Hospital Competition and Quality: Evidence from the Entry of the High-Speed Train in South Korea*

Hyesung Yoo† Maria Ana Vitorino‡ Song Yao§

September 2023

PRELIMINARY AND INCOMPLETE.
DO NOT CITE OR CIRCULATE WITHOUT THE AUTHORS' PERMISSION.

Abstract

This paper leverages the entry of a high-speed train (HST) system in South Korea as a quasi-experiment to establish the causal effect of competition among hospitals on consumer welfare and health care quality. We implement a difference-in-differences research design that exploits the differential effect of the HST entry on hospitals based on their distance to train stations. Our results show that hospitals located closer to train stations experience lower mortality rates after the introduction of the HST, thus suggesting that increased accessibility resulted in improved clinical outcomes. To formally evaluate the impact of competition on quality, we estimate a demand model of hospital choice wherein patients evaluate the tradeoff between hospital quality and travel costs when selecting from different hospitals. The model results reveal that patients living closer to HST stations experienced positive gains in welfare as a result of the entry of the HST. Further, we show that the expansion of patients' consideration sets not only resulted in improved health outcomes due to better patient sorting, but also prompted increased competition among hospitals to increase their quality, which in turn also had a significant impact on health outcomes.

*We thank Dinara Akchurina, Mark Bergen, Andrew Ching, Thomas Holmes, Nitin Mehta, Amil Petrin, Katja Seim, Mengze Shi, Joel Waldfogel and Linli Xu for helpful comments. We also thank the discussants Ashvin Gandhi, Stephan Seiler and Ying Xie for their feedback as well as seminar participants at the University of Toronto, University of Minnesota, Sorbonne University, Cornell University, University of Chicago, Washington University in St. Louis, Bocconi University, CEPR Industrial Organization Seminar Series, European Quantitative Marketing Seminar, INFORMS Marketing Science Conference 2018, UT Dallas Bass FORMS Conference 2021, IIOC 2022 and SICS 2022. The opinions expressed in this article are the authors' and do not reflect the view of the South Korean National Health Insurance Services and of the South Korean Health Insurance Review Services.

†University of Toronto: hyesung.yoo@utoronto.ca
‡INSEAD: maria-ana.vitorino@insead.edu
§Washington University in St. Louis: songyao@wustl.edu

1 Introduction

Upgrades to transportation infrastructure can have a considerable impact on the economy, the environment, and people's quality of life. For example, upgrading road systems, and expanding public transportation options can alter commuting patterns, have an effect on traffic congestion, and improve the overall efficiency of transportation systems (e.g., Allen and Arkolakis 2022, Fajgelbaum and Schaal 2020, Barwick et al. 2022). In addition, improved transportation infrastructure can provide better access to various economic opportunities, such as employment, education, and healthcare (e.g., Adukia, Asher, and Novosad 2020, Aggarwal 2021, Manning and Petrongolo 2017). By reducing travel time and increasing accessibility, improved transportation infrastructure can provide individuals with greater access to essential services. Evaluating the benefits of improved transportation infrastructure on critical services such as healthcare can be difficult, despite its importance. This is due to the complex interplay of various factors that influence healthcare access and clinical outcomes. For instance, it can be challenging to determine how much better access to healthcare facilities or services results from improved transportation networks, and how this improved access translates into improved clinical outcomes.

In this paper, we evaluate the impact of the introduction of high-speed train (HST) services in South Korea on patient welfare, health outcomes, and quality of healthcare. The HST's arrival in 2004 improved access to hospitals for a substantial portion of the population, reducing travel costs and enabling them to seek more suitable care. Moreover, the new transport option altered the hospital market structure by increasing patient choice and decreasing hospital concentration.

Although the introduction of HST services is expected to lead to favorable outcomes such as reduced travel costs and improved patient sorting, the impact on health outcomes resulting from changes in the hospital market structure can be ambiguous. The existing literature has not definitively established whether increased competition in healthcare markets results in improved or diminished healthcare quality (e.g., Gaynor 2006, Gaynor, Ho, and Town 2015). Therefore, the impact of better transportation and healthcare access on health outcomes is not straightforward, as various complex effects on both demand and supply sides are involved.

The South Korean healthcare industry is an ideal setting for our analysis because all residents in South Korea are insured by the National Health Insurance (NHI), and patients have the freedom to go to any hospital of their choice. Moreover, in South Korea, prices for insured treatments are fixed eliminating any price-based competition. As a result, our attention can be solely directed towards competition based on quality, without considering potential price reactions.

We use unique data obtained from the South Korea National Health Insurance Services

(NHIS) comprising health insurance claims for a representative sample of the South Korean population and hospital characteristics from the years 2003 to 2007. The data include detailed patient information including demographics, diagnosis, chosen hospital and mortality. In line with extant health economics literature, we focus on inpatient individuals who have undergone a surgical procedure at a hospital, and use data on patient mortality to construct a measure of hospital quality for the period before and after the introduction of the HST. While critical for our analysis, the NHIS does not contain information regarding exact hospital location as hospitals in the data are anonymized. However, based on the hospitals' characteristics and other public information we are able to obtain exact geographical coordinates for each hospital. We combine this data with information on the HST geographical network and focus on the effect of the introduction of the system's two main lines which were introduced simultaneously in 2005. Using this information we construct itineraries that detail the distances covered and time taken for each patient-hospital pair.

We exploit this rich data, and leverage the variation in the HST coverage across regions, to provide reduced-form evidence on how both patients and hospitals responded to the introduction of the HST. We find that patients living in close proximity to train stations prefer hospitals that are, on average, located at a greater distance from their homes following the introduction of the HST. We do not observe a similar pattern among other patients who reside further away from train stations. Further, we use the variation in HST coverage across regions and time to estimate the causal impact of increased hospital competition, due to increased patients' accessibility, on quality of care.

We argue and show that the entry of the HST represents a plausibly exogenous source of variation on hospital concentration as the entry of the HST is unlikely to be associated with changes in health policies that could also lead to changes in health outcomes. First, the design of new HST lines were built following existing train lines which already relied on historical railroad networks. Further, we demonstrate that changes in health outcomes for patients residing far from train stations but accessing hospitals near these stations are not significantly different from those observed for patients residing in close proximity to the train line, thus precluding the possibility that concurrent health policies coinciding with the train line may positively impact the health of the population residing in proximity to train stations and seeking medical care there.

As a result of the introduction of the HST, certain regions of the country witnessed enhanced accessibility, while others did not, and the level of accessibility tended to decrease with proximity to the train station. This variation thus allow us to compare outcomes for hospitals that experienced varying levels of changes in market concentration, following the introduction of the HST. In our analysis, we use adjusted measures of hospital quality which we construct using instruments to account for the fact that that patients' unobserved (to the researcher) severity of illness is likely to be correlated with hospital choice, thus contaminating raw mortality rates. Using a difference-in-differences design, we show that hospitals located closer to train stations experience lower mortality rates after the introduction of the HST, thus suggesting that increased competition results in better quality of clinical care. On average, mortality rate decreases by 0.25 percentage points per minute of proximity to a train station.

We proceed to develop a structural model of hospital choice, wherein patients evaluate the tradeoff between hospital quality and travel costs when selecting from different hospitals.[1] The structural model allows us to obtain estimates of economic primitives such as elasticities to travel time and to hospital quality. Further, it allows us to quantify patients' welfare gains and conduct counterfactuals. Ultimately, the structural model allows us to show the different mechanisms through which the introduction of the HST affects health outcomes. Our findings confirm the significant impact of travel costs on patients' hospital preferences, as patients experience significant disutility associated with the inconvenience of traveling to visit a hospital.

Using the estimated parameters from the model, we conduct simulations to assess the impact of the introduction of the high-speed train (HST) on patients' hospital choices and subsequent welfare and health outcomes. Our results reveal significant welfare gains, particularly for patients residing in close proximity to train stations, due to the reduction in travel time facilitated by the HST, even while holding quality constant. Moreover, we find that the sorting of patients to better hospitals as a result of lower travel costs leads to an annual saving of 49 lives. Notably, rural patients who can now access the HST as a means of transportation experience the greatest benefits, with estimates indicating a 0.88 percentage decrease in mortality for urban patients and a 1.61 percentage decrease for rural patients.

Furthermore, our findings highlight positive externalities for patients who do not have direct access to the new transportation system, but still benefit from improved access to higher quality healthcare. This underscores the wider impact of the HST on healthcare accessibility and quality, beyond just the immediate beneficiaries of the new transportation system.

We also show that the introduction of the HST makes patients more sensitive to hospital quality, as reduced travel costs diminish the significance of distance as a differentiating factor among hospitals. Consequently, hospitals respond to this change in patient elasticities to quality by enhancing their quality, with hospitals located closer to the train station experiencing more pronounced effects. Therefore, we show that the expansion of patients' consideration sets not only resulted in improved health outcomes due to better patient sort-

[1] The importance of the tradeoff between quality and travel time that patients face has been highlighted in Tay (2003). This tradeoff between quality and travel time is what gives hospitals market power, especially when patients have the full freedom to choose any hospital.

ing, but also prompted increased competition among hospitals to increase their quality, which in turn also had a significant impact on health outcomes.

Our paper contributes to two distinct literatures. First, the paper contributes to the growing literature on transportation. Recent research has developed richer transportation and spatial equilibrium models which address a variety of topics.[2] Spatial models have been used, for instance, to study the role of network effects on trade costs (e.g., Brancaccio, Kalouptsidi, and Papageorgiou 2020), the consequences of transportation policies on congestion (e.g., Barwick et al. 2022), the spatial sorting of labor (e.g., Fajgelbaum and Gaubert 2020), and search frictions in decentralized spatial markets (e.g., Fréchette, Lizzeri, and Salz 2019, Liu, Wan, and Yang 2021, Brancaccio et al. 2022, Buchholz 2022). Our research is especially related to a subset of the literature that studies the impact of infrastructure development on economic activity. Fajgelbaum and Schaal (2020) and Allen and Arkolakis (2022) have recently studied optimal (and endogenous) transport network design within a general equilibrium spatial trade framework. Different from our focus, Allen and Arkolakis (2022) measure the impact of road infrastructure investments on congestion and transportation costs, while Fajgelbaum and Schaal (2020) study the social planner's optimal transport (road) network investments subject to congestion in shipping. Barwick et al. (2022) builds a model of housing location and commuting mode choice to study the impact of subway expansion (together with other transportation policies) on congestion and residential sorting. Most closely related are papers that estimate the impact of developments in the railway network. Heblich, Redding, and Sturm (2020) quantify the impact of the invention of the steam railway on the separation of workplace and residence in London. Donaldson and Hornbeck (2016) assesses the impact of railroad development in the US on the agricultural sector, and Donaldson (2018) evaluate the welfare implications of railroad development in India by looking at how trade costs and trade and income levels are impacted by the development of the railroad network in India. Qin, John, and Vitorino (2023) investigate the impact of the introduction of the HST on the airline industry in China. Different from these papers, our research focuses on the link between infrastructure improvements and health outcomes, and shows how improvements in transportation infrastructure can affect the healthcare industry, both directly through reduced travel costs and better patient sorting into hospitals but also via hospitals' quality competition.

Secondly, our paper contributes to the literature on how hospital competition affects quality of care. While several countries, such as the United Kingdom and Sweden, which historically have been providing healthcare through centralized non-market means have recently adopted or are considering market oriented reforms, but the empirical evidence on the

[2] Redding and Rossi-Hansberg (2017) and Redding (2021) offer two reviews on the broader literature on economic geography and spatial economics.

effect of health services competition on clinical quality and patient outcomes is mixed. Assessing the impact of competition on health care is complex due to the fact that competition in health care markets is based on geography. Hospitals compete in geographical markets because patients have a strong preference, among other things, for hospitals that are located close to their home. Since some geographies are intrinsically more competitive than others, it is difficult to separate the effect of competition from geographical factors using only cross-sectional analysis. Therefore, many researchers have used changes in cross-sectional variation in levels of market structure over time to identify the impact of competition. However, the challenge again lies in the fact that the market structure is endogenous: quality of incumbent hospitals and potential entrants in a given geographical region may affect their strategic entry and exit decisions. Kessler and McClellan (2000), who examine the impact of market concentration on hospital quality in the US Medicare program. They find that higher market concentration leads to significantly higher mortality rates for heart attack patients. On the other hand, some papers find opposite results. Using similar methods to Kessler and McClellan (2000), Gowrisankaran and Town (2003) find that mortality rates are higher for Medicare heart attack and pneumonia patients that are treated in less concentrated markets. This is in contrast to the classical theoretical literature which predicts that increased competition under fixed prices results in improved quality.[3] While these papers use the predicted market share based on exogenous characteristics of the hospitals and patients to solve the endogeneity in market shares, they do not deal with the issue that the number of hospitals itself may be endogenous due to entry and exit.

To address the issues related with the endogeneity of market concentration when measuring its effect on health outcomes, more recently, researchers have explored changes in market structure induced by health-related policies, which are seen as exogenous shocks that spur competition. Propper, Burgess, and Green (2004) leverage on the 1991 Health Reform in the UK National Health Service, and find that the relationship between competition and AMI mortality rates is negative Propper, Burgess, and Gossage (2008) further investigate this policy change and find that increased competition reduces waiting times, suggesting that hospitals facing more competition cut-on services that affect mortality rates (which are unobserved, in their setting, by consumers) in order to focus on other activities which are better observed by health-care buyers Cooper et al. (2011) and Gaynor, Moreno-Serra, and Propper (2013) exploit the 2006 English pro-competitive policy shift to study the impact of competition on quality using a difference-in-differences research design. Both papers find that increased competition improves the quality of clinical care. Leveraging on the same reform, Gaynor, Propper, and Seiler (2016) find coronary artery bypass graft patients to

[3] Gowrisankaran and Town (2003) suggest as a possible explanation for their results that a sufficiently low profit margin on Medicare patients coupled with increased competition can cause hospitals to focus on more profitable HMO patients at the expense of Medicare patients.

become more responsive to clinical quality post-reform and hospitals to be responsive to changes in demand through quality improvements.[4] Moscelli, Gravelle, and Siciliani (2021), on the other hand, find mixed results from the same reform. Goetz (2021) studies the intensified health care competition induced by direct-to-consumer telemedicine entrants following Covid-19, and find that incumbents stop offering income-based discounts. Yet when policies themselves are *health*-related, the analyses can be complicated by the fact that they may affect the behavior of the agents involved in ways unanticipated by researchers. For example, the U.K. government mandated in 2006 that patients be offered a choice of five hospitals when referred to a hospital by their physician. However, there is evidence that not all primary case physicians thought that patients were able to or wanted to make choices (Gaynor, Moreno-Serra, and Propper 2013). If such behavior are not accounted for in the analysis, conclusions may be biased.

Our paper contributes to this literature by leveraging the entry of the HST to measure the effect of increasing hospital competition on health outcomes and patient welfare.The introduction of the HST represents an exogenous shock to the healthcare market thus providing a unique and novel quasi-experiment to identify the impact of competition on quality. Bloom et al. (2015) also use an identification strategy unrelated to aspects of the healthcare market in which they exploit the variation in hospital closures driven by political changes in the U.K. to study the impact of competition on hospital performance. Compared to Bloom et al. (2015) who use cross-sectional data for a single year, we leverage the cross-sectional variation in the degree of HST entry across regions, and also across time. In addition, we explicitly model patients' choice sets to take into account changes in travel time induced by the HST. This allows us to decompose the effect of the HST along several dimensions, such as patient sorting and changes in quality of care.

The rest of this paper is structured as follows. In the next section we describe the relevant aspects of the health care industry and the entry of the high-speed train. Section 3 describes our data and section 4 describes our differences-in-differences estimation strategy and issues concerning measures of hospital quality. Section 5 describes our data and present descriptive statistics. In section 5 we present the differences-in-differences regression results. Section 7 outlines the structural model of hospital choice, and section 8 presents the structural model estimates. In section 9 we measure patients' welfare changes and changes in health outcomes through a series of counterfactual exercises. Section 10 concludes.

[4] In addition to Gaynor, Propper, and Seiler (2016), other papers in the healthcare literature also focus on the effects of removing choice constraints within the health care context (e.g., Ho 2006a, Dafny, Ho, and Varela 2013)

2 Industry Details

2.1 Health Care Industry

The National Health Insurance (NHI) program in South Korea is a compulsory solo-payer public insurance system which covers the entire resident population. The social insurance system of South Korea was established in 1977, and initially covered only 8.79% of the population, but expanded to approximately 97% of the population by 1989. It operated as a multi-insurance fund system with more than 370 insurers until July 2000, when the funds were integrated to form a single-payer system. It is managed by a single insurer, the National Health Insurance Corporation (NHIC), and is supervised by the Ministry of Health, Welfare and Family Affairs (MIHWFA). The Health Insurance Review and Assessment Service (HIRA), also supervised by MIHWFA, reviews the cost and healthcare benefits and evaluates the appropriateness of health care services provided by hospitals. The system is funded by compulsory contributions from the entire resident population and government subsidies. The amount paid as NHIC contributions by an individual depends on his income and wealth; the elderly and disabled pay less.

The healthcare delivery system in South Korea is classified into three tiers: primary (clinics), secondary (hospitals and general hospitals) and tertiary care (general hospitals). Starting in 1989, hospitals that met the criteria in terms of facilities, workforce, equipment, patient composition, etc, could apply to be designated as a tertiary care institution subject to demand for number of hospital beds from each health region.[5] There were 42 tertiary care institutions, and the composition of these hospitals did not change during the period of our analysis. During this period, there was little to no room for new tertiary care entry. This is because the number of hospital beds provided by the then-tertiary care hospitals saturated the market for each health region, and tertiary hospitals were "renewed" every 3 years instead of being re-selected.

As opposed to public-sector dominant healthcare financing, healthcare delivery in South Korea is predominantly provided by the private sector: approximately 90% of hospitals are private institutions. Since the launch of the NHI program, private providers are not allowed to opt out from the program. Private health-care providers mainly supply health care services, and the fee schedule is established through annual negotiations between the NHIC and provider associations.[6] The fixed price schedule includes fees for each medical procedure, with adjustments for whether a hospital is a primary, secondary, or a tertiary care institution. Patients are responsible for any co-payments applicable to the medical

[5] There were 9 health regions during this period.

[6] The Korean Medical Association (KMA) and the Korean Hospital Association (KHA) are among the most important provider organizations.

services they receive, and the NHIC reimburses healthcare providers for the share of medical costs not borne directly by the patient on the basis of the fee schedule. Therefore, the price is exogenous to both the hospitals and patients. Fee regulation has been the subject of recurrent complaints by providers in South Korea, who claim that they are not adequately compensated for their services as a result of historically low levels of NHI fees.

Although the NHI service flow is designed to progress from primary to secondary to tertiary care, patients have the complete freedom to choose any healthcare provider at any level, with some financial incentives. To achieve an efficient distribution of limited healthcare resources, insurance coverage largely depends on the tier of the hospital. For example, the NHI insurance coverage for clinics is 70%, and it is 60% and 50% for hospitals and general hospitals, respectively. To receive treatment in tertiary hospitals, patients must be referred by primary or secondary care hospitals, in which case 40% of their bills are covered by insurance − otherwise, they can expect to pay 100% of the bill. The referral by a primary or secondary care physician is easy to obtain, and can be obtained even after the patient is admitted to the hospital (before paying the bill), so there is essentially no gatekeeping system. The insurance coverage is identical at all levels of hospitals for inpatient care, with patients being responsible for 20% of medical expenses.

2.2 Entry of the High-Speed Train

South Korea's HST system, Korea Train eXpress (KTX), began commercial operations on April 1st 2004 with the objective to alleviate (foreseeable) traffic congestion. Construction of the HST system occurred in two stages.[7] The first-stage construction involved building the Gyeongbu HST Line connecting Seoul to Daegu and electrifying the existing Gyeongbu Line connecting Daegu-Busan, as well as electrifying the existing Honam Line connecting Daejeon-Mokpo.[8] The second-stage HST system, which involved the construction of the new Gyeongbu HST line connecting Daegu to Busan replacing the existing electrified tracks, went into service in November of 2010. In this paper we only focus on the first-stage HST system. Although the launch of the second-stage HST system enabled the HST to reach full speed

[7]Note that here we are referring to the construction of the Gyeongbu HST system. The construction of additional HST systems was completed only after 2015. Additional electrified (existing) lines were added by the end of 2010.

[8]Newly constructed links included 51.6 miles of viaducts and 47.0 miles of tunnels. Electrification of the existing rail comprised of 82.5 miles across Daegu to Busan, 12.9 miles across Daejeon, and 164.3 miles from Daejeon to Mokpo and Gwangju. First stage Gyeongbu HST stations include Seoul Station, Gwangmyeong, Cheonan-Asan, Daejon, Dongdaegu stations, and the electrified Gyeongbu line connecting Dongdaegu and Busan includes Miryang, Gupo and Busan stations. Honam line includes Yongsan station, Seodaejeon, Dungyae, Nonsan, Iksan, Gimje, Jeongeub, Jangseong, Songjeongni, Gwangju, Naju, and Mokpo stations. There exists a depot for HST along the Gyeongui Line at Haengsin station. Thus some HST services continue beyond Seoul and Yongsan station and terminate at Haengsin station. For detailed information on HST services see Cho and Chung (2008).

through the Daegu-Busan corridor, this shock was much smaller in magnitude compared to the shock generated by the first-stage HST system. Figure 1 displays two HST lines of the first-stage HST system, the Gyeongbu Line (blue) connecting Seoul-Busan and the Honam line (green) connecting Seoul-Mokpo. The figure also plots the hospitals that are included in our final sample (more on this in the next section).

==========================

Insert Figure 1 about here

==========================

At the time of its launch in 2004, the HST operated 128 times per day (94 times on Gyeongbu Line, and 34 times on the Honam Line), and the daily frequency increased to 163 in the following years, greatly reducing travel time. As an example, the HST system has reduced the travel time from Seoul to Busan from more than 5 hours by car to 2 hours and 40 minutes by train. HST fares were fixed and kept low, at approximately 55% of the corresponding air fares for the same routes, to encourage the use of the HST.[9]

3 Data

We rely on a number of data sources at a patient and hospital level. Our patient data comes from the National Health Insurance Services (NHIS) which is a health insurance claims dataset collected by the solo insurer system NHIS. Our data consists of a nationally representative random sample, which accounts for 2% of the entire South Korean population who received medical treatment at a hospital. The data contain anonymized patient-level information on medical procedures that a patient received at a hospital. Detailed information on patient demographics, diagnosis, patient's home location, the chosen hospital and the date of hospital admission are observed. In addition, if the patient died, we observe the month/year of the patient's death.[10] The geographic unit of our data (and hence patients' home location) is defined either at a city, county or at a district level depending on where a patient lives. This is because some counties are not populated enough to qualify for a city,

[9] In addition to low regular prices, various discounts (60% off the regular passes and 20% off the reserved tickets) were available to attract as many passengers as possible.

[10] We would like to use the 30-day mortality following a surgery as our measure of hospital quality as it is the most commonly used outcome-based measure. However, we do not observe the exact date of the surgery in our data. To complicate matters further, we only observe the year and month of patients' death instead of the exact date. Therefore our (proxy) measure of 30-day mortality rate is obtained as follows: We construct a dummy variable M whose element m_i takes value 1 if (i) patient i who was admitted to hospital in month mm_i day dd_i and year $yyyy_i$ dies either in month mm_i and year $yyyy_i$ or in month $mm_i + 1$ and year $yyyy_i$ for $mm_i = 1, ...11$ and (ii) length of hospital-stay does not exceed 30 days. If patient was admitted to hospital in $mm_i = 12$ and year $yyyy_i$, μ_i takes value 1 if patient dies in month mm_i and year $yyyy_i$ or in January of year $yyyy_i + 1$.

while some smaller cities are not populated enough to be sub-divided into districts.[11] To simplify the exposition, we will henceforth ignore the distinction between city/country/district and denote the smallest geographic unit that we observe in the data as a "district". The boundaries of each "district" are delineated in figure 1. Since patients' home location is at the district level, we use the coordinates of the centroid of each district as patients' location.

The hospital data also comes from the NHIS dataset. Hospitals in the NHIS dataset are anonymized and their location is observable only at the city-province level. To get a more precise location of the hospitals, which is essential for our analysis, we combine the NHIS dataset with that obtained from the HIRA (Health Insurance Review Assessment). Although the identity of the hospitals in the HIRA dataset is also anonymized, we are able to match this dataset to the NHIS dataset using hospital characteristics. In addition to the hospital characteristics such as number of hospital beds and the tier of the hospital, the HIRA dataset contains hospital location at the district level. We use this information to obtain exact coordinates for each hospital using hospital's district and the corporation type of the hospital (educational, personal, foundation, public, special) through https://www.goodhosrank.com.

Our sample selection process is as follows. We define January 2003 to March 2004 as the pre-HST time period and then define January 2006 to March 2007 as the post-HST time period after allowing for some adjustment time.[12] We focus on inpatient individuals who underwent a surgery at a hospital. We consider all surgeries that were performed during the data period with mortality rate of greater than 1 percent. Ideally we would look at patients suffering from one specific illness, or those who underwent one specific type of surgery in order to minimize the contamination of hospital quality (impact on mortality rates) with patient selection.[13] Constraining our analysis to a single type of surgery, however, leaves us with too few observations (too few patients for each hospital). Limiting our attention to only one "category" of surgery (e.g., cardiovascular surgery) also leaves us with too few observations per hospital. To attenuate the contamination of hospital quality from pooling patients across multiple types of surgeries, we control for the riskiness of each type of surgery in addition to patient demographics.

We further drop patients living on islands (Jeju and Ulleng Islands, as well as Shin-

[11] South Korea is made up of 17 first-tier administrative divisions (province level). These are further subdivided into cities (si), counties (gun), districts (gu), towns (eup), townships (myeon), neighborhoods (dong) and villages (ri). Once a country attains a population of at least 150,000, it becomes a city. Cities with a population of over 500,000 are subdivided into districts. Districts are then further divided into neighborhoods (dong). Cities with a population of less than 500,000 are directly divided into neighborhoods (dong).

[12] We choose pre-HST period to start from year 2003 because patient mortality information is only available from 2003.

[13] Gowrisankaran and Town (2003) look at pneumonia patients, Kessler and McClellan (2000), Propper, Burgess, and Green (2004) look at acute myocardial infarction (AMI) patients, and Gaynor, Propper, and Seiler (2016) look at patients receiving coronary artery bypass grafting (CABG) surgery.

ahn and Ong-jin Gun) because it is difficult to calculate travel time to hospitals by car for these patients, a necessary component for estimating our demand model and performing counterfactuals. Following Tay (2003) and Ho (2006b), we exclude hospitals with fewer than 10 admissions per period, and we only keep hospitals that appear in both pre- and post-HST periods to facilitate the comparison of hospital quality. The key feature of our setting is that the entry of the HST enabled patients to exercise choice among alternatives with different travel distances. To take advantage of this feature, we removed patients who were transferred into the hospital via intra-hospital transfer since many intra-hospital transfers occurs between hospitals that are affiliated with each other, and it is the physician who makes the choice of the hospital in this case. Our final sample consists 9,103 patients who went to 89 hospitals, all of which are either secondary or tertiary hospitals.[14]

4 Differences-in-Differences Analysis

The goal of our paper is to study the impact of increased hospital competition on hospital quality. Post-HST a hospital located closer to the HST station faces more competition than hospitals that are located further away from the HST station because the HST allows for greater substitutability between hospitals that are close to the HST. Therefore, to examine whether hospitals that are located closer to the HST experience an improvement in hospital quality after the entry of HST, we conduct our analysis using a difference-in-differences (DiD) approach by exploiting the variation in distance from each hospital to the nearest train station. We identify the impact of competition from the interaction of a continuous treatment intensity variable (hospital's distance to the nearest HST station) with a dummy indicator for the post-HST period. This specification was employed by Gaynor, Moreno-Serra, and Propper (2013) to study the impact of hospital competition.[15] Specifically, the DiD regression specification is given by

$$outcome_{jt} = b_{0j} + b_1 I(t=1) + b_2 I(t=1) \times dist_j^- + \varepsilon_{jt}. \tag{1}$$

We collapse time periods into pre- and post-HST periods so that $t = 0$ denotes pre-HST and $t = 1$ denotes post-HST. The variable $outcome_{jt}$ measures the quality of clinical care at hospital j in period t. As mentioned earlier, we use hospital-level 30-day mortality rates as the outcome variable after adjusting for patient selection; b_{0j} denotes a full set of hospital dummies; $I(\cdot)$ is an indicator function for the post-HST period which takes the value 1 for the post-HST period and 0 otherwise, and ε_{jt} is a random noise. The DiD coefficient of

[14] Korean hospitals are "clinics" rather than general hospitals with multiple departments.

[15] See Card (1992) and Acemoglu, Autor, and Lyle (2004) for more about continuous treatment.

interest is b_2, which corresponds to the interaction term between a post-HST dummy and the distance from hospital j to the nearest train station, denoted as $dist_j^-$. For ease of interpretation, we use the negative value of distance in the regression. The coefficient b_2 then measures the change in the effect of proximity to the nearest train station pre- and post-HST on the outcomes variable. If the outcome variable is hospital-level death rate, a negative value of b_2 implies that death rate is lower as hospitals are located closer to the HST station in the post-HST period. The identifying assumption is that without the entry of the HST, the trend in mortality rates would have been the same regardless of the distance to the train station. The entry of the HST induces a deviation from this parallel trend. We provide evidence supporting this assumption in Section 5.

4.1 Measure of Hospital Quality

Using raw mortality rates as a measure of quality is problematic due to patient selection bias: hospital selection is non-random. The existing literature address this selection bias by obtaining adjusted mortality rates (Gowrisankaran and Town (1999), Gowrisankaran and Town (2003), Kessler and McClellan (2000), Geweke, Gowrisankaran, and Town (2003), Tay (2003)). For instance, Gowrisankaran and Town (1999) propose controlling for patients' severity of illness with an instrumental variables (IV) framework using geographic location data, i.e. distance from each patient to all hospitals. Although the distance to the chosen hospital will be correlated with the patient's severity of illness, and hence cannot be a valid instrument, where a patient chooses to live relative to all hospitals is uncorrelated to patient's severity of illness. The identifying assumption is that where a patient chooses to live from alternative hospitals is uncorrelated to patient's severity of illness - an assumption that has been commonly used in empirical models of hospital choice e.g. Kessler and McClellan (2000), Gowrisankaran and Town (1999), Capps, Dranove, and Satterthwaite (2003), Gaynor and Vogt (2003), Ho (2009), Beckert, Christensen, and Collyer (2012). Geweke, Gowrisankaran, and Town (2003), on the other hand, develop a method to infer hospital quality using a model where mortality is described by a binary probit and hospital choice by a multinomial probit model. In the structural model of Geweke, Gowrisankaran, and Town (2003) that is used to obtain hospital quality, the quality of the hospital per se does not enter patient's utility, and hence does not affect his choice of the hospital. Since the goal of our paper is to study the consequences of patients sorting to better quality hospitals and the impact of resulting competition, our hospital demand model in section 6 requires us to include hospital quality in patient's utility. Therefore, to obtain adjusted mortality rates, we follow the approach by Gowrisankaran and Town (1999) which allows us to develop a more flexible model of hospital choice.

In our setting, the HST facilitates long-distance travel for severely ill patients, and hence the degree of patient selection may be aggravated as a result of the entry of the HST. To allow for this change in the degree of patient selection resulting from the reduction in travel time, we use different sets of instruments in pre- and post-HST periods. We follow Gowrisankaran and Town (1999) but use travel time rather than travel distance from each patient to all hospitals as instruments for hospital choice. This is to account for the changes in travel time for patients living sufficiently close to the HST station in post-HST era (because, even with HST, the actual distance to the hospitals does not change - what changes in the post-HST period is the travel time).

Specifically, we obtain adjusted mortality rates by estimating a linear probability model where we regress an indicator for whether a patient dies approximately 30 days following the admission (conditional on choosing hospital j) on a set of hospital/time period dummies and patient's observed characteristics.[16] The mortality of patient i in period t is given as

$$\mu_{it} = \boldsymbol{\psi}' \boldsymbol{c}_i + \boldsymbol{\gamma}' \boldsymbol{h}_i + s_{it} + \eta_{it} \tag{2}$$

where μ_{it} is a dummy variable that denotes the death of patient i within 30 days of the admission, $\boldsymbol{c}_i$ is a vector of dummy variables $(c_{i1pre}, ..., c_{iJpre}, c_{i1post}, ...c_{iJpost})$ where c_{ijt} equals 1 if patient i chooses hospital j in period t, $\boldsymbol{h}_i$ is a vector of patient characteristics that can affect mortality, s_{it} is unobserved (by the researcher) severity of illness, and η_{it} is an i.i.d. normal error term. The parameter vectors to estimate are $\boldsymbol{\psi}$ and $\boldsymbol{\gamma}$. Each element of estimated vector of fixed effects $\hat{\boldsymbol{\psi}}$ can be interpreted as the incremental probability of death from choosing a particular hospital conditional on observed health status, and is what we use as a measure of the quality of care. The coefficient vector $\boldsymbol{\gamma}$ captures the impact of patients' observed health status on the probability of death. We refer to the estimated measures of quality of care in $\hat{\boldsymbol{\psi}}$ as adjusted mortality rates. Note that there is a slight abuse of terminology here as $\hat{\boldsymbol{\psi}}$ are not adjusted mortality probabilities per se, but rather the hospitals' impact on patients' mortality conditional on observed characteristics. Because hospital choice is likely to be correlated with patients' unobserved severity of illness, estimating equation (2) using OLS will lead to biased estimates. For instance, if sicker patients are more likely to choose a certain hospital j, s_{it} and c_{ijt} will be positively correlated, and hence $\hat{\boldsymbol{\psi}}_{\boldsymbol{j}}$ will be overestimated.

To address the endogeneity of hospital choice, we use two sets of instrumental variables for hospital choice dummy variables ($\boldsymbol{c}_i$): (i) travel times to each alternative hospital, and (ii) nonlinear transformations of travel time defined as $exp(-\kappa \times \text{traveltime}_{ijt})$ to capture the non-linear effect of travel time.[17] As mentioned before, this is based on the assumption

[16] We choose to use a linear probability model as opposed to a non-linear model with a binary dependent variable due to the difficulties that result from addressing endogeneity in those types of models (see Gowrisankaran and Town 1999 for a discussion of this topic in the hospital quality context).

[17] To estimate κ, we follow Gowrisankaran and Town (1999) and estimate a series of the following single

that where a patient chooses to live relative to *all* hospitals is uncorrelated to her severity of illness. We define travel time for patient i to hospital j in period t as

$$\text{traveltime}_{ijt} = \begin{cases} \min(\text{cartime}_{ij}, \text{traintime}_{ij}) & \text{if } t = \text{post-HST and dist}_i^{pat}{<}30 \text{ and dist}_j^h{<}30 \\ \text{cartime}_{ij} & \text{otherwise,} \end{cases} \tag{3}$$

where cartime_{ij} denotes the drive time from patient i's location to hospital j by car and traintime_{ij} is the travel time from patient i's location to hospital j by HST. Driving times by car are obtained using the *georoute* routine developed by Weber and Péclat (2017) which calculate the driving time between two points under normal traffic conditions. Note that traintime_{ij} is obtained by summing the following three components: (i) drive time from i's location to i's nearest HST station h, (ii) travel time from station h to station k, which is the closest HST station to hospital j and (iii) drive time from station k to hospital j. The variables $dist_i^{pat}$ and $dist_j^h$ are, as described earlier, travel time from patient i to the closest train station and travel time from hospital j to the closest train station, respectively. While the effect of HST does not have physical boundaries, we nevertheless constrain the effect of the HST to patients and hospitals that are located within 30 minutes of the train station. This is to account for changes in travel time only for patients that live (and visit hospitals) sufficiently close to the HST station, and is reflective of the data which reveal that there are no significant differences in travel times between pre- and post- HST for patients living beyond 30 minutes of the HST station. Tests of the validity of our IV strategy and further details on estimating adjusted mortality rates are provided in the appendix.

5 Descriptive Statistics

Table 1 provides summary statistics of patient characteristics. Approximately 30 percent of patients in pre-HST period are female, whereas this number increases to 42 percent in the post-HST period. The majority of patients are aged between 50 and 75 (approximately 60 percent), followed by patients aged between 25 and 50 (approximately 20-25 percent), patients over 75 years of age (10-15 percent), and patients who are younger than 25 years of age (roughly 6 percent). A large proportion of patients are residents of Seoul, which is the capitol and the largest city. There are 11 (group 0 - group 10) income groups in our data. We classify groups 0-3 as low income, groups 4-7 as medium income, and groups 8-10 as high income. Approximately 20 percent of patients have low income. The average deathrate

equation non-linear regressions separately for each hospital in the data: $c_{ij} = \delta_{1j} + \delta_{2j} traveltime_{ijt} + \delta_{3j} exp(-\kappa \times traveltime_{ij}) + u_{ij}$. The mean estimated coefficient for κ across all hospitals is approximately 0.24. Therefore, we set $\kappa = 0.25$, which is identical to the value of κ used in Gowrisankaran and Town (1999).

of the diagnosis that patients have is roughly 4.6 percent, and the average deathrate of the surgeries that patients in our sample go through is roughly 6.5 percent. In the data, 4.9 percent of the patients died in pre-HST period, and 4.5 percent of the patients died in the post-HST period.

==========================

Insert Table 1 about here

==========================

5.1 Patients' Response to the Entry of the HST

We first show that patients' travel patterns changed following the entry of the HST. If patients indeed responded to the entry of the HST, we expect patients living closer to the HST stations to choose hospitals that are located further away from their home. In our setting, there are "Treated Patients", patients who live within 10 miles of the HST station. "Control Patients" are patients who live beyond 10 miles of the HST station. The robustness of our 10-mile definition of treatment is discussed in Appendix B.

In Table 2 we present descriptive evidence on changes in patients' travel patterns following the entry of HST. Panel A reports the average travel distance (in miles) before- and after the introduction of HST, defining patients living within 10 miles of the HST station as treated. While there are no significant changes in travel distances for patients living in control regions, patients living in treated regions traveled significantly further distances after the entry of the HST (approximately 19 percent increase in travel distance post HST). We see consistent patterns when we only focus on patients living in non-Seoul areas (Panel B): while there is no difference in travel distance for patients living in control regions, the average travel distance increase by 17 percent for patients living in treated regions. We also look at the impact of the HST on travel time separately for patients living in urban and rural regions. To do so, we define urban regions as 7 metropolitan cities consisting of Seoul, Busan, Daegu, Incheon, Gwangju, Daejeon, and Ulsan, and define all other regions as rural. The results are reported in Panel C and D. For both, urban and rural residents, treatment leads to marginally significant increase in travel time (19 percent increase in travel distance post HST for both urban and rural residents).

==========================

Insert Table 2 about here

==========================

Having established that the entry of the HST makes patients travel longer distances, we want to see whether those patients who traveled were seeking to go to better hospitals. We look at this in Table 3. Panel A reports the change in patient care seeking post-HST by hospital quality. To reduce the likelihood of simultaneous determination of mortality and patient volume, we use pre-HST adjusted mortality rates as a measure of quality. If treated patients became more responsive to clinical quality with the entry of the HST, we should see them going to better treated hospitals relative to worse hospitals. We classify all hospitals whose adjusted mortality rates are below the median as good hospitals, and hospitals whose adjusted mortality rates are above the median as bad hospitals. Although the number of admissions rose similarly for better and worse hospitals, the share of treated patients who went to hospitals located in a province different from their home increased for better hospitals that are located within 10 miles of HST station, while there is no significant difference for worse hospitals. The standard error shows that the difference in share of travelers for the better hospitals is statistically significant. We repeat the same exercise using control patients (Panel B) and also hospitals that are located beyond 10 miles of the HST station (Panels C and D). We do not find a significant change in share of traveling patients pre and post-HST for these cases.

==========================

Insert Table 3 about here

==========================

5.2 Hospital Characteristics

Table 4 reports summary statistics of hospital characteristics. Considering that our data is a 2 percent sample of the entire population, an average hospital has approximately 2,235 admissions in pre-HST period, and 2,880 admissions in post-HST period. Number of hospital beds did not change before and after the HST. There are approximately 250-270 doctors across the two periods. 31 out of 89 hospitals are located in Seoul. Average hospital-level mortality rate in pre-HST period is 5.5 percent, and is reduced to 5 percent in post-HST period.

==========================

Insert Table 4 about here

==========================

Figure 2 presents the relationship over the entire period of our analysis (including the adjustment period) between distance to the nearest train station and raw 30-day mortality rates. Due to data limitations, we do not have patient death information prior to 2003. Since the HST entered in April 2004, it is difficult to see (if any) pre-HST trends of mortality rates at the annual level. Therefore, for this analysis, we calculate 30-day mortality rates at the quarter level. Four time series lines are presented for the mean of the mortality rates, one for patients who visited hospitals in each quartile of the hospital's distance to the nearest train station. The series is rather noisy, but we can see that all four series fluctuate together. While the time series lines for the hospitals in the 3rd and 4th quartile of distance show gradual decline over time, the series of the hospitals in the 1st and 2nd quartile of distance display disproportionately sudden drop in mortality rates around the 2nd quarter of 2004. The drop in mortality rates is greater for hospitals in the 1st quartile, compared to hospitals in the 2nd quartile.

==========================
Insert Figure 2 about here
==========================

6 Difference-in-Differences Estimation Results

We use the measures of clinical quality obtained in section 4.1 to study the impact of increased hospital competition on hospital quality. As a starting point to this analysis, we first estimate equation (1) using hospital-level *raw* mortality rates as the outcome variable. Since hospitals located near the HST station are the ones that are most affected by the entry of the HST, the DiD coefficient on $d_{post} \cdot dist^{-}_{j}$ captures the impact of increased hospital competition. A negative value of the DiD coefficient implies that death rate is lower as hospitals are located closer to the HST station in the post-HST period. Column (1) in Table 5 reports the results. While marginally significant, the DiD coefficient is negative: when the travel time from the hospital to its closest train station decreases by 1 minute (i.e., the hospital is closer to the train station), the hospital-level raw mortality rate decreases by 0.05 percentage points.

==========================
Insert Table 5 about here
==========================

As discussed earlier, however, hospital-level raw mortality rates do not correctly reflect the true quality of clinical care due to differences in patients' health status across hospitals (referred to as hospital's "case-mix") i.e., hospitals with a larger number of sicker patients are more likely to have higher mortality rates. It is therefore necessary to take into account differences in patient case-mix across hospitals, for both observed and unobserved patient characteristics. In order to control for the observed case-mix at the patient-level, we first estimate equation (A.1) using OLS, and use estimated $\hat{\psi}$ as a measure of clinical quality to estimate equation (1). Note that, although this measure of quality controls for observed health status at the individual patient-level, it does not control for unobserved (to the researcher) severity of illness which may be correlated with patients' hospital choice, and hence may be biased. The results are reported in Table 5, column (3). The DiD coefficient is negative and significant ($\beta_2 = 0.0006$), i.e. when a hospital's travel time to a closest train station decreases by 1 minute (i.e. hospital is closer to the train station), (adjusted) mortality rate decreases by 0.06 percentage points.

As already mentioned, however, simply controlling for observed patient case-mix is not sufficient to correctly measure the quality of clinical care. Patients' unobserved (to the researcher) severity of illness, which may be correlated with hospital choice, may contaminate the quality of clinical care. We further account for patients' unobserved severity of illness by instrumenting hospital choice dummy variables for each period with travel time to each hospital, and use these adjusted mortality rates as the dependent variable to estimate equation (1). This measure of hospital quality was obtained by instrumenting hospital choice with travel time to alternative hospitals, and therefore resolves the patient selection issue. The results are reported in Table 5, column (2). The DiD coefficient is negative and significant ($\beta_2 = 0.0025$), suggesting that more competition leads to improved hospital quality. The results from this regression suggest that a 1 minute reduction in travel time from the hospital to the nearest train station decreases adjusted mortality rates by 0.25 percentage points. Note that the magnitude of the DiD coefficient is larger compared to the case where unobserved severity of illness was not accounted for (0.0006 versus 0.0025). This suggests that ignoring selection may lead to misleading inferences about hospital quality. In Appendix C we present results with alternative specifications (without hospital fixed effects, and controlling for number of admissions). We find consistent results. The results in in this section suggest that increased competition leads to an improvement in hospital clinical quality. To evaluate the impact on patient welfare, we next estimate a demand model of hospital choice and use the model estimates to perform welfare analysis and various counterfactuals.

7 Model of Patient Hospital Choice

Our goal lies in formally evaluating the effect of increased competition on the quality of clinical care, and also evaluating the impact of the HST on patient welfare and health outcomes. Consequently, we specify a model of patient hospital choice and estimate patient preferences using the data both pre and post-HST on hospital choices, hospital's clinical quality, and other attributes. Using model estimates we then simulate elasticities that hospitals face with respect to clinical quality, pre and post-HST and assess the impact of increased competition on the quality of clinical care by looking at the relationship between changes in elasticities and changes in clinical quality pre and post-HST. We then evaluate the impact of the HST on patient welfare by conducting a reverse counterfactual analysis by switching off the impact of the HST in the post-HST period.

We consider a discrete choice model of hospital demand. Following the literature, we assume that a patient derives utility from pertinent characteristics of the hospital and that the utility differs systematically with the demographic attributes of the patient. In the analysis, we assume that patients observe all relevant hospital attributes.

Each patient i makes a choice based on a utility comparison among J hospitals, where J is the total number of hospitals in the data. Following previous literature on hospital choice, we assume that all patients are admitted to some hospital, and hence there is no outside option in our model. The indirect utility of patient i choosing hospital j, $j = 1, ..., J$ is defined as

$$u_{ij} = \delta_j + \sum_{l=1}^{L} X_{j,k} \mathbf{Y}_i^{'} \beta_{.,l}^{xy} + Q_j \mathbf{Y}_i^{'} \alpha^z + f(D_{ij}) + \mathbf{X}_j^{'} \beta^x + \alpha Q_j + \varepsilon_{ij}, \tag{4}$$

where $\mathbf{X}_j$ is a vector of hospital characteristics (excluding hospital-level mortality rate) with length L; $\mathbf{Y}_i$ is a K vector of patient-specific demographics; D_{ij} is the travel time from patient i's home to hospital j; Q_j denotes the quality of clinical care at hospital j; ε_{ij} is an unobservable (to the econometrician) error term that we assume to be mean independent of the included right-hand side variables.

One might be concerned about the endogeneity of quality of clinical care in the utility function. Previous literature has found that treating a larger number of cases is associated with better outcomes. Hospitals with higher unobserved quality will attract larger volume of patients, and this will in turn lead to higher quality of clinical care.[18] Following Gaynor, Propper, and Seiler (2016), we mitigate this concern by including an entire set of hospital indicators to estimate hospital fixed effects, δ_j.

We allow travel time to enter nonlinearly into the utility function as

$$f(D_{ij}) = \beta_{d1} D_{ij} + \beta_{d2} \mathbb{I}_{\{j=\text{closest}\}} \tag{5}$$

where $\mathbb{I}_{\{j=\text{closest}\}}$ is an indicator variable equal to 1 if hospital j is the closest hospital to patient i. β^{xy}, α^z and β^x are $K \times L$, $K \times 1$, and $L \times 1$ matrices of coefficients, respectively. β_{d1} and β_{d2} are scalars. The interactions between patient attributes $\mathbf{Y}_i$ and hospital characteristics $\mathbf{X}_j$ account for observable individual heterogeneity in how different patients value particular hospital characteristics.

[18] For more literature on volume-quality relationship, see Birkmeyer et al. (2002), Silber et al. (2010), and Halm, Lee, and Chassin (2002).

As discussed earlier, the price that a patient has to pay depends on the tier of the hospital. In our final data, tertiary hospitals will have different price tags due to their tier. Since the identity of tertiary hospitals did not change during the period of our analysis, hospital fixed effects will capture the differences in prices across hospitals.

Assuming that ε_{ij} follows an i.i.d. type I extreme value distribution, the probability that patient i chooses hospital j, $\Pr(ch_{ij}) = 1$ can then be written as

$$\Pr(ch_{ij} = 1) = \frac{\exp\left\{\delta_j + \sum_{l=1}^{L} X_{j,k}\mathbf{Y}_i^{\prime}\beta^{xy}_{.,l} + Q_j\mathbf{Y}_i^{\prime}\alpha^z + f(D_{ij}) + \mathbf{X}_j^{\prime}\beta^x + \alpha Q_j\right\}}{\sum_{j^{\prime}=1}^{J}\exp\left\{\delta_j + \sum_{l=1}^{L} X_{j^{\prime},k}\mathbf{Y}_i^{\prime}\beta^{xy}_{.,l} + Q_{j^{\prime}}\mathbf{Y}_i^{\prime}\alpha^z + f(D_{ij^{\prime}}) + \mathbf{X}_{j^{\prime}}^{\prime}\beta^x + \alpha Q_{j^{\prime}}\right\}}. \tag{6}$$

We estimate the parameters in equation (4) using a maximum likelihood approach.

8 Estimation Results: Hospital Demand Model

We first report the parameter estimates from our hospital demand model, and then proceed to how how these translate into changes in elasticities of demand at the patient and hospital level.

8.1 Parameter Estimates

The covariates that enter the utility function are as follows. Mortality is the adjusted hospital quality obtained using the IV approach described in section 4.1.[19] TravelTime refers to travel time (as defined in equation 3) between the patient and a hospital in his choice set, and is in units of 100 minutes. DrPerBed refers to ratio of number of doctors to number of hospital beds. We also interact the following patient characteristics with AdjustedMortality and DrPerBed variables: Female indicator variable; Age[25-50) is a dummy variable that equals 1 if a patient is between 25 and 49 years old and and 0 otherwise; Age[50-75) is a dummy variable that equals 1 if a patient is between 50 and 74 years old and and 0 otherwise; Age[75+) is a dummy variable that equals 1 if a patient is above 75 years of age; LowIncome is a dummy variable that equals 1 if a patient falls in the bottom first quartile of the income distribution; SurgeryRisk[25-50) is a dummy variable that equals 1 if a patient undergoes a surgery for which the risk of death belongs between 25th percentile and 49th percentile, and 0 otherwise; SurgeryRisk[50-75) is a dummy variable that equals 1 if a patient undergoes a surgery for which the risk of death belongs between 50th percentile and 75th percentile, and

[19]Since adjusted mortality rates are fixed effect estimates of a linear probability model, they sometimes take on negative values. To calculate changes in demand responsiveness with regards to adjusted mortality rates, we shift the mean and the variance of the adjusted mortality rates so that its minimum and maximum values are the same those of of the raw mortality distribution. The structural model is estimated using this modified adjusted mortality rate.

0 otherwise; SurgeryRisk[75+) is a dummy variable that equals 1 if a patient undergoes a surgery for which the risk of death belongs in the 75th percentile and 0 otherwise.

The estimation results are reported in Table 6. We present the results for two specifications. The results are, for the most part, intuitive. Across the two specifications, and as expected, travel time plays a large role in patients' decisions when choosing a hospital – the negative coefficient on travel time suggests that patients are less likely to go to hospitals that are located further away from their home. Similarly, the positive coefficient on the closest hospital dummy variable means that patients prefer hospitals that are close to their home. Across the two specifications, the negative coefficient on the MortalityRate variable suggests that patients care about the clinical quality of hospitals, which is consistent with findings by Gaynor, Propper, and Seiler (2016). Female patients are less sensitive to clinical quality than male patients. In terms of age, patients between 50 and 75 years of age are the most sensitive to clinical quality. Patients' income level has no significant relationship with respect to patients' preference to clinical quality. We find a bimodal relationship between clinical quality and riskiness of the surgery. Similarly, we find a bimodal relationship between clinical quality and the riskiness of the diagnosis. Our estimates also suggest that patients prefer hospitals with higher doctor-to-bed ratio. Low income patients prefer hospitals with higher doctor-to-bed ratio. We also find that patients who undergo more severe surgeries (SurgeryRisk[50-75)) prefer hospitals with higher doctor-to-bed ratio.

=========================

Insert Table 6 about here

=========================

8.2 Elasticities of Demand

We are interested to see if the reduction in travel time caused by the entry of the HST made treated patients more elastic with respect to hospital quality. To study this, we compute elasticities for individual patients with respect to the mortality rate (adjusted mortality rate), pre and post-HST, separately for treated and control patients. For each group of patients, we also consider all possible combinations of their severity of illness (low and high severity). For high-severity, we set SurgeryRisk[75+) to one, and set all other variables related to categories of SurgeryRisk to zero. For low-severity, we set all variables related to categories of SurgeryRisk to zero. We set all other patient characteristics variables (gender, age, income) to their respective mean level.

Patient-level elasticities are computed as the change in choice probabilities for each patient following a one standard deviation shift in the mortality rate for each hospital, for their respective time period. The changes are then averaged across groups of patients. Panel

A of Table 7 reports patient-level mean elasticity with respect to mortality for different combination of groups of patients pre and post-HST. Bootstrapped standard errors are in parentheses.

==========================

Insert Table 7 about here

==========================

For treated patients, irrespective of the severity of illness, sensitivity increases post HST. Sensitivity changes by 0.1089 for treated patients with high-severity, and by 0.0870 for treated patients for low-severity. While the magnitude of this change is not big, the mean of the difference for treated patients is statistically significant. For control patients, as expected, we do not see a significant change in sensitivity post-HST for neither low- and high-severity cases.

Having shown that the entry of the HST made treated patients more responsive to quality, we now turn to examine hospital-level demand sensitivity. If increased competition due to the entry of the HST made the demand that hospitals face more elastic with respect to quality, it increases hospitals' incentives to provide better clinical quality. Hospital-level elasticities are calculated by simulating a one standard deviation shift in mortality for each hospital and computing the percentage change in the hospital's market share. The distribution of hospital-level elasticities are reported in Panel B of Table 7. Post-HST, one standard deviation increase in mortality rate for an average hospital leads to 4.5879 percent drop n market share, which is 1.4041 percent greater than in the pre-HST period. The difference is statistically significant. These results suggest that increased competition due to the entry of the HST increased hospitals' incentives to provide better clinical quality.

We further test whether hospitals that are located closer to the HST station experienced greater changes in elasticity. We test this by regressing change in elasticity on the hospitals' distance to the nearest train station (as before we use a negative distance for ease of interpretation) :

$$\Delta Elasticity_{j,Mortality} = \phi_0 + \phi_1 dist_j^- + e_j \tag{7}$$

The result of this regression is reported in Panel C of Table 8. The coefficient on the (negative) distance is positive. In other words, 1 mile reduction in distance from hospital to the train station leads to 0.0056 increase in change in elasticity.

==========================

Insert Table 8 about here

==========================

9 Counterfactual Analyses

9.1 Changes in Patient Welfare

We compute the changes in patient welfare from the entry of the HST as follows. Using the parameter estimates from the demand model, we simulate a post-HST scenario where the HST enters. In other words, we consider a scenario where the HST is removed in the post-HST period. From our demand model, some hospitals that previously provided lower utility due to long travel-time than others in the absence of the HST can now be chosen if the reduction in travel time is sufficiently high.

The expected patient surplus (in utils) for patient i with HST can be expressed as

$$E\left[Surplus_i(t_1, q_1)\right] = E\left[\max_{j \in J}(\bar{U}_{ij} + \varepsilon_{ij})\right], \tag{8}$$

where t_1 and $q_1$denote travel time and hospital quality with HST, respectively. Similarly, the expected patient surplus when the HST is removed can be expressed as

$$E\left[Surplus_i(t_0, q_1)\right] = E\left[\max_{j \in J}(\bar{U}_{ij} + \varepsilon_{ij})\right], \tag{9}$$

where t_0 denotes travel time when the HST is removed (i.e., travel time by car). Assuming that ε_{ij} is distributed i.i.d extreme value, the above expression can be rewritten as a logit-inclusive value

$$E\left[Surplus_i(t_1, q_1)\right] = \ln\left(\sum_{j \in J} \exp(\bar{U}_{ij})\right), \tag{10}$$

and

$$E\left[Surplus_i(t_0, q_1)\right] = \ln\left(\sum_{j \in J} \exp(\bar{U}_{ij})\right) \tag{11}$$

The average change in surplus is then given by

$$E\left[\Delta Surplus\right] = \frac{1}{N}\sum_{i=1}^{N}\left[E\left[Surplus_i(t_1, q_1)\right] - E\left[Surplus_i(t_0, q_1)\right]\right], \tag{12}$$

where N is the number of patients in post-HST period.

Welfare calculations are reported in Table 8 Panel A. Assuming the quality of clinical care does not change, patients on average experience an increase of 0.1412 units in expected utility. This increase in welfare arises from a reduction in travel time, and the resulting ability of patients to sort into better hospitals. Since there is no price coefficient in the demand model due to the absence of a price mechanism in this market, we cannot directly convert the welfare change from utils into a dollar value. Therefore, following Gaynor, Propper, and Seiler (2016), we first translate the gains in terms of the preference over distance, and then convert the welfare estimates into a dollar value using additional data from other sources.[20] Comparing the gains in utils to the preference over distance, we find that the welfare effect of the reduction in travel distance for patients belonging to the first quartile corresponds to a 2.5-minute reduction in travel time.[21] Applying a \$167 value per minute reduction in travel time (Gaynor, Propper, and Seiler 2016; Gowrisankaran, Nevo, and Town 2015), the reduction in travel time yields a welfare effect of approximately \$517 ($167 \times 3.1 = 517.7$) per patient.

To look at the gains in welfare based on how close patients live from the train station, we calculate changes in welfare separately for treated and control patients. As expected, treated patients experience disproportionately larger increase in welfare compared to control patients. Treated patients gain an average increase of 0.23 units in expected utility, which amounts to approximately 2.7 percent increase in utils. This quantity is similar regardless of whether a treated patient is a resident in urban or a rural region. Using the same calculation as before, this welfare effect corresponds to approximately \$865.6 per patient. Control patients gain an average increase of 0.0504 units in expected utility (0.67 percent increase in utils). This welfare effect corresponds to approximately \$184.7 per patient.

9.2 The Impact of Patients' Sorting on Survival

The HST has enabled patients to choose hospitals that were previously difficult to consider due to long travel distances. Therefore the HST has not only improved the quality of clinical care through increased competition among hospitals, but has also allowed patients to sort to better hospitals. One way to directly measure the benefits generated by the HST through its impact on patient sorting is to calculate how many patients would have survived in the pre-HST period if the HST had entered, i.e. pre-HST period patients are faced with the post-HST level travel time to the hospitals.

To implement this, we closely follow Gaynor, Propper, and Seiler (2016) and calculate the expected differences in mortality across all patients:

$$E(\Delta Mortality) = \sum_{i \in \mathrm{Pre}HST} \left[E\left[Mortality_i(t_1, q_1)\right] - E\left[Mortality_i(t_0, q_1)\right]\right], \qquad (13)$$

[20] Gowrisankaran, Nevo, and Town (2015) estimate that a one minute reduction in travel time to hospitals increases patient surplus by \$167.

[21] $0.1412/(-4.5553) = -0.0310$, where -4.5553 is the coefficient on travel time. Travel time in the regression is defined in units of 100 minutes.

where

$$E\left[Mortality_i(t_1, q_1)\right] = \sum_j \Pr(ch_{ij} = 1, t_1, q_1) \cdot \text{Prob}(Mortality_i | choice = j, Health_i), \quad (14)$$

and

$$E\left[Mortality_i(t_0, q_1)\right] = \sum_j \Pr(ch_{ij} = 1, t_0, q_1) \cdot \text{Prob}(Mortality_i | choice = j, Health_i). \quad (15)$$

The probability of patient i choosing hospital j is denoted by $\Pr(ch_{ij} = 1, t, q)$. The variable $Mortality_i$ is an indicator variable which takes value 1 if the patient dies and 0 otherwise. $\text{Prob}(Mortality_i | choice = j, Health_i)$ is the death probability of patient $i's$ when he chooses hospital j conditional on his health being $Health_i$, and is the predicted value of equation (2). Equations (14) and (15) denote the mortality probability with HST and without HST, respectively.

The results are reported in Table 8 Panel B. Our estimates from this counterfactual analysis suggest that 1.2238 lives of patients can be saved from patients' sorting. Since our data corresponds to a 2-percent random sample of the entire population, this translates to approximately 61.19 lives over the five quarters, which is equivalent to roughly 49 lives on an annual basis.[22] As before, we calculate the number of lives saved separately for treated and control patients. Our calculations show that 41.3 lives of treated patients and 7.6 lives of control patients can be saved on an annual basis due to patients' sorting. Among treated patients who survive due to the HST, roughly 20 are from urban regions and 21 are from rural regions. In terms of percentages, treated rural patients survive disproportionately due to the HST compared to treated urban patients: the HST leads to 0.88 percentage less death for patients living in urban regions, and 1.61 percentage less death for patients living in rural regions. This suggests that transportation barriers to health care can have disproportionate impact on the health of individuals who live in rural regions, and that a better access to health care through the development of transportation infrastructure can reduce the health care inequalities.

9.3 Hospitals' Response to Changes in Competitive Environment

We now turn to the main question of this paper: does increased competition lead to improved clinical quality? We expect that hospitals whose demand became more elastic to quality due to the entry of the HST to have a higher incentive to provide better quality than other hospitals. This will make hospitals whose demand became more sensitive to quality to put

[22] $1.2238 \times 50 \times (4/5) = 48.95$

more effort into improving their clinical quality than other hospitals. We follow Gaynor, Propper, and Seiler (2016) and test this by regressing the change in the mortality rate on the change in hospitals' elasticity of demand with respect to quality.

We estimate the following equation using OLS:

$$\Delta Mortality_j = \phi_0 + \phi_1 \Delta Elasticity_{j,Mortality} + e_j \tag{16}$$

where $\Delta Mortality_j$ is the percent change in mortality rate for hospital j, and $\Delta Elasticity_{j,Mortality}$ is the percentage change in market share for hospital j when the mortality rate is increased by one standard deviation.

The results are reported in Table 9. To facilitate interpretation, we use the absolute value of elasticities in this regression. The coefficient on the change in elasticity is negative, which means that hospitals whose demand became more responsive to quality lowered mortality rates more than other hospitals. Since the mean change in elasticity is 1.4041 percent, this translates to 2.370 percent change for the average hospital.[23] This suggests, together with the results in Panel C of Table 8, that the changes in the competitive environment due to the entry of the HST led hospitals to respond to changes in demand elasticity with regards to quality.

==========================

Insert Table 9 about here

==========================

10 Conclusion

This paper exploits the entry of HST in South Korea, which reduced patients' travel costs, increasing substitutability among hospitals and thereby increasing hospital competition. This exogenous shock allows us to look at the impact of reduced travel time on patient behavior as well as to study the causal impact of increased competition on hospital quality. Taking advantage of the differential effects of the entry of the HST on hospitals located in different regions of the country, we use a difference-in-differences approach to examine the impact of competition on health outcomes measured by 30-day mortality rates following admissions for surgeries. On the methodological side, we utilize the heterogeneous effects of the entry of the HST on patients living in different areas of the country to obtain a reliable measure of hospital-level quality of clinical care. We find that the entry of the HST improves patient mobility, and that intensified hospital competition leads to an improvement in clinical quality.

[23] $1.4041 \times 1.6882 = 2.370$

To formally evaluate the impact of competition on quality, we estimate a model of hospital choice and use model estimates to simulate patients' elasticity with respect to hospital quality. Our results show that hospitals that were affected by the HST became more elastic with respect to hospital's clinical quality. At the hospital level, we also find that hospitals responded to increased patient substitutability by improving their quality of care. Overall, our paper suggests that increased hospital competition can lead to beneficial health outcomes and that an improvement in transportation infrastructure can have a beneficial impact on patients' health by facilitating patients' sorting to better hospitals through lower travel costs and by reducing health care inequalities through better access to health care.

References

Acemoglu, Daron, David H. Autor, and David Lyle (2004), "Women, War, and Wages: The Effect of Female Labor Supply on the Wage Structure at Midcentury," *Journal of Political Economy*, 112 (3), 497–551.

Adukia, Anjali, Sam Asher, and Paul Novosad (2020), "Educational Investment Responses to Economic Opportunity," *Americal Economic Journal: Applied Economics*, 12 (1), 348–376.

Aggarwal, Shilpa (2021), "The long road to health: Healthcare utilization impacts of a road pavement policy in rural India," *Journal of Development Economics*, 151, 102667.

Allen, Treb and Costas Arkolakis (2022), "The Welfare Effects of Transportation Infrastructure Improvements," *The Review of Economic Studies*.

Barwick, Panle Jia, Shanjun Li, Andrew R Waxman, Jing Wu, and Tianli Xia (2022), "Efficiency and equity impacts of urban transportation policies with equilibrium sorting," *Working Paper*.

Beckert, Walter, Mette Christensen, and Kate Collyer (2012), "Choice of NHS-funded Hospital Services in England," *The Economic Journal*, 122 (560), 400–417.

Birkmeyer, John D., Andrea E. Siewers, Emily V.A. Finlayson, Therese A. Stukel, F. Lee Lucas, Ida Batista, H. Gilbert Welch, and David E. Wennberg (2002), "Hospital Volume and Surgical Mortality in the United States," *The New England Journal of Medicine*, 346, 1128–37.

Bloom, Nicholas, Carol Propper, Stephan Seiler, and John Van Reenen (2015), "The Impact of Competition on Management Quality: Evidence from Public Hospitals," *The Review of Economic Studies*, 82 (2), 457–489.

Brancaccio, Giulia, Myrto Kalouptsidi, and Theodore Papageorgiou (2020), "Geography, Transportation, and Endogenous Trade Costs," *Econometrica*, 88 (2), 657–691.

Brancaccio, Giulia, Myrto Kalouptsidi, Theodore Papageorgiou, and Nicola Rosaia (2022), "Search Frictions and Efficiency in Decentralized Transport Markets," *Working Paper*.

Buchholz, Nicholas (2022), "Spatial Equilibrium, Search Frictions, and Dynamic Efficiency in the Taxi Industry," *The Review of Economic Studies*, 89 (2), 556–591.

Capps, Cory, David Dranove, and Mark Satterthwaite (2003), "Competition and Market Power in Option Demand Markets," *The RAND Journal of Economics*, 34 (4), 737–763.

Card, David (1992), "Using regional variation in wages to measure the effects of the federal minimum wage," *Industrial and Labor Relations Review*, 46 (1), 22–37.

Cho, Nam-Geon and Jin-Kyu Chung (2008), "High speed rail construction of Korea and its impact," *Korea Research Institute for Human Settlement*, 12.

Cooper, Zack, Stephen Gibbons, Simon Jones, and Alistair McGuire (2011), "Does Hospital Competition Save Lives? Evidence from the English NHS Patient Choice Reforms," *Economic Journal*, 121 (554), F228–F260.

Dafny, Leemore, Kate Ho, and Mauricio Varela (2013), "Let Them Have Choice: Gains from Shifting Away from Employer-Sponsored Health Insurance and toward an Individual Exchange," *American Economic Journal: Economic Policy*, 5 (1), 32–58.

Donaldson, Dave (2018), "Railroads of the Raj: Estimating the Impact of Transportation Infrastructure," *American Economic Review*, 108 (4-5), 899–934.

Donaldson, Dave and Richard Hornbeck (2016), " Railroads and American Economic Growth: A 'Market Access' Approach," *The Quarterly Journal of Economics*, 131 (2), 799–858.

Fajgelbaum, Pablo D and Cecile Gaubert (2020), "Optimal Spatial Policies, Geography, and Sorting*," *The Quarterly Journal of Economics*, 135 (2), 959–1036.

Fajgelbaum, Pablo D. and Edouard Schaal (2020), "Optimal Transport Networks in Spatial Equilibrium," *Econometrica*, 88 (4), 1411–1452.

Fréchette, Guillaume R., Alessandro Lizzeri, and Tobias Salz (2019), "Frictions in a Competitive, Regulated Market: Evidence from Taxis," *American Economic Review*, 109 (8), 2954–92.

Gaynor, Martin (2006), "What Do We Know About Competition and Quality in Health Care Markets?" Working Paper 12301, National Bureau of Economic Research.

Gaynor, Martin, Kate Ho, and Robert J. Town (2015), "The Industrial Organization of Health-Care Markets," *Journal of Economic Literature*, 53 (2), 235–84.

Gaynor, Martin, Rodrigo Moreno-Serra, and Carol Propper (2013), "Death by Market Power: Reform, Competition, and Patient Outcomes in the National Health Service," *American Economic Journal: Economic Policy*, 5 (4), 134–66.

Gaynor, Martin, Carol Propper, and Stephan Seiler (2016), "Free to Choose? Reform, Choice, and Consideration Sets in the English National Health Service," *American Economic Review*, 106 (11), 3521–57.

Gaynor, Martin and William B. Vogt (2003), "Competition among Hospitals," *The RAND Journal of Economics*, 34 (4), 764–785.

Geweke, John, Gautam Gowrisankaran, and Robert J. Town (2003), "Bayesian Inference for Hospital Quality in a Selection Model," *Econometrica*, 71 (4), 1215–1238.

Goetz, Daniel (2021), "Telemedicine Competition, Pricing, and TechnologyAdoption: Evidence from Talk Therapists," *Working Paper*.

Gowrisankaran, Gautam, Aviv Nevo, and Robert Town (2015), "Mergers When Prices Are Negotiated: Evidence from the Hospital Industry," *American Economic Review*, 105 (1), 172–203.

Gowrisankaran, Gautam and Robert J Town (1999), "Estimating the quality of care in hospitals using instrumental variables," *Journal of Health Economics*, 18 (6), 747–767.

Gowrisankaran, Gautam and Robert J. Town (2003), "Competition, Payers, and Hospital Quality," *Health Services Research*, 38 (6pt1), 1403–1422.

Halm, E.A, C. Lee, and M.R. Chassin (2002), "Is volume related to outcome in health care? A systematic review and methodologic critique of the literature," *Annals of Internal Medicine*, 137 (6), 511–20.

Heblich, Stephan, Stephen J Redding, and Daniel M Sturm (2020), "The Making of the Modern Metropolis: Evidence from London," *The Quarterly Journal of Economics*, 135 (4), 2059–2133.

Ho, Katherine (2006a), "The welfare effects of restricted hospital choice in the US medical care market," *Journal of Applied Econometrics*, 21 (7), 1039–1079.

— (2006b), "The welfare effects of restricted hospital choice in the US medical care market," *Journal of Applied Econometrics*, 21 (7), 1039–1079.

— (2009), "Insurer-Provider Networks in the Medical Care Market," *American Economic Review*, 99 (1), 393–430.

Kessler, Daniel P. and Mark B. McClellan (2000), "Is Hospital Competition Socially Wasteful?" *The Quarterly Journal of Economics*, 115 (2), 577–615.

Liu, Tracy, Zhixi Wan, and Chenyu Yang (2021), "The efficiency of a dynamic decentralized two-sided matching market," *Working Paper*.

Manning, Alan and Barbara Petrongolo (2017), "How Local are Labor Markets? Evidence form a Spatial Job Search Model," *The American Economic Review*, 107 (10), 2877–2907.

Moscelli, Giuseppe, Hugh Gravelle, and Luigi Siciliani (2021), "Hospital competitionand Quality for Non-Emergency Patients in the English NHS," *RAND Journal of Economics*, 52 (2), 382–414.

Propper, Carol, Simon Burgess, and Denise Gossage (2008), "Competition and Quality: Evidence from the NHS Internal Market 1991-9," *The Economic Journal*, 118 (525), 138–170.

Propper, Carol, Simon Burgess, and Katherine Green (2004), "Does competition between hospitals improve the quality of care?: Hospital death rates and the NHS internal market," *Journal of Public Economics*, 88 (7-8), 1247–1272.

Qin, Marco, George John, and Maria Ana Vitorino (2023), "Planes, Trains and Co-Opetition: Evidence from China," *Working Paper*.

Redding, Stephen J (2021), "Trade and geography," *Working Paper*.

Redding, Stephen J. and Esteban Rossi-Hansberg (2017), "Quantitative Spatial Economics," *Annual Review of Economics*, 9 (1), 21–58.

Silber, Jeffrey H., Paul R. Rosenbaum, J.Brachet Tanguy, Richard N. Ross, Laura J. Bressler, Orit Even-Shoshan, Scott A. Lorch, and Kevin G. Volpp (2010), "The Hospital Compare Mortality Model and the Volume-Outcome Relationship," *Health Services Research*, 45 (5), 1148–6773.

Tay, Abigail (2003), "Assessing Competition in Hospital Care Markets: The Importance of Accounting for Quality Differentiation," *The RAND Journal of Economics*, 34 (4), 786–814.

Weber, Sylvain and Martin Péclat (2017), "A simple command to calculate traveldistance and travel time," *The STATA Journal*, 17 (4), 962–971.

Figures and Tables

Figure 1: HST line and hospitals

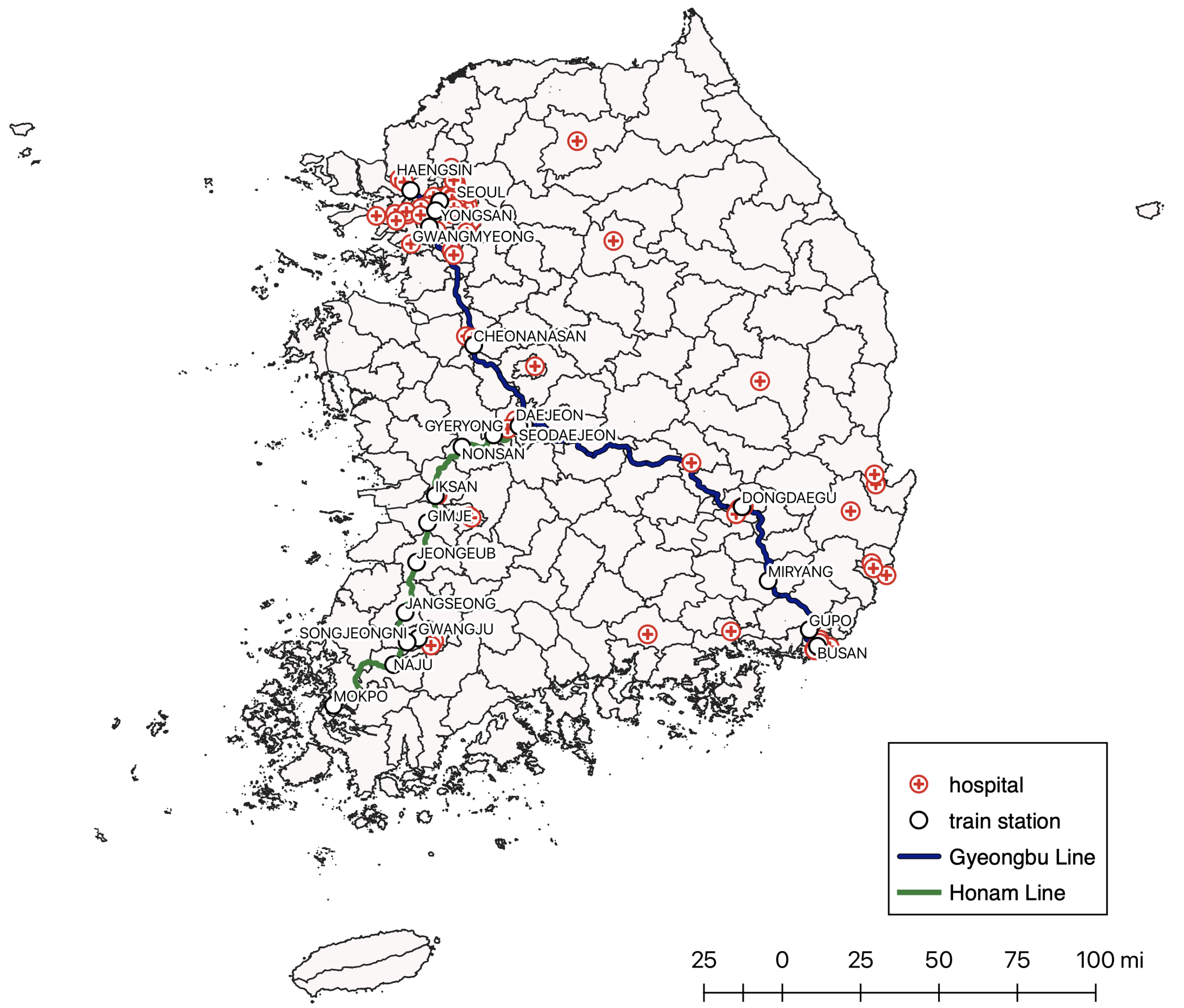

Figure 2: Trend of mortality rates (2003-2007)

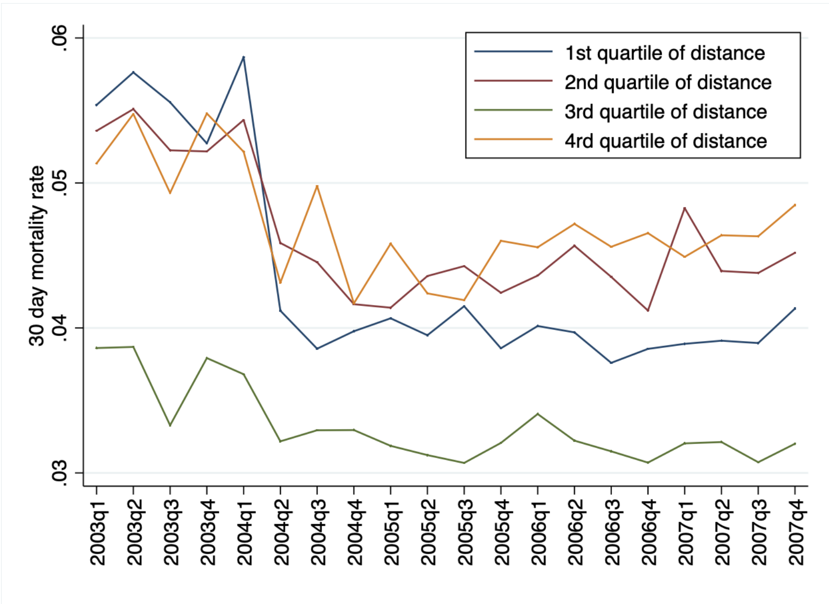

Table 1: Patient Characteristics

	pre-HST		post-HST	
	Mean	SD	Mean	SD
female	0.3034	0.4623	0.4157	0.4956
age 0-24	0.0679	0.2516	0.0560	0.2299
age 25-49	0.2420	0.4284	0.1972	0.3979
age 50-74	0.5847	0.4928	0.6014	0.4897
age 75 +	0.1054	0.3071	0.1455	0.3526
Seoul resident	0.2501	0.4331	0.2410	0.4278
low income	0.2	0.4001	0.1878	0.3906
medium income	0.3406	0.4740	0.3346	0.4719
high income	0.4594	0.4984	0.4776	0.4995
diagnosis risk	0.0463	0.0463	0.0466	0.0456
surgery risk	0.0659	0.0744	0.0637	0.0755
death	0.0488	0.2155	0.0447	0.2066
Observations	3,975		5,128	

Notes: Most of the patient characteristics are binary variables, and therefore the mean represents the fraction. “Seoul resident” is a binary variable that equals 1 if a patient lives in Seoul and 0 otherwise. There are 11 (group 0 - group 10) income groups in our data. We classify groups 0-3 as low income, groups 4-7 as medium income, and groups 8-10 as high income. “death” is binary variable that equals 1 if patient dies within 30 days of admission to the hospital, and 0 otherwise.

Table 2: Descriptive Evidence of Changes in Travel Distance

	Control patients			Treated patients		
	pre-HST	post-HST	Diff	pre-HST	post-HST	Diff
A. All patients	47.8944	46.0378	1.8567	23.7077	28.1051	4.3973**
	(1.4805)	(79.2676)	(1.9250)	(1.2311)	(1.2027)	(1.7439)
Observations	2,031	1.247224		1,944	2,509	
B. Excluding Seoul residents	51.8106	49.3218	2.4887	34.7804	40.6531	5.8727**
	(1.5924)	(1.3332)	(2.0637)	(1.9898)	(1.8662)	(2.7578)
Observations	1,853	2,395		1,128	1,497	
C. Urban area residents	22.6283	23.6347	1.0064	20.0735	23.8738	3.8003*
	(2.4179)	(2.2067)	(3.2819)	(1.4004)	(1.3567)	(1.9762)
Observations	476	598		1,427	1,863	
D. Rural area residents	55.6286	52.6667	-2.9620	33.7388	40.3077	6.5688*
	(1.7403)	(1.4462)	(2.2469)	(2.4967)	(2.4922)	(3.5707)
Observations	1,555	2,021		517	646	

Notes: Average distance traveled by patients to the hospital of their choice (in miles). Standard errors are reported in parentheses.

Table 3: Patient Sorting to Better Hospitals

	Better Hospitals (N=16)			Worse Hospitals (N=20)		
	Pre-HST	Post-HST	DIFF	Pre-HST	Post-HST	DIFF
Panel A. Patients who live within 10 miles of HST station, hospitals within 10 miles						
Share of Travelers (different province)	0.2337	0.3046	-0.0709**	0.2189	0.2220	-0.0031
	(0.0208)	(0.0202)	(0.0292)	(0.0215)	(0.0191)	(0.0288)
Observations	415	522		370	473	
Panel B. Patients who live outside 10 miles of HST station, hospitals within 10 miles						
Share of Travelers (different province)	0.6782	0.71517	-0.0369	0.7168	0.7270	-0.0101
	(0.0263)	(0.0206)	(0.0332)	(0.0270)	(0.0251)	(0.0369)
Observations	317	481		279	315	
Panel C. Patients who live within 10 miles of HST station, hospitals beyond 10 miles						
Share of Travelers (different province)	0.5	0.5846	-0.0846	0.4032	0.5517	-0.1485*
	(0.1147)	(0.0616)	(0.1280)	(0.0628)	(0.0536)	(0.0827)
Observations	20	65		62	87	
Panel D. Patients who live outside 10 miles of HST station, hospitals beyond 10 miles						
Share of Travelers (different province)	0.1165	0.1306	-0.0141	0.1706	0.1263	0.0443
	(0.0224)	(0.0178)	(0.0290)	(0.0220)	(0.0171)	(0.0274)
Observations	206	360		293	380	

Notes: Standard errors are reported in parentheses.

Table 4: Hospital Characteristics

	pre-HST					post-HST				
	mean	median	sd	min	max	mean	median	sd	min	max
number of admissions	44.7	32	45.5	10	333	57.6	40	61.7	10	450
number of beds	890.9	837	419.1	121	2,993	890.9	837	419.1	121	2,993
number of doctors	250.1	193	188.8	31	962	266.4	223	208.7	32	1,174
located in Seoul	0.3483	0	0.4791	0	1	0.3483	0	0.4791	0	1
mortality rate	0.0551	0.0455	0.0426	0	0.2	0.0502	0.0470	0.0371	0	0.1875
Observations			89					89		

Notes: Variable "located in Seoul" is a binary variable that equals 1 if a hospital is located in Seoul and 0 otherwise. The mean of "located in Seoul" is a fraction hospitals that are located in Seoul.

Table 5: Diff-in-Diff Estimates of the Impact of Competition on Quality of Clinical Care

This table reports the results for the difference-in-difference regressions. The dependent variable in columns (1) through (4) is the number of airlines operating in a given route. The unit of analysis is a year-route combination. "HST" is an indicator variable that equals 1 if the HST is present in a given route and year (even if for part of the year), and 0 otherwise. "No. of HST connections" is the number of HST lines that pass through one (but not both) of the route endpoints. "No. of airline connections" is the number of distinct operating air routes that connect to either of the route endpoints. "Average GDP" is the average of the GDP (in billions of US dollars) for a route's endpoints. We categorize the routes into three groups in terms of route length: short, medium and long, using 600km and 1200km as cutoff points. The indicator variables "Medium Distance" and "Long Distance" correspond to the last two groups. Whenever route-fixed effects are included in the model, the route-specific covariates that do not change over time (i.e., route length) are naturally not identified (only their interaction with other covariates that change over time is identified). Robust and clustered (at the route level) standard errors are reported in parentheses. (***), (**) and (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) raw-mortality	(2) IV	(3) OLS
post HST	-0.0116	-0.0445	-0.0143*
	(0.0075)	(0.0334)	(0.0079)
post HST $\times dist_j^-$	-0.0005*	-0.0025**	-0.0006**
	(0.0003)	(0.0010)	(0.0003)
R^2	0.5422	0.5949	0.5334
hospital FE	✓	✓	✓
number hospitals	89	89	89
Observations	178	178	178

Notes: Models are estimated using OLS with standard errors (in parentheses under coefficients). First column uses hospital-level raw mortality rates as the dependent variable. In the third column mortality rates are adjusted for observed patient characteristics using OLS. In the second column, mortality rates are further adjusted for unobserved severity of illness using instruments. All regressions include constants.

Table 6: Demand Model Estimates

	(1)		(2)	
Mortality	-1.4964***	0.4754	-1.6951***	0.4831
TravelTime	-4.5553***	0.8384	-5.2264***	0.7510
ClosestHospital	1.8055***	0.1918	1.6433***	0.2275
DrPerBed	5.1385*	2.7419	7.9111***	1.6838
Mortality×Female	1.2526**	0.5324		
Mortality×Age[25-50)	0.8734*	0.5101		
Mortality×Age[50-75)	-0.1663	0.9403		
Mortality×Age[75+)	0.51966	0.7538		
Mortality×LowIncome	-0.4014	0.5974		
Mortality×SurgeryRisk[25-50)	-0.9930	0.4904		
Mortality×SurgeryRisk[50-75)	-5.1842***	1.8030		
Mortality×SurgeryRisk[75+)	-0.2877	0.5971		
DrPerBed×Female	-1.2261	0.8128		
DrPerBed×Age[40-59)	-2.3532	1.5437		
DrPerBed×Age[60-79)	-0.2913	1.1754		
DrPerBed×Age[80+)	-1.0430	0.8798		
DrPerBed×LowIncome	2.9558***	0.7379		
DrPerBed×SurgeryRisk[25-50)	-3.5785**	1.8085		
DrPerBed×SurgeryRisk[50-75)	3.4682***	1.2210		
DrPerBed×SurgeryRisk[75+)	0.7539	1.2446		
Log Likelihood	-24,011.7 (349.6)		-24,244.6 (240.5)	

Notes: This table reports the results from two different specifications of a multinomial logit model of hospital choice. Interactions between patient and hospital characteristics are denoted with an "×". Mortality is the adjusted hospital quality obtained after controlling for both observed and unobserved severity of illness using instrumental variable approach. Travel time is in units of 100 minutes. To account for the standard errors of the adjusted mortality rates, we employ bootstrapping, and report the means and standard deviations of the parameter estimates across the 100 bootstrap replications. We also report the mean of the log-likelihood across all bootstrap replications and the standard deviation in parentheses. *** Significant at the 1 percent level; ** Significant at the 5 percent level;* Significant at the 10 percent level.

Table 7: Sensitivity of Demand

Panel A. Patient Sensitivity to Quality

	sensitivity Pre-HST	sensitivity Post-HST	Diff
High severity, Treated	-1.7379	-1.8468	0.1089***
	(0.6192)	(0.6931)	(0.0091)
Low severity, Treated	-1.5012	-1.5882	0.0870***
	(0.5328)	(0.5937)	(0.0074)
High severity, Control	-1.8423	-1.8467	0.0044
	(0.6397)	(0.6353)	(0.0102)
Low severity, Control	-1.5774	-1.5787	0.00130
	(0.5466)	(0.5418)	(0.0089)

Panel B. Patient Sensitivity to Quality Aggregated at the Hospital-level

	Mean	SD	25th percentile	Median	75th percentile
Pre-HST	-3.1838	0.5746	-3.4466	-3.1854	-2.9292
	(0.4133)				
Post-HST	-4.5879	2.1635	-4.8298	-4.5113	-3.6503
	(0.5153)				
Change	-1.4041	0.4044	-1.2191	-1.3769	-1.6044
	(0.6738)				

Panel C. Hospital Response to Changes in Patient Sensitivity to Quality

	DV: $\Delta Elasticity_{j,Mortality}$
$dist_j^-$	0.0056**
	(0.0027)
Observations	89

Notes: Bootstrapped standard errors are reported in parentheses. Panel A reports patient-level elasticity with respect to adjusted mortality rates. Panel B reports the distribution of percentage changes (across all hospitals) in market share when a hospital increases the mortality rate by one standard deviation. Panel C reports the relationship between change in hospital-level elasticity with respect to quality and the distance from the hospital to the nearest train station.

Table 8: Changes in Patient Welfare and Health Outcomes

	A. Welfare Gains			B. Impact on Survival	
	ΔUtility	Dollar Value	%Δ	Number of Deaths	%Δ
treated (10 miles)	0.2361	865.6	2.66	-1.0336	-1.16
treated (urban)	0.2380	872.5	2.66	-0.5021	-0.88
treated (rural)	0.2308	846.1	2.67	-0.5315	-1.61
control	0.0504	184.7	0.66	-0.1902	-0.15
total	0.1412	517.7	1.72	-1.2238	-0.45

Table 9: Hospitals' Response to Changes in Competitive Environment

	Change in mortality rate
Change in Elasticity	-1.6882**
	0.7807
Observations	89

Notes: *** Significant at the 1 percent level; ** Significant at the 5 percent level;* Significant at the 10 percent level. Standard errors are reported in parentheses.

Appendix

A Adjusted Mortality Rates

Here we present estimation results of equation 1 using an alternative measure of hospital quality as in Gowrisankaran and Town (1999). Specifically, we obtain measure of hospital quality by estimating a linear probability model where we regress m_i on a set of hospital dummies and patient's observed characteristics. The mortality of patient i is given as

$$\mu_{it} = \boldsymbol{\psi}' \boldsymbol{c}_i + \boldsymbol{\gamma}' \boldsymbol{h}_i + s_{it} + \eta_{it} \tag{A.1}$$

where μ_{it} is a dummy variable that denotes the death of patient i within 30 days of the admission, $\boldsymbol{c}_i$ is a vector of dummy variables where c_{ijt} equals 1 if patient i ($i = 1, ..., N$) chooses hospital j ($j = 1, ..., J$), $\boldsymbol{h}_i$ is a vector of patient characteristics that can affect mortality, s_{it} is unobserved (by the researcher) severity of illness, and η_{it} is an i.i.d. normal error term. The parameter vectors to estimate are $\boldsymbol{\psi}$ and $\boldsymbol{\gamma}$. With the linear probability model, the elements of estimated fixed effects $\hat{\boldsymbol{\psi}}$ are interpreted as the incremental probability of death from choosing a particular hospital conditional on observed health status, and is used as our measure of quality of care. The coefficient vector $\boldsymbol{\gamma}$ captures the impact of patients' observed health status on the probability of death. Following section 4.1, we will refer to the estimated measure of quality of care, $\hat{\boldsymbol{\psi}}$ as the adjusted mortality rate. Because hospital choice is likely to be correlated with patients' unobserved severity of illness, estimating equation (A.1) using OLS will lead to biased estimates. For instance, if sicker patients are more likely to choose a certain hospital j, then s_{it} and c_{ijt} will be positively correlated, and hence $\hat{\boldsymbol{\psi}}_{\boldsymbol{j}}$ will be overestimated.

To address the endogeneity of hospital choice, we use two sets of instrumental variables for hospital choice dummy variables ($\boldsymbol{c}_i$) : (i) the travel time to each hospital, and (ii) and instruments of the form $exp(-\kappa \times \text{traveltime}_{ijt})$, where we define travel time for patient i to hospital j in period t as

$$\text{traveltime}_{ijt} = \begin{cases} \min(\text{cartime}_{ij}, \text{traintime}_{ij}) & \text{if } t = \text{post-HST \& dist}_i^{pat} < 30 \\ \text{cartime}_{ij} & \text{otherwise} \end{cases} \tag{A.2}$$

Here cartime_{ij} denotes the drive time from patient i's location to hospital j by car, and traintime_{ij} is the travel time from patient i's location to hospital j by HST. [24] $dist_i^{pat}$ is

[24] Note that traintime_{ij} is obtained by summing the following three components: (i) drive time from i's location to i's nearest HST station h, (ii) travel time from station h to station k, which is the closest HST station to hospital j and (iii) drive time from station k to hospital j. We obtain driving time by car by using *georoute* routine developed by Weber and Péclat (2017) which calculates the driving time between two

the travel time from patient i to the closest train station and $dist_j^h$ is the travel time from hospital j to the closest train station. We constrain the effect of the HST to patients and hospitals living 30 minutes within the train station. This is to account for the changes in travel time only for patients living sufficiently close to the HST station in the post-HST era, and is based on the pattern in the data where there are no significant differences in travel times in pre- and post- HST for patients living beyond 30 minutes of the HST station.

For observed patient characteristics, $\boldsymbol{h}_i$, we include female dummy variable, low income dummy variable, age group (10 age groups with increments of 10), and a dummy variable for each surgery type and diagnosis type. There are 81 surgery types and 49 diagnosis types.

Formal specification tests for the validity of our instruments are provided in Table A.1.[25] Our overidentifying restrictions are valid as we fail to reject the null of the Sargan-Hansen overidentification test. We reject the null hypothesis of the Hausman Endogeneity test which means that our OLS and IV estimates are statistically different. We also perform the Wald-Test of Weak Instruments and reject the hypothesis that our instruments are weak. These tests provide support for the validity of our IV specification.

Sargan-Hansen	χ^2	91.88
Overidentification Test	p-value	1
Hausman	χ^2	8,885
Endogeneity Test	p-value	0.0000
Wald-Test of	χ^2	981.37
Weak Instruments	p-value	0.0000

Table A.1: Tests for Validity of Instruments

points under normal traffic conditions.

[25]Note that we perform the specification tests for the data pooled across pre- and post- HST periods.

B Robustness Check for Travel Distance Metric

distance traveled (miles)	Control patients			Treated patients		
	pre-HST	post-HST	Diff	pre-HST	post-HST	Diff
8 miles treatment	41.9693	41.6336	0.3357	26.1775	30.1597	-3.9822*
	(1.2751)	(1.1032)	(1.6814)	(1.5117)	(1.4264)	(2.1007)
Observations	2,489	3,175		1,486	1,953	
12 miles treatment	51.2437	49.0636	2.1802	22.9320	26.9070	-3.9751**
	(1.5899)	(1.3319)	(2.0617)	(1.1459)	(1.1208)	(1.6231)
Observations	1,844	2,397		2,131	2,731	
14 miles treatment	55.6976	53.5222	2.1754	23.0327	26.0607	-3.0280**
	(1.7519)	(1.4600)	(2.2667)	(1.0765)	(1.0377)	(1.5101)
Observations	1,586	2,092		2,389	3,036	

Notes: Average distance traveled by patients to the hospital of their choice (in miles). Standard errors are reported in parentheses.

Table B.1: Robustness of 10-mile Treatment: Descriptive Evidence of Changes in Travel Distance

We repeat the analysis of Table 2 using alternative definitions of treatment. Specifically, we use 8 mile, 12 mile, and 14 mile definitions of treatment. Results are consistent with the findings of Table 2, and show that patient living closer to the HST station show significant increases in travel distance to the hospital of their choice, whereas patients living further away from HST stations do not.

C Robustness Checks for Difference-in-Differences Analysis

We test the robustness of our DID results using alternative specifications, (i) not including hospital fixed effects, and (ii) including number of hospital admissions as an additional control variable. Results do not change.

	(1) raw-mortality	(2) IV	(3) OLS
$dist_j^-$	0.0006***	0.0024**	0.0006***
	(0.0002)	(0.0010)	(0.0002)
post HST	-0.0116	-0.0445	-0.0143*
	(0.0080)	(0.0380)	(0.0084)
post HST $\times dist_j^-$	-0.0005	-0.0025**	-0.0006
	(0.0003)	(0.0012)	(0.0004)
R^2	0.0352	0.0261	0.0339
hospital FE	No	No	No
number hospitals	89	89	89
Observations	178	178	178

Notes: Models are estimated using OLS with standard errors (in parentheses under coefficients). First column uses hospital-level raw mortality rates as the dependent variable. In the third column mortality rates are adjusted for observed patient characteristics using OLS. In the second column, mortality rates are further adjusted for unobserved severity of illness using instruments. All regressions include constants. *** Significant at the 1 percent level; ** Significant at the 5 percent level;* Significant at the 10 percent level.

Table C.1: Diff-in-Diff Estimates of the Impact of Competition on Quality of Clinical Care

	(1) raw-mortality	(2) IV	(3) OLS
post HST	-0.0102	-0.0539	-0.0140
	(0.0084)	(0.0393)	(0.0089)
post HST $\times dist_j^-$	-0.0005	-0.0025**	-0.0006**
	(0.0003)	(0.0010)	(0.0003)
# admissions	-0.0001	0.0007	-0.0000
	(0.0002)	(0.0010)	(0.0002)
R^2	0.5430	0.5968	0.5335
hospital FE	✓	✓	✓
number hospitals	89	89	89
Observations	178	178	178

Notes: Models are estimated using OLS with standard errors (in parentheses under coefficients). First column uses hospital-level raw mortality rates as the dependent variable. In the third column mortality rates are adjusted for observed patient characteristics using OLS. In the second column, mortality rates are further adjusted for unobserved severity of illness using instruments. All regressions include constants. *** Significant at the 1 percent level; ** Significant at the 5 percent level;* Significant at the 10 percent level.

Table C.2: Diff-in-Diff Estimates of the Impact of Competition on Quality of Clinical Care

	(1) raw-mortality	(2) IV	(3) OLS
post HST	-0.0104	-0.0485	-0.0132
	(0.0081)	(0.0363)	(0.0086)
post HST $\times dist_j^-$	-0.0005*	-0.0026**	-0.0006**
	(0.0003)	(0.0011)	(0.0003)
R^2	0.5430	0.5953	0.5404
hospital FE	✓	✓	✓
number hospitals	81	81	81
Observations	162	162	162

Notes: Models are estimated using OLS with standard errors (in parentheses under coefficients). First column uses hospital-level raw mortality rates as the dependent variable. In the third column mortality rates are adjusted for observed patient characteristics using OLS. In the second column, mortality rates are further adjusted for unobserved severity of illness using instruments. All regressions include constants. *** Significant at the 1 percent level; ** Significant at the 5 percent level;* Significant at the 10 percent level.

Table C.3: Excluding Hospitals that Received Government Subsidy