Hospital Switching and Duplicate Tests: Can Health Information Exchange Reduce Redundant Testing?

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ABSTRACT

Recent healthcare reform has pointed out the excessive amount of redundancies and waste in US healthcare spending, in which duplicate testing is one contributing factor. In this research, we investigate the sources of waste in terms of duplication of radiology imaging tests when information sharing across providers are fragmented and patients may switch from one hospital to another throughout their treatment processes. We hypothesize that switching hospitals will result in increased duplicate procedures due to lack of visibility into patient medical history. In our econometric approach, we utilize a comprehensive dataset of 39,600+ Congestive Heart Failure patient visits across outpatient clinics of 68 hospitals in North Texas from 2005 to 2012. We simultaneously estimate the hospital switching and duplicate testing models using two-step maximum likelihood estimation. Our results suggest that hospital switching is significantly associated with greater levels of test duplication. We also show that the rate of duplication of patients with private insurance is higher than that of Medicare patients. Our results support the need to implement health information exchanges to share patient medical data across hospitals as one avenue to reduce the incidence of test duplication and the overall cost of healthcare.

Keywords: Duplicate testing, hospital switching, health information sharing, health information exchange.

INTRODUCTION

Healthcare services in the U.S. cost twice as much as the average costs incurred by Organization for Economic Cooperation and Development (OECD) countries. Annual healthcare expenses in the U.S. amounts to $2.2 trillion, or 17.6% of GDP in 2011 (OECD 2012), and is projected to grow to reach $4.4 trillion, or 20.3% of GDP by 2018 (Sisko et al. 2009). At the same time, several studies have shown that the U.S lags behind other developed nations in terms of quality of care delivery and patient outcomes. For example, the rate of hospital admission for Asthma patients was 120.6 (per 100,000 population) while the OECD average was 51.8 (OECD 2012).

It is estimated that 40-50% of U.S. healthcare spending is wasted, of which overuse of resources is a significant contributor (Bentley et al. 2008; Hillestad et al. 2005). Waste due to inefficient use of resources can arise in situations like excessive antibiotic use for viral infections, avoidable hospitalizations for nursing home patients, unnecessary admission of chest pain patients, and overuse of screening and imaging procedures (Bentley et al. 2008).

Our primary objective in this research is to develop a model to better understand the drivers of unnecessary health expenditures in US. Specifically, we focus on inefficiencies as a result of duplicate tests (e.g. duplicate imaging, tests, and procedures) performed on congestive heart failure (CHF) patients who are treated at outpatient clinics.

Recent evidence shows that the prevalence of unnecessary, duplicate imaging tests can explain a significant portion of waste in the US healthcare system (OECD 2012). Table 1 shows that the U.S. ranks near the top in terms of MRI and CT equipment, and the amount of procedures performed per patient is double that of OCED average. Farrell et al. (2008) reports that the average reimbursement per CT scan is $616 in the US, whereas it costs only $146 in Germany. Likewise, the average reimbursement in the US is $1,057 per MRI exam, while it only costs $216 in Germany. A recent article by Steven Brill enumerated several contributing factors to the high cost of healthcare in U.S. (Brill 2013). Brill (2013) attributed *information asymmetry* as one of the main factors that leads to significantly higher costs in the US. Patients are buyers with little knowledge or ability to negotiate in a seller's market where providers unilaterally set the price for their services. For example, non-Medicare patient is charged $283 for a chest x-ray (CPT code 71020), while Medicare patients are charged only $20.44 for the same procedure.

A likely cause of the excessive use of imaging tests is the lack of information sharing among disparate entities. If patient medical data is not shared between different providers and healthcare systems, it may lead to redundant medical procedures and with a corresponding increase in medical expenditures (Bates et al. 1998; LaBorde et al. 2011). Kripalani et al. (2007) found that the percentage of direct communication between hospital physicians and primary care providers was only 3% - 20%. Furthermore, at discharge, 33%-63% of discharge summaries lack important information about diagnostic test results or other relevant information that may potentially cause readmission, dissatisfaction, delay in treatment, or patient safety issues (Kripalani et al. 2007; Solis 1982).

Because of personal preferences or medical reasons, patients may switch providers and visit different hospitals during an episode of a treatment (LaBorde et al. 2011). Yet, these providers and/or hospitals generally do not have a common IT infrastructure to share patients' medical information. In situations where providers cannot easily access patient medical history, often patients or their families are asked to provide the relevant medical information prior to hospitalization (Kripalani et al. 2007). This may include patients' prior medical history, diagnosis, allergies, and medication history. However, patients may not be able to accurately remember crucial information related to previous hospital visits, such as diagnoses, medications, and procedures, due to a variety of factors including age, patient condition, and recall bias (Johnson et al. 2011). The resulting information asymmetry, when patients switch across different hospitals, can induce providers to repeat tests and procedures in order to diagnose the patient. Hence, our research focuses on studying the impact of patient switching behavior (across hospital visits) on the incidence of duplicate testing.

High rates of redundant tests can be explained through the term 'defensive medicine', which is the possibility of physicians' trying to reduce their likelihood of future lawsuits if such tests lead to detection of significant findings (Currie and MacLeod 2013). However, it is also found that defensive medicine may not be a significant driver of the overuse of resources; doctors may have other motives besides the fear of lawsuits (Baicker et al. 2007; Currie and MacLeod 2008). It is suggested that another likely cause of redundant testing would be the profit motives of providers (Gruber et al. 1999; Gruber and Owings 1994). As Brill (2013) lay down in his article, there are huge margin gaps for the prices charged to Medicare and non-Medicare patients. Thus in order to shed light on to the drivers of the inefficiencies in U.S. healthcare system, we also study the economic incentives behind the overuse of resources, i.e., duplicate testing.

We empirically test our model using a comprehensive dataset of more than 39600+ CHF patient visits to outpatient clinics across 68 hospitals in North Texas. This dataset records information for each patient's visit tracked over a relatively long period from 2005 to 2012. Our results suggest that hospital switching and the amount of duplicate testing among outpatients are positively associated. In addition, we observe that patients with private insurance are more likely to incur higher levels of duplicate tests compared to Medicare patients. We also find that transfer patients are also more likely to incur higher duplicate tests compared to patients who are admitted through physician referrals. Our study makes two salient contributions. First, we conceptualize and test a model that explains patients' switching behavior, when they migrate across hospitals. Second, our results provide a foundation to estimate the avoidable costs that can be attributed to duplication of outpatient tests that are incurred 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 duplicate tests and procedures, our study provides a glimpse at the possibilities for reduction in redundant costs associated with imaging tests on outpatients who are diagnosed with CHF, a chronic disease that is typically associated with other comorbidities (such as diabetes, renal disease, and hypertension) and requires regular treatment and physician office visits. Additionally, we obtain hospital level information about imaging distribution to various locations from HIMSS Analytics and provide descriptive statistics on how the rate of duplicate testing changes with respect to the implementation of imaging distribution services.

The rest of this paper is organized as follows. We develop a theoretical foundation and propose our conceptual framework along with related hypotheses in Section 2. Section 3 describes the data and estimation method, followed by a discussion of the results in Section 4. We conclude with a summary of the key findings and implications for research and practice.

THEORY FOUNDATION and HYPOTHESES

We present our conceptual research model in Figure 1. The incidence of duplicate testing, which is a major source of operational waste in healthcare, is the primary dependent variable in our research model. We theorize the factors, which may explain variations in our dependent variable, can be grouped under three categories: hospital switching, economic incentives, and patient health/admission status. We propose several hypotheses related to hospital switching behavior and duplicate testing.

Factors Affecting Hospital Switching

Switching occurs when patients are readmitted (for the same primary diagnosis) to a hospital that is different from the hospital of their previous visit. Patients' switching behavior across hospitals bears similarity with customers' who switch across brands over time. The marketing literature suggests that customers differ along three dimensions: loyalty, satisfaction, and involvement or engagement (Ganesh et al. 2000). Customer satisfaction is central to firm profitability and customer relationship management (Ganesh et al. 2000; Zeithaml et al. 1996). Satisfied customers are more likely to repeat purchases and become loyal followers of the brand (Zeithaml et al. 1996). Interactions with people, locational convenience, ease of transaction and cost are found to significantly impact customer satisfaction (Ganesh et al. (2000).

Porell and Adams (1995) model hospital choice as a statistical model that explains the event of discrete admissions (to hospitals) as a function of patient and/or hospital characteristics.[1] Prior research argues that patient sensitivity to rising healthcare costs is one of the factors that is associated with patient switching behavior (Robinson 2003). In the U.S., health insurance premium increases have far outpaced the inflation rate during the last two decades. At the same time, hospitals have raised their billable charges to compensate for reduced margins resulting from new managed care plans (Robinson 2003). Medicare patients have not been exempted either, as they have witnessed higher copays and deductibles for outpatient services. Among other types of patients, self-pay patients and those with private insurance were affected greatly (Medicare 2013a; Reinhardt 2006). In a healthcare context, Buchmueller and Feldstein (1996) found that employees responded strongly to a change in premium contributions and switch to lower-cost plans when insurance premiums increase. Considering all these instances, we hypothesize that higher cost of patient care is associated with a greater likelihood of patient switching behavior across providers.

H1a. *The cost of patient care is positively associated with an increase in the likelihood of hospital switching among patients.*

In a healthcare context, inconvenience may be associated with a healthcare provider's location, hours of operation, waiting time for service or waiting time to get an appointment (Keaveney 1995). Distance from the provider and location (urban/rural) are found to be important indicators of patient switching behavior (Buczko 1992; Porell and Adams 1995; Tai et al. 2004). Even in metropolitan areas where there were numerous (hospital) alternatives within reasonable distance, patients demonstrated a strong preference towards the closest hospital to their homes (Morrill et al. 1970; Porell and Adams 1995; Shannon et al. 1973). Hence, we argue that greater distance from a hospital will cause a reduction in the overall involvement of patients in choosing that hospital since travel time may be associated with greater inconvenience. We hypothesize that:

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[1] Porell and Adams (1995) conceptualize a hospital choice model using three sets of factors, which include (a) medical needs including measures related to perceived health status, limitation of activity, and presence of a medical condition, (b) predisposition including age, education or race affecting a patient's likelihood to seek care, and (c) enabling factors including income, insurance coverage, and access to physicians and care sites (Andersen 1968).

H1b. *Greater distance between patients and the provider (hospital) will increase the likelihood of hospital switching*.

Economic Incentives

We consider the economic situation of providers to analyze the impact of economic incentives on duplicate tests. The type of insurance and coverage play a key role in determining the procedures and tests that are covered. The Commonwealth Fund Biennial Health Insurance Survey reported that 19% of uninsured adults are given a duplicate test that is twice the rate of duplication of insured adults (Collins 2006). As shown in Table 1, the U.S. not only has a higher imaging equipment utilization, but also patients undergo a higher rate of imaging procedures (Farrell et al. 2008; OECD 2012). Since Medicare patients are less profitable than other non-governmental insured patients, hospitals are more inclined to over-utilize imaging equipment for non-Medicare or uninsured patients. In 2004, for every $100 in Medicare-allowable costs, the average hospital charge for self-pay patients was $307 (Anderson 2007). [2] Performing C-section over natural birth is found to be over utilized for low risk patients because C-section takes less time and exceeds the fee for performing vaginal deliveries (Currie and MacLeod 2013). Hence, considering the economic incentives from the providers' perspective, we argue that uninsured or self-pay patients will encounter higher rate of duplicate tests compared to Medicare patients. In a similar manner, we expect that patients with private insurance will exhibit a higher rate of duplicate tests compared to Medicare patients.

H2a. *The rate of duplicate testing for self-pay patients is higher than that of Medicare patients.*

H2b. *The rate of test duplication for patients with private insurance will be higher than that of Medicare patients.*

Patient Health and Admission Status

Patient admission type, whether emergency or elective, reflects the severity of illness and the complexity of treatment processes required. Major clinical and demographic differences exist between elective (planned) and emergency admissions (Weissman and Klein 2008). Since elective admissions are mostly pre-planned, the required information for treatment might already be available to the physician at the time of admission through prior exchange with the referring physician. This information availability can preempt the need for ordering unnecessary tests as well as reduce the incidence of medical errors. On the other hand, emergency patients tend to have more severe illnesses, undergo various and shorter operations, require longer hospital stays, and also have higher

[2] In most cases, hospitals justify the high charges imposed on self-pay patients by referring to their charity-care policies that reduce or eliminate obligations if the patient belongs to a low income group (Anderson 2007)

mortality rates (Weissman and Klein 2008). In addition, some researches show that emergency surgery patients consume greater financial resources, since they are more likely to have complications and be mechanically ventilated for longer periods (Dasta et al. 2005; Weissman and Klein 2008). Hence, we hypothesize that duplicate test rate for emergency patients will be higher for emergency admissions compared to patients with elective admissions.

H3a. *Patients with emergency admission status will have higher duplication rates than patient with elective admission status.*

The source of patient admission can explain a major portion of the information availability at the time of a patient visit. In most cases, admission can either be a transfer from another facility or a physician referral. For instance, patient can be transferred from a nursing home or long-term care facility (Jones et al. 1997). When a patient is being transferred from a nursing home, important information on symptoms, including baseline functions and ongoing treatments, do not necessarily follow the patient during their visit to a physician (Brooks et al. 1994). Sometimes, patients have multiple comorbidities that are aggravated by the transfer which may further complicate assessment and treatment, resulting in over-treatment and misdiagnosis. Thus, the complicated nature of patient transfers may necessitate a certain level of duplicate tests and procedures. For physician referrals, we expect to see a lower rate of duplicate tests since the patient's prior information (including prior tests) can be available or accessible through the index source of the admission. Hence, we argue that patients who are transferred from other facilities are more likely to undergo duplicate tests compared to referral patients whose patient records are likely to be forwarded by the referring provider. Hence we hypothesize that:

H3b. *Transfer patients are more likely to exhibit a higher duplication rate compared to patients with a physician referral.*

Hospital Switching and Duplicate Tests

In order to investigate the consequences of hospital switching behavior of patients, it is important to consider the information asymmetry across disparate health providers. When a patient switches from one provider to another, the patient's prior health information must follow the patient in an ideal scenario. However, information flow distortion may arise in the form of barriers to information sharing, such as physical constraints or emergency needs. For example, patients may not recall the various providers locations at which they received care or providers may be reluctant to retrieve clinical information because it is cumbersome and time consuming (Johnson et al. 2011).[3] Other factors such as patients' inability to recall or communicate accurate clinical information, as well as logistical barriers stemming from fragmented medical data among hospitals, laboratories and medical offices (Overhage et al. 2002), may lead to further distortions in the patient's medical record.

When medical data is unable to move between different provider offices and healthcare systems, an increase in diagnostic or treatment errors can arise as a result of increased information asymmetry (Bates et al. 1998; LaBorde et al. 2011). For example, LaBorde et al. (2011) argues that patients transferred from one facility to another likely underwent duplicate diagnostic laboratory tests and other diagnostic studies due to lack of healthcare IT integration across facilities.[4] In the light of the prior evidence, we argue that the impact of hospital switching between providers on the incidence of duplicate testing emerges as an important phenomenon worthy of empirical investigation. This phenomenon is of importance to health IT policy makers in the context of the current debate on healthcare payment reform since it may help to justify the significant investments that are currently being made on health information exchanges (HIEs). Therefore, we hypothesize that when there is lack of information sharing across hospitals, patients' switching behavior (i.e. admission to a different hospital) across visits will result in an increase in duplicate testing.

H4. *The rate of duplicate testing when a patient is admitted to a different hospital (system) will be greater than when a patient is admitted to the same hospital (system)*

RESEARCH METHODOLOGY

Data and Variables

To test our conceptual research model, we obtain a comprehensive dataset of 39600+ Congestive Heart Failure (CHF) patient visits across outpatient clinics of 68 hospitals and 26 hospital 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). In this dataset we only included patients with CHF as the principal diagnosis, i.e., ICD9 code of "428.xx". In addition, we focus on outpatient admissions because patients receive radiology imaging procedures mostly in an outpatient setting (Lee et al. 2007, Lee et al. 2012). We use a time window of 90 days for an imaging

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[3] When a patient is admitted as an emergency case, the issue of retrieving historical medical data becomes more severe due to time constraints.
[4] Hillestad et al. (2005) argues that adoption of electronic medical records may lead to approximately $7.9 billion of efficiency savings by reducing the need for redundant lab and radiology tests.

test to be considered as a duplicate test in our analysis. This is because the typical life span of a radiological imaging test is about 3 months.[5] Since the duplication rate and switching event are calculated with respect to prior admission information, we exclude the index admissions in our analysis. Table 2 reports the descriptive statistics of our model variables.

Duplication Rate

In our data set, clinical information about the outpatient procedures is reported via the common procedure terminology (CPT) coding scheme. Since our focus is on measuring the duplication rate of outpatient imaging procedures, we use only the CPT codes related to X-rays, computed tomography (CT scans), magnetic resonance imaging (MRI) and ultrasounds.[6] For each patient's admission, we count the number of duplicate tests for each CPT code that appears in the current admission. Each of these CPT codes is matched against the CPT codes in all previous admissions that occur within the 90 days prior to the current visit. If the CPT code appears in any of the prior relevant admissions (i.e. ≤ 90 days), it is flagged as a duplicate procedure and counted towards the total number of duplicate procedures for the current admission. We then calculate the percentage of duplication as the ratio of the total number of duplicates to total number of all CPT procedures for the current admission. According to Table 2, the visit-level averages for duplication count, procedure count and duplication percentage are 0.18, 0.40 and 15.35% respectively. In addition, we report the top 10 procedures with the highest duplication rates in Table 4. We note that chest X-ray procedures demonstrate the highest duplication percentages at the admission level.

Hospital Switching

Two new variables are generated for hospital switching events. These variables are named as "Visit to different hospital" and "Visit to different (health) system". For readmissions, if the recent admission is to a different hospital (health system), then the value of "Visit to different hospital (health system)" is one, otherwise it is equal to zero. Accordingly, we report that 10% of all patient admissions are to different hospitals within 90 days, whereas this ratio is equal to 5% for switching across different health systems. We report the duplication rate with respect to patient behavior for switching across hospitals and health systems in Table 3. We observe that there are significant differences in the duplication rate between patients who are readmitted to the same hospital (system) versus those who switch across hospitals (systems). T-tests of the means of the two distributions show that the p-values are statistically significant at $p < 0.001$.

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[5] For instance, a majority of repeat radiological imaging tests happened in the first 2 months of initial examination as reported by Lee et al. (2007).

[6] The list consists of 417 unique CPT codes in total.

Patient Insurance

For each admission, the type of health insurance reported is tracked via the payer description information available in the data. Accordingly, 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 2013b). Because we are analyzing the duplication of procedures performed in an outpatient setting, we use Medicare Part-B as our baseline insurance type for hypothesis testing.

Patient Admission Type and Admission Source

Our data contains three admission types: Emergency/urgent, elective and other. As observed from Table 2, 16% of all admissions are classified as emergency admissions, while 55% of the admissions are elective (planned). Table 2 shows that 91% of admissions are physician referrals, while less than 1% of admissions are transfers from other facilities.

Controls

Additionally, we track patient-specific demographic information on patient gender (female or male), age, race (white or non-white), and zip code. We also obtained 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 hospital length of stay, which is defined as the number of days from the date of admission to discharge, patient distance to hospital (measured by using patient and hospital zip codes), total visit charges, an indicator for emergency department visit, and another indicator if a patient has been to the same hospital (or health system) before.

Model Specification

In this section, we describe our estimation model to study the factors that contribute to duplicate testing during a patient admission. Since we hypothesize that hospital switching is driven by patient- and hospital-specific factors, as shown in Figure 1, we estimate hospital switching using a logistic regression estimated model specified in equation (1) as follows:

$$Visit_{DiffHos_{it}} = \delta_0 + \delta_1 \log(PtHsDist_{it-1}) + \delta_2 \log(TotCharge_{it-1}) + Exogenous\ \delta_e + YearDummies\ \delta_y + \omega_{it} \quad (\mathbf{1})$$

where i denotes a patient and t denotes admission time index. $Visit\_DiffHos_{it}$ is measured as a binary variable and is equal to one if the patient is admitted to a different hospital (compared to the previous admission).[7]

For the duplication, since the dependent variable *DupPer* is calculated as a percentage, we treat it as a limited dependent variable, and use a two-limit Tobit regression as our estimation model which is expressed in Equation (2) (Maddala 1983):

$$\begin{aligned} DupPer_{it} = \beta_0 + \beta_1 Visit\_DiffHos_{it} + \beta_2 InsSelfPay_{it} + \beta_3 InsPrivate_{it} + \beta_4 InsOther_{it} \\ + \beta_5 InsMedicareA_{it} + \beta_6 InsMedicaid_{it} + \beta_7 TypEmergent_{it} + \beta_8 TypOther_{it} \\ + \beta_9 SrcTrans_{it} + \beta_{10} SrcOther_{it} + Controls\ \beta_c + YearDummies\ \beta_y + \epsilon_{it} \quad \mathbf{(2)} \end{aligned}$$

where ϵ_{it}'s are i.i.d. $\sim N(0, \sigma^2)$ and $Controls$ is a vector of variables consisting of *PtFemale, PtWhite, PtAge, log(PtHsDist), DaysSince, HsCMI, HsTeach, HsUrban, log(Hs_Beds),* and *EDVisit.*[8] In the second model, $log(PtHsDist_{it-1})$ and $log(TotCharge_{it-1})$ are excluded to satisfy the order condition for identification. For a consistency check we also perform the same analysis for health system variables.

To account for the possibility of correlation in the error terms across models (1) and (2), we estimate our models using the two-step maximum likelihood estimation rather than full information maximum likelihood estimation. Two-step estimation is numerically less complicated and more feasible than joint log-likelihood estimation of two models (Greene 2003). However, we need to adjust the covariance matrix of the second stage. Murphy and Topel (2002) propose a procedure to obtain consistent and asymptotically normally distributed asymptotic covariance matrix of the second stage regression parameters. Following their proposed methodology, we apply a logistic regression to obtain the predicted value of the endogenous variable $Visit\_DiffHos_{it}$. After obtaining the predicted probability values from the logistic regression-- $\widehat{VisitDiffHs}_{it}$, we plug this variable into Equation (2) and estimate the Tobit model by accordingly adjusting the second-step covariance matrix (Murphy and Topel 2002). Our approach also addresses the possibility of endogeneity between hospital switching behavior and duplicate testing.

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[7] The Exogenous vector $Exogenous_e$ represents exogenous variables in our model including Insurance, Admission Type, Admission Source variables as well as *PtFemale, PtWhite, PtAge, DaysSince, HsCMI, HsTeach, HsUrban, log(Hs_Beds),* and YearDummies which is a vector of year dummies from 2006 to 2012.

[8] Since insurance, admission type and admission source are categorical variables, their values are transformed into dummy variables. *InsMedicareB, TypElective, SrcRefer* are used to represent patient insurance type, admission type and admission source respectively.

RESULTS

We now present our results for hospital- and health system-level estimation. The two-step maximum likelihood estimation results are shown in Table 5 in which the first and third columns represent the logistic regression results, while the second and fourth columns represent Tobit regression results for hospital and health system switching, respectively. We also obtain data about the presence of imaging distribution services for hospitals from HIMSS Analytics for the years between 2006 and 2011. At the end of this section, we report preliminary descriptive results that will help us build an econometric model to explore the impact of health information exchanges on the duplicate testing.

Hospital Switching

Hypothesis 1a suggests that previous admission's total cost will increase the chances of hospital switching. The coefficient of *log(TotCharge_t-1)* is positive and significant at the 0.01 level suggesting that high values of *TotCharge_t-1* are associated with higher likelihood of switching. These results support our hypothesis 1a.

Hypothesis 1b suggests that longer patient-to-hospital distance will decrease patient satisfaction and therefore increase the likelihood of hospital switching. As expected, the log of distance to hospital resulted in significant and positive coefficient $\delta_2 = 0.266, p < 0.01$, which indicates that distance is positively associated with hospital switching event and 1% increase in the patient-to-hospital distance of previous admission will increase the odds ratio of switching hospitals by 30.4%, supporting Hypotheses 1b. For system switching, coefficient δ_2 is insignificant, therefore not supporting Hypothesis 1b.

Among the control variables, self-pay patients are more likely to switch systems than Medicare Part-B patients are. Private insurance patients are not significantly different from Medicare Part-B patients in either their hospital or system switching propensity. If a patient is admitted as an emergency, then she will have higher likelihood to switch to a different hospital (or system) than a patient with an elective or planned admission. In addition, we find that the likelihood to switch to a different hospital for transfer patients is higher than for referral patients. The likelihood of hospital switching by older patients is less compared to younger patients, as shown by the significant coefficient of -0.0146 at the 0.001 level. For hospital specific covariates, *HsCMI_t* and *HsUrban_t* have significant and positive impact on the log of odds of hospital switching event. On the other hand, *HsTeach_t* is negatively associated with hospital switching.

Duplication Rates

After incorporating the previously predicted switching probabilities into the second step, we correct the resulting covariance matrix of the Tobit regression (Murphy and Topel 2002). Regression results with corrected covariance matrix for the dependent variable *DupPer* are provided in columns two and four of Table 5. The pseudo R^2 values of hospital- and health system-level analysis are 0.193 and 0.196, respectively.

Hypothesis 2a posits that the rate of duplication of self pay patients will be higher than Medicare patients'. This hypothesis is not supported because the coefficient of *InsSelfPay* is not significant for hospital while it is negative and significant for system level analysis ($\beta_{2,sys} = -178.7, p < 0.01$). In addition, compared to Medicare Part-B patients, patients with a private insurance have significantly higher duplication percentage confirmed from the coefficient of *InsPrivate*: $\beta_{3,hosp} = 164.7, p < 0.05$ for hospital and $\beta_{3,sys} = 182.4, p < 0.05$ for system level, which support Hypothesis 2b. Furthermore, Hypothesis 3a proposes that patients with emergency admission status will have higher duplication rates compared to patients with elective admission status. However, we do not find support for Hypothesis 3a in both hospital and system level analyses. In addition, Hypothesis 3b postulates that a transferred patient will have higher duplication rate than a patient with a physician referral. Thus, coefficients both in hospital and system level are positive and significant ($\beta_{9,hosp} = 322.9, p < 0.05$, $\beta_{9,sys} = 421.5, p < 0.01$) showing that relative to physician referral admissions, transferred admission will have higher duplication percentage, supporting Hypothesis 3b. Consistent with Hypothesis 4, the Tobit results indicate a positive and significant association between duplication rate and switching event both at the hospital and system level ($\beta_{1,hosp} = 263.1, p < 0.10$ and $\beta_{1,sys} = 1394.6, p < 0.01$). Thus, we find that patients with higher likelihood of switching are also more likely to incur higher levels of duplicate tests, supporting Hypothesis 4. We summarize the results of hypotheses testing in Table 6.

Additional Analyses for Health Information Sharing

To further shed light on the impact of information sharing on duplicate testing, we directly examine if implementing information systems that enable health information sharing has a bearing on hospitals' duplication rate. We collected hospital level IT data from HIMSS Analytics database for six years between 2006 and 2011 (Bardhan et al. 2011). Initially, we only focused on five different measures of imaging distribution variable for each hospital in our data. These five (dummy) variables correspond to distribution of images: 1) to critical care unit (CCU), 2) to emergency room (ER), 3) to intensive care unit (ICU), 4) to operating room (OR), and 5) over Web. For each year and for each hospital we created one combined variable measuring the intensity of imaging distribution across various medical units. If a hospital at a year possesses at least four out of these five imaging distribution variables, we assign a value of 1 to the combined imaging distribution variable and 0 otherwise. We report the percentage of hospitals who are assigned 1 to the combined imaging distribution variable, as well as the percentage of hospitals who answered 'yes' to these five imaging distribution questions in Table 7. Overall, our combined variable follows the same increasing trend over years as its five precedent question variables. That is, more and more hospitals in our dataset started implementing distribution of images to various locations over time.

We observed three groups of hospitals with respect to the presence of imaging distribution services to various locations. First group of hospitals always had imaging distribution services between 2006 and 2011 while the second group of hospitals never implemented imaging distribution services during the same period. The hospitals that started using imaging distribution services any year between 2006 and 2011 formed the third group. Next, we compared the yearly average duplication rate of admissions of these three different groups of hospitals in Table 8. Our results indicate that the difference in the duplication rate of group-2 and group-3 is statistically significant (t-tests on mean difference) across all years.[9] Surprisingly this result shows that hospitals who implement imaging distribution services in the middle of the six year span had lower duplication rate compared to those already had imaging distribution services in place before 2006. We conjecture that self-selection plays a role here: those hospitals in group-2 who implemented imaging distribution systems earlier than 2006 may well be those who need such systems most to reduce duplication or they may had impetus other than reducing duplication rates before 2006 to implement such systems. In addition, the overall duplication (Column All) for group-1 is statistically higher than the overall duplication rate of group-3 with a p-value of 0.015. We also report the overall duplication rate of hospitals in group-3 for pre and post periods of implementation of imaging distribution services.[10] Most interestingly, according to the Table-9, hospitals' average duplication rates drop after the implementation of imaging distribution services, which is significant with a p-value of 0.03.

These preliminary descriptive statistics about the implementation of imaging distribution services give us a good foundation to explore the impact of health information exchanges on the

[9] We observe low number of admissions for the first group over the years. Therefore, it is difficult to make any comparison between group-1 and group-2 or group-1 and group-3.
[10] Since the year each of these hospitals implements imaging distribution services are different, we cannot specify a fixed year cutoff for other groups of hospitals.

duplication rate, since these imaging distribution services are foundational for health information exchanges.

CONCLUSIONS

Findings

This paper examines the factors leading to duplicate imaging procedures and investigates whether hospital switching (or health systems) is a significant contributor to duplicate tests. Our results show that patients who switch hospitals are more likely to undergo higher duplicate tests than patients who do not. This may be directly driven by the fact that hospitals are still unable to share medical information. Insurance type is also found to be a significant contributor to high duplication rates. Private insurance patients are likely to incur higher duplication rates compared to Medicare patients. However, we do not find any significant difference in duplication rates between self-pay patients and Medicare patients at the hospital level analysis whereas self-pay patients would have lower duplication rates compared to Medicare patients at the health system level analysis. One explanation suggests that these self-pay patients are being informed by the provider whether or not they are willing to undergo a testing procedure. Hence, providers cannot exercise over-utilization of testing procedures on informed self-pay patients. For private insurance patients, result suggests that hospitals may try to over-utilize the most profitable patients because there is a big "profit margin gap" per procedure between the reimbursement rate of Medicare patients and the charged price to private insurance patients, who have low bargaining power over the pricing of the procedures.

We do not detect any significant effect of emergency admission type on the amount of duplicate tests relative to the effect of elective admission type. One possible explanation can be attributed to the domain of our analysis, i.e. outpatient admissions. In other words, for outpatients, risk-averse providers are willing to perform all the tests required for the treatment of patient, regardless of whether they are emergency or elective admissions. Another line of thought suggests that medical data of elective (planned) patients due to lack of information sharing may not be retrieved at the time of admission which may explain why we do not see any difference between emergency and elective admissions' duplication rates. We show that likelihood of duplicate tests is much higher for transfer patients than for physician referrals.

Our results also suggest that patients tend to switch hospitals as charges increase (on their previous admission). This finding suggests that patients can become price-sensitive if total charges increase above a threshold. Consistent with our hypotheses, distance is a significant determinant of hospital switching behavior. This is because longer distances can reduce the utility obtained from a treatment process.

Implications

To the best of our knowledge, our study represents one of the first attempts to empirically explore the antecedents of duplicate tests 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 we include economic incentives as well as hospital admission and health status of patients. Since duplicate tests represent a significant portion of the inefficiency in the U.S. healthcare system, balancing economic incentives among patients, providers and insurance companies may result in improved efficiencies through better allocation of resources, i.e., utilization of imaging equipments in our context. Lower margins of Medicare reimbursements may cross-impact the amount charged to private insurance patients. Transfer patients and hospital switching also raise concerns regarding information asymmetry across disparate stakeholders in the healthcare environment. Furthermore, similar to customers in service industries, patients may try to avoid high costs and switch to a different hospital if their medical bills are too high. Hospital location or inconvenience can also impact the hospital switching decision of patients. Our results imply that health systems should try to serve rural areas through better accessible outpatient facilities.

Implications for Health Information Exchanges

In this research we show that information asymmetry caused by hospital switching intentions of patients can increase the waste produced in the U.S. healthcare system. We argue that if hospitals were able to communicate through a common IT infrastructure, they can share patient medical history even when patients switch hospitals and consequently reduce the extent of redundant testing. One possible solution to this issue could be to promote implementation of Health Information Exchanges (HIE) nationwide. Forecasts suggest that enabling better information transparency and increasing information availability, HIEs can reduce significant portion of waste and inefficiencies in U.S. healthcare system (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 overall cost of duplicate imaging tests for CHF patients amounts to $1,120,914 in the North Texas region, with an average cost of $649.43 per imaging procedure and 1,797 duplicate procedures. In this study, we only focus on admission of CHF patients to outpatient clinics and impose a time window of 90 days to define the incidence of duplication and hospital switching. Therefore our cost calculation is on the conservative side. According to Walker et al. (2005), net savings from HIE implementation can reach up to $77.8 billion annually, if a national fully standardized interoperability was established between providers and other types of organizations, such as Laboratories, radiology centers, pharmacies, payers and public health departments. Walker et al. (2005) show 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. As mentioned by Vest and Gamm (2010), HIEs can benefit rural patients, physicians, and hospitals if there is a need to exchange information about rural patients' with urban specialists or hospitals, which can ensure effective management and quality of care. Thus, our research complements the aforementioned benefits of HIE by actually showing that lack of information sharing and existence of information asymmetry can lead to waste production in the form of high levels of duplicate testing. Therefore, our research also addresses the call from Dixon et al. (2010) who highlight the rarity of published studies for evaluating the business case for HIEs.

Limitations and Future Work

We report several limitations of this study. First, we do not have any procedural information that can identify a duplicate procedure as truly redundant or a required one. However, we contend that constraining the life span of imaging procedures to 90 days could serve as a baseline for classifying procedures as redundant (duplicate) or not, based on our communications with cardiology specialists. Second, our results only reflect the duplication rates of imaging procedures and their antecedents for outpatients having 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. Third, the decision maker for ordering tests is primarily the physician, and our approach does not take into account physician- specific attributes such as number of physicians in the hospital, physician fatigue or physician experience. However, hospital bed size and case mix index can proxy for some of the variations that can explain these physician-specific attributes.

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TABLES and FIGURES

Table 1. Utilization of Imaging Procedures in the US and OECD Countries

	United States	U.S. Rank Compared to OECD countries	OECD Average
MRI Units	**31.6** per million	2nd	**12.5** per million
MRI Exams	**97.7** per 1000	2nd	**46.3** per 1000
CT Scanners	**40.7** per million	3rd	**22.6** per million
CT Exams	**265.0** per 1000	3rd	**123.8** per 1000

Source: OECD Health Data 2012

Figure 1 Conceptual Research Model

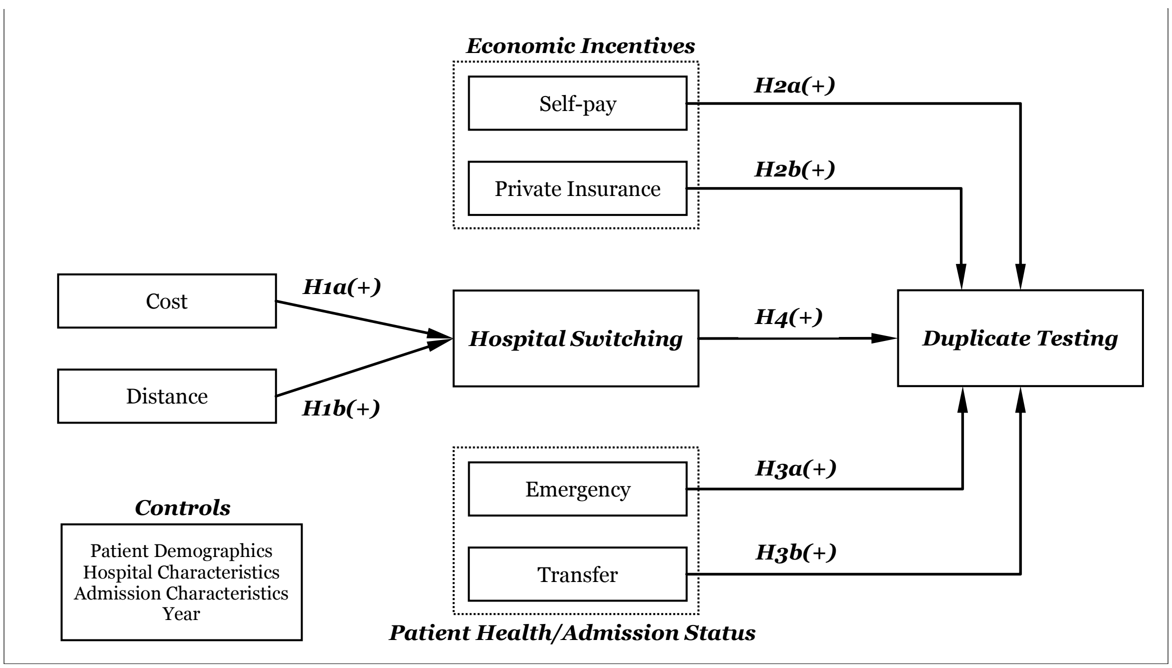

Table 2. Descriptive Statistics of Variables

Variable	Variable Definition	Dimension	Mean	Std Dev	Min	Max
DupPer	*Duplicate Procedures (percentage)*	%	15.35	35.1	0	100
DupAbs	*Duplicate Procedures (absolute)*	*Count*	0.18	0.44	0	6
NumProc	*Number of Procedures*	*Count*	0.4	0.75	0	10
Visit_DiffHos	*Binary (1 = if Visit to Different Hospital)*	*0 or 1*	0.1	0.3	0	1
Visit_DiffSys	*Binary (1= if Visit to Different Health System)*	*0 or 1*	0.05	0.21	0	1
DaysSince	*Days Between Consecutive Visits*	*days*	23.13	25.28	0	90
Days_Hos	*Days Between Hospital Switching*	*days*	24.58	27.38	0	90
Days_Sys	*Days Between System Switching*	*days*	36.79	26.82	0	90
Pt_Female	*Binary (1 = if Patient Gender: Female)*	*0 or 1*	0.52	0.5	0	1
Pt_White	*Binary (1 = if Patient Race: White)*	*0 or 1*	0.65	0.48	0	1
Pt_Age	*Patient Age*	*Continuous*	67.75	16.87	1	90
Pt_HosDist	*Patient Hospital Distance*	*miles*	12.15	27.3	0	545.1
Hs_CMI	*Hospital Case Mix Index*	*Continuous*	1.67	0.26	0.93	3.08
Hs_Teach	*Binary(1 = if Hospital: Teaching)*	*0 or 1*	0.4	0.49	0	1
Hs_Urban	*Binary(1 = if Hospital: Urban)*	*0 or 1*	0.66	0.47	0	1
Hs_Beds	*Number of Hospital Beds*	*Continuous*	491.38	304.97	0	1029
SrcRefer	*Binary(1 = if Admission Source is Physician Referral)*	*0 or 1*	0.91	0.29	0	1
SrcTrans	*Binary(1 = if Admission Source is Transfer)*	*0 or 1*	0	0.05	0	1
SrcOther	*Binary(1 = if Admission Source: Other)*	*0 or 1*	0.09	0.28	0	1
TypEmergency	*Binary(1 = if Admission Type: Emergency/Urgent)*	*0 or 1*	0.16	0.36	0	1
TypElective	*Binary(1 = if Admission Type: Elective)*	*0 or 1*	0.55	0.5	0	1
TypOther	*Binary(1 = if Admission Type: Other)*	*0 or 1*	0.29	0.45	0	1
InsPrivate	*Binary(1 = if PayerDesc: Private)*	*0 or 1*	0.03	0.16	0	1
InsMedicaid	*Binary(1 = if PayerDesc: Medicaid)*	*0 or 1*	0.06	0.24	0	1
InsMedicareA	*Binary(1 = if PayerDesc: Medicare Part A)*	*0 or 1*	0.45	0.5	0	1
InsMedicareB	*Binary(1 = if PayerDesc: Medicare Part B)*	*0 or 1*	0.18	0.39	0	1
InsSelfPay	*Binary(1 = if PayerDesc: Self Pay)*	*0 or 1*	0.07	0.26	0	1
InsOther	*Binary(1 = if PayerDesc: Other)*	*0 or 1*	0.2	0.4	0	1
TotCharge	*Total Charges in dollars*	*$ 1000s*	3.36	14.45	0	210.87
EDVisit	*Binary (1 = if Emergency Dept Visit)*	*0 or 1*	0.23	0.42	0	1

Table 3. Duplicate Imaging Test Rates in Hospitals and Health Systems

		Hospital		Health System	
Switching Event	**Stat**	**Duplication (%)**	**Duplication (abs)**	**Duplication (%)**	**Duplication (abs)**
Admitted to same hospital (health system)	**Avg**	**14.24**	**0.17**	**14.93**	**0.18**
	Std	34.02	0.41	34.74	0.44
	N	8484	8484	8957	8957
Admitted to diff hospital (health system)	**Avg**	**25.62**	**0.33**	**23.84**	**0.28**
	Std	42.46	0.63	40.82	0.47
	N	919	919	446	446
Mean t-test	***Pr>|t|***	**0.000**	**0.000**	**0.000**	**0.000**

Table 4. Duplication Rate for Top 10 Imaging Procedures

	By Admission			By Patient		
CPT Description	**Total**	**Duplicate**	**%**	**Total**	**Duplicate**	**%**
Radiologic examination, chest; single view, frontal	1428	970	67.93%	1076	708	65.80%
Radiologic examination, chest, 2 views, frontal and lateral;	1036	558	53.86%	845	449	53.14%
Echocardiography, transthoracic, real-time with image documentation (2D), includes M-mode recording, when performed, complete, with spectral Doppler echocardiography, and with color flow Doppler echocardiography	217	60	27.65%	204	56	27.45%
Echocardiography, transthoracic, real-time with image documentation (2D), includes M-mode recording, when performed, complete, without spectral or color Doppler echocardiography	148	21	14.19%	137	19	13.87%
Doppler echocardiography color flow velocity mapping	135	19	14.07%	124	17	13.71%
Doppler echocardiography, pulses wave and/or continuous wave with spectral display;	124	14	11.29%	116	13	11.21%
Computed tomography (CT), thorax; with contrast material(s)	38	10	26.32%	34	9	26.47%
Duplex scan of extremity veins including responses to compression and other maneuvers; complete bilateral study	50	8	16%	48	8	16.67%
Echocardiography, transthoracic, real-time with image documentation (2D), includes M-mode recording, when performed, follow-up or limited study	31	7	22.58%	28	7	25%
Computed tomographic angiography, chest (noncoronary), with contrast material(s), including noncontrast images, if performed, and image postprocessing	48	5	10.42%	47	5	10.64%

Table 5. Two-step ML Estimation Results for Hospital and System Switching

	HOSPITAL		***HEALTH SYSTEM***	
	Model 1: Logistic Visit_DiffHs	***Model 2: Tobit DupPer***	***Model 1: Logistic Visit_DiffSys***	***Model 2: Tobit DupPer***
Intercept	-9.793*** (0.723)	-847.5*** (174.9)	-7.104*** (0.920)	-945.3*** (189.6)
Pr(Visit_DiffHos$_t$)		263.1* (151.3)		
Pr(Visit_DiffSys$_t$)				1394.6*** (270.2)
InsSelfPay$_t$	0.315** (0.157)	-56.29 (50.14)	0.869*** (0.208)	-178.7*** (63.92)
InsPrivate$_t$	-0.175 (0.282)	164.7** (75.67)	-0.605 (0.511)	182.4** (80.39)
InsOther$_t$	-0.107 (0.123)	156.4*** (36.35)	0.291 (0.187)	132.2*** (40.30)
InsMedicareA$_t$	-0.330*** (0.124)	-61.64* (34.98)	0.403** (0.191)	-108.8*** (39.12)
InsMedicaid$_t$	0.238 (0.180)	198.9*** (53.09)	0.622*** (0.227)	126.0** (62.91)
TypEmergency$_t$	1.394*** (0.113)	16.41 (46.31)	1.291*** (0.152)	-32.83 (47.26)
TypOther$_t$	0.986*** (0.109)	-41.97 (39.56)	0.950*** (0.166)	-73.64* (42.21)
SrcTransfer$_t$	0.992* (0.506)	322.9** (158.2)	-1.015 (1.083)	421.5*** (142.8)
SrcOther$_t$	-0.325* (0.184)	-244.0*** (56.48)	-0.190 (0.244)	-215.0*** (61.76)
PtFemale$_t$	-0.0970 (0.080)	-54.40** (22.19)	-0.110 (0.107)	-47.89* (24.53)
PtWhite$_t$	-0.0656 (0.089)	58.60** (25.78)	-0.470*** (0.122)	103.4*** (30.33)
PtAge$_t$	-0.0146*** (0.003)	1.614* (0.911)	-0.0187*** (0.004)	2.563** (1.005)
log(PtHsDist$_{t-1}$)	0.266*** (0.039)		-0.0539 (0.055)	
DaysSince$_t$	-0.006*** (0.002)	-0.519 (0.460)	0.009*** (0.02)	-1.700*** (0.549)
HsCMI$_t$	2.730*** (0.200)	199.6** (84.83)	0.193 (0.308)	255.6*** (74.36)
HsTeach$_t$	-1.633*** (0.148)	-58.71 (50.43)	0.00439 (0.201)	-114.7** (46.07)
HsUrban$_t$	3.074*** (0.296)	66.60 (43.00)	1.683*** (0.321)	72.27* (43.93)
log(HsBeds$_t$)	-0.0848 (0.063)	-63.54*** (19.16)	-0.0177 (0.097)	-68.32*** (20.85)
log(TotCharge$_{t-1}$)	0.177*** (0.024)		0.341*** (0.039)	
EDVisit$_t$		922.7*** (63.95)		881.0*** (62.59)
_Sigma		601.4*** (35.62)		597.5*** (35.41)
LogLikelihood	-2216.60	-5036.49	-1397.45	-5018.11
Pseudo R2	0.264	0.193	0.221	0.196
Model p-value	0.000	0.000	0.000	0.000
N	9403	9403	9403	9403

Standard errors in parentheses
Time fixed effects are included
Murphy/Topel correction applied for Tobit models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Summary of Hypotheses Testing

HYPOTHESES	HOSPITAL	SYSTEM
H1A: (+ assoc.) Cost →Hospital (System) Switching	*Supported*	*Supported*
H1B: (+ assoc.) Distance → Hospital (System) Switching	*Supported*	Not supported
H2A: (+ assoc.) Self-pay Insurance → Duplicate Testing	Not supported	Not supported
H2B: (+ assoc.) Private Insurance → Duplicate Testing	*Supported*	*Supported*
H3A: (+ assoc.) Emergency → Duplicate Testing	Not supported	Not supported
H3B: (+ assoc.) Transfer → Duplicate Testing	*Supported*	*Supported*
H4 : (+ assoc.) Hospital (System) Switching → Duplicate Testing	*Supported*	*Supported*

Table 7. Percent of Hospitals where Images are distributed across Locations

Variable	2006	2007	2008	2009	2010	2011
Image distributed to CCU	36.8%	52.9%	60.3%	67.6%	75.0%	76.5%
Image distributed to ER	47.1%	61.8%	76.5%	82.4%	86.8%	89.7%
Image distributed to ICU	44.1%	55.9%	73.5%	80.9%	82.4%	82.4%
Image distributed to OR	38.2%	58.8%	75.0%	82.4%	83.8%	86.8%
Image distributed over Web	41.2%	57.4%	76.5%	83.8%	86.8%	89.7%
Combined image distribution	**41.2%**	**55.9%**	**69.1%**	**77.9%**	**80.9%**	**83.8%**

*Numbers represent the percentage of hospitals who answered yes to the implementation of the corresponding imaging distribution question

**Total number of hospitals is 68 for each year

Table 8. Percent Duplication for Three Groups of Hospitals over Years

Group Name		Year						
		2006	**2007**	**2008**	**2009**	**2010**	**2011**	**All**
Group-1 NOT IMPLEMENTED	**Mean %**	6.25	27.59	14.22	19.57	30.43	25	**20.2**
	StdDev	25	45.49	34.73	39.14	47.05	42.87	**39.7**
	N	16	29	51	23	23	18	**160**
Group-2 ALL YEARS IMPLEMENTED	**Mean %**	27.6	24.69	23.86	18.4	29.23	19.15	**22.4**
	StdDev	42.3	41.59	41.33	36.51	42.95	38.13	**39.9**
	N	230	272	298	387	282	843	**2312**
Group-3 IMPLEMENTED OVER TIME	**Mean %**	19.03	16.77	14.46	12.46	8.61	8.98	**12.4**
	StdDev	38.73	36.5	34.41	32.72	27.71	27.9	**32.35**
	N	865	614	860	979	1515	1395	**6228**
Mean T-Tests (P values)	**1 vs 2**	**0.005**	**0.725**	**0.116**	**0.882**	**0.898**	**0.521**	**0.501**
	1 vs 3	**0.189**	**0.124**	**0.961**	**0.306**	**0.037**	**0.132**	**0.015**
	2 vs 3	**0.004**	**0.007**	**0.000**	**0.005**	**0.000**	**0.000**	**0.000**

Table 9. Duplication Rate of Group-3 Hospitals for Pre and Post Implementation Periods

Group Name		Pre-Imp	Post-Imp	Mean t-test
Group-3 IMPLEMENTED OVER TIME	**Mean**	15.72	12.13	p-value = 0.03
	StdDev	35.99	32.08	
	N	396	5832	