1998–1999 is larger than the magnitudes in New York or Pennsylvania during similar periods,[32] the latter two states may not be a good control group because they also had a CABG surgery report-card system.

Notwithstanding these limitations, I believe that this paper greatly contributes to providing an avenue for understanding the patient reallocation problems induced by quality information disclosure, and thus it points out the importance of positive assortative matching between patients and healthcare providers in the healthcare industry.

[32] The statewide death rate for isolated CABG surgeries in New Jersey improved from 3.75% during the years 1994–1995 to 2.89% during the years 1998–1999. In New York, it improved from 2.57% during the years 1993–1995 to 2.20% during the years 1997–1999. In Pennsylvania, it improved from 3.1% during the years 1994–1995 to 2.4% during the year 2000.

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Tables

Table 1. Descriptive Statistics

Variable	Mean	S.D.	Min	Max	N
Patient Characteristics					
Age	66.537	10.384	26	96	23922
Female	0.294	0.456	0	1	23922
Distance to hospital (mile)	24.860	144.796	0.000	6541.12	23922
# of Days from Cath to Op	7.757	11.137	0	98	23922
Preoperative Status					
Elective	0.451	0.498	0	1	23922
Urgent	0.496	0.500	0	1	23922
Emergent	0.053	0.225	0	1	23922
Patient Death	0.040	0.196	0	1	23922
Risk Factors					
max(50-Ejection Fraction,0)	6.926	9.059	0	47	23922
Congestive Heart Failure	0.323	0.467	0	1	23922
Cardiogenic Shock	0.032	0.177	0	1	23922
AMI	0.311	0.463	0	1	23922
Unstable Angina	0.706	0.455	0	1	23922
Left Main CHD	0.239	0.426	0	1	23922
# of Stenotic arteries	2.616	0.648	1	3	23922
Previous Heart Op	0.057	0.232	0	1	23922
Chronic Lung Disease	0.152	0.359	0	1	23922
Diabetes	0.347	0.476	0	1	23922
Hypertension	0.771	0.420	0	1	23922
Renal Failure without Dialysis	0.074	0.262	0	1	23922
Renal Failure with Dialysis	0.016	0.126	0	1	23922
Inotropes or IABP	0.109	0.312	0	1	23922
Immunosuppressant	0.009	0.092	0	1	23922
Peripheral Vessel Disease	0.149	0.356	0	1	23922
Cerebrovascular Disease	0.083	0.276	0	1	23922
Cerebrovascular Accident	0.012	0.110	0	1	23922
Valve Disorder	0.166	0.372	0	1	23922
Arrhythmia	0.452	0.498	0	1	23922
Surgeon Characteristics					
CABG Surgery Cases	724.909	356.150	278	1779	33
1994-1995 RAMR (%)	3.325	1.206	1.56	5.75	33

"Cath" means catheterization. "Op" means operation.

Table 2. Patient Risk Model

	Coefficient	Standard error
1994, 2nd half	0.19	(0.14)
1995, 1st half	0.096	(0.14)
1995, 2nd half	0.28**	(0.14)
1996, 1st half	0.12	(0.14)
1996, 2nd half	0.15	(0.14)
1997, 1st half	-0.089	(0.14)
1997, 2nd half	-0.13	(0.14)
1998, 1st half	-0.28*	(0.14)
1998, 2nd half	-0.42***	(0.16)
1999, 1st half	-0.28*	(0.15)
1999, 2nd half	-0.27*	(0.15)
Age	0.038***	(0.0033)
Female	0.41***	(0.056)
Congenital Heart Failure	0.39***	(0.062)
Diabetes	0.048	(0.058)
Renal Failure without Dialysis	1.64***	(0.067)
Renal Failure with Dialysis	2.08***	(0.11)
Hypertension	0.045	(0.070)
Inotropes or IABP	0.75***	(0.074)
Immunosuppressant	0.67***	(0.22)
Left Main CHD	0.16**	(0.061)
Previous Myocardial Infarct	-0.036	(0.066)
# of Stenotic arteries - 1	0.046	(0.043)
Peripheral Vessel Disease	0.35***	(0.066)
Previous Heart Op, =1	1.13***	(0.085)
Previous Heart Op, >=2	1.12***	(0.34)
Cardiogenic Shock	1.40***	(0.098)
Status Urgent	0.090	(0.071)
Status Emergent	0.40***	(0.10)
Stable Angina	-0.18*	(0.097)
Unstable Angina	-0.017	(0.083)
Chronic Lung Disease	0.15**	(0.068)
AMI	0.20***	(0.068)
Cerebrovascular Disease	0.37***	(0.088)
Cerebrovascular Accident	1.17***	(0.16)
Valve Disorder	0.43***	(0.065)
Arrhythmia	0.35***	(0.057)
constant	-7.55***	(0.58)
Surgeon Fixed Effect	Yes	
N	43579	
Log likelihood	-5778.8	
c-statistics	0.868	

The sample includes patients of the 87 cardiac surgeons during the years 1994-1999. The dependent variable is a binary variable that indicates a patient death. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table 3. Patient Urgency Status from 1995 to 1999

	1995		1996		1997		1998		1999	
Urgency	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Elective	2,578	55.86	2,342	46.43	2,300	48.30	1,953	39.53	1,606	35.21
Urgent	1,735	37.59	2,387	47.32	2,209	46.39	2,767	56.01	2,769	60.71
Emergency	302	6.54	315	6.25	253	5.31	220	4.45	186	4.08
Total	4,615	100	5,044	100	4,762	100	4,940	100	4,561	100

Table 4. Logistic Regressions to Estimate Propensity Scores

	(1) 1995 and 1999 urgent patients		(2) 1995 and 1999 elective patients	
	Coefficient	Standard error	Coefficient	Standard error
Age	-0.0092***	(0.0033)	0.0057	(0.0036)
Female	0.098	(0.071)	-0.052	(0.077)
Congenital Heart Failure	0.27***	(0.078)	-0.12	(0.087)
Diabetes	-0.19***	(0.069)	0.15**	(0.072)
Renal failure wo Dialysis	-0.22*	(0.12)	-0.034	(0.15)
Renal failure w dialysis	-0.14	(0.23)	0.27	(0.30)
max(50-Ejection Fraction,0)	-0.028***	(0.0040)	0.0015	(0.0045)
Hypertension	-0.48***	(0.076)	0.48***	(0.082)
Inotropes or IABP	-0.019	(0.11)	-0.79***	(0.19)
Immunosuppressant	-3.82***	(1.01)	1.72**	(0.68)
Left Main CHD	-0.0070	(0.071)	0.33***	(0.093)
# of Stenotic Arteries - 1	0.15***	(0.051)	0.071	(0.051)
Peripheral Vessel Disease	-0.040	(0.091)	0.34***	(0.100)
Previous Heart Op, =1	0.17	(0.14)	0.021	(0.14)
Previous Heart Op, >=2	0.11	(0.63)	-0.14	(0.72)
Cardiogenic Shock	0.57***	(0.20)	0.010	(0.38)
Stable Angina	0.16**	(0.077)	-0.24***	(0.070)
Unstable Angina	0.018	(0.087)	-0.65***	(0.072)
Chronic Lung Disease	-0.16*	(0.088)	0.080	(0.099)
AMI	0.25***	(0.067)	-0.84***	(0.090)
Cerebrovascular Disease	-0.083	(0.12)	-0.076	(0.13)
Cerebrovascular Accident	-0.14	(0.34)	-0.063	(0.31)
Valve Disorder	-0.31***	(0.093)	0.21**	(0.094)
Arrhythmia	-0.023	(0.066)	0.050	(0.070)
constant	0.38	(0.24)	-0.83***	(0.25)
N	4504		4184	
Log likelihood	-2881.5		-2627.2	

In (1), the dependent variable indicates whether urgent patients received CABG surgery in 1995. In (2), the dependent variable indicates whether elective patients received CABG surgery in 1999. Standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table 5. Patient Mix and Death Rate Changes from 1995-1996 to 1998-1999

Non-matched sample

	1995-1996			1998-1999		
	Elective	Urgent	Total	Elective	Urgent	Total
High Quality	2111	2343	4454	1781	2701	4482
Low Quality	2809	1779	4588	1778	2835	4613
Total	4920	4122	9042	3559	5536	9095

Propensity score-matched sample

	1995-1996			1998-1999			Difference		1995-1996 Death Rate (%)		1998-1999 Death Rate (%)	
	Elective	Urgent	Total	Elective	Urgent	Total	ΔElective	ΔUrgent	Elective	Urgent	Elective	Urgent
High Quality	1386	1987	3373	1606	1736	3342	220	-251	2.81	3.17	1.81	2.48
Low Quality	1826	1483	3309	1606	1734	3340	-220	251	3.23	6.81	2.49	4.21
Total	3212	3470	6682	3212	3470	6682			3.05	4.73	2.15	3.34

High Quality: 17 cardiac surgeons whose RAMR on the 1994-1995 report card is lower than 3.18%

Low Quality: 16 cardiac surgeons whose RAMR on the 1994-1995 report card is higher than 3.18%

Table 6. The Impact of the Report Cards on Surgeon Choice

	(1)		(2)	
	Coefficient	Standard error	Coefficient	Standard error
RAMR (baseline)	-0.070***	(0.011)	-0.049***	(0.014)
RAMR x Post1	0.013	(0.019)	0.0082	(0.026)
RAMR x Post2	-0.0084	(0.016)	-0.017	(0.022)
RAMR x Post3	0.0028	(0.021)	-0.00017	(0.028)
1 year OMR (baseline)	-0.014***	(0.0048)	0.014***	(0.0053)
1 year OMR x urgent	-0.016**	(0.0066)	-0.020***	(0.0070)
1 year OMR x emergent	0.028*	(0.015)	0.023	(0.016)
1 year case (baseline)	0.0044***	(0.00012)	0.0043***	(0.00014)
1 year case x urgent	0.00058***	(0.00015)	0.00060***	(0.00017)
1 year case x emergent	-0.0011***	(0.00038)	-0.0013***	(0.00041)
Distance	-0.10***	(0.0022)	-0.11***	(0.0023)
Distance x urgent	-0.0015	(0.0032)	-0.00044	(0.0033)
Distance x emergent	-0.018**	(0.0084)	-0.019**	(0.0088)
Hospital FE x Time FE	No		Yes	
Hospital FE x age	No		Yes	
Hospital FE x gender	No		Yes	
N	23922		23922	
Log Likelihood	-41613.4		-40247.7	

Equation (5.1) is estimated using the propensity score-matched final subsample which includes patients of the 33 cardiac surgeons. The dependent variable is a binary variable to indicate patients' choice of cardiac surgeons. RAMR is risk-adjusted mortality rates of surgeons in the 1994-1995 report cards. 1 year OMR means each surgeon's observed mortality rate for the year before each patient's operation date. 1 year case means each surgeon's total CABG surgery cases for the year before each patient's operation date. Time FE consists of baseline, Post1, Post2, and Post3. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table 7. Patient Volume Changes from 1995 to 1999

	1995		1996		1997		1998		1999		Total	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
High Quality Hospitals	1,743	40.4	1,841	38.9	1,611	35.7	1,736	36.8	1,573	36.0	8,504	37.6
Medium Quality Hospitals	1,375	31.9	1,576	33.3	1,574	34.9	1,947	41.3	1,813	41.4	8,285	36.6
Low Quality Hospitals	1,195	27.7	1,312	27.7	1,324	29.4	1,037	22.0	989	22.6	5,857	25.9
Total	4,313	100	4,729	100	4,509	100	4,720	100	4,375	100	22,646	100

High quality hospitals: The four best hospitals based on the 1994-1995 report cards, Medium quality hospitals: The 4 second best hospitals based on the 1994-1995 report cards, Low Quality hospitals: The five worst hospitals based on the 1994-1995 report cards. The total number of patients is not 23,922 because one hospital started to do CABG surgeries in 1998 and thus was not evaluated in the first report cards.

Table 8. Within-Hospital Reallocation and Between-Hospital Reallocation

		(1)		(2)	
		Coefficient	Standard error	Coefficient	Standard error
Elective	dRAMR (baseline)	0.051**	(0.023)	0.042*	(0.023)
	dRAMR x Post1	-0.13***	(0.041)	-0.11***	(0.041)
	dRAMR x Post2	-0.19***	(0.036)	-0.14***	(0.034)
	dRAMR x Post3	-0.21***	(0.043)	-0.18***	(0.046)
Urgent	dRAMR (baseline)	-0.13***	(0.025)	-0.17***	(0.032)
	dRAMR x Post1	0.22***	(0.046)	0.26***	(0.054)
	dRAMR x Post2	0.19***	(0.038)	0.22***	(0.043)
	dRAMR x Post3	0.22***	(0.044)	0.25***	(0.048)
Emergent	dRAMR (baseline)	-0.0011	(0.052)	0.031	(0.058)
	dRAMR x Post1	0.11	(0.10)	0.14	(0.12)
	dRAMR x Post2	0.20**	(0.091)	0.27**	(0.10)
	dRAMR x Post3	-0.018	(0.11)	-0.020	(0.11)
Elective	Hospital RAMR (baseline)	-0.00095	(0.029)	-0.60***	(0.064)
	Hospital RAMR x Post1	0.025	(0.048)	0.099	(0.11)
	Hospital RAMR x Post2	-0.019	(0.044)	0.046	(0.089)
	Hospital RAMR x Post3	-0.12**	(0.055)	0.62***	(0.096)
Urgent	Hospital RAMR (baseline)	-0.41***	(0.034)	0.21***	(0.060)
	Hospital RAMR x Post1	0.12**	(0.055)	-0.060	(0.098)
	Hospital RAMR x Post2	0.062	(0.056)	-0.26***	(0.094)
	Hospital RAMR x Post3	0.075	(0.064)	-0.72***	(0.13)
Emergent	Hospital RAMR (baseline)	-0.22***	(0.083)	0.060	(0.14)
	Hospital RAMR x Post1	-0.15	(0.16)	-0.40	(0.28)
	Hospital RAMR x Post2	-0.23*	(0.14)	0.0073	(0.25)
	Hospital RAMR x Post3	0.21	(0.19)	0.42*	(0.24)
1 year OMR (baseline)		-0.033***	(0.0059)	-0.011	(0.0079)
1 year OMR x urgent		0.024***	(0.0085)	0.014	(0.011)
1 year OMR x emergent		0.054***	(0.018)	0.0050	(0.023)
1 year case (baseline)		0.0041***	(0.00014)	0.0039***	(0.00015)
1 year case x urgent		0.0011***	(0.00019)	0.00064***	(0.00022)
1 year case x emergent		-0.00066	(0.00041)	-0.00055	(0.00047)
Distance		-0.10***	(0.0027)	-0.090***	(0.0031)
Distance x urgent		-0.0018	(0.0040)	-0.0063	(0.0047)
Distance x emergent		-0.020**	(0.0088)	-0.017*	(0.010)
N		17981		11022	
Log likelihood		-30781.0		-16303.6	

The dependent variable is a binary variable to indicate patients' choice of cardiac surgeons. dRAMR is demeaned risk-adjusted mortality rates of surgeons using the hospital RAMRs in the 1994-1995 report cards. 1 year OMR means each surgeon's observed mortality rate for the year before each patient's operation date. 1 year case means each surgeon's total CABG surgery cases for the year before each patient's operation date. In (1), the sample includes the propensity score-matched patients of the 33 cardiac surgeons. In (2), the sample includes the propensity score-matched patients of the cardiac surgeons who worked at medium- or low-quality hospitals. Time FE consists of baseline, Post1, Post2, and Post3. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table 9. Within-Hospital Patient Reallocation on Urgency and Severity Dimensions

		(1)		(2)	
		Coefficient	Standard error	Coefficient	Standard error
Elective	RAMR (baseline)	0.024	(0.021)	0.028	(0.024)
	RAMR x Post1	-0.11***	(0.038)	-0.12***	(0.044)
	RAMR x Post2	-0.15***	(0.034)	-0.17***	(0.038)
	RAMR x Post3	-0.20***	(0.047)	-0.24***	(0.055)
Urgent	RAMR (baseline)	-0.13***	(0.025)	-0.15***	(0.029)
	RAMR x Post1	0.17***	(0.043)	0.22***	(0.048)
	RAMR x Post2	0.16***	(0.036)	0.18***	(0.040)
	RAMR x Post3	0.16***	(0.044)	0.16***	(0.048)
Emergent	RAMR (baseline)	0.0041	(0.050)	0.00087	(0.058)
	RAMR x Post1	0.051	(0.096)	0.057	(0.11)
	RAMR x Post2	0.14*	(0.086)	0.050	(0.11)
	RAMR x Post3	0.018	(0.096)	-0.024	(0.12)
Elective	Severity x RAMR (baseline)			-0.15	(0.42)
	Severity x RAMR x Post1			0.32	(0.80)
	Severity x RAMR x Post2			0.93	(0.60)
	Severity x RAMR x Post3			1.32	(0.97)
Urgent	Severity x RAMR (baseline)			0.51*	(0.31)
	Severity x RAMR x Post1			-1.10**	(0.54)
	Severity x RAMR x Post2			-0.36	(0.42)
	Severity x RAMR x Post3			-0.015	(0.50)
Emergent	Severity x RAMR (baseline)			0.031	(0.31)
	Severity x RAMR x Post1			-0.059	(0.59)
	Severity x RAMR x Post2			0.79	(0.53)
	Severity x RAMR x Post3			0.29	(0.46)
1 year OMR (baseline)		0.0090	(0.0068)	0.0090	(0.0068)
1 year OMR x urgent		-0.013	(0.0090)	-0.013	(0.0090)
1 year OMR x emergent		0.013	(0.019)	0.013	(0.019)
1 year case (baseline)		0.0047***	(0.00018)	0.0047***	(0.00018)
1 year case x urgent		0.00064***	(0.00023)	0.00065***	(0.00023)
1 year case x emergent		-0.0010**	(0.00047)	-0.0010**	(0.00047)
Distance		-0.069***	(0.0044)	-0.069***	(0.0044)
Distance x urgent		-0.0039	(0.0061)	-0.0039	(0.0061)
Distance x emergent		0.013	(0.014)	0.012	(0.014)
Hospital FE x Time FE		Yes		Yes	
Hospital FE x age		Yes		Yes	
Hospital FE x gender		Yes		Yes	
N		17981		17981	
Log likelihood		-22185.3		-22176.3	

In (1) and (2), the propensity score-matched final subsample is used. The dependent variable is a binary variable to indicate patients' choice of cardiac surgeons. RAMR is risk-adjusted mortality rates of surgeons in the 1994-1995 report cards. 1 year OMR means each surgeon's observed mortality rate for the year before each patient's operation date. 1 year case means each surgeon's total CABG surgery cases for the year before each patient's operation date. Severity means patient severity of illness measured by the prediction using the risk model (3.1). Time FE consists of baseline, Post1, Post2, and Post3. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table 10. Difference in Patient Reallocation Between Border Hospitals and Nonborder Hospitals

		Coefficient	Standard error
Border hospitals			
Elective	RAMR (baseline)	-0.23***	(0.038)
	RAMR x Post1	0.056	(0.067)
	RAMR x Post2	-0.094	(0.060)
	RAMR x Post3	0.13*	(0.071)
Urgent	RAMR (baseline)	-0.19***	(0.040)
	RAMR x Post1	0.0045	(0.071)
	RAMR x Post2	0.051	(0.065)
	RAMR x Post3	-0.011	(0.076)
Emergent	RAMR (baseline)	-0.37***	(0.082)
	RAMR x Post1	0.35**	(0.17)
	RAMR x Post2	0.35**	(0.17)
	RAMR x Post3	0.44**	(0.19)
Nonborder hospitals			
Elective	RAMR (baseline)	0.10***	(0.024)
	RAMR x Post1	-0.18***	(0.043)
	RAMR x Post2	-0.16***	(0.039)
	RAMR x Post3	-0.38***	(0.062)
Urgent	RAMR (baseline)	-0.14***	(0.031)
	RAMR x Post1	0.27***	(0.050)
	RAMR x Post2	0.22***	(0.042)
	RAMR x Post3	0.26***	(0.050)
Emergent	RAMR (baseline)	0.17***	(0.059)
	RAMR x Post1	-0.11	(0.12)
	RAMR x Post2	0.0040	(0.100)
	RAMR x Post3	-0.17	(0.11)
1 year OMR (baseline)		0.0084	(0.0069)
1 year OMR x urgent		-0.013	(0.0091)
1 year OMR x emergent		0.016	(0.019)
1 year case (baseline)		0.0046***	(0.00018)
1 year case x urgent		0.00060**	(0.00024)
1 year case x emergent		-0.0011**	(0.00048)
Distance		-0.069***	(0.0044)
Distance x urgent		-0.0037	(0.0062)
Distance x emergent		0.014	(0.014)
Hospital FE x Time FE		Yes	
Hospital FE x age		Yes	
Hospital FE x gender		Yes	
N		17981	
Log likelihood		-22101.4	

The propensity score-matched final subsample (patients of the 33 cardiac surgeons) is used. The dependent variable is a binary variable to indicate patients' choice of cardiac surgeons. RAMR is risk-adjusted mortality rates of surgeons in the 1994-1995 report cards. 1 year OMR means each surgeon's observed mortality rate for the year before each patient's operation date. 1 year case means each surgeon's total CABG surgery cases for the year before each patient's operation date. Time FE consists of baseline, Post1, Post2, and Post3. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table 11. Patient Reallocation across Rated and Unrated Surgeons

			Coefficient	Standard error
Rated Surgeons				
	Elective	RAMR (baseline)	0.0011	(0.015)
		RAMR x Post1	-0.082***	(0.029)
		RAMR x Post2	-0.15***	(0.027)
		RAMR x Post3	-0.18***	(0.035)
	Urgent	RAMR (baseline)	-0.081***	(0.020)
		RAMR x Post1	0.16***	(0.037)
		RAMR x Post2	0.094***	(0.031)
		RAMR x Post3	0.12***	(0.036)
	Emergent	RAMR (baseline)	0.0060	(0.035)
		RAMR x Post1	0.073	(0.074)
		RAMR x Post2	0.11*	(0.065)
		RAMR x Post3	0.14*	(0.079)
Unrated Surgeons				
	Elective	unrated (baseline)	-0.54***	(0.073)
		unrated x Post1	-0.16	(0.12)
		unrated x Post2	-0.37***	(0.11)
		unrated x Post3	-0.34**	(0.14)
	Urgent	unrated (baseline)	-0.49***	(0.086)
		unrated x Post1	0.88***	(0.15)
		unrated x Post2	0.86***	(0.12)
		unrated x Post3	0.81***	(0.14)
	Emergent	unrated (baseline)	-0.086	(0.15)
		unrated x Post1	0.74**	(0.30)
		unrated x Post2	1.03***	(0.26)
		unrated x Post3	1.21***	(0.31)
1 year OMR (baseline)			0.00066	(0.0021)
1 year OMR x urgent			-0.014***	(0.0037)
1 year OMR x emergent			-0.0013	(0.0040)
1 year case (baseline)			0.0045***	(0.00014)
1 year case x urgent			0.00084***	(0.00019)
1 year case x emergent			-0.0012***	(0.00034)
Distance			-0.076***	(0.0040)
Distance x urgent			0.0059	(0.0055)
Distance x emergent			-0.0014	(0.013)
Hospital FE x Time FE			Yes	
Hospital FE x age			Yes	
Hospital FE x gender			Yes	
N			25541	
Log likelihood			-45083.3	

The propensity score-matched sample that includes patients of the 87 cardiac surgeons is used. The dependent variable is a binary variable to indicate patients' choice of cardiac surgeons. RAMR is risk-adjusted mortality rates of surgeons in the 1994-1995 report cards. 1 year OMR means each surgeon's observed mortality rate for the year before each patient's operation date. 1 year case means each surgeon's total CABG surgery cases for the year before each patient's operation date. "unrated" indicates surgeons who were not rated on the 1994-1995 report cards. Time FE consists of baseline, Post1, Post2, and Post3. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

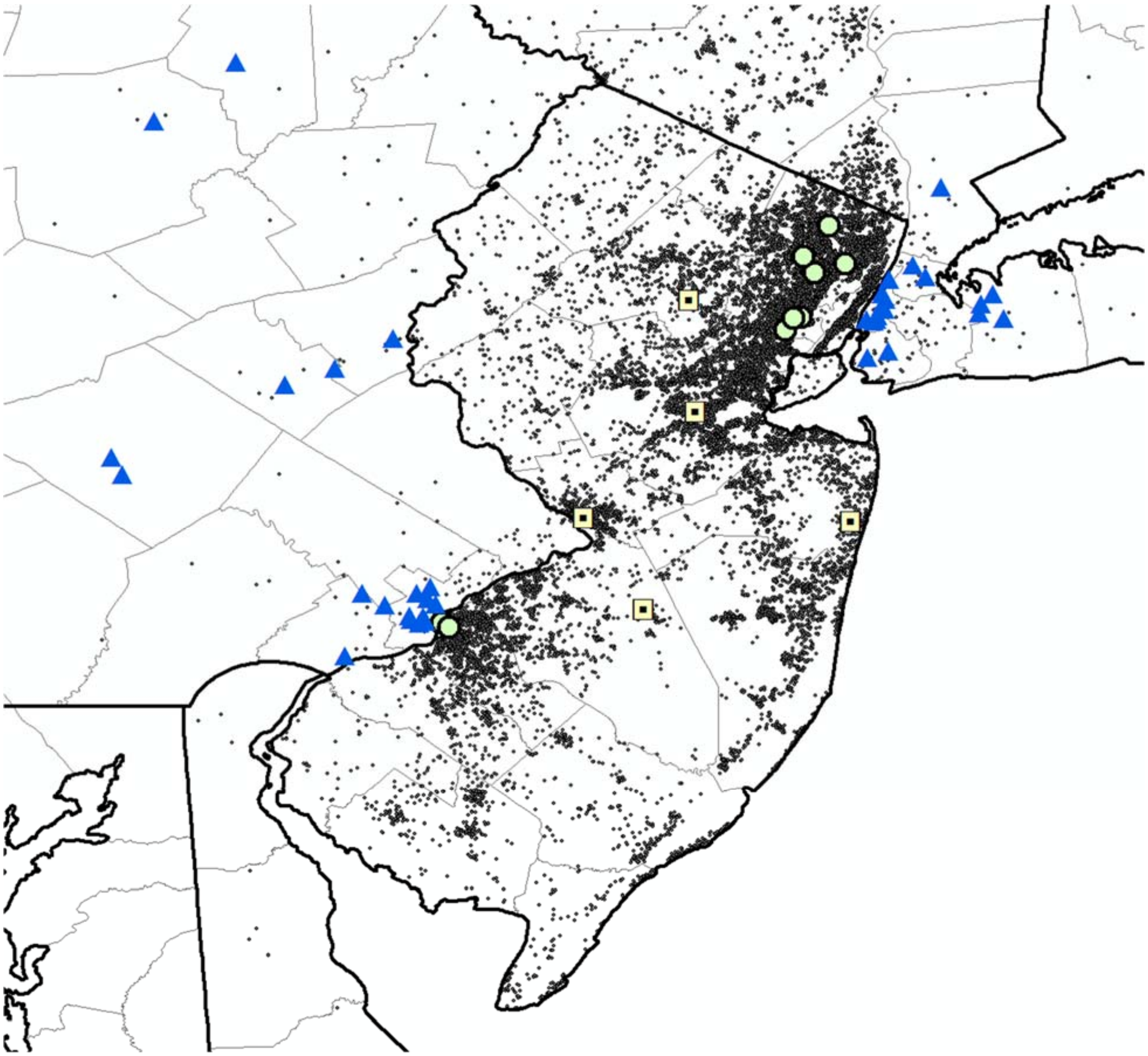
Table 12. Effects of Report Cards on Surgeon Capacity Status When Cardiac Surgeons Accept Patients (Nonborder Hospitals)

	Waiting time	Number of scheduled patients in the two-week capacity slot	
	(1) All patients	(2) Urgent patients	(3) Elective patients
Mean of dependent variable	9.33	5.11	2.66
	[12.38]	[3.73]	[2.74]
Post1	1.70	0.85**	-0.50
	(1.14)	(0.36)	(0.36)
Post2	0.22	0.87**	-0.58**
	(1.02)	(0.36)	(0.28)
Post3	4.96***	1.81***	0.52*
	(1.19)	(0.45)	(0.30)
RAMR (baseline)	0.35*	0.19**	0.070
	(0.20)	(0.077)	(0.053)
RAMR x Post1	-0.31	-0.26**	0.10
	(0.37)	(0.13)	(0.12)
RAMR x Post2	-0.84***	-0.39***	0.0065
	(0.32)	(0.13)	(0.089)
RAMR x Post3	-1.23***	-0.56***	-0.12
	(0.37)	(0.16)	(0.10)
Hospital FE x Time FE	Yes	Yes	Yes
N	7932	3732	3638
Adjusted R-squared	0.031	0.180	0.058

The propensity score-matched final subsample is used. RAMR is risk-adjusted mortality rates of surgeons in the 1994-1995 report cards. Time FE consists of baseline, Post1, Post2, and Post3. In (1), "All" means elective, urgent, and emergent patients. Standard deviations are in brackets. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

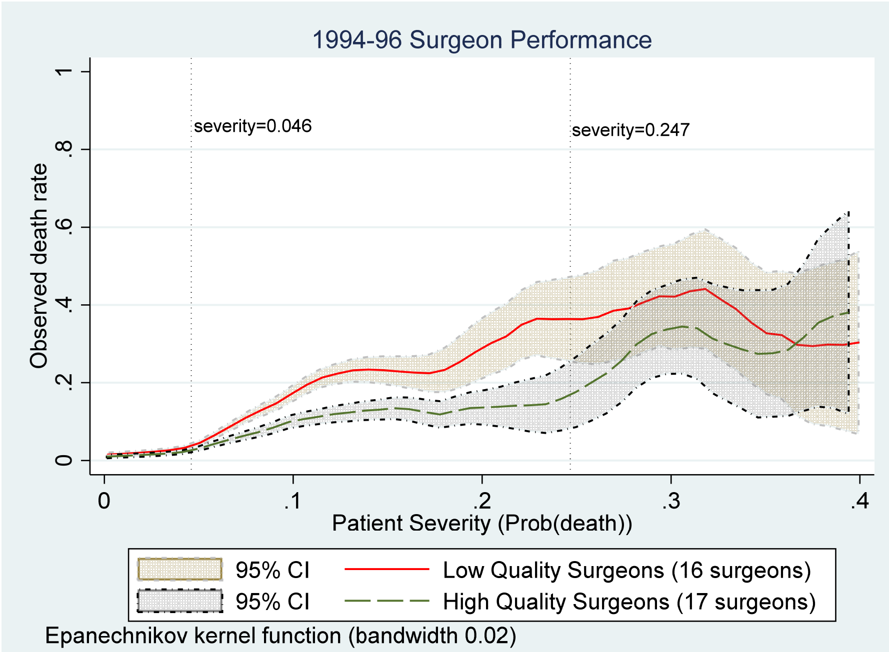
Figures

Figure 1. Cardiac Surgery Hospital and Patient Locations (1995-1999)



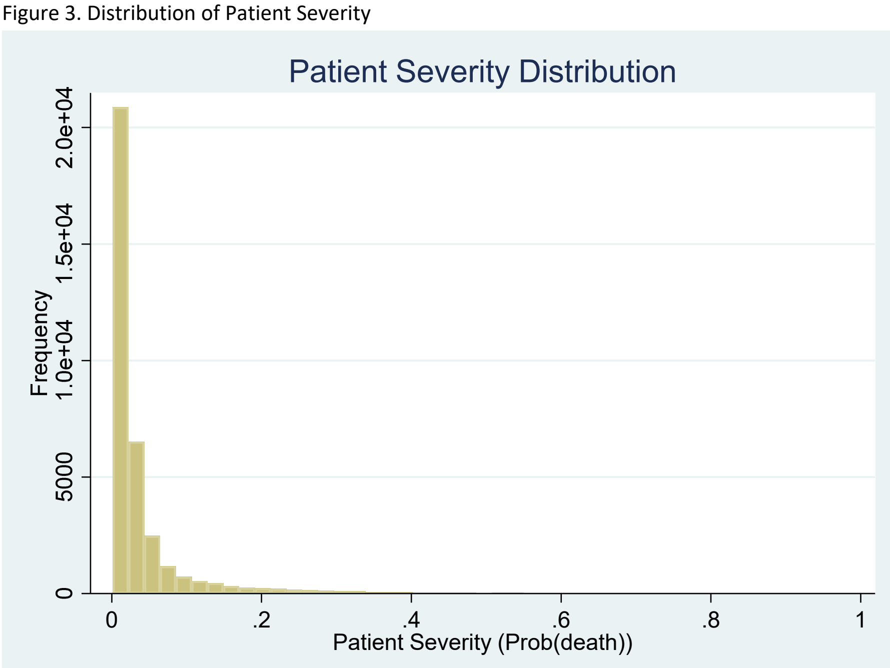
Green circle: The locations of the CABG hospitals in New Jersey that were located within 20 miles of Manhattan, NY or Philadelphia, PA
Yellow dot-in-square: The locations of the CABG hospitals in New Jersey that were located more than 20 miles away from Manhattan, NY or Philadelphia, PA
Blue triangle: The locations of the CABG hospitals in New York or Pennsylvania
Black dot: The locations of the patients who received CABG surgery in New Jersey from 1995 to 1999

Figure 2. Interaction of Patient Illness Severity and Surgeon Quality in the Outcome of CABG Surgery



The sample in this graph includes patients of the 33 cardiac surgeons during the years 1994-1996. "Patient Severity" is measured by the prediction using the patient risk model Equation (3.1).

Figure 3. Distribution of Patient Severity



The sample in this graph includes patients of the 33 cardiac surgeons. "Patient Severity" is measured by the prediction using the patient risk model Equation (3.1).

Figure 4. Balanced Risk Factors After Propensity Score Matching

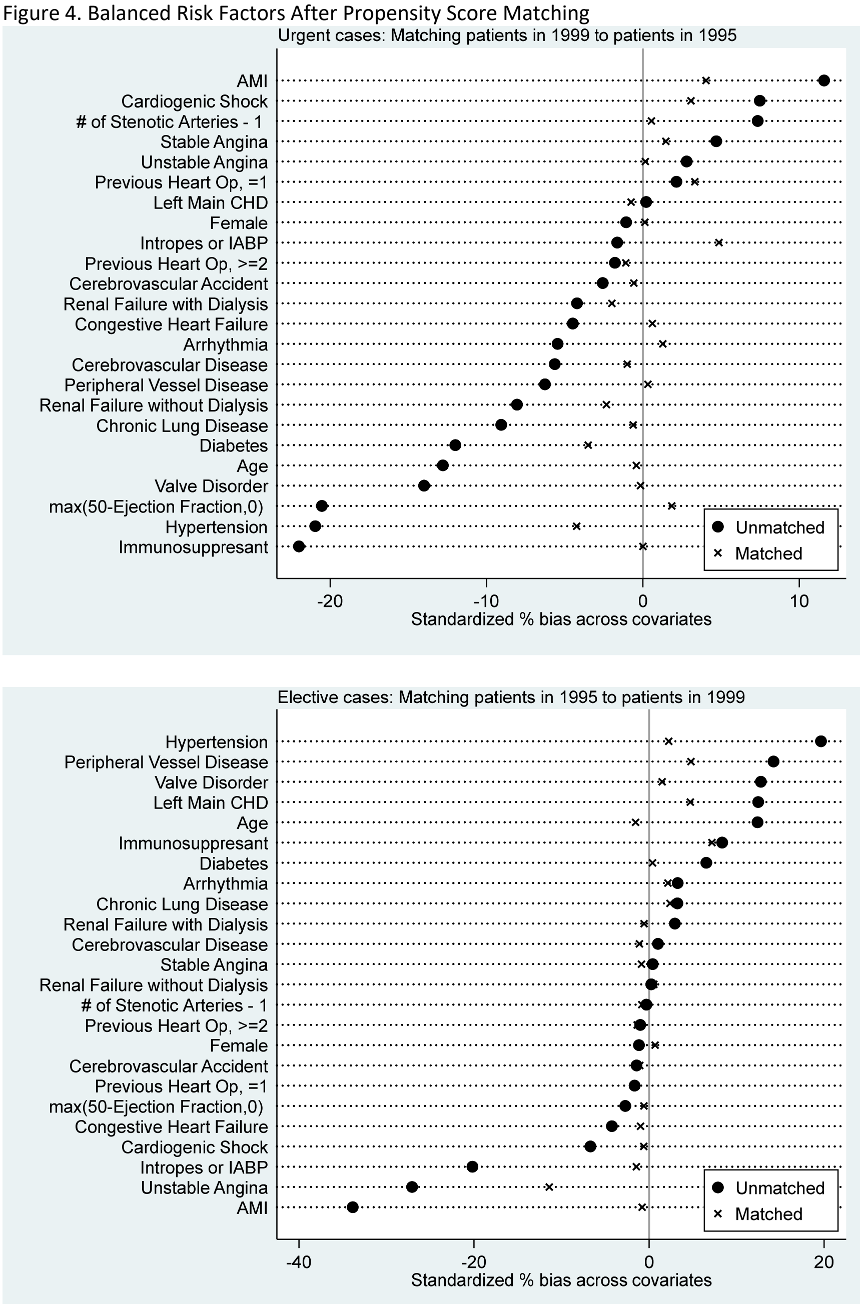


Figure 5. Pre- and Post-Publication Time Periods of the New Jersey Cardiac Surgery Report Cards

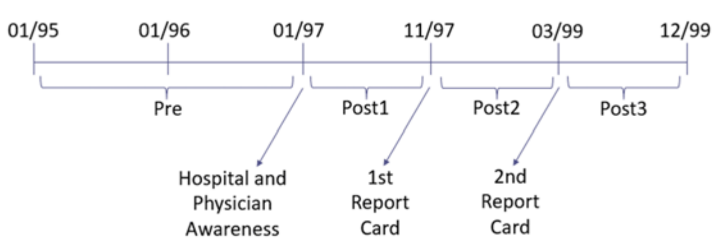
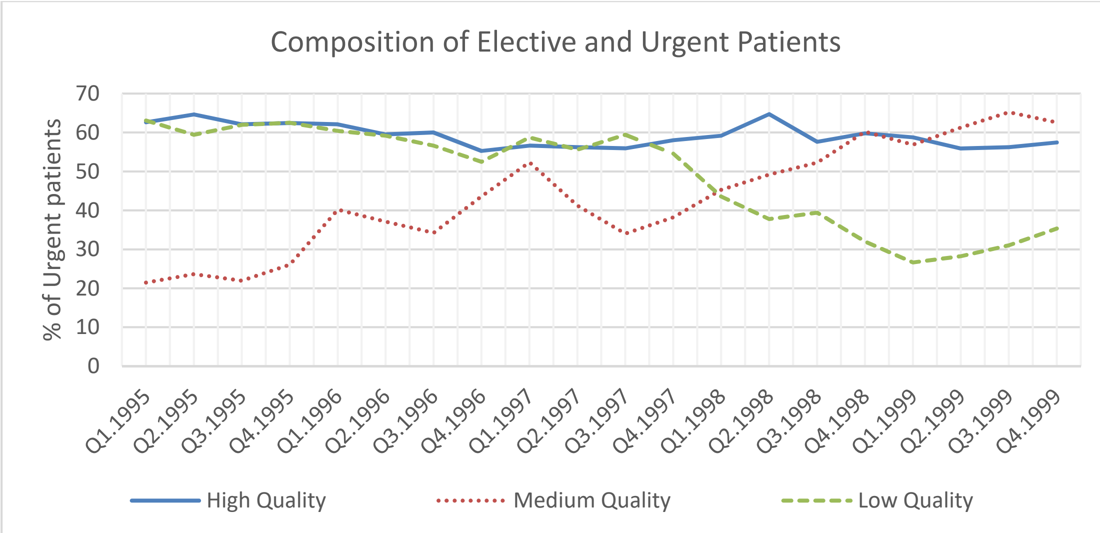
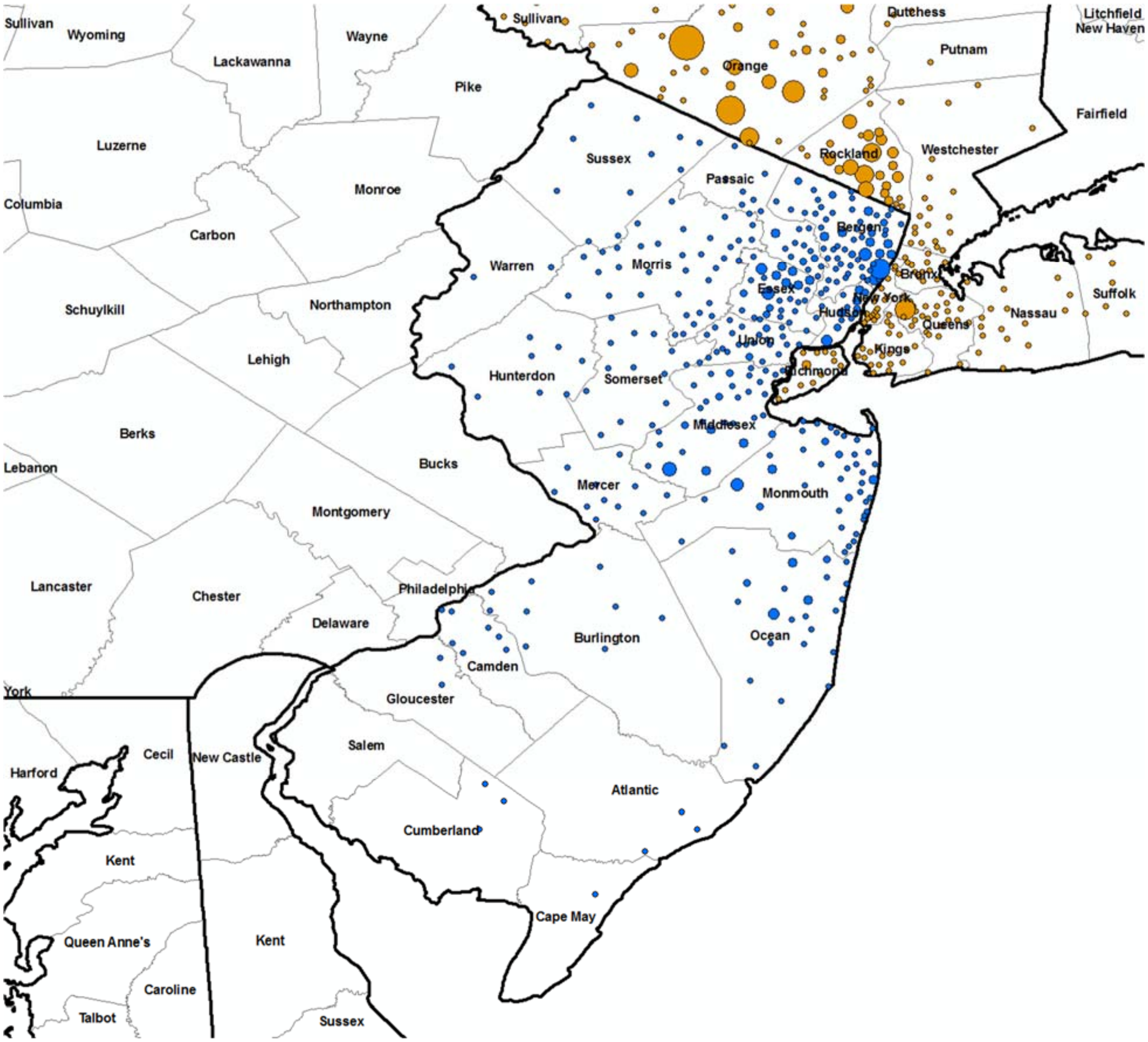


Figure 6. Quarterly Changes in Patient Mix from 1995 to 1999 in Each Hospital Group (Propensity-score Matched Sample)



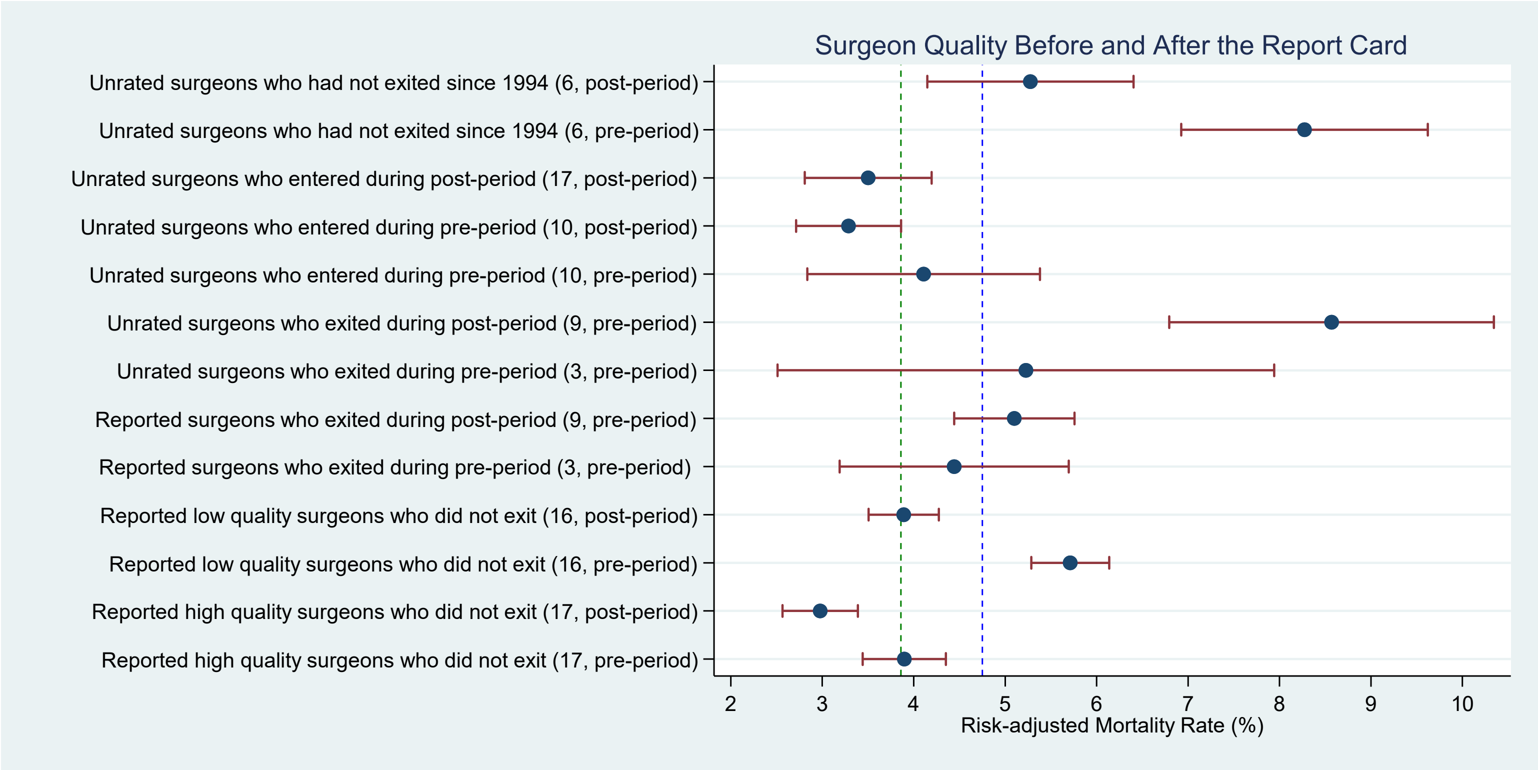
High Quality: The four best hospitals based on the 1994-1995 report cards, Medium quality: The four second best hospitals based on the 1994-1995 report cards, Low Quality: The five worst hospitals based on the 1994-1995 report cards.

Figure 7. Distribution of Patients Who Crossed the New Jersey – New York Border



The blue circles represent the zip code-level locations of patients in New Jersey who received CABG surgeries in New York during the years 1995, 1997, 1998, and 1999. The orange circles represent the zip code-level locations of patients in New York who received CABG surgeries in New Jersey during the years 1995, 1997, 1998, and 1999. The size of each circle represents how many patients crossed the border from its zip code location.

Figure 8. Quality Improvement of Cardiac Surgeons After the Report-Card Publication



The 87 cardiac surgeons are evaluated in this figure. The numbers in the parentheses denote the number of surgeons in each group. "pre-period" in the parentheses means that the displayed dot and interval of risk-adjusted mortality rate represent the corresponding group's average quality and 95% confidence interval during the years 1994-1996. "post-period" in the parentheses means that the displayed dot and interval of risk-adjusted mortality rate represent the corresponding group's average quality and 95% confidence interval during the years 1997-1999. The green dashed line represents the statewide observed death rate (4.75%) during the years 1994-1996. The blue dashed line represents the statewide observed death rate (3.86%) during the years 1997-1999. These statewide observed death rates are higher than those reported in the report cards because the sample in this paper includes both isolated CABG and CABG plus cardiac valve surgeries. "Unrated" means that their quality was not reported on the first report cards. "Reported" means that their quality was reported on the first report cards.

Online Appendix A: Additional Tables and Figures

Table A1. Change in Relationship between Urgent Status and Risk Factors from 1995 to 1999

	Patients in 1995		Patients in 1996		Patients in 1997		Patients in 1998		Patients in 1999	
max(50-Ejection Fraction,0)	-0.0015	(0.0039)	0.0010	(0.0033)	0.0094***	(0.0034)	0.0023	(0.0032)	0.014***	(0.0036)
Immunosuppressant	-1.54*	(0.81)	-0.54	(0.44)	-0.55	(0.35)	0.98***	(0.26)	1.25***	(0.32)
Left Main CHD	0.86***	(0.072)	0.68***	(0.063)	0.74***	(0.062)	0.68***	(0.063)	0.62***	(0.067)
Previous Myocardial Infarct	-0.23***	(0.065)	-0.37***	(0.061)	-0.30***	(0.061)	0.010	(0.061)	0.15**	(0.067)
# of Stenotic Arteries - 1	0.032	(0.047)	0.095**	(0.045)	-0.070	(0.044)	-0.12***	(0.042)	-0.11**	(0.044)
Previous Heart Op, =1	-0.14	(0.12)	-0.20*	(0.12)	-0.13	(0.12)	-0.27**	(0.12)	-0.45***	(0.12)
Previous Heart Op, >=2	0.13	(0.60)	-0.35	(0.49)	0.60	(0.64)	-0.24	(0.58)	0.52	(0.56)
Age	0.00046	(0.0031)	0.0038	(0.0028)	0.0053*	(0.0028)	0.0040	(0.0028)	0.0026	(0.0029)
Female	0.074	(0.066)	0.12*	(0.061)	0.041	(0.060)	0.25***	(0.060)	0.16**	(0.064)
Congenital Heart Failure	0.21***	(0.073)	0.25***	(0.065)	0.094	(0.067)	0.15**	(0.066)	0.092	(0.070)
Chronic Lung Disease	-0.17**	(0.085)	-0.12	(0.076)	-0.22***	(0.073)	-0.11	(0.071)	0.16**	(0.077)
Diabetes	-0.12*	(0.064)	-0.15**	(0.057)	-0.17***	(0.058)	-0.036	(0.056)	-0.010	(0.060)
Renal failure without Dialysis	-0.021	(0.12)	0.028	(0.11)	0.32***	(0.11)	0.28***	(0.11)	0.35***	(0.12)
Renal failure with Dialysis	0.54**	(0.24)	0.26	(0.25)	0.60***	(0.22)	0.46**	(0.22)	0.25	(0.22)
Hypertension	-0.100	(0.067)	-0.18***	(0.064)	-0.073	(0.066)	-0.12*	(0.064)	-0.12*	(0.072)
Inotropes or IABP	0.25**	(0.11)	0.41***	(0.098)	0.40***	(0.10)	0.95***	(0.12)	1.06***	(0.15)
AMI	0.66***	(0.067)	0.76***	(0.065)	0.67***	(0.066)	0.94***	(0.071)	0.83***	(0.078)
Peripheral Vessel Disease	0.37***	(0.089)	0.094	(0.080)	0.049	(0.077)	0.057	(0.073)	-0.018	(0.077)
Cardiogenic Shock	0.48**	(0.19)	0.35*	(0.20)	0.83***	(0.23)	0.015	(0.24)	0.099	(0.31)
Unstable Angina	0.71***	(0.074)	0.50***	(0.065)	0.63***	(0.065)	1.09***	(0.059)	1.16***	(0.062)
Stable Angina	-0.61***	(0.065)	-0.58***	(0.058)	-0.59***	(0.058)	-0.31***	(0.055)	-0.62***	(0.059)
Cerebrovascular Disease	-0.099	(0.12)	-0.20*	(0.11)	0.031	(0.11)	0.16	(0.099)	0.090	(0.10)
Cerebrovascular Accident	-0.60**	(0.29)	-0.48*	(0.26)	-0.66**	(0.26)	-0.37	(0.23)	-0.43	(0.28)
Valve Disorder	-0.011	(0.088)	-0.020	(0.079)	-0.045	(0.077)	0.061	(0.076)	0.0060	(0.077)
Arrhythmia	0.061	(0.061)	0.14***	(0.055)	-0.015	(0.055)	0.089	(0.055)	0.068	(0.058)
constant	-1.18***	(0.22)	-0.88***	(0.20)	-0.86***	(0.20)	-0.86***	(0.20)	-0.56***	(0.21)
N	5669		6393		6458		7223		7067	
Log likelihood	-3451.2		-4098.6		-4104.5		-4282.6		-3885.5	

The sample includes patients of the 87 cardiac surgeons. The dependent variable is a binary variable that indicates whether patient status is urgent. The results are estimated using logistic regressions. They show the relationship between the probability of being classified as "urgent" and each risk factor. The estimated coefficients for Inotropes or IABP, AMI, and Unstable Angina suddenly increase in the years 1998 and 1999 compared to the years 1995 to 1997. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table A2. Patient Reallocation in Medium and Low Quality Hospitals on the Urgency and Severity Dimensions

		Coefficient	Standard error
Elective	dRAMR (baseline)	0.042*	(0.023)
	dRAMR x Post1	-0.11***	(0.041)
	dRAMR x Post2	-0.14***	(0.034)
	dRAMR x Post3	-0.17***	(0.046)
Urgent	dRAMR (baseline)	-0.17***	(0.032)
	dRAMR x Post1	0.26***	(0.054)
	dRAMR x Post2	0.22***	(0.043)
	dRAMR x Post3	0.25***	(0.048)
Emergent	dRAMR (baseline)	0.031	(0.059)
	dRAMR x Post1	0.14	(0.12)
	dRAMR x Post2	0.27**	(0.10)
	dRAMR x Post3	-0.018	(0.11)
Elective	Hospital RAMR (baseline)	-0.61***	(0.070)
	Hospital RAMR x Post1	0.091	(0.13)
	Hospital RAMR x Post2	-0.00061	(0.098)
	Hospital RAMR x Post3	0.43***	(0.11)
	Severity x Hospital RAMR (baseline)	0.12	(0.82)
	Severity x Hospital RAMR x Post1	0.38	(2.37)
	Severity x Hospital RAMR x Post2	1.41	(1.42)
	Severity x Hospital RAMR x Post3	6.12***	(1.63)
Urgent	Hospital RAMR (baseline)	0.20***	(0.067)
	Hospital RAMR x Post1	-0.079	(0.11)
	Hospital RAMR x Post2	-0.27**	(0.11)
	Hospital RAMR x Post3	-0.67***	(0.14)
	Severity x Hospital RAMR (baseline)	0.37	(0.70)
	Severity x Hospital RAMR x Post1	0.40	(1.43)
	Severity x Hospital RAMR x Post2	0.061	(0.95)
	Severity x Hospital RAMR x Post3	-1.21	(1.33)
Emergent	Hospital RAMR (baseline)	0.033	(0.17)
	Hospital RAMR x Post1	-0.40	(0.33)
	Hospital RAMR x Post2	0.28	(0.36)
	Hospital RAMR x Post3	0.99***	(0.31)
	Severity x Hospital RAMR (baseline)	0.27	(0.74)
	Severity x Hospital RAMR x Post1	0.11	(1.82)
	Severity x Hospital RAMR x Post2	-1.94	(1.59)
	Severity x Hospital RAMR x Post3	-5.27**	(2.15)
1 year OMR (baseline)		-0.011	(0.0079)
1 year OMR x urgent		0.014	(0.011)
1 year OMR x emergent		0.0043	(0.023)
1 year case (baseline)		0.0039***	(0.00015)
1 year case x urgent		0.00064***	(0.00022)
1 year case x emergent		-0.00057	(0.00047)
Distance		-0.090***	(0.0031)
Distance x urgent		-0.0062	(0.0047)
Distance x emergent		-0.017*	(0.010)
N		11022	
Log likelihood		-16290.0	

The sample includes patients of the cardiac surgeons who worked at the medium and low quality hospitals. The dependent variable is a binary variable to indicate patients' choice of cardiac surgeons. dRAMR is demeaned risk-adjusted mortality rates of surgeons using the hospital RAMRs in the 1994-1995 report cards. 1 year OMR means each surgeon's observed mortality rate for the year before each patient's operation date. 1 year case means each surgeon's total CABG surgery cases for the year before each patient's operation date. Severity means patient severity of illness measured by the prediction using the patient risk model Equation (1). Time FE consists of baseline, Post1, Post2, and Post3. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table A3. Monthly Within-Hospital Patient Sorting from January 1996 to November 1997

		Coefficient	Standard error
Elective	RAMR (baseline, Jan-Dec 1995)	0.014	(0.027)
	RAMR x Jan 1996	0.12	(0.10)
	RAMR x Feb 1996	-0.0057	(0.093)
	RAMR x Mar 1996	-0.015	(0.085)
	RAMR x Apr 1996	0.051	(0.092)
	RAMR x May 1996	-0.012	(0.099)
	RAMR x Jun 1996	0.10	(0.098)
	RAMR x Jul 1996	-0.077	(0.10)
	RAMR x Aug 1996	-0.12	(0.090)
	RAMR x Sep 1996	0.060	(0.11)
	RAMR x Oct 1996	0.24**	(0.10)
	RAMR x Nov 1996	-0.045	(0.086)
	RAMR x Dec 1996	-0.053	(0.094)
	RAMR x Jan 1997	-0.051	(0.10)
	RAMR x Feb 1997	-0.097	(0.10)
	RAMR x Mar 1997	-0.040	(0.081)
	RAMR x Apr 1997	-0.077	(0.085)
	RAMR x May 1997	-0.065	(0.094)
	RAMR x Jun 1997	-0.049	(0.095)
	RAMR x Jul 1997	-0.13	(0.11)
	RAMR x Aug 1997	-0.15	(0.10)
	RAMR x Sep 1997	-0.27**	(0.11)
	RAMR x Oct 1997	-0.070	(0.10)
	RAMR x Nov 1997	-0.18	(0.12)
	RAMR x Post2	-0.14***	(0.038)
	RAMR x Post3	-0.19***	(0.051)
Urgent	RAMR (baseline, Jan-Dec 1995)	-0.11***	(0.038)
	RAMR x Jan 1996	-0.053	(0.096)
	RAMR x Feb 1996	-0.028	(0.092)
	RAMR x Mar 1996	-0.039	(0.10)
	RAMR x Apr 1996	-0.0026	(0.095)
	RAMR x May 1996	-0.016	(0.10)
	RAMR x Jun 1996	-0.16	(0.11)
	RAMR x Jul 1996	-0.10	(0.11)
	RAMR x Aug 1996	0.049	(0.11)
	RAMR x Sep 1996	0.10	(0.12)
	RAMR x Oct 1996	0.13	(0.10)
	RAMR x Nov 1996	-0.041	(0.099)
	RAMR x Dec 1996	-0.25**	(0.10)
	RAMR x Jan 1997	0.23***	(0.085)
	RAMR x Feb 1997	0.053	(0.092)
	RAMR x Mar 1997	0.14	(0.10)
	RAMR x Apr 1997	0.045	(0.10)
	RAMR x May 1997	0.25**	(0.10)
	RAMR x Jun 1997	-0.022	(0.11)
	RAMR x Jul 1997	0.22*	(0.13)
	RAMR x Aug 1997	0.21	(0.14)
	RAMR x Sep 1997	0.22*	(0.12)
	RAMR x Oct 1997	0.084	(0.11)
	RAMR x Nov 1997	0.38***	(0.13)
	RAMR x Post2	0.14***	(0.046)
	RAMR x Post3	0.14***	(0.052)
Emergent	RAMR (baseline, Jan-Dec 1995)	-0.038	(0.077)
	RAMR x Jan 1996	0.47***	(0.18)
	RAMR x Feb 1996	0.19	(0.23)
	RAMR x Mar 1996	0.56**	(0.24)
	RAMR x Apr 1996	-0.78**	(0.36)
	RAMR x May 1996	-0.025	(0.22)

(continued on the next page)

RAMR x Jun 1996	0.022	(0.26)
RAMR x Jul 1996	0.34	(0.27)
RAMR x Aug 1996	0.089	(0.22)
RAMR x Sep 1996	0.15	(0.22)
RAMR x Oct 1996	-0.36*	(0.20)
RAMR x Nov 1996	-0.32	(0.26)
RAMR x Dec 1996	0.049	(0.15)
RAMR x Jan 1997	-0.51	(0.41)
RAMR x Feb 1997	0.080	(0.24)
RAMR x Mar 1997	-0.21	(0.34)
RAMR x Apr 1997	0.046	(0.32)
RAMR x May 1997	0.59***	(0.20)
RAMR x Jun 1997	-0.11	(0.25)
RAMR x Jul 1997	-0.41	(0.35)
RAMR x Aug 1997	0.48	(0.34)
RAMR x Sep 1997	0.14	(0.33)
RAMR x Oct 1997	0.20	(0.21)
RAMR x Nov 1997	-0.30	(0.54)
RAMR x Post2	0.20*	(0.10)
RAMR x Post3	0.061	(0.11)
1 year OMR (baseline)	0.0088	(0.0068)
1 year OMR x urgent	-0.013	(0.0090)
1 year OMR x emergent	0.014	(0.019)
1 year case (baseline)	0.0047***	(0.00018)
1 year case x urgent	0.00064***	(0.00023)
1 year case x emergent	-0.00093*	(0.00048)
Distance	-0.069***	(0.0044)
Distance x urgent	-0.0037	(0.0061)
Distance x emergent	0.013	(0.014)
Hospital FE x Time FE	Yes	
Hospital FE x age	Yes	
Hospital FE x gender	Yes	
N	17981	
Log likelihood	-22141.6	

The propensity score-matched final subsample (patients of the 33 cardiac surgeons) is used. The dependent variable is a binary variable to indicate patients' choice of cardiac surgeons. RAMR is risk-adjusted mortality rates of surgeons in the 1994-1995 report cards. 1 year OMR means each surgeon's observed mortality rate for the year before each patient's operation date. 1 year case means each surgeon's total CABG surgery cases for the year before each patient's operation date. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table A4. Effects of Report Cards on Surgeon Capacity Status When Cardiac Surgeons Accept Patients (Border Hospitals)

	Waiting time	Number of scheduled patients in the two-week capacity slot	
	(1) All patients	(2) Urgent patients	(3) Elective patients
Mean of dependent variable	6.93	4.68	2.25
	[10.49]	[4.07]	[2.46]
Post1	2.14	-0.86**	-0.49
	(1.55)	(0.43)	(0.47)
Post2	3.98***	1.03**	0.95**
	(1.39)	(0.44)	(0.42)
Post3	5.86***	3.33***	1.55***
	(1.71)	(0.54)	(0.47)
RAMR (baseline)	0.085	0.14	0.066
	(0.32)	(0.090)	(0.10)
RAMR x Post1	-0.76	0.24	0.20
	(0.59)	(0.16)	(0.16)
RAMR x Post2	-0.50	-0.055	-0.075
	(0.52)	(0.17)	(0.15)
RAMR x Post3	-0.57	-0.90***	-0.33*
	(0.69)	(0.24)	(0.17)
Hospital FE x Time FE	Yes	Yes	Yes
N	10049	4943	4392
Adjusted R-squared	0.044	0.463	0.122

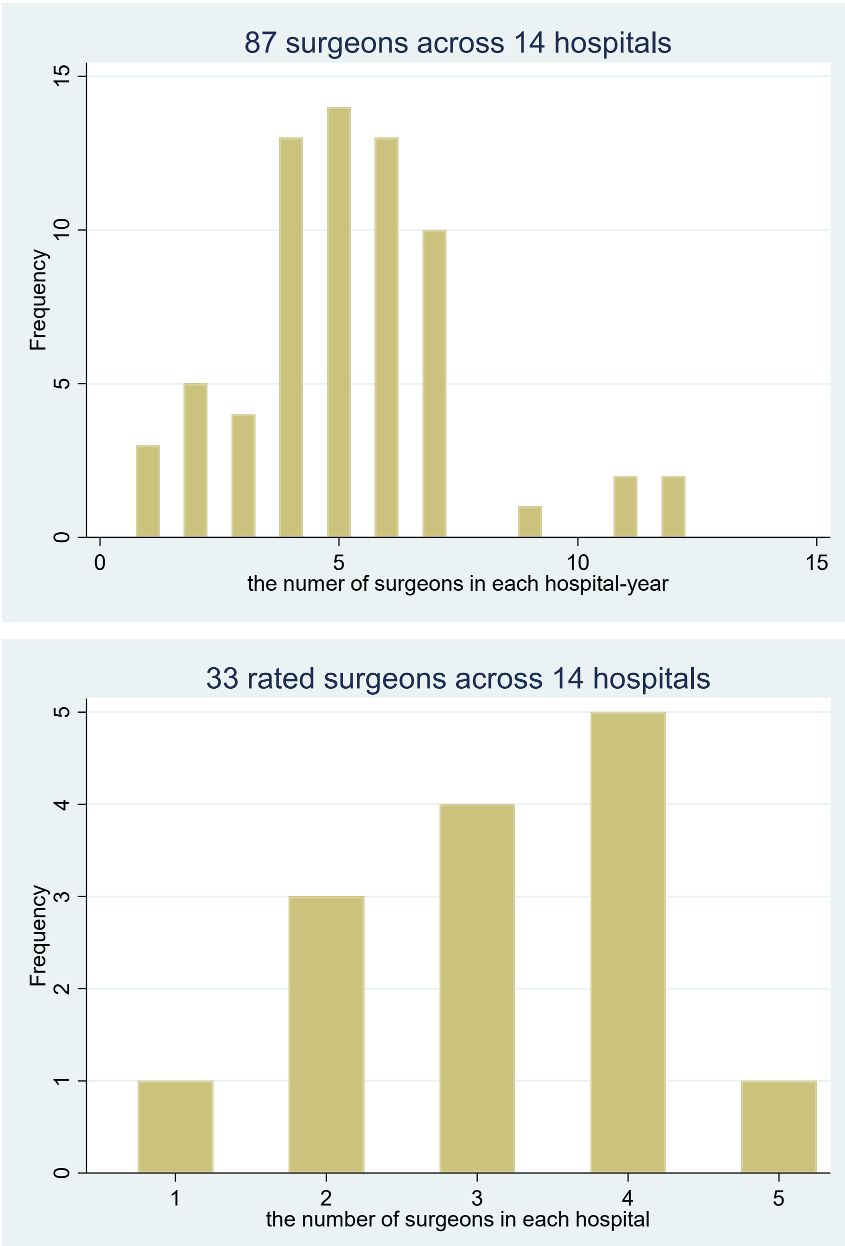
The propensity score-matched final subsample is used. RAMR is risk-adjusted mortality rates of surgeons in the 1994-1995 report cards. Time FE consists of baseline, Post1, Post2, and Post3. In (1), “All” means elective, urgent, and emergent patients. Standard deviations are in brackets. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Table A5. p-values for Differences of the Half-Year Fixed Effects

		Pre-Publication Period						Post-Publication Period				
		baseline	1994, 2nd half	1995, 1st half	1995, 2nd half	1996, 1st half	1996, 2nd half	1997, 1st half	1997, 2nd half	1998, 1st half	1998, 2nd half	1999, 1st half
Pre-Publication Period	1994, 2nd half	0.167										
	1995, 1st half	0.492	0.462									
	1995, 2nd half	0.041**	0.501	0.149								
	1996, 1st half	0.390	0.552	0.868	0.185							
	1996, 2nd half	0.288	0.708	0.698	0.273	0.802						
Post-Publication Period	1997, 1st half	0.516	0.030**	0.148	0.003***	0.094*	0.053*					
	1997, 2nd half	0.337	0.013**	0.079*	0.001***	0.046**	0.025**	0.714				
	1998, 1st half	0.052*	0.0006***	0.006***	2.6×10^{-5}***	0.002***	0.001***	0.136	0.262			
	1998, 2nd half	0.007***	4.2×10^{-5}***	0.0005***	1.2×10^{-6}***	0.0002***	0.0001***	0.019**	0.046**	0.338		
	1999, 1st half	0.065*	0.001***	0.008***	0.0001***	0.004***	0.002***	0.159	0.292	0.991	0.342	
	1999, 2nd half	0.069*	0.001***	0.009***	0.0001***	0.005***	0.002***	0.169	0.310	0.962	0.327	0.971

This table reports the p-values from the chi-square tests for differences of the half-year fixed effects in Table 2. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

Figure A1. Distribution of Number of Surgeons per Hospital



The top histogram shows the number of surgeons in each hospital in each calendar year for the 87 surgeons. Among the 87 cardiac surgeons, some surgeons exited or entered the CABG market in New Jersey from 1995 to 1999. Because of these exits and entries, I use a hospital-year unit to show the distribution of the number of surgeons per hospital for the 87 surgeons. The bottom histogram shows the number of surgeons in each hospital for the 33 surgeons who were rated on the first report cards and did not exit the market during the study period. There were 14 hospitals during the study period in this paper. St. Francis Medical Center started to do CABG surgeries in 1998 and had only one cardiac surgeon during the study period.

Online Appendix B: Additional Robustness Check

In Online Appendix B, I show that other quality information that did not appear in the first report cards did not drive the patient reallocation within hospitals. This strengthens the main finding of this paper that the within-hospital patient reallocation problem was induced by the quality information in the report cards. I use the following conditional logit model:

$$u_{ijht} = \boldsymbol{\alpha}_1' q_j(\boldsymbol{T_t} \otimes [EL_i\ UR_i\ EM_i]') + \boldsymbol{\alpha}_2'(\boldsymbol{q_{2jt}} \otimes \boldsymbol{T_t}) \otimes [EL_i\ UR_i\ EM_i]' +$$

$$\boldsymbol{\beta}' D_{ih}[1\ UR_i\ EM_i]' + H_h \times \boldsymbol{T_t} + H_h \times age_i + H_h \times gender_i + \varepsilon_{ijht}, \qquad \text{(B1)}$$

In Equation (B1), I include several quality measures ($\boldsymbol{q_{2jt}}$) that are not provided in the first report cards. The definitions of the other variables are the same as in the previous models. I performed an intensive search for available information on surgeon quality for the period under study. However, such information was rarely available from online sources such as research papers, hospital websites, governmental websites, and newspaper articles. The only information I could find comes from an As*bury Park Press* newspaper article published in November 17, 1996 (Becker 1996), almost one year before the NJDOH's first report cards were published. This article reported hospital-level quality information on CABG surgeries performed during the years 1993 and 1994. The quality information includes patient volume, number of patient deaths, number of uninsured patients, and whether each hospital's mortality rate and average length of stay fell within acceptable ranges. However, there was no surgeon-specific information. Apart from this article, I found no articles that directly compared hospital or surgeon quality of CABG surgery.

Since I could not find any public surgeon-specific information other than that provided in the report cards, I calculate four possible quality measures ($\boldsymbol{q_{2jt}}$ in Equation (B1)) using the data in this paper that hospitals, cardiologists, or patients might have used. Two of these measures are surgeon *j*'s observed death rate and number of CABG surgeries during the year preceding date *t*. These measures are already used in the previous models, Equations (3), (4), (5), (6), and (7), as $\boldsymbol{X_{jt}}$. But they are not interacted with the time periods in these equations. The other two measures are surgeon *j*'s risk-adjusted mortality rate during 1996 and the risk-adjusted mortality rate for the CABG surgeries that surgeon *j* performed during the year preceding date *t*, which is time-varying. These four quality measures are interacted with the time periods baseline, *Post1*, *Post2*, and *Post3* for each patient's urgency type.

Table B1 shows that the reported RAMR on the first report cards induced the reallocation of urgent patients to low-quality surgeons and the reallocation of elective patients to high-quality surgeons, even controlling for the other quality measures. However, in Table B1, the other quality measures do not seem to drive the within-hospital patient reallocation during *Post1*, *Post2*, and *Post3* that this paper finds in Section 5. This suggests that RAMR, the quality information on the first report cards, actually drove it.

Furthermore, the coefficients for RAMR96, which indicates surgeons' risk-adjusted mortality rates based on their CABG surgeries during 1996, provide additional evidence. These coefficients show that RAMR96 did not affect patient reallocations at the 5% significance level during *Post1* and *Post2*, but it reallocated more elective patients to high-quality surgeons and more urgent patients to low-quality surgeons during *Post3* at the 5% significance level. This result implies that the market responded to the surgeon quality information for the year 1996 (RAMR96) in 1999 because it was released to the public through the second report cards at the beginning of *Post3* (March 8, 1999 to December 31, 1999) that evaluated surgeon quality for isolated CABG surgeries performed in 1996 and 1997.

Table B1. The Effects of Alternative Quality Measures on Patient Reallocation

		Coefficient	Standard error
Elective	RAMR (baseline)	-0.031	(0.024)
	RAMR x Post1	-0.11**	(0.043)
	RAMR x Post2	-0.099***	(0.038)
	RAMR x Post3	-0.14***	(0.052)
Urgent	RAMR (baseline)	-0.12***	(0.028)
	RAMR x Post1	0.14***	(0.046)
	RAMR x Post2	0.15***	(0.040)
	RAMR x Post3	0.12**	(0.048)
Emergent	RAMR (baseline)	-0.0046	(0.053)
	RAMR x Post1	0.058	(0.10)
	RAMR x Post2	0.19*	(0.097)
	RAMR x Post3	0.055	(0.12)
Elective	RAMR96 (baseline)	0.085***	(0.014)
	RAMR96 x Post1	-0.026	(0.026)
	RAMR96 x Post2	-0.034*	(0.021)
	RAMR96 x Post3	-0.082***	(0.023)
Urgent	RAMR96 (baseline)	-0.012	(0.013)
	RAMR96 x Post1	0.063*	(0.033)
	RAMR96 x Post2	0.0013	(0.022)
	RAMR96 x Post3	0.057**	(0.024)
Emergent	RAMR96 (baseline)	0.030	(0.030)
	RAMR96 x Post1	0.024	(0.069)
	RAMR96 x Post2	-0.11*	(0.062)
	RAMR96 x Post3	-0.11	(0.070)
Elective	1 year RAMR (baseline)	0.049***	(0.016)
	1 year RAMR x Post1	0.068**	(0.034)
	1 year RAMR x Post2	-0.012	(0.038)
	1 year RAMR x Post3	0.071	(0.051)
Urgent	1 year RAMR (baseline)	-0.029	(0.021)
	1 year RAMR x Post1	-0.11**	(0.043)
	1 year RAMR x Post2	-0.048	(0.037)
	1 year RAMR x Post3	0.090*	(0.048)

(continued on the right columns)

		Coefficient	Standard error
Emergent	1 year RAMR (baseline)	-0.035	(0.044)
	1 year RAMR x Post1	0.021	(0.10)
	1 year RAMR x Post2	-0.13	(0.090)
	1 year RAMR x Post3	-0.18	(0.12)
Elective	1 year OMR (baseline)	-0.052***	(0.018)
	1 year OMR x Post1	-0.013	(0.033)
	1 year OMR x Post2	0.0021	(0.037)
	1 year OMR x Post3	-0.033	(0.039)
Urgent	1 year OMR (baseline)	0.0034	(0.017)
	1 year OMR x Post1	0.037	(0.032)
	1 year OMR x Post2	0.069**	(0.032)
	1 year OMR x Post3	-0.0086	(0.035)
Emergent	1 year OMR (baseline)	0.042	(0.041)
	1 year OMR x Post1	-0.070	(0.079)
	1 year OMR x Post2	0.11	(0.083)
	1 year OMR x Post3	0.23**	(0.10)
Elective	1 year case (baseline)	0.0062***	(0.00031)
	1 year case x Post1	-0.0021***	(0.00053)
	1 year case x Post2	-0.0019***	(0.00050)
	1 year case x Post3	-0.0017***	(0.00046)
Urgent	1 year case (baseline)	0.0058***	(0.00033)
	1 year case x Post1	-0.0023***	(0.00054)
	1 year case x Post2	-0.00015	(0.00049)
	1 year case x Post3	-0.00057	(0.00045)
Emergent	1 year case (baseline)	0.0030***	(0.00070)
	1 year case x Post1	-0.0026*	(0.0014)
	1 year case x Post2	0.0015	(0.0013)
	1 year case x Post3	0.0024**	(0.0012)
Distance		-0.069***	(0.0044)
Distance x urgent		-0.0047	(0.0061)
Distance x emergent		0.012	(0.014)
Hospital FE x Time FE		Yes	
Hospital FE x age		Yes	
Hospital FE x gender		Yes	
N		17981	
Log likelihood		-22078.8	

The propensity score-matched final subsample (patients of the 33 cardiac surgeons) is used. The dependent variable is a binary variable to indicate patients' choice of cardiac surgeons. RAMR is risk-adjusted mortality rates of surgeons in the 1994-1995 report cards. RAMR96 is risk-adjusted mortality rates of surgeons based on their surgeries performed during 1996. 1 year RAMR means each surgeon's risk-adjusted mortality rate for the year before each patient's operation date. RAMR96 and 1 year RAMR are calculated using the patient risk model Equation (1). 1 year OMR means each surgeon's observed mortality rate for the year before each patient's operation date. 1 year case means each surgeon's total CABG surgery cases for the year before each patient's operation date. Time FE consists of baseline, Post1, Post2, and Post3. Robust standard errors are reported in parentheses. sig: * p-value < 0.1 ** p-value < 0.05 *** p-value < 0.01

References

Becker, C (1996, November 17). Little equity in bypass for poor and uninsured. *Asbury Park Press*, p. C6.