

# Value of Health Information Sharing in Reducing Healthcare Waste: An analysis of duplicate testing across hospitals

*Completed Research Paper*

## **Sezgin Ayabakan**

Assistant Professor  
University of Baltimore  
1420 N Charles St,  
Baltimore, MD, 21201  
sayabakan@ubalt.edu

## **Indranil R. Bardhan**

Professor  
University of Texas at Dallas  
800 W Campbell Road, SM 33,  
Richardson, TX, 75080  
bardhan@utdallas.edu

## **Zhiqiang (Eric) Zheng**

Associate Professor  
University of Texas at Dallas  
800 W Campbell Road, SM 33,  
Richardson, TX, 75080  
ericz@utdallas.edu

## **Kirk Kirksey**

Vice President for Information  
Resources  
UT Southwestern Medical Center  
5323 Harry Hines Blvd,  
Dallas, TX 75390  
kirk.kirksey@utsouthwestern.edu

## **Abstract**

*Recent healthcare reform has focused on reducing excessive waste in the US healthcare system, with duplicate testing being one of the main culprits. We explore the factors associated with duplication of radiology tests when information sharing across healthcare providers is fragmented, and patients switch from one hospital to another. We hypothesize that patients' switching behavior across hospitals is associated with a higher levels of duplicate testing, and argue that implementation of intra- and inter-hospital information sharing technologies will help to reduce duplicate tests. We utilize a panel data set consisting of 39,600 patient visits across outpatient clinics of 68 hospitals from 2005 to 2012. Our results indicate that hospital switching is associated with greater duplicate testing and usage of inter-hospital information systems is associated with lower duplication. Our results support the need for implementation of health information exchanges as a potential solution to reduce the incidence of duplicate tests.*

**Keywords:** Electronic medical records, econometrics, healthcare information systems

## **Introduction**

The disparity between the costs incurred and quality outcomes realized within the U.S. healthcare system are striking. On average, healthcare services in the U.S. cost twice as much as similar services in the Organization for Economic Cooperation and Development (OECD) countries. Annual healthcare expenses in the U.S. amount to \$2.2 trillion, or 17.6% of GDP in 2011 (OECD 2012), and are projected to grow to \$4.4 trillion, or 20.3% of GDP, by 2018 if the current trend is not nixed (Sisko et al. 2009). It is estimated that 40-50% of U.S. healthcare spending amounts to waste, of which overuse of resources is a significant contributor (Bentley et al. 2008; Hillestad et al. 2005). The Congressional Budget Office estimates that around \$700 billion per year, or 5 percent of the US GDP, is expended on tests and treatments that do not actually improve health outcomes (Orszag 2008). Waste due to inefficient use of resources can arise in many situations such as excessive antibiotic use for viral infections, avoidable hospitalizations for nursing home patients, unnecessary admissions of patients with chest pain, and overuse of screening and imaging procedures (Bentley et al. 2008). Recent enactment of the Affordable Care Act (ACA) aims to replace the current fee-for-service structure where providers are paid more for ordering frequent tests and treatments with an accountable, pay-for quality system that rewards cost-effective care, in an endeavor to reduce avoidable costs (Beck 2013).

In this study, we specifically focus on the duplication of imaging procedures related to the diagnosis and treatment of congestive heart failure (CHF) outpatients. A likely cause of the excessive use of imaging tests is the lack of information sharing among disparate healthcare entities. Redundant medical procedures are likely to arise if patient medical data is not shared between different providers (Bates et al. 1998; LaBorde et al. 2011). For example, Kripalani et al. (2007) report that between 3% and 20% of attending physicians communicate with their patients' primary care providers. To make matters worse, it is estimated that between 33% and 63% of patient discharge summaries lack important information on diagnostic test results and other relevant information that may potentially cause readmission, dissatisfaction, delay in treatment, or other patient safety issues (Kripalani et al. 2007; Solis 1982), thus exacerbating the possibility of incurring duplication in the future. We argue that one of the main drivers of duplicate testing is the lack of information sharing among healthcare providers, a problem that is exacerbated when patients migrate across hospitals due to technological barriers to information sharing across organizations. Technological barriers are created when healthcare providers do not have access to IT platforms that allow patient data to be shared across health systems in a standard format.

Hence, we hypothesize that patients' switching behavior across hospitals will be associated with an increase in duplicate tests due to lack of access to their prior medical history, and argue that implementation of intra- and inter-hospital information sharing technologies will help reduce the rate of duplicate tests. We empirically test our hypotheses using a comprehensive dataset of more than 39,600 CHF patient visits to outpatient clinics across 68 hospitals in North Texas. This dataset records information for each patient's visit tracked across a relatively long period from 2005 to 2012. We observe that CHF patients who switch across hospitals (across consecutive visits) also exhibit a high rate of duplicate imaging tests. We then examine hospital IT capabilities that are enabled by implementation and usage of health information sharing technologies, and their impact on the extent of duplication. We implement a quasi-experiment approach to study changes in the rate of duplicate testing with respect to the implementation timeline of hospital information sharing systems.

Our results indicate that usage of inter-hospital information sharing technologies is associated with a significant reduction in the rate of duplicate tests, with respect to imaging and radiology, conducted on CHF patients. Our study provides a foundation to empirically demonstrate the value of health information exchanges (HIE) by estimating the costs attributed to duplication of outpatient tests due to a lack of information sharing across healthcare providers. In the context of the current debate on healthcare reform and the need to reduce healthcare costs through reduction in redundant procedures, our study lends support to the possibility of reducing costs associated with patient diagnosis and treatment through implementation of health information exchanges.

## **Theory Foundation**

### ***Duplication of Imaging Tests***

Recent evidence shows that the prevalence of duplicate imaging tests may explain a significant portion of waste in the US healthcare system (OECD 2012). The U.S. ranks near the top in terms of MRI and CT usage, and the amount of procedures performed per patient is double that of the OECD average (OECD 2012). There are many reasons for the high rate of duplication (Dai et al. 2011). Some duplicate tests are necessary because a patient's condition may change from one visit to another and it may need a re-test to detect the changes. Physicians also exhibit 'defensive medicine', a term reflecting their tendency to overuse tests in order to fend off future litigation (Currie and MacLeod 2013).

A significant problem associated with research on the determinants of duplicate testing is the potential for patients to switch providers and visit different hospitals during an episode of a treatment (LaBorde et al. 2011). When providers cannot easily access their patients' medical histories (including diagnosis, allergies, medication history, and test results) due to the lack of information-sharing infrastructure in the current healthcare environment, they tend to order repeat diagnostic tests and procedures which contribute to higher duplication rates. Hence, we need to develop a better understanding of the impact of patient switching behavior (across multiple hospital visits) on the incidence of duplicate testing (Kripalani et al. 2007, Johnson et al. 2011). This is a significant problem, especially among uninsured and under-insured patients who tend to migrate across hospitals depending on the severity of their health status.

We argue that the prevalence of hospital switching among patients creates a need for inter-organizational information sharing across providers. Hence, the focus of this study is to evaluate the impact of intra- and inter-hospital image sharing technologies on the extent of duplicate imaging tests. Since these types of technologies are critical to building health information exchanges, we examine the potential benefits that may be accrued from implementation and usage of these technologies in order to develop a better understanding of their role in reducing the duplication rate associated with outpatient imaging tests in the healthcare system. Such analysis may provide supporting evidence to better inform policy makers and other stakeholders who are considering funding the implementation and rollout of HIEs as a vehicle to reduce inefficiencies related to the costs of duplicate testing.

It is important to note that we focus on the determinants of duplicate testing and do not differentiate whether a specific test is necessary or truly redundant. Determining which test is necessary or redundant is a subjective exercise and can vary from patient to patient (i.e. some patients may request additional tests), and from one physician to another. There are no guidelines on ways to differentiate between necessary and redundant tests, which are often determined by physician expertise and experience, due to significant variations in patient health status as well as other factors (Sridhar et al. 2012).

Nevertheless, a research study on the determinants of duplicate testing is an interesting, significant and valid problem in its own right for the following reasons. First, the U.S. healthcare system suffers from excessive overuse of tests. At the national level, it is estimated that close to 50% of procedures performed per patient may be unnecessary compared to the OECD average (OECD 2012). For tests such as CT scans, the New York Times reported that more than 30% of duplicate CT scans across 200 hospitals are hard to justify, while some hospitals, such as the St. John health System in Tulsa, abused CT scans with a staggering duplication rate of 80% in 2008, resulting in \$250,000 of unjustified Medicare charges. Second, developing a better understanding of the drivers of duplication represents a first step to help healthcare policy makers, providers, insurance companies, and consumers determine the factors that contribute to the duplication rate, so that appropriate steps can be implemented to reduce the extent of duplication.

### ***Inter-organizational Information Sharing***

Demonstrating the economic value of information sharing has long been a central theme of the literature on information systems, operations and strategy. For example, electronic information sharing across organizations for business transaction was enabled through implementation of Electronic Data Interchange (EDI) standards. Prior studies in the IS literature have reported significant benefits with respect to the business value of EDI in facilitating inter-organizational information sharing (Li et al.

2006). EDI increases the efficiency of business transactions and improve coordination between trading partners in a market that is characterized by the presence of multiple standards, new software requirements and substantial reorganization of business processes (Barua and Lee 1997). Seidmann and Sundararajan (1998) classify information sharing under four categories according to its impact on the parties involved in a vertically positioned market: ordering, operational, strategic and competitive information sharing. The benefits of information sharing in a healthcare environment span all four dimensions. Sharing health information across healthcare providers can reduce the time needed to provide healthcare services, thus reducing wait time; it directly affects operational and clinical decision making by enabling providers with access to a patient's health history; and lastly, it can exert a level of influence on competing hospitals by demanding transparent information sharing.

We liken the importance of health information sharing to that of the “bullwhip effect”, a phenomenon that is associated with information transfer in supply chains. For example, the bullwhip effect occurs when slight variations in demand at the consumer results in wild fluctuations in demand signals at the supplier end (Lee et al. 1997). Thus, sharing demand information with supplier can be beneficial to the entire supply chain by reducing uncertainty related to distortion of information and product variety (Li et al. 2006). Similarly, when a healthcare provider is uninformed about the patient's prior health history, their decision-making is clouded by uncertainty with respect to the patients' prior tests and procedure history. In such cases, providers typically resort to repeat (duplicate) tests, partly to develop their independent assessment of the patient and partially to mitigate the risk of litigation.

The strategy and organizational behavior literatures have also highlighted the importance of information sharing among organizations. Lack of information sharing and information distortion are important considerations in inter-organizational process design (Carley and Lin 1997; Cohen and March 1986). In an organizational setting, incorrect information can cause information distortion which may affect the performance of organizations. In the strategy literature, the mediating role of information technology and training have been explored as potential solutions to the problem of information distortion (Carley and Lin 1997; Neuhauser 1971). Yang and Maxwell (2011) observe that interoperability across organizations represents cross-boundary information sharing. Research in the public sector suggests that overcoming barriers related to information privacy and technology standards is critical to develop a robust foundation for inter-organizational information sharing (Landbergen and Wolken 2001). Rather than relying on (the often) imprecise narratives provided by patients, it is important to develop a better understanding of the types of prior procedures and tests that have been performed on a patient, in order to reduce the level of information distortion as patients move from one healthcare provider to another.

## **Research Hypotheses**

We now develop our hypotheses to investigate the role of patients' hospital switching and hospital health information sharing, and their impact on the extent of duplicate testing during the course of patients' diagnosis and treatment.

### ***Hospital Switching***

A typical patient receives care from multiple, geographically disparate providers over the course of their treatment (Flanders 2009). Mobility of patients not only leads to more voluminous health data but also greater fragmentation of information due to barriers to information sharing across competing providers (Flanders 2009). There exist significant organizational and technological barriers to sharing patient health information across disparate health providers in the present environment. In an ideal scenario, when a patient switches from one provider to another, the patient's prior health information must follow. However, patients may not always be able to accurately recall or communicate clinical information and treatment details with their prior care providers. Care providers may also lack incentives to share health information; they may be reluctant to retrieve clinical information because it is cumbersome and time consuming; and even if providers are willing to share, logistical barriers stemming from fragmented medical data across hospitals, laboratories and clinics may lead to inconsistencies and distortions in the patient's medical record (Johnson et al. 2011).

When medical data is unable to move between providers, diagnostic or treatment errors can arise as a result of providers' inability to retrieve patients' prior health data (Bates et al. 1998; Flanders 2009;

LaBorde et al. 2011). For example, LaBorde et al. (2011) contend that lack of healthcare IT (e.g EMR and HIE) integration across facilities can lead to more duplicate diagnostic laboratory tests. Hillestad et al. (2005) argue that EMRs can greatly facilitate information flow among providers and estimate that EMRs can save \$7.9 billion annually by reducing the need for redundant laboratory and radiology tests. Understanding how duplicate testing occurs when patients switch hospitals is of importance to health policy makers, considering the Affordable Care Act's (ACA) initiative in reducing waste and abuse in the US healthcare system (<http://www.hhs.gov/opa/affordable-care-act/index.html>). We conjecture that patients' switching hospitals will result in an increase in duplicate testing. Hence, we posit that,

**H1.** Patients who switch hospitals across readmissions will exhibit a higher rate of duplicate tests compared to patients who are readmitted to the same hospital (as the prior visit).

### **Health Information Sharing**

Enabling access to patient health information sharing across various stakeholders can greatly reduce inefficiencies in the US healthcare industry. Health information technologies can facilitate actions related to capture, storage, sharing and retrieval of patient health information. Accessing related information about patient's medical and surgical history, allergies, current and past medication lists through health information technologies will allow providers to make better decisions regarding patient's diagnosis and treatment (Booth 2003). Electronic Health Records (EHRs) provide the technological foundation for sharing patient health information across organizational boundaries. EHRs are software platforms that enable interoperability among multiple stakeholders such as delivery and sharing of patient health information to physician offices and hospitals (Mishra et al. 2012). Yet, EHR systems are also criticized for not being able to communicate with each other, resulting in islands of fragmented information (Ozdemir et al. 2011). DesRoches et al. (2013) argue that exchanging patient clinical summaries, laboratory and diagnostic test results with outside entities are among the least likely adopted functionalities of an EHR.

Integrating EHRs for the purpose of information sharing can happen at two levels - internal and external integration – according to the strategic health IT framework proposed by Raghupathi and Tan (2002). Internal integration refers to the degree to which systems and technologies are integrated with one another within an organization, whereas external integration refers to their integration with outside organizations and partners. Accordingly, we examine HIT application usage in terms of the impact of sharing patient health information within (intra) and across (inter) hospitals on duplicate tests.

Computerized provider order entry (CPOE) and picture archival and communication systems (PACS) represent two types of health IT that can facilitate intra-hospital information sharing. Prior research has shown that CPOE implementation is associated with a reduction in hospital length of stay, and drug and radiology usage in outpatient settings (Hillestad et al. 2005). For radiology tests, CPOE can benefit users by reducing the rate of duplicate imaging tests, such as X-rays and CT scans (Bates et al. 1999; Chin and Wallace 1999) As an imaging informatics tool, PACS enables distribution of radiology images to various medical units within a hospital (Branstetter 2007). The ability to obtain timely and accurately access to radiology images within hospitals, through EHRs that are integrated with PACS, reduces the utilization of radiology imaging services and can provide efficiency gains through reduced repeat (duplicate) imaging examinations (Lu et al. 2012; Sodickson et al. 2011). Hence, we hypothesize that,

**H2a.** Intra-hospital information sharing of radiology images across departments is associated with a decrease in overall test duplication rate.

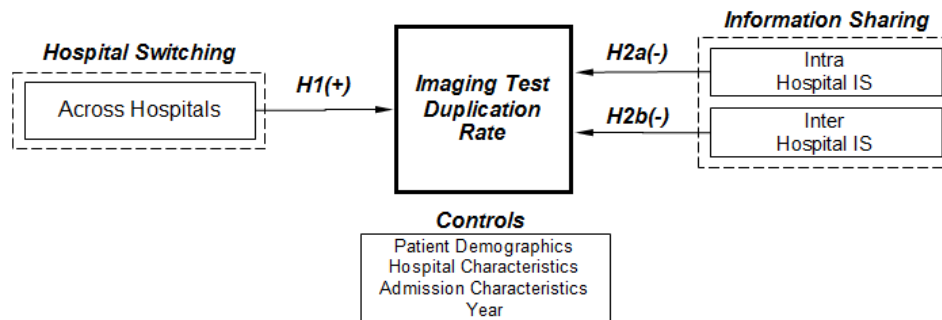
Information sharing across hospitals is crucial when patients are mobile and visit providers across disparate health systems. The fact that providers often do not have access to virtual private network (VPN) connection to disparate PACS has made inter-hospital information sharing uncommon or even impossible (Mendelson 2011). However, recent adoption of cloud-based systems and web-based personal health records (PHRs) have emerged as potential solutions to overcome barrier associated with inter-hospital information sharing (Mendelson 2011; Shrestha 2011). Due to the distributed nature of digital images, radiologists need access to images not only at the point of care, but from multiple locations with full access to patient information. Cloud-based solutions have been developed to facilitate inter-hospital information sharing by offering the ability to share patient images and report data across multiple locations securely and conveniently. Such systems can allow access to patient medical information

(including previously performed imaging tests and reports) from disparate locations -- resulting in efficiency gains through reduced duplication of tests and procedures (Shini et al. 2012). Likewise, Internet-enabled image transfer systems have been recently proposed as a solution to enable greater inter-hospital information sharing. For instance, Flanagan et al. (2012) report that implementation of an Internet-enabled image transfer system at Harborview Medical Center was associated with a reduction in duplication rate to 8.1%. In the light of possible benefits that can accrue from information sharing, we hypothesize that inter-hospital information sharing will increase information availability, reduce latency, and therefore reduce the extent of duplicate testing.

**H2b.** Inter-hospital information sharing of radiology images across hospital locations will decrease duplication rate.

Based on these hypotheses, we depict our conceptual research model in Figure 1.

**Figure 1. Conceptual Research Model**



## Research Methodology

To test our conceptual research model in Figure 1, we obtain data from two sources: the Dallas-Fort Worth Hospital Council (DFWHC) Research Foundation and HIMSS Analytics. We use the DFWHC data to empirically test the hypotheses related to hospital switching (H1), while we draw on the HIMSS Analytics data along with DFWHC to test our hypotheses on the impact of information sharing (H2a, H2b). We first describe the data and variables that we use to operationalize our conceptual research model and test our research hypotheses.

### Data

The focus of our study is on CHF patients because CHF is one of the three diseases (along with pneumonia and myocardial infarction) subject to the new ACA penalties stemming from excessive readmissions that started in 2012. Access to outpatient care and discharge destinations are critical for CHF patients because CHF is characterized by high readmission rates, significant deterioration in functioning, reduction in quality of life, increased dependence on caregivers, and a high ongoing cost of treatment (Wolinsky et al. 1997). Depending on the strength of these factors, a patient with CHF will have high likelihood of readmission following a discharge. High readmission rate will possibly result in high hospital switching rate. Hence, CHF becomes an ideal chronic illness candidate for our research purposes. We obtained a comprehensive dataset of 39,600 Congestive Heart Failure (CHF) patient visits across outpatient clinics of 68 non-Federal hospitals and 26 health systems in North Texas. Based on patient-level administrative claims data, each patient's visit history is tracked from 2005 to 2012 through a unique patient identifier number, the regional master patient index (REMPI) developed by the DFWHC Foundation (Bardhan et al. 2011). The REMPI is a unique ID number assigned to each patient that allows us to track patient visits over time and across all hospitals in the region. In other words, the REMPI allows us to obtain the patient's entire visit and diagnosis history and enables us to study the patterns of patient care and diagnosis (including tests) received across multiple outpatient clinics. In this dataset we only include patients with CHF as the principal diagnosis, i.e., patient admissions with ICD-9 code of "428.xx". Focusing only on their principal diagnosis alleviates possible patient heterogeneity arising from treatment procedures and imaging tests that vary across different diagnoses. Furthermore, we focus specifically on outpatient admissions because patients receive radiology imaging procedures, such as X-rays, CT scans,

MRI scans, and ultrasound tests, primarily in an outpatient setting which also account for a majority of these tests (Lee et al. 2012).

Based on feedback provided by leading CHF physicians, we apply a conservative cutoff of 90 days to determine whether an imaging test can be considered as duplicate. This is because the typical life span of a radiology imaging test is about 3 months. For example, Lu et al. (2012) define repeat imaging as “that performed when a previous CT or MRI examination of the abdomen was followed by a second examination with the same modality, body part, and type in 4 months.” In addition, Lee et al. (2007) define the time window of a repeat imaging test as seven months, but report that a majority of repeat radiological imaging tests happened in the first two months of initial examination.

In our analysis, we exclude the index visit since the duplication rate and hospital switching events are calculated with respect to the prior visit information. Based on these criteria, we focus on the visit history of 4,038 CHF outpatients who exhibit at least two (or more) outpatient visits during our study period. Their admissions comprise a total of 9,403 consecutive visits, where the consecutive visits occurred within ninety days (of the prior visit). Table 1 reports the descriptive statistics of our model variables.

**Error! Reference source not found.** Figure 2 provides an illustrative profile of the outpatient visit history for a 62-year old, non-white, female CHF patient along with all the imaging tests performed on the patient during these visits. The very first visit of the patient is the index visit. Visits 4 and 7 fall outside the 90-day time window from their respective previous visit, and accordingly, both are treated as index admissions. In her second visit (i.e., visit 2), she visits hospital 14, after her previous visit to hospital 60 which was only 22 days ago. Since this is a different hospital visit within a 90-day time window, we label the *Hospital\_Switch* variable as a “Yes.” To calculate the duplication rate of each visit, we compare the current set of procedures to the previous visits’ procedures that happened within the 90-day window. For example, during Visit 5, the patient received three different echocardiography (ECG) tests coded as 93220, 93307, 93325 and one chest x-ray coded as 71010. We compare these CPT codes to the previous visits’ CPT codes, and observe that 71010 had been performed 43 days ago during visit 4. Therefore, this chest x-ray (coded as 71010 during visit 5) is flagged as a duplicate procedure and we increase the duplication count (*Duplicate\_Count*) by 1, whereas the *Duplicate\_Rate* is calculated as *Duplicate\_Count* divided by the total number of procedures performed during visit 5, and is equal to 25%.

We collected hospital level information sharing data from the HIMSS Analytics database for these 68 hospitals. This database is one of the most widely used data sources with respect to the adoption and usage of health IT systems in US hospitals. Intra-hospital information sharing data was available for the years between 2006 and 2012, whereas inter-hospital information sharing data was available for the years between 2009 and 2012 (Bardhan et al. 2011).

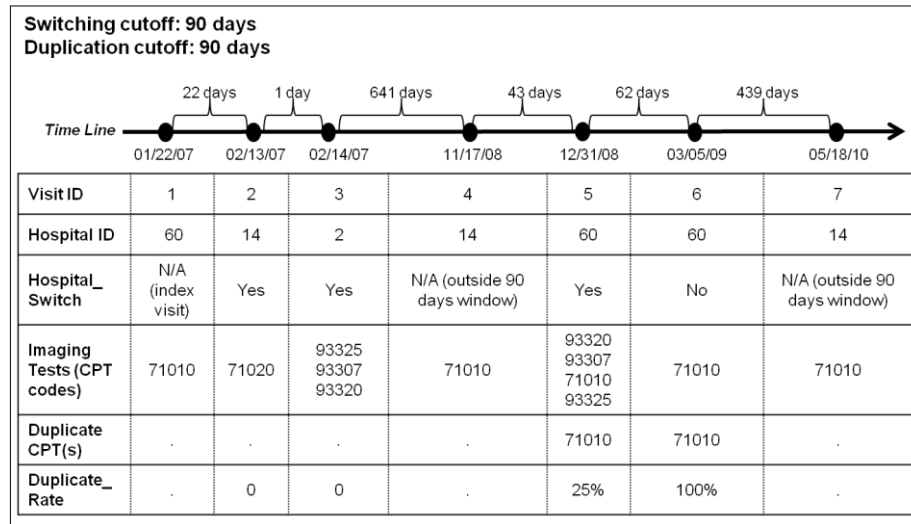
### **Variable Definitions**

Clinical information about the outpatient procedures in our data is reported via the common procedure terminology (CPT) coding scheme. Since our focus is on measuring the duplication rate associated with outpatient imaging procedures, we use only CPT codes related to X-rays, computed tomography (CT scans), magnetic resonance imaging (MRI) and ultrasounds.<sup>1</sup> For each patient visit, we count the number of duplicate tests for each CPT code that appears in the current visit. Each CPT code is matched against the CPT codes recorded across all prior visits that occur within the 90 days prior to the current visit. If the CPT code appears in any of the prior visits (within the prior 90-day period), it is flagged as a duplicate procedure and counted towards the total number of duplicate procedures for the current visit. We then calculate the percentage of duplication as the ratio of the total number of duplicates to total number of all CPT imaging procedures for the current visit. According to Table 1, the visit-level averages for duplication count, procedure count and duplication rate are 0.18, 0.40 and 15.35% respectively.

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<sup>1</sup> This list consists of 417 unique CPT codes in total.

**Figure 2. Illustrative Example of Outpatient Visits and Imaging Tests Performed**



We construct a new variable to index hospital switching event. This variable is termed: “Visit across hospitals (*Hospital\_Switch*)”. For a current repeat visit, if the prior admission was to a different hospital within the last 90 days, then variable *Hospital\_Switch* takes the value of one, and zero otherwise. Based on our data, 9.7% of all patient visits are to different hospitals. We calculate the duplication rate with respect to patients’ switching behavior across hospitals. We observe that there are significant differences in the duplication rates between patients who visit the same hospital versus those who switched hospitals (14.2% vs 25.6%). T-tests of the means of the two distributions show statistically significant differences at  $p < 0.001$ .

In order to capture the extent of intra-hospital sharing of imaging data, we focus on five different measures of imaging distribution through PACS to different units/departments within a hospital. These five (dummy) variables capture the extent of intra-hospital distribution of images through health IT. Our data measures the extent to which radiology images are distributed to the following departments within a hospital: (a) critical care unit (*Image\_Share\_CCU*), (b) emergency room (*Image\_Share\_ER*), (c) intensive care unit (*Image\_Share\_ICU*), (d) operating room (*Image\_Share\_OR*), and (e) over the Worldwide Web (*Image\_Share\_WEB*). For each hospital year, we create a single variable (*Intra\_Image\_Share*) which measures the intensity of imaging distribution across various departments within a hospital. If a hospital has implemented all five imaging distribution systems, we assign a value of one to the combined imaging distribution variable (i.e. *Intra\_Image\_Share*), and zero otherwise. We calculate the percentage of hospitals who have implemented the five types of imaging distribution systems, as well as the percentage of hospitals who answered ‘yes’ to the individual imaging questions. Overall, our combined intra-hospital image distribution variable, *Intra\_Image\_Share*, follows an increasing trend over time as more hospitals started implementing distribution of images to various departments over time (from 26.% in 2006 to 73.5% in 2012).

In order to capture the extent of inter-hospital information sharing, we use the binary variable defined as “image access via the internet from outside locations (*Inter\_Image\_Share*)” as provided by HIMSS Analytics. In other words, hospitals are assigned a value of one for *Inter\_Image\_Share* if they allow Internet-enabled access to radiology images to external providers and hospitals (i.e. beyond the boundaries of the hospital hosting the images). We observe that hospitals have increased their access to images via the Web over time from 69.1% in 2009 to 86.8% in 2012.



Table 1. Descriptive Statistics

Variable	Variable Definition	Dim.	Mean	Std Dev	Min	Max
<b>Admission Characteristics</b>						
<b>Duplicate_Rate</b>	Duplicate Procedures (percentage)	%	15.35	35.1	0	100
<b>Duplicate_Count</b>	Duplicate Procedures (absolute)	Count	0.18	0.44	0	6
<b>Procedure_Count</b>	Number of Procedures	Count	0.4	0.75	0	10
<b>Hospital_Switch</b>	Binary (1 = if Visit Across Hospitals)	0 or 1	0.097	0.29	0	1
<b>Days_Between_Visits</b>	Days Between Consecutive Visits	days	23.13	25.28	0	90
<b>Days_Between_Switches</b>	Days Between Hospital Switching	days	24.58	27.38	0	90
<b>Total_Charge</b>	Total Charges in dollars	\$ 1000s	3.36	14.45	0	210.87
<b>Hospital_Distance</b>	Patient's Distance to Hospital Based on Zipcodes	miles	12.15	27.3	0	545.1
<b>Admission Source</b>						
<b>Referral_Source</b>	Binary(1 = if Admission Source is Physician Referral_Source)	0 or 1	0.91	0.29	0	1
<b>Transfer_Source</b>	Binary(1 = if Admission Source is Transfer)	0 or 1	0	0.05	0	1
<b>Other_Source</b>	Binary(1 = if Admission Source: Other)	0 or 1	0.09	0.28	0	1
<b>Admission Type</b>						
<b>Emergency_Admission</b>	Binary(1 = if Admission Type: Emergency/Urgent)	0 or 1	0.16	0.36	0	1
<b>Elective_Admission</b>	Binary(1 = if Admission Type: Elective)	0 or 1	0.55	0.5	0	1
<b>Other_Admission</b>	Binary(1 = if Admission Type: Other)	0 or 1	0.29	0.45	0	1
<b>Patient Demographics</b>						
<b>Female</b>	Binary (1 = if Patient Gender: Female)	0 or 1	0.52	0.5	0	1
<b>White</b>	Binary (1 = if Patient Race: White)	0 or 1	0.65	0.48	0	1
<b>Age</b>	Patient Age	Cont.	67.75	16.87	1	90
<b>Hospital Characteristics</b>						
<b>CMI</b>	Hospital Case Mix Index	Cont.	1.67	0.26	0.93	3.08
<b>Teaching</b>	Binary(1 = if Hospital: Teaching)	0 or 1	0.4	0.49	0	1
<b>Urban</b>	Binary(1 = if Hospital: Urban)	0 or 1	0.66	0.47	0	1
<b>Bed_Size</b>	Number of Hospital Beds	Cont.	491.38	304.97	0	1029
<b>Insurance Type</b>						
<b>Private</b>	Binary(1 = if Payer: Private)	0 or 1	0.03	0.16	0	1
<b>Medicaid</b>	Binary(1 = if Payer: Medicaid)	0 or 1	0.06	0.24	0	1
<b>MedicareA</b>	Binary(1 = if Payer: Medicare Part A)	0 or 1	0.45	0.5	0	1
<b>MedicareB</b>	Binary(1 = if Payer: Medicare Part B)	0 or 1	0.18	0.39	0	1
<b>Selfpay</b>	Binary(1 = if Payer: Self Pay)	0 or 1	0.07	0.26	0	1
<b>Other_Insurance</b>	Binary(1 = if Payer: Other)	0 or 1	0.2	0.4	0	1

In our model, we also account for the effect of several control variables. These controls include patient insurance type, admission characteristics, patient demographics and hospital specific factors. For each patient visit, the type of health insurance is reported via the payer description information. We classify this information into six different insurance variables: Private, Medicaid, Medicare Part-A, Medicare Part-B, Self-pay and other. Medicare Part-B covers preventive and medically necessary services such as clinical research, ambulance services and durable medical equipment, whereas Medicare Part-A covers hospital care, skilled nursing facility care, nursing home care, hospice and home health services (Medicare 2013). We use Medicare Part-B as our baseline insurance type because we are interested in the duplication of procedures performed in an outpatient setting.

Our data contains three types of patient visits: Emergency/urgent, elective and other. Table 1 indicates that 16% of all visits are classified as emergencies, while 55% of the visits are elective (planned). Table 1 also shows that 91% of visits are accounted by physician referrals. We also track patient-specific demographic information on gender (female or male), age, race (white or non-white), and zip code. We also obtain hospital-specific information from CMS (Centers for Medicare and Medicaid Services). CMS classifies hospitals according to their teaching status and geographic locations (urban, rural), hospital case mix index (CMI), and hospital size (number of beds). Other variables include patient distance to hospital (measured in miles by using the distance between patient home and hospital zip code), and total visit charges.

## Model Specification

We now describe our econometric models along with our estimation methods.

### Hospital Switching

In equation (1), we regress the dependent variable *Duplicate\_Rate* on the hospital switching variable, *Hospital\_Switch*. We control for insurance, patient visit type and admission source variables, patient demographics, hospital specific factors. We also control year-specific fixed effects and hospital fixed effects. Accordingly,

$$\text{Duplicate\_Rate}_{it} = \beta_0 + \beta_1 \text{Hospital\_Switch}_{it} + \text{Controls } \beta_c + \text{Health\_System\_Dummies } \beta_{hs} + \text{Year\_Dummies } \beta_y + \epsilon_{it} \quad (1)$$

where Controls represents a vector of variables consisting of Selfpay, Private, Other\_Insurance, MedicareA, Medicaid, *Emergency\_Admission*, *Other\_Admission*, *Transfer\_Source*, *Other\_Source*, *Female*, *White*, *Age*, *Days\_Between\_Visits*, *CMI*, *Teaching*, *Urban*,  $\log(\text{Bed\_Size})$ .<sup>2</sup> Note that we opt not to control for patient-specific fixed effects for two reasons: (a) we only observe one data point for many patients, and adding individual fixed-effects will disregard these observations; (b) we are also interested in estimating the effects of several time-invariant patient-specific variables such as sex and race. These variables have already absorbed a large portion of heterogeneity that individual fixed-effects aim to capture.

The specification in model (1) may be subject to potential endogeneity as arising from the hospital switching variable. That is, patient- or hospital-specific factors can drive hospital switching decisions of patients. At the same time, a high level of duplicate tests encountered in a prior admission may lead patients to switch hospitals. Since our switching variable is binary, we follow the two step Heckman approach described in Bharadwaj et al. (2007), Mani et al. (2010) and Shaver (1998) to address potential endogeneity concerns. In the first step, we obtain the inverse Mills ratio ( $\lambda$ ) based on a first-stage probit model with an estimation equation  $P(y_2=1 | X_2) = \Phi(X_2\beta_2)$  (Heckman 1976; Heckman 1979). Next, the inverse Mills ratio is introduced in full treatment model (Mani et al. 2010; Shaver 1998), and estimated as:

$$\hat{\lambda} = \lambda(X_2\hat{\beta}_2) = \frac{\phi(X_2\hat{\beta}_2)}{\Phi(X_2\hat{\beta}_2)} \text{ for } y_2 = 1 \text{ (patients who switch hospitals)}$$

$$\hat{\lambda} = \lambda(X_2\hat{\beta}_2) = \frac{-\phi(X_2\hat{\beta}_2)}{(1 - \Phi(X_2\hat{\beta}_2))} \text{ for } y_2 = 0 \text{ ( patients who do not switch)} \quad (2)$$

In the second stage, we obtain  $\hat{\beta}_1$  and  $\hat{\gamma}_1$  from the OLS estimation of  $E(y_1 | X_1, y_2=1) = X_1\beta_1 + \gamma_1\lambda(X_2\hat{\beta}_2)$ . Incorporating the *inverse Mills ratio* ( $\lambda$ ) into the second stage as a control variable accounts for endogeneity (Wooldridge 2010)<sup>3</sup>. Thus, our second stage model is expressed as:

$$\text{Duplicate\_Rate}_{it} = \beta_0 + \beta_1 \text{Hospital\_Switch}_{it} + \gamma_1 \lambda(X_2\hat{\beta}_2) + \text{Controls } \beta_c + \text{Health\_System\_Dummies } \beta_{hs} + \text{Year\_Dummies } \beta_y + \epsilon_{it} \quad (3)$$

We note that the inverse Mills ratios are prone to collinearity, leading to incorrect standard errors in the second stage (Dow and Norton 2003; Leung and Yu 1996). To overcome this problem, we impose an exclusion restriction in the second stage equation in order to increase the variation in  $\lambda$ s. This can be achieved by adding at least one exogenous explanatory variable to the selection model (Leung and Yu 1996; Little and Rubin 1987). We introduce three exogenous variables that are available in our data.

<sup>2</sup> Since patient insurance, visit type and admission source are categorical variables, their values are transformed into dummy variables.

<sup>3</sup>  $\phi(\cdot)$  and  $\Phi(\cdot)$  denote the probability density and cumulative distribution functions of a standard normal distribution, respectively.  $X_1, X_2$  are observed vectors of explanatory variables. In addition, whenever  $y_1$  is observed,  $y_2$  takes the value of 1, and 0 otherwise.

These variables include the charges associated with the patient's previous visit ( $\log(\text{Total\_Charge}_{t-1})$ ), distance from patient home to hospital in the previous visit ( $\log(\text{Hospital\_Distance}_{t-1})$ ), and number of providers within a 5-mile radius of patient's zipcode in the previous visit ( $\text{Provider\_Count\_5miles}_{t-1}$ ). After the first and second stage estimation, we correct the standard errors in the second stage with respect to the asymptotic variance-covariance matrix (Catsiapis and Robinson 1982). We report the OLS estimation results for Model (3), using the two-step Heckman correction approach, in Table 2.

### Health Information Sharing

The second part of our econometric estimation examines the impact of health information sharing technologies on the extent of duplicate testing. To examine if implementation of intra or inter-hospital information sharing systems has a bearing on hospitals' duplication rate, we deploy a difference-in-difference (DID) specification which is used in the literature extensively within natural and *quasi-natural experimental* settings (Kumar and Telang 2012; Meyer 1995). DID compares the *Treatment* group against the *Control* group, where the treatment effect is measured against a control group in the pre- and post-treatment periods. This setting allows us to handle potential confounding effects of unobserved factors and time-invariant features from treatment effects (Kumar and Telang 2012; Meyer 1995). We focus on two groups of hospitals with respect to the presence of imaging distribution systems. The first group of hospitals (*Control* group) did not implement intra-hospital (inter-hospital) imaging distribution systems between 2006 and 2012, while the second group of hospitals (*Treatment* group) started using imaging distribution services at some point between 2006 and 2012<sup>4</sup>. Hence, the *Treatment* binary variable takes the value of one if the observation belongs to a hospital in the Treatment group. In order to compare the Treatment to the Control group, during pre- and post-treatment periods, a second binary variable has to be assigned to each observation. This binary variable, labeled as *Post*, takes a value of one if we observe an instance after the treatment is applied.

In general, quasi-experiments require two observations per subject, one which receives treatment and the other that does not. The timing of the treatment is fixed and typically the same for all subjects that receive treatment. To construct the binary *Post* variable for those instances in the control group, the reference time point is assumed to be the time when the treatment was provided to the members of the treatment group. However, in our sample, hospitals in the treatment group may implement HIT implementation at different years. To tackle this, for a control group hospital we identify the most similar hospital among the treatment group hospitals and designate the implementation time of this 'treated' hospital as the corresponding time for this 'control' hospital. We use a propensity score matching approach to match hospitals from the control group to the treatment group (Rosenbaum and Rubin 1985). We followed a one-to-many matching strategy with respect to the hospital characteristic variables *CMI*, *Bed\_Size*, *Teaching* and *Urban* and matched hospitals in the treatment group to the hospitals in the control group which yield the closest propensity score. Accordingly, we calculate the *PostIntra<sub>ht</sub>* (*PostInter<sub>ht</sub>*) variable (one or zero).

Our quasi-natural experiment involves comparison of the treatment group to the control group. Hence, we incorporate control variables into DID specification and estimate the following models for intra and inter-hospital sharing, respectively:

$$\text{Duplicate\_Rate}_{iht} = \alpha_0 + \alpha_1 \text{TreatmentIntra}_{ht} + \alpha_2 \text{PostIntra}_{ht} + \alpha_3 \text{TreatmentIntra} * \text{PostIntra}_{ht} + \text{Controls } \alpha_c + \vartheta_{iht} \quad (4)$$

$$\text{Duplicate\_Rate}_{iht} = \theta_0 + \theta_1 \text{TreatmentInter}_{ht} + \theta_2 \text{PostInter}_{ht} + \theta_3 \text{TreatmentInter} * \text{PostInter}_{ht} + \text{Controls } \theta_c + \tau_{iht} \quad (5)$$

where *i* denotes a patient, *h* denotes a hospital and *t* denotes admission time index. *TreatmentIntra<sub>ht</sub>* (*TreatmentInter<sub>ht</sub>*) equals one if a patient *i* visits (at time *t*) hospital *h* where intra-hospital (inter-

<sup>4</sup> There were very few hospitals which always had intra-hospital (inter-hospital) information sharing systems throughout the years between 2006 and 2012. We excluded these few hospitals and thus our experimental setup focuses on examining two groups of hospitals: One control group without having any treatment factor and one treatment group having HIT implemented at some point in time.

hospital) information sharing has been implemented.  $PostIntra_{ht}$  ( $PostInter_{ht}$ ) equals one if patient  $i$ 's visit at time  $t$  is in the post-treatment time period of hospital  $h$  that has implemented intra-hospital (inter-hospital) information sharing technologies. The coefficient estimate of  $\alpha_3$  ( $\theta_3$ ) for  $TreatmentIntra_{ht} * PostIntra_{ht}$  ( $TreatmentInter_{ht} * PostInter_{ht}$ ) is of interest since it captures the change in the duplication rate for hospitals which implement intra-hospital (inter-hospital) information sharing technologies relative to hospitals which do not. We also account for insurance type, admission source, visit type, patient age, gender, race and hospital characteristics in our DID estimation approach.

### **Robustness Checks**

We have further addressed several econometric concerns to ensure robust estimation of our models. First, since the patients and hospitals in our sample are quite diverse in terms of patient and hospital characteristics, we control for several sources of heterogeneity by including patient age, race, gender and also hospital bed size, teaching status, case mix index, and location (urban/suburban). Second, we check for the presence of multi-collinearity among our explanatory variables by calculating the correlation matrix and the Variance Inflation Factors (VIFs). Accordingly, the highest correlation is 0.78, which is between *CMI* and *Teaching* with a VIF value of 2.96 and 4.45 respectively. Since these VIF values are less than 10 we conclude that we don't have a severe multi-collinearity problem in our data.

Next, we examine an alternative approach to address the endogeneity concerns of our hospital switching variable, *Hospital\_Switch*. We follow a two-step estimation procedure using instrumental variables (IV). For possible IV candidates, we use the variables that constitute the exclusion restriction in Model (3) using  $\log(Total\_Charge_{t-1})$ ,  $\log(Hospital\_Distance_{t-1})$ , and  $Provider\_Count\_5miles_{t-1}$ . Our results are qualitatively consistent with those reported earlier in Table 2, and support our hypothesis H1 with respect to the relationship between patient switching behavior and duplicate tests.

Lastly, one may argue that the duplication rate on a patient's prior visit may impact the switching intention of patients (on the next visit) and that the incidence of prior switching may affect duplication testing. That is, it may form a cross-lag panel system. We deploy a Panel Vector Autoregression (PVAR) estimation method and observe that  $Duplicate\_Rate_{t-1}$  is not significant in explaining the variations in  $Hospital\_Switch_t$ <sup>5</sup>. In other words, we did not find significant evidence for cases where patients might switch hospitals because of high duplication rates on their prior visits.

## **Results**

First, we present our estimation results for Model (3) with the two-step Heckman approach. The OLS estimation results that incorporate the inverse Mills ratio are shown in the second column of Table 2, whereas the Tobit results with robust standard errors are shown in the third column of Table 2.

### **Hospital Switching and Duplication Rates**

For hospital switching, our results show a positive impact of hospital switching on the rate of duplicate tests. We find that the coefficient of *Hospital\_Switch* ( $\beta_1=34.86$ ,  $p<0.001$ ) in Table 2 is statistically significant, supporting hypothesis H1. Accordingly, when a patient switches to a different hospital, her duplication rate increases by 34.86% (holding all other variables constant at their mean values), compared to the case if she had visited the same hospital. We also report the Tobit results with robust standard errors in column (3) along with the marginal effects at their mean values in column (5). Accordingly, the coefficient of *Hospital\_Switch* stays positive and statistically significant ( $\beta_1=718.3$ ,  $p<0.001$ ) supporting Hypothesis 1. *Hospital\_Switch*'s marginal effect in Tobit estimation suggests an increase of 20.38% in duplication rate holding all other variables at their mean values.

Our results also indicate a significant and positive coefficient for *Emergency\_Admission*. This suggests that emergency visits exhibit an increase of 34% in the duplication rate, relative to elective visits. However, transfer patients do not show any significant difference in duplication rate compared to physician referrals. Among patient demographics variables, Female shows a negative and significant

<sup>5</sup> Due to manuscript length limitations, we have not provided the results of our robustness tests, including our two-step estimation as well as PVAR estimation results. Interested readers can contact authors to obtain related information.

coefficient, suggesting that females are less likely to undergo duplicate imaging testing. As patients grow older they tend to undergo higher duplicate imaging testing. We also observe negative relationships between CMI, log(Beds) and duplicate imaging test rate, while there is a statistically significant positive association between Teaching and duplication rate. These results suggest a decrease in the duplication rate for larger hospitals and higher case mix index values, while teaching hospitals exhibit a lower rate of duplicate imaging tests.

**Table 2. Two-step Heckman Estimation Results**

	<b>Second Stage: OLS</b> <b>DV: Duplicate_Rate</b>		<b>Second Stage: Tobit</b> <b>DV: Duplicate_Rate</b>		
	<b>(1)</b> <b>Est.</b>	<b>(2)</b> <b>Std. Err.<sup>1</sup></b>	<b>(3)</b> <b>Est.</b>	<b>(4)</b> <b>Std. Err.<sup>2</sup></b>	<b>(5)</b> <b>MEM<sup>3</sup></b>
<b>Intercept</b>	24.075***	(8.4)	-680.7**	(264.6)	[-]
<b>Hospital_Switch</b>	34.86***	(4.857)	718.3***	(176.4)	[20.38]
<b>InvMills_Hospital_Switch</b>	-20.124***	(2.676)	-414.4***	(102.4)	[-11.76]
<b>Selfpay</b>	-2.766	(1.771)	-73.51	(53.32)	[-2.086]
<b>Private</b>	-1.112	(2.718)	-10.34	(88.37)	[-0.293]
<b>Other_Insurance</b>	3.371**	(1.531)	119.6***	(46.18)	[3.395]
<b>MedicareA</b>	-5.318***	(1.545)	-153.3***	(48.80)	[-4.351]
<b>Medicaid</b>	9.345***	(2.039)	246.2***	(61.86)	[6.986]
<b>Emergency_Admission</b>	34.792***	(1.332)	903.3***	(67.64)	[25.63]
<b>Other_Admission</b>	7.459***	(1.412)	301.3***	(46.24)	[8.549]
<b>Transfer_Source</b>	-5.982	(6.69)	-119.4	(193.2)	[-3.387]
<b>Other_Source</b>	-11.049***	(1.97)	-280.5***	(66.14)	[-7.961]
<b>Female</b>	-1.85***	(0.708)	-76.79***	(23.58)	[-2.179]
<b>White</b>	0.173	(0.861)	15.53	(27.82)	[0.441]
<b>Age</b>	0.062**	(0.031)	1.943*	(1.021)	[0.0551]
<b>CMI</b>	-18.233***	(3.444)	0.688	(0.469)	[0.0195]
<b>Bed_Size (log)</b>	-2.71***	(0.858)	-336.0***	(109.7)	[-9.536]
<b>Teaching</b>	13.425***	(2.115)	-75.69***	(27.43)	[-2.148]
<b>Urban</b>	-3.253	(3.895)	270.8***	(69.28)	[7.684]
<b>Days_Between_Visits</b>	0.027*	(0.015)	-46.41	(102.4)	[-1.317]
<b>Sigma</b>	-	-	653.5***	(39.59)	[-]
<b>R<sup>2</sup> (Psuedo for Tobit)</b>	0.2065		0.148		
<b>LogLikelihood</b>	-45712.0		-5314.22		
<b>N</b>	9403		9403		

First step probit results are provided in the appendix in which Hospital\_Switch is regressed on log(Hospital\_Distance<sub>t-1</sub>), Provider\_Count\_5miles<sub>t-1</sub>, log(Total\_Charge<sub>t-1</sub>) and all other exogenous variables. Standard errors in parentheses. Time and system fixed effects are included.

<sup>1</sup>Asymptotic standard errors are reported for 2nd stage OLS estimation

<sup>2</sup>Robust standard errors are reported for 2nd stage Tobit estimation

<sup>3</sup>Marginal effects (dy/dx) at the means of variables for Tobit estimation are reported inside the brackets

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

### **Health Information Sharing and Duplication Rates: Instrumental Variables Approach**

Though our quasi-experimental approach using propensity score matching is a well-accepted methodology to purge out confounding effects, one may still argue that our *TreatmentIntra* and *TreatmentInter* variables might be subject to potential endogeneity. For example, hospitals with higher duplication rates may be more likely to implement intra- and inter-hospital information sharing technologies. To address this endogeneity problem, we applied an instrumental variable estimation approach. Valid IV candidates should explain the variation in our endogenous variables (i.e., *TreatmentIntra* and *TreatmentInter*), while they should not be systematically determined by *Duplicate\_Rate* (Kumar and Telang 2012). One possible IV is the age of a hospital in terms of the number of years that it has been in operation (*Age\_Hosp*). We conjecture that relatively new hospitals would be more likely to implement new types of health information sharing technologies and older hospitals are usually slow adopters of such systems due to the difficulty of replacing legacy systems. At the same time,

the age of a hospital may not be systematically co-determined with its imaging duplication rate. The Hausman test rejects the non-existence of endogeneity in the intra-hospital information sharing ( $p = 0.033$ ) and the inter-hospital information sharing models ( $p = 0.085$ ).

Therefore, we apply two-stage least squares (2SLS) estimation to Models (4) and (5). To test the validity of  $Age\_Hosp$  as an instrument for  $TreatmentIntra$ , we first check the correlation between these two variables and report that it is significant at 0.01 level, i.e.,  $Corr(TreatmentIntra, Age\_Hosp) = 0.42$  and  $Corr(TreatmentInter, Age\_Hosp) = 0.48$ , and the first-stage regression is also significant. Next, we regress the residuals on  $Age\_Hosp$ ,  $Age\_Hosp^2$  and  $Age\_Hosp^3$ , in which the residuals are obtained from regressing  $Duplicate\_Rate$  on the IVs and all other exogenous variables. The resulting coefficients of  $Age\_Hosp$ ,  $Age\_Hosp^2$  and  $Age\_Hosp^3$  are insignificant with p values of 0.49, 0.51 and 0.61, respectively, which suggests that endogeneity of these IVs is not a concern in our models

One possible estimation approach is to use the estimated  $TreatmentIntra^{\wedge}$  and  $TreatmentInter^{\wedge}$  values from the first stage, which is referred as the “non-interacted 2SLS” or the “hat” approach (Gopal and Koka 2012, Harrison 2008). Although this strategy might work and provide unbiased results for a linear case, it might not give consistent estimates when one of the endogenous interaction terms is nonlinear (Wooldridge 2010). Another suggested approach to estimate the endogenous interaction effect is to treat the interaction term itself as a new endogenous variable (Wooldridge 2010, Gopal and Koka 2012). Hence, we incorporate another first stage equation into our model for the interaction term along with the separate equation for the Treatment variable. Our first stage equations for the intra-hospital information sharing model are given as (same approach is followed for the inter-hospital information sharing):

$$TreatmentIntra_{ht} = g(Age\_Hosp_{ht}, Age\_Hosp_{ht}^2, Exogenous\ Vars) + e_{1, iht} \quad (6)$$

$$TreatmentIntra * PostIntra_{ht} = f(Age\_Hosp_{ht}, Age\_Hosp_{ht}^2, Age\_Hosp_{ht}^3, Exogenous\ Vars) + e_{2, iht} \quad (7)$$

where  $f(.)$  and  $g(.)$  are nonlinear functions, i.e., probit, and  $Age\_Hosp^3$  is used as an exclusion restriction in the first equation above. Next, we estimate the first and second stage equations using non-linear 2SLS and report the second stage results in Table 3. In this non-linear 2SLS model, we control for insurance type (*Selfpay, Private, Other\_Insurance, MedicareA, Medicaid*), admission source (*Transfer\_source, Other\_source*), admission type (*Emergency\_Admission, Other\_Admission*), patient age (*Age*), gender (*Female*), race (*White*), days between consecutive visits (*Days\_between\_visits*) and other hospital characteristics (*CMI, Bed\_size, Teaching, Urban*). We also include these control variables as instrument variables in the first stage estimation while we use  $Age\_Hosp$ ,  $Age\_Hosp^2$  and  $Age\_Hosp^3$  as exclusion restrictions.

**Table 3. Non-linear Two-stage Least Squares Results of Difference-in-Difference Estimation**

Parameters	Intra-hospital Info. Sharing		Inter-hospital Info. Sharing	
	Est.	Std. Err.	Est.	Std. Err.
$\widehat{Treatment}$	30.43***	(9.19)	-2.36	(4.77)
$\widehat{Post}$	12.39	(7.84)	30.24***	(10.79)
$\widehat{Treatment} * \widehat{Post}$	-12.47	(8.69)	-58.24***	(20.32)
<i>Model</i>	$R^2 = 0.255$ $N = 8508$		$R^2 = 0.174$ $N = 1258$	

$Age\_Hosp$ ,  $Age\_Hosp^2$  are used as instruments for endogenous Treatment  
 $Age\_Hosp$ ,  $Age\_Hosp^2$ ,  $Age\_Hosp^3$  are used as instruments for endogenous Treatment \* Post  
 Second stage estimates are reported. One sided p-values, \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$   
 Control variables included are insurance type, admission source, admission type, patient age, gender, race, and hospital characteristics

The nonlinear 2SLS analysis results suggest that intra-hospital information sharing does not have a significant impact on reduction in duplication tests with the coefficient of the interaction term,  $Treatment * Post$ , being statistically insignificant. Hence, our DID results do not support hypothesis H2a. ( $\alpha_3 = -12.47$ ). However, we observe that the interaction term associated with H2b is negative and significant ( $\theta_3 = -58.24$ ,  $p < 0.01$ ). This result suggests that hospitals with inter-hospital image sharing technologies

exhibit a lower duplication (after implementation) rate compared hospitals without these technologies, lending further support to hypothesis H2b.

Table 4 provides a summary of the results of our hypothesis tests including changes in the duplicate test rate based on changes in our model variables.

**Table 4. Summary of Hypotheses Tests**

<b>HYPOTHESES</b>	<b>Result</b>	<b>Impact on Duplication Rate</b>
<b>H1:</b> (+ assoc.) Hospital Switching → Duplicate Testing	<i>Supported</i>	+42.93%
<b>H2A:</b> (- assoc.) Intra-hospital Info. Sharing → Duplicate Testing	Not supported	.
<b>H2B:</b> (- assoc.) Inter-hospital Info. Sharing → Duplicate Testing	<i>Supported</i>	-58.24%

## Conclusion

We investigate the role of hospital switching and health information sharing technologies in duplicate testing. Our results show that patients who switch hospitals are more likely to undergo higher duplicate tests than patients who do not (42.93% higher). We also report a differential impact of hospital information sharing on duplicate imaging procedures in terms of implementing intra- and inter-hospital image sharing technologies. Our results suggest that inter-hospital image sharing technologies (i.e., image access ability from external locations) is associated with a decrease in the overall duplicate imaging tests conducted on patients (58.24% lower). As a result, providers who can access radiology images across different hospitals exhibit a lower rate of duplicate imaging procedures. However, intra-hospital image sharing (i.e., image distribution across departments within a hospital) is not significantly associated with a reduction in the overall rate of duplicate imaging. This result can be attributed to the possibility that EMR applications may already serve as a medium to share patient across various departments within a hospital. Providers within the same hospital may access relevant patient information (such as radiology imaging reports) through their EMR systems which may serve to intrinsically reduce the rate of duplicate imaging procedures.

Our results suggest that there are no significant differences in duplicate testing rates between self-pay and Medicare patients, as well as between private insurance and Medicare patients. Our results indicate that likelihood of duplicate tests is much higher for emergency admissions relative to elective admissions. One possible explanation could be the critical condition of patients visiting hospital as an emergency admission. Time limitation or unavailability of information may increase the possibility of performing duplicate imaging tests. This result also supports the importance of implementing health information sharing technologies across disparate health providers.

## Health Policy Implications

To the best of our knowledge, our study represents the first attempt to empirically explore the antecedents of duplicate testing using a large panel of patient data tracked across a relatively long period of time. In this research, we not only account for simultaneity between hospital switching and duplicate testing, but also include non-clinical data, including hospital and payer characteristics, as well as hospital admission and health status of patients. Our results indicate that unavailability of information caused by hospital switching behavior of patients can increase the extent of duplication (or resource wastage) in the U.S. healthcare system. Furthermore, our study reveals that implementation of inter-hospital image sharing technologies reduces the overall rate of duplicate testing. We argue that if hospitals were able to communicate through a common, federated IT infrastructure to share patient medical history, especially when patients switch across providers, it could lead to a significant reduction in the extent of redundant testing. Health information technologies (HITs) can help overcome the technological barriers of information sharing and enable information flow among previously disparate entities. Electronic health records (EHRs) are seen as the hub of all HITs, enabling the interoperability of multiple entities via the delivery and sharing of patient health information to physician offices and hospitals (Mishra et al. 2012). It is estimated that EHRs can save US \$7.9 billion annually by reducing the need for redundant laboratory

and radiology tests (Hillestad et al. 2005). One another solution to cutting high healthcare costs (due to redundant testing) is the widespread implementation of health information exchanges (HIEs). Indeed, researchers have suggested that HIEs can reduce a significant portion of waste and duplication in the U.S. healthcare system through better information transparency and increasing information availability, (LaBorde et al. 2011). Improvements can be observed in the form of reduced duplicate testing, medical errors, inpatient hospitalizations and length-of-stay (Frisse and Holmes 2007; Hillestad et al. 2005; LaBorde et al. 2011).

For our sample data, we estimate that the cost of duplicate imaging tests for CHF patients amounts to \$1,120,914 in the North Texas region, which amounts to an average, additional cost saving of \$300 for every CHF patient treated. This is a very conservative estimate of the overall cost savings due to health information sharing, since we only focus on a small sliver of CHF patient visits to outpatient clinics and imposed a time window of 90 days to define the incidence of duplication and hospital switching. According to Walker et al. (2005), net savings from HIE implementation can reach up to \$77.8 billion annually, if a fully standardized, nationally interoperable system is established between providers and other types of organizations, such as laboratories, radiology centers, pharmacies, payers and public health departments. Walker et al. (2005) suggest that savings from avoided radiology tests and improved efficiencies is projected to be between \$8.34 billion and \$26.2 billion depending on the level of HIE implementation. Thus, our research complements the aforementioned benefits of HIEs by empirically showing that lack of information sharing and the resulting unavailability of information can lead to waste in the form of high levels of duplicate testing. Our research also addresses the call from Dixon et al. (2010) who highlight the need for published studies on evaluating the business case for HIEs.

### ***Limitations and Future Work***

Our study does have a few limitations. First, we do not have any procedural information (or access to physician notes) that can identify whether a duplicate procedure is truly redundant or an essential one. However, we contend that constraining the life span of imaging procedures to 90 days can serve as a useful baseline for classifying procedures as redundant (duplicate) or not, based on our communications with radiologists. Second, our results only reflect the duplication rates of imaging procedures for outpatients with CHF as their principal diagnosis. For a generic view of overall duplicate tests, other chronic illnesses should also be taken into account, such as pneumonia, asthma, and COPD, many of which are comorbidities for CHF patients. Third, the decision maker for ordering tests is primarily the physician, and our approach does not take into account physician-specific attributes such as the physician training, workload, or experience. However, we believe that our consideration of hospital size and case mix index can proxy for some of the variations that can explain these physician-specific attributes.

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