Can Public Reporting Cure Healthcare? The Role of Quality Transparency in Improving Patient-Provider Alignment

Soroush Saghafian[1], Wallace J. Hopp[2]

[1]Harvard Kennedy School, Harvard University, Cambridge, MA
[2]Ross School of Business, University of Michigan, Ann Arbor, MI

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Public reporting of medical treatment outcomes is being widely adopted by policymakers in an effort to increase quality transparency and improve alignment between patient choices and provider capabilities. We examine the soundness of this approach by studying the effects of quality transparency on patient choices, hospital investments, societal outcomes (e.g., patients' social welfare and inequality), and the healthcare market structure (e.g., medical or geographical specialization). Our results offer insights into why previous public reporting efforts have been less than fully successful and suggest ways in which future efforts can be more effective. Specifically, our analytical and simulation results calibrated with empirical data from Centers for Medicare and Medicaid Services (CMS) reveal that increasing quality transparency promotes increased medical specialization, results in decreased geographical specialization, and induces hospitals to invest in their strengths rather than their weakness. Furthermore, increasing quality transparency in the short-term typically improves social welfare and reduces inequality among patients. In the long-term, however, we find that increasing transparency can decrease social welfare, and fail to yield socially optimal outcomes even under full transparency. Hence, a policymaker concerned with societal outcomes should accompany increasing quality transparency with other policies that correct the allocation of patients to hospitals. Among these, we find that policies that incentivize hospitals are generally more effective than policies that incentivize patients. Finally, our results indicate that, to achieve maximal benefits from increasing quality transparency, policymakers should target younger, more affluent, or urban (i.e., high hospital density area) patients, or those requiring non-emergency treatment.

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1. Introduction

Connecting patients and providers is an important function of any healthcare system. Ideally, patients should be diagnosed and treated according to their needs, providers should serve patients according to their abilities, and the entire system should maximize social welfare. We label this fundamental challenge of healthcare systems the *Patient-Provider Alignment (PPA)* problem.

Because healthcare is complex, choices are many, and information is limited, the PPA problem is much easier to state than to solve. Healthcare systems use various practices, such as requiring a referral from a primary care physician to see a specialist, to influence the alignment between patients and providers. However, while research shows that patients value quality in a healthcare provider (see, e.g., Faber et al. (2009) and Santos et al. (2017)), few patients make formal use of quality information in their choice process (see, e.g., Dixon et al. (2010)). Hence, to promote better patient-provider alignment, government and private organizations are increasing efforts to measure and publicly report clinical outcomes, a practice known as "public reporting."

The conventional theory behind public reporting (see, e.g., Hibbard (2008), James (2012), AHRQ (2011), and the references therein) and other activities aimed at increasing quality transparency is that collecting quality outcome measures and making them publicly available will (1) enable patients to choose providers with higher quality, and (2) induce providers to improve quality in order to protect and increase their market shares. These two outcomes are then hypothesized to serve the common good by creating a healthcare system in which expected social welfare is increased.

This reasoning has prompted policymakers to address the PPA problem via transparency initiatives. For example, in 2005 the Center for Medicare and Medicaid Services (CMS) launched the website Hospital Compare to provide information about the quality of care at over 4,000 Medicare-certified hospitals. In 2011, the U.K. Prime Minister David Cameron pledged that the National Health Service (NHS) would make performance data publicly available, and announced that *"Information is power, and by sharing it, we can deliver modern, personalized, and sustainable public services"* (Henke et al. (2011), p. 65). Other examples of increasing transparency of healthcare outcomes include CalHospitalCompare.org, the ProPublica Surgeon Scorecard, the Compare Hospitals site by the Leapfrog Group, and the hospital rating websites of Healthgrades, Consumer Reports, Yelp, and U.S. News.

Mixed Evidence. Despite the common sense appeal of increasing quality transparency, the macro level data suggest that the reality of public reporting initiatives has fallen short of the promise. For example, several empirical studies show that the launch of the Hospital Compare website and other efforts to increase quality transparency have not resulted in tangible improvements in outcomes (see, e.g., Ryan et al. (2012), DeVore et al. (2012), Smith et al. (2012), Fung et al. (2008), and Hibbard (2008)). The simplest explanation for this is that the reality of public reporting has not yet caught up with the promise. That is, patients are not aware of (or able to understand) the information being provided. If this is the only obstacle, then it is reasonable to assume that policymakers will eventually figure out how to make publicly reported healthcare information usable (e.g., by improving websites and/or engaging health care professionals to help patients interpret the data).

It is possible, however, that more fundamental issues in the healthcare sector may be impeding progress toward quality-based decision-making by patients. The first is that quality may not be as easily measurable in healthcare as is in other industries, and that the healthcare sector uses wrong measures of quality (see, e.g., Lilford and Pronovost (2010), Gestel et al. (2012), Porter and Lee (2013), and Austin et al. (2015)). However, a recent study by Doyle et al. (2017) concluded that CMS and other scoring systems do measure quality in a meaningful way. The second is that healthcare is "exceptional" and contains idiosyncratic factors that prevent typical market forces from leading consumers to choose higher quality providers (see, e.g., Cutler (2011), Skinner (2012), and the related discussion in Chandra et al. (2016)). But recent studies suggest that healthcare is not as exceptional as previously thought. For example, Chandra et al. (2016) reported robust evidence that the healthcare sector has much in common with other sectors, and that higher quality hospitals do indeed gain market share over time. This bolsters earlier empirical studies by Dranove et al. (2003) and Dranove and Sfekas (2008) that found evidence that patients do respond to quality information of the type provided through public reporting initiatives.

Taken together, these studies support the view that increasing quality transparency will eventually alter patient decisions and the healthcare market. Our goals are to understand the implications of this impending shift and to use this understanding to identify policy options for leveraging quality transparency to improve societal outcomes. We also seek to shed light on some potential reasons behind the failure of previous public reporting efforts, and discuss ways to improve the effectiveness of future efforts.

Research Questions. To achieve these goals, we address the following research questions, which build on one another.

1. *Patient Response:* How will different patients respond differently to increasingly transparent quality information? Which patients are most/least likely affected by this information?
2. *Provider and Market Response:* How will increased transparency in quality information and the patient behavior it promotes impact competition among providers? Will providers respond by becoming more specialized with regard to either medical procedures or geographic market?
3. *Social Welfare Impact:* What effect will increased transparency have on patient social welfare in both the short-term and long-term? Is it an unmitigated good, or are there limits to the beneficial effects of transparency?
4. *Policy Interventions:* If there are negative impacts of increased transparency on patient social welfare, are there policy options to mitigate them? What policies are most effective?
5. *Public Reporting:* Why have public reporting efforts so far failed to meet expectations, and what can be done to make efforts to increase transparency more effective?

Framework. To address these five questions, we focus on hospitals (although we could easily adapt our analysis to other types of healthcare providers, such as clinics, physicians, or surgeons). We consider three decision-makers that influence alignment of patients and hospitals: patients, hospital administrators, and policymakers. We assume that a patient needing treatment chooses the hospital that maximizes his/her perceived utility. However, when hospital outcomes are not fully transparent, perceived utility will be a distorted approximation of actual utility. We use multivariate regression to model the association between perceived patient utility of choosing a particular hospital and various main covariates that affect this choice including distance to the hospital, hospital volume, actual (risk-adjusted) quality, and perception of quality that can be influenced by marketing (or similar) activities. We assume hospital administrators compete to maximize their gains from patients' contributions by investing in quality improvements and/or marketing efforts to attract patients. Finally, we assume that policymakers seek to maximize social welfare, and also to

reduce inequality among patients, by promoting transparency and correcting potential alignment distortions via incentives to patients and/or hospitals. We examine the five questions above by using our framework both analytically and via simulation analyses calibrated with CMS data on Medicare Part A claims for patients with Heart Failure (HF) or Acute Myocardial Infarction (AMI).
Findings. Our structural analyses of patient response to increased levels of transparency (Research Question 1) suggest that increased transparency has the largest impact on the decisions of younger, more affluent, or urban (i.e., high hospital density area) patients, or those with diseases that can be deferred. The intuition behind this finding is that convenience of access is not the primary concern for these patients, and hence, more precise information about providers is likely to influence their choice. Our analyses with respect to provider and market response (Research Question 2) indicate that increasing quality transparency will induce hospitals to direct a greater portion of their budget toward quality improvement investments, as opposed to marketing investments, which aligns with evidence from the empirical literature (see, e.g., Fung et al. (2008)). Another finding from our analyses is that as transparency increases, hospitals tend to shift their process/quality improvement investments toward their strength and away from their weakness. Increasing transparency can also decrease the total investment made by a hospital in marketing and process/quality improvement. We also find that increasing transparency promotes increased medical specialization by encouraging hospitals to focus on particular treatment and/or patient types. Furthermore, we observe that the effect of increasing transparency on medical specialization is stronger for patients that have a higher willingness to travel (e.g., AMI patients compared to HF patients). To the extent that hospitals increase their medical specialization (as quality transparency increases), they will decrease their geographic specialization—a term used throughout the paper in contrast with "medical specialization" to refer to scenarios where hospitals have a narrow catchment area, and focus primarily on serving patients from their own geographic area—by attracting more distant patients. This, in turn, increases the mean in distance travelled by patients.

With respect to social welfare impact (Research Question 3), we find that increasing quality transparency unambiguously serves the common good in the short-term (i.e., before hospital investment strategies and their organizational learning from performing more procedures can take effect) by increasing social welfare and decreasing inequality among patients, but it does so at a diminishing rate. Because higher levels of transparency will become increasingly expensive (e.g., due to the need for educational efforts beyond posting ratings on websites to enable some patients to make effective use of the posted results), this suggests that something less than full transparency is socially optimal. In the long term, however, we find that economies-of-scale in care delivery will prevent even a fully transparent healthcare system from achieving a socially optimal outcome. The reason is that some hospitals will receive patient volumes below the level needed to achieve high quality outcomes. Importantly, we find that it is possible for increasing transparency to harm social welfare in the long term. However, policymakers (and possibly payers) can correct this failure of the market to converge to the socially optimal structure by accompanying increased transparency with policy interventions that provide corrective incentives to either hospitals or patients. Hence, we make use of our model to identify and evaluate such policies (Research Question 4). While it is possible to modify the market allocation by providing incentives to patients and/or hospitals, we find that incentivizing hospitals is typically more effective than incentivizing patients. Specifically, our results indicate that it is generally better to use any fixed amount of money to incentivize hospitals (e.g., to improve their quality via pay-for-performance type mechanisms) rather than patients (e.g., to increase their willingness to travel via travel subsidies). Finally, the calibration of our model with CMS data suggests a quality transparency level for AMI and HF patients in 2008 that is roughly half way between no transparency and full transparency. This implies that there is significant room for improved public reporting efforts to increase healthcare quality transparency.

These findings imply three potential explanations for the mixed success of public reporting efforts, which in turn imply ways to make such efforts more effective in the future (Research Question 5): (1) Public reporting efforts failed to increase transparency to the levels anticipated by researchers and policy analysts. Our estimate based on Medicare data suggests that the actual transparency level was indeed lower than previously thought, which means that at least some of the mixed evidence is due to the fact that public reporting efforts were not as effective as anticipated in improving transparency. This suggests that policymakers need to find better ways to make outcome information both more accessible and more comprehensible to patients. Options for achieving this include improving public reporting websites, translating outcome information for consumers without statistical training, reporting patient-centric level information as opposed to average patient data, and developing and delivering training to both patients and primary care providers. (2) Policymakers aimed public reporting efforts at the entire population rather than at specific groups of patients. We find that increasing transparency can be more effective if it is targeted at specific categories of patients that are most responsive to outcome information such as younger, urban and/or more affluent patients, as well as patients whose treatment can be deferred. (3) Public reporting efforts were not accompanied by other policy interventions. Our results indicate that policy interventions such as pay-for-performance plans that incentivize hospitals to invest in process improvements are needed to ensure that societal outcomes improve as transparency increases.

2. Related Studies

Studies on Public Reporting. A study of mortality among Medicare patients with heart attack, heart failure, and pneumonia in the five years before and the three years after launch of the Hospital Compare website revealed almost no change in the outcomes for heart attack and pneumonia patients, while the percentage of heart failure patients who died within 30 days was reduced by only 3% (Ryan et al. (2012)). Similarly, DeVore et al. (2012) found that the release of the CMS public reporting of hospital readmission rates was not associated with any measurable change in

30-day readmission trends for acute myocardial infarction, heart failure, or pneumonia, although it was associated with a slight decrease in hospital-based acute care for heart failure patients. Another study concluded that public reporting of the quality of diabetes care led to an increase in implementation of diabetes improvement interventions by clinics, but did not detect an effect on patient outcomes (Smith et al. (2012)). Analyzing evidence from 45 studies of the impact of public reporting of hospital outcomes published since 1986, Fung et al. (2008) found that public reporting stimulates hospitals to increase effort devoted to quality improvement activities. However, the evidence on the association between public reporting and actual improvement in outcomes was found to be inconsistent (see Hibbard (2008)).

Studies on Patient Choice. Studies in this literature generally reveal that the main determinants of patient choice of hospitals are quality and distance (see, e.g., Luft et al. (1990), Tay (2003), Varkevisser and van der Geest (2007), Varkevisser et al. (2010), Dixon et al. (2010), Chandra et al. (2016), and the references therein). Furthermore, as we will discuss later, a wide range of papers in the literature have found that quality itself depends on volume. We utilize these facts in our framework for representing patient choice.

Tay (2003) used a random-coefficient discrete choice model to predict how patients choose hospitals, and found that hospital demand is associated with input measures like the nurse to bed ratio, the range of specialized services offered, teaching status, and hospital size, as well as outcome measures such as one-year mortality and complication rates. Focusing on kidney transplantation, Howard (2006) used a data set of patient registrations in conjunction with a mixed logit model to gauge consumers' responsiveness to quality (i.e., reported graft failure rate) when choosing hospitals, and found that patients do indeed care about hospital quality. Varkevisser et al. (2012) studied the relationship between hospital quality (measured by publicly available quality ratings) and patients hospital choices for angioplasty, and found that patients prefer hospitals with (a) a good reputation (both overall and for cardiology), and (b) a low readmission rate for treatment of heart failure. While this result does not describe the correlation between patient choice and true quality, it does suggest that patients consider proxies for quality. Since patients presumably know that such proxies are imperfect, one would expect them to place less weight on them than they would on true quality metrics.

Studies of Hospital Efforts. Unlike the vast literature on patient choice, the literature on hospital decisions (i.e., their investments) is relatively limited. Smith and Dynan (2016) studied the effect of investment in quality improvement on patient safety, and determined that hospital quality investments have favorable, though not significant, effects on quality. Salkever (2000) reviewed regulations on various types of hospital investments in the U.S., and concluded that relatively little is known about the effect of such regulations on quality improvements. McCarthy (1987) examined hospital investment in marketing/advertising, pointed out a rapid increase in such investments, and discussed a variety of methods hospitals use to establish an advertising budget. We also refer to Fischer (2014) for a more recent review of hospital positioning and marketing activities.

Studies of Healthcare Market Forces and Structures. Efforts to gain a deeper understanding of the drivers of healthcare market structure started with the seminal work of Arrow (1963), which shed light on key features of the healthcare sector that differentiate it from other industries. For a long time, it was widely assumed that healthcare exceptionalism made it resistant to conventional market forces (see, e.g., Chandra et al. (2016), and the references therein for more discussion). However, recent studies have called this assumption into question. Chandra et al. (2016) used an empirical study of Medicare patients with AMI, HF, pneumonia, and hip and knee replacements, to provide evidence that the healthcare sector has more in common with other sectors than was previously thought. Wilson (2016) studied hemodialysis patients in Atlanta, and found that market structure is indeed influenced by hospital quality outcomes. Furthermore, the results in Wilson (2016) suggested that the match between patient and facility is an important determinant of outcomes. However, unlike our work, these studies do not explore the consequences of increasing quality transparency on competitive behavior and market structure. Finally, we note that some papers in the literature have studied the effect of payment mechanisms that can improve the observability of patient outcome (see, e.g., Ma and Mak (2015), and the references therein). While transparency can potentially be gained by changing payment mechanisms, our focus in this paper is on improving transparency via public reporting efforts, which (a) may eliminate the need for changing payment mechanisms, and (b) does not require engagement and coordination of insurers.

Studies on the Impact of Volume on Quality. Various studies in the literature examine how volume affects quality of care in hospitals. Among these, studies such as Chandra and Staiger (2007), Epstein (2002), and Birkmeyer et al. (2002) provide evidence for "learning-by-doing" type mechanisms in hospitals, and refer to the positive impact of volume on quality in healthcare as "productivity spillover" or "volume-outcome effect". Epstein (2002), Birkmeyer et al. (2002), Gammie et al. (2009), and Varkevisser et al. (2012) report that high-volume hospitals tend to perform better than low-volume hospitals. Studying cardiothoracic surgery, Pisano et al. (2001) found that as surgeons perform more procedures their experience accumulates. Huckman and Pisano (2006) showed that the quality of a surgeon's performance at a hospital considerably improves (in terms of mortality) as his/her procedure volume at that hospital increases. In our study, we make use of these findings on the positive impact of volume on quality, and incorporate it in our model. Finally, we note that some studies in the literature have established an economy-of-scale effect in hospitals (see, e.g., Freeman et al. (2018), and the references therein). This literature, however, is typically concerned with the impact of increasing patient volume on hospital costs, while our focus in this study is on hospital quality.

3. The Model

To create a model that helps us understand the impact of increasing quality transparency on the PPA problem, we consider a fixed patient population composed of n patient types that seek treatment from m hospitals. Patient types can be formed along dimensions such as medical condition (e.g., primary condition for which treatment is being sought, indicators obtained from tests or observations, comorbid conditions, etc.) and/or individual characteristics (e.g., age, gender, behaviors such as smoking, etc.), among others.

To model patient choices, we assume the *true* random utility to a patient of type $i \in \mathcal{I} \triangleq \{1, 2, \ldots, n\}$ who chooses hospital $j \in \mathcal{J} \triangleq \{1, 2, \ldots, m\}$ depends on hospital quality and travel distance, and can be written as:

$$U_j^i = \beta^i(x_j^i) + \alpha_j^i p_j^i - \gamma^i D_j^i + \varepsilon_j^i. \tag{1}$$

Here, $\beta^i(x_j^j)$ is a "coefficient of quality" for type i patients that depends on hospital j investment in actual quality/process improvement for treating such patients (x_j^i). The parameter α_j^i represents the effect of volume on quality, and p_j^i is the percentage[1] of patients of type i that choose hospital j (which, as we will see, in turn depends on various hospitals' investments in attracting such patients). This adjustment to quality represents the learning-by-doing effect, which is often called "productivity spillover" or "volume-outcome effect" in healthcare (Chandra and Staiger (2007), Epstein (2002), and Birkmeyer et al. (2002)). We refer to this effect as the "spillover effect" hereafter.[2] D_j^i is a random variable that represents the travel distance to hospital j for a patient of type i, and γ^i represents the weight a patient of type i places on travel time and inconvenience. Finally, ε_j^i is an error term (a random variable) that represents all other factors (including psychological or behavioral) that affect the utility to a patient of type i, which are known to the patient but unobservable by hospital administrators or policymakers. For example, a patient may value being treated in hospital j because a physician or friend recommended it, or dislike it due to a prior traumatic experience at that hospital.

To observe the rationale behind the utility function in (1), note that the success rate of treating a type i patient at hospital j, denoted by S_j^i, can be expressed as:[3]

$$S_j^i = \beta^i(x_j^i) + \alpha_j^i p_j^i + \varepsilon_j^{s,i}. \tag{2}$$

[1] Since the size of patient population is fixed, α_j^i is scaled so as to consider p_j^i as a covariate (instead of volume).

[2] As noted in Section 2, the extant literature provides evidence for the existence of this effect for patients that have similar conditions. However, there is no significant evidence for the existence of this effect across patients of different types. Furthermore, it should be noted that the definition of patient types in our model is flexible, and can be made such that the effect is not significant across patients of different types.

[3] It should be noted that this success rate is often risk-adjusted to account for different patient mixes and to discourage hospitals from "cherry picking" patients to improve their statistics (see, e.g., Dranove et al. (2003)). Furthermore, depending on the procedure, success can be measured by survival rate, rate of complications, readmission rate, patient satisfaction, or other metrics, including compound measures (see, e.g., CMS's Hospital Compare website for some examples of such measures).

Furthermore, a wide range of empirical studies have found that distance and quality are the key determinants of patient hospital choices (see, e.g., Luft et al. (1990), Tay (2003), Varkevisser and van der Geest (2007), Varkevisser et al. (2010), Dixon et al. (2010), Chandra et al. (2016), and the references therein). This is especially the case for procedures like those we consider in this paper (AMI and HF), where hospital waiting lists and other factors related to capacity do not systematically influence patient choice. Consistent with these, we model the utility to a patient of type i from choosing hospital j as:

$$U_j^i = S_j^i - \gamma^i D_j^i + \varepsilon_j'^i, \tag{3}$$

where the coefficient γ^i reflects the willingness of a type i patient to travel to obtain a higher success rate. Of note, the dependency of γ^i on patient type represents the fact that the disutility of distance depends on both socio-economic factors and medical conditions of patients (e.g., for elderly or less affluent patients, or for those with severe medical conditions, distance has a higher impact). Replacing (2) in (3), and letting $\varepsilon_j^i = \varepsilon_j^{s,i} + \varepsilon_j'^i$, yields the utility form defined in (1), which represents the *true* utility to type i patient from choosing hospital j.

However, because hospital outcomes are not fully transparent, patients are not able to make choices based on comparisons of true utility. Instead, they must rely on their *perceived utility*, which we model for patient i at hospital j as:

$$\hat{U}_j^i = \hat{\beta}^i(x_j^i, y_j^i) + \alpha_j^i p_j^i - \gamma^i D_j^i + \varepsilon_j^i, \tag{4}$$

where $\hat{\beta}^i(x_j^i, y_j^i)$ is a "perceived coefficient of quality," and is given by

$$\hat{\beta}^i(x_j^i, y_j^i) = \tau^i(e^i)\,\beta^i(x_j^i) + (1 - \tau^i(e^i))\,\theta^i(y_j^i). \tag{5}$$

In (5), $\tau^i(e^i) \in [0,1]$ represents the level of transparency for patients of type i as a function of e^i, where e^i is public reporting effort level aimed at type i patients. Furthermore, y_j^i denotes investment by hospital j in activities aimed at changing the perception of patients of type i without improving actual quality for them (hereafter marketing activities), and $\theta^i(y_j^i)$ represents the impact of this investment on patient perception.

In this setting, a lower (higher) $\tau^i(e^i)$ represents a less (more) transparent market for type i patients. We define the vector $\underline{\tau} \triangleq \left(\tau^i(e^i)\right)_{i\in\mathcal{I}}$, and refer to it as the *market transparency* of the healthcare sector for the patient types under consideration (i.e., defined by set $\mathcal{I}$). This type of transparency can be affected by public reporting efforts (e.g., posting outcome information on CMS's Hospital Compare website) and increasing it may reduce the need for hospitals to influence patient perception via marketing activities. Specifically, when $\underline{\tau} = \underline{0}$, the market is *fully non-transparent* (FNT), and patient perceptions of quality depend only on the effectiveness of marketing. In contrast, when $\underline{\tau} = \underline{1}$, the market is *fully transparent* (FT), and marketing efforts no longer influence patient's quality perceptions because patients can see for themselves the true quality information about the hospital. The extremes represented by the FNT and FT cases are unlikely to occur in practice, since some patients will always have access to at least some quality proxies (e.g., physician recommendations), and there will always be some patients who are very difficult to educate to fully understand and use the quality information. Nevertheless, these cases offer useful benchmarks for evaluating the impact of increasing transparency. Finally, the reader should note that, in our setting, the impact of increasing transparency on patient (perceived) utility is heterogeneous across patient types. Furthermore, even among patients of the same type, this impact is typically different among individual patients and depends on their education level, age, access to internet or informed primary care physicians, and various other personal characteristics. Our only assumption here is that changing the transparency changes the average effect (i.e., the regression line) on patient (perceived) utility.

Remark 1 (**Marketing Activities of Hospitals**). Hospitals' marketing activities play a critical role in the PPA problem introduced earlier. From a societal perspective, this role can be useful or wasteful in that, in a market with a fixed level of transparency, such activities can improve or impede the way patients are allocated to hospitals. We do not impose any assumption on whether hospitals' marketing activities are useful or wasteful. Our only assumptions with respect to hospital marketing are that (a) marketing activities can influence patient perception of quality, and (b) all else (e.g., marketing investment, patient type, etc.) equal, the level of this influence depends on the quality transparency level, $\tau^i(e^i)$. Although there are not many empirical studies of the marketing behavior of hospitals, these assumptions have strong face validity and seem to be fairly accepted. Reviewing the literature on hospital advertising, for instance, Nanda et al. (2012) cited studies such as Darby and Karni (1973) and Jaegher and Jegers (2000), and argued that *"the peculiarities of the health-credence-good"* prevent patients from verifying *"even ex-post the true quality provided by hospital and consequently, their demand depends on a perceived quality which may be influenced by advertising"* (Nanda et al. (2012), p. 30).

Remark 2 (**Cost to the Patients**). Cost to the patients (e.g., co-payments) is another factor that might affect hospital choice, but we focus on a cohort of patients with same medical insurance and assume hospitals belong to the same network. For instance, for the Medicare patients that we consider in our numerical experiments, almost no cost is borne by the patients. In Online Appendix D, we extend our analysis to consider heterogenous out-of-pocket costs (e.g., when patients have different insurance plans), and show that the main insights gained for a cohort of patients with the same medical insurance continue to hold under this extension.

To perform our analyses, and when needed, we assume $\tau^i(e^i)$ is differentiable and non-decreasing in e^i. In addition, we assume functions $\beta^i(\cdot)$ and $\theta^i(\cdot)$ (which represent the impact of investments in process improvement and marketing, respectively) are both twice continuously differentiable and nondecreasing (for all $i \in \mathcal{I}$). Furthermore, we assume vectors $\underline{D} = (D^i_j)_{i\in\mathcal{I},j\in\mathcal{J}}$ and $\underline{\varepsilon} = (\varepsilon^i_j)_{i\in\mathcal{I},j\in\mathcal{J}}$

follow joint distributions $F_{\underline{D}}$, and $F_{\underline{\varepsilon}}$, respectively, where $F_{\underline{D}}$, and $F_{\underline{\varepsilon}}$ are twice continuously differentiable. We note that the covariances between D^i_j variables may not be zero in general. However, we assume random variables $\underline{D}$, and $\underline{\varepsilon}$ are independent.

To model hospital decisions regarding investments, we let $\underline{x}_j = (x^i_j)_{i\in\mathcal{I}}$, $\underline{y}_j = (y^i_j)_{i\in\mathcal{I}}$. Assuming that hospitals receive a *net reimbursement* r^i for a patient of type i,[4] and that the population size of patients of type i is κ^i, we can express the problem faced by hospital j to maximize its total expected net reimbursement less investment cost subject to its budget as:

$$\max_{\underline{x}_j,\underline{y}_j\geq\underline{0}\ :\ \sum_{i\in\mathcal{I}}(x^i_j+y^i_j)\leq b_j} f_j(\underline{x}_j,\underline{y}_j,\underline{x}_{j^-},\underline{y}_{j^-}), \tag{6}$$

where b_j is the investment budget of hospital j, $\underline{x}_{j^-}$ and $\underline{y}_{j^-}$ represent the investments of other hospitals (in quality improvement and marketing activities, respectively), and

$$f_j(\underline{x}_j,\underline{y}_j,\underline{x}_{j^-},\underline{y}_{j^-}) = \sum_{i\in\mathcal{I}} \left(r^i\, p^i_j\, \kappa^i - x^i_j - y^i_j\right). \tag{7}$$

In this setting, any vector of optimal investments of all hospitals denoted by $(\underline{x}^*_j,\underline{y}^*_j)_{j\in\mathcal{J}}$ that satisfies

$$(\underline{x}^*_j,\underline{y}^*_j) = \operatorname*{argmax}_{\underline{x}_j,\underline{y}_j} f_j(\underline{x}_j,\underline{y}_j,\underline{x}^*_{j^-},\underline{y}^*_{j^-}) \tag{8}$$

$$s.t.$$

$$\sum_{i\in\mathcal{I}}(x^i_j+y^i_j) \leq b_j, \tag{9}$$

$$\underline{x}_j,\underline{y}_j \geq \underline{0}, \tag{10}$$

for all $j\in\mathcal{J}$ is a *Nash equilibrium* for the constrained m-player game implied by our formulation. Of note, in (7), p^i_j clearly depends on the hospital investments, although this dependency is suppressed for notational convenience.

Remark 3 (**Nonprofit Hospitals**). The profit maximization framework introduced above can be utilized for nonprofit hospitals as well as for-profit hospitals. First, we note that many researchers have found little difference between various behaviors of these types of hospitals (see, e.g., Sloan (2000)). Second, while there is no consensus about the exact objective of nonprofit hospitals, as Horwitz and Nichols (2009) describe, two of the prominent theories of nonprofit hospitals are known as "output maximizing" (Newhouse (1970)) and "for-profits in disguise" (Pauly and Redisch (1973)). The former theory posits that nonprofit hospitals maximize their own output, and the latter theory suggests that both nonprofit and for-profit hospitals maximize profit (with the difference that profit is sent to share holders in one and to some specific employees in the other). While our framework above can be directly used under the latter theory, it can also be used under the former theory by setting $r_i = 1$ for all $i\in\mathcal{I}$. However, in both cases, adjustments to the budgets are needed to represent the difference between budgets of for-profit and nonprofit hospitals.

[4] An example of a system with this type of payment is the Inpatient Prospective Payment System (IPPS), in which each case is categorized into a Diagnosis-Related Group (DRG), and each DRG has a specified associated payment.

To model the overall perspective of society, or equivalently those of a policymaker charged with protecting the societal interest, we define *social welfare* as the sum of the expected true utilities received by all patients, given by:

$$\mathbb{E}[\Pi] = \sum_{i\in\mathcal{I}} \kappa^i \, \mathbb{E}_{\underline{D},\underline{\varepsilon}}\Big[U^i_{j^*}\Big], \tag{11}$$

where $j^* = \text{argmax}_{j\in\mathcal{J}} \hat{U}^i_j$. We note that under full transparency

$$\mathbb{E}[\Pi] = \sum_{i\in\mathcal{I}} \kappa^i \, \mathbb{E}_{\underline{D},\underline{\varepsilon}}\Big[\max_{j\in\mathcal{J}} U^i_j\Big]. \tag{12}$$

However, (12) may not hold when $\underline{\tau} < \underline{1}$. In addition to expected social welfare, we also consider *inequality* among patients as measured by the variance (and/or standard deviation) of achieved true utilities.

To simplify our exposition, we consider a reduced version of our model in which there are only two hospitals that can serve patients ($m = 2$). However, the basic insights from this reduced model carry over to an arbitrary number of hospitals (see Online Appendix E for further details).

In what follows, we first characterize patient choice when hospital investments are fixed, and then use our patient choice model as the basis for a hospital competition model to characterize hospital investments. We also use these in a simulation study calibrated with Medicare data for Heart Failure (HF) and Acute Myocardial Infarction (AMI) patients to characterize the impact of increasing transparency on the healthcare market structure and on the societal outcomes. We then characterize policy interventions that are needed to accompany increasing transparency to ensure achieving a socially optimal solution to the PPA problem. Finally, we use our results to identify some reasons for the underwhelming outcomes from previous public reporting efforts, and discuss ways to make future efforts more impactful.

4. Characterizing Patient Choice

We examine patient choices by assuming they seek to maximize their individual *perceived* utility. We do this by using the utility function (4) in the Roy (1951) framework of *self-selection*, which has been widely applied in the labor economics literature. That is, we assume that an individual patient of type i chooses hospital 1 if, and only if, $\hat{u}^i_1 > \hat{u}^i_2$, where $\hat{u}^i_j$ is the realization of the random variable $\hat{U}^i_j$. However, in contrast with the standard Roy model, in our framework p^i_1 (and hence $p^i_2 = 1 - p^i_1$) must satisfy the following *equilibrium condition*:

$$\begin{aligned} p^i_1 &= Pr\{\text{choosing hospital 1 by a type } i \text{ patient}\} = Pr\{\hat{U}^i_1 > \hat{U}^i_2\} \\ &= Pr\{\bar{\beta}^i(\underline{x}^i, \underline{y}^i) + \alpha^i p^i_1 - \alpha^i_2 - \gamma^i D^i + \varepsilon^i > 0\}, \end{aligned} \tag{13}$$

where $\bar{\beta}^i(\underline{x}^i, \underline{y}^i) \triangleq \hat{\beta}^i(x^i_1, y^i_1) - \hat{\beta}^i(x^i_2, y^i_2)$, $\alpha^i \triangleq \alpha^i_1 + \alpha^i_2$, $D^i \triangleq D^i_1 - D^i_2$, and $\varepsilon^i \triangleq \varepsilon^i_1 - \varepsilon^i_2$.

Note that, unless $\alpha^i = 0$, p_1^i appears in both the RHS and LHS of (13). We let p_1^{*i} denote the fixed point solution to (13), and call this the *equilibrium proportion* of type i patients choosing hospital 1. To characterize this proportion, we define the random variable

$$\Xi^i \triangleq \frac{\gamma^i D^i - \bar{\beta}^i(\underline{x}^i, \underline{y}^i) - \varepsilon^i + \alpha_2^i}{\alpha^i} \tag{14}$$

with cdf F_{Ξ^i}, where (without loss of generality) we assume $\alpha^i > 0$. The equilibrium proportion is the *fixed point* solution:

$$p_1^{*i} = F_{\Xi^i}(p_1^{*i}). \tag{15}$$

Note that the equilibrium proportion p_1^{*i} depends on the distribution of random variables D^i and ε^i, and not just their mean and variance. Obviously, it also depends on the hospital investments (which are assumed constant in this section), but we have suppressed this dependency for notational convenience. We also focus only on the equilibrium conditions of the market, rather than on its transient dynamics.

Due to random variables D^i and ε^i in (14), the domain of F_{Ξ^i} is in general $(-\infty, \infty)$. However, to analyze the market equilibrium, we first note that if we consider F_{Ξ^i} as a continuous function and focus on $[0,1]$ as a subdomain (the region in which p_1^{*i} should be sought), it follows from *Brouwer's Fixed Point Theorem* that F_{Ξ^i} always has a fixed point in $[0,1]$, which means that p_1^{*i} always exists. In general, however, F_{Ξ^i} could have multiple fixed points. For tractability, we assume that the following holds for the range of parameters of interest.

ASSUMPTION 1 **(Unique Fixed Point)**. *F_{Ξ^i} has a unique fixed point in $(0,1)$ for all investment ranges of interest, $\underline{x}^i$ and $\underline{y}^i$ $(\forall i \in \mathcal{I})$.*

There are many conditions under which Assumption 1 holds. Below, we provide one set of sufficient conditions. All proofs are provided in the appendix.

PROPOSITION 1 **(Sufficient Condition for Assumption 1)**. *Suppose, for all $i \in \mathcal{I}$, $F_{\Xi^i}(\xi)$ is strictly concave in $\xi \in [0,1]$, and $Pr(\Xi^i \le 0)$ and $Pr(\Xi^i > 1)$ are both non-zero. Then, Assumption 1 holds.*

Similarly, it follows from the *Banach Fixed Point Theorem* that Assumption 1 holds if F_{Ξ^i} is a contraction mapping in $[0,1]$. Both this condition and the condition in the above proposition can be directly verified using the definition of the random variable Ξ^i in (14) and using the required convolution operators on the distribution of the underlying random variables in (14). It should be also noted that the strict concavity of a cdf in the range [0,1] that is required in the above proposition is not a strong assumption and holds for various distributions among families such as Normal, Exponential, Gamma, Beta, Logistic, Hyperbolic Secant, Weibull, Chi-Square, and Laplace (see Online Appendix C for more details).

For future use, we also present the following lemma which allows us to study policies that have a monotonic impact on the percentage of patients that choose each hospital.

Lemma 1 (**Fixed Point Monotonicity**). *Let p_1^{*i} and $\tilde{p}_1^{*i}$ denote the (unique) fixed points of F_{Ξ^i} and $F_{\tilde{\Xi}^i}$, respectively. If $\Xi^i \leq_{st} \tilde{\Xi}^i$, then $\tilde{p}_1^{*i} \leq p_1^{*i}$.*

The result above states that any change (e.g., a governmental policy intervention) that makes the random variable Ξ^i stochastically larger (denoted by $\leq_{st}$) will result in a lower (higher) percentage of type i patients that go to hospital 1 (hospital 2). This result can be extended to situations where Assumption 1 is relaxed, but either the largest or the smallest fixed point in $[0,1]$ is of interest.

We can give a sharper description of allocation of patients to hospitals via the following lemma, which shows that the allocation of patients to hospitals due to their choice (i.e., perceived utility) for any given profile of hospital investments has a *threshold* structure.

Lemma 2 (**Threshold Structure**). *Fix hospitals' investment levels $\underline{x}^i$ and $\underline{y}^i$, and define the following distance threshold (as a random variable):*

$$\bar{D}^i \triangleq \frac{\bar{\beta}^i(\underline{x}^i, \underline{y}^i) + \alpha^i p_1^{*i}(\underline{x}^i, \underline{y}^i) - \alpha_2^i + \epsilon^i}{\gamma^i}. \tag{16}$$

Under Assumption 1, there exists an equilibrium in which the market share of hospital 1 (2) among all type i patients consists of all those who have $d^i \leq (\geq) \bar{d}^i$, where d^i and $\bar{d}^i$ are the realizations of $D^i \triangleq D_1^i - D_2^i$ and $\bar{D}^i$, respectively.

Lemma 2 establishes that there is a threshold on the distance difference between hospitals that defines patient choice (for each patient type). The threshold depends on many factors, including individual error terms. A factor that will become central in our analysis of provider behavior in the next section is hospital investment. Hospitals can influence the perceptions of patients via quality improvement and/or marketing activities, which in turn alter the threshold, and thereby market shares. For example, a well-perceived hospital can attract patients from a wider range of geographical locations than an unknown or ill-reputed hospital. Thus, we can think of the competition among hospitals as being fought with thresholds purchased with quality and marketing investments.

Lemma 2 offers insight into Question 1 from Introduction about how transparency affects patient behavior. In particular, the following result presents sufficient conditions under which increasing quality transparency makes the threshold $\bar{D}^i$ introduced in Lemma 2 stochastically larger. Thus, it provides sufficient conditions under which hospital 1 becomes more attractive for type i patients as the healthcare system becomes more transparent.

Proposition 2 (**Effect of Transparency on Patient Choice**). *Fix hospitals' investment levels $\underline{x}^i$ and $\underline{y}^i$. If Assumption 1 holds and $\beta^i(x_1^i) - \beta^i(x_2^i) \geq \theta^i(y_1^i) - \theta^i(y_2^i)$, then increasing τ^i stochastically increases the threshold $\bar{D}^i$.*

Proposition 2 states that, if for type i patients the difference between the impact of process/quality improvement investments by hospitals 1 and 2 is greater than that of marketing investments, then increasing transparency for type i patients will increase their distance threshold for choosing hospital 1. Hence, as transparency increases, some type i patients who would have chosen hospital 2 because of its advantage in access convenience will change their choice, and travel further to seek care from hospital 1. This, of course, hurts the market share of type i patients for hospital 2, unless hospital 2 changes its investment strategy so as to violate the condition of Proposition 2. We study hospitals' responses in the next section.

To finish answering Question 1, we next identify characteristics of patients whose decisions are least (most) likely to be affected by increased levels of transparency. To this end, we define

$$\delta^i \triangleq \mathbb{E}[\hat{U}_1^i - \hat{U}_2^i | \hat{U}_1^i - \hat{U}_2^i \geq 0], \tag{17}$$

and analyze it to examine patient characterises that make the value of δ^i higher. That is, we consider (without loss of generality) patients who choose hospital 1 over hospital 2, and seek to shed light on factors that will make their *perceived* gain on average higher. This is because, all else equal, a higher δ^i indicates a group of patients whose choice is harder (and hence, less likely) to be altered. Thus, when planning to influence patients' choice (i.e., routing some patients from hospital 1 to hospital 2), policymakers should typically avoid directing their limited resources and attention to patients with a high δ^i, and instead focus on those with a low δ^i.

To examine patient characterises that make the value of δ^i higher, we note from (4) that (17) can be written as

$$\delta^i = c^i - \mathbb{E}[\breve{\Xi}^i | \breve{\Xi}^i \leq c^i], \tag{18}$$

where $\breve{\Xi}^i \triangleq \gamma^i D^i - \varepsilon^i$, and $c^i \triangleq \bar{\beta}^i(\underline{x}^i, \underline{y}^i) + \alpha^i p_1^{*i} - \alpha_2^i$ (recall that $\bar{\beta}^i(\underline{x}^i, \underline{y}^i) \triangleq \hat{\beta}^i(x_1^i, y_1^i) - \hat{\beta}^i(x_2^i, y_2^i)$, $\alpha^i \triangleq \alpha_1^i + \alpha_2^i$, $D^i \triangleq D_1^i - D_2^i$, and $\varepsilon^i \triangleq \varepsilon_1^i - \varepsilon_2^i$).

Since c^i is a constant, using (18) we can show that if $\breve{\Xi}^i$ is a *log-concave* random variable (defined below), then δ^i is nondecreasing in c^i: the rate of increase in $\mathbb{E}[\breve{\Xi}^i | \breve{\Xi}^i \leq c^i]$ as c^i increases is at most linear. Thus, we can focus on patient characteristics that make the constant c^i high.

Definition 1 (**Log-Concavity**). A real-valued function f is said to be log-concave if $f(\lambda\xi_1 + (1-\lambda)\xi_2) \geq [f(\xi_1)]^\lambda [f(\xi_2)]^{(1-\lambda)}$ for all $\lambda \in [0,1]$ and ξ_1 and ξ_2 in the support of f. A random variable is said to be log-concave if its density is log-concave.

Several well-known densities are log-concave, including normal, exponential, logistic, uniform, chi-squared (with degrees of freedom ≥ 2), gamma (with shape parameter ≥ 1), beta (with both parameters ≥ 1), extreme value, and Weibull densities (with shape parameter ≥ 1). Thus, log-concavity is not a very restrictive assumption. Furthermore, any positive concave function is log-concave, and hence, under the conditions of Proposition 1, log-concavity of $\breve{\Xi}^i$ (which is an affine transformation of Ξ^i) is not a strong assumption.

Lemma 3 (**Monotonicity of Perceived Gains**). *If $\breve{\Xi}^i$ is a log-concave random variable, then δ^i is nondecreasing in c^i.*

The implication of the above lemma is the following result.

Corollary 1 **(Effect of Patient Characteristics on Perceived Gains)**. *Suppose* $\breve{\Xi}^i$ *is a* log-concave *random variable. All else equal,* δ^i *is (weakly) higher for the patient type that has a (i) higher* $\bar{\beta}^i(\underline{x}^i, \underline{y}^i)$*, (ii) higher* $\alpha^i p_1^{*i}$*, or (iii) lower* α_2^i*.*

Corollary 1 highlights patient characteristics that result in higher perceived gains from choosing a specific hospital. Part (i) of this corollary implies the intuitive result that for any fixed investments by hospitals, patients with a higher perceived coefficient of quality difference between hospitals 1 and 2 (higher $\bar{\beta}^i(\underline{x}^i, \underline{y}^i)$) have a higher perceived gain from choosing hospital 1. Part (ii) implies that patients with diseases for which the overall spillover effect (α^i) is more pronounced, and/or a higher percentage of patients choose hospital 1, perceive a higher gain from choosing hospital 1. For instance, if hospital 1 has a greater spillover effect for AMI patients than for HF patients, but hospital 2 has the same level of spillover effect for both types of patients, then (all else equal) AMI patients who choose hospital 1 perceive a higher gain on average from their choice compared to HF patients who make the same choice. This implies that AMI patients require less incentives than HF patients to change their choice of hospital. Similarly, if AMI and HF patients have nearly equal spillover effects, but a higher percentage of AMI patients seek treatment from hospital 1 (part (ii)), or if hospital 2 cannot leverage the spillover effect for AMI patients as effectively as for HF patients, yielding a low α_2^i (part (iii)), then AMI patients will be easier to induce to change their choice.

Further insights into Question 1 can be gained by considering the effect of distance. In particular, it can be easily seen that, within a specific patient type, those who choose hospital 1 and live close to hospital 1 but far from hospital 2 (i.e., patients with high $D_2^i - D_1^i$), on average have a higher perceived utility gain from their choice compared to patients who make the same choice but have a similar distance to both hospitals (i.e., patients with small $D_2^i - D_1^i$). This is because the latter group of patients choose hospital 1 primarily because of its (perceived) quality advantage, but the former group of patients are also strongly influenced by the fact that hospital 1 is far more convenient for them. Similarly, it can be easily shown that while it might be hard to change the choice of patients who have a high $|D_2^i - D_1^i|$ (due to their high perceived gain), it is not hard to affect the choice of patients with small $|D_2^i - D_1^i|$. The latter situation (small $|D_2^i - D_1^i|$) might characterize an urban patient, for whom the travel distance to all candidate hospitals is similar. It might also be the case for patients for whom the inconvenience of travel (captured via γ^i) is less than others (e.g., younger or more affluent patients). These observations will be useful in Section 8 where we discuss ways to make public reporting efforts more effective.

5. Characterizing Hospital Investments

Now that we have modeled patient choice, we turn our attention to the providers. We begin by providing sufficient conditions under which there exists a Nash equilibrium $(\underline{x}_j^*, \underline{y}_j^*)_{j \in \mathcal{J}}$ that satisfies $(8) - (10)$ for all $j \in \mathcal{J}$.

PROPOSITION 3 **(Existence of Optimal Hospital Investments)**. *Suppose the conditions of Proposition 1 (and hence Assumption 1) hold. If the investment effectiveness functions* $\beta^i(\cdot)$ *and* $\theta^i(\cdot)$ *are concave (i.e., have a diminishing rate of return) for all* $i \in \mathcal{I}$*, then:*
(i) Each hospital payoff $f_j(\underline{x}_j, \underline{y}_j, \underline{x}^*_{j-}, \underline{y}^*_{j-})$ *is concave in its own investment,* $(\underline{x}_j, \underline{y}_j)$ *(for all* $j \in \mathcal{J}$ *and any feasible investment vector* $(\underline{x}_j, \underline{y}_j, \underline{x}^*_{j-}, \underline{y}^*_{j-})$*).*
(ii) There exists a Nash equilibrium $(\underline{x}^*_j, \underline{y}^*_j)_{j\in\mathcal{J}}$ *that satisfies* $(8)-(10)$ *for all* $j \in \mathcal{J}$*.*

Next, we seek conditions under which the Nash equilibrium $(\underline{x}^*_j, \underline{y}^*_j)_{j\in\mathcal{J}}$ satisfying $(8)-(10)$ for all $j \in \mathcal{J}$ is *unique*. To describe these, we need some preliminary definitions and results. The first is a property known as *Diagonal Strict Concavity* (see Rosen (1965)).

DEFINITION 2 (**Diagonally Strictly Concave (DSC)**). We say that the hospital payoff functions $\big(f_j(\cdot)\big)_{j\in\mathcal{J}}$ are Diagonally Strictly Concave (DSC), if for any two feasible investment vectors $\hat{\underline{z}} \triangleq (\hat{\underline{x}}_j, \hat{\underline{y}}_j)_{j\in\mathcal{J}}$ and $\tilde{\underline{z}} \triangleq (\tilde{\underline{x}}_j, \tilde{\underline{y}}_j)_{j\in\mathcal{J}}$ we have

$$(\hat{\underline{z}} - \tilde{\underline{z}})^T \nabla f(\tilde{\underline{z}}) + (\tilde{\underline{z}} - \hat{\underline{z}})^T \nabla f(\hat{\underline{z}}) > 0,$$

where the notation " ^{T} " denotes the transpose operator, $\nabla f(\underline{z}) \triangleq \big((\nabla_j f_j(\underline{z}))_{j\in\mathcal{J}}\big)^T$, and $\nabla_j f_j(\underline{z}) \triangleq \big((\frac{\partial f_j(\underline{z})}{\partial x^i_j})_{i\in\mathcal{I}}, (\frac{\partial f_j(\underline{z})}{\partial y^i_j})_{i\in\mathcal{I}}\big)^T$.

Using the DSC property, we can define the notion of *well-behaved market shares* as follows:

DEFINITION 3 (**Well-Behaved Market Shares**). We say that hospital market shares $(p^{i*}_j)_{i\in\mathcal{I}, j\in\mathcal{J}}$ are well-behaved if they (i) are unique (e.g., Assumption 1 holds), and (ii) induce DSC hospital payoffs.

REMARK 4 (**Sufficient Condition for Well-Behaved Market Shares**). Since the set of feasible hospital investments is convex, a sufficient condition for the hospital market shares to be well-behaved under the conditions of Proposition 1 (and hence Assumption 1) is that the symmetric matrix $J(\nabla f(\underline{z})) + \big(J(\nabla f(\underline{z}))\big)^T$ is negative definite, where $J(\cdot)$ denotes Jacobian (see Rosen (1965)).

With these definitions, we can state the following sufficient condition under which the vector of optimal hospitals' investments is unique.

PROPOSITION 4 **(Unique Optimal Hospital Investments)**. *If hospital market shares are well-behaved, then there exists a unique Nash equilibrium* $(\underline{x}^*_j, \underline{y}^*_j)_{j\in\mathcal{J}}$ *which satisfies* $(8)-(10)$ *for all* $j \in \mathcal{J}$*, and defines the optimal investment of firms in process improvement and marketing activities.*

Since the market will adjust to the equilibrium described in Proposition 4 as market parameters change, we can characterize the the impact of quality transparency on hospital investments:

PROPOSITION 5 **(Effect of Transparency on Investments)**. *If the conditions of Proposition 1 hold, and there exists a unique Nash equilibrium* $(\underline{x}^*_j, \underline{y}^*_j)_{j\in\mathcal{J}}$ *which satisfies* $(8)-(10)$ *for all* $j \in \mathcal{J}$*, then for all* $i \in \mathcal{I}$ *and* $j \in \mathcal{J}$*:*

(i) Both p_j^{*i} and $f_j(\underline{x}_j, \underline{y}_j, \underline{x}_{j-}, \underline{y}_{j-})$ are supermodular in (x_j^i, τ^i) and submodular in (y_j^i, τ^i).
(ii) Fixing $(\underline{x}_{j-}^*, \underline{y}_{j-}^*)$, the optimal investments of hospital j, x_j^{*i} and y_j^{*i}, are nondecreasing and nonincreasing in τ^i, respectively.

The supermodularity and submodularity properties established in part (i) of Proposition 5 allow us to understand whether hospital investments and quality transparency are economic complements or substitutes. This understanding is summarized in part (ii) of Proposition 5, and partially addresses Question 2 of the Introduction by showing that, as quality transparency increases, hospitals will shift their investments from marketing to process improvement. Since increasing public reporting efforts increases transparency level ($\tau^i(e^i)$ is nondecreasing in e^i), this result is consistent with the findings of Fung et al. (2008) who found empirical evidence that public reporting of outcomes induces hospitals to make quality improvement efforts (see also Hibbard (2008) for a related discussion). Of course, the magnitude of the shift as well as its actual impact on the healthcare market structure depends on the value of several parameters. Hence, in the next section, we use a data set of Medicare patients and address the remainder of Question 2 via a numerical study.

5.1. Numerical Study

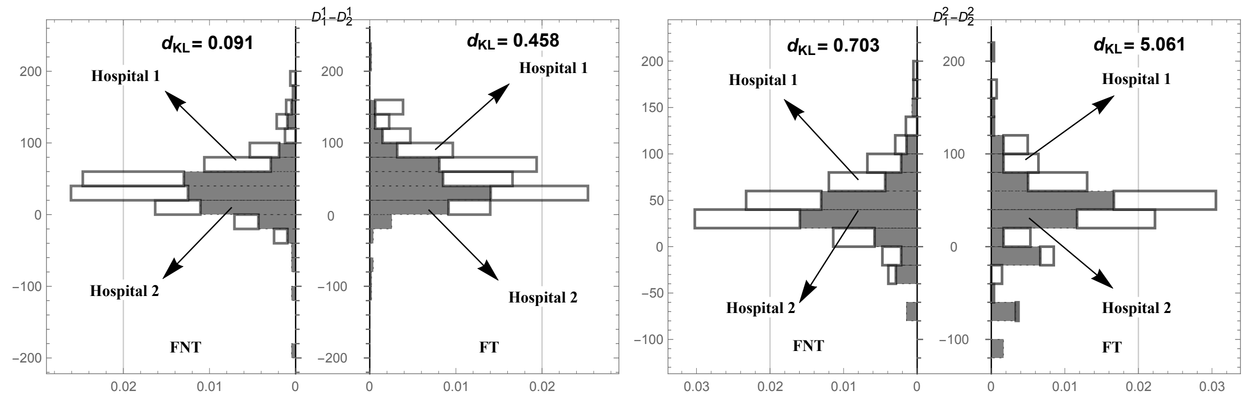
To gain insights beyond the above analytical results, we make use of our framework to conduct simulation analyses calibrated with real-world data. After describing the data set, we first analyze the short-term effects of increasing quality transparency, and then study its long-term effects.
Data Set. To facilitate our numerical studies, we make use of data from Medicare Part A claims that include inpatient hospital visits of individuals aged 66 and older. We focus on visits during 2008, because for this year many quality and related measures have been reported by CMS and other researchers (see, e.g., Chandra et al. (2016)).
Patient Types. We focus on Heart Failure (HF) and Acute Myocardial Infarction (AMI) patients as our two patient types. For notational purposes, we index HF patients as $i = 1$ and AMI patients as $i = 2$. We choose these procedures for various reasons including data availability, availability of various related studies on patient choice for these procedures, and the fact that willingness to travel is in a mid-range for these procedures with a good proportion of patients choosing the hospital with a better risk-adjusted outcomes (and not the closer hospital).
Hospitals. There are many hospitals that treated HF and AMI patients in the data set, and considering all of them in our experiments is computationally intractable. Therefore, to create a computationally tractable yet representative two-hospital scenario that (a) captures the essence of the trade-offs we would like to investigate, and (b) avoids trivial insights when one of the hospitals is the best (or the worst) in treating all the underlying procedures, we divided these hospitals into two groups: those that are typically better (i.e., have a higher coefficient of quality) at treating HF patients than AMI patients, and those that are typically better at treating AMI patients than HF patients (after eliminating a few hospitals that cannot be categorized in this way). We replaced

each group with a single hypothetical hospital with outcome statistics that are representative of the group as a whole. We label the two representative hospitals such that Hospital 1 (2) is better at treating HF (AMI) patients. Finally, we locate the two hospitals (i.e., simulate distance) so as to match the average traveled distance of patients in the data set, where traveled distance is calculated based on the centroid of a patient's ZIP code to that of the hospital. This represents an "average" duopolistic competition between hospitals. One can appeal to our earlier analytical results to analyze situations where the pair of hospitals serve more concentrated populations with a shorter travel distance distribution (e.g., urban hospitals) or with a longer travel distance distribution (e.g., rural hospitals).

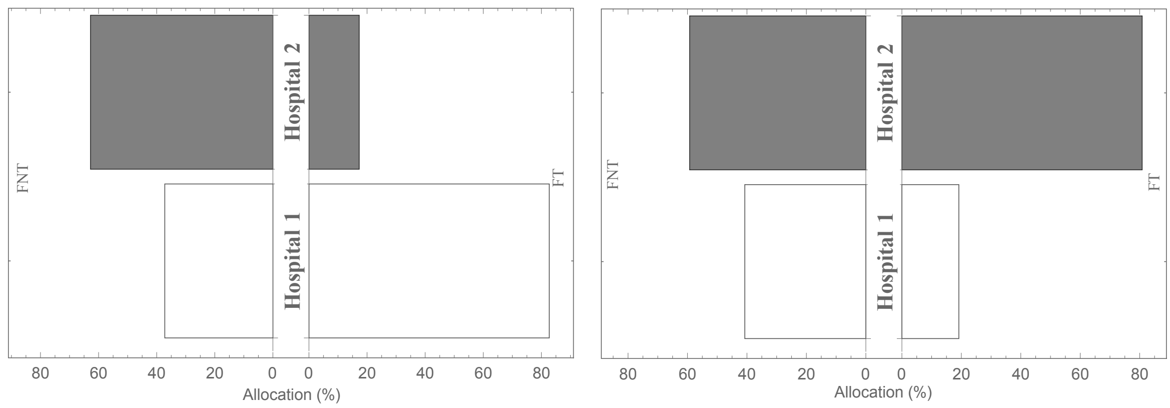
5.1.1. Short-Term Effects To examine the short-term impact of increasing quality transparency, we consider the special case where (1) $\alpha_1 = \alpha_2 = 0$, and (2) hospital investments are fixed. That is, we consider the impact of a change in quality transparency before hospital investment strategies or spillover effects on hospital learning have had time to take effect.

Parameter Estimation (Short-Term Analysis). Chandra et al. (2016) found that, for the data set described above, an average AMI (HF) patient is willing to travel 1.8 (1.03) more miles to gain access to a hospital with 1% point greater risk-adjusted survival (see, e.g., Tay (2003) and Romley and Goldman (2011)) for similar estimates). We use these numbers as our base estimates of parameters γ^i ($i \in \mathcal{I} \triangleq \{1,2\}$), and also note that based on them AMI patients are less distance-sensitive than HF patients. From the 275,671 HF patients and 165,005 AMI patients used in their study, we randomly sample 1 per 1000 patients, and send them to either Hospital 1 or 2 depending on their simulated perceived utility. This results in $\kappa^1 = 275$ and $\kappa^2 = 165$. Consistent with the fact Hospital 1 (2) has been constructed to be better at treating HF (AMI) patients, in the base setting for our short-term analysis, we consider a set of feasible hospital investments such that Hospital 1 (2) has a higher coefficient of quality for such patients. Distance distributions and error terms are assumed to follow log-normal and normal distributions, respectively.

Effect of Quality Transparency on Medical Specialization. Figure 1 illustrates the effect of increasing quality transparency on medical specialization by showing a histogram of patients that go to each hospital. Figures 1(a) and 1(b) depict the changes in the histogram based on difference in the patients' distance to Hospitals 1 and 2 as we move from a FNT market to a FT one for HF ($i = 1$) and AMI ($i = 2$) patients, respectively. In these figures, Kullback-Leibler Divergence (denoted by d_{KL} and defined as $d_{kl}(p||q) \triangleq \int_{-\infty}^{+\infty} p(x) \log \frac{p(x)}{q(x)} dx$ for two distribution functions p and q) is used to formally measure the sepration/distance between distributions. Using this measure, we observe that (i) the distributions are more distant/separated in the FT market than in the FNT market, and (ii) the separation occurring as we move from the FNT market to the FT one is stronger for AMI patients than for HF patients (619% vs. 403% increase in d_{KL}). Similarly, for both FNT and FT scenarios, Figures 1(c) and 1(d) depict the percentage allocation of HF and



(a) HF patients (b) AMI patients



(c) HF patients (d) AMI patients

Figure 1 The short-term effect of quality transparency on medical specialization (d_{KL}: Kullback-Leibler Divergence as a measure of sepration/distance between distributions).

AMI patients to Hospital 1 (the higher quality hospital for HF patients) and Hospital 2 (the higher quality hospital for AMI patients), respectively. These motivate the following:

OBSERVATION 1 (**Transparency and Medical Specialization**). *Increasing quality transparency promotes increased medical specialization. Furthermore, the effect of increasing transparency on medical specialization is stronger for patients who are more able/willing to travel (AMI patients) compared to other patients (HF patients).*

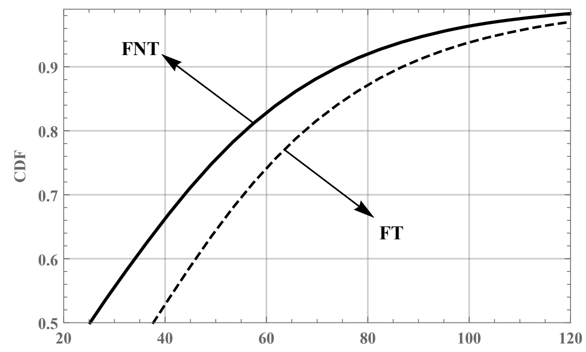
In general, medical specialization can be driven by actions of patients, hospitals, and/or policymakers. The medical specialization in Observation 1 is caused by a response from patients to a change made by policymakers (increased transparency). Although this medical specialization is not initiated by the hospitals, it is still the case that as quality transparency becomes higher, patients will become more able to seek care from the hospital that better matches their need. Furthermore, the resulting medical specialization will be more pronounced for AMI patients compared to HF patients. This is because AMI patients have a higher willingness to travel, and hence, increased transparency is more effective in inducing them to choose higher quality hospitals. In the long-term, these shifts may also induce responses from hospitals (e.g., investments in quality improvement), and can prompt them to further focus on their core competencies. Furthermore, in the long-term the spillover effects will come into play, allowing hospitals to further increase their market shares of their successful procedures. Thus, we expect to see an even more pronounced medical specialization effect in the long-term. However, because patients will need to see the quality improvement results before changing their behavior, and hospitals may need to observe patient shifts before fully committing to quality investments, these shifts may occur incrementally.

Effect of Quality Transparency on Geographic Specialization. Similar to medical specialization, geographical specialization can in general occur because of a response from patients, hospitals, and/or policymakers. In short-term, increasing quality transparency could reduce geographical specialization (as measured by average patient travel distance) if patients (armed with better quality information) choose to travel further to the hospital that is best for them. However, the opposite could occur if data signals in the non-transparent scenario are particularly distorted (e.g., by marketing). In this situation, as transparency increases, patients might realize that their local hospital that does not advertise extensively is actually as good (or better) for them as a distant hospital that does advertise.

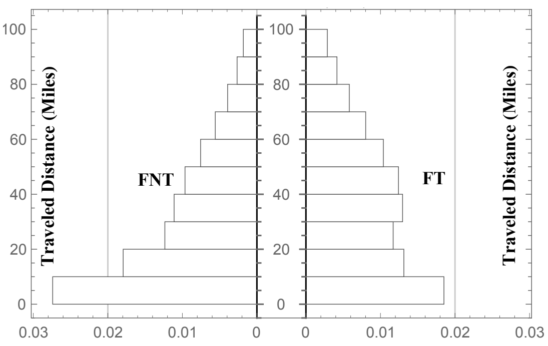
We could create data for our model that leads to either of these cases. But to provide insight into Question 2 about the impact of transparency on market structure, we take advantage of the Medicare data for HF and AMI patients introduced earlier. As a point of comparison, we note that utilizing the same data set we are using, Chandra et al. (2016) concluded that 52% of HF patients and 43% of AMI patients chose the closer hospital. Our model enables us to estimate how much this would change, if the healthcare system were fully transparent.

The results are shown in Figures 2(a) and 2(b), which compare the c.d.f. and histogram of traveled distance by patients under the FT and FNT scenarios. Figure 2(a) shows that traveled distance in the FT case is stochastically larger than that in the FNT case. Furthermore, as Figure 2(c) shows the average traveled distance is increasing in quality transparency, where for the ease of presentation it is assumed that $\tau^1 = \tau^2 = \tau$ (this assumption also reflects the fact that AMI and HF are similar procedures with almost equal levels of transparency.) However, as can be seen from Figure 2(d), this increase in average traveled distance occurs in spite of the fact that traveled distance decreases for most patients that have a higher than median traveled distance in the FNT scenario. The implication is that the decrease in traveled distance for this half of the patients is dominated by the increase in traveled distance for the other half. Since there is a strong correlation between traveled distance and living in rural (versus urban) areas, this suggests that the impact of increasing transparency is stronger for patients living in relatively urban areas than those living in relatively rural areas. This, in turn, strengthens our previous insight from Section 4 that increasing transparency has a lower impact on rural populations than on urban populations (see Section 8 for more discussion on using this insight for improving public reporting efforts).

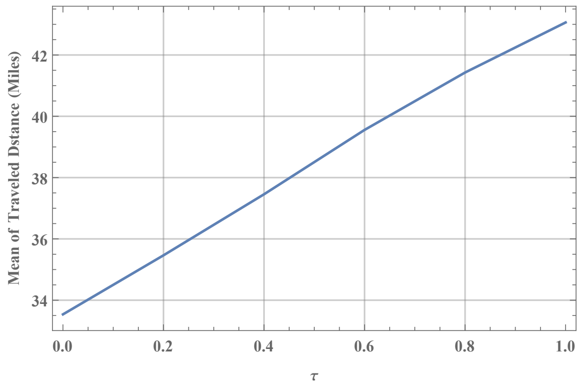
Observation 2 (**Transparency and Geographic Specialization**). *Increasing quality transparency creates incentives for decreased geographic specialization under which patients tend to travel*



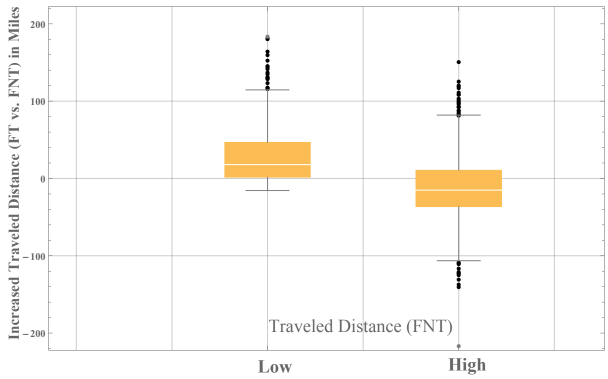
(a) CDF of traveled distance (miles)



(b) Histogram of traveled distance (miles)



(c) Mean of traveled distance (miles)



(d) Box plot of increased traveled distance (miles)

Figure 2 Geographical specialization and quality transparency (negligible splliover effect and fixed hospital investments)

more on average to receive treatment from a hospital that better matches their needs. This increase in average traveled distance is despite a decrease for patients with higher than median traveled distance (e.g., rural patients), and is primarily due to an increase in traveled distance for patients with lower than median traveled distance (e.g., urban patients).

5.1.2. Long-Term Effects We now use the same data set (for Medicare HF and AMI patients) to examine the long-term impact of increasing transparency. In the long-term, two behaviors arise that were not present in our short-term analysis: (1) positive spillover effects will enhance the quality of hospitals with higher patient volumes, and (2) hospitals will adjust their investments to compete for patients and profits.

Parameter Estimation (Long-Term Analysis). We estimate the reimbursements for treating HF and AMI patients based on average Medicare Part A hospital reimbursement rates with a similar DRG to each of our patient types.[5] We assume both hospitals have a budget of $200 million to spend on quality improvement and/or marketing activities, but the qualitative insights we gain are not sensitive to these budget sizes. We estimate the spillover effects based on the statistical

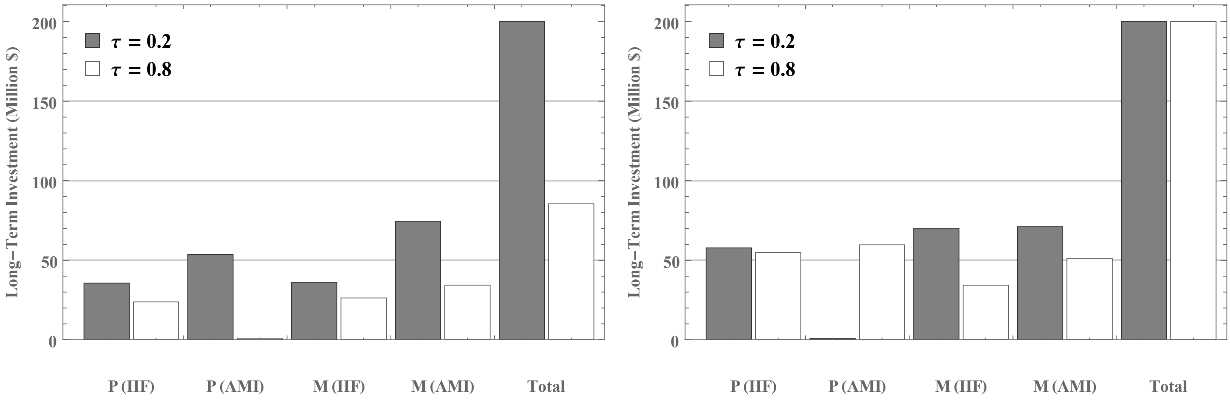
[5] In addition to DRG, Medicare hospital reimbursement rates depend on nation-wide factors (e.g., the cost to treat a nationwide average patient with the same DRG) and hospital-specific factors (e.g. local wage rate, resident training program, etc.); see, e.g., Office of Evaluation and Inspections (2001) and Chandra et al. (2016). We consider an average reimbursement amount among patients with the same DRG.

quality-vs-volume estimates of Birkmeyer et al. (2002) (see also Chandra and Staiger (2007)). Other parameters are the same as in the previous (short-term) analyses.

Computational Methodology (Long-Term Analysis). There are various computational challenges involved in calculating a Nash equilibrium solution. In our setting, this challenge is exacerbated by the following: (1) The functional form of the hospital objective functions is not known a priori, since it in turn depends on another equilibrium (i.e., the fixed point solution, p_1^{*i}) which needs to be calculated first. (2) The game is constrained, requiring investment strategies to satisfy feasibility conditions (e.g., non-negativity and budget limit). (3) The game is of a high dimension: any feasible investment level by the two hospitals is an eight dimensional vector. We overcome these computational challenges via discretization, interpolation, and simulation optimization. To elaborate, for a given feasible investment of Hospital 1 (a four dimensional vector), for all feasible investments of Hospital 2 (four dimensional vectors) that fall on a grid, we simulate the random variables Ξ^i ($i \in \{1,2\}$), and find the fixed points of their distributions (values of p_1^{*i}). We then interpolate these values to find the values of p_1^{*i} for any Hospital 2 investments (fixing Hospital 1 investment). We find the best response of Hospital 2 (a four dimensional vector) to the given investment of Hospital 1. We then fix Hospital 2 investment at these levels, and find the best response of Hospital 1. We iterate this procedure (which includes simulation, interpolation, and four dimensional optimization) until the investments by hospitals reach an equilibrium (i.e., until the changes in best responses are negligible), or a maximum number of iterations is reached. Once the equilibrium investments are determined, we simulate patient choices (based on their perceived utilities), and collect the required measures.

Long-Term Effect of Quality Transparency on Hospital Investments and Market Structure. The long-term effect of increasing quality transparency on medical and geographic specialization is qualitatively similar to its short-term effect, which we described earlier. That is, we observe similar insights as those summarized in Observations 1 and 2. Thus, we next utilize our simulation framework to consider the effect of increasing quality transparency on hospital investments in process improvement and marketing activities across different patient types.

Figure 3 illustrates these investments under both low and high transparency levels, where for the ease of illustration it is assumed that $\tau^1 = \tau^2 = \tau$, and low and high transparency levels are considered at $\tau = 0.2$ and $\tau = 0.8$, respectively. Recalling that Hospital 1 is the best at treating HF patients, and Hospital 2 is the best at treating AMI patients, we observe that as transparency increases, both hospitals tend to invest more in their strength (i.e., serving patients for which they have a comparative advantage) than in their weakness. For instance, as transparency increases from low ($\tau = 0.2$) to high ($\tau = 0.8$), the ratio of process improvement investment in HF patients to that in AMI patients (x_1^j/x_2^j) shows a dramatic increase for Hospital 1, and a dramatic decrease for Hospital 2. Furthermore, we observe that increasing transparency can impact total investment in marketing and process improvement by a hospital. For instance, while Hospital 1 uses its entire bud-



(a) Hospital 1

(b) Hospital 2

Figure 3 Hospital Investments (P: Process; M: Marketing).

get when transparency is low, it uses less than half of it when transparency is high. This is because increasing transparency makes the strength of Hospital 2 in treating AMI patients more apparent, which makes Hospital 1 less competitive for these patients. When transparency is high, process improvement investments in AMI patients are not economically attractive to Hospital 1 because Hospital 2 can counter them with more effective investments of its own. Marketing investments in AMI patients are also not attractive to Hospital 1 because increasing transparency diminishes the weight patients place on marketing induced brand image. Hence, it is optimal for Hospital 1 to retain (rather than spend) part of its budget in the high transparency scenario. This summary allows us to make the following:

Observation 3 (**Investment Shifts**). *As transparency increases, each hospital becomes more specialized by shifting its process improvement investment toward its strength instead of its weakness. Increasing transparency may also decrease the total investment made by a hospital in marketing and process improvement.*

As we expect from the structure of our model, we observe that increased transparency reduces the incentive for both hospitals to invest in marketing. However, we note that reduced spending on marketing by Hospital 2 provides a counter-balancing incentive for Hospital 1 to increase investment in marketing. Nevertheless, considering the combined investments of both hospitals, we see that marketing investment, in both absolute and percentage terms, is lower in the high transparency case than in the low transparency case. Specifically, as transparency increases from low to high, the percentage of the total investment that is directed at marketing decreases from 63% to 51%. Since the high transparency scenario with $\tau = 0.8$ may well be close to the economically practical upper limit, these results suggest that hospital marketing efforts may remain an important part of hospital competition even in the face of successful public reporting efforts to promote quality transparency.

6. Characterizing Societal Impact

Question 3 from Introduction asks what effects increasing transparency has on societal outcomes. To address this question, we begin by asking whether and how the process in which each patient chooses the hospital that maximizes his/her perceived utility produces a socially optimal allocation of patients to hospitals. Obviously, when the market is not fully transparent ($\underline{\tau} < \underline{1}$), individual patients cannot maximize their own true utilities, and so, as we expect, the outcome is both individually and socially suboptimal. Interestingly, however, we find that even under full transparency ($\underline{\tau} = \underline{1}$) social welfare is not maximized simply by allowing individual patients to maximize their true utilities. We demonstrate this in the following, which also enables us to identify hospital investment levels that will yield a socially optimal welfare when transparency is full:

PROPOSITION 6 **(Effect of Transparency on Social Welfare)**. *If the market is fully transparent ($\underline{\tau} = \underline{1}$) and Assumption 1 holds, then:*
(i) Under any given profile of hospital investments $(\underline{x}_j, \underline{y}_j)_{j \in \mathcal{J}}$, the effect of increasing the self-selection PPA equilibrium proportion p_1^{*i} ($\forall i \in \mathcal{I}$) on the expected social welfare is

$$\frac{\partial}{\partial p} \mathbb{E}[\Pi | p_1^i = p] \Big|_{p = p_1^{*i}} = \kappa^i \left(\alpha_1^i p_1^{*i} - \alpha_2^i (1 - p_1^{*i}) \right) = \kappa^i \left(\alpha^i p_1^{*i} - \alpha_2^i \right), \tag{19}$$

where $\alpha^i \triangleq \alpha_1^i + \alpha_2^i$. Thus, if p_1^{*i} is greater (smaller) than α_2^i / α^i, increasing (decreasing) the self-selection PPA equilibrium proportion p_1^{*i} can improve the social welfare.
(ii) Optimal hospital investments $(\underline{x}_j^*, \underline{y}_j^*)_{j \in \mathcal{J}}$ under the self-selection PPA mechanism will yield a socially optimal welfare only when they result in $p_1^{*i} = \alpha_2^i / \alpha^i$ ($\forall i \in \mathcal{I}$).

The intuition behind this result is as follows. When $\frac{\alpha_2^i}{\alpha^i}$ is relatively high (meaning that $\frac{\alpha_2^i}{\alpha^i} > p_1^{*i}$), the spillover effect in hospital 2 is high compared to that in hospital 1. Therefore, it would improve social welfare to have a larger proportion of type i patients treated at hospital 2, and thus, social welfare would increase if we decrease p_1^{*i} by shifting some patients from hospital 1 to hospital 2. Similarly, when $\frac{\alpha_2^i}{\alpha^i}$ is relatively low (meaning that $\frac{\alpha_2^i}{\alpha^i} < p_1^{*i}$), the spillover effect in hospital 1 is high compared to that in hospital 2. Hence, social welfare would increase if we increase p_1^{*i} by shifting some patients from hospital 2 to hospital 1. The driver of this result is the spillover effect. When a patient chooses a particular hospital s/he affects not only his/her own utility, but also the utilities of subsequent patients who choose the same hospital. By increasing the hospital's volume, a patient improves the hospital's quality for treating patients of same type via the spillover effect, and hence, improves the outcomes of future patients. However, patients who are maximizing their own utilities do not take this positive externality into account, and therefore, do not make socially optimal choices. As a result, it is possible that increasing transparency may not increase total patient utility: some transparency increases could actually harm social welfare. The most natural remedy would be to encourage or require some patients to make suboptimal personal choices for the collective good. However, since it is ethically indefensible, in Section 7 we will seek policy interventions that can accompany increasing transparency to achieve socially optimal allocations without coercion.

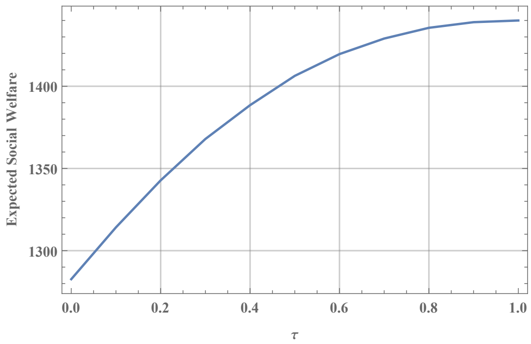
Before exploring such policy interventions, however, we utilize our simulation framework calibrated with Medicare data to gain further insights into the impact of increasing transparency on social welfare and inequality both in the short-term and in the long-term.

6.1. Short-Term Effects

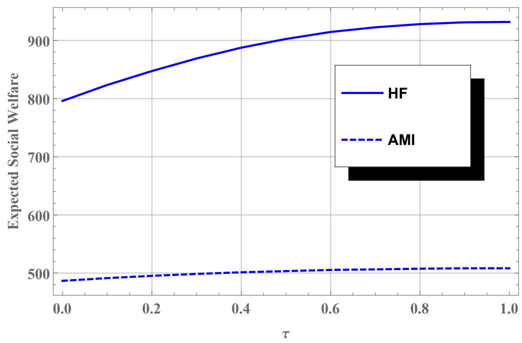
Effect of Quality Transparency on Social Welfare. Figure EC.1 in Online Appendix B illustrates the effect of increasing quality transparency on individual patient choices (made based on their perceived utilities) by displaying the simulated outcomes for the FNT and FT scenarios. Instead of focusing on individual patients, Figure 4 depicts the effect on the expected social welfare (the average sum of the true simulated utilities patients receive based on their choices calculated over 5,000 replications), where for the ease of illustration it is assumed that $\tau^1 = \tau^2 = \tau$. This figure shows that social welfare is monotonically increasing in quality transparency in the short-term. This is expected, because in the short-term spillover effects are negligible, and hospital investments are fixed. Interestingly, however, Figure 4 shows that increasing quality transparency has a diminishing rate of return. This is of practical importance, because the cost to increase transparency will increase as the level of transparency rises. The most medically and statistically savvy patients can be informed simply by posting quality statistics to a website. But other patients will need more support, possibly including personalized instructions, in order to understand their options. Educating every patient to fully understand the outcome statistics and their implications is likely to be prohibitively expensive. This observation, along with the diminishing return from transparency, implies that the social optimum will occur at less than full transparency.

Estimating Quality Transparency Level. We can also use our model to estimate the level of quality transparency, which gives us a sense of how much potential there is for improvement. We do this by comparing the simulated traveled distance to actual traveled distance, which, for our data set, has been reported to be 33.7 (45.0) miles for HF (AMI) patients (see, e.g., Table A3 of Chandra et al. (2016)). Since we randomly sampled 1 per 1000 patients from these populations ($\kappa^1 = 275$ and $\kappa^2 = 165$), we expect to observe a mean traveled distance of approximately $(275 \times 33.7 + 165 \times 45.0)/(265 + 165) = 38.81$ miles. Using this result in Figure 2(c), along with the first moment estimation method and the practical consideration that the transparency level for HF and AMI patients should be almost equal (due to the similarity between these procedures in terms of data collection and measurements), this corresponds to a quality transparency of $\tau^1 = \tau^2 = \tau = 0.53$ in 2008. Hence, we make the following:

Observation 4 (**Quality Transparency Estimation**). *Our analysis suggests that quality transparency for HF and AMI procedures on Medicare patients in 2008 was about 53% (i.e., roughly*



(a) Overall effect



(b) Effect on each patient type

Figure 4 The effect of increasing quality transparency on expected social welfare (short-term)

half way between full non-transparency and full transparency), which implies that there was significant opportunity to achieve higher levels of transparency.

Combining the above observation with Figure 4, which shows the effect of increasing transparency on social welfare, indicates an opportunity for policymakers to improve patient social welfare by increasing quality transparency. However, whether or not this can be achieved with a reasonable level of public reporting effort requires detailed cost analyses to closely approximate the functions $\tau^i(e^i)$ (i.e., transparency as a function of public reporting effort).

Effect of Quality Transparency on Inequality. Although increasing quality transparency increases expected social welfare in the short-term, the benefits may not be distributed evenly across the patient population. Considering the impact of increasing transparency on inequality is important because many healthcare systems, including the one in the U.S., suffer from wide disparities.

To characterize inequality, we consider the standard deviation of true achieved utilities among patients as our metric. Figure 5 shows the effect of increasing quality transparency on this metric, where we assume that $\tau^1 = \tau^2 = \tau$. Based on this figure, we make the following:

Observation 5 (**Quality Transparency and Inequality**). *Increasing quality transparency helps to reduce inequality in the short-term.*

Note, however, that this result assumes that outcome information is equally accessible by all patients. In societies where the access to (or the interpretation of) such information is vastly different among patients (e.g., due to significant differences in access to Internet, education, etc.), increasing transparency may aggravate inequality in the healthcare system.

Finally, in Online Appendix F, we test the robustness of our findings on the impact of increasing transparency on social welfare and inequality after excluding distance from the calculations of these societal outcomes (that is, by merely considering the impact of transparency on achieved qualities among patients). Our results indicate that while the magnitudes of social welfare and inequality change, our observations regarding the impact of increasing transparency on social welfare and inequality remain intact.

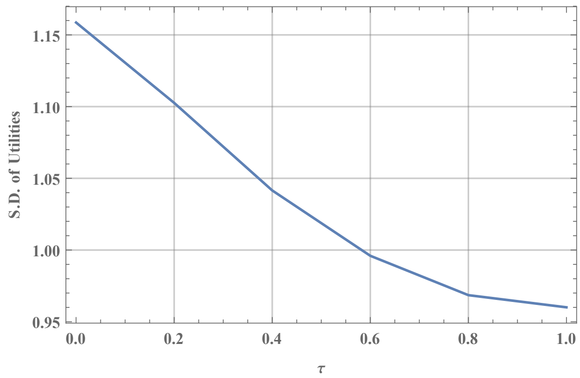


Figure 5 Inequality and quality transparency (short-term)

6.2. Long-Term Effects

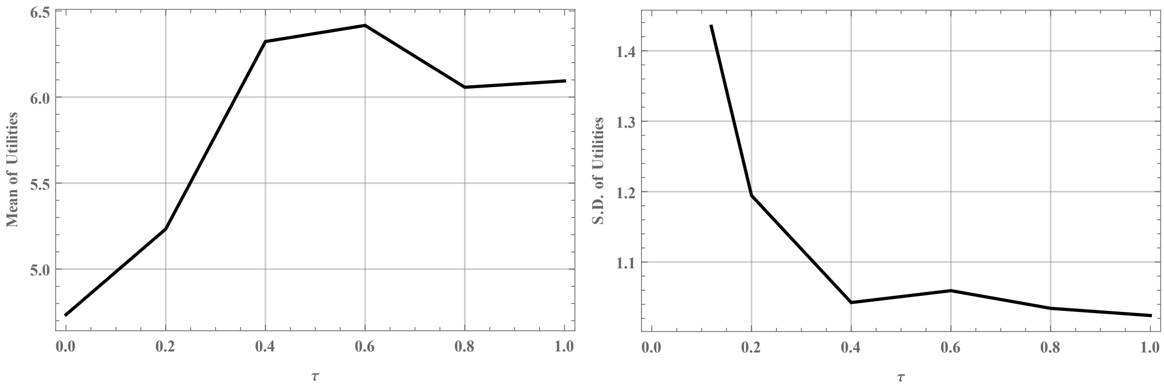
Long-Term Effect of Quality Transparency on Social Welfare and Inequality. By using the previously described approach to generate market equilibriums for a range of $\tau^1 = \tau^2 = \tau$ values, we can examine the effect of quality transparency on patient outcomes. Figure 6 summarizes the outcomes in terms of mean patient utility (social welfare) and standard deviation of patient utility (inequality). From these, we make the following:

OBSERVATION 6 (**Long-Term Societal Impact of Increasing Quality Transparency**). *In contrast to the short-term impact of transparency, in the long term the effect of increasing quality transparency on social welfare and inequality may not be monotonic. Because of the spillover effect, social welfare may decline at higher levels of transparency. This is another reason (in addition to cost) that striving for full transparency may not be desirable.*

The above result is consistent with Proposition 6, and the discussion following it. As noted there, when spillover effects are not negligible, the market share of hospitals in the equilibrium might differ from that of a socially optimal PPA, even in a fully transparent market. That is, even under full transparency, having some patients deviate from their best interest can yield an increase in social welfare, since patient choices have spillover effects on the choices made by other patients. A less-than-full transparency level may achieve this (possibly with only a tiny sacrifice of quality), thus resulting in improved overall benefits in the long-term, and a non-monotonic trend as transparency increases. Inequality among patients is also non-monotonic, as shown in Figure 6(b). Finally, we note that the potential need to have some patients deviate from their best interest only exists when increasing transparency is not accompanied with other policy interventions. In the next section, we discuss some policy interventions that can remove this need.

7. Characterizing Policy Interventions

As we observed in the previous section, in a market with unrestricted patient choice and hospital competition, social welfare may decline when transparency reaches high levels. Thus, to assure transparency improves social welfare, it may need to be accompanied by policy interventions that



(a) Mean of achieved utilities (b) Standard deviation of achieved utilities

Figure 6 Mean and standard deviation of achieved utilities (long-term)

adjust the allocation of patients to hospitals. In the following proposition, we provide some insights into such policies, and thereby address Question 4 from Introduction.

PROPOSITION 7 **(Policies for Improving Social Welfare)**. *If, in a fully transparent market with well-behaved market shares, $p_1^{*i} > \alpha_2^i/\alpha^i$, then the following policy approaches can be utilized to improve expected social welfare:*

(I) Incentivizing patients. *(i) Providing travel subsidies for patients of type i to visit hospital 1, and/or (ii) Changing hospital densities by building more hospitals similar to hospital 1.*

(II) Incentivizing hospitals. *(iii) Incentivizing hospital 1 for quality improvements (e.g., through pay-for-performance mechanisms) for the treatment of patients of type i, and/or (iv) Increasing the net reimbursement for patients of type i who visit hospital 1.*

Each of the above categories of policies can improve social welfare by pushing the hospital market shares closer to the socially optimal mix. Although our numerical experiments focused on Medicare patients, we note that some of these policy levers are already being used for privately insured patients. For example, Walmart, Lowe's, and Boeing reimburse their employees for travel costs to hospitals designated as "Centers of Excellence" (see, e.g., Zeltner (2012)). Similarly, some private insurers waive or reduce co-pay to incent patients to choose designated hospitals. They also reward hospitals in various ways for outcome quality, which in turn influences hospital investments in quality. In single payer systems, such as those in Canada or the U.K., the central government can directly influence the densities of different hospital types. In the U.S., closed systems (e.g., the VA) and states with certificate of need legislation can influence hospital density to a smaller degree.

While all of the policies in Proposition 7 can in theory correct market allocations, they may differ in their effectiveness. To gain insight into whether it is more effective to follow policies that provide incentives to patients or to hospitals, and thereby address the remainder of Question 4 from Introduction, we again utilize our simulation framework. Specifically, we assume that a fixed amount of money can be used to either incentivize hospitals or patients, where such incentives can improve hospital quality by η^β percent (increasing $\beta^i(\cdot)$ to $(1+\eta^\beta)\beta^i(\cdot)$) or improve patients

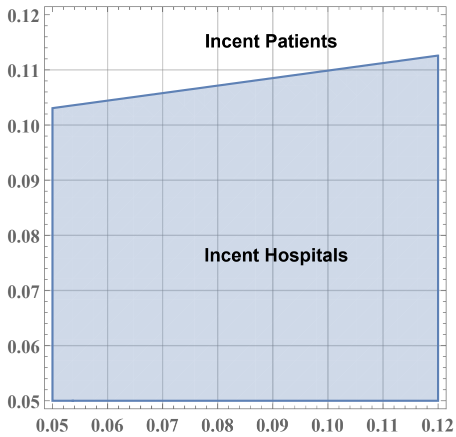


Figure 7 Who to incentivize, hospitals or patients? (x-axis: η^β; y-axis: η^γ)

willingness to travel by η^γ percent (decreasing γ^i to $(1-\eta^\gamma)\gamma^i$). To be consistent with Proposition 7, we also assume that the market is fully transparent, and seek to find the range of η^β and η^γ for which one strategy dominates the other (in terms of proving a higher level of social welfare).

Figure 7 depicts the result of varying η^β and η^γ in the range $[5\%, 12\%]$ as a practical/feasible set. As can be seen from this figure, incentivizing hospitals dominates incentivizing patients except for a small set of (η^β, η^γ) values. Figure 7 also suggests that mix strategies in which some proportion of money is allocated to incentivizing hospitals and some to incentivizing patients are typically dominated by a pure strategy that allocates the whole budget to incentivizing hospitals. Thus, we make the following:

OBSERVATION 7 (**Who to Incentivize?**). *It is generally more effective to use a fixed amount of money to incentivize hospitals rather than patients.*

Finally, an important practical issue in selecting an appropriate policy is implementation. In theory, a policymaker can evaluate the socially optimal solution to the PPA problem, and make use of any of the mechanisms in Proposition 7 to push the market toward this solution. But in actual practice, it will be impossible to obtain the data to compute the optimum precisely. Furthermore, because providers are continually evolving their capabilities, the parameters in our model that represent the coefficients of quality for hospitals and spillover effects for the industry will change over time. Policies that incentivize patients (by subsidizing choice of individual hospitals or by actually building new hospitals) are both highly sensitive to errors in parameter estimation and not at all adaptive to changes in environmental variables. In contrast, pay-for-performance policies that reward hospitals for the quality of their patient outcomes are easier to tune through trial-and-error, and are self-adaptive to process improvements across the industry. These observations reinforce the conclusion of Observation 7 that hospital incentives are likely to be more effective than patient incentives in improving social welfare.

8. Public Reporting Efforts

Finally, we turn to Question 5 from Introduction that asks for reasons previous public reporting efforts have failed to meet expectations, and how such efforts could be made more effective in the future. Our results highlight three likely causes of prior failures, each of which offers an avenue for making public reporting efforts more effective:

1. *Public reporting does not necessarily increase patient awareness:* To begin with, our simulation analyses calibrated with data for HF and AMI Medicare patients reveal a rough estimate of $\tau^1 = \tau^2 = \tau = 53\%$ for these procedures in 2008. These patients were not acting remotely as we would expect of well-informed patients. While we lack data to evaluate how much this gap has been closed in the intervening years, it is a distinct possibility that public reporting efforts did not raise patient awareness of hospitals' performance. As a result, many patients may not have acted on this information. If this is the case, the first step toward achieving the goals of public reporting is to figure out ways to make outcome information not only more accessible, but also more understandable and useful for patients. This can be achieved by improving public reporting websites to be more intuitive for non-statically minded consumers, and by developing and delivering training to patients as well as primary care providers who refer patients for specialized care.

2. *Public reporting requires targeting:* The results in Section 4 indicate that the impact of providing outcome information is not uniform across patient types. Specifically, the results in that section provide a mechanism for identifying patients who are particularly responsive to public reporting. For example, they suggest that patients in urban areas (whose choices are not highly influenced by distance) are more likely to be influenced by increasing transparency than are rural patients. Similarly, younger patients, more affluent patients, patients with diseases for which treatment that can be deferred, or those with a low $\bar{\beta}^i(\underline{x}^i, \underline{y}^i)$, low $\alpha^i p_1^{*i}$, or high α_2^i are more likely to be impacted by public reporting efforts (see Corollary 1, and the discussion following it). These suggest that, once public reporting efforts have been made effective in increasing patient awareness, the second step is to target specific groups of patients. To our knowledge, previous public reporting efforts have been directed at a general population of patients without any specific targeting mechanism. Future efforts that focus on patients that benefit most from transparency will have more impact.

3. *Public reporting needs to be accompanied by other policy interventions:* The results of Sections 6 and 7 show that full transparency does not necessarily maximize social welfare. This suggests that even public reporting efforts that successfully communicate outcome information to all of the patients who would benefit from it may fall short of their full potential in improving societal outcomes. While public reporting efforts to date have not been accompanied by other policy interventions, our results in Section 7 shed led on the type of policy interventions that can effectively correct for the failure of increased levels of transparency to achieve a socially optimal allocation of patients to hospitals. In particular, our results suggest that the third step in implementing pub-

lic reporting is to implement policies aimed at incentivizing hospitals (e.g., pay-for-performance rewards) to make socially optimal investments.

9. Conclusion

The advocates of public reporting base their arguments on a claim that increased transparency will lead to higher social welfare because patients will be able to make better healthcare decisions. Our analysis supports this claim in the short-term. However, in the long-term, spillover effects and hospital competition create a more nuanced picture. We conclude that targeting of public reporting efforts at certain patient populations and hospital incentives to correct market distortions are needed to obtain the full social benefit of outcome transparency.

The picture becomes even more nuanced if the behavior of multiple interacting payers is considered. For example, by guiding patients to certain centers of excellence, large employers like Walmart and Lowes are taking those patients away from smaller local hospitals. This will eventually cause quality at the smaller hospitals to decline due to a lack of scale, and result in reduced utility to patients not subsidized to go to other hospitals. Understanding the market equilibrium that will result from multiple competitive payers will require another layer of modeling beyond that of this paper. This complex but vital question is an important opportunity for future research.

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